Electric Vehicle Subsidies: Cost-Effectiveness and Emission Reductions

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Abstract

This paper studies the environmental performance of electric vehicle subsidy programs in Canada. I leverage changes in the provincial-level subsidies to study their short-run impact on sales and charging station deployment using a natural experiment setting. My findings suggest that subsidies are very effective at increasing electric vehicle adoption, but failed to induce additional charging station installations in the short-run. To evaluate the environmental impact of subsidies, I rely on a structural estimation of the demand for cars and the supply of charging stations. My results suggests that Canadian rebate programs led to an increase in adoption of 93%, and an increase in the size of the charging station network of 19%. I take these results as additional evidence of weak network effects. I propose a unified framework to conduct a cost-benefit analysis. I estimate the marginal cost of abating carbon emissions to be between \$311 and \$423 per ton, well above conventional estimates of the social cost of carbon. Part of the reason behind these high estimated costs is that half of the subsidies went to inframarginal consumers who would have purchased an electric vehicle whether or not rebates are available. Finally, I evaluate the performance of two alternative policies: an income threshold on eligibility and a cash for clunker program. I find that the additional emission reductions tied to the removal of clunkers are crucial for improving the environmental performance of rebate programs. JEL Codes: L, L91, L98, Q5, Q58.

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1 Introduction

Electric vehicles 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 purchase cost or the low availability of charging locations 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 electric vehicle. If demand for these vehicles is low, there is little incentive for charging station operators to expand local networks of charging stations, or for car manufacturers to develop better and cheaper products, slowing down the transition to electric.

In an effort to break this chicken-and-egg problem, policymakers introduced a wide range of incentives to convince consumers to adopt this new technology. Perhaps the most common intervention is to subsidize the purchase of an electric vehicle directly, which helps close the price gap between fuel and electric vehicles. One narrative in support of financial incentives is that they generate additional electric vehicle sales beyond the initial recipients through strong network effects. New electric vehicle owners increase the total demand for charging, which leads to a larger charging station infrastructure. Since consumers care about being able to charge on the go, a larger network should lead to more electric vehicle adoption, potentially at no cost to the government once the rebate program is phased out.

This paper focuses on the introduction of the electric car in Canada and on the role of financial incentives in speeding up the adoption of this new technology. I evaluate whether subsidizing electric vehicles is a cost-effective way to reduce emissions from the transportation sector, which accounted for 22% of all Canadian greenhouse gas emissions in 2021.[1] Whether or not subsidizing electric vehicles is cost-effective depends crucially on several factors: how fuel-efficient are the vehicles that are being replaced by electrics, and on the magnitude of the network effects, since the deployment of charging stations depends on electric vehicle adoption and vice versa. I focus this study around two Canadian provinces, Quebec and Ontario, which together account for 65% of the country's population. Both offered generous subsidies (around \$8,000–\$8,500) to new electric vehicle owners as early as 2010, right when the technology was made available. Moreover, electricity production in these provinces is almost exclusively emission-free. This provides a clean setup to study emission abatement.

In the first part of the paper, I leverage the fact that Ontario's rebate program was

[1]Source: Environment and Climate Change Canada.

substantially changed twice between 2012 and 2020 to analyze the short-run impact of rebates on electric vehicle adoption and charging stations deployment. My results suggest that raising rebates by $1,000 is associated with a 7.7% increase in electric vehicle sales. This is similar in magnitude to findings by Muehlegger and Rapson (2018), who estimate the impact of financial incentives on electric vehicle adoption in California using a quasi-experimental setup. I also analyze the indirect effect of electric vehicle subsidies on charging station deployment. I find no evidence that the policy changed the network configuration in the short-run. I also find no evidence that local networks changed along other dimensions, for example, in terms of the number of chargers per station, the share of fast charging station, or the share of public stations available. These findings together suggest that network provision is rigid in the short-run and cannot be adjusted to satisfy an unpredicted surge in demand for charging from new electric vehicle owners. To the best of my knowledge, this is a new result in the literature.

The second part of the paper is devoted to studying the environmental performance of Quebec's electric vehicle rebate program. I propose a structural approach to address this important question. I model demand for cars following the random coefficient specification in Berry et al. (1995), which allows for consumers to have heterogeneous tastes for car characteristics. Following Nevo (2001), I augment the model with county-level demographics which I interact with car characteristics.[2] I find that these demographic interactions help with the identification of random coefficients in the absence of a supply side.

I propose a flexible model to explain network supply, in the spirit of Springel (2021) and Berry and Reiss (2007). I adapt these methodologies to mirror the Quebec market, where county-level governments are responsible for the provision of a public charging infrastructure in their region. My specification allows for very flexible patterns for both the supply and the elasticity of supply of stations. To fix ideas, the model allows for the elasticity of supply to vary non-linearly with the characteristics of each market, producing more realistic and varied supply curves across regions and over time.

I conduct a counterfactual analysis to validate the findings from the difference in differences analysis. I find that electric vehicle rebates led to a 93% increase in sales of electric vehicles in Quebec between 2012 and 2020. This translates to a 10.8% increase per $1,000 in subsidies. Meanwhile network size increased by 19% over the same period. I interpret these findings as evidence of weak network effects in the long-run. This is in sharp contrast with the literature which instead provides evidence that network effects are important in

[2]See also Gandhi and Houde (2019) and Lesellier et al. (2023).

electric vehicle markets.[3] This could be a unique feature of the Canadian market. The significant involvement of the public sector in the provision of stations could explain this finding. In other countries, the development of a charging station infrastructure is typically left to private operators which have a stronger incentive to compete for new consumers.

I construct a flexible framework to study the environmental performance of the Canadian rebate programs. I consider the case of a social planner who maximizes social welfare taking into account the environmental externalities tied to emissions from new car sales. I use this framework along with the structural model primitives to conduct a rigorous cost-benefit analysis. My findings suggest that the marginal abatement cost of emissions is between \$311 and \$423 per ton of CO_2 at the current rebate levels. This is above conventional measures of the social cost of carbons, which suggest an over-investment on subsidies beyond what is optimal. A competing explanation is that policymakers are instead internalizing future carbon emission savings not captured by the model, for example, once the program is phased out. Evaluating these future gains is difficult in practice, and outside the scope of this work.

One of the reason that explains these high costs is that the program subsidized a large number of infra-marginal consumers. I find that 52% of electric vehicle owners would have purchased an electric vehicle without incentives. The program also led to a modest increase in total sales of vehicles, which means that the rebates induced some consumers to substitute from the outside good. This does not generate emission reductions, therefore lowers effectiveness. I propose two alternative policies to improve on the current policy. First, I try to improve targeting by restricting the eligibility to the program to consumers with a high price sensitivity. In practice, this could be implemented with a simple income threshold, if price sensitivity correlates with income. Second, I attach eligibility to a cash clunker condition. While this does not help with targeting, removing old vehicles generates additional emission savings which lowers the marginal cost of abatement.

I find that restricting access to the program typically does not improve cost-effectiveness and lead to lower electric vehicle sales. Since consumers preferences vary along several dimensions, it is very difficult in practice to select a simple criterion that accurately targets the marginal consumers. On the other hand, the cash for clunker program is more effective at reducing emissions than current rebates for virtually any level of government spending. It yields however the lowest electric vehicle adoption rate. These findings raise an interesting question about policy design: it is clear from my findings that setting targets in terms of electric vehicle adoption (as is done in Quebec) does not produce the best environmental

[3] See for example Li et al. (2017), Springel (2021), or Remmy (2022).

outcome.

Related literature. This paper contributes to the literature on several fronts. First, I contribute the the growing literature that studies electric vehicle markets. Notable contributions include Li et al. (2017) and Springel (2021) on network effects, Remmy (2022) on driving range provision, Li (2023) on compatibility across networks, Armitage and Pinter (2021) on electric vehicle mandates, Dorsey et al. (2022) on the impact of fuel prices on electric vehicle adoption, and Johansen and Munk-Nielsen (2020) on the synergy between fuel and electric vehicles within a multi-car household. Tsanko (2023) studies the environmental benefits of subsidizing plug-in hybrids when consumers do not recharge them optimally. Closest to this research is the work by Xing et al. (2021) who show that estimating precise substitution patterns is crucial to estimate the impact of electric vehicle subsidies on the environment. Other works have studied the environmental performance of subsidies (Beresteanu and Li, 2011; d'Haultfoeuille et al., 2014; Huse and Lucinda, 2014; DeShazo et al., 2017) or electric vehicle rebates passthrough (Beresteanu and Li, 2011; Sallee, 2011; Muehlegger and Rapson, 2018).

This paper fits in the wider literature that studies the environmental regulation of the car market. Several works have focussed on other policy tools such as gas taxes (Allcott and Wozny, 2014; Barla et al., 2016; Grigolon et al., 2018), emission standards (Klier et al., 2013; Durrmeyer and Samano, 2018; Reynaert, 2021), cash for clunker programs (Li et al., 2013; Grigolon et al., 2016; Li et al., 2022; Kitano, 2023), attribute-based regulation and taxation (Knittel, 2011; Ito and Sallee, 2018; Chaves, 2019), or comparing financial and non-monetary incentives (Jenn et al., 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, and Archsmith et al. (2015) and Muehlegger and 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 (Pavan, 2017; Li et al., 2017; Springel, 2021; Remmy, 2022; Li, 2023), compact discs (Gandal et al., 2000), video games (Clements and Ohashi, 2005; Corts and Lederman, 2009), software (Gandal, 1995), microcomputer chips (Gandal et al., 1999), and personal digital assistants (Nair et al., 2004).

The rest of the paper is organized as follows. Section 2 provides background information on the Canadian electric vehicle market, and the data. Section 3 studies the short-run effect of subsidies on electric vehicle sales and charging station deployment. I describe a structural model of demand for cars and the supply of a charging station infrastructure in section 4. Estimation and counterfactual results are presented in section 5. Finally, I conduct a rigorous cost-benefit analysis in section 6 to assess the environmental performance of subsidy programs. Section 7 provides concluding remarks.

2 The Canadian Market for Electric Vehicles

2.1 Policy environment

2.2 Data

To estimate the environmental performance of subsidies, I assemble a novel and rich dataset of all car registrations and charging stations available in Ontario and Quebec between 2012. The data is aggregated at the county level, following Statistics Canada Census Divisions. Markets are defined as a county-year combination. I choose this level of aggregation for two reasons. First, counties capture relatively well the day to day commuting area of car owners: about 72% of them work within their county of residence. Also, county-level governments are large contributors to networks, which reinforces the idea that decisions about network provision are made at the level of the county, at least for a good part of the network.

The data on car registrations comes from two sources: the Ministry of Transportation of Ontario, and the Société d'Assurance Automobile du Québec. The Ontario dataset is constituted of aggregated sales by make, model, engine type, county, year, and quarter. The Quebec dataset is recorded at the individual level, and contains additional informations which are useful to the analysis such as owners' demographics (age, gender, county of residence) and a limited number of car characteristics (cylinder capacity, curb weight, color).

I match this data with car characteristics obtained from The Car Guide. The Car Guide collects and shares comprehensive information on cars through their website, and is one of the leading references in the country. Their data includes the list price, performances, fuel economy, emissions per kilometre, and the physical attributes of currently available and past models sold in Canada.

The data on charging stations comes from Natural Resources Canada and Hydro-Quebec. They contain the exact geographical location of each station, the entry date, the operator's name, pricing, and relevant physical attributes (the type of station, the number of chargers, public vs privately owned).

I complement these datasets with data from various other sources. Information on gas prices and gas stations are obtained from the Régie de l'Énergie. Consumer demographics are taken from the Canadian Census Survey, the Institut de la Statistique du Québec, and Election Canada. Additional details on the data are available in Appendix B.

3 The Short-run Impact of Rebates

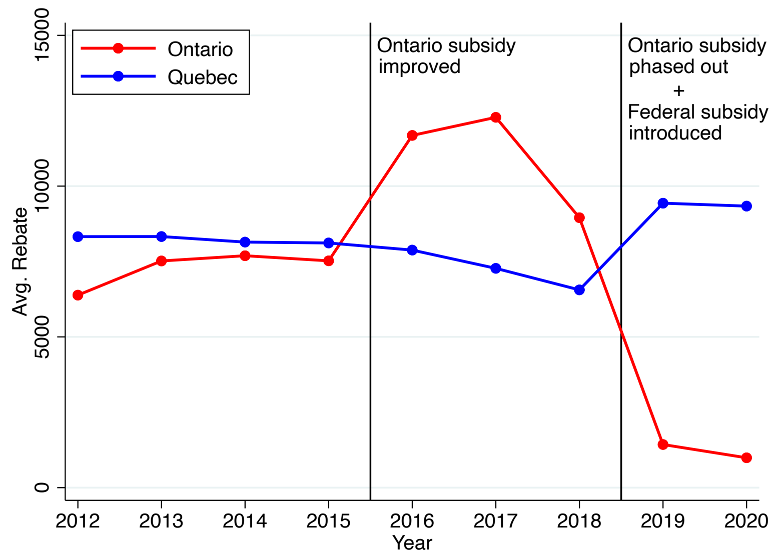
3.1 Setup

The Canadian market provides an ideal setup to study the short-run impact of electric vehicles subsidies using a difference in differences analysis. I leverage the fact that Ontario saw two changes in its electric vehicle rebate program to study the effect of rebates on electric vehicle adoption and on charging station deployment. Meanwhile, electric vehicle subsidies have been stable in Quebec which provides me with an adequate control group.

Figure 1 depicts the average rebate received by consumers of each province between 2012 and 2020. Initially, both province had very similar rebate programs. I will refer the period from 2012 to 2015 as the pre-treatment period. We observe a first policy shock in 2016 when Ontario's rebate program was substantially increased, then a second policy shock at the end of 2018 when Ontario's program was phased out. The federal rebate program was introduced in early 2019. Since the phasing out of Ontario's program and the introduction of the federal programs occurred in a short time window, I will consider them as a single policy shock. I will refer to these periods as the first and second post-treatment periods.

Similarly to the vast majority of studies that rely on a natural experiment for identification, it is important to discuss the potential endogeneity of these policy changes. Muehlegger and Rapson (2018) describe best the threat to the identification of a causal effect between subsidies and electric vehicle adoption. Their main point is that states are more likely to offer an incentive if the population they represent is predisposed to purchase an electric vehicle, which leads to the endogeneity issue. There is some anecdotal evidence that points in that direction: the government in Ontario significantly increased rebates because adoption of electric vehicles was low compared to other provinces. In this case, endogeneity would arise from a negative correlation between consumers and the policymaker's preferences. The program was discontinued after Ontario exited the Canadian carbon market, which cut the main source of funding for subsidies. In this case, there is more chance that the change was exogenous.

Figure 1: Average rebate by province



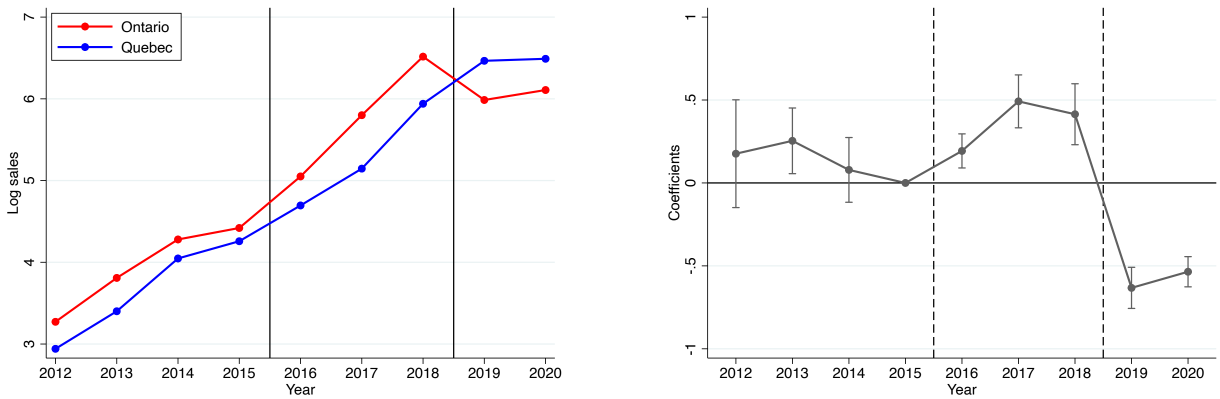
It is very hard in practice to test the exogeneity assumption. The analysis is performed at the county level. This plays the double role of avoiding selection into treatment, but also differences across counties make it less likely that the policy correlates with the outcomes since it is defined at the provincial level. I include several county-level demographics and a rich set of fixed effects to control as best as possible for the potential unobserved factors that could bias my estimates. Summary statistics are available in Table A.1. There are some significant differences between the two provinces, especially in terms of household income which is much higher in Ontario. This is mitigated by the fact that housing costs are also much higher in Ontario than in Quebec. Ontario residents are also on average more educated, more conservative, more likely to be homeowners, and more likely to belong to a visible minority group. Finally, Ontario counties are on average three times as populous as Quebec counties.

3.2 Effect on sales

I first consider the effect of rebates on electric vehicle sales. The dependent variable is the number of registrations by county-year. Figure 2a plots the raw data averaged over counties by province and year while Figure 2b reports the coefficients from an event study specification.[4] I observe a similar trend in the pre-treatment period and a departure from

[4]All regressions are weighted by population. Standard errors are clustered at the county level.

Figure 2: Effect on electric vehicle registrations



(a) Log of electric vehicle sales

(b) Event study

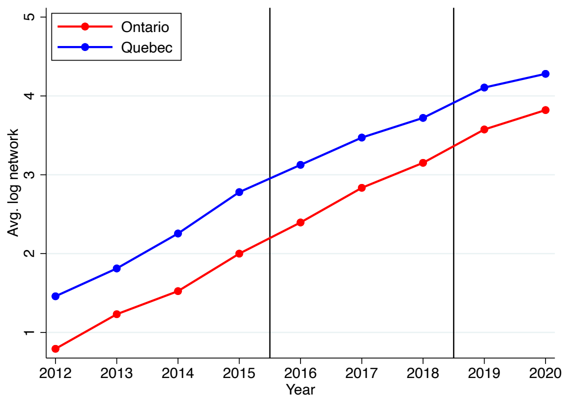
the common trend in both post-treatment periods. The effects all have the expected signs and are highly significant. I observe a small effect in 2016 which suggests that the effect from the increase in rebates occurred with a lag. This makes sense if information transmission is not perfect and not all consumers are aware of the change right away. The phasing out of the program however had an immediate effect on sales compared to the pre-treatment period.

3.3 Effect on networks

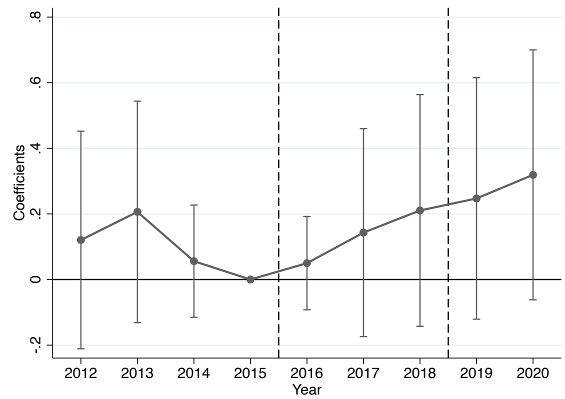
I next consider the effect of rebates on network deployment. This channel is often invoked by policymakers to justify electric vehicle subsidies. The idea is that subsidies increase sales, which leads to more charging stations. Since consumers care about the the availability of charging stations, each additional station should generate additional current and future sales at no additional cost to the policymaker.

Figure 3a and Figure 3b presents the raw data and the results from the event study. I consider each charging location to be a single charging station, even though a typical location can accommodate 1-4 cars simultaneously. I do not find evidence that electric vehicle subsidies increased charging station deployment in the short-run. To my knowledge, this is a novel result that was not studied before. One possible explanation is that installing stations requires planning (i.e. securing funding, finding adequate locations) and thus networks cannot be adjusted immediately to satisfy a surge in demand for charging.

Figure 3: Effect on local networks



(a) Log of network size



(b) Event study

3.4 Robustness analysis

I perform several robustness checks to ensure the validity of my previous results. In particular, I am concerned that my definition of network could influence the results. Since I have defined networks as a stock variable rather than a flow variable, it is possible that I do not pick up an effect if the stock of station is large relative to the flow. Another concern is that networks could have changed in other dimensions not captured by network size. For example, a larger proportion of fast charging stations or more chargers per stations could have been installed. These would not require finding additional locations which shorten planning horizon.

I use a two-way fixed effect specification to address these issues.[5] Results are presented in Table 1. I report the results for a specification without covariates, and a specification with county-level demographics. My results seem robust to the definition of networks. I use three additional definitions: new location openings, the total number of chargers, and new charger installations. I find insignificant results almost everywhere which confirms that networks were irresponsive to the policy.

I also perform several checks to make sure networks did not change in terms of their characteristics. I use as a dependent variable the share of fast charging stations, the share of public stations, and the average number of chargers per station. I construct the variable for both the stock and the flow of charging station locations. I find that networks did not change in their underlying characteristics.

[5]The corresponding event studies are available in Appendix A.

Table 1: Difference in differences analysis

Dependent variable	Control mean	Observations	No Covariates		With Demographics	
			Treatment 1	Treatment 2	Treatment 1	Treatment 2
Log of sales						
(a) All electric vehicles	4.85	1,305	0.240***	-0.710***	0.267***	-0.667***
			(0.048)	(0.078)	(0.052)	(0.048)
(b) Battery electric only	4.61	1,305	0.163***	-0.539***	0.188***	-0.533***
			(0.056)	(0.095)	(0.059)	(0.053)
(c) Plug-in hybrid only	3.12	1,305	0.251	-1.363***	0.183**	-1.429***
			(0.157)	(0.150)	(0.075)	(0.092)
Log of network						
(d) Nb. of locations	3.02	1,305	0.040	0.188	0.002	0.145
			(0.198)	(0.250)	(0.129)	(0.157)
(e) New location openings	2.01	1,305	0.278	0.315	0.188	0.160
			(0.322)	(0.291)	(0.230)	(0.196)
(f) Nb. of chargers	3.48	1,305	0.039	0.359	-0.113	0.258
			(0.193)	(0.243)	(0.144)	(0.198)
(g) New charger installations	2.42	1,305	0.427	0.521*	0.243	0.313
			(0.376)	(0.303)	(0.297)	(0.241)
Network characteristics						
(h) Share of Fast DC stations, full network	0.05	1,305	0.022	0.026	0.051	0.100***
			(0.037)	(0.041)	(0.032)	(0.028)
(i) Share of Fast DC stations, new locations	0.09	1,305	0.005	-0.037	0.009	0.010
			(0.052)	(0.047)	(0.057)	(0.049)
(j) Share of public stations, full network	0.96	1,305	0.074	0.100*	0.015	0.011
			(0.045)	(0.050)	(0.030)	(0.026)
(k) Share of public stations, new locations	0.97	1,305	0.056	0.092**	-0.014	-0.030
			(0.048)	(0.044)	(0.036)	(0.043)
(l) Avg. chargers per location, full network	1.77	1,305	-0.362	0.290	-0.758**	0.059
			(0.407)	(0.338)	(0.316)	(0.285)
(m) Avg. chargers per location, new locations	1.87	1,305	0.399	0.382	0.192	0.406
			(0.313)	(0.276)	(0.490)	(0.380)

NOTE: All regressions include county and year fixed effects and are weighted by population. Standard errors in parenthesis are clustered at the county level. Significance: * < 0.10, ** < 0.05, *** < 0.01.

3.5 Continuous treatment effect

In this section, I further the analysis and study the effect of rebates at the intensive margin. This allows me to identify the underlying elasticity of demand for electric vehicles using a similar approach to Muehlegger and Rapson (2018). I start by constructing a continuous measure of the treatment variable, $\bar{\tau}_{mt}$, the average rebate received in county m and year t. I then estimate the following continuous treatment effect specification,

$$\ln(q^{ev}_{mt}) = \alpha\bar{\tau}_{mt} + \mathbf{D}'_{mt}\gamma + \mu_m + \lambda_t + \epsilon_{mt},$$

where $\mathbf{D}_{mt}$ is a vector of county-level demographics, and μ_m and λ_t are fixed effects. The parameter of interest is α, the semi-elasticity to the rebate. We can recover the elasticity of demand as

$$\begin{aligned}\varepsilon &= \frac{\partial \ln(q)}{\partial p} \cdot \mathbb{E}(p) \\ &= \frac{\partial \ln(q)}{\partial \tau} \cdot \frac{\partial \tau}{\partial p} \cdot \mathbb{E}(p) \\ &= -\frac{\alpha}{\rho} \cdot \mathbb{E}(p)\end{aligned}$$

for any given passthrough ρ.

The average rebate is constructed by aggregating over individual-level rebates within a county and year, hence depends on the composition of the underlying fleet of electric vehicles. It is endogenous by construction. If the proportion of plug-in hybrids is higher in a given county, the average rebate would decrease mechanically as plug-in hybrids are usually not eligible for the same subsidy as battery electric vehicles. Endogeneity arises if unobserved shocks to consumer preference for green technologies shift both the total quantity of electric vehicles sold and the proportion of battery electrics to plug-in hybrids together.

I propose two different instrumental variables to address this issue. First, I consider using the discrete version of the treatment variable as an instrument. These instruments are of course highly correlated with the average rebate. The exclusion restriction would be satisfied if the timing of the policy changes in Ontario's rebate program were uncorrelated with shocks that affect all counties in Ontario at the same time. This assumption is difficult to test in practice. I construct a second instrument in the spirit of Hausman (1996) and Nevo (2001). The idea is to use the cross-sectional variation in the data to construct a valid instrument for the average rebate. In this case, this reduces to using the average rebate in other counties within a province and year as an instrument. The instrument's validity rests on the assumption that the proportion of battery electrics to plug-in hybrids in other counties is uncorrelated with local preference shocks. This assumption would be violated if preference shocks not accounted for by fixed effects affected the ratio of battery electrics to plug-in hybrids in many counties simultaneously.

Results are presented in Table 2. Both sets of instruments yield a very similar result, a \$1,000 increase in rebates is associated with a 7.7% increase in sales of electric vehicles. My dataset of car characteristics includes the list price of each model, but not individual transaction prices. In this context, I cannot identify passthrough using this framework. I can still provide bounds for the implied elasticity of demand using different values of passthrough and the average list price of electric vehicles.

Table 2: Continuous treatment effect

	OLS	Instrumental variable	
		(1)	(2)
Avg. Rebate	0.067***	0.076***	0.077***
	(0.005)	(0.005)	(0.005)
First stage			
$\text{Post}_1 \times$ Ontario		5.541***	
		(0.122)	
$\text{Post}_2 \times$ Ontario		-6.640***	
		(0.143)	
Avg. rebate in other counties			1.015***
			(0.010)
Observations	1,232	1,232	1,232

NOTE: *Avg. rebate* is in thousand 2018 CAD. All regressions include county-level demographics, county and year fixed effects, and are weighted by population. Standard error in parenthesis are clustered at the county level. Significance: * $<$ 0.10, ** $<$ 0.05, *** $<$ 0.01.

Results are presented in Table 3. My results are in the same range as the results obtained by Muehlegger and Rapson (2018): they estimate own-price elasticities between -3.4 and -3.2 using a passthrough of 100%. I estimate own-price elasticity to be -3.79 using the same methodology. One of the difference that could explain this difference is that I am using list prices, whereas they have access to transaction prices which are typically slightly lower after bargaining. My results are also close to other works that focus on a structural estimation of demand. Xing et al. (2021), Remmy (2022), and Li (2023) find an average own-price elasticities of -2.75, -3.54, and -3.70 respectively. Springel (2021) on the other hand finds an own-price elasticity between -1.49 and 1.07. Pavan (2017) estimate the own-price elasticity of alternative fuel vehicles to be between -4.42 and -2.85.

Unfortunately, this methodology does not allow for studying the impact of subsidies on emissions or other environmental outcomes. To achieve this, I build on the findings presented in this section and estimate a structural model of demand for cars and the supply of a charging station infrastructure. I recover fundamental parameters which allow conducting counterfactual experiments and evaluate the environmental performance of the Canadian subsidy programs. I present the model and the results in the following sections.

Table 3: Implied elasticity of demand

	Rebate Passthrough (ρ)				
	100%	90%	75%	50%	25%
Implied elasticity (ε)	-3.788***	-4.209***	-5.050***	-7.575***	-15.151***
	0.237	0.263	0.316	0.474	0.948
$\mathbb{E}(p)$	49.234				
$\widehat{\alpha}$	0.077				

NOTE: $\mathbb{E}(p)$ is in thousand 2018 CAD. Standard errors are computed using the Delta method. Significance: * < 0.10, ** < 0.05, *** < 0.01.

4 The Model

I define a structural model to analyse the cost-efficiency and the emission reduction potential of electric vehicle subsidies. Demand for cars is determined using the random coefficient logit model as in Berry et al. (1995). I augment the demand specification using county-level average demographics, following Nevo (2001), Gandhi and Houde (2019) and Lesellier et al. (2023). I do not model or estimate a supply side for cars. I assume that car manufacturers set prices at the North American level to avoid arbitrage opportunities between Canada and the United States. In this context, it is unlikely that manufacturers would react to local Canadian policies, since Canada represents only a small share of the North American market. Finally, I derive a model for charging station deployment inspired by Springel (2021), Pavan (2017), and Berry and Reiss (2007). I adapt these methodologies to fit the specific economic and political context in Quebec, where local county-level government are responsible for developing a charging station infrastructure in their jurisdiction.

4.1 Demand

Consider consumer i living in county m. Each period t, this consumer chooses to purchase one of the $j = 1, ..., J_{mt}$ car makes available or to purchase nothing at all, denoted $j = 0$. In choosing which product to purchase, consumers consider the price net of subsidies of each product, $p_{jt} - \tau_{jt}$, but also car characteristics such as horsepower, the driving cost, or the engine type. I denote the vector of observed product attributes by $\mathbf{x}_{jt}$ and unobserved product quality by ξ_{jmt}. For all models with an electric engine, the number of charging stations that are available locally, enters consumers' utility as an extra product characteristic, denoted N_{jmt}. I follow previous literatures and impose decreasing returns from additional charging station.[6] Finally, I allow for consumers to have heterogenous preferences in the various observed characteristics. Heterogeneity is introduced in two ways. First, I allow for the average taste for characteristics to vary across regions by interacting them with county-level average demographics. Second, I allow for random coefficients to model the heterogeneity within county. Formally, the utility consumer i receives from product j is

$$u_{ijmt} = \beta_i^{\mathbf{p}}(p_{jt} - \tau_{jt}) + \beta_i^{\mathbf{N}} \ln(N_{jmt}) + \mathbf{x}_{jt}'\beta_i^{\mathbf{x}} + (\mathbf{x}_{jt}' \otimes \mathbf{D}_{mt}')\beta^{\mathbf{D}} + \xi_{jmt} + \epsilon_{ijmt}^{\mathbf{d}}.$$

Consumers' taste parameters take the following form,

$$\beta_i^{\mathbf{p}} = \beta^{\mathbf{p}} + \sigma^{\mathbf{p}}\nu_i^{\mathbf{p}},$$
$$\beta_i^{\mathbf{N}} = \beta^{\mathbf{N}} + \sigma^{\mathbf{N}}\nu_i^{\mathbf{N}},$$
$$\beta_{ik}^{\mathbf{x}} = \beta_k^{\mathbf{x}} + \sigma_k^{\mathbf{x}}\nu_{ik}^{\mathbf{x}},$$

where the ν_i are distributed as independent standard normal. The utility of the outside option is normalized to $u_{i0mt} = \epsilon_{i0mt}^{\mathbf{d}}$ in each market. I follow the literature and rewrite the utility function in terms of a mean utility and a consumer-specific deviation,

$$u_{ijmt} = \delta_{jmt} + \mu_{ijmt} + \epsilon_{ijmt}^{\mathbf{d}},$$

with

$$\delta_{jmt} = \beta^{\mathbf{p}}(p_{jt} - \tau_{jt}) + \beta^{\mathbf{N}} \ln(N_{jmt}) + \mathbf{x}_{jt}'\beta^{\mathbf{x}} + (\mathbf{x}_{jt}' \otimes \mathbf{D}_{mt}')\beta^{\mathbf{D}} + \xi_{jmt},$$
$$\mu_{ijmt} = \sigma^{\mathbf{p}}\nu_i^{\mathbf{p}}(p_{jt} - \tau_{jt}) + \sigma^{\mathbf{N}}\nu_i^{\mathbf{N}} \ln(1 + N_{jmt}) + \sum_k x_{jt}^k \sigma_k^{\mathbf{x}} \nu_{ik}^{\mathbf{x}}.$$

Assuming that the taste shocks $\epsilon_{ijmt}^{\mathbf{d}}$ are independent and identically distributed as extreme value type I, the probability that consumer i purchases product j is given by

$$s_{ijmt}(\mathbf{p}_t, N_{mt}, \mathbf{x}_t, \mathbf{D}_{mt}, \nu_i) = \frac{e^{\delta_{jmt}+\mu_{ijmt}}}{1 + \sum_{k=1}^{J_{mt}} e^{\delta_{kmt}+\mu_{ikmt}}}.$$

[6] See for example Springel (2021), Li (2023), or Remmy (2022).

Taking expectation over all consumers yields the following aggregate demand for product j,

$$s_{jmt}(\mathbf{p}_t, N_{mt}, \mathbf{x}_t, \mathbf{D}_{mt}) = \int s_{ijmt}(\mathbf{p}_t, N_{mt}, \mathbf{x}_t, \mathbf{D}_{mt}, \nu_i) dF(\nu_i).$$

Given this market demand function, the elasticity of demand takes the following form,

$$\varepsilon_{mt}^{j,k} = \frac{\partial s_{jmt}(\mathbf{p}_t, N_{mt})}{\partial p_{kt}} \cdot \frac{p_{kt}}{s_{jmt}},$$

where

$$\frac{\partial s_{jmt}(\mathbf{p}_t, N_{mt})}{\partial p_{kt}} = \frac{\partial s_{jmt}}{\partial p_{kt}} + \frac{\partial s_{jmt}}{\partial N_{mt}} \cdot \frac{\partial N_{mt}}{\partial Q_{mt}^{ev}} \cdot \frac{\partial Q_{mt}^{ev}}{\partial p_{kt}}.$$

4.2 Network supply

I consider the case of county-level governments (henceforth "local planner") responsible for supplying charging stations in their region. Throughout, I maintain the assumption that these local planers do not coordinate on a common deployment strategy, and that they control both the installation decision and the location of stations within their county. Define the benefits associated with operating station n as

$$B_{mt}(n) = Q_{mt}^{ev} \cdot b(n, \mathbf{D_{mt}}), \tag{1}$$

where Q_{mt}^{ev} is the current stock of electric vehicles in the county, $\mathbf{D}_{mt}$ is a vector of county-level demographics, and $b(n, \mathbf{D}_{mt})$ is the average per driver benefit derived from operating station n. I impose three important assumptions on the average benefit function. First, I assume that local planners are price takers in the charging market. This assumption can be verified in this setup: Quebec's provincial government regulates both energy prices and charging prices. Second, I assume that the average benefit function is weakly decreasing in n, that is, $b(n, \mathbf{D}_{mt}) \geq b(n+1, \mathbf{D}_{mt})$ for all $n \in \mathbb{N}$. This condition is sufficient to have a unique equilibrium in network size for a given stock of electric vehicles. In practice, this can be trivially satisfied if each local planner ranks potential charging sites in order of profitability and enters in high benefit locations first. Lastly, I assume that there exists a saturation point S, such that $b(n, \mathbf{D}_{mt}) = 0$ for all $n > S$. This last assumption is not absolutely necessary, but it simplifies the computation of counterfactuals.[7] Throughout, I

[7] In practice, my analysis is very robust to the saturation point assumption, as long as saturation points are chosen to be well above current network sizes. At the estimation stage, I set $S_{mt} = L_{mt}/200$ to match broadly the targets set by the government to have roughly one charging station for every 200 electric vehicle.

am silent about what these benefits represent for the local planner. They could correspond to revenues from charging, but also to political support from electric vehicle owners, some measure of social welfare, or a combination of these factors.

A local planner which chooses to installs station n pays a one-time fixed cost F_{mt}, then reaps the lifetime benefits of operating that station. Therefore, the value of station n to the local planner is

$$V_{mt}(n) = -F_{mt} + \sum_{s=t}^{\infty} \left(\frac{1}{1+r}\right)^{s-t} \mathbb{E}_t B_{ms}(n). \tag{2}$$

A local planer m will choose to install station n in period t if it is more profitable than waiting. Its entry decision can be summarized as follows:

$$e_{mt}(n) = \begin{cases} \text{Enter,} & \text{if} \quad V_{mt}(n) \geq \left(\frac{1}{1+r}\right) \mathbb{E}_t V_{m,t+1}(n) \\ \text{Not enter,} & \text{otherwise} \end{cases}.$$

where $\left(\frac{1}{1+r}\right)$ is a discount factor. Denote the last station installed by N. It must be that the local planner found it weakly profitable to install station N, but unprofitable to install station $N+1$. Hence the equilibrium network size at any given point in time has to satisfy the following two inequality conditions:

$$V_{mt}(N) \geq \left(\frac{1}{1+r}\right) \mathbb{E}_t V_{m,t+1}(N) \tag{3}$$

and

$$V_{mt}(N+1) < \left(\frac{1}{1+r}\right) \mathbb{E}_t V_{m,t+1}(N+1). \tag{4}$$

Replacing equations (1) and (2) into equations (3) and (4) yields the following inequality condition which must be satisfied in equilibrium,

$$Q^{ev}_{mt} \cdot b(N, \mathbf{D}_{mt}) \geq F_{mt} - \left(\frac{1}{1+r}\right) \mathbb{E}_t F_{m,t+1} > Q^{ev}_{mt} \cdot b(N+1, \mathbf{D}_{mt}). \tag{5}$$

I impose a similar functional form assumption as Springel (2021) on the average benefits. Let $b(n, \mathbf{D}_{mt}) = a_0 n^{-a_1} e^{\mathbf{D}_{mt} a_2}$. Substituting in equation (5) and taking logs gives the following equilibrium condition,

$$\frac{\ln(N_{mt}) - \lambda^{\mathbf{Q}} \ln(Q^{ev}_{mt}) - \mathbf{D}'_{mt}\lambda^{\mathbf{D}}}{\omega} \leq \epsilon^{\mathbf{n}}_{mt} < \frac{\ln(N_{mt}+1) - \lambda^{\mathbf{Q}} \ln(Q^{ev}_{mt}) - \mathbf{D}'_{mt}\lambda^{\mathbf{D}}}{\omega},$$

where $\epsilon^{\mathbf{n}}_{mt}$ is unobserved to the econometrician and is assumed to follow the standard normal distribution. Define S_{mt} as the network saturation point. Charging station supply can be written as follows,

$$\begin{aligned} N_{mt} = & \sum_{k=1}^{S_{mt}-1} k \cdot \mathbb{1}\left(\frac{\ln(k) - \lambda^{\mathbf{Q}} \ln(Q^{ev}_{mt}) - \mathbf{D}'_{mt}\lambda^{\mathbf{D}}}{\omega} \leq \epsilon^{\mathbf{n}}_{mt} < \frac{\ln(k+1) - \lambda^{\mathbf{Q}} \ln(Q^{ev}_{mt}) - \mathbf{D}'_{mt}\lambda^{\mathbf{D}}}{\omega}\right) \\ & + S_{mt} \cdot \mathbb{1}\left(\frac{\ln(S_{mt})) - \lambda^{\mathbf{Q}} \ln(Q^{ev}_{mt}) - \mathbf{D}'_{mt}\lambda^{\mathbf{D}}}{\omega} \leq \epsilon^{\mathbf{n}}_{mt}\right). \end{aligned} \tag{6}$$

4.3 Elasticity of network supply

One of the key quantity required for economic analysis is the elasticity of network supply,

$$\eta_{mt} = \frac{\partial N_{mt}}{\partial Q^{ev}_{mt}} \cdot \frac{Q^{ev}_{mt}}{N_{mt}}.$$

The supply equation is a step function, hence its derivative is either zero or it is not differentiable. To recover an expression for the partial effect, it is useful to rewrite the structural function as $N_{mt} = H(Q^{ev}_{mt}, \mathbf{D}_{mt}, \epsilon^{\mathbf{n}}_{mt})$, and consider the average structural function,

$$ASF_{mt} = \mathbb{E}_{\epsilon^{\mathbf{n}}}(N_{mt} \mid Q^{ev}_{mt}, \mathbf{D}_{mt}) = \int H(Q^{ev}_{mt}, \mathbf{D}_{mt}, \epsilon^{\mathbf{n}}) dF(\epsilon^{\mathbf{n}}).$$

We can show that if $\epsilon^{\mathbf{n}}_{mt}$ is distributed as standard normal, then the average structural function takes the following form,

$$ASF_{mt} = S_{mt} - \sum_{k=1}^{S_{mt}} \Phi\left(\frac{\ln(k) - \lambda^{\mathbf{Q}} \ln(Q^{ev}_{mt}) - \mathbf{D}'_{mt}\lambda^{\mathbf{D}}}{\omega}\right).$$

Following Blundell and Powell (2004), the partial effect can be recovered as the derivative of the average structural function, that is,

$$\frac{\partial N_{mt}}{\partial Q^{ev}_{mt}} = \frac{\partial ASF_{mt}}{\partial Q^{ev}_{mt}} = \sum_{k=1}^{S_{mt}} \phi\left(\frac{\ln(k) - \lambda^{\mathbf{Q}} \ln(Q^{ev}_{mt}) - \mathbf{D}'_{mt}\lambda^{\mathbf{D}}}{\omega}\right) \cdot \frac{\lambda^{\mathbf{Q}}}{\omega Q^{ev}_{mt}}.$$

4.4 Identification and estimation

Demand. I have to deal with several sources of endogeneity. First, prices depend not only on observed product characteristics but also on unobserved product quality (to the econometrician), leading to the price endogeneity issue described in Berry et al. (1995). Second, our estimation routine relies on the inversion of the market shares to recover mean utilities $\delta(\mathbf{s}, \sigma)$. This implies that market shares are also endogenous since they are determined jointly with unobserved car attributes (Conlon and Gortmaker, 2020; Gandhi and Houde, 2019). Concretely, this means that instrumental variables are needed for prices and market shares in the demand model. Finally, network deployment occurs simultaneously with electric vehicle sales, hence network size is also endogenous. 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 supply models, hence they are correlated.

I solve the various endogeneity issues using instrumental variables. I use two separate cost shifters to instrument for prices. Similarly to Durrmeyer et al. (2018), I construct a composite price index to capture variations in the production cost of the various car makes. I use four key input prices: steel, iron, plastics, and aluminum. I compute a weighted average cost per ton which I interact with each vehicle's curb weight to create the composite price index.[8] Next, I follow Grieco et al. (2022) and use the real exchange rate between Canada and the country each car was manufactured as an additional cost shifter.[9] The real exchange rate captures among other things variations in the cost of labor between Canada and the car's country of origin which affects marginal production cost. Similarly to Grieco et al. (2022), I lag both cost shifters by one year to reflect planning horizons. I denote the set of price instruments by $\mathbf{z^p}$.

To solve for the endogeneity of the market shares, I use the intuition in Gandhi and Houde (2019) to construct instruments based on characteristic differences. I use the fact that the marketing segment is a strong dimension of differentiation, and interact it with other

[8] I assume cars are made of 56% steel, 8% iron, 8% plastics, 10% aluminum, and 18% of other materials not captured by the index.

[9] Real exchange rates are obtained from Penn World Tables, version 10.0, `pl_con`. See Grieco et al. (2022).

characteristics to construct basis functions. Formally, I construct the following instruments,

$$\mathbf{z}_j^{\mathbf{s}} = \begin{cases} \sum_{k \notin \mathcal{J}_j} \mathbb{1}(k \text{ is in same segment as } j) \\ \sum_{k \notin \mathcal{J}_j} \mathbb{1}(k \text{ is in same segment as } j) \times \mathbb{1}(k \text{ has same engine type as } j) \\ \sum_{k \notin \mathcal{J}_j} \mathbb{1}(k \text{ is in same segment as } j) \times d_{k,j}^{\widehat{p}} \\ \sum_{k \notin \mathcal{J}_j} \mathbb{1}(k \text{ is in same segment as } j) \times \mathbf{d}_{k,j}^{\mathbf{x}} \\ \sum_{k \notin \mathcal{J}_j} \mathbb{1}(k \text{ is in same segment as } j) \times (\mathbf{D}_{mt} \otimes \mathbf{d}_{k,j}^{\mathbf{x}}) \end{cases},$$

where $d_{k,j}^{x} = x_k - x_j$ for some continuous characteristic $x \in \mathbf{x}$. To put it plainly, these instruments are the number of competitors within segment, the number of competitors within segment with the same engine type, the sum of predicted price differences, and the sum of exogenous characteristics differences between competing products in the same segment. Interactions between observed characteristics and county-level average demographics are also used to construct instruments. Since price is endogenous, it cannot be used to construct instruments. It still contains a useful source of variation to identify consumers' heterogeneity in price sensitivity. To circumvent this issue, I follow Reynaert and Verboven (2014) and Gandhi and Houde (2019) and use the projection of price on exogenous characteristics and cost shifters, denoted $\widehat{p}_{jt} = \mathbb{E}(p_{jt} \mid \mathbf{x}_{jt}, \mathbf{z}_{jt}^{\mathbf{p}})$, to construct instruments based on the exogenous variation in price.

I now address the endogeneity of charging stations in the demand equation. I follow the approach in Hausman (1996) and Nevo (2001), which use the panel structure of the data to construct instruments. Formally, the idea is to use networks in other regions to instrument for local charging stations. 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 consumption once we account for region fixed effects. Networks in other regions are valid instruments for local stations as long as the correlation between station networks 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 or other daily activities and these commuting patterns could lead to a significant portion of charging within a region to come from electric vehicle owners outside the region and vice-versa. However, it is unlikely that a significant portion of consumers charge over region lines for two counties that are geographically distant from each other.

I impose a distance threshold to select networks that are far enough to construct a valid instrument for local network size,

$$z^{\mathbf{N}}_{jmt} = \frac{\sum_{\ell \neq m} \mathbb{1}(\text{dist}_{\ell,m} > K) \cdot \ln(N_{j\ell t})}{\sum_{\ell \neq m} \mathbb{1}(\text{dist}_{\ell,m} > K)}.$$

I use a radius of 300 km from the county's centroid to determine which networks enter the basis function. The choice of a threshold is rather arbitrary. To document the robustness of my results to this assumption, I estimate a simple logit demand model, and vary the threshold in increments of 50km. Results are available in Table A.3.

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. The full set of demand instruments is then $\mathbf{Z} = (\mathbf{z}^{\mathbf{p}}, \mathbf{z}^{\mathbf{s}}, \mathbf{z}^{\mathbf{N}})$.

Estimation is done using the Nested Fixed Point algorithm described in Berry et al. (1995). I perform the market share inversion to recover $\xi(\beta, \sigma)$, then minimize the following objective function,

$$(\beta^*, \sigma^*) = \underset{\beta,\sigma}{\text{argmin}}\ \xi'(\beta, \sigma)\mathbf{ZWZ}'\xi(\beta, \sigma),$$

where $\mathbf{W}$ is some weighting matrix. As usual, the $\beta = (\beta^{\mathbf{p}}, \beta^{\mathbf{N}}, \beta^{\mathbf{x}}, \beta^{\mathbf{D}})$ can be partialled out, and the optimization is done over the $\sigma = (\sigma^{\mathbf{p}}, \sigma^{\mathbf{N}}, \sigma^{\mathbf{x}})$. Additional details on the estimation routine can be found in Appendix C.

Station supply. I estimate the parameters of the station supply equation by maximum likelihood. For $\epsilon^{\mathbf{n}}_{mt}$ distributed as standard normal, the probability of observing a network of size k is given by the following expression:

$$\Pr(N = k \mid \lambda, \omega) = \Pr\left(\frac{\ln(k) - \lambda^{\mathbf{Q}} \ln(Q^{ev}_{mt}) - \mathbf{D}'_{mt}\lambda^{\mathbf{D}}}{\omega} \leq \epsilon^{\mathbf{n}}_{mt} < \frac{\ln(k+1) - \lambda^{\mathbf{Q}} \ln(Q^{ev}_{mt}) - \mathbf{D}'_{mt}\lambda^{\mathbf{D}}}{\omega}\right),$$

$$= \Phi\left(\frac{\ln(k+1) - \lambda^{\mathbf{Q}} \ln(Q^{ev}_{mt}) - \mathbf{D}'_{mt}\lambda^{\mathbf{D}}}{\omega}\right) - \Phi\left(\frac{\ln(k) - \lambda^{\mathbf{Q}} \ln(Q^{ev}_{mt}) - \mathbf{D}'_{mt}\lambda^{\mathbf{D}}}{\omega}\right).$$

The conditional likelihood is then

$$\begin{aligned}\ell(\lambda, \omega \mid \mathbf{Q}^{ev}, \mathbf{D}) &= \sum_m \sum_t \ln \Pr(N = N_{mt} \mid \mathbf{Q}^{ev}, \mathbf{D}, \lambda, \omega), \\ &= \sum_m \sum_t \ln \Bigg[\Phi\left(\frac{\ln(N_{mt}+1) - \lambda^{\mathbf{Q}} \ln(Q^{ev}_{mt}) - \mathbf{D}'_{mt}\lambda^{\mathbf{D}}}{\omega} \right) \\ &\qquad - \Phi\left(\frac{\ln(N_{mt}) - \lambda^{\mathbf{Q}} \ln(Q^{ev}_{mt}) - \mathbf{D}'_{mt}\lambda^{\mathbf{D}}}{\omega} \right) \Bigg].\end{aligned}$$

I now address the issue of the endogeneity of the stock of electric vehicles in the structural station supply model. Since the 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. Consider a set of valid instruments for $\mathbf{Q}^{ev}$, denoted $\mathbf{w} = (\mathbf{w}_1, \mathbf{D})$, and define the control function to be the linear projection of $\mathbf{Q}^{ev}$ on $\mathbf{w}$,

$$Q^{ev}_{mt} = \mathbf{w}'_{mt}\Gamma + v_{mt}, \tag{7}$$

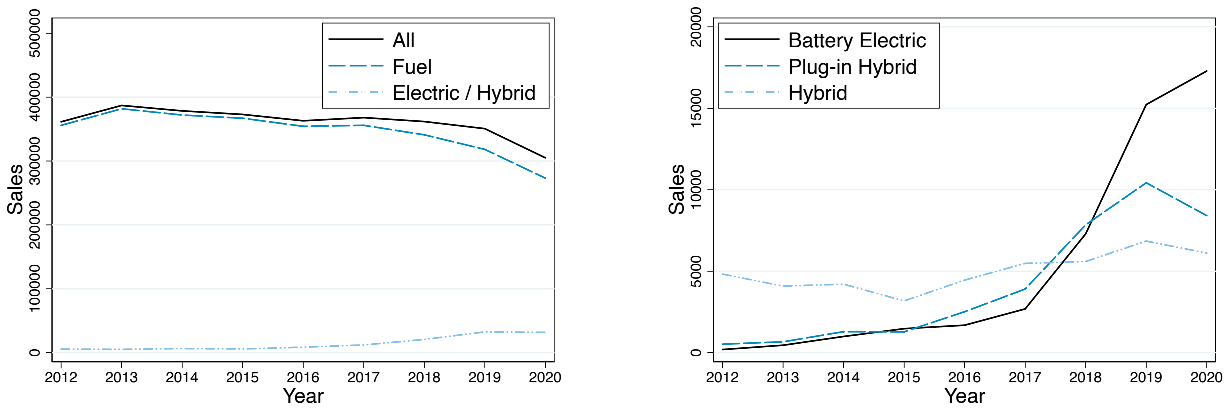
where $(\epsilon^{\mathbf{n}}, v) \perp \mathbf{w}$. The estimation of (λ, ω) is done in two stages: first, obtain a consistent estimate of $\widehat{v}_{mt}$ by estimating equation (7), then add $\widehat{v}_{mt}$ as an extra regressor in the conditional log-likelihood,

$$\begin{aligned}\ell(\lambda, \omega \mid \mathbf{Q}^{ev}, \mathbf{D}, \widehat{\mathbf{v}}) = \sum_m \sum_t \ln \Bigg[&\Phi\left(\frac{\ln(N_{mt}+1) - \lambda^{\mathbf{Q}} \ln(Q^{ev}_{mt}) - \mathbf{D}'_{mt}\lambda^{\mathbf{D}} + \lambda^{\mathbf{v}}\widehat{v}_{mt}}{\omega} \right) \\ &- \Phi\left(\frac{\ln(N_{mt}) - \lambda^{\mathbf{Q}} \ln(Q^{ev}_{mt}) - \mathbf{D}'_{mt}\lambda^{\mathbf{D}} + \lambda^{\mathbf{v}}\widehat{v}_{mt}}{\omega} \right) \Bigg].\end{aligned}$$

Similarly to Springel (2021), I use gas station density, gas prices, and the interaction between the two to instrument for the fleet of electric vehicles in a given region.[10]. Gas prices and gas station density measure the level of competition in the fuel market 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 vehicle sales are realized. Also, common shocks are unlikely to affect both markets together: electricity prices are regulated by the provincial

[10]Gas station density is calculated as the number of gas station in a given region divided by population, in 5,000. I construct the gaz price index based on regular, premium and diesel prices yearly average prices for each region.

Figure 4: Evolution of sales



(a) All vehicles

(b) Electric and hybrid vehicles

government and do not fluctuate with the price of gas such that it is unlikely that shocks that affect the fuel market also affect charging station entry through higher electricity prices.

5 Estimation Results and Counterfactuals

5.1 Demand

Summary statistics. I estimate both the demand for cars and supply of stations at the county-year level. I define a product as a make-model-engine combination, and I set the market size to the number of households in each market. Table A.2 presents a summary of the characteristics of the available products. Battery electric vehicles are on average \$18,000 more expansive than traditional combustion engines while plug-in hybrids are on average \$6,000 more expansive. The combined rebates seem to cover the price difference fully for plug-in hybrids, but not for battery electric vehicles.

The evolution of vehicle sales in Quebec is presented in Figure 4. We can see from Panel (a) that total sales are roughly constant until 2019, but decrease in 2020 due to supply chain disruptions and economic uncertainty caused by COVID-19. Panel (b) offers a breakdown by engine type for electric and hybrid vehicles. Sales of battery electrics and plug-in hybrids are rising steadily, with a sharp increase towards the end of the period. Sales of non-rechargeable hybrids are rising but only slightly.

Several factors unrelated to the policy under study could explain the surge in sales of electric vehicles. One of them is the improvement of the electric vehicle offering, summarized

Table 4: Number of available products

Year	Fuel	Battery Electric	Plug-in Hybrid	Hybrid	Total
2012	165	4	1	9	179
2013	176	5	3	9	193
2014	187	7	4	9	207
2015	188	7	4	10	209
2016	186	7	6	10	209
2017	184	10	13	13	220
2018	184	10	16	13	223
2019	177	14	15	13	219
2020	173	16	15	13	217

Table 5: Evolution of charging station infrastructure

Year	Number of Stations	Share of counties with				
		0 station	1-5 stations	6-10 stations	11-25 stations	> 25 stations
2012	100	0.69	0.24	0.01	0.03	0.02
2013	192	0.48	0.44	0.02	0.04	0.02
2014	339	0.29	0.55	0.07	0.04	0.05
2015	623	0.13	0.50	0.22	0.09	0.05
2016	914	0.03	0.49	0.20	0.22	0.05
2017	1,266	0.02	0.40	0.21	0.31	0.06
2018	1,616	0	0.28	0.29	0.30	0.14
2019	2,371	0	0.11	0.28	0.39	0.22
2020	2,811	0	0.08	0.16	0.44	0.32

in Table 4. We can see that the offering of battery electric and plug-in hybrid are both rising steadily between 2012 and 2020. Meanwhile, the offering of internal combustion engines seems to decline slightly in 2019 and 2020, when sales of electric vehicles are highest. The increased availability of charging stations could also explain part of the increase in electric vehicle sales. Table 5 shows the evolution of the charging station infrastructure over time. The number of stations available goes from 165 stations in 2012 to more than 2800 in 2020. Local networks are also getting denser over time. This is especially important in predominantly rural counties, which have low population density. A large share of counties initially had no charging station network. In this case, electric vehicle owners are constrained to charging at home, which act as a deterrent to the purchase of a fully electric vehicle. By 2020, 76% of counties have more than 10 stations available (32% have more than 25 stations), and all counties have at least one open charging location.

Estimation. Results from the demand estimation are presented in Table 6. I include horsepower (in 100 kW), weight (in 100 kg), driving cost[11] (CAD per km), and the engine type as observed characteristics. I also interact these car characteristics with average county-level demographics. The chosen demographics are the average income, the average age, the proportion of female, the population density (number of households per sq. km), and a time trend.[12] I include a large number of fixed effects: car makes (34 different makes), market segments (subcompact, compact, midsize, large/luxury, crossover utility, sport utility, and minivan), counties (98 counties), and years (9 years). These fixed effects capture unobservables such as brand perception, or local unobserved consumer characteristics. Finally, I allow for heterogeneous preferences by including a random coefficient on the net price, on the battery electric dummy, and on the constant. In practice, including a random coefficient on price (or on one of the continuous characteristics) helps producing more diverse substitution patterns between products. In this case, it also allows for heterogenous response to the financial incentives. On the other hand, the random coefficient on the constant is useful to break the independence to irrelevant alternative between the inside and the outside good. Since this study aims at measuring the emission reduction potential of electric vehicle subsidies, it is crucial that we measure substitution patterns accurately.

I estimate the price coefficient and its standard deviation to be -0.785 and 0.149 respectively. Both are highly significant. The average own-price elasticity implied by these estimates is -3.24, which is in the same range as the estimate I obtain in the reduced form analysis (-3.79). The coefficient on network size is 0.343 and significant, which means that consumers care about the availability of charging stations when considering the purchase of an electric vehicle. Interestingly, the interactions with average demographics seem to capture fairly well the heterogeneity in preferences for observed characteristics. For example, the model suggests that the preference for powerful vehicle increases with income or age, and that women typically prefer more powerful vehicles compared to men.[13] The model also predict that women prefer electric and hybrid vehicles more than men. The estimates

[11]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 10.9 cents 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.

[12]All demographics are demeaned such that they do not affect the coefficients on the observed characteristics they are interacted with. The choice of the exact specification is discussed in Appendix C.

[13]The consumer-level data also suggests that women (on average) purchase larger, hence more powerful cars than men. Men on the other hand, tend to purchase cars with better acceleration (power-to-weight ratio).

Table 6: Demand estimation

	ESTIMATE	INCOME	AGE	GENDER	POP DENSITY	TREND	σ
Price - Rebate	-0.785***						-0.149***
	(0.032)						(0.022)
Log network	0.344***						
	(0.037)						
Power	0.923***	0.072***	0.209***	0.041***			
	(0.021)	(0.013)	(0.020)	(0.004)			
Weight	-0.21***					0.083***	
	(0.037)					(0.004)	
Driving cost	-0.036***	0.001					
	(0.004)	(0.003)					
Battery electric	-2.196***	-0.089		0.175***	-0.337***		0.161
	(0.545)	(0.056)		(0.029)	(0.047)		(3.73)
Plug-in hybrid	-2.120***	-0.215***		0.148***	-0.385***		
	(0.090)	(0.036)		(0.025)	(0.047)		
Hybrid	-1.725***		0.389***	0.148***			
	(0.022)		(0.051)	(0.016)			
Constant							5.884***
							(2.366)
Observations	126,397						
Nb. of markets	864						
Avg. Own-price elasticity	-3.24						
Nb. Elasticity > -1	0						

NOTE: Includes brand, market segment, county, and year fixed effects. Robust standard errors in parenthesis. Significance: * < 0.10; ** < 0.05; *** < 0.01.

suggests that consumers in large cities dislike electric vehicles. One explanation is that the interactions between population density and the electric vehicle dummies capture the potential for home charging which is lower in urban areas compared to rural areas. Finally, my estimates suggest that consumers' preference for weight (a proxy for security) increases over time.

5.2 Network supply

Results from the network supply estimation are presented in Table 7. I include several demographics that try to capture regional differences in consumer characteristics that may induce station operators to install chargers. I use the share of residents that have an undergraduate degree as a proxy for environmental awareness and the aggregate taste for green technologies. Additionally, I measure the potential for home charging by the share of homeowners and an indicator for urban counties. Demand for charging on the network should be higher if electric vehicle owners cannot install and use a home charger. This in turn should lead to more station installations. Because of the highly non-linear nature of the model being

Table 7: Staion supply estimation

	ESTIMATE		CONTROL FUNCTION	
Log Q^{ev}	0.225**	(0.110)		
Avg. household income	0.105	(0.087)	-0.052	(0.117)
Avg. age	0.357	(0.271)	-0.661	(0.412)
Avg. household hize	-0.571	(0.794)	0.763	(0.965)
Share of graduates	4.149***	(1.339)	5.249***	(1.533)
Share of homeowners	-3.535***	(1.109)	-2.651*	(1.387)
Urban	0.213	(0.215)	0.856***	(0.195)
$\widehat{v}$ (control function)	0.156	(0.141)		
ω	0.564***	(0.029)		
Gas station density			-1.031**	(0.400)
Gas price index			-3.713**	(1.651)
Gas price $\times$ Gas density			0.266	(0.265)
Observations	864		864	
Log-likelihood	2.448			
R-squared			0.895	
F-stat			20.34	
Prob. > F-stat			0.000	
Avg. partial effect $\left(\frac{\partial N}{\partial Q^{ev}}\right)$	0.039			
EV for one additional station	25.9			

NOTE: Includes year fixed effects. The F-statistic tests for the null hypothesis that the instruments are jointly zero. Bootstrap standard errors in parenthesis are clustered at the county level. Significance level: * $<$ 0.10, ** $<$ 0.05, *** $<$ 0.01.

estimated, I cannot include county fixed effects, as these would not be identified with only nine years of data. Instead, I include the average income, the average age, and the average household size to account for any remaining regional differences.

I report both the coefficients of the structural model and the control function. The share of graduates and the share of homeowners are significant and have the correct sign in both cases. This reinforce the idea that environmental awareness and the potential for home charging are two important drivers of charging station entry. Meanwhile, the urban indicator is significant in the control function, but not in the structural equation. The coefficient on the log of the stock of electric vehicle is the main coefficient of interest. I estimate it to be 0.225, significant at the 5% level. The average partial effect implied by this estimate is 0.039. This suggest that one additional station is installed for every 25.9 electric vehicles sold. This figure seems fairly large, however it is driven by counties with few or no stations.

In this case, even small changes in the stock of electric vehicles are sufficient to generate an additional station installation.

The structural model allows for the estimation of very flexible network supply and network elasticity of supply curves. Figure A.3 and Figure A.4 provide examples for selected counties. This is one of the strengths of the proposed methodology: it does not restrict the network elasticity of supply to be fixed across markets, or when the number of potential users vary within markets. This allows the model to explain the data better if network provision is not homogeneous across counties or over time in reality.

5.3 Counterfactual analysis

Before we move on to studying the environmental performance of electric vehicle incentives, it is useful to conduct a few basic counterfactual experiments. We want to assess the quality of the estimation, and understand the model's predictions in a simple setup. To that end, I perform three counterfactual experiments. First, I remove provincial level subsidies and evaluate how sales, charging station deployment, and other key economic outcomes change in this context. Second, I remove federal level subsidies. Finally, I remove both sets of incentives to provide a baseline case without government intervention. I rely on a simple fixed point iteration to determine jointly electric vehicle sales and network size in each market. Since network deployment depends on the stock of electric vehicles available, counterfactuals must be computed iteratively year by year to reconstruct the evolution of the stock of vehicles. Computational details are available in Appendix D.

The result of the counterfactual experiments are reported in Table 8. As mentioned above, I set the baseline to be the "no rebates" case. I focus my analysis around the main counterfactual, presented in column (1). The first salient fact is that financial incentives are very effective at improving electric vehicle take-up. Sales of battery electric and plug-in hybrids which were targeted by the policies increased by 93% compared to baseline. Moreover, most of these additional electric vehicles (around 68%) are replacing internal combustion engines, which leads to reductions in total carbon emissions. Around 30% of consumers which purchased an electric vehicle would not have purchased any vehicle without subsidies. This affects the performance of the program, since in this case no emission reduction occurs.

The impact of these additional sales on network deployment is modest. The total number of charging stations available increases by 18% compared to baseline. This seems underwhelming considering that the number of electric vehicle owners almost doubled due to the financial incentives. I take it as evidence of weak indirect network effects. This contrasts

Table 8: Counterfactual analysis

	(1) Both rebates (Data)	(2) Federal rebate only	(3) Provincial rebate only	(4) No rebates (Baseline)
Total sales	+12,209	+1,752	+9,159	3.236e+06
Sales (fuel)	-27,981	-3,922	-21,379	3.147e+06
Sales (battery electric)	+24,939	+3,317	+18,770	22,366
Sales (plug-in hybrid)	+15,800	+2,445	+12,169	21,069
Sales (hybrid)	-549	-87	-402	45,337
Stations	+434	+78	+346	2,377
CO_2 Emissions	-1.117	-0.151	-0.856	142.6
Consumer surplus	562.8	78.9	428.0	0
Total cost	723.2	86.7	506.5	0
Total cost (prov)	573.1	0	506.5	0
Total cost (fed)	150.1	86.7	0	0
Avg. cost per ton CO_2	647	573	592	
Avg. cost per electric vehicle	17,753	15,050	16,371	

NOTE: *CO_2 emissions* is the present-value of CO_2 emissions over the lifetime of vehicles, in million tons. Lifetime emissions are computed based on a 22,053 average mileage per year and an average lifetime of 12.02 years. *Consumer surplus* and *Total cost* are in million 2018 CAD. *Avg. cost per ton CO_2* and *Avg. cost per electric vehicle* are in 2018 CAD.

the existing literature on electric vehicle markets which instead show that network effects are important.[14] This could be a feature of the Canadian market: local governments play an active role in network deployment and may not respond to the increased demand in the same way a private operator does.

The provincial and federal rebate programs together are responsible for abating 1.117 million tons of CO_2 emissions. This is equivalent to a 0.78% reduction in total emission from these new car sales. To avoid including additional assumptions on the driving patterns of consumers, I measure emission abatement over the lifetime of vehicles. The underlying assumption is that while consumers may change their utilization in response to the program (if for example they acquire a second vehicle which is electric), the lifetime mileage will be unaffected. This would be satisfied if for example consumers that switch early to purchase an electric car resell their old vehicle on the secondary market instead of scraping it. It also makes sense from the point of view of the policymaker to consider the present-value of current and future emissions when investing on financial incentives.

[14] See Li et al. (2017), Springel (2021), or Remmy (2022).

Total spending on subsidies by both levels of government reached \$723.2 million by 2020. I use this figure to compute some preliminary cost measures, which is useful to compare our results with previous literatures. I estimate the average cost of reducing emissions to be between \$573 and \$647 per ton of CO_2. This is similar to Xing et al. (2021), which estimate an average abatement cost between \$581 and \$662 (484 – 552 USD) per ton of CO_2 for a similar rebate program in the United States. Other studies of similar incentives typically find lower estimated costs.[15] I estimate the average cost per additional electric vehicle to be between \$15,050 and \$17,753. This is much higher than the per vehicle subsidy (\$8,592). This high cost can be explained by the high number of infra-marginal consumers that did not need to be incentivized to purchase an electric vehicle. This suggests that improvements could be achieved if the policymaker targeted switchers more accurately.

6 Cost-Benefit Analysis

6.1 Setup

I propose a calibration exercise to study the cost-effectiveness of the Canadian rebate programs. I setup the calibration in a very general way which could be used to study other types of environmental regulations (e.g. gas taxes, emission standards, etc). Consider the following social planner objective, where τ is the targeted policy variable,

$$\tau^* = \underset{\tau \geq 0}{\text{argmax}} \underbrace{\mathcal{W}(\tau) - \phi\,\text{Cost}(\tau)}_{\text{Value to society}} - \underbrace{\text{E}(\tau) \cdot P^E}_{\text{Value of emissions}} .$$

The social planner is looking to pick the policy τ^* that maximizes its value to society and minimize the value of emissions that arise from the policy. For now, we take the carbon price P^E as given. The government objective function has three key inputs: a social welfare function $\mathcal{W}(\tau)$, a cost function $\phi\,\text{Cost}(\tau)$ which summarizes government spendings,[16] and an emission function $\text{E}(\tau)$. Provided all three functions are continuously differentiable, the

[15] See for example Huse and Lucinda (2014) on the Swedish green car rebate (\$131 – 158) or Beresteanu and Li (2011) on tax incentives on hybrids in the United States (\$212).

[16] In the case of a tax, government spendings would be negative.

optimal policy rule $\tau^*(P^E)$ can be obtained by inverting the following first-order condition,

$$\underbrace{\frac{\partial \mathcal{W}(\tau^*)}{\partial \mathrm{E}(\tau^*)} - \phi \frac{\partial \mathrm{Cost}(\tau^*)}{\partial \mathrm{E}(\tau^*)}}_{\substack{\text{Marginal}\\ \text{Abatement}\\ \text{Cost}}} = \underbrace{P^E}_{\substack{\text{Cost of}\\ \text{Carbon}}}. \tag{8}$$

I now provide more details on each component of the objective function.

Social welfare function. Let $\theta = (\beta, \sigma, \lambda, \omega)$ be the fundamental parameters governing consumers' preferences and network deployment. I define the social welfare function as a weighted sum of the firms' profits and consumers' welfare (defined by consumer surplus). Let ψ_1 and ψ_2 be welfare weights. The social welfare function is

$$\mathcal{W}(\tau) = \mathcal{W}(\tau, \theta) = \psi_1 \, \Pi(\tau, \theta) + \psi_2 \, \mathcal{CS}(\tau, \theta),$$

where

$$\Pi(\tau, \theta) = \sum_t \sum_m \sum_j q_{jmt}(\tau, \theta) \cdot (p_{jt} - c_{jt})$$

are the firms' aggregated profits, and

$$\mathcal{CS}(\tau, \theta) = -\sum_t \sum_m L_{mt} \int \frac{1}{\beta_i^{\mathbf{P}}} \cdot \frac{1}{s_{i0mt}(\tau, \theta, \nu_i)} \cdot dF(\nu_i) + K$$

is the aggregated (expected) consumers' surplus.[17]

Cost function. The cost function accounts for all government expenditures on the policy. Recall that $\tau > 0$ represents a subsidy in the utiilty specification (and $\tau < 0$ a tax). The cost function can be computed as the sum of all government subsidies,

$$\mathrm{Cost}(\tau) = \mathrm{Cost}(\tau, \theta) = \sum_t \sum_m \sum_j q_{jmt}(\tau, \theta) \cdot \tau_{jt},$$

weighted by the marginal cost of public funds ϕ.

[17]This is the usual log-sum formula for consumer surplus, which is identified up to a constant K.

Emission function. Lifetime emissions depend on several parameters, including the car's level of emission e_{jt}, its expected lifetime T_j, and the average mileage by year that a typical owner travels m_{js}. I assume that the policymaker discounts future emissions at rate r. The present-value of the aggregated emissions can be computed as

$$\mathrm{E}(\tau) = \mathrm{E}(\tau, \theta) = \sum_t \sum_m \sum_j \left(q_{jmt}(\tau, \theta) \cdot \sum_{s=t}^{t+T_j} \left(\frac{1}{1+r} \right)^{t-s} m_{js} e_{jt} \right).$$

6.2 Calibration

I calibrate the various parameters of the social planner's objective function. The parameters are the welfare weights (ψ_1, ψ_2), the marginal cost of public funds (ϕ), the discount rate (r), the average mileage per year (m_{js}), and the expected lifetime of vehicles (T_j).

I assume that the social planner cares about consumer surplus but not profits, to reflect the fact that no car production occurs in Quebec. Therefore, I set the welfare weight on profit to zero. The discount rate is set to 5%. I use data on fuel spending from the Canadian Survey of Household Spending and local fuel costs to compute the average mileage of a representative Quebec household in 2017. Unfortunately, the data doesn't distinguish between households that own one versus two cars, so I assume that all mileage is done on one vehicle. The average mileage is set to 22,053 kilometres for all j and s. Finally, I compute the expected lifetime of vehicles using the micro-level car registration data. I have access to the full fleet of vehicles in 10 successive years which I use to track vehicles of various ages estimate their expected lifetime. The expected lifetime of a new vehicle estimated to be 12.02 years.[18]

I use two different values for the marginal cost of public funds. In the first calibration, I assume that the government can provide subsidies without frictions at no additional cost. In the second set of results, I assume that governments have to pay an administrative fee to provide subsidies. In this case the marginal cost of social funds is set to 1.15. As a reference, the calibrated parameters are reported in Table 9.

I restrict the policy space to rebate programs that are proportional to the currently implemented scheme. To fix ideas, let τ_0 be the currently available rebate program. The set of policies that are available to the policymaker satisfies

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

[18]Combining the expected lifetime with the average mileage by year implies that cars have an expected total mileage of around 265,000 kilometres.

Table 9: Calibrated parameters

		Calibration	
Description	Parameter	(1)	(2)
Social welfare function			
(a) Profit weight	ψ_1	0	0
(b) Consumer surplus weight	ψ_2	1	1
Cost function			
(c) Marginal cost of public funds	ϕ	1	1.15
Emissions function			
(d) Discount factor	r	0.05	0.05
(e) Avg. mileage by year	m_{js}	22,053	22,053
(f) Avg. lifetime of vehicles	T_j	12.02	12.02

With this restriction, the marginal abatement cost can be computed as

$$\text{MAC}(\kappa) = \frac{\partial \mathcal{W}(\kappa)}{\partial \text{E}(\kappa)} - \phi \, \frac{\partial \text{Cost}(\kappa)}{\partial \text{E}(\kappa)}.$$

Restricting the policy space serves two purposes. First, it reduces the computational burden associated with evaluating all possible policies. With J different electric vehicle models available, solving for the optimal rebate program entails solving a problem of dimension $\mathbb{R}^J$ which is impractical or infeasible. More importantly, there are strong incentives for policymakers to subsidize all models equally to avoid picking winners and losers among firms.

6.3 Optimal policy

I study the cost-effectiveness of rebates by considering the social planner's optimality condition. I compute counterfactuals on a grid $\{\kappa_1, ..., \kappa_N\}$, then estimate the marginal abatement cost as

$$\text{MAC}(\kappa_n) = \frac{\mathcal{W}(\kappa_{n+1}) - \mathcal{W}(\kappa_n)}{\text{E}(\kappa_{n+1}) - \text{E}(\kappa_n)} - \phi \, \frac{\text{Cost}(\kappa_{n+1}) - \text{Cost}(\kappa_n)}{\text{E}(\kappa n + 1) - \text{E}(\kappa_n)}.$$

I then collect the results to construct the marginal abatement cost curve as a function of κ. There are two interpretations to the social planner's optimality condition. On one hand, we can assume that it holds at the current rebates. In this case, equation (8) provides an estimate for the cost of carbon, $P^E = \text{MAC}(1)$. On the other hand, we can calibrate the cost of carbon to known estimates and recover an optimal policy $\kappa^*(P^E)$ given these estimates. In what follows, I focus on the second interpretation.

Figure 5 depicts the marginal abatement cost curve and the optimal policy curve for both sets of calibrated parameters. Panel (a) and (b) assume that the policymaker can provide subsidies at no cost, while Panel (c) and (d) involve a higher marginal cost of public funds. I obverse that the marginal abatement cost is strictly increasing in the subsidy, which insures that a stable solution to the planner's problem exists and is unique at a given P^E. In practice, we expect rebates to exhibit decreasing returns in term of emission abatement, since the number of infra-marginal consumers increases with the rebate but emissions abated per new owner does not. I evaluate the marginal abatement cost at current rebates to be between \$311 and \$423. This is higher than contemporaneous measures of the social cost of carbon.

Figure 5 also reports the corresponding average abatement costs (built from the same social planner's objective function). A key observation is that the average abatement cost is below the marginal abatement cost over the full policy space. This has important implications for policy design: determining the optimal policy based on the average abatement cost systematically leads to an over-investment from the policymaker.

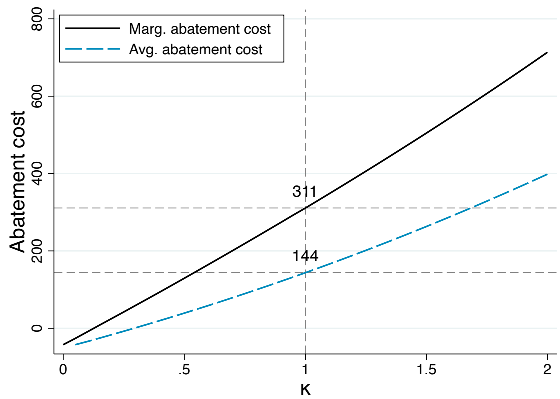
I invert the marginal abatement cost curves to recover optimal policy curves. I evaluate the optimal policy for two separate estimates of the social cost of carbon. The chosen values are \$45 and \$183, which correspond to the average social cost of carbon and the 95th percentile of the distribution.[19] For the low estimate, the optimal policy correspond to 4.7 – 25.8% of the current rebate programs. For the high social cost of carbon, the optimal policy correspond instead to 39.8 – 65% of current rebates. In all cases, our analysis suggest that policymakers in Canada are over-investing on rebates. In the most favorable scenario, the provincial and federal rebate programs should subsidize battery electric vehicles by \$5,200 and \$3,250 respectively. For completeness, Table A.4 summarizes these findings.

6.4 Improving the performance of rebate programs

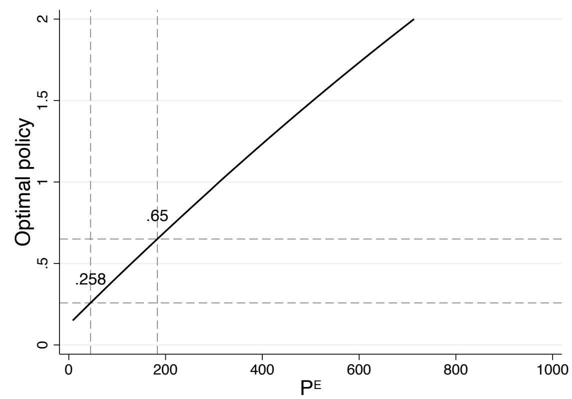
To provide more perspective on these results, I consider two alternative policies. First, I try to improve on the emission reduction potential of rebates by combining them with a cash for clunker component. Specifically, I define a clunker to be any car above 10 years old, and I allow consumers to trade in their clunker for the electric vehicle subsidy. Since these

[19] *Source:* Environment and Natural Resources Canada.

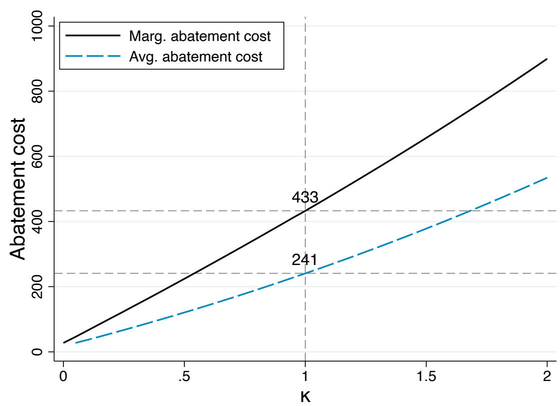
Figure 5: Abatement cost and optimal policy curves



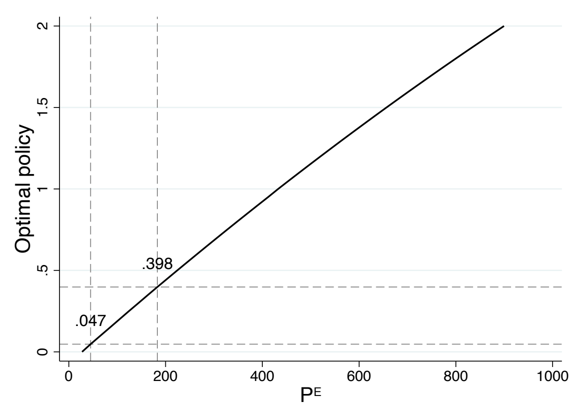
(a) Abatement cost ($\phi = 1$)



(b) Optimal policy ($\phi = 1$)



(c) Abatement cost ($\phi = 1.15$)



(d) Optimal policy ($\phi = 1.15$)

clunkers are not resold on the secondary market, their removal leads to additional emission abatement. I determine the distribution of clunkers in the population by looking at the full fleet of vehicles at the beginning of each year, and integrating over that distribution to compute the counterfactual. The additional emission reduction related to these clunkers is computed using their expected remaining lifetime and their average emissions per kilometre. These additional calibrated values are available in Table A.5. The second policy tries to improve the targeting of the current program by restricting the access to subsidies to the most price sensitive consumers. In practice, this could be implemented by restricting access to low income households, under the assumption that income and price sensitivity are highly correlated.

The results of these two experiments are presented in Table 10. One of the key finding

Table 10: Counterfactual analysis

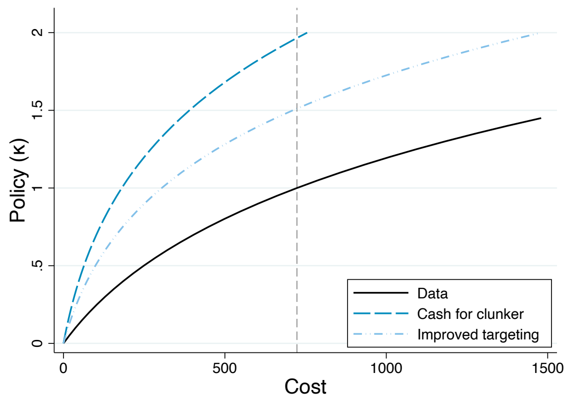
	(1) Both rebates (Data)	(2) Cash for clunker	(3) Improved targeting	(4) No rebates (Baseline)
Total sales	+12,209	+3,058	+6,014	3.236e+06
Sales (fuel)	-27,981	-7,128	-13,221	3.147e+06
Sales(battery electric)	+24,939	+6,319	+11,566	22,366
Sales (plug-in hybrid)	+15,800	+4,008	+7,925	21,069
Sales (hybrid)	-549	-140	-256	45,337
Stations	+434	+133	+235	2,377
EV subsidized	84,174	21,033	34,718	0
CO_2 Emissions	-1.117	-0.732	-0.512	142.6
Consumer surplus	562.8	143,4	229.5	0
Total cost	723.2	180.6	304.3	0
Total cost (prov)	573.1	142,9	236.4	0
Total cost (fed)	150.1	37.63	67.86	0
Avg. cost per ton CO_2	647	247	594	
Avg. cost per electric vehicle	17,753	17,486	15,612	

NOTE: *CO_2 emissions* is the present-value of CO_2 equivalent emissions over the lifetime of vehicles, in million tons. Includes emissions abated from clunker program. Lifetime emissions are computed based on a 22,053 average mileage per year, and a total lifetime of 12.02 years. *Consumer surplus* and *Total cost* are in million 2018 CAD. *Avg. cost per ton CO_2* and *Avg. cost per electric vehicle* are in 2018 CAD.

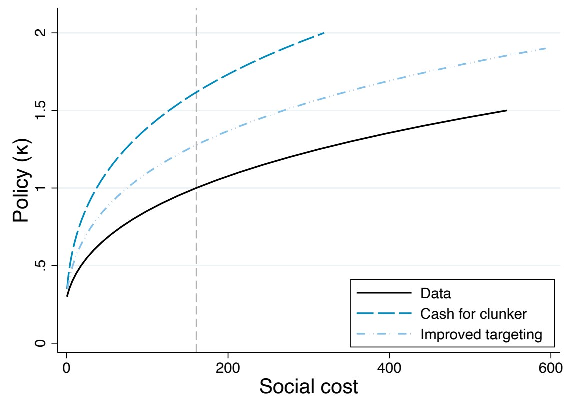
is that these two new programs (henceforth "cash for clunker" and "improved targeting") generate far fewer electric vehicle sales than the current program. This follows naturally from the fact that we are restricting the access to subsidies. The "cash for clunker" and the "improved targeting" programs reach 25% and 40% respectively of the potential electric vehicle owners.

To study the cost efficiency of the "cash for clunker" and the "improved targeting" programs relative to the current rebate schemes, it is useful to use total spending as a point of comparison. Figure 6 depicts the total emission abatement for various levels of government spending and the associated policies. I present two sets of results. In Panel (a) and (c), I plot total emission abatement against total government spending, while Panel (b) and (d) instead plots emissions against the social cost of the policy, defined as cost minus social welfare. For any level of government spending, the "cash for clunker" program dominates

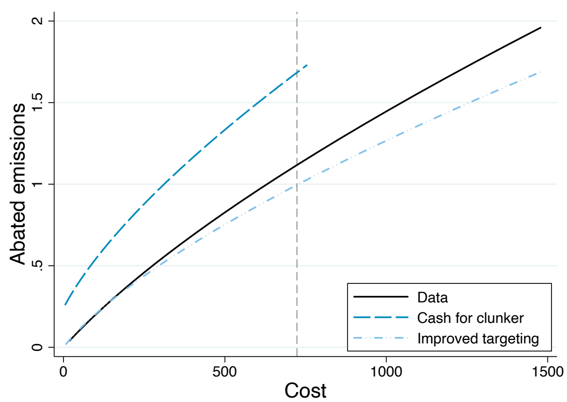
Figure 6: Cost efficiency



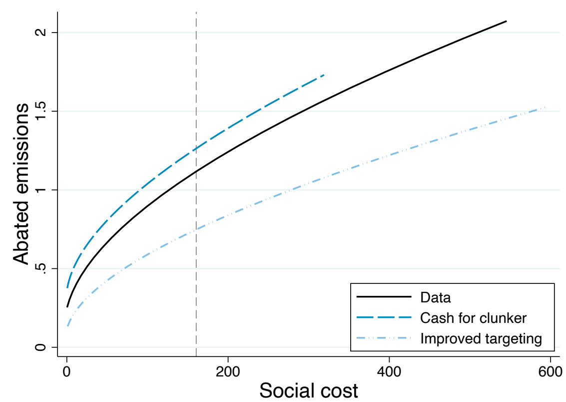
(a) Cost equivalent



(b) Social cost equivalent



(c) Cost equivalent



(d) Social cost equivalent

both the current rebates and the "improved targeting" programs. My result suggests that imposing the cash for clunker restriction could lead to 1.5 times more abated emissions for the same level of costs. While this is a significant improvement over the current program, there are a few caveats to consider. First, this analysis does not account for reactions on the secondary market. Our results hold so long as the fall in supply in the secondary market did not push extra buyers on the primary market. This could lead to more fuel car sales, increasing emissions, and mitigating my results.

The "improved targeting" program underperforms compared to all other policies under consideration. To reach the same level of spending, the policymaker needs to increase subsidies substantially in order to convince the same number of buyers to purchase electric vehicles. Overall, it is more costly at the margin to decrease emissions: there are consumers in the low price sensitivity group who would convert to electric for cheaper. When we consider gains to consumer surplus, the "improved targeting" policy vastly underperforms as it fails to increase surplus at the same rate as the current policy. I general, the main takeaway is that imposing restrictions do not produce a better environmental outcome, unless additional emission reductions occur elsewhere as is the case in the "cash for clunker" program.

7 Conclusion

The Canadian electric car market presents a unique opportunity to study the impact of subsidizing electric vehicle sales on key economic outcomes. Evaluating the environmental performance of such policies is important. With limited financial resources, policymakers should strive to reduce emissions at the lowest cost possible. My findings suggest that electric vehicle subsidies are an effective way to diffuse the technology and increase adoption. I find no evidence that these additional sales generate additional charging station installations in the short run. In the long run, I find that the program led to a moderate increase in network size. This study provides a rigorous cost-benefit analysis to evaluate the cost-effectiveness of rebate programs. I find in general that the marginal cost of abatement remains high compared to traditional measures of the social cost of carbon. This suggests that the provincial and federal governments in Canada over-invest on electric vehicle subsidies compared to the optimum. I find that one way to improve on the current program is to restrict the access to rebates to buyers who turn in their old car in exchange for an electric vehicle subsidy.

These results should be considered as part of a broader set of environmental policies. For example, investments into cleaner electricity production, reforestation, or the modernization of particularly polluting industries could abate emissions at a lower marginal cost. This study contributes to creating a unified framework to study and compare environmental policies and help policymakers make these crucial decisions.

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A Additional Tables and Figures

Table A.1: County-level demographics

	Ontario			Quebec		
Demographics	Pre	Post 1	Post 2	Pre	Post 1	Post 2
Avg. household income	96,484	100,837	114,341	74,654	79,399	90,459
	(15,509)	(15,337)	(15,866)	(11,158)	(10,651)	(11,100)
Avg. after-tax household income	80,070	82,742	93,967	61,881	65,102	73,978
	(11,229)	(10,810)	(11,105)	(8,192)	(7,745)	(8,030)
Unemployment rate	0.081	0.074	0.12	0.073	0.073	0.075
	(0.012)	(0.010)	(0.018)	(0.024)	(0.022)	(0.020)
Avg. household size	2.65	2.63	2.62	2.34	2.32	2.28
	(0.28)	(0.29)	(0.28)	(0.17)	(0.17)	(0.17)
Avg. age	40.6	41.0	41.8	42.0	41.9	42.8
	(2.66)	(2.02)	(2.03)	(3.35)	(2.52)	(2.6 4)
Share of graduates	0.25	0.32	0.36	0.20	0.25	0.29
	(0.10)	(0.11)	(0.12)	(0.09)	(0.11)	(0.12)
Share of conservatives	0.42	0.35	0.33	0.17	0.16	0.16
	(0.10)	(0.08)	(0.08)	(0.10)	(0.11)	(0.11)
Work location < 30 min drive	–	0.57	0.61	–	0.61	0.66
		(0.14)	(0.11)		(0.14)	(0.11)
Work location within county of residence	–	0.74	0.76	–	0.67	0.69
		(0.15)	(0.12)		(0.24)	(0.21)
Median commuting time	23.4	–	–	22.0	–	–
	(6.64)			(6.68)		
Share of homeowners	0.72	0.70	0.69	0.62	0.62	0.60
	(0.11)	(0.11)	(0.10)	(0.15)	(0.14)	0.14
Share of visible minority	0.27	0.29	0.34	0.11	0.13	0.16
	(0.21)	(0.21)	(0.22)	(0.12)	(0.13)	(0.15)
Population, in million	13.07	13.45	14.22	7.95	8.11	8.44
# of counties	49	49	49	98	98	98

NOTE: All values are averaged over counties, weighted by population. Standard deviation in parenthesis. *Pre* period is based on the 2011 Canadian Census Survey. *Post 1* period is based on the the 2016 Canadian Census Survey. *Post 2* period is based on the 2021 Canadian Census Survey. Income not adjusted for inflation.

Table A.2: Average characteristics, by engine type

VARIABLE	Fuel	Battery electric	Plug-in hybrid	Hybrid
Characteristics				
Price, in CAD	36,780	54,531	42,830	36,844
Rebate, in CAD	0	9,836	6,996	364
Power, in kW	149.6	168.9	154.9	163.5
Length, in m	4.55	4.41	4.63	4.65
Width, in m	1.83	1.85	1.82	1.83
Height, in m	1.57	1.52	1.51	1.58
Weight, in 100kg	15.8	16.9	16.9	16.0
Driving Range, in km	661	349	809	873
Fuel consumption, in L/100km	8.85	0	5.94	5.89
Electricity consumption, in kWh/100km	0	16.1	24.8	0
Cost of driving 100km	11.40	1.74	6.79	7.35
CO^2 emissions, in g/km	205.6	0	60.1	137.5
Transmission				
Manual	0.10	0	0	0
Automatic	0.90	1	1	1
Fuel type				
Regular	0.82	0	0.88	1
Premium	0.15	0	0.12	0
Diesel	0.03	0	0	0
Market segment				
Subcompact	0.11	0.19	0.02	0
Compact	0.33	0.59	0.66	0.11
Midsize	0.05	0	0.09	0.19
Luxury/Executive	0.02	0.03	0	0
Crossover Utility (CUV)	0.18	0.18	0.06	0.64
Sport Utility (SUV)	0.27	0.01	0.15	0.05
Minivan	0.03	0	0.02	0

NOTE: All characteristics are weighted by sales. All dollars values are in 2018 CAD.

Table A.3: Robustness to distance threshold

	(1) No instr	(2) 0 km	(3) 50 km	(4) 100 km	(5) 150 km	(6) 200 km	(7) 250 km	(8) 300 km	(9) 350 km	(10) 400 km	(11) 450 km	(12) 500 km
Price - Rebate	-0.662***	-0.675***	-0.675***	-0.675***	-0.675***	-0.675***	-0.676***	-0.676***	-0.677***	-0.677***	-0.678***	-0.678***
	(0.031)	(0.031)	(0.031)	(0.031)	(0.031)	(0.031)	(0.031)	(0.031)	(0.031)	(0.031)	(0.031)	(0.031)
Log network	0.248***	0.411***	0.402***	0.383***	0.366***	0.362***	0.379***	0.393***	0.391***	0.397***	0.397***	0.383***
	(0.024)	(0.031)	(0.031)	(0.032)	(0.033)	(0.033)	(0.034)	(0.035)	(0.035)	(0.035)	(0.036)	(0.035)
Observations	126,397	126,397	126,397	126,397	126,397	126,397	126,397	126,397	126,397	126,397	126,397	126,397
R-squared	0.120	0.112	0.112	0.113	0.113	0.113	0.112	0.112	0.112	0.111	0.111	0.111

NOTE: This table highlights how the coefficients on *Log of stations* changes as we increase the distance threshold which is used to construct the charging station instrument. Distance thresholds are in km from centroid to centroid for each region pair. Column (1) instruments for price 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. All regressions include car characteristics and their interaction with county-level average demographics. All regressions include brand, market segment, county, and year fixed effects. All regression include cost shifters and Gandhi-Houde differentiation instruments. Standard error in parenthesis are clustered at the product $\times$ county level. Significance: * $<$ 0.10; ** $<$ 0.05; *** $<$ 0.01.

Table A.4: Optimal policy

	Calibration	
	(1)	(2)
PANEL A: Low SCC ($45)		
Optimal policy	$\kappa^* = 0.258$	$\kappa^* = 0.047$
Provincial rebate	2,064	376
Federall rebate	1,290	235
PANEL B: High SCC ($183)		
Optimal policy	$\kappa^* = 0.650$	$\kappa^* = 0.398$
Provincial rebate	5,200	3,184
Federall rebate	3,250	1,990
PANEL C: Abatement cost		
Marginal cost of public funds	$\phi = 1$	$\phi = 1.15$
Marginal abatement cost	311	423
Average abatement cost	160	252

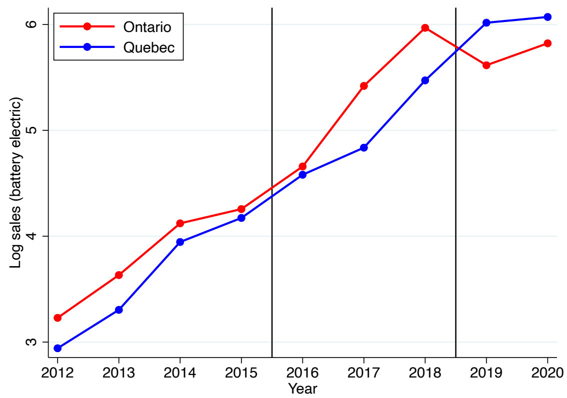
NOTE: *Provincial rebate* and *Federal rebate* are based on an $8,000 and a $5,000 subsidy respectively. Abatement costs are measured at the current policy ($\kappa = 1$). All values are in 2018 CAD.

Table A.5: Average lifetime and emissions of clunkers

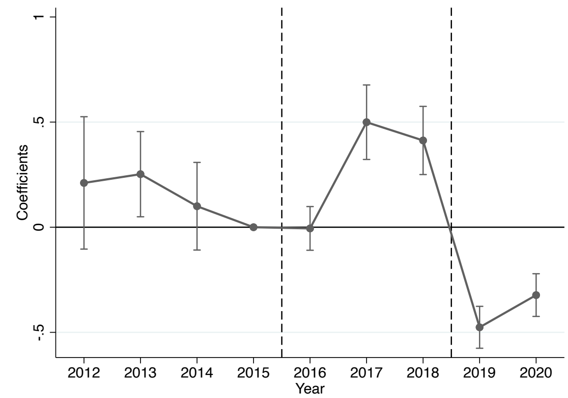
Age of Vehicle	Expected lifetime	Avg. CO_2 emissions
NEW	12.02	215.6
1	11.02	214.8
2	10.41	213.4
3	9.96	211.7
4	9.34	210.6
5	8.54	209.2
6	7.78	208.9
7	7.05	208.0
8	6.33	208.2
9	5.64	208.0
10	4.99	206.7
11	4.46	206.1
12	4.05	206.6
13	3.75	206.8
14	3.54	207.6
15	3.42	208.1
16	3.37	210.1
17	3.40	212.1
18	3.50	215.0
19	3.64	217.7
20	3.80	220.8
21	3.94	223.7
22	4.00	227.7
23	3.96	232.4
24	3.81	235.8
25	3.50	236.5
26	3.07	236.7
27	2.49	235.4
28	1.77	234.7
29	0.93	234.4
30	0.00	235.8

NOTE: Expected lifetime of vehicles is computed using the micro-level data on car registrations, which includes all vehicles in circulation. We track each vehicle over 10 years. *Average CO2 emissions* are imputed using vehicle weight, the cylinder capacity, and the number of cylinders which are available for all vehicles in the registration data, and carbon emissions per kilometre which is available for cars produced after 2011.

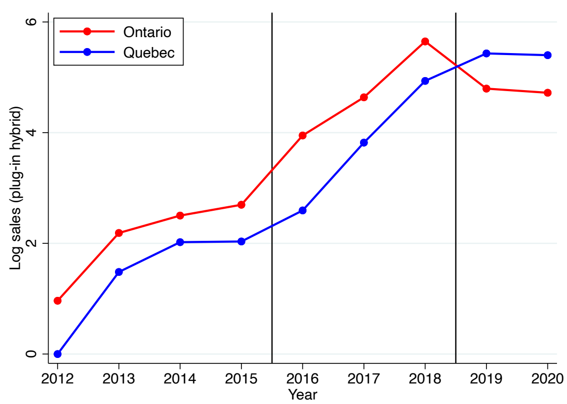
Figure A.1: Difference in differences analysis (robustness)



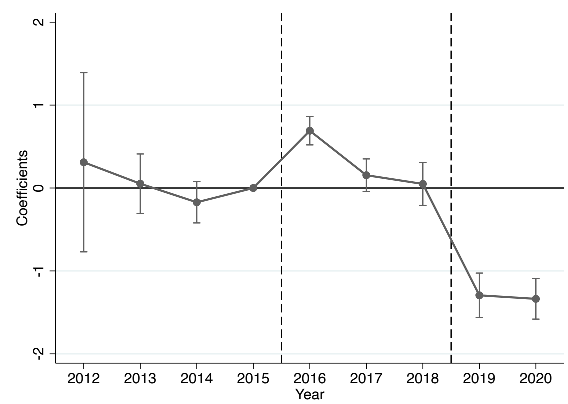
(a) Sales battery electric



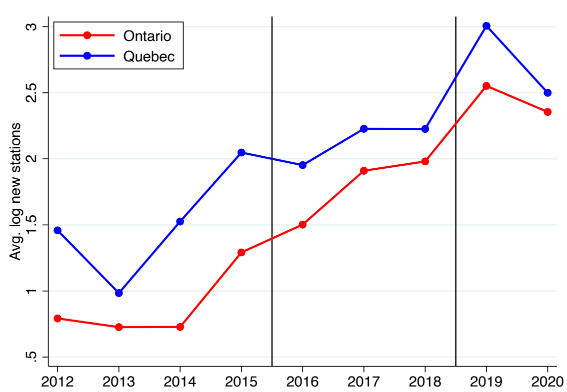
(b) Sales battery electric (event study)



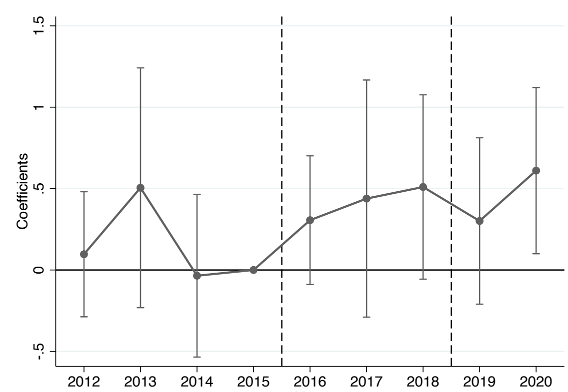
(c) Sales plug-in hybrid



(d) Sales plug-in hybrid (event study)

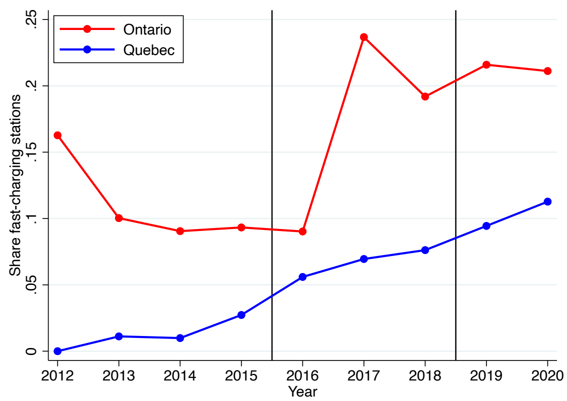


(e) New station installations

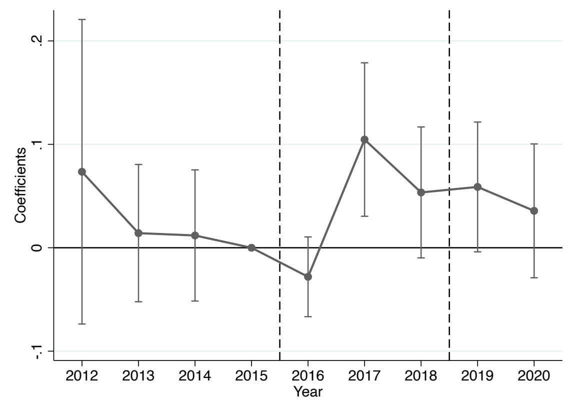


(f) New station installations (event study)

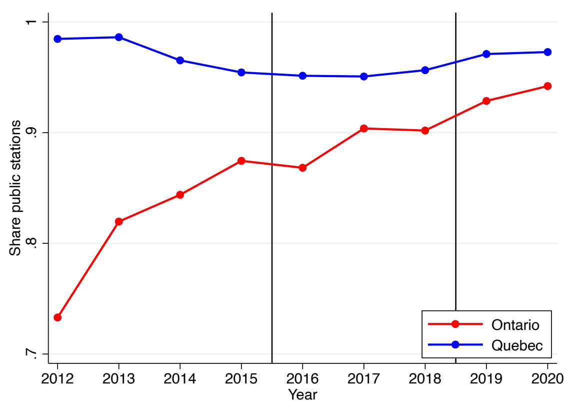
Figure A.2: Difference in differences analysis (network characteristics)



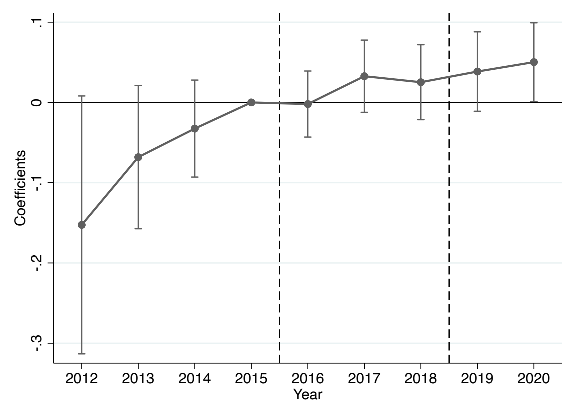
(a) Share fast charging



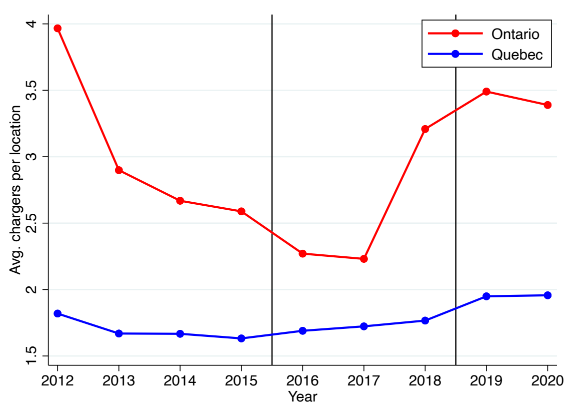
(b) Share fast charging (event study)



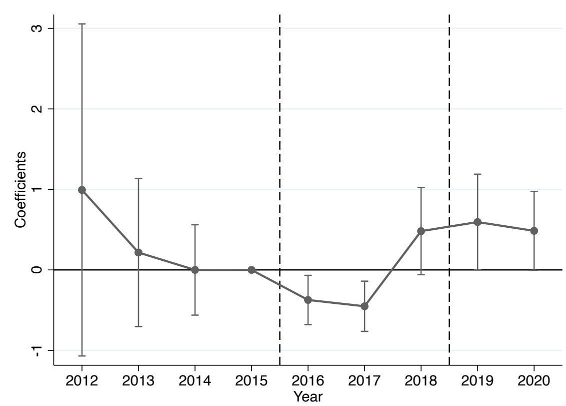
(c) Share public station



(d) Share public station (event study)

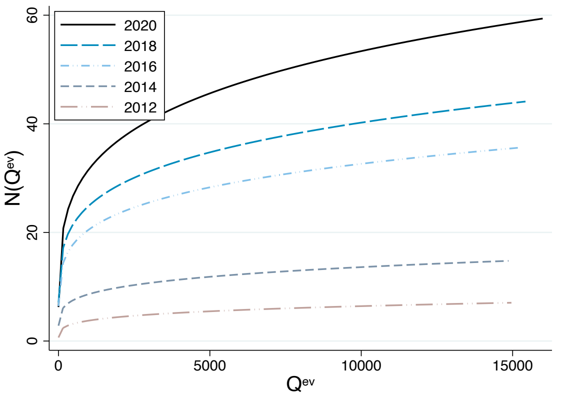


(e) Avg. chargers per location

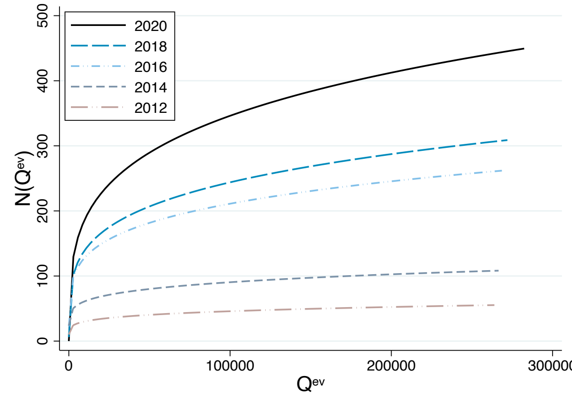


(f) Avg. chargers per location (event study)

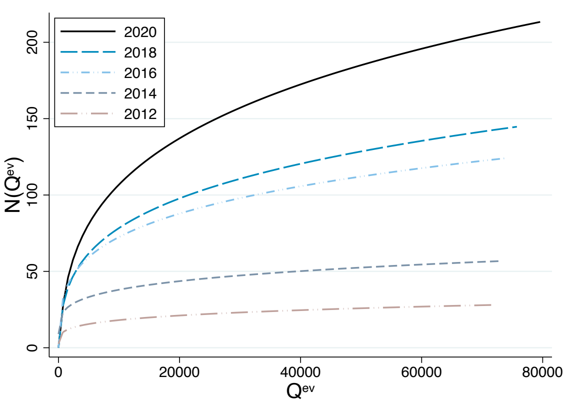
Figure A.3: Station supply curves, for selected counties



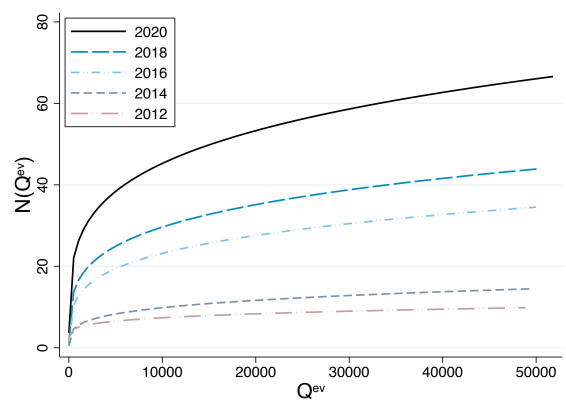
(a) Rivière-du-Loup (12)



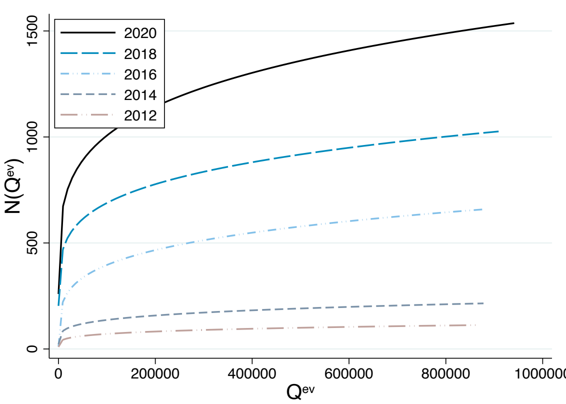
(b) Québec (23)



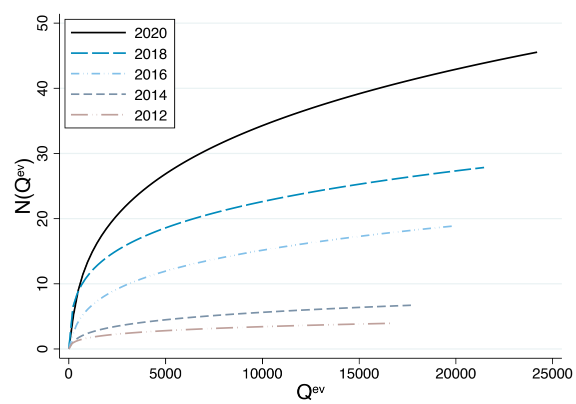
(c) Sherbrooke (43)



(d) L'Assomption (60)

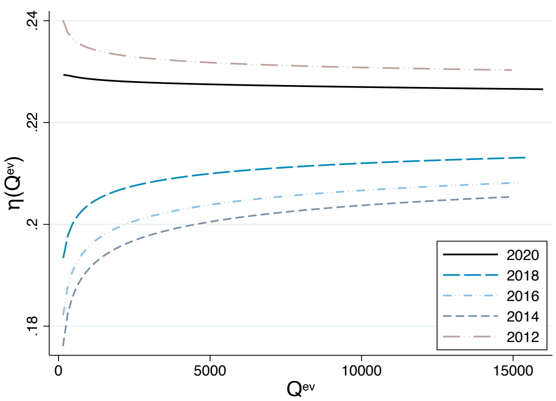


(e) Montréal (66)

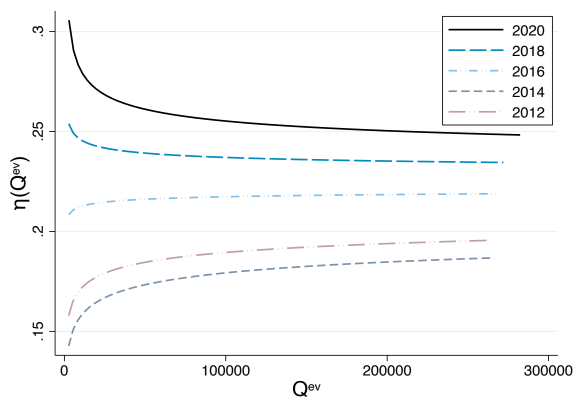


(f) Mirabel (74)

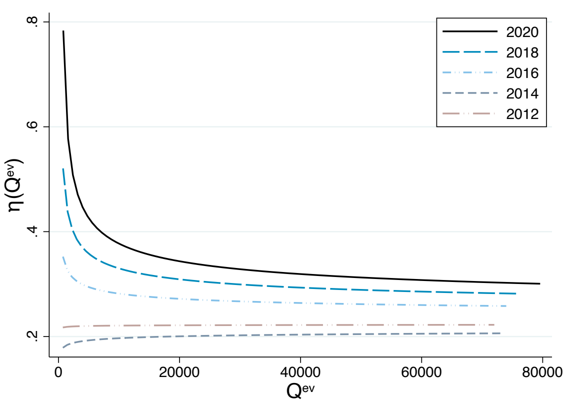
Figure A.4: Station elasticity of supply curves, for selected counties



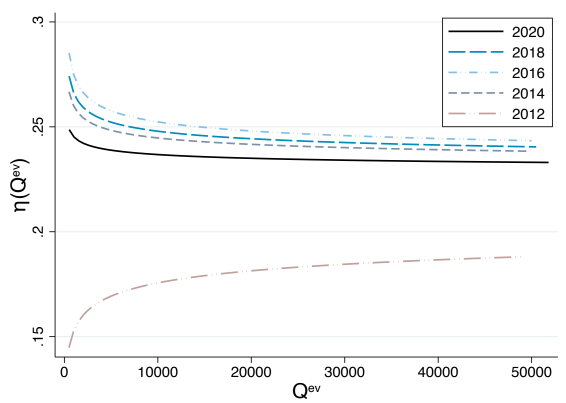
(a) Rivière-du-Loup (12)



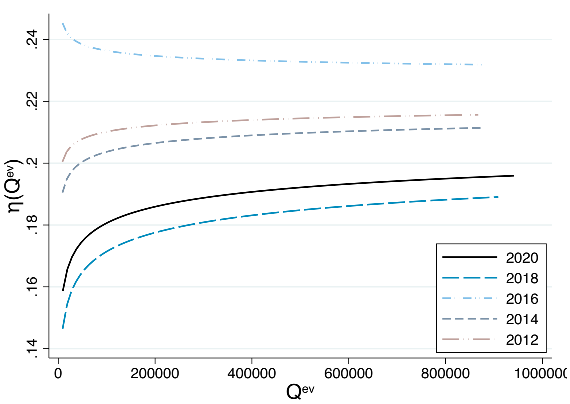
(b) Québec (23)



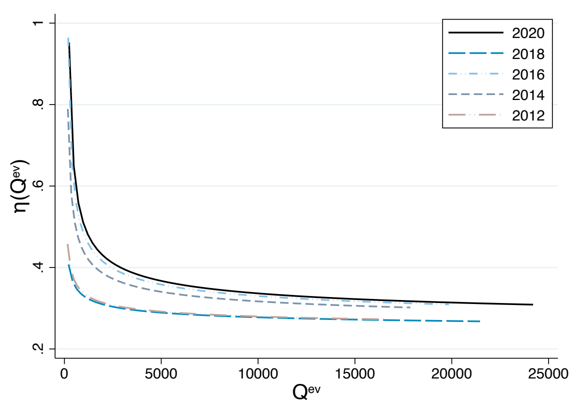
(c) Sherbrooke (43)



(d) L'Assomption (60)



(e) Montréal (66)



(f) Mirabel (74)

B Details on the Data

Car registration. The data on car registration comes from two main sources: the Ministry of Transportation of Ontario (MTO) and the Société d'Assurance Automobile du Québec (SAAQ). The Ontario dataset includes quarterly car registrations aggregated at the product-county level for the years 2011-2021. The data includes the make (i.e. Ford), the model (i.e. Focus), and the engine type (i.e. Electric), and the quantity sold.

The Quebec dataset comprises 10 yearly datasets that detail the full fleet of vehicles in circulation at the end of each year, from 2011 to 2020. The data includes the make, the model, the model year, some demographics of the owner (age, gender, county of residence), as well as additional vehicle characteristics (colour, number of cylinders, cylinder capacity, and curb weight). The engine type is available from the 2017 dataset onwards. I impute the engine type in the 2011-2016 datasets using the information available in the 2017 dataset. Since battery pack are relatively heavy, I find that the make, the model, the model year, and the curb weight of the vehicles allow me to identify battery electric, plug in hybrids, and hybrids reliably. In some cutting edge cases, I also leverage information in the other variables (number of cylinder, cylinder capacity, and the consumer demographics) to assign an engine type to all vehicles. Vehicles with a model year prior to 2011 are assumed to be internal combustion engines.

I use the following algorithm to reconstruct sales in Quebec in each year between 2012 and 2020.

1. Take dataset t;
2. Keep model years that could have been sold as new in year t (i.e. $t-1, t, t+1$);
3. Remove vehicles that also appear in dataset $t-1$, by comparing the make, the model, the model year, the colour of the vehicle, the age of the owner, the gender of the owner, and the county of residence of the owner;
4. Repeat for dataset $t+1$.

Since vehicles could have been resold in the first year of ownership, or owners could have moved to a different county, I risk overestimating sales. After a careful verification against governmental statistics, I find that this is not a serious issue.

Car characteristics. The car characteristics were scrapped from The Car Guide[20] which publishes on their website comprehensive information on all makes and models available in Canada. This website has been one of the go-to reference for information about the different car makes since the mid-90s and has widespread public recognition in Canada. The car characteristics dataset includes retail prices 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). The data has a non-negligible number of missing values in key variables. Specifications with a missing price or a missing curb weight are removed entirely.[21] Missing values in other variables are filled in using the data from other specification that share the same make-model-year. If an information is missing for all specifications for a make-model-year combination, I use information from other vehicles with the same make-model but a different model year. Remaining missing values are imputed using data collected on the Auto Trader website.[22]

Product definition. I define a product to be a combination between the make, the model, and the engine type. The final dataset is aggregated at the product-county-year level. The car characteristics dataset is at a more disaggregated level than the registration data. I select the characteristics of the most sold specification over all sales to define product attributes. To find this most popular specification, I first recover the exact specification for each entry in the registration data by matching on the make, the model, the engine type, and then picking the specification with the closest curb weight.[23] I then aggregate the data over counties and keep the specification with the most sales. Once the specification is chosen, I assign these characteristics to all products.

To avoid the proliferation of products in the structural estimation, I remove all products with fewer than 1000 sales over all counties and years (100 sales for battery electric and plug-in hybrid vehicles). I also remove exotic makes, and all vehicles with a retail price above $150,000. Finally, I remove pick-up trucks which are poor substitutes to electric vehicles and are not relevant to this study.

[20] See `https://www.guideautoweb.com/en/`.

[21] Curb weight is particularly important in this context since I use it to match the make-model-year registration data to the make-model-year-specification characteristics data.

[22] See `https://www.autotrader.ca`.

[23] In case two specifications have the same weight in the characteristics data, I keep the specification that is closest to the base model.

C Details on the Demand Estimation

C.1 Estimation

The estimation of the demand side parameters follows the best practices described in Conlon and Gortmaker (2020). I include three random coefficients to capture consumers heterogeneity. The random coefficient on prices captures differences in price sensitivity, while the random coefficients on the constant and the battery electric dummy variable control for the substitution between the inside good and the outside good, and between battery electric and other vehicles. I find that these are important to make sure I do not overestimate the environmental gains due to rebate programs.

Estimation is done in two-stages using the Nested Fixed Point algorithm. I set a tight tolerance threshold on the objective function of 1e-5 as suggested in Conlon and Gortmaker (2020). I partial out the β parameters and focus the estimation on the σ random coefficients. Fixed effect are differentiated out using Frisch-Waugh-Lovell Theorem. The integration of the market shares is performed using 1,000 independent Halton draws. Finally, I perform the inversion of the market shares using the `squarem` algorithm[24] and a tight convergence threshold of 1e-12. Reynaert and Verboven (2014) and Conlon and Gortmaker (2020) both show that the `squarem` algorithm is significantly faster than the contraction mapping described in Berry et al. (1995).

I do not use the optimal instruments described in Reynaert and Verboven (2014) and Conlon and Gortmaker (2020). I find that they did not work well in this particular application, since network size is determined jointly with electric vehicle sales. It is not clear how to deal with the endogenous network size while computing the optimal instruments since it is a stock variable. I also do not include a supply side for cars. As pointed out by Conlon and Gortmaker (2020), including a supply side helps identifying the random coefficients, but can lead to misleading results in case it is misspecified. Prices for cars are set at the North American level, hence assuming that manufacturers change prices in response to a local Canadian policy would lead to one such misspecification. I instead assume that prices do not respond to the policy, although they are still endogenous since they are correlated to unobserved car attributes.

[24] See Varadhan and Roland (2008).

Table A.6: Choice of the demographic interactions

VARIABLE	ESTIMATE	INCOME	AGE	GENDER	POP DENSITY	TREND	σ
Price - Rebate	-0.671***						
	(0.031)						
Log network	0.394***						
	(0.035)						
Power	0.885***	0.105***	0.227***	0.043***			
	(0.036)	(0.018)	(0.035)	(0.008)			
Weight	-0.253***					0.074***	
	(0.055)					(0.005)	
Driving cost	-0.042***	-0.005					
	(0.005)	(0.003)					
Battery electric	-2.342***	-0.134**		0.181***	-0.414***		
	(0.104)	(0.062)		(0.038)	(0.086)		
Plug-in hybrid	-2.246***	-0.251***		0.157***	-0.445***		
	(0.100)	(0.052)		(0.040)	(0.070)		
Hybrid	-1.746***		0.413***	0.148***			
	(0.035)		(0.083)	(0.028)			
Observations	126,397						
Nb. of markets	864						
Avg. Own-price elasticity	-2.97						
Nb. Elasticity > -1	0						

NOTE: Includes brand, market segment, county, and year fixed effects. Standard errors in parenthesis are clustered at the product $\times$ county level. Significance: * < 0.10; ** < 0.05; *** < 0.01.

C.2 Selection of demographics

I include interactions between car characteristics and average county level demographics to help in the estimation of random coefficients. The chosen demographics are the average income, the average age, the share of female, population density, and a time trend. I select the exact specification using a standard logit model without consumer heterogeneity. I first estimate the model with all possible interactions,[25] then remove interactions one by one based on the p-value. The process stops when all demographic interactions are significant at the 1% level. Table A.6 shows the chosen specification. I reintroduce two interactions in the final specification that did not survive the iterative procedure: income interacted with driving cost, and income interacted with the battery electric dummy. I find that these interactions help identify the random coefficients in the full model.

[25]Population density reflects the home charging potential and is interacted with the engine types only in the starting specification. The time trend is not interacted with the engine types, to avoid confounding the estimate on network size.

C.3 Elasticities

The elasticity to price can be computed following Springel (2021). Using chain rule, we have that

$$\varepsilon_{mt}^{j,k} = \frac{\partial s_{jmt}(\mathbf{p}_{mt}, N_{mt})}{\partial p_{kt}} \cdot \frac{p_{kt}}{s_{jmt}},$$

where

$$\frac{\partial s_{jmt}(\mathbf{p}_{mt}, N_{mt})}{\partial p_{kt}} = \frac{\partial s_{jmt}}{\partial p_{kt}} + \frac{\partial s_{jmt}}{\partial N_{mt}} \cdot \frac{\partial N_{mt}}{\partial Q_{mt}^{ev}} \cdot \frac{\partial Q_{mt}^{ev}}{\partial p_{kt}}. \tag{9}$$

It can be shown that the terms in (9) are

$$\frac{\partial s_{jmt}}{\partial p_{kt}} = \begin{cases} \int \beta_i^{\mathbf{P}}\, s_{ijmt}\,(1 - s_{ijmt})\, dF(\nu) & \text{if } j = k \\ -\int \beta_i^{\mathbf{P}}\, s_{ijmt}\, s_{ikmt}\, dF(\nu) & \text{if } j \neq k \end{cases},$$

$$\frac{\partial s_{jmt}}{\partial N_{mt}} = \begin{cases} \int \frac{\beta_i^{\mathbf{N}}}{N_{mt}}\, s_{ijmt} \sum_{\ell \in EV} s_{i\ell mt}\, dF(\nu) & \text{if } j \in EV \\ -\int \frac{\beta_i^{\mathbf{N}}}{N_{mt}} \sum_{\ell \in EV} s_{i\ell mt}\, dF(\nu) & \text{if } j \notin EV \end{cases},$$

$$\frac{\partial N_{mt}}{\partial Q_{mt}^{ev}} = \sum_{k=1}^{S_{mt}} \int \phi \left(\frac{\ln(k) - \lambda^{\mathbf{Q}} \ln(Q_{mt}^{ev}) - \mathbf{D}_{mt}'\lambda^{\mathbf{D}} + \lambda^{\mathbf{v}} v}{\omega} \right) \cdot \frac{\lambda^{\mathbf{Q}}}{\omega Q_{mt}^{ev}} \cdot dF(v),$$

$$\frac{\partial Q_{mt}^{ev}}{\partial p_{kt}} = \frac{L_{mt} \cdot \sum_{\ell \in EV} \frac{\partial s_{\ell mt}}{\partial p_{kt}}}{1 - L_{mt} \cdot \frac{\partial N_{mt}}{\partial Q_{mt}^{ev}} \cdot \sum_{\ell \in EV} \frac{\partial s_{\ell mt}}{\partial N_{mt}}}.$$

Demand elasticities are not used in the computation of counterfactuals in this particular study since I do not include a supply side for cars. Nevertheless, they are useful to assess the quality of the estimation. Figure A.5 depicts the distribution of own price elasticities. The average elasticity is -3.24, which is comparable to other studies on the car market. Springel (2021) and Remmy (2022) both find that the cross price elasticities between electric vehicles are negative, suggesting that these products become complements once we account for network effects. I find a similar result as these works. Table A.7 reports the full elasticity matrix for selected battery electric and plug-in hybrid vehicles, in 2018.

Figure A.5: Distribution of own-price elasticities

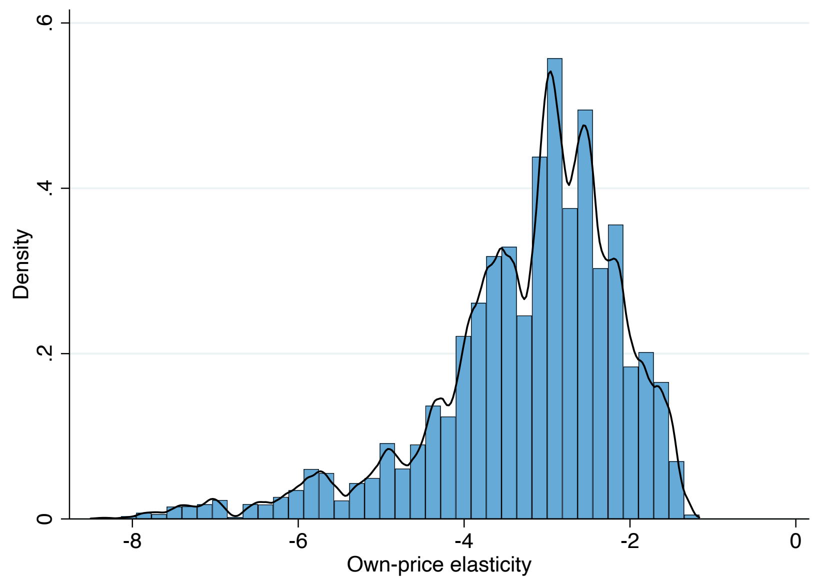


Table A.7: Average elasticities of electric vehicles, in 2018

	Bolt EV	Volt	Pacifica	C-Max	Fusion	Soul EV	Outlander	Leaf	Model 3	e-Golf
Chevrolet Bolt EV	-2.916	-0.00415	-0.000813	-0.000134	-0.00139	-0.000581	-0.00578	-0.00342	-0.00310	-0.000947
Chevrolet Volt	-0.00224	-2.545	-0.000803	-0.000105	-0.00145	-0.000533	-0.00570	-0.00351	-0.00340	-0.000944
Chrysler Pacifica	-0.00244	-0.00433	-3.759	-0.000117	-0.00134	-0.000573	-0.00490	-0.00402	-0.00292	-0.00116
Ford C-Max	-0.00176	-0.00258	-0.000583	-2.176	-0.00103	-0.000239	-0.00418	-0.00284	-0.00328	-0.000625
Ford Fusion	-0.00231	-0.00409	-0.000796	-0.000135	-3.238	-0.000609	-0.00560	-0.00387	-0.00315	-0.00107
Kia Soul EV	-0.00181	-0.00331	-0.000663	-8.75e-05	-0.00116	-2.326	-0.00525	-0.00304	-0.00302	-0.000760
Mitsubishi Outlander	-0.00253	-0.00444	-0.000803	-0.000151	-0.00158	-0.000765	-3.545	-0.00406	-0.00322	-0.00114
Nissan Leaf	-0.00205	-0.00392	-0.000812	-0.000112	-0.00145	-0.000583	-0.00573	-2.770	-0.00301	-0.000943
Tesla Model 3	-0.00229	-0.00469	-0.000641	-0.000164	-0.00137	-0.000652	-0.00546	-0.00401	-4.162	-0.00114
Volkswagen e-Golf	-0.00177	-0.00318	-0.000767	-7.05e-05	-0.00114	-0.000412	-0.00503	-0.00298	-0.00309	-2.349

D Computing Counterfactuals

Computing counterfactuals relies on a simple fixed point iteration to determine jointly network size and electric vehicle sales. Recall that the structural model can be written as

$$N_{mt} = H(Q^{ev}_{mt}, \mathbf{D}_{mt}, \widehat{v}_{mt}, \epsilon^{\mathbf{n}}).$$

In what follow, I adopt the notation which includes the residuals from the control function $\widehat{v}_{mt}$. Notice that any structural function N_{mt} can be decomposed into it's conditional expectation and a residual, that is,

$$N_{mt} = \mathbb{E}_{\epsilon^{\mathbf{n}}}(N_{mt} \mid Q^{ev}_{mt}, \mathbf{D}_{mt}, \widehat{v}_{mt}) + \epsilon_{mt}, \tag{10}$$

$$= \mathbb{E}_{\epsilon^{\mathbf{n}}}\mathbb{E}_{v}(N_{mt} \mid Q^{ev}_{mt}, \mathbf{D}_{mt}) + \epsilon_{mt}, \tag{11}$$

where the second equality holds by a simple application of the Law of Iterated Expectations. Following Blundell and Powell (2004), the conditional expectation in equation (11) can be computed as

$$\mathbb{E}_{\epsilon^{n}}\mathbb{E}_{v}(N_{mt} \mid Q^{ev}_{mt}, \mathbf{D}_{mt}) = \int\int H(Q^{ev}_{mt}, \mathbf{D}_{mt}, v, \epsilon^{\mathbf{n}})dF(v)dF(\epsilon^{\mathbf{n}}), \tag{12}$$

$$= S_{mt} - \sum_{k}^{S_{mt}} \int \Phi\left(\frac{\ln(k) - \lambda^{\mathbf{Q}}\ln(Q^{ev}_{mt}) - \mathbf{D}'_{mt}\lambda^{\mathbf{D}} - \lambda^{\mathbf{v}}v}{\omega}\right) dF(v). \tag{13}$$

We can estimate $\widehat{\epsilon}$ using parameter estimates and the data, that is,

$$\widehat{\epsilon}_{mt} = N_{mt} - \mathbb{E}_{\epsilon^{\mathbf{n}}}\mathbb{E}_{v}(N_{mt} \mid Q^{ev}_{mt}, \mathbf{D}_{mt}). \tag{14}$$

With this estimate in hand, we can compute counterfactual networks as

$$\widetilde{N}_{mt} = \mathbb{E}_{\epsilon^{\mathbf{n}}}\mathbb{E}_{v}(N_{mt} \mid \widetilde{Q}^{ev}_{mt}, \mathbf{D}_{mt}) + \widehat{\epsilon}_{mt}, \tag{15}$$

for any $\widetilde{Q}^{ev}_{mt}$. Since the structural model takes as inputs the stock of electric vehicles and the stock of available charging stations, we need to solve counterfactuals recursively starting from $t = 1$. The algoritm is as follows:

1. Start from $t = 1$;

2. For each county, the initial fleet of electric vehicles is $Q^{ev}_{m,t-1}$;
3. Set initial network size $\widetilde{N}^0_{mt} = N_{m,t-1}$;
4. Compute market shares $s_{jmt}(\widetilde{N}^0_{mt})$;
5. Compute electric vehicle fleet $\widetilde{Q}^0_{mt} = Q^{ev}_{m,t-1} + L_{mt} \cdot \sum_{j \in EV} s_{jmt}(\widetilde{N}^0_{mt})$;
6. Update network size $\widetilde{N}^1_{mt} = \mathbb{E}_{\epsilon^{\mathbf{n}}} \mathbb{E}_v(N_{mt} \mid \widetilde{Q}^0_{mt}, \mathbf{D}_{mt}) + \widehat{\epsilon}_{mt}$;
7. Repeat steps 4-6 until convergence in $\widetilde{N}_{mt}$;
8. Repeat steps 2-7 recursively for $t = 2, 3, ..., T$.