Electric Vehicle Subsidies: Cost-Effectiveness and Emission Reductions

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Abstract

I design a structural model of demand for electric vehicles and the supply of a public charging infrastructure by forward-looking local planners. Using Canadian data, I study the cost-effectiveness of electric vehicle incentives in this context. Subsidizing electric vehicle purchases doubled adoption in Quebec but had only a small impact on network provision. I conduct a rigorous cost-benefit analysis to study the environmental performance of Quebec's rebate program. I find that the marginal abatement cost of emissions is substantially higher than the social cost of carbon, suggesting that policymakers in Quebec overinvested on electric vehicle incentives.

Keywords: electric vehicles, charging stations, subsidies, emission abatement, cost-benefit analysis, indirect network effects.
JEL Codes: L91, H41, Q58.

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1 Introduction

Electric vehicles (EV) constitute one of the most promising innovations for lowering carbon emissions from the transportation sector, as long as clean energy production is available. Several barriers prevent the widespread adoption of this technology. The high initial purchase cost or the low availability of recharging sites 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. At the same time, if few people own and use an electric vehicle, there is little incentive for network operators to invest in local charging infrastructures. This slows down the transition to electric vehicles.

Policymakers have 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 new electric vehicles directly. This narrows the price gap between internal combustion and electric vehicles, and leads to increased adoption. At the same time, financial incentives contribute to establishing a market demand for charging services. This encourages network operators to invest in charging station infrastructures, which yields additional electric vehicle sales through indirect network effects.

While some jurisdictions leave the development of charging infrastructure to the private sector (often subsidizing new stations), others choose to provide charging services to electric vehicle owners in the form of a public good. This is the case of the Canadian province of Quebec, where county-level governments are responsible for the provision of local charging infrastructures. I propose a structural model that reflects this reality. Its key innovation compared to previous works is that charging networks are provided by forward-looking local planners.[1] I find that ignoring the forward-looking behavior of network operators overestimates the importance of network effects in electric vehicle markets. This result is important for the design of electric vehicle incentive programs as this would lead to overestimating their performance.

I study the introduction of the electric car in Canada and the cost-effectiveness of electric vehicle incentive programs. I gather a novel dataset of vehicle registrations and charging station installations in two Canadian provinces, Ontario and Quebec, for the period spanning 2012 to 2020. I start with a difference-in-differences analysis to study the direct impact of subsidies on sales, and their indirect impact on charging station provision. The identifying variation comes from changes to Ontario's rebate program that occurred in 2016 and 2018. Originally, Ontario and Quebec offered similar electric vehicle subsidies ($8,500 and $8,000

[1]See for example Li et al. (2017), Pavan (2017), Springel (2021), Remmy (2025), or Li (2023).

respectively per electric vehicle sold). The government of Ontario improved subsidies to \$14,000 in February 2016, and phased out its incentive program in late 2018.

Subsidies are very effective at increasing electric vehicle adoption. The estimated intent-to-treat effect suggest that the improvements to Ontario's subsidies led to a 26.7% increase in electric vehicle adoption, while the abolition of the program reduced sales by 66.7% compared to baseline. I extend the analysis and estimate a continuous treatment effect model. I find that \$1,000 in subsidies is associated with a 7.9% increase in electric vehicle sales. This is qualitatively similar to findings by Muehlegger and Rapson (2022), who study an electric vehicle incentive program in California using a quasi-experimental setup.

I also study the indirect effect of these subsidies on charging station deployment. The idea is that network supply might respond to shifts in the aggregate demand for charging services emanating from new electric vehicle owners.[2] I do not find evidence that the policy changed the configuration of local networks in the short-run. Furthermore, I cannot find evidence that local networks changed along other dimensions. For example, I see no change in the number of charging points at each site or the share of fast charging stations available. Together, these findings suggest that network provision is rigid in the short-run and cannot respond immediately to an unpredicted surge in demand from new electric vehicle owners. To the best of my knowledge, this is a new result in the literature.

I rely on a structural estimation to address the cost-effectiveness of electric vehicles subsidies and their overall environmental performance. I focus the analysis around the province of Quebec, where charging infrastructures are provided to users as a public good by local county-level governments. This contrasts with other jurisdictions where network providers are private, profit maximizing firms. This setup is appealing for several reasons. First, it allows me to ignore the effects of price competition or product differentiation in the charging market. Charging and energy prices in Quebec are regulated, and the vast majority of chargers are homogeneous. Second, it avoids spatial competition concerns which can lead to multiple equilibria when networks are provided by more than one firm. Finally, it avoids issues related to platform competition, as all local networks are connected to the unified government provided platform.

I develop a structural model of consumers' demand for cars and the public provision of charging station infrastructures. In the model, consumers consider the current provision of charging stations in their surroundings at the time of purchase and are myopic about future states of the market. Charging stations are provided by forward-looking local planners in the form of a public good. Specifically, each local planner chooses the size of their charging

[2] Springel (2021) and Remmy (2025) have studied this question using a structural estimation. Both works focus on electric vehicle subsidies, charging station subsidies, and their interaction.

infrastructure in each period, taking into account the aggregate valuation of the network by users and the fixed cost of installing additional capacity. I show that ignoring the forward-looking behavior of local planners leads to overestimating their response to increases in the electric vehicle base. In the case of Quebec, this translates to overestimating the contribution of network effects to sales by 10.5%.

I conduct counterfactual simulations to validate the findings from the difference-in-differences analysis. I find that electric vehicle rebates doubled electric vehicle sales in Quebec between 2012 and 2020. This translates to a 11.7% increase per $1,000 in subsidies. Meanwhile network size increased by 15.3% over the same period. This suggests that the rigidities in network provision vanish in the long-run, leading to additional charging stations and electric vehicle sales. However, the indirect impact of electric vehicle incentives on charging station deployment remains small. To place these results in perspective, my results imply that charging stations are provided to electric vehicle owners at the rate of one station per 113 electric vehicles sold. This is slightly lower than findings by Springel (2021).

Finally, I construct a flexible framework to study the environmental performance of non-marginal environmental policies. 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 alongside the structural model primitives to conduct a rigorous cost-benefit analysis of the Canadian electric vehicle incentive programs. My findings suggest that the marginal abatement cost of emissions is $328 per ton of CO_2. This is above conventional measures of the social cost of carbons, which suggest an overinvestment on subsidies beyond what is efficient.

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 Pavan (2017), Li et al. (2017), Springel (2021) on network effects in both alternative fuel and electric vehicle markets. I add to this literature by considering the case where network operators are forward-looking. As mentioned above, ignoring the forward-looking behavior of network operators inflates the contribution of network effects in counterfactual simulations. Li (2023) studies the impact of unifying competing standards for charging electric vehicles. She focuses on the case where car manufacturers both provide electric vehicles and the infrastructure to charge them. I instead focus on the case where charging stations are provided publicly by regional governments and compatibility is not an issue. Other works on electric vehicles include Remmy (2025) on driving range provision, Armitage and Pinter (2021) on electric vehicle mandates, Dorsey et al. (2022) on consumers' valuation of charging networks, and Johansen and Munk-Nielsen (2020) on the synergy between fuel and electric vehicles within a multi-car household. Close to this research is the work of Xing et al. (2021) who show that recovering precise substitution patterns is crucial to estimating the environmental impact of electric vehicle incentives. My methodology allows for estimating very flexible elasticities of network supply which in turn enrich the substitution patterns on the demand side. In particular, this helps identifying the substitution between internal combustion and electric vehicles which is important for environmental policy analysis.

This paper fits in the wider literature that studies the environmental regulation of the car market. Previous works have focussed on the environmental performance of subsidies (Beresteanu and Li, 2011; D'Haultfoeuille et al., 2014; Huse and Lucinda, 2014; DeShazo et al., 2017; Azarafshar and Vermeulen, 2020; Sheldon and Dua, 2020), electric vehicle rebates passthrough (Beresteanu and Li, 2011; Sallee, 2011; Muehlegger and Rapson, 2022), gas taxes (Allcott and Wozny, 2014; Barla et al., 2016; Grigolon et al., 2018), emission standards (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), and comparing financial and non-monetary incentives (Jenn et al., 2018). Advances on estimating the environmental impacts of these policies include Durrmeyer (2022) who studies the distributional impacts of the French rebate program, Tsanko (2023) on the environmental benefits of subsidizing plug-in hybrids when consumers do not recharge them optimally, and Holland et al. (2019) on air pollution patterns that occur upstream in the production process. I provide a general framework for conducting cost-benefit analysis based on the marginal cost of abatement rather than the average cost. I show that policy design based on the average abatement cost produces misleading policy recommendations (unless the policy change under study is marginal). My framework could be used to study a wide array of environmental regulations including those described above.

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, 2025; 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). I extend these literatures to include the case where the complementary product (here, the charging station) is provided as a public good by forward-looking local planners. I find in general that network effects are weaker in this context.

The rest of the paper is organized as follows. Section 2 provides background information on the Canadian electric vehicle market. Section 3 studies the short-run effect of electric vehicle subsidies on sales and charging station deployment. I describe a structural model of demand for cars and the supply of a public charging infrastructure in Section 4. Estimation and counterfactual results are presented in Section 5. 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 Background and data

The transportation of passengers and freight accounted for 22% of all Canadian greenhouse gas emissions in 2021, ranking second behind oil and gas production.[3] As such, the electrification of transportation has become a prime concern to both provincial- and federal-level policymakers in Canada.

I focus my analysis of electric vehicle incentives around the two largest Canadian provinces, Quebec and Ontario, which together account for two thirds of Canada's population. Both provinces offered generous rebates to new electric vehicle owners, starting as early as 2010. Moreover, electricity production in these provinces is almost exclusively emission-free. This provides a clean setup to study emission reductions resulting from the electrification of transportation, as selling additional electric vehicles does not result in additional emissions upstream.

I begin with a description of the various Canadian policies that are relevant to the analysis. I focus on three financial incentive programs offered by the provincial government of Ontario, the provincial government of Quebec, and the federal government of Canada. To paint the broadest picture possible, I discuss the financial and the non-financial incentives that are offered in each jurisdiction. I also describe how charging station networks are developed, as there are significant differences between the two provinces. Ontario relies on a more traditional model which leaves the development of local networks to the private sector. Meanwhile, the government of Quebec develops public networks in partnership with county-level governments, with little contribution from private operators.

My analysis combines novel data from three sources. I obtain car registration data from the Société d'Assurance Automobile du Québec and the Ministry of Transportation of Ontario. The Quebec dataset is at the individual registration level while the Ontario dataset is aggregated at the product-county-quarter level. I combine the registration data with car

[3]Source: Environment and Climate Change Canada.

characteristics obtained online from The Car Guide and the Auto Trader websites.[4] Both are leading source of information on passenger vehicles in Canada. Finally, I obtain the location, the operator's name, and the installation date of each charging station in Quebec and Ontario from Natural Resources Canada and Hydro-Québec. Additional details on the data are relayed to Appendix B.

2.2 Policy environment

Timeline. The transportation sector is one of the leading contributor to carbon emissions in Canada. Absent federal initiative, the provincial governments in Ontario and Quebec launched separate electric vehicle incentive programs in 2010 and 2012 respectively.[5] The stated goals of the policies were to support the transition to electric vehicles, reward first adopters, and create a market demand for this new technology. Increasing adoption also creates a market demand for charging services, which encourages investments into charging stations from private and public operators.

While Quebec's Roulez Vert Program was maintained over time, the government of Ontario modernized its Electric Vehicle Incentive Program in February 2016.[6] On that occasion, subsidies for battery electrics and long-range plug-in hybrids were significantly increased, from $8,500 to $14,000. For short-range plug-in hybrids, the rebate was slightly increased and made progressive in the capacity of the battery. Policymakers justified these improvements with Ontario's poor performance in terms of electric vehicle adoption, compared to the rest of Canada.

The election of a conservative government in June 2018 led to the abolition of Ontario's cap-and-trade carbon tax in early October 2018. Since this carbon tax was the principal source of funding for electric vehicle subsidies, the Electric Vehicle Incentive Program was terminated at the same time. There is some anecdotal evidence in news reports that consumers were taken by surprise by this sudden change, as the government did not campaign extensively on these subsidies during the 2018 election cycle. With only a few weeks' notice, there was not a lot of time to capitalize on the rebate before the program expired, since ordering an electric vehicle usually took between 6 to 12 months at the time.

In May 2019, the federal government of Canada stepped in with its Incentives for Light-Duty Zero-Emission Vehicles Program. The stated objectives were to make subsidies available to all Canadians and to ensure that electric vehicle sales targets were met nationwide.

[4] See `https://www.guideautoweb.com/en/` and `https://www.autotrader.ca`.

[5] Other Canadian provinces also offer subsidies. These include British Columbia (up to $4,000), Newfoundland and Labrador (up to $2,500), Prince Edward Island (up to $5,000), New Brunswick (up to $5,000), and Nova Scotia (up to $3,000).

[6] The implementation was made retroactive to November of 2015.

Table 1: Canadian incentive programs

	Batery electric	Plug-in hybrid (long range)	Plug-in hybrid (short range)
Ontario program, phase 1 (2010 – 2015)			
MSRP below $150,000, batt. cap. 17 kWh or above	8,500	8,500	8,500
MSRP below $150,000, batt. cap. 4 kWh – 17 kWh	n/a	5,000	5,000
Non-financial incentives:			
• Privileged access to high occupancy vehicle lanes	✓	✓	✓
• Free access to high occupancy toll lanes	✓	✓	✓
• Free parking when charging	✓	✓	✓
Ontario program, phase 2 (2016 – 2018)			
MSRP below $75,000, batt. cap. 16 kWh or above	13,000	13,000	n/a
MSRP below $75,000, batt. cap. 5 kWh – 16 kWh	n/a	n/a	6,000 – 9,600
MSRP below $75,000, 5 seatbelts	+1,000	+1,000	+1,000
MSRP between $75,000 and $150,000	3,000	3,000	3,000
Non-financial incentives:			
• Privileged access to high occupancy vehicle lanes	✓	✓	✓
• Free access to high occupancy toll lanes	✓	✓	✓
• Free parking when charging	✓	✓	✓
Quebec program (2012 – pres.)			
MSRP below $75,000	8,000	8,000	4,000
MSRP between $75,000 and $125,000	3,000	0	0
Other financial incentives:			
• Used vehicle (original MSRP below $75,000)	4,000	0	0
• Installation of a home charger	600	600	600
Non-financial incentives:			
• Privileged access to reserved lanes	✓	✓	✓
• Free access to toll bridges and toll lanes	✓	✓	✓
• Free parking (in some municipalities)	✓	✓	✓
• Free access to several ferries	✓	✓	✓
Federal program (2019 – pres.)			
Passenger car, base model MRSP below $55,000	5,000	5,000	2,500
SUV and minivan, base model MRSP below $60,000	5,000	5,000	2,500

Notes: All values are in current Canadian dollars. MSRP is the manufacturer's suggested retail price. The rebate for plug-in hybrids in Ontario, phase 2, increases from $6,000 to $9,600, in steps of $365 per kWh of battery capacity. The Chevrolet Volt is the only plug-in hybrid that qualifies as "long range" in Quebec. For the federal rebates, plug-in hybrids with a driving range above 50km on electric mode qualify as "long range".

Financial incentives. The detailed list of incentives is summarized in Table 1. Rebates are obtained automatically at the point of sale and are deducted from the transaction price.[7] To be eligible, consumers must either purchase the vehicle, or sign a long-term lease. Short-term leases are eligible for a fraction of the rebate, determined on a *pro rata* basis.

Additional financial incentives are offered in Quebec. For example, the program includes subsidizing the purchased of a used electric vehicle (up to $4,000), the installation of a home charger ($600), and the installation of large-scale charging capacity in multi-unit housing

[7]Tesla is an exception, as they did not have points of sale in Canada in that period. In that case, consumers must fill in additional paperwork and receive a mail-in refund a few weeks later.

or in workplaces (up to 50% of installation costs). While these policies are interesting and could play a role in increasing adoption, I am forced to ignore their contribution due to data limitations.

I do not observe car ownership through time. As such, transactions on the secondary market are unobservable. To assess the relative size of the secondary market, I compare the total spending on used car subsidies to the total program expenditure. I find that 1.8% of the program's funds went to subsidizing used cars. To fix ideas, 94.1% of total spending went to subsidizing new cars. Back of the enveloppe calculations suggest that the primary market was around 30 times larger than the secondary market between 2012 and 2020.

I also ignore the effect of subsidizing home chargers due to data limitations. The key problem is that I do not observe which consumer applied for and received a home charger subsidy. Furthermore, there is no requirement that new owners install a home charger in the same year as they purchase an electric vehicle. Acquiring a home charger can cost between a few hundred to a few thousand dollars, but is not absolutely necessary to charge at home. Government spending on home chargers totalized 4% of the total program expenditure in Quebec.

Non-financial incentives. Several non-financial incentives are offered to encourage electric vehicle adoption. They are normally tied to registering the car under a green license plate, which provides advantages all over Canada and in the United States. Registering an electric vehicle under a green license plate is mandatory for safety reasons. Both provinces offer similar non-financial incentives. They include a privileged access to dedicated lanes (e.g., carpool lanes), a free access to toll lanes or bridges, and dedicated free parking spaces. Additional details on non-financial incentives are available in Table 1.

2.3 Network deployment

Table 2 presents the distribution of all charging stations by province and operating network. There are striking differences between the two provinces. The first one is the sheer difference in the size of the networks. In per capita terms, there are more than four times more stations in Quebec than in Ontario. Second, Ontario's network is predominantly operated and developed by private firms (even though most stations are installed on the street and are considered as public). In contrast, Quebec's market is dominated by the government provided platform, the Electric Circuit, with little competition from private firms.[8]

[8] Tesla and Flo are the only other firms involved in Quebec. Tesla is involved in the development of its own network, which insure that Tesla owners can reach every destination in North America. Stations are typically located in strategic locations that facilitate long distance travels. Flo is the network developed by

Table 2: Network operators

	Ontario		Quebec	
	Nb. stations	Share total	Nb. stations	Share total
ChargeLab	18	0.02	1	4e-4
ChargePoint Network	219	0.20	70	0.03
Electric Circuit	29	0.03	1,960	0.70
Electrify Canada	4	4e-3	0	0
EV Connect	20	0.02	0	0
Flo	209	0.19	376	0.13
Ivy	23	0.02	0	0
Petro-Canada	19	0.02	7	2e-3
Shell Recharge	6	5e-3	0	0
SWTCH Energy	20	0.02	0	0
Tesla Destination	222	0.20	160	0.06
Non-networked	318	0.29	237	0.08
Total	1,107	1	2,811	1
Population, in 2020	14.22		8.44	
Nb. of counties	49		96	

Notes: The Electric Circuit is Quebec's public platform. All other networks are operated by private firms. The network size is reported for year 2020. Population is in million.

Network provision in Quebec does not follow a traditional model of demand and supply. Instead, the provincial government enters partnerships with regional governments, shopping malls, restaurant chains, and workplaces for the development of local charging station infrastructures. On the one hand, the provincial government provides the platform (including the software infrastructure, the phone app, and billing services) and coordinates maintenance. It also regulates both the the charging price paid by consumers and the wholesale energy price paid by the partner. On the other hand, the partner pays for the physical infrastructure (the actual station) and the installation cost. It then collects revenues from operating that station. Importantly, partners decide where and when to install stations, since they own property rights on the land.

The vast majority of partners are county-level governments. I assume throughout that they control the final decision about the size of local networks in Quebec. In practice, they can forgo installing some stations if more private installations occur. I also maintain the assumption that they do not coordinate on a common deployment strategy. There are no unified political parties in Quebec that span both provincial and regional politics. County-

AddÉnergie, a company based in Quebec that manufactures and sells chargers.

level governments usually form around local political figures and are insulated from provincial or federal politics. In that context, decisions are taken in isolation from other counties or higher levels of government.

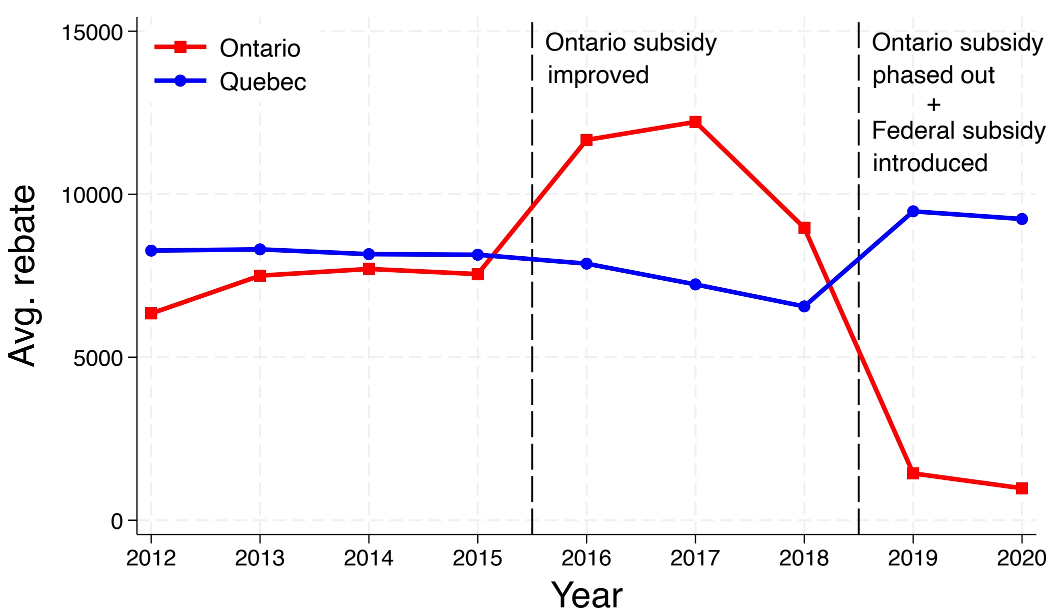
3 The Short-run Impact of Rebates

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 their indirect effect on charging station installations. Electric vehicle subsidies have been more or less constant in Quebec since their introduction in 2012 which provides me with an adequate control group.

Figure 1 depicts the average rebate offered to consumers of each province between 2012 and 2020. All values are converted to 2018 Canadian dollars (CAD). Initially, both provinces had similar rebate programs. I will refer the period from 2012 to 2015 as the pre-treatment

Figure 1: Average rebate by province



Notes: This figure reports the average electric vehicle subsidy received by consumers, by province and year. The average rebate is weighted by sales and includes both battery electric and plug-in hybrid. All values are in 2018 CAD.

period. I observe a first policy shock in 2016 when Ontario's rebate program was substantially increased and 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 program 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 (2022) describe best the threat to the identification of a causal effect between subsidies and electric vehicle adoption: states are more likely to offer an incentive if the population they represent is predisposed to purchasing an electric vehicle. There is some anecdotal evidence that points in that direction. The government of 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 and would lead to underestimating the causal effect. The program was discontinued after Ontario abolished its cap-and-trade carbon tax which cut the main source of funding for subsidies. In this case, there is more chance that the change was exogenous.

It is very hard in practice to test the exogeneity assumption. I perform the analysis 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. I am also very careful in my interpretation of the results.

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 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.

Table 3: Difference-in-differences analysis

Dependent variable	Control mean	Observations	No covariates		With covariates	
			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)
Log of price						
(n) All vehicles	3.88	2,415	-0.018	-0.009	0.004	-0.002
			(0.058)	(0.059)	(0.046)	(0.044)

Notes: Regressions (a) to (m) include county and year fixed effects, and are weighted by population. Standard errors in parenthesis are clustered at the county level. Regression (n) is unweighted and includes product and year fixed effects. Standard errors in parenthesis are clustered at the product level. Significance: * < 0.10, ** < 0.05, *** < 0.01.

3.2 Effect on electric vehicle registrations

I first study the effect of rebates on electric vehicle adoption using a difference-in-differences analysis. I index counties by m and years by t. The difference-in-differences specification is

$$y_{mt} = \beta_1(\text{Ontario} \times \text{Post1})_{mt} + \beta_2(\text{Ontario} \times \text{Post2})_{mt} + X_{mt}\gamma + \mu_m + \lambda_t + \epsilon_{mt},$$

where μ_m and λ_t are county and year fixed effects, and X_{mt} is a set of county-level demographics and controls. The treatment group contains counties located in Ontario and the two treatment periods are as defined above. The dependent variable, y_{mt}, is the log of electric vehicle registrations by county and year.

Results are presented in the first panel of Table 3. I estimate the model first using all electric vehicle registrations, then battery electric vehicles and plug-in hybrids separately to ensure that the overall effect is not carried by only one of the two segments. The effects all have the expected signs and are significant almost everywhere. The estimated intent-to-treat effects on electric vehicle registration are 0.267 and -0.667 respectively, meaning that the improvement to subsidies increased sales by 26.7% over baseline, and the abolition of the program reduced sales by 66.7%. Interestingly, the effect of the two treatments are asymmetric. The abolition of the Ontario rebate program had a larger impact on registrations than its bonification (this is especially true for plug-in hybrids). This does not seem to be explained completely by the magnitude of the changes to subsidies in Ontario.

Instead, the overall smaller impact of the first treatment seems to be attributed to a smaller response to the policy in 2016. Since the increased rebates were announced and introduced in February of 2016, imperfect information transmission about the new policy environment or delivery times of new electric vehicles could have contributed to reducing the impact of the policy in the first year post-treatment. In contrast, information transmission or delivery times do not play a role when the program is phased out: consumers learn that rebates are no longer available at the point of sale and change their mind about purchasing an electric vehicle. In this case, the drop in demand would be immediate.

The corresponding event studies are available in Figure A.1. They corroborate the results from the difference-in-differences analysis. A careful observation of these figures reveal that I cannot reject the parallel trend assumption.

3.3 Effect on networks

I next consider the effect of electric vehicle rebates on network deployment. I use four different definitions for network size: the total number of charging locations, the total number of chargers, new location openings, and new charger installations. Results are presented in the second panel of Table 3. The corresponding event studies are available in Figure A.2 and Figure A.3.

I do not find evidence that electric vehicle subsidies increased charging station deployment through network effects. Since installing stations requires planning (e.g., securing funding, finding adequate locations), network supply may react slowly to new market conditions. It is possible that I do not observe networks for long enough to capture an effect since there were two opposing policy changes in a short period of time. Therefore, these findings must be carefully interpreted as short-run effects. I rely on a structural estimation in the second half of the paper to address long-run effects.

Finally, I verify if networks changed along other dimensions not captured by network size.

For example, network operators could respond to the policy by installing more powerful chargers or stations that can accommodate more users simultaneously. This would not require finding additional sites. I re-estimate the model using network characteristics that are available in the data. Results are presented in the third panel of Table 3. The corresponding event studies are available in Figure A.4 and Figure A.5. Again, I do not find evidence that subsidies changed networks along other dimensions in the short-run.

3.4 Effect on prices

I consider the effect of subsidies on the prices of electric vehicles. Since I am using list prices that are the same in both provinces, variation across counties cannot be used to conduct a difference-in-differences analysis. I construct instead a dataset at the product level, and consider vehicles that were eligible to the Ontario rebate program as being part of the treatment group. This includes all electric vehicles with a battery capacity above 4 kWh and a list price below $150,000. Other vehicles are used as a control group.[9] I index products by j and years by t. The difference-in-differences specification is

$$y_{jt} = \beta_1(\text{Eligible} \times \text{Post1})_{jt} + \beta_2(\text{Eligible} \times \text{Post2})_{jt} + X_{jt}\gamma + \mu_j + \lambda_t + \epsilon_{jt},$$

where μ_j and λ_t are product and year fixed effects, and X_{jt} is a set of product characteristics and cost shifters. The dependent variable, y_{jt}, is the log of the list price.

Results are presented in the fourth panel of Table 3. I do not find evidence that changes to the Ontario rebate schedule changed firms pricing decisions, at least in the short-run. The estimated effects are very small, 0.4% and -0.2%, and I can bound the price response to be below 10%. This aligns with anecdotal evidence that firms responded to both policy changes by moving inventory in and out of Ontario, towards other provinces, rather than changing prices. This means that consumers benefited almost exclusively from the rebate programs and car manufacturers benefited from increased sales.

To rule out the possibility that the effect is driven by a composition effect, I plot the evolution of prices for the top selling battery electric and plug-in hybrid vehicles, see Figure A.6 and Figure A.7. Prices are very stable at the product level over the period of study, with the exception of Tesla's Model S, see Figure A.8. For completeness, I also report the event study corresponding to the difference-in-differences specification in Figure A.9. Again, the price responses can be bound to values very close to zero.

[9] I ignore strategic effects that could lead car manufacturers to change the price of fuel vehicles when electric vehicles are subsidized.In practice, such strategic effects are possible. In this case, the estimated effect would be biased away from zero and I would overestimate the effect of rebates on electric vehicle prices.

3.5 Continous treatment effect

I further the analysis and study the effect of rebates on sales and prices using a continuous treatment effect specification. Details are relayed to Appendix C. I estimate that $1,000 in additional subsidies is associated to a 7.9% increase in electric vehicle registrations and I cannot reject the hypothesis of complete passthrough of the rebate to consumers. This is additional evidence that car manufacturers did not change list prices to take advantage of the subsidies over time. Allcott et al. (2024) provide evidence of complete passthrough in their study of the Inflation Reduction Act's electric vehicle incentives while Muehlegger and Rapson (2022) finds evidence of incomplete passthrough in their study of an electric vehicle incentive program in California. Both studies focus on transaction prices which are more likely to be manipulated by firms in the presence of subsidies than list prices.

The estimated parameters implies a market elasticity to price of -3.0 for electric vehicles. Muehlegger and Rapson (2022) obtain a slightly lower estimate using a similar methodology. They report an elasticity of demand of -2.1. The difference between the two estimates can be explained partly by the fact that they use transaction prices which are typically lower after bargaining, while I rely on list prices.

Due to data limitations, it is not possible to study the environmental performance of Canadian subsidies using the natural experiment setting. The difficulty arises from the fact that electric vehicles reduce emissions to the extent that they replace internal combustion engines. Extending the analysis to include emission abatement would require a survey of electric vehicle owners that inform me about their second choices (and therefore the exact composition of the counterfactual fleet of vehicles) or unreasonably strong assumptions about consumers' substitution patterns.

To circumvent these issues, I build on the findings presented in this section and estimate a structural model of the demand for cars and the supply of a charging station infrastructure. I recover fundamental parameters which allow me to perform counterfactual experiments and evaluate the environmental performance of the Canadian subsidy programs. I present the model and the results in the following sections.

4 Model

I define a structural model to analyse the cost-effectiveness 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 with county-level average demographics to capture differences in preferences among consumers, following Nevo (2001) and Gandhi and Houde (2019). Similarly to most works on the car market, I maintain the assumption that consumers are not forward-looking, and the demand for cars is static. Springel (2021) provides some evidence in support of this assumption for electric vehicle markets.

I do not model or estimate a supply side for cars. This is motivated both by the reduced form evidence of the previous section and the fact that list prices are determined at the national level to avoid arbitrage opportunities between provinces. Since my analysis of the environmental performance of rebates is restricted to Quebec, I find it unlikely that car manufacturers would change the national list price in response to a local policy.

Finally, I define a model for charging station supply which fits the specific economic and political context in Quebec, where county-level government are responsible for providing a public charging station infrastructure in their jurisdiction. The network supply model takes into account the forward-looking behavior of these local planners in a tractable, easy to implement way. Moreover, it solves the simultaneity issue between electric vehicle sales and station deployment by fully internalizing the demand response from potential electric vehicle owners in the supply equation. This allow for estimating the model without relying on instrumental variables. These advances improve on the currently available best practices.

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, the consumer considers the net price of each product, $p_{jt} - \tau_{jt}$, where p_{jt} is the retail price and τ_{jt} a government subsidy on product j. It also considers observed product characteristics such as the horsepower, the driving cost, or the engine type. I denote the vector of observed product attributes by $\mathbf{x}_{jt}$. Furthermore, the consumer considers characteristics that are unobserved to the econometrician, summarized by the quality index ξ_{jmt}.

For all models with an electric engine, the consumer cares about the opportunity of charging at home or on the network. Let N_{mt} be the size of the charging network in county m at time t, and define the utility of charging as the deterministic function $v(N_{mt}, \theta_i)$, where θ_i is a consumer-specific preference parameter. For any product j, the associated utility of charging is

$$v_j(N_{mt}, \theta_i) = \begin{cases} v(N_{mt}, \theta_i), & \text{if } j \in EV \\ 0, & \text{if } j \notin EV \end{cases}.$$

I select a flexible functional form for the utility of charging,

$$v(N_{mt}, \theta_i) = \theta_i \frac{(1 + N_{mt})^{\zeta} - 1}{\zeta},$$

where N_{mt} represents the stations available to consumer i in his county of residence, and the "1" represents the opportunity to charge at home. This means that, when no stations are available in a region, consumers are assumed to always have the option to charge at home. The parameter ζ controls the curvature of $v(N_{mt}, \theta_i)$.[10] The function $v(N_{mt}, \theta_i)$ is increasing at a decreasing rate in N_{mt} for $\theta_i > 0$ and $\zeta < 1$, such that each additional station is less valuable to the consumer than the previous one.

I allow consumers to have heterogenous preferences in the observed product characteristics. Heterogeneity is introduced in two ways. First, the average taste for observed characteristics varies across regions through interactions with county-level average demographics, denoted $\mathbf{D}_{mt}$. Second, I allow for random coefficients to model the heterogeneity within county. Formally, the utility consumer i receives from purchasing product j is

$$u_{ijmt} = \beta_i^{\mathbf{p}}(p_{jt} - \tau_{jt}) + v_j(N_{mt}, \theta_i) + \mathbf{x}_{jt}\beta_i^{\mathbf{x}} + \xi_{jmt} + \epsilon_{ijmt}^{\mathbf{d}},$$

where $\epsilon_{ijmt}^{\mathbf{d}}$ is a consumer-specific disturbance. Consumers' taste parameters take the following form,

$$\beta_i^{\mathbf{p}} = \beta^{\mathbf{p}} + \mathbf{D}_{mt}\Gamma^{\mathbf{p}} + \sigma^{\mathbf{p}}\nu_i^{\mathbf{p}},$$

$$\beta_{ik}^{\mathbf{x}} = \beta_k^{\mathbf{x}} + \mathbf{D}_{mt}\Gamma_k^{\mathbf{x}} + \sigma_k^{\mathbf{x}}\nu_{ik}^{\mathbf{x}},$$

$$\theta_i = \theta + \mathbf{D}_{mt}\Gamma^{\mathbf{N}} + \sigma^{\mathbf{N}}\nu_i^{\mathbf{N}},$$

where k indexes the different product characteristics in $\mathbf{x}_{jt}$ and the $\nu_i = \{\nu_i^{\mathbf{p}}, \nu_i^{\mathbf{x}}, \nu_i^{\mathbf{N}}\}$ are jointly distributed as independent standard normal. The utility of the outside option is normalized to $u_{i0mt} = \epsilon_{i0mt}^{\mathbf{d}}$ in each market. I rewrite the utility function in terms of a mean utility and a consumer-specific deviation,

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

[10]The utility of charging follows the isoelastic (or constant relative risk aversion) functional form and is defined for $\zeta \leq 1$, $\zeta \neq 0$. It covers useful parametrizations as special cases: (1) linear ($\zeta = 1$), and (2) logarithmic ($\zeta \to 0$).

with

$$\delta_{jmt} = \beta^{\mathbf{p}}(p_{jt} - \tau_{jt}) + \big((p_{jt} - \tau_{jt}) \otimes \mathbf{D}_{mt}\big)\Gamma^{\mathbf{p}} + \mathbf{x}_{jt}\beta^{\mathbf{x}} + \big(\mathbf{x}_{jt} \otimes \mathbf{D}_{mt}\big)\Gamma^{\mathbf{x}} + \xi_{jmt},$$

$$\mu_{ijmt} = \sigma^{\mathbf{p}}\nu_i^{\mathbf{p}}(p_{jt} - \tau_{jt}) + v_j(N_{mt}, \theta_i) + \sum_k x_{jt}^k \sigma_k^{\mathbf{x}} \nu_{ik}^{\mathbf{x}}.$$

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

$$s_{ijmt}(\mathbf{p}_t, N_{mt}, \mathbf{x}_t, \mathbf{D}_{mt}, \nu_i) = \frac{\exp(\delta_{jmt} + \mu_{ijmt})}{1 + \sum_{j'=1}^{J_{mt}} \exp(\delta_{j'mt} + \mu_{ij'mt})}.$$

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

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

4.2 Network supply

I consider the case of county-level governments (henceforth "local planners") responsible for supplying a public network of charging stations in their respective jurisdiction.[11] Throughout, I maintain the assumption that these local planners are forward-looking: they install chargers in their jurisdiction to maximize the current and future utility of consumers for the network, given installation costs. Additionally, I assume that they do not coordinate on a joint deployment strategy and that they control both the installation decision and the location of stations within their county. Finally, I consider local networks to be public goods, that is, they are non-excludable, non-rivalrous, and publicly supplied by local planners. Since I define each station as a charging site that can accomodate two to four drivers simultaneously, I consider the non-rivalrous assumption to be satisfied in most cases.

Local governments perceive revenues from operating their local network. However, anectodal evidence suggests that they pursue non-profit motives in installing charging stations and revenues mostly cover operational costs and maintenance. Non-profit objectives could include reducing local emissions, maximizing local adoption, maximizing political support from electric vehicle owners, or maximizing consumers' utility, to give a few examples. I could not find evidence that local government in Quebec had emission targets (related to electric

[11] In practice, network ownership in Quebec is split between the local planners and a number of fringe firms. Since local planners control around 70% of all stations, I assume throughout that they are the sole operator in each region. The remaining stations are installed by workplaces, shopping malls, or restaurant chains, and are typically not organized into what I consider as competing network operators.

vehicles) or electric vehicle targets over the period of study, hence I leave these motives out of the local planners' problem. This introduces a friction between local planners' decisions about networks and the goal of the central government which is to boost adoption and reduce emissions. I discuss and study the excluded local planner objectives in Appendix F.

Law of motion. Before I define the local planners' problem, I consider the law of motion of the electric vehicle base. In what follow, I consider a network of size $n \in \mathbb{N}$, where I leave the market indices out as n does not represent a particular observed outcome. I also do not restrict n to represent the optimal network provision in a given market at a given point in time. Let $Q^{ev}_{mt}(n)$ be the stock of electric vehicles in circulation (e.g., cummulative sales up to period t) and $q^{ev}_{mt}(n)$ be the flow of electric vehicles (e.g., sales) in county m and period t, given a network of size n. The law of motion of $Q^{ev}_{mt}(n)$ can be written as

$$Q^{ev}_{mt}(n) = (1-d)\, Q^{ev}_{m,t-1} + q^{ev}_{mt}(n), \tag{1}$$

where d is the fleet depreciation rate and $Q^{ev}_{m,t-1}$ includes only past sales, hence it is predetermined and does not depend on n. The term $q^{ev}_{mt}(n)$ can be recovered in each market by aggregating over market shares and multiplying by the market size L_{mt}, that is,

$$q^{ev}_{mt}(n) = L_{mt} \cdot \sum_{j \in EV} s_{jmt}(\mathbf{p}_t, n, \mathbf{x}_t, \mathbf{D}_{mt}),$$

where $\mathbf{p}_{jt}$, $\mathbf{x}_{jt}$, and $\mathbf{D}_{mt}$ are defined in the previous section.

Benefit function. I now turn to the local planners' problem. In what follows, the index m represents both a local planner and its associated county. Each local planner m installs charging stations in its jurisdiction to maximizes the aggregate value of the network to electric vehicle owners, given the fixed cost of adding capacity.

Recall from the previous section that electric vehicle owner i derives a lifetime indirect utility of $v(n, \theta_i)$ from a network of size n, given preference parameter θ_i. For a given (consumer) discount rate of r and a scrapage rate of d, we can show that the per period indirect utility of charging is $\widetilde{r}v(n, \theta_i)$, where $\widetilde{r} = \frac{r+d}{1-d}$ is a composite discount rate.

I define the local planner's contemporaneous benefits of increasing the network size from

$n-1$ to n as a function of consumers' network utilities, that is,

$$B_{mt}(n) = \underbrace{Q^{ev}_{mt}(n)}_{\substack{\text{Number of}\\\text{EV owners}}} \cdot \left(\underbrace{\int \frac{\widetilde{r}v(n,\theta_i) - \widetilde{r}v(n-1,\theta_i)}{-\beta^{\mathbf{P}}_i}\, dF(\nu_i)}_{\substack{\text{Average gain in utility per EV owner}\\\text{from station } n_{mt}}} \right)^{\gamma},$$

where $Q^{ev}_{mt}(n)$ and $v(n,\theta_i)$ are defined above, $-\beta^{\mathbf{P}}_i$ is the marginal utility of income of consumer i ($\beta^{\mathbf{P}}_i$ is the price sensitivity), and γ is a local planner preference parameter.

The term in parenthesis represents the monetary equivalent of the expected gain in utility that an electric vehicle owner receives when the network size increases from $n-1$ to n. The local planner's benefit function, $B_{mt}(n)$, can therefore be seen as the aggregate gain in (expected) utility from all electric vehicle owners in county m and period t, accruing from the installation of station n, scaled by a preference parameter γ. The preference parameter is included to allow for the planner to value more or less charging on the network than electric vehicle owners themselves. To simplify the notation in what follows, I denote

$$\Delta v(n) = \int \frac{\widetilde{r}v(n,\theta_i) - \widetilde{r}v(n-1,\theta_i)}{-\beta^{\mathbf{P}}_i}\, dF(\nu_i),$$

and I can rewrite the benefit function as

$$B_{mt}(n) = Q^{ev}_{mt}(n) \cdot \Delta v(n)^{\gamma} \tag{2}$$

I impose three assumptions on the local planners' benefit function. First, I assume that local planners are price-takers in the charging market. This prevents local planners from affecting consumers' utility via driving costs. This is easily satisfied as Quebec's provincial government regulates both energy prices and charging prices. Second, I assume that $B(n)$ is positive and decreasing in n. This condition is sufficient to have a unique equilibrium in network size for a given stock of electric vehicles. This is trivially satisfied over some range of γ if $\frac{\partial v(n,\theta_i)}{\partial n} \geq 0$ and $\frac{\partial^2 v(n,\theta_i)}{\partial n^2} < 0, \forall n \in \mathbb{N}$, and $\beta^{\mathbf{P}}_i < 0, \forall i$. Finally, I assume that there exists a saturation point S, such that $\Delta v(n) = 0$ for all $n > S$. This last assumption is not absolutely necessary, but it simplifies the computation of counterfactuals.[12]

[12] 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 $S_{mt} = L_{mt}/200$, where L_{mt} is the number of households in county m and period t.

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

$$V_{mt}(n) = -F_{mt} + B_{mt}(n) + \sum_{s=t+1}^{\infty} \rho^{s-t} \mathbb{E}_t B_{ms}(n, \mathcal{I}_t), \tag{3}$$

$$= -F_{mt} + B_{mt}(n) + \rho \mathbb{E}_t \overline{V}_{m,t+1}(n, \mathcal{I}_t), \tag{4}$$

where ρ is the planner's discount factor and $\overline{V}_{mt} = V_{mt} + F_{mt}$. Equation (3) introduces some new notation for the expected benefits. Let $\mathcal{I}_{t+k}$ indicate that station n was installed in period $t+k$. I define $\mathbb{E}_t B_{ms}(n, \mathcal{I}_{t+k})$ as the expected benefit of station n in period $s > t+k$ given that station n was installed in period $t+k$. Keeping track of the installation date is important as the electric vehicle base accumulates differently before and after the installation of station n.

The local planner chooses to install station n in period t if it is more profitable than waiting. Its installation decision can be summarized as follows,

$$a_{mt}(n) = \begin{cases} \text{Install,} & \text{if} \quad V_{mt}(n) \geq \max\limits_{k \geq 1} \left\{ \rho^k \mathbb{E}_t V_{m,t+k}(n, \mathcal{I}_{t+k}) \right\} \\ \text{Not install,} & \text{otherwise} \end{cases}, \tag{5}$$

where the notation for $\mathbb{E}_t V_{ms}(n, \mathcal{I}_{t+k})$ is similar to that of $\mathbb{E}_t B_{ms}(n, \mathcal{I}_{t+k})$.

To simplify the expression in (5) and make the model tractable, I impose some additional assumptions on the planners' expectations. These assumptions are:

A1. $0 \leq \mathbb{E}_t F_{m,t+k} - \rho \mathbb{E}_t F_{m,t+k+1} \leq K(\rho), \quad \forall k \geq 1;$

A2. $\mathbb{E}_t q_{m,t+k}(n) = (1 + g_t)^k \, q_{mt}(n), \quad \forall n \in \mathbb{N}, \quad \forall k \geq 1;$

A3. $q_{mt}(n) > q_{mt}(n-1), \quad \forall n \in \mathbb{N}.$

Assumption **A1** is the most restrictive and imposes limits on how the expected fixed costs vary over time from the point of view of period t.[13] There is some anecdotal evidence that the costs of charging infrastructure decreases over time as a result of learning-by-doing and Assumption **A1** imposes that these costs do not decrease too fast. Assumption **A2** states that the local planners' best guess about future electric vehicle sales are current sales, multiplied by some exogenous growth rate $(1+g_t)$. In some sense, local planners are uncertain about future market conditions, such that their expectations about future sales are based

[13] The constant $K(\rho)$ is defined explicitly in Appendix D, Lemma 1.

on current market conditions. Finally, assumption **A3** holds trivially by strict monotonicity of consumer preferences.

Under these assumptions, I can show that

$$\max_{k\geq 1}\left\{\rho^k \mathbb{E}_t V_{m,t+k}(n,\mathcal{I}_{t+k})\right\} = \rho \mathbb{E}_t V_{m,t+1}(n,\mathcal{I}_{t+1}), \tag{6}$$

and the installation condition in (5) collapses to a comparison between period t and $t+1$. The full proof and an extended discussion on assumptions **A1** – **A3** is available in Appendix D, Lemma 1.

Optimal network provision. I denote the last station installed by $N \in \mathbb{N}$, also representing the optimal network provision. Again I omit market indices as N does not represent a particular observed market outcome. Since N represents the optimal network size, it must be that local planner m found it weakly beneficial to install station N, but not $N+1$. Hence, the optimal network size at any given point in time has to satisfy the following two inequality conditions,

$$V_{mt}(N) \geq \rho \mathbb{E}_t V_{m,t+1}(N,\mathcal{I}_{t+1}) \tag{7}$$

and

$$V_{mt}(N+1) < \rho \mathbb{E}_t V_{m,t+1}(N+1,\mathcal{I}_{t+1}). \tag{8}$$

I focus on equation (7) as solving (8) follows the same logic with the reversed inequality. Consider first the right-hand side of the inequality. By taking expectation over $V_{m,t+1}$, I can show that

$$\begin{aligned}\rho \mathbb{E}_t V_{m,t+1}(N,\mathcal{I}_{t+1}) &= -\rho \mathbb{E}_t F_{m,t+1} + \sum_{s=t+1}^{\infty} \rho^{s-t} \mathbb{E}_t B_{ms}(N,\mathcal{I}_{t+1}),\\ &= -\rho \mathbb{E}_t F_{m,t+1} + \rho \mathbb{E}_t \overline{V}_{m,t+1}(N,\mathcal{I}_{t+1}).\end{aligned}$$

I can then rewrite the inequality condition in (7) as

$$B_{mt}(N) + \underbrace{\rho \mathbb{E}_t \overline{V}_{m,t+1}(N,\mathcal{I}_t) - \rho \mathbb{E}_t \overline{V}_{m,t+1}(N,\mathcal{I}_{t+1})}_{\substack{\text{Discounted future value of installing station N}\\ \text{in period } t \text{ versus period } t+1}} \geq F_{mt} - \rho \mathbb{E}_t F_{m,t+1}. \tag{9}$$

The bracketed term in equation (9) is the discounted future value of installing station N in period t compared to installing it in period $t+1$. Very intuitively, installing station N will convince some additional consumers to buy an electric vehicle in period t which permanently increases the stock of electric vehicle. Then, the local planners will reap benefits from these marginal consumers into the future. I can show that

$$\rho \mathbb{E}_t \overline{V}_{m,t+1}(N, \mathcal{I}_t) - \rho \mathbb{E}_t \overline{V}_{m,t+1}(N, \mathcal{I}_{t+1}) = \underbrace{\frac{\widetilde{\rho}}{1-\widetilde{\rho}} \Delta v(N)^{\gamma} \big(q^{ev}_{mt}(N) - q^{ev}_{mt}(N-1) \big)}_{\substack{\text{Discounted lifetime benefits} \\ \text{of marginal consumers}}}, \tag{10}$$

where $q^{ev}_{mt}(N) - q^{ev}_{mt}(N-1)$ are the marginal consumers that purchase an electric vehicle when station N is installed, $\frac{\widetilde{\rho}}{1-\widetilde{\rho}} \Delta v(N)^{\gamma}$ is the per driver discounted lifetime benefit of the local planner, and $\widetilde{\rho} = \rho\,(1-d)$ is a composite local planner discount factor. The full proof is relayed to Appendix D, Lemma 2.

To simplify the notation in what follow, I denote

$$\Delta q^{ev}_{mt}(N) = q^{ev}_{mt}(N) - q^{ev}_{mt}(N-1),$$

and I rewrite the inequality conditions in (7) and (8) as

$$\Big(Q^{ev}_{mt}(N) + \frac{\widetilde{\rho}}{1-\widetilde{\rho}} \Delta q^{ev}_{mt}(N) \Big) \Delta v(N)^{\gamma} \geq F_{mt} - \rho \mathbb{E}_t F_{m,t+1} \tag{7'}$$

and

$$\Big(Q^{ev}_{mt}(N+1) + \frac{\widetilde{\rho}}{1-\widetilde{\rho}} \Delta q^{ev}_{mt}(N+1) \Big) \Delta v(N+1)^{\gamma} < F_{mt} - \rho \mathbb{E}_t F_{m,t+1} \tag{8'}$$

Combining and taking logs yield the equilibrium condition,

$$\begin{aligned}
\lambda^{\mathbf{N}} \ln \big(\Delta v(N_{mt}) \big) &+ \lambda^{\mathbf{Q}} \ln \Big(Q^{ev}_{mt}(N_{mt}) + \frac{\widetilde{\rho}}{1-\widetilde{\rho}} \Delta q^{ev}_{mt}(N_{mt}) \Big) \\
&\geq \epsilon^{\mathbf{n}}_{mt} \\
&> \lambda^{\mathbf{N}} \ln \big(\Delta v(N_{mt}+1) \big) + \lambda^{\mathbf{Q}} \ln \Big(Q^{ev}_{mt}(N_{mt}+1) + \frac{\widetilde{\rho}}{1-\widetilde{\rho}} \Delta q^{ev}_{mt}(N_{mt}+1) \Big),
\end{aligned}$$

where $\epsilon^{\mathbf{n}}_{mt} = \frac{1}{\omega} \ln(F_{mt} - \rho \mathbb{E}_t F_{m,t+1})$ is distributed as standard normal, $\lambda^{N} = \frac{\gamma}{\omega}$, and $\lambda^{Q} = \frac{1}{\omega}$.

Network supply. Define S_{mt} as the network saturation point. Charging station supply can be written as follows,

$$
\begin{aligned}
N_{mt} = \sum_{n=1}^{S_{mt}-1} n \cdot \mathbb{1}\Big\{ & \lambda^{\mathbf{N}} \ln\big(\Delta v(n)\big) + \lambda^{\mathbf{Q}} \ln\Big(Q^{ev}_{mt}(n) + \frac{\widetilde{\rho}}{1-\widetilde{\rho}}\Delta q^{ev}_{mt}(n)\Big) \geq \epsilon^{\mathbf{n}}_{mt} \\
& > \lambda^{\mathbf{N}} \ln\big(\Delta v(n+1)\big) + \lambda^{\mathbf{Q}} \ln\Big(Q^{ev}_{mt}(n+1) + \frac{\widetilde{\rho}}{1-\widetilde{\rho}}\Delta q^{ev}_{mt}(n+1)\Big)\Big\} \\
+ S_{mt} \cdot \mathbb{1}\Big\{ & \lambda^{\mathbf{N}} \ln\big(\Delta v(S_{mt})\big) + \lambda^{\mathbf{Q}} \ln\Big(Q^{ev}_{mt}(S_{mt}) + \frac{\widetilde{\rho}}{1-\widetilde{\rho}}\Delta q^{ev}_{mt}(S_{mt})\Big) \geq \epsilon^{\mathbf{n}}_{mt}\Big\}.
\end{aligned} \tag{11}
$$

The network supply function in (11) emphasizes two important features of the model. First, the forward-looking behavior of local planners is explicit. For example, by setting ρ to zero, local planners stop valuing the future benefits of the network associated to marginal consumers and the term $\frac{\widetilde{\rho}}{1-\widetilde{\rho}}\Delta q^{ev}_{mt}$ vanishes. In this case, we obtain a static model similar in spirit to Springel (2021).

Second, it clearly shows how the model internalizes the changes to the stock of electric vehicle arising from more station installations. A careful inspection of the law of motion and the network supply equation reveals that network supply depends on $Q^{ev}_{m,t-1}$ which is predetermined, but not on Q^{ev}_{mt} which is endogenous. Instead, station supply depends on q^{ev}_{mt} which is constructed from market shares and fully internalizes the impact of the planner's decisions on electric vehicle adoption. This solves the simultaneity issue between charging station deployment and electric vehicle sales and suggests a path for estimating station supply without relying on instrumental variables. I discuss the simultaneity and endogeneity issues in more details in Section 4.3.

4.3 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 $\delta(\mathbf{s}_t, \sigma)$. This implies that market shares are also endogenous since they are determined jointly with unobserved car attributes.[14] Concretely, this means that instrumental variables are needed for the prices and the market shares in the demand model. Finally, network deployment occurs simultaneously with electric vehicle sales, hence network size is also endogenous in the demand model.

[14]See Conlon and Gortmaker (2020) and Gandhi and Houde (2019).

I solve the various endogeneity issues using instrumental variables. I use two separate cost shifters to instrument for prices. Similarly to D'Haultfoeuille et al. (2019), 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.[15] Next, I follow Grieco et al. (2023) and use the real exchange rate between Canada and the country each car was manufactured as an additional cost shifter.[16] 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 the marginal production cost. Similarly to Grieco et al. (2023), I lag both cost shifters by one year to reflect planning horizons. I denote the set of price instruments by $\mathbf{z}^{\mathbf{p}}$.

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

$$\mathbf{z}^{\mathbf{s}}_{jmt} = \begin{cases} \text{(a)} \ \sum_{j' \notin \mathcal{J}_f} \mathbb{1}(j' \text{ is in same segment as } j) \\ \text{(b)} \ \sum_{j' \notin \mathcal{J}_f} \mathbb{1}(j' \text{ is in same segment as } j) \times \mathbb{1}(j' \text{ has same engine type as } j) \\ \text{(c)} \ \sum_{j' \notin \mathcal{J}_f} \mathbb{1}(j' \text{ is in same segment as } j) \times d^{\widehat{p}}_{j',j} \\ \text{(d)} \ \sum_{j' \notin \mathcal{J}_f} \mathbb{1}(j' \text{ is in same segment as } j) \times \mathbf{d}^{\mathbf{x}}_{j',j} \\ \text{(e)} \ \sum_{j' \notin \mathcal{J}_f} \mathbb{1}(j' \text{ is in same segment as } j) \times (\mathbf{D}_{mt} \otimes d^{\widehat{p}}_{j',j}) \\ \text{(f)} \ \sum_{j' \notin \mathcal{J}_f} \mathbb{1}(j' \text{ is in same segment as } j) \times (\mathbf{D}_{mt} \otimes \mathbf{d}^{\mathbf{x}}_{j',j}) \end{cases},$$

where $d^x_{j',j} = x_{j'} - x_j$ for some continuous characteristic $x \in \mathbf{x}$. To put it plainly, these instruments are (a) the number of competitors within segment, (b) the number of competitors within segment with the same engine type, (c) the sum of predicted price differences, and (d) the sum of exogenous characteristics differences between products of competitors in the same segment. Since prices are endogenous, they cannot be used to construct a differentiation instrument. They still contains a useful source of variation to identify consumers' heterogeneity in price sensitivity. I follow Reynaert and Verboven (2014) and Gandhi and

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

[16] Real exchange rates are obtained from Penn World Tables, version 10.0, `pl_con`. See Grieco et al. (2023).

Houde (2019) and use the projection of prices on exogenous characteristics and cost shifters, denoted $\widehat{p}_{jt} = \mathbb{E}(p_{jt} \mid \mathbf{x}_{jt}, \mathbf{z}^{\mathbf{P}}_{jt})$ to construct the instruments in (c). Finally, interactions with county-level average demographics in $\mathbf{D}_{mt}$ are used to construct instruments in (e) and (f).

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 I account for region fixed effects. Networks in other regions are valid instruments for local stations as long as the correlation between networks comes only from sharing a common cost component 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 can travel between neighboring regions for work or other daily activities. These commuting patterns could lead to a significant portion of charging in 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.

Let $\text{dist}_{\ell,m}$ be the distance in kilometers between county ℓ and m. I impose a distance threshold, denoted by K, to select networks that are far enough to be valid instrument for local network size. I then construct a basis function, aggregating over these distant networks, that is,

$$z^{\mathbf{N}}_{jmt} = \begin{cases} \frac{\sum_{\ell \neq m} \mathbb{1}(\text{dist}_{\ell,m} > K)\, N_{\ell t}}{\sum_{\ell \neq m} \mathbb{1}(\text{dist}_{\ell,m} > K)} & \text{if } j \in EV \\ 0, & \text{if } j \notin EV \end{cases}.$$

To identify the curvature parameter ζ in the network utility function, I form additional instruments, based on $z^{\mathbf{N}}_{jmt}$, where I aggregate over functions of N_{mt} that map to particular realizations of ζ, see Birchall et al. (2024). The chosen functions are $\sqrt{N_{mt}}$ and $\ln(1 + N_{mt})$, which correspond to curvature parameters $\zeta = 0.5$, and $\zeta \to 0$.

I use a radius of 300 kilometers from each 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 50 kilometers. The robustness analysis shows that even very short distance threshold are appropriate. Results are available in Table A.2.

Several factors could break this instrumental variable strategy. A large scale advertisement campaign that raises awareness about environmental issues or a significant 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 environment over the period of interest that would threaten identification. The full set of demand instruments is $\mathbf{Z}_{jmt} = \{\mathbf{z}^{\mathbf{P}}_{jmt}, \mathbf{z}^{\mathbf{s}}_{jmt}, \mathbf{z}^{\mathbf{N}}_{jmt}, (\mathbf{z}^{\mathbf{P}}_{jmt} \otimes \mathbf{D}_{mt}), (\mathbf{z}^{\mathbf{N}}_{jmt} \otimes \mathbf{D}_{mt})\}$, which includes interactions with county-level demographics in $\mathbf{D}_{mt}$.

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,

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

where $\mathbf{W}$ is some weighting matrix. As usual, the linear parameters $\beta = \{\beta^{\mathbf{P}}, \beta^{\mathbf{x}}, \theta, \Gamma^{\mathbf{P}}, \Gamma^{\mathbf{x}}, \Gamma^{\mathbf{N}}\}$ can be concentrated out, and the optimization is done over $\sigma = \{\sigma^{\mathbf{P}}, \sigma^{\mathbf{x}}, \sigma^{\mathbf{N}}, \zeta\}$. Additional details about the estimation routine can be found in Appendix E.1.

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 N_{mt} is given by the following expression,

$$\begin{aligned}
&\Pr(N = N_{mt} \mid Q^{ev}_{m,t-1}, \mathbf{D}_{mt}) \\
&\quad = \Phi\Big(\lambda^{\mathbf{N}} \ln\left(\Delta v(N_{mt})\right) + \lambda^{\mathbf{Q}} \ln\Big(Q^{ev}_{mt}(N_{mt}) + \frac{\widetilde{\rho}}{1-\widetilde{\rho}}\Delta q^{ev}_{mt}(N_{mt})\Big) + \mathbf{D}_{mt}\lambda^{\mathbf{D}}\Big) \\
&\quad\quad - \Phi\Big(\lambda^{\mathbf{N}} \ln\left(\Delta v(N_{mt}+1)\right) + \lambda^{\mathbf{Q}} \ln\Big(Q^{ev}_{mt}(N_{mt}+1) + \frac{\widetilde{\rho}}{1-\widetilde{\rho}}\Delta q^{ev}_{mt}(N_{mt}+1)\Big) + \mathbf{D}_{mt}\lambda^{\mathbf{D}}\Big),
\end{aligned}$$

where $\mathbf{D}_{mt}$ is a set of county-level demographics. The conditional log-likelihood is then

$$\begin{aligned}
\ell(\lambda \mid Q^{ev}_{m,t-1}, \mathbf{D}_{mt}) &= \sum_m \sum_t \ln \Pr(N = N_{mt} \mid Q^{ev}_{m,t-1}, \mathbf{D}_{mt}), \\
= \sum_m \sum_t \ln \Bigg[&\Phi\Big(\lambda^{\mathbf{N}} \ln\left(\Delta v(N_{mt})\right) + \lambda^{\mathbf{Q}} \ln\Big(Q^{ev}_{mt}(N_{mt}) + \frac{\widetilde{\rho}}{1-\widetilde{\rho}}\Delta q^{ev}_{mt}(N_{mt})\Big) + \mathbf{D}_{mt}\lambda^{\mathbf{D}}\Big), \\
&- \Phi\Big(\lambda^{\mathbf{N}} \ln\left(\Delta v(N_{mt}+1)\right) + \lambda^{\mathbf{Q}} \ln\Big(Q^{ev}_{mt}(N_{mt}+1) + \frac{\widetilde{\rho}}{1-\widetilde{\rho}}\Delta q^{ev}_{mt}(N_{mt}+1)\Big) + \mathbf{D}_{mt}\lambda^{\mathbf{D}}\Big)\Bigg].
\end{aligned}$$

The discount factor $\widetilde{\rho} = \rho\,(1-d)$ is not identified without additional restrictions on the likelihood. The chosen approach to deal with this identification issue is to calibrate ρ and d to some known values, and perform the estimation on the remaining parameters

$\lambda = \{\lambda^{\mathbf{N}}, \lambda^{\mathbf{Q}}, \lambda^{\mathbf{D}}\}$. The chosen values are $\rho = 0.95$ for the discount factor and $d = 0.0832$ for the depreciation rate (the expected lifetime of vehicles in the data is 12.02 years), so $\widetilde{\rho} = 0.871$. Estimation is done by maximizing the conditional log-likelihood function,

$$\lambda^* = \underset{\lambda}{\operatorname{argmax}}\ \ell(\lambda \mid Q^{ev}_{m,t-1}, \mathbf{D}_{mt}).$$

Computational details are relayed to Appendix E.2.

I now address the issue of the endogeneity of the stock of electric vehicles in the station supply model. As stated above, the supply equation depends on Q^{ev}_{t-1} which is predermined but not on Q^{ev}_{mt} which is endogenous. Instead, supply depends on demand-side parameters and prices through the function $q^{ev}_{mt}(n)$. While this specification correctly accounts for the equilibrium relationship between electric vehicle sales and station deployment at the estimation stage, identification relies on the assumption that prices and the unobserved quality of products, ξ_{jmt}, are uncorrelated with the supply shocks $\epsilon^{\mathbf{n}}_{mt}$. I discuss both potential issues in what follows.

I first address the issue of the potential endogeneity of prices. The concern is that car manufacturers' pricing decisions could correlate with local shocks to network provision. This could occur if firms set prices at the local level or if the analysis relied on transaction prices (also set at the local level by dealers). In practice, I am relying on national list prices which are unlikely to correlate strongly with county-specific shocks, as the overwhelming majority of counties are atomistic in size compared to the Canadian population. More broadly, if prices did correlate with local network supply shocks, including a supply side for cars and re-optimizing prices in the calculation of $q^{ev}_{mt}(n)$ would internalize the change in prices (alongside the demand-side response) and solve the simultaneity issue between prices and network.

I now turn to the potential endogeneity of ξ_{jmt}. Endogeneity can arise if local planners are more likely to install chargers where the population they represent is predisposed to purchase electric vehicles. In this case, the (positive) correlation between ξ_{jmt} and $\epsilon^{\mathbf{n}}_{mt}$ implies that I would overestimate $\lambda^{\mathbf{Q}}$. In practice, $q^{ev}_{mt}(\cdot)$ is a complicated functions of all the product-level ξ_{jmt} (including non-electric vehicles) so the impact of individual realizations of ξ_{jmt} is likely to be small since $\epsilon^{\mathbf{n}}_{mt}$ is defined at the county level. Also, the network supply model includes a rich set of demographics and controls that account for shifts in consumers perception for green technology. In this context, it is even less likely that ξ_{jmt} and $\epsilon^{\mathbf{n}}_{mt}$ are correlated as described above.

I gather some empirical evidence to document whether or not this potential source of endogeneity is problematic in practice. The results are presented in Table A.3. I consider the static counterpart of the model (with $\rho = 0$) to remove the influence of marginal electric vehicle owners in the estimation. I estimate three specifications and compare the results. First, I consider the full model that internalizes the demand response from potential electric vehicle owners. I compare the results to a version of the model without internalization, where the endogeneity is treated using a control function approach. This is done be replacing $Q^{ev}(N_{mt})$ and $Q^{ev}(N_{mt}+1)$ by their data counterpart, Q^{ev}_{mt}, in the conditional likelihood, and including the residuals from the linear projection of Q^{ev}_{mt} on instrumental variables and demographics in $\mathbf{D}_{mt}$. Finally, I estimate the model without internalization and without treatment of the endogeneity issue.

I recover very similar estimates using the static model with internalization compared to using the control function approach. In both cases, the parameter estimate for λ^Q is significantly lower than the one obtained from the specification that ignores the endogeneity issue. This reassures that the model correctly accounts for the equilibrium relationship and that endogeneity is not an issue.

5 Estimation results and counterfactuals

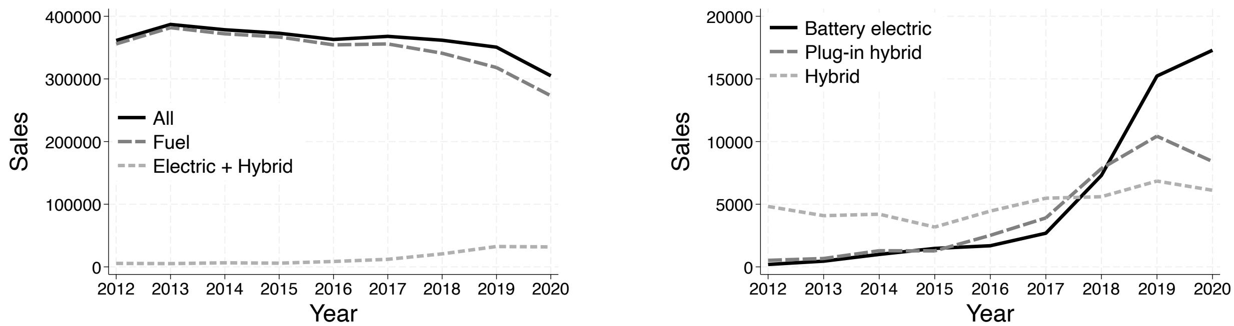
5.1 Demand

Summary statistics. I estimate both the demand for cars and supply of stations at the county-year level. I focus on the province of Quebec, where stations are provided publicly (charging stations are provided by private firms in Ontario). I define a product as a make-model-engine type combination and I set the market size to the number of households in each market. Table A.4 presents a summary of the characteristics of the available products. Battery electric vehicles are on average \$18,000 more expensive than traditional combustion engines while plug-in hybrids are on average \$6,000 more expensive. The combined rebates seem to cover fully the price difference for plug-in hybrids, but not for battery electric vehicles.

The evolution of vehicle sales in Quebec is depicted in Figure 2. Panel (a) shows that total sales are roughly constant until 2019, but then decrease 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 sample period. Sales of non-rechargeable hybrids are rising but slightly.

Several factors unrelated to the policy under study help explaining the sustained growth in electric vehicle sales. One of them is the increasing electric vehicle offering, summarized in

Figure 2: Evolution of sales



(a) All vehicles

(b) Electric and hybrid vehicles

Notes: This figure presents the evolution of aggregate sales over time, by engine type. Panel (a) groups all electric and hybrid vehicles as these sales are marginal compared to fuel vehicles. Panel (b) offer a breakdown between battery electric, plug-in hybrid, and non-rechargeable hybrid vehicles.

Table 4. The number of battery electric and plug-in hybrid alternatives is rising steadily from 5 products available in 2012 to 31 in 2020. Meanwhile, the offering of internal combustion engines seems to decline slightly in 2019 and 2020, when sales of electric vehicles are highest.

The increasing availability of charging stations could also explain part of the growth in electric vehicle sales. The right-hand side of Table 4 shows the evolution of the charging station infrastructure over time. The number of stations available goes from 100 stations in 2012 to more than 2800 in 2020. Local networks are also densifying 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 battery electric vehicle. By 2020, 76% of counties had more than 10 stations available, 32% had more than 25 stations, and all counties had at least one open charging location.

Estimation. Results from the demand estimation are presented in Table 5. I include the horsepower (in 100 kW), the weight (in 100 kg), the driving cost (in CAD per 100 km),[17] 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

[17]For fuel and hybrid vehicles, driving cost is computed by multiplying fuel consumed for traveling 100 kilometers with the gas price in that county and year. For battery electric vehicles, driving cost is measured as power required for traveling 100 kilometers, 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.

Table 4: Evolution of choice set and charging infrastructure

Year	Number of products			Nb. stations	Share of counties with			
	Fuel	Electric	Hybrid		0 station	1-10 stations	11-25 stations	25+ stations
2012	165	5	9	100	0.69	0.25	0.03	0.02
2013	176	8	9	192	0.48	0.46	0.04	0.02
2014	187	11	9	339	0.29	0.62	0.04	0.05
2015	188	11	10	623	0.13	0.72	0.09	0.05
2016	186	13	10	914	0.03	0.69	0.22	0.05
2017	184	23	13	1,266	0.02	0.61	0.31	0.06
2018	184	26	13	1,616	0	0.57	0.30	0.14
2019	177	29	13	2,371	0	0.39	0.39	0.22
2020	173	31	13	2,811	0	0.24	0.44	0.32

square kilometer), and a time trend.[18]

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 (96 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 and on the constant.[19]

In practice, including a random coefficient on the price (or on one of the continuous characteristics) helps producing more diverse substitution patterns between products. In this case, it also allows for heterogenous responses to the financial incentives. 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 I measure the substitution to the outside option accurately, or I am at risk of under-evaluating the emission reduction potential of subsidies.

I estimate the price coefficient and its standard deviation to be -0.801 and 0.154 respectively. Both are highly significant. The interaction of the price coefficient with income is slightly positive but insignificant. Since income is calculated at the county level rather than for individual consumers, this means that consumers in richer counties are slightly less price sensitive.

The main coefficient on network size is 0.214 and significant, which means that consumers

[18] All demographics are demeaned (including the time trend) such that they do not affect the coefficients on the observed characteristics they are interacted with.

[19] I also estimate a specification with a random coefficient on θ. However, the random coefficient was estimated to be small with a large variance. Additionally, including this random coefficient produced insignificant estimates for the curvature parameter in the indirect utility of charging function. To avoid producing misleading results in counterfactual simulations, the final specification does not include a random coefficient on θ. For completeness, these results are available in Table A.5.

Table 5: Demand estimation

		Demographic interractions						
	Estimate	Income	Age	Gender	Pop. density	Trend	ζ	σ
Price – Rebate	-0.801	0.004						-0.154
	(0.035)	(0.003)						(0.021)
$v_j(N, \theta_i)$	0.214	0.068	-0.064				0.212	
	(0.069)	(0.034)	(0.022)				(0.124)	
Power	0.940		0.043	0.033				
	(0.021)		(0.017)	(0.004)				
Weight	0.203					0.093		
	(0.034)					(0.004)		
Driving cost	-0.037							
	(0.004)							
Battery electric	-2.114	-0.281		0.193	-0.617			
	(0.105)	(0.083)		(0.028)	(0.115)			
Plug-in hybrid	-2.055	-0.415		0.174	-0.662			
	(0.098)	(0.086)		(0.029)	(0.127)			
Hybrid	-1.720		0.329	0.152				
	(0.021)		(0.04)	(0.015)				
Constant								5.115
								(2.099)
Observations	126,397							
Nb. of markets	864							
Obj. Function	3,425.4							

Notes: Includes brand, market segment, county, and year fixed effects. Robust standard errors in parenthesis.

care about the availability of charging stations when considering the purchase of an electric vehicle. I observe a positive interaction with income and a negative interaction with age, both significant. The curvature parameter on the network utility function is estimated to be 0.212. To fix ideas, this implies a curvature in between the linear and logarithmic functions (close to the logarithmic function, but statistically significantly different).

Interestingly, the interactions with average demographics seem to capture fairly well the heterogeneity in preferences for the observed car characteristics. For example, the model suggests that the preference for powerful vehicle increases with age, and that women typically prefer more powerful vehicles compared to men. 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). The model also predict that women prefer electric and hybrid vehicles more than men. The estimates suggests that consumers in large cities dislike electric vehicles. One explanation is that the interactions between population density and the electric vehicle dummies capture partially the potential for home charging which is lower in urban areas compared to suburban and rural areas. Finally, my estimates suggest that consumers' prefer heavier vehicles (a proxy for security) and that this preference increases over time.

The market-level elasticities implied by these estimates are presented in Table 6. The market-level own-price elasticities for battery electric and plug-in hybrid vehicles are -3.15 and -2.68, respectively, which leads to a combined elasticity of -2.78. This is close to what I estimate in the reduced form analysis (-3.0).

Table 6 reveals other interesting patterns. Increasing the price of all fuel vehicles (together) induces substitution towards electric and hybrid engines. The cross-price elasticities range between 1.78 and 1.84, suggesting that taxing internal combustion engines may be an effective way to promote electric vehicle adoption. The large magnitude of these cross-price elasticities is due to the fact that fuel vehicles represent more than 95% of all sales and small transfers from fuel to electric generate large increases in the electric vehicle base. Finally, I report the market-level elasticity to network provision. I find large elasticities, in the range of 0.56 to 0.62, suggesting that network effects are strong on the consumer side. This is in line with previous findings by Springel (2021) and Remmy (2025).

Table 6: Market-level elasticities

	Fuel	Battery electric	Plug-in hybrid	Hybrid	Network
Fuel	-0.972	0.030	0.020	0.026	-0.010
Battery electric	1.781	-3.149	0.046	0.036	0.618
Plug-in hybrid	1.825	0.073	-2.684	0.034	0.562
Hybrid	1.842	0.042	0.026	-2.748	-0.015
Outside option	6.16e-04	8.80e-06	6.85e-06	7.72e-06	-2.38e-06

Notes: The market-level elasticities are computed by increasing the prices of all products by 1%, by engine type, and computing the resulting change on sales (including the outside option) keeping everything else constant. The market-level elasticity to network size is computed similarly by increasing all local network sizes by 1%.

5.2 Network supply

Results from the network supply estimation are presented in Table 7. I include several demographics that capture regional differences in consumer characteristics which may induce local planners to install chargers. I use the share of residents that have an undergraduate degree as a proxy for consumers' environmental awareness and their 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 services should be higher if some electric vehicle owners cannot install and use a home-charger. This in turn should lead to more station installations.

Table 7: Station supply estimation

	Forward-looking		Static	
	Estimate	S.E.	Estimate	S.E.
$\lambda^{\mathbf{N}}$	2.376	(0.132)	2.436	(0.139)
$\lambda^{\mathbf{Q}}$	0.372	(0.111)	0.413	(0.111)
Avg. income	-0.578	(0.239)	-0.589	(0.242)
Avg. age	1.857	(0.560)	1.888	(0.562)
Avg. household size	-0.018	(1.504)	-0.027	(1.524)
Share graduates	8.512	(2.480)	8.436	(2.508)
Share homeowners	-6.099	(1.995)	-5.989	(1.997)
Urban	0.426	(0.328)	0.380	(0.327)
Elasticity to EV	0.1078		0.1435	
EV for one additional station	75.71		57.36	
Observations	830		830	
Log-likelihood	-2,125.2		-2,119.2	

Notes: Includes year fixed effects. Markets where electric vehicles are not in the choice set and which have no electric vehicle in circulation are excluded. The forward-looking model is estimated using a discount factor or $\widetilde{\rho} = 0.871$. Standard errors in parenthesis are clustered at the county level and are computed using 500 bootstrap replications.

Because of the highly nonlinear nature of the model, 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 the coefficients of both the model with forward-looking planners and the static model. The coefficients on the share of graduates, the share of homeowners, and the urban indicator are significant and have the correct signs. This reinforces the idea that environmental awareness and the potential for home-charging are two important drivers of charging station supply.

The coefficients $\lambda^{\mathbf{N}}$ and $\lambda^{\mathbf{Q}}$ are difficult to interpret directly. I use them to recover the underlying local-planner preference parameter, γ, estimated to be 6.39 and highly significant. This means that local planners value charging more than the underlying electric vehicle owners. I also recover the elasticity of network supply to assess the magnitude of the network effects on the station supply side. The elasticity implied by the forward-looking model is 0.108, meaning that a 10% increase in the stock of electric vehicles is associated with a 1.08% increase in network size. This is much smaller than the demand elasticity to network size (0.562–0.618), meaning that network effects are much stronger on the consumer side than on the network supply side. To put things in perspective, the estimates from the forward-looking model suggest that one additional station is installed for every 76 electric vehicles sold.

Alternatively, the estimates from the static model imply an elasticity of supply of 0.144 and that one additional station is installed for every 57 electric vehicle sold. Ignoring the forward-looking behavior of the social planner therefore leads to overestimating the magnitude of the elasticity of supply and the marginal effect by about 33% and 32% respecfively. This happens because ignoring the future gains from marginal consumers at the estimation stage means that local planners' decisions are explained entirely by users current valuation of networks, which leads to a larger estimated coefficient. At the same time, the term $\frac{\widetilde{\rho}}{1-\widetilde{\rho}}\Delta q^{ev}_{mt}(n)$ representing the marginal users decreases mechanically the marginal effect, see Appendix E.3. Both factor contributes to overestimating the elasticity of network supply and the marginal effect when ignoring the forward-looking behavior of network suppliers.

5.3 Counterfactual analysis

I conduct several counterfactual simulations. Computational details are relayed to Appendix E.4. I want first to disentangle the direct effect of subsidies from network effects. To that end, I compare the outcomes of a counterfactual experiment where I remove all subsidies, keeping networks at their original levels, to another experiment where network is updated using the forward-looking supply model. Second, I want to understand the impact of ignoring the forward-looking behavior of local planners in the station supply model. To achieve this, I compare a counterfactual experiment where the local planner is forward-looking to the case where the re-optimization of networks is done using the static model.

The results of the counterfactual experiments are reported in Table 8. I set the baseline to be the observed outcomes from the data (with rebates). I first consider the direct effect of the rebate program, when networks are fixed at their observed values. The rebates contributed to increasing sales of electric vehicles by 38,312 units, representing 45.5% of all registrations. Around two thirds of these additional electric vehicles replaced internal combustion engines and non-rechargeable hybrids. This led to a reduction in total carbon emissions in the range of 0.987 million metric tons over the lifetime of these vehicles, or 0.7% of the total emissions attributed to the vehicles sold between 2012 and 2020. The reduction is small compared to total fleet emissions, since electric vehicle sales represent a small fraction of total sales.

I next focus on the contribution of network effects when the local planners are forward-looking. I find that allowing for the re-optimization of local networks leads to an additional 3,876 electric vehicle sales and 373 additional charging station installations. These additional sales attributed to the network expansion represent around 10% of the direct effect of

Table 8: Counterfactual simulation

	Observed						
		Counterfactuals: No Subsidies					
	(1) Baseline	(2) Fixed network		(3) Forward-looking		(4) Static	
Key outcomes							
Δ Total sales	3,248,085	-12,940	(-0.40%)	-14,219	(-0.44%)	-14,376	(-0.44%)
Δ Sales (fuel)	3,119,123	+24,884	(+0.80%)	+27,430	(+0.88%)	+27,748	(+0.89%)
Δ Sales (electric)	84,174	-38,312	(-45.51%)	-42,188	(-50.12%)	-42,669	(-50.69%)
Δ Sales (hybrid)	44,788	+487	(+1.09%)	+539	(+1.20%)	+545	(+1.22%)
Δ Charging stations	2,811	0	(0.00%)	-373	(-13.27%)	-412	(-14.66%)
Δ CO_2 emissions	141.46	+0.987	(+0.70%)	+1.083	(+0.77%)	+1.095	(+0.77%)
Δ Consumer surplus	0	-520.8	–	-576.4	–	-583.2	–
Δ Total cost	721.5	0	(-100%)	0	(-100%)	0	(-100%)
Implied abatement costs							
Avg. cost per ton CO_2	–	-731	–	-666	–	-659	–
Avg. cost per electric vehicle	–	-18,834	–	-17,102	–	-16,910	–

Notes: Column (1) reports the baseline values from the data, where rebates are available. Columns (2) to (4) report the change from baseline for various counterfactuals where rebates are removed. Sales of electric vehicles includes both battery electric and plug-in hybrid vehicles. CO_2 emissions are calculated over the lifetime of vehicles, in million tons, based on a 22,053 average mileage per year, an average lifetime of 12.02 years, and a discount factor of 0.95. Consumer surplus in the baseline case is normalized to zero. Consumer surplus and the total cost of the program are in million 2018 CAD. The average cost per ton of CO_2 and the average cost per electric vehicle are in 2018 CAD.

subsidies and the additional stations represent around 13% of the observed networks. Out of the 3,876 new electric vehicle sales, 2,598 replace internal combustion engines or non-rechargeable hybrids, leading to further emission reductions. The abated emissions reach 1.083 million tons, or 0.77% of total emissions, and network effects account for roughly 9.1% of these abated emissions.

We can compare these estimates with previous works. For example, Springel (2021) and Remmy (2025) find that electric vehicle adoptions generate additional station installations at a rate of 1:38 and 1:11 respectively.[20] They define charging stations as separate chargers, while I define charging stations as sites that can host more than one charger. In the data, I observe that each charging site holds on average 2.27 chargers. Using back of the enveloppe calculations, my results imply that new chargers are installed at a rate of 1:50 electric vehicle sold (new charing sites are opened at a rate of 1:113 electric vehicle sold). Using the estimates from the static model, I find that new chargers are installed at a rate of 1:45. In both cases, the results are close to the findings in Springel (2021).

I compare the estimated impact of the subsidy from the structural estimation to the

[20]These figures are computed from Table 5 in each paper.

reduced form results of Section 3. The counterfactual simulation in column (3) of Table 8 suggests that electric vehicle sales increased from 41,986 to 84,174 due to subsidies over the full period. This is an increase of slightly above 100%. Back of the enveloppe calculations suggest that this is equivalent to a 11.7% increase in sales per $1,000 in average subsidy. Meanwhile, the reduced form estimates suggests an increase of 7.9% per $1,000 in subsidies.

The structural model predicts that total network size increases from 2,441 to 2,811. That is, the total number of charging locations increased by 15.3%. In contrast, the reduced form estimates revealed no significant change in network size due to the policy. These findings shed light on the rigidities affecting network supply which ultimately affect electric vehicle adoption in the short-run. For example, the opening of new location requires planning to find appropriate sites, approving budgets, ordering the required material, and allocating human resources for installation. This makes it difficult for network operators to change supply in the short-run following a sudden surge in demand for charging services. However, network supply eventually adapts to the new market condition in the long-run, as evidenced from the counterfactual simulations.

I next quantify the effect of ignoring the forward-looking behavior of local planers in the station supply model. I find that doing so leads to overestimating the impact of network effects. For example, the simulation predicts that network size increases by 412 instead of 373 and the network effect contribution to sales is 4,357 instead of 3,876. That is, the counterfactual simulation which rely on the static supply model overestimates the contribution of network effects to key outcomes by 10.5% and 12.4% respectively. These differences are relatively small, and given that network effects are small compared to the direct effect of the policy, they do not translate into meaningful differences in terms of emission abatement, or abatement costs. This could, however, be problematic in other contexts where network effects are more important.

The total spending on subsidies by both levels of government reached $723.2 million. I use this figure to compute some preliminary cost measures, which are useful to compare my results to previous literatures that use simple measures of abatement cost. I estimate the average cost of reducing emissions to be $666 per ton of CO_2. This is close the results from Xing et al. (2021), who estimate an average abatement cost between $581 and $662 (484–552 USD) per ton for a similar rebate program in the United States. Other studies of similar financial incentives typically find lower estimated costs. Examples include Huse and Lucinda (2014) on the Swedish green car rebate ($131–158), Beresteanu and Li (2011) on tax incentives on hybrids in the United States ($212), and Azarafshar and Vermeulen (2020) on the Canadian electric vehicle market ($480).

These cost measures, while informative, are inadequate to study the cost-effectiveness of environmental policies. The reason is that the policies under study are non-marginal, so the average abatement cost measured in these works is potentially far from the marginal abatement cost. They also ignore the fiscal externalities to consumers, firms, and the policymaker, and the marginal cost of providing public funds. These factors could drastically change how we evaluate different programs. I propose a unifying framework for studying non-marginal environmental policies in what follows.

6 Cost-benefit analysis

6.1 Setup

I propose a calibration exercise to study the cost-effectiveness of the Canadian electric vehicle 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). In what follows, I consider a social planner providing electric vehicle incentives to abate emissions, distinct from the local planners who develop the charging infrastructures.

Consider the following social planner objective, where τ is the targeted policy variable,

$$\tau^* = \underset{\tau \geq 0}{\operatorname{argmax}} \quad \underbrace{\mathcal{W}(\tau) - \mathrm{Cost}(\tau) + \mathrm{Tax}(\tau)}_{\text{Value to society}} - \underbrace{\mathrm{E}(\tau) \cdot P^E}_{\substack{\text{Value of} \\ \text{environmental} \\ \text{damage}}}.$$

The social planner is looking to pick the policy τ^* that maximizes the value to society and minimize the value of the environmental damage that arise from the policy. For now, I take the carbon price P^E as given.

The government objective function has four key inputs: a social welfare function $\mathcal{W}(\tau)$ which accounts for the fiscal externalities of the policy on consumers and firms, a cost function $\mathrm{Cost}(\tau)$ which summarizes government spending on the policy, a tax function $\mathrm{Tax}(\tau)$ which account for revenues from the provincial gas tax (or other taxes associated with the purchase and driving of vehicles), and an emission function $\mathrm{E}(\tau)$ which accounts for the lifetime environmental impact of vehicles.

Provided all functions are continuously differentiable, the cost-effective policy rule $\tau^*(P^E)$

can be obtained by inverting the following first-order condition,[21]

$$\underbrace{\frac{\partial \mathcal{W}(\tau^*)}{\partial \mathrm{E}(\tau^*)} - \frac{\partial \mathrm{Cost}(\tau^*)}{\partial \mathrm{E}(\tau^*)} + \frac{\partial \mathrm{Tax}(\tau^*)}{\partial \mathrm{E}(\tau^*)}}_{\substack{\text{Marginal}\\\text{Abatement}\\\text{Cost}}} = \underbrace{P^E}_{\substack{\text{Cost of}\\\text{Carbon}}}. \tag{12}$$

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

Social welfare function. Let Θ be the fundamental parameters governing consumers' preferences and network provision. I define the social welfare function as a weighted sum of the firms' variable profits and consumers' welfare (defined by consumer surplus). Let ψ_1 and ψ_2 be welfare weights and $q_{jmt}(\tau)$ be the quantity sold of model j in county m and period t, given policy τ. Furthermore, let c_{jt} be the marginal cost of product j in period t.[22] 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' aggregate variable profits, and

$$\mathcal{CS}(\tau, \Theta) = \sum_t \sum_m L_{mt} \int \frac{1}{-\beta_i^{\mathbf{p}}} \ln \left(1 + \sum_{j=1}^{J} \exp \Big(\delta_{jmt}(\tau, \Theta) + \mu_{ijmt}(\tau, \Theta, \nu_i) \Big) \right) dF(\nu_i) + C$$

is the aggregate expected consumers' surplus (identified up to a constant C).

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

[21] The social planner problem could in principle be more complex. For example, the policymaker could take into account congestion issues, mileage decisions of users (i.e. through modal choices), fairness concerns, political constraints, or other types of externalities. Therefore the solution to the problem is the "cost-effective policy" (for lack of a better terminology) only in terms of equating the marginal abatement cost to the social cost of carbon.

[22] Marginal costs can be estimated from demand side parameters and car manufacturers' first-order conditions, see Berry et al. (1995).

function can be computed as the sum of all government subsidies,

$$\text{Cost}(\tau) = \text{Cost}(\tau, \Theta) = \phi \cdot \sum_t \sum_m \sum_j q_{jmt}(\tau, \Theta) \cdot \tau_{jt},$$

weighted by the marginal cost of providing public funds ϕ.

Tax function. The tax function accounts for the revenues from the 19.2 cents per liter provincial gas tax, computed over the lifetime consumption of vehicle sold under subsidy τ. It depends on each car's fuel consumption f_{jt}, its expected lifetime T_j, and the average mileage by year traveled by a typical owner $\boldsymbol{m}_{js}$. I assume that the policymaker discounts future revenues at some discount factor ρ. Under these assumptions, the present-value of the gas tax revenues is

$$\text{Tax}(\tau) = \text{Tax}(\tau, \Theta) = 0.192 \cdot \sum_t \sum_m \sum_j \left(q_{jmt}(\tau, \Theta) \cdot \sum_{s=t}^{t+T_j} \rho^{t-s} \boldsymbol{m}_{js} f_{jt} \right).$$

Emission function. Lifetime emissions depend on several parameters, including the car's level of emission per kilometre e_{jt}, its expected lifetime T_j, and the average mileage by year that a typical owner travels $\boldsymbol{m}_{js}$. I assume that the policymaker discounts future emissions according to the same discount factor ρ. The present-value of the aggregated emissions can be computed as

$$\text{E}(\tau) = \text{E}(\tau, \Theta) = \sum_t \sum_m \sum_j \left(q_{jmt}(\tau, \Theta) \cdot \sum_{s=t}^{t+T_j} \rho^{t-s} \boldsymbol{m}_{js} e_{jt} \right).$$

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 factor (ρ), the average mileage per year $(\boldsymbol{m}_{js})$, and the expected lifetime of vehicles (T_j).

I assume that the social planner cares about consumer surplus and the taxable part of firms' profits, to account for the fiscal externality of firms on the social planner's finances. The corporate tax rate in Quebec is around 27% for large firms, so I set the welfare weight on profits to 0.27 and the welfare weight on consumer surplus to one. The discount factor is set to 0.95 as previously. 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 kilometers for all j and s. I compute the expected lifetime of vehicles using the micro-level car registration data. I have access to the full fleet of vehicles in ten successive years which I use to track vehicles of various ages and estimate their expected lifetime. The expected lifetime of a new vehicle estimated to be 12.02 years.[23] Finally, I assume that the government can provide subsidies without friction at no additional cost, hence I set the marginal cost of public funds to one. I consider alternative calibrations in which the government incurs an administrative fee for providing subsidies in Section 6.5.

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

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

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

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

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 cost-effective rebate program entails solving a problem in $\mathbb{R}^J$ 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 Cost-effective policy

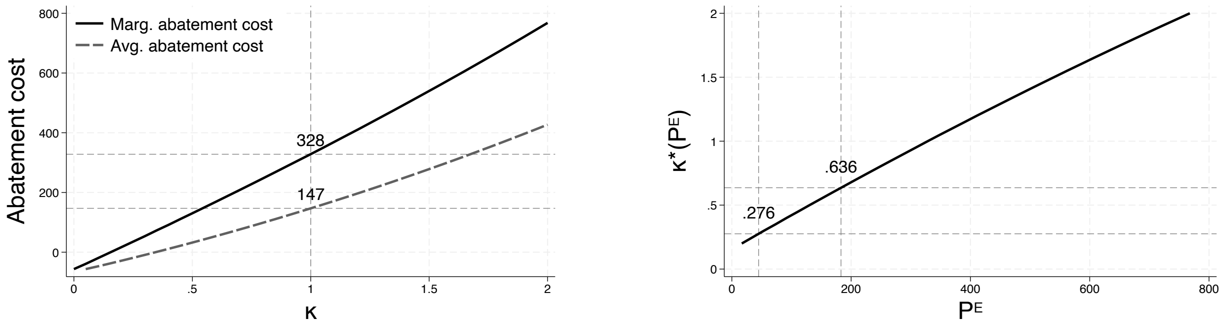
I study the cost-effectiveness of rebates by considering the social planner's optimality condition. I compute counterfactuals on a grid $\{\kappa_1, ..., \kappa_{\mathcal{N}}\}$ using the forward-looking supply model, then I estimate the marginal abatement cost as

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

I collect the results to construct the marginal abatement cost curve as a function of κ. There are two interpretations to the social planner's first-order condition. On the one hand, I can assume that it holds at the current rebates. In this case, equation (12) provides an

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

Figure 3: Abatement cost and cost-effective policy curves



(a) Abatement cost (b) Cost-effective policy

Notes: This figure presents the average and marginal abatement costs as a function of the government's policy in panel (a) and the optimal government policy as a function of the price of carbon in panel (b). Both graphs represent the same relationship between the policy and the marginal abatement cost (which is equal to the price of carbon at the optimum).

estimate for the cost of carbon, $P^E = \text{MAC}(\kappa = 1)$. On the other hand, I can calibrate the cost of carbon to known estimates and recover the cost-effective policy $\kappa^*(P^E)$. In what follows, I focus on the second interpretation.

Figure 3, panel (a), depicts the marginal abatement cost curve and the cost-effective policy curve for the chosen calibrated parameters. I observe 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, for a given P^E. In practice, I 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 \$328 per ton of carbon emissions. This is larger than current measures of the social cost of carbon.

Figure 3, panel (a), also reports the corresponding average abatement costs.[24] A key observation is that the average abatement cost sits below the marginal abatement cost over the full policy support. This has important implications for policy design: determining the cost-effective policy based on the average abatement cost systematically leads to an overinvestment from the social planner.

I invert the marginal abatement cost curve to recover the cost-effective policy curve. I evaluate the cost-effective 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 in 2018, according to the Government of Canada. For the lowest estimate, the cost-effective policy corresponds to 28% of the current rebate

[24] I construct the average abatement curve as $AAC(\kappa_n) = \frac{\mathcal{W}(\kappa_n)-\mathcal{W}(0)}{\text{E}(\kappa_n)-\text{E}(0)} - \frac{\text{Cost}(\kappa_n)-\text{Cost}(0)}{\text{E}(\kappa_n)-\text{E}(0)} + \frac{\text{Tax}(\kappa_n)-\text{Tax}(0)}{\text{E}(\kappa_n)-\text{E}(0)}$.

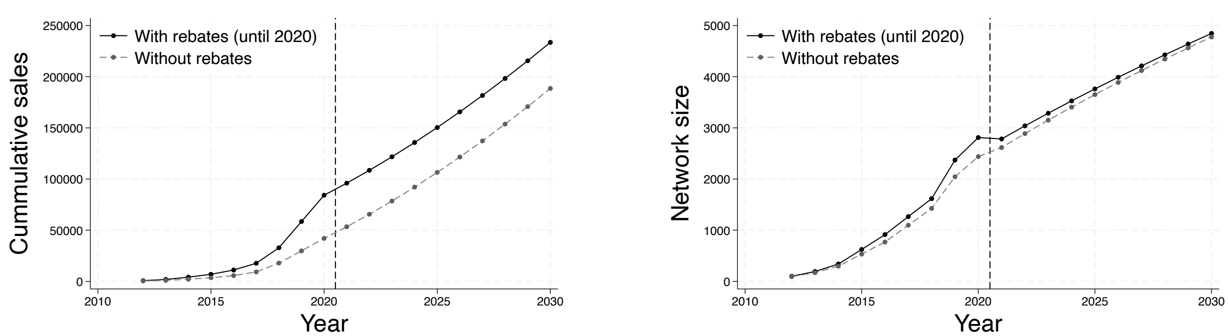
programs. For the highest estimate, the cost-effective policy corresponds instead to 64% of current rebates. In both cases, my analysis suggests that policymakers are overinvesting on rebates.

6.4 Accounting for future environmental gains

One reason why governments may be ready to overinvest on subsidies is that quickly increasing the stock of electric vehicles and charging stations may lead to future environmental benefits through network effects, once subsidies are phased out. In that spirit, I consider a counterfactual experiment where the policymaker subsidizes electric vehicles from 2012 to 2020, phases out rebates in 2021, and I measure the environmental benefits until 2030. I compare the results to another counterfactual experiment where electric vehicles are never subsidized between 2012 and 2030. Computational details and limitations are discussed in Appendix G.

Figure 4 depicts the evolution of the stock of electric vehicles and charging stations under both counterfactual experiments described above. The first observation concerns electric vehicle adoption, see panel (a) of Figure 4. Providing subsidies for a period of time leads to a permanently higher stock of electric vehicles, as electric vehicle sales accumulate faster when subsidies are offered. However, this improved growth in electric vehicle sales does not continue once subsidies are phased out and electric vehicle adoption is essentially the same between 2021 and 2030, whether or not subsidies were initially offered. This occurs because I estimate the contribution of network effects to be relatively small and the direct effect of

Figure 4: Evolution of the stock of electric vehicles and charging stations, from 2012 to 2030

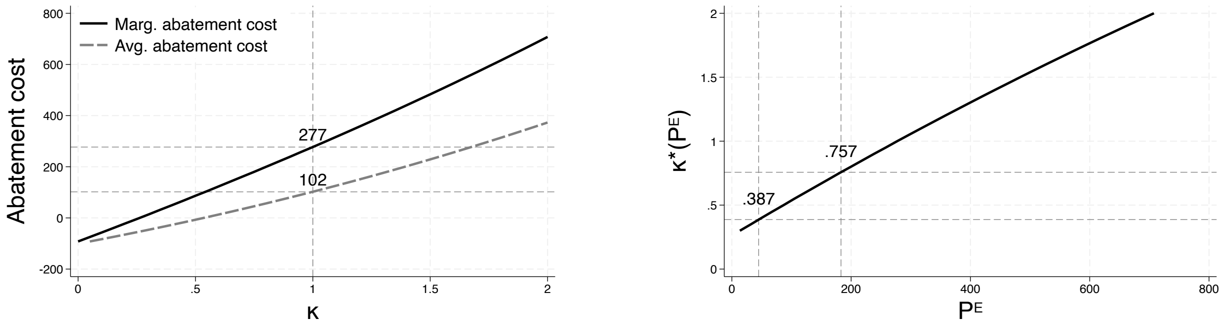


(a) Cumulative EV sales

(b) Network size

Notes: This figure presents the evolution of the stock of electric vehicles and the stock of charging stations, from 2012 to 2030, under two alternative counterfactual experiments. In the first case, subsidies are offered from 2012 to 2020, and I forecast the outcomes from 2021 to 2030 using the 2020 data as reference. In the second counterfactual, subsidies are never available, and I forecast the outcomes from 2021 to 2030 using the 2020 data as reference.

Figure 5: Abatement cost and policy curves, accounting for future environmental gains



(a) Abatement cost

(b) Cost-effective policy

Notes: This figure presents the average and marginal abatement costs as a function of the government's policy in panel (a) and the optimal government policy as a function of the price of carbon in panel (b). The policymaker phases out subsidies in 2021, and sales and network size are forecasted until 2030. Both graphs represent the same relationship between the policy and the marginal abatement cost (which is equal to the price of carbon at the optimum).

subsidies explains most of the additional electric vehicle sales.

The second observation concerns network provision, see panel (b) of Figure 4. An interesting pattern emerges. I observe that networks grow slightly faster while subsidies are offered. However, once rebates are phased out, network operators forgo installing some stations, as they expect significantly fewer future sales, and network size is almost the same in both counterfactual experiments between 2021 and 2030. This limits the potential future gains from the policy that could occur if network provision was kept at a permanently higher level once rebates are phased out.

I re-evaluate the marginal abatement cost curve and the cost-effective policy curve, accounting for the future environmental benefits of the policy. The results are available in Figure 5. I find that the marginal abatement cost is slightly lower, \$277 instead of \$328 per ton of carbon, and the cost effective policy associated with a \$183 social cost of carbon correspond to 76% of the currently implemented rebates instead of 64%.

6.5 Alternative parametrizations

To paint the broadest picture possible, I redo the cost-benefit analysis using alternative sets of calibrated parameters. The results are available in Table 9. I start from the extreme case in which the policymaker cares only about government spendings and not welfare. This calibration is used widely in the literature related to the car market. In this case, the cost-effective policy is a corner solution: the marginal abatement cost is well above any conventional measures for the social cost of carbon for any level of the subsidy, hence the

Table 9: Alternative calibration results

Description	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Parameters							
• Profit weight (ψ_1)	0	0	0	0.27	0.27	1	1
• Consumer surplus weight (ψ_2)	0	1	1	1	1	1	1
• Marginal cost of public funds (ϕ)	1	1.3	1	1.3	1	1.3	1
Cost-benefit analysis, without future environmental gains							
• Marginal abatement cost	916	635	378	585	328	450	194
• Average abatement cost	736	399	196	349	147	216	14
• Cost-effective policy (κ^*)	0	0.101	0.509	0.204	0.636	0.476	0.974
• Cost-effective provincial rebate (τ^*_{prov})	0	808	4,072	1,632	5,088	3,808	7,792
• Cost-effective federal rebate (τ^*_{fed})	0	505	2,545	1,020	3,180	2,380	4,870
Cost-benefit analysis, with future environmental gains							
• Marginal abatement cost	869	570	327	519	277	384	141
• Average abatement cost	695	342	152	293	102	159	-32
• Cost-effective policy (κ^*)	0	0.204	0.626	0.311	0.757	0.594	1.11
• Cost-effective provincial rebate (τ^*_{prov})	0	1,632	5,008	2,488	6,056	4,752	8,840
• Cost-effective federal rebate (τ^*_{fed})	0	1,020	3,130	1,555	3,785	2,970	5,525

Notes: In all parametrization, we have $\rho = 0.95$, $T_j = 12.02$, and $m_{js} = 22,083$. The social cost of carbon (SCC) is set to \$183 per ton of carbon. Column (5) is the main specification. It is reproduced for comparability. The marginal abatement cost and average abatement cost are in CAD per metric ton of carbon. The provincial rebate is computed by multiplying the cost-effective policy κ^* by \$8,000. The federal rebate is computed by multiplying the cost-effective policy κ^* by \$5,000. The federal rebate is available starting in 2019.

social planner chooses not to subsidize electric vehicles.

I repeat the exercise for various combinations of the welfare weights and the marginal cost of providing public funds. I consider three cases for the welfare weights. In the first case, the policymaker takes into account consumer surplus but not profits. In the second case, it takes into account consumer surplus and the taxable part of firms' profits (the corporate tax rate is around 27% in Quebec). Finally, I consider the case where the policymaker cares fully about consumer surplus and profits. I interact these welfare weights with two distinct values for the marginal cost of public funds and I focus on the highest value for the social cost of carbon, that is, \$183 per metric ton of carbon. Finally, I provide two sets of results, one in which the government ignores the future environmental gains associated with the policy and one where it takes into account these future benefits.

In almost all parametrizations, the I find that the social planner overinvests on subsidies.

The cost-effective policy varies between 10.1% of the currently implemented rebate schemes for the least favorable specification (excluding cases with a corner solution) and 111% for the most favorable specification. The estimated marginal costs of abatement are between \$141 and \$916.

7 Conclusion

The Canadian electric car market presents a unique opportunity to study the cost-effectiveness of subsidizing electric vehicle adoption. 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 small increase in network provision. 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.

Whether or not government should subsidize electric vehicle adoption should be carefully considered against a broader set of alternative 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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“For Online Publication” (all appendices)

A Additional Tables and Figures

Table A.1: County-level demographics

	Ontario			Quebec		
	Pre	Post1	Post2	Pre	Post1	Post2
Avg. household income	96,484	100,837	114,341	74,594	79,322	90,373
	(15,509)	(15,337)	(15,866)	(11,134)	(10,625)	(11,074)
Avg. after-tax household income	80,070	82,742	93,967	61,805	65,007	73,869
	(11,229)	(10,810)	(11,105)	(8,128)	(7,658)	(7,921)
Unemployment rate	0.081	0.074	0.12	0.073	0.073	0.075
	(0.012)	(0.010)	(0.018)	(0.023)	(0.022)	(0.020)
Avg. household size	2.65	2.63	2.62	2.33	2.32	2.28
	(0.28)	(0.29)	(0.28)	(0.16)	(0.16)	(0.16)
Avg. age	40.6	41.0	41.8	42.0	42.0	42.8
	(2.66)	(2.02)	(2.03)	(3.22)	(2.41)	(2.65)
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 within 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	–	–	22.1	–	–
	(6.64)			(6.57)		
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	0.12	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
Nb. of counties	49	49	49	98	96	96

Notes: All values are averaged over counties, weighted by population. Standard deviation are in parenthesis. “Pre” is based on the 2011 Canadian Census Survey. “Post1” is based on the the 2016 Canadian Census Survey. “Post2” is based on the 2021 Canadian Census Survey. Income variables are not adjusted for inflation.

Table A.2: 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	-0.662***	-0.677***	-0.675***	-0.671***	-0.669***	-0.674***	-0.672***	-0.677***	-0.676***	-0.677***	-0.676***	-0.675***
	(0.031)	(0.031)	(0.031)	(0.031)	(0.031)	(0.031)	(0.031)	(0.031)	(0.031)	(0.031)	(0.031)	(0.031)
Price × Income	0.007*	0.007*	0.007*	0.007*	0.007*	0.007*	0.007*	0.007*	0.007*	0.007*	0.007*	0.007*
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Log network	0.134***	0.248***	0.242***	0.229***	0.246***	0.235***	0.234***	0.243***	0.244***	0.239***	0.237***	0.238***
	(0.016)	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)	(0.019)	(0.019)
Log network × Income	0.037***	0.041***	0.049***	0.057***	0.053***	0.056***	0.062***	0.058***	0.055***	0.056***	0.055***	0.052***
	(0.009)	(0.013)	(0.012)	(0.012)	(0.012)	(0.013)	(0.013)	(0.012)	(0.012)	(0.013)	(0.013)	(0.013)
Log network × Age	-0.004	-0.081***	-0.080***	-0.073**	-0.077***	-0.076***	-0.074**	-0.088***	-0.086***	-0.086***	-0.086***	-0.080***
	(0.027)	(0.029)	(0.029)	(0.029)	(0.030)	(0.029)	(0.029)	(0.029)	(0.029)	(0.029)	(0.029)	(0.029)
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	0.121	0.112	0.113	0.115	0.116	0.114	0.115	0.112	0.112	0.112	0.112	0.113

Notes: This table highlights how the coefficients on network utility and its interactions with demographics change as I vary the distance threshold used to construct the network instrument $\mathbf{z^N}$. The model is estimated with an IV logit specification, without the random coefficients, and I fix the curvature parameter to $\zeta = 0.2115$ to avoid performing a nonlinear optimization. Distance thresholds are in kilometre from centroid to centroid for each region pair. Column (1) does not instrument for the network (i.e., excludes $\mathbf{z^N}$) and networks are taken as exogenous. Column (2) uses all stations that are located outside of a 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 regressions include the instruments described in Section 4.3. Standard error in parenthesis are clustered at the product × county level. SIgnificance: * < 0.10, ** < 0.05, *** < 0.01.

Table A.3: Endogeneity and network supply

	With internalization	No internalization	
	(1) Static model	(2) Control function	(3) No control function
$\lambda^{\mathbf{N}}$	2.436	2.474	2.464
	(0.139)	(0.139)	(0.14)
$\lambda^{\mathbf{Q}}$	0.413	0.399	0.569
	(0.111)	(0.207)	(0.105)
Avg. income	-0.589	-0.599	-0.602
	(0.242)	(0.251)	(0.25)
Avg. age	1.888	1.887	2.041
	(0.562)	(0.607)	(0.553)
Avg. household size	-0.027	-0.049	-0.074
	(1.524)	(1.564)	(1.576)
Share graduates	8.436	8.743	7.503
	(2.508)	(2.762)	(2.535)
Share homeowner	-5.989	-6.090	-5.490
	(1.997)	(-6.09)	(1.974)
Urban	0.380	0.404	0.224
	(0.327)	(0.402)	(0.326)
Control function		0.235	
		(0.245)	
Observations	830	830	830
Likelihood	-2,119.2	-2,084.7	-2,087.1

Notes: This table compares alternative methods for dealing with the simultaneity and the endogeneity issues in the network supply model. Column (1) reports the estimates from the static version of the model presented in Section 4. Column (2) reports the estimates from a static model that does not internalize the demand response in electric vehicle sales from additional stations. The endogeneity issue is tackled using a control function approach. The set of instrumental variables includes the county-level demographics, as well as the gas station density (number of gas stations per 5,000 inhabitant), a fuel price index, and an interaction between the two, similarly to Springel (2021). The identifying assumptions are that competition in the fuel market affects electric vehicle sales through substitution between fuel and electric and that network operators and refueling stations do not compete with each other once sales are realized. Column (3) reports estimates for the same model as in (2), without the control function approach such that the endogeneity issue is not addressed. Standard errors in parenthesis are clustered at the county level and are computed using 500 bootstrap replications.

Table A.4: Average characteristics, by engine type

	Fuel	Battery electric	Plug-in hybrid	Hybrid
Characteristics				
List price, in CAD	36,780	54,531	42,830	36,844
Net price, in CAD	36,780	44,695	35,834	36,480
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/single-speed	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

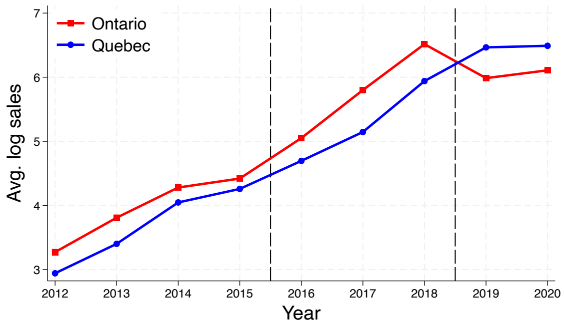
Notes: All averages are weighted by sales. All dollars values are in 2018 CAD.

Table A.5: Alternative demand specification

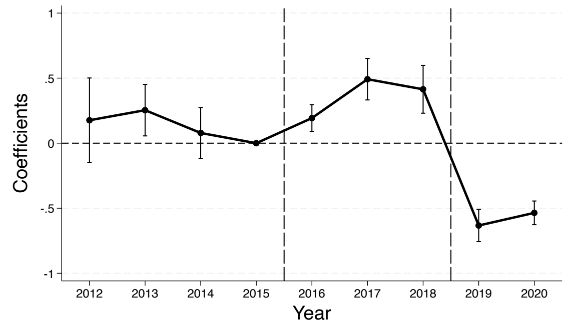
		Demographic interractions						
	Estimate	Income	Age	Gender	Pop. density	Trend	ζ	σ
Price	-0.844	0.006						0.167
	(0.032)	(0.003)						(0.014)
$v_j(N, \theta_i)$	0.206	0.066	-0.063				0.211	-0.038
	(0.067)	(0.037)	(0.024)				(0.174)	(0.395)
Power	0.947		0.043	0.034				
	(0.021)		(0.017)	(0.004)				
Weight	0.233					0.093		
	(0.034)					(0.004)		
Driving cost	-0.033					0.330		
	(0.004)							
Battery electric	-2.064	-0.274		0.193	-0.615			
	(0.104)	(0.084)		(0.028)	(0.128)			
Plug-in hybrid	-2.024	-0.405		0.173	-0.658			
	(0.096)	(0.086)		(0.029)	(0.145)			
Hybrid	-1.708		0.330	0.153				
	(0.021)		(0.041)	(0.016)				
Constant								5.536
								(1.987)
Observations	126,397							
Nb. of markets	864							
Obj. Function	3,397.3							

Notes: The table presents the results from an alternative demand specification with a random coefficient on the network utility. The additional random coefficient is insignificant. The other parameters are robust to including this additional random coefficient, but we lose significance on the curvature parameter, ζ. Includes brand, market segment, county, and year fixed effects. Robust standard errors in parenthesis.

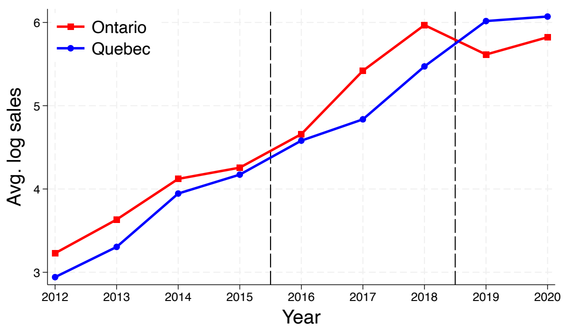
Figure A.1: Event-study, log of sales



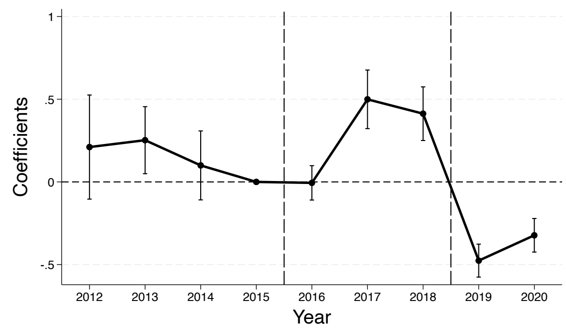
(a) All electric vehicles



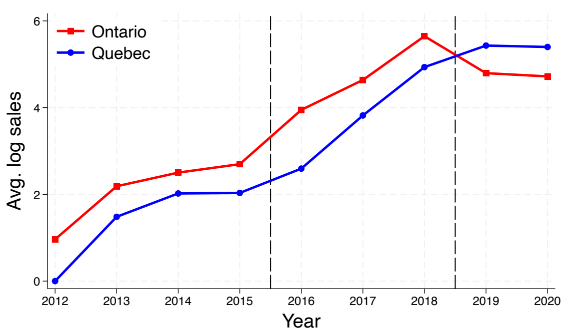
(b) Event study estimates



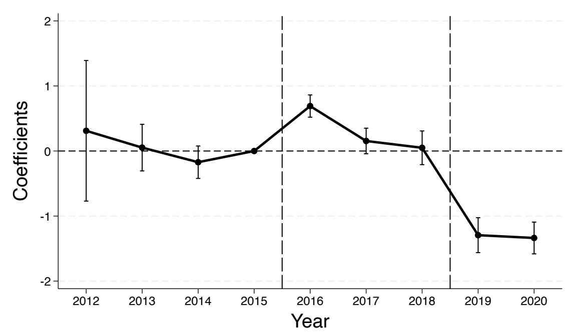
(c) Battery electric only



(d) Event study estimates



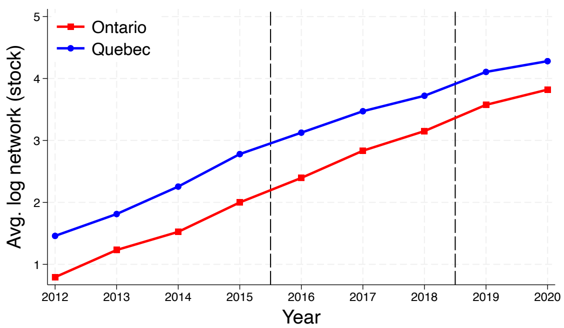
(e) Plug-in hybrid only



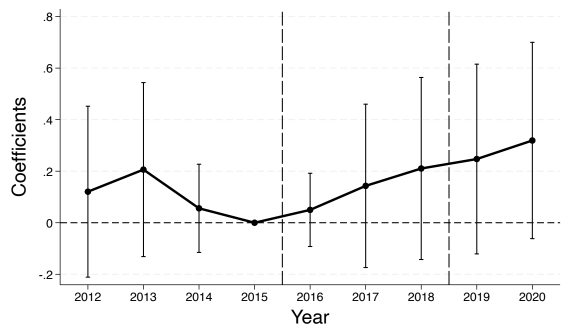
(f) Event study estimates

Notes: All regressions include county-level demographics and are weighted by population. Standard errors are clustered at the county level.

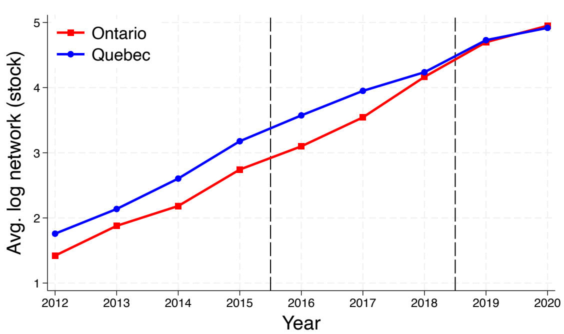
Figure A.2: Event-study, log of network size (stock)



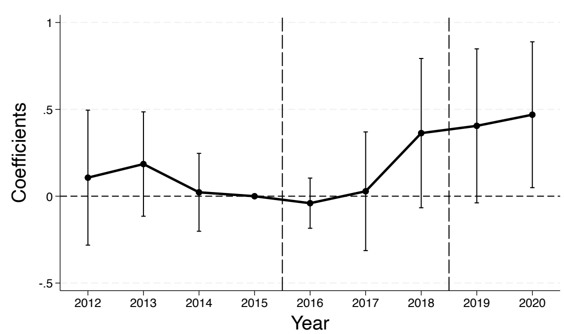
(a) Nb. of locations



(b) Event study estimates



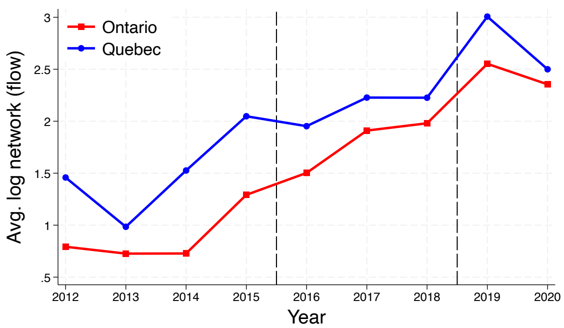
(c) Nb. of chargers



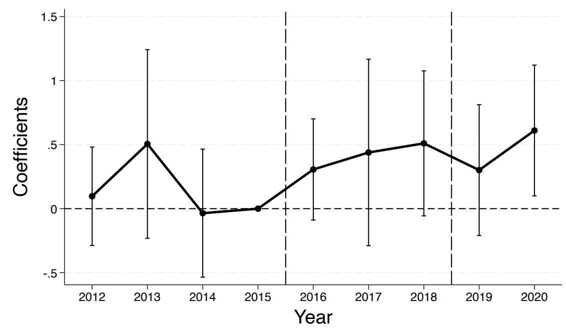
(d) Event study estimates

Notes: All regressions include county-level demographics and are weighted by population. Standard errors are clustered at the county level.

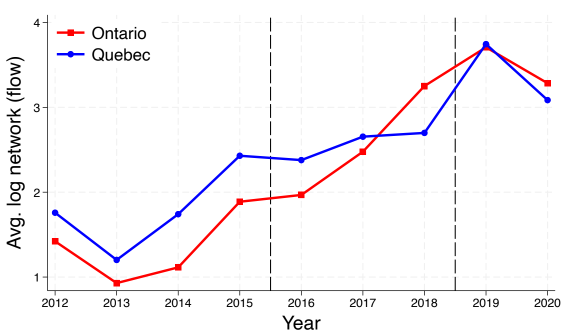
Figure A.3: Event-study, log of network size (flow)



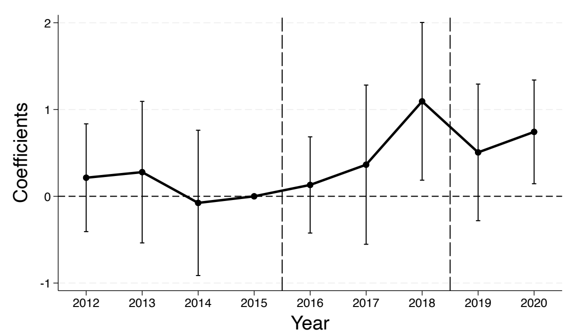
(a) New location openings



(b) Event study estimates



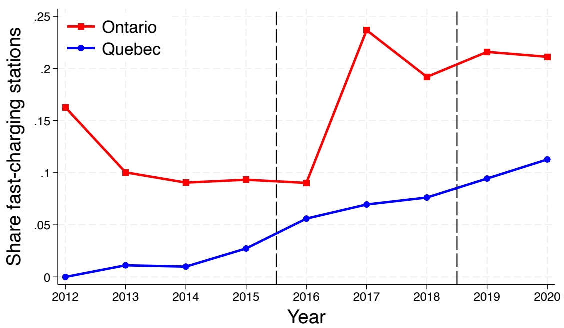
(c) New charger installations



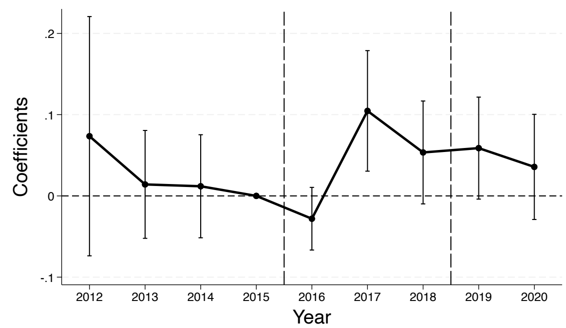
(d) Event study estimates

Notes: All regressions include county-level demographics and are weighted by population. Standard errors are clustered at the county level.

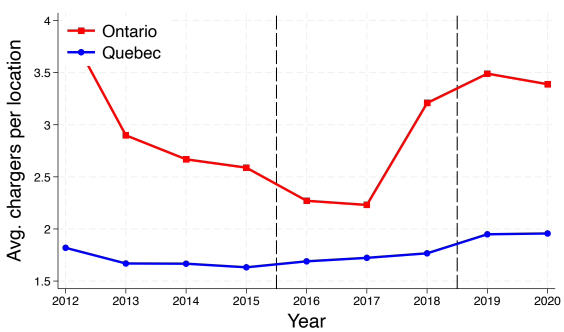
Figure A.4: Event-study, network characteristics (stock)



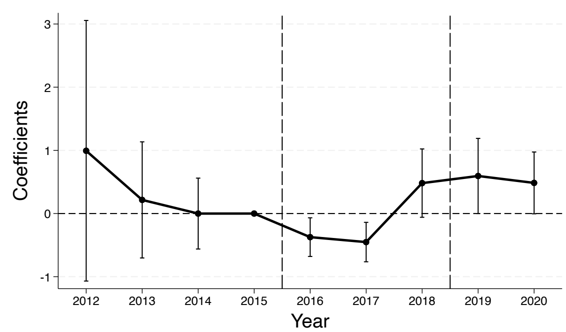
(a) Ratio fast-charging stations (stock)



(b) Event study estimates



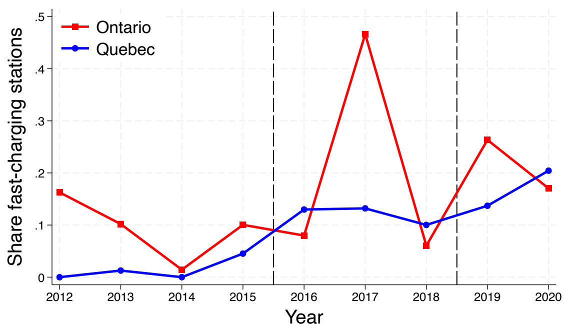
(c) Avg. chargers per location (stock)



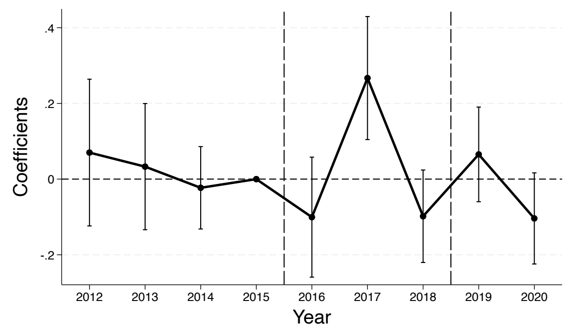
(d) Event study estimates

Notes: All regressions include county-level demographics and are weighted by population. Standard errors are clustered at the county level.

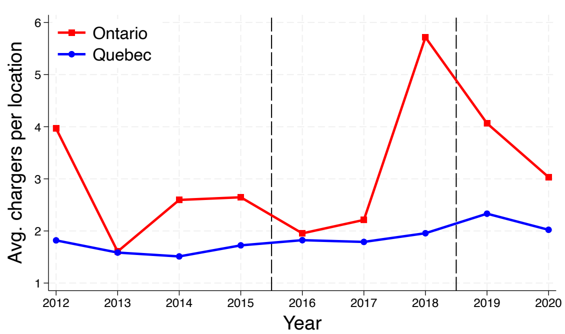
Figure A.5: Event-study, network characteristics (flow)



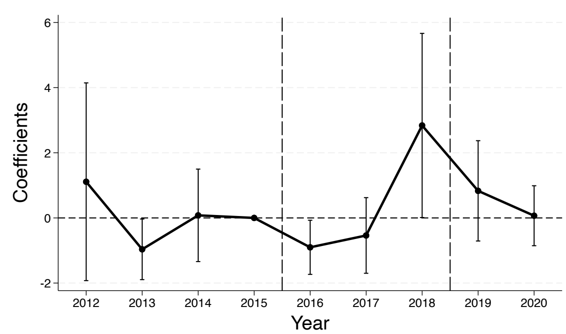
(a) Ratio fast-charging stations (flow)



(b) Event study estimates



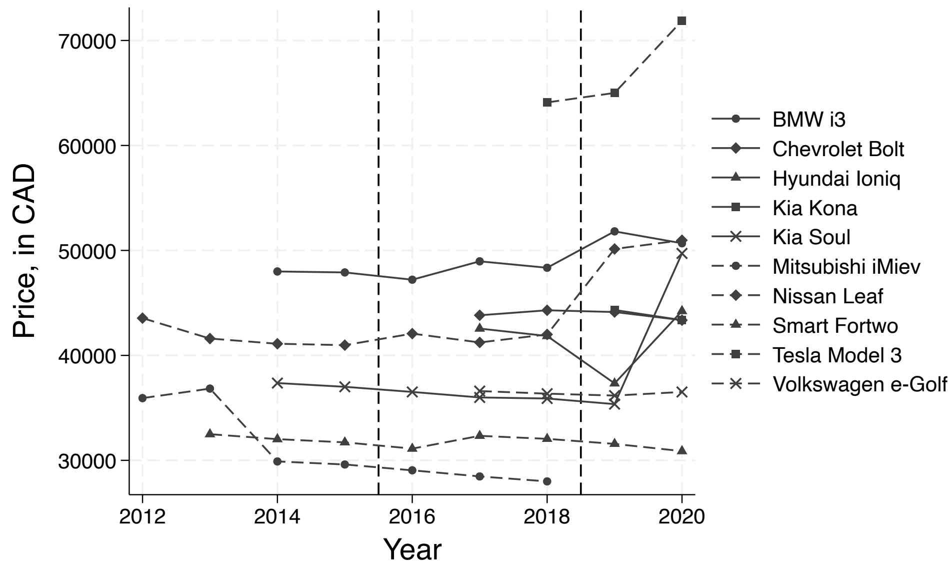
(c) Avg. chargers per location (flow)



(d) Event study estimates

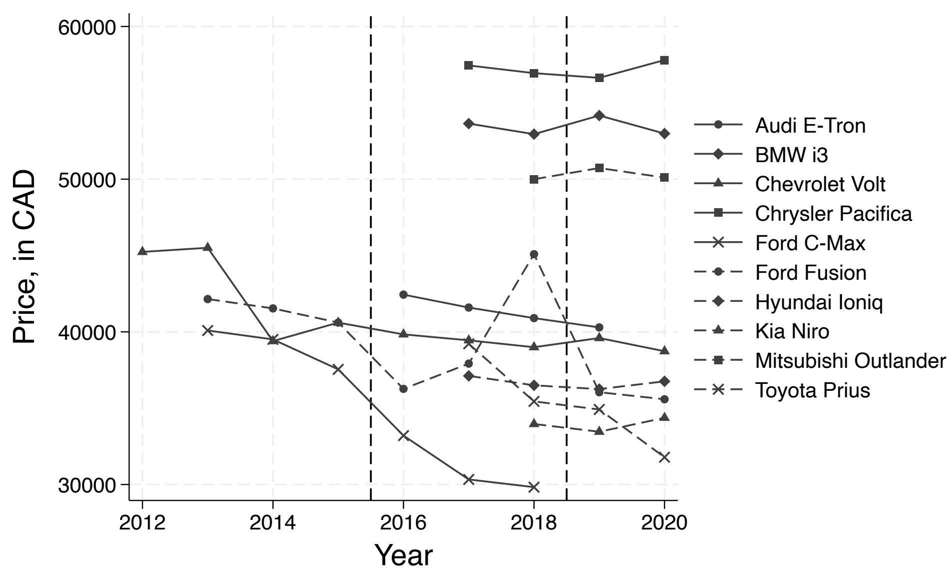
Notes: All regressions include county-level demographics and are weighted by population. Standard errors are clustered at the county level.

Figure A.6: Evolution of prices for selected battery electric vehicles



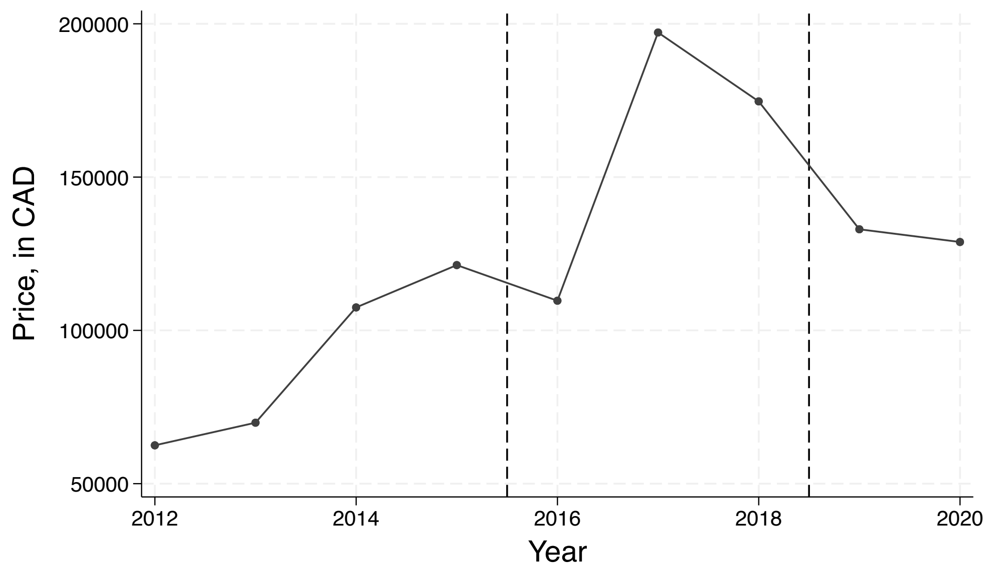
Notes: This figures depicts the evolution of prices for the top 10 selling battery electric vehicles, excluding Tesla Model S (see Figure A.8).

Figure A.7: Evolution of prices for selected battery electric vehicles



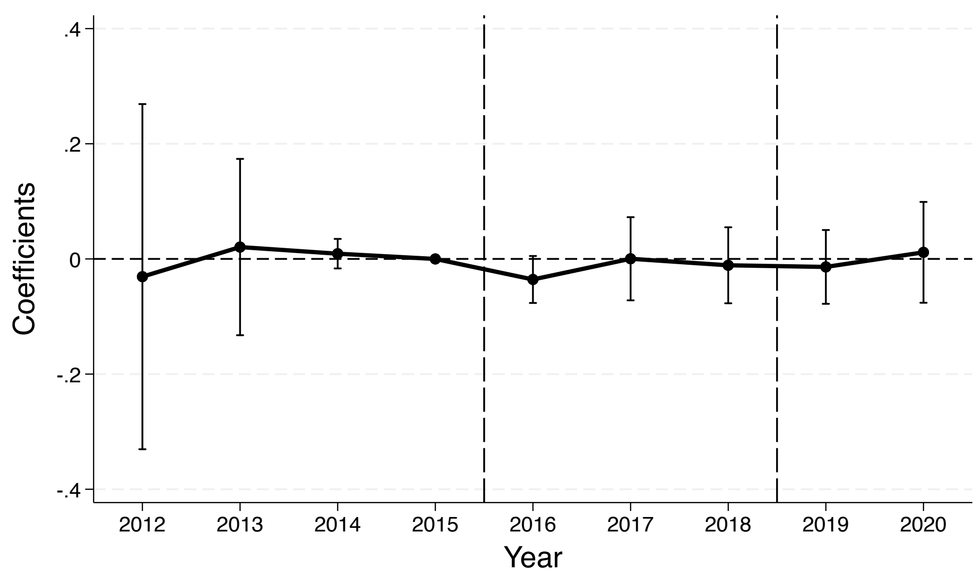
Notes: This figures depicts the evolution of prices for the top 10 selling plug-in hybrid vehicles.

Figure A.8: Evolution of prices for Tesla Model S



Notes: This figures depicts the evolution of prices for Tesla Model S.

Figure A.9: Event-study, log of price



Notes: Event-study for the effect of rebates on prices. The treatment group includes all electric vehicles eligible under Ontario's rebate program. The control group includes all other car models, including fuel and non-rechargeable hybrid vehicles. The regression is unweghted and includes product fixed effects. Standard errors are clustered at the product level.

B Details on the Data

I use data from several sources, described below. The data is aggregated at the county level, following Statistics Canada's Census Divisions. Markets are defined as county-year combinations. 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 the largest contributors to charging networks, which reinforces the idea that network provision is decided at the level of the county.

Car registration. The data on car registration comes from two main sources: the Ministry of Transportation of Ontario and the Société d'Assurance Automobile du Québec. The Ontario dataset includes quarterly car registrations aggregated at the product-county level for the years 2011-2021. The data includes the make (e.g., Ford), the model (e.g., Focus), the engine type (e.g., battery 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 (color, 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, unless the model is exclusively electric or exclusively hybrid with no other engine type variant.

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 (e.g., $t-1, t, t+1$);

3. Remove vehicles that also appear in dataset $t-1$, by comparing the make, the model, the model year, the color 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[25] which publishes on their website comprehensive information on all makes and models available in Canada. This website has been one of the go-to references for information about the different car makes since the mid-90s and has widespread public recognition in Canada. The car characteristics dataset includes the manufacturer's suggested retail price and various characteristics such as the engine type, horsepower, size, fuel consumption, and carbon emissions, all recorded at the brand-model-year-specification level (e.g., 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.[26] 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's website.[27]

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.[28] 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 1,000 sales over all counties and years (100 sales for battery electric and

[25] See https://www.guideautoweb.com/en/.

[26] 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.

[27] See https://www.autotrader.ca.

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

plug-in hybrid vehicles). I also remove exotic makes, and all vehicles with a retail price above \$150,000. Finally, I remove pickup trucks which are poor substitutes for electric vehicles and are not relevant to this study.

Other data sources. I complement these datasets with data from various other sources. 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 such as the type of station, the number of chargers, and whether a station is publicly or privately owned. I obtain detailed data on government expenditure on rebates, which include the exact rebate that was given to each model in each year. Consumer demographics are taken from the Canadian Census Survey, the Institut de la Statistique du Québec, and Election Canada. Information on gas prices and gas stations are obtained from the Régie de l'Énergie du Québec.

C Continuous treatment effect

Effect on electric vehicle registrations. I study the effect of rebates at the intensive margin using a continuous treatment effect specification. This allows me to identify the underlying market elasticity of demand for electric vehicles using a similar approach to Muehlegger and Rapson (2022). I start by constructing a continuous measure of the treatment variable, $\overline{\tau}_{mt}$, the average rebate received in county m and year t. I then estimate the following continuous treatment effect specification,

$$y_{mt} = \alpha\overline{\tau}_{mt} + X_{mt}\gamma + \mu_m + \lambda_t + \epsilon_{mt},$$

where μ_m and λ_t are fixed effects, and X_{mt} is a vector of county-level demographics as previously. The dependent variable is the log of electric vehicle registrations by county and year. The parameter of interest is α, the semi-elasticity to the rebate.

The average rebate is constructed by aggregating over individual-level rebates within a county and year. Therefore, it depends on the composition of the underlying fleet of electric vehicles and 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 preferences shift both the total quantity of electric vehicles sold and the proportion of battery electrics to plug-in hybrids.

I propose two different instrumental variables to address this issue. First, I consider

Table C.1: Effect of rebates on electric vehicle registrations

	Log of EV sales		
	(1) OLS	(2) IV	(3) IV
Avg. rebate	0.120***	0.079***	0.078***
	(0.007)	(0.003)	(0.003)
First stage:			
Ontario × Post1		4.940***	
		(0.170)	
Ontario × Post2		-6.792***	
		(0.155)	
Avg. rebate in other counties			0.981***
			(0.012)
Covariates	Y	Y	Y
County FE	Y	Y	Y
Year FE	Y	Y	Y
Observations	1,232	1,232	1,232

Notes: The dependent variable is the log of electric vehicle sales. The average rebate is computed at the county-year level, in thousand 2018 CAD. Covariates include the average household income, the average age, the average household size, the share of conservative voters, the share of graduates, and the share of homeowners by county and year. All regressions are weighted by county-level populations. Standard error in parenthesis are clustered at the county level. Significance: * < 0.10, ** < 0.05, *** < 0.01.

using the discrete version of the treatment variable as instruments. These instruments are naturally highly correlated to the average rebate. The exclusion restriction would be satisfied if the timing of the policy changes in Ontario were uncorrelated with local shocks. 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 context, this means using the average rebate in other counties within a province. 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.

The results are presented in Table C.1. I report the main coeficient of interest for a specification estimated by least squares and two specifications estimated using the instrumental

Table C.2: Effect of rebates on prices

	Net price		Log of net price	
	(1) OLS	(2) IV	(3) OLS	(4) IV
Avg. rebate	-0.952***	-0.982**	-0.026***	-0.026***
	(0.282)	(0.418)	(0.005)	(0.006)
First stage:				
Eligible × Post1		3.228***		3.228***
		(0.552)		(0.552)
Eligible × Post2		-2.827***		-2.827***
		(0.673)		(0.673)
Covariates	N	N	N	N
Product FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Observations	2,415	2,415	2,415	2,415

Notes: The dependent variables are the list price after rebates, in thousand 2018 CAD, and the log of the list price after rebates. The average rebate is computed at the product-year level, also in thousand 2018 CAD. All regressions are unweighted. Standard errors in parenthesis are clustered at the product level. Significance: * < 0.10, ** < 0.05, *** < 0.01.

variables described above. Both instrumental variable regressions give a very similar result: a \$1,000 increase in rebates is associated with a 7.9% increase in sales of electric vehicles. This is significantly lower than the specification estimated without instruments.

Effect on prices. I am also interested in the effect of rebates on prices. Since I am using national prices that do not vary across provinces, aggregating at the county level does not allow me to identify the effect of rebates on prices. I rely instead on data aggregated at the product level, including both electric vehicles (treated), fuel vehicles, and hybrid vehicles (not treated). The continuous measure of the treatment variable, $\overline{\tau}_{jt}$, is the average rebate offered to consumers purchasing product j in year t. I then estimate the following continuous treatment effect specification,

$$y_{jt} = \psi\overline{\tau}_{jt} + X_{jt}\gamma + \mu_j + \lambda_t + \epsilon_{jt},$$

where μ_j and λ_t are fixed effects, and X_{jt} is a vector of product characteristics and cost shifters. The dependent variable is the price of product j after rebates, and the parameter of interest is ψ, the rebate passthrough.

The results are presented in Table C.2. I consider the net price both in levels and in logs. The average rebate is constructed by aggregating over counties at the product level, hence it depends on how many sales of each product occured in each province. This could lead to endogeneity if preference shocks that change the composition of the fleet at the province level correlate with prices. To instrument for the average rebate, I use the discrete version of the treatment variable, that is, I interact a rebate eligibility indicator variable with post-treatment period dummies.

I find that the estimation leads to very similar results with or without instrumental variables, indicating that endogeneity is not a serious issue in this case. Column (1) and (2) of Table C.2 report the estimated effect of rebates on the net price in levels. I find that increasing subsidies by one dollar changed the net price by \$0.95–0.98 and I cannot reject the hypothesis of perfect passthrough (although the coefficients are not very precisely estimated and have a large standard error). This provides some additional evidence that firms did not respond to changes in the Ontario rebate program by increasing the prices of electric vehicles nationwide. Column (3) and (4) report the impact of rebates on the net price in logs. These coefficients are hard to interpret on their own, however, they are useful to recover the elasticity to price for electric vehicle.

Market elasticity and passthrough. Combining both sets of results allows me to recover the market elasticity of demand for electric vehicles. Denote by ε the market elasticity to price of electric vehicles. We have that

$$\varepsilon = \frac{d\ln(q)}{d\ln(p-\tau)} = \frac{d\ln(q)}{d\tau} \cdot \frac{d\tau}{d\ln(p-\tau)} = \frac{\alpha}{\psi},$$

where α is the semi-elasticity to the rebate, estimated in Table C.1, column (2), and ψ is the rebate passthrough to the the log of price, estimated in Table C.2, column (4).

The resulting elasticity and the associated passthrough are reported in Table C.3. I recover a market elasticity for electric vehicles of -2.995 which is comparable to the estimated elasticity in Muehlegger and Rapson (2022). They estimate a market elasticity of -2.1 and incomplete an passthrough of the rebates to consumers. The difference between the two estimates arises partly from the fact that I am using list prices, whereas they have access to transaction prices which are typically lower after bargaining.

Table C.3: Implied elasticity of demand and passthrough of rebates

	(1) Implied elasticity	(2) Implied Passthrough
Estimate	-2.995	0.982
Std. error	(0.636)	(0.418)

Notes: Standard errors are computed using the Delta method. Significance: * $<$ 0.10, ** $<$ 0.05, *** $<$ 0.01.

My results are also close to other works that estimate demand using a structural estimation. Xing et al. (2021), Remmy (2025), and Li (2023) find an average own-price elasticity 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. All of these studies use list prices to perform their respective analysis.

D Proofs

I prove formally the statements in equations (6) and (10) using Lemma 1 an 2 below. In what follows, I omit the subscript m and the superscript ev to avoid cluttering the notation, such that $q_t(\cdot)$ and $Q_t(\cdot)$ represent the flow and the stock of electric vehicles in period t, for a given county.

Assumptions. I impose the following three assumptions on the local planner's expectations, which are sufficient conditions for Lemma 1:

A1. $0 \leq \mathbb{E}_t F_{t+k} - \rho \mathbb{E}_t F_{t+k+1} \leq K(\rho), \quad \forall k \geq 1;$

A2. $\mathbb{E}_t q_{t+k}(n) = (1+g_t)^k q_t(n), \quad \forall n \in \mathbb{N}, \quad \forall k \geq 1;$

A3. $q_t(n) > q_t(n-1), \quad \forall n \in \mathbb{N}.$

Assumption **A1** imposes some restrictions on the local planner's expectations about the evolution of the installation costs. The fixed cost of installation could go up if the technology improves over time (i.e., faster, more powerful chargers become available), or decrease with economies of scale or increased competition. For reasonable values of ρ, assumption **A1** imposes bounds on the evolution of the expected fixed costs of installation. They can increase over time, at a rate no larger than $(1-\rho)/\rho$, or decrease at a rate defined by the constant

$K(\rho)$ which I define below. Assumption **A2** states that the local planner's expectation about future sales is the same as current sales multiplied by some exogenous growth rate g_t. In some sense, the local planner is uncertain about future advances in electric vehicle technology, the expansion of the choice set, and consumers evolving preferences. In this context, his best guess about future sales is based on the current market conditions. Assumption **A3** holds trivially by strict monotonicity of consumer preferences, as long as $\theta_i > 0, \forall i$.

LEMMA 1. *Let* ***A1*** *–* ***A3*** *hold, and* $\rho \in [0, 1)$*. Then*

$$\max_{k \geq 1} \left\{ \rho^k \mathbb{E}_t V_{t+k}(n, \mathcal{I}_{t+k}) \right\} = \rho \mathbb{E}_t V_{t+1}(n, \mathcal{I}_{t+1}).$$

Proof. First, notice that Lemma 1 holds trivially for $\rho = 0$. For $\rho \in (0, 1)$, it is sufficient to show that

$$\rho \mathbb{E}_t V_{t+1}(n, \mathcal{I}_{t+1}) - \rho^k \mathbb{E}_t V_{t+k}(n, \mathcal{I}_{t+k}) \geq 0, \quad \forall k > 1,$$

or

$$\rho \mathbb{E}_t \overline{V}_{t+1}(n, \mathcal{I}_{t+1}) - \rho^k \mathbb{E}_t \overline{V}_{t+k}(n, \mathcal{I}_{t+k}) \geq \rho \mathbb{E}_t F_{t+1} - \rho^k \mathbb{E}_t F_{t+k}, \quad \forall k > 1. \tag{13}$$

By Assumption **A1**, we can rewrite the right-hand side of (13) as

$$\rho \mathbb{E}_t F_{t+1} - \rho^k \mathbb{E}_t F_{t+k} = \sum_{s=1}^{k-1} \rho^s \left(\mathbb{E}_t F_{t+s} - \rho \mathbb{E}_t F_{t+s+1} \right) \leq a_k K(\rho),$$

where the constant a_k is equal to $\frac{\rho - \rho^k}{1-\rho}$. I now prove the Lemma by finding a value $K(\rho)$ such that

$$\rho \mathbb{E}_t \overline{V}_{t+1}(n, \mathcal{I}_{t+1}) - \rho^k \mathbb{E}_t \overline{V}_{t+k}(n, \mathcal{I}_{t+k}) \geq a_k K(\rho) \geq 0, \quad \forall k > 1. \tag{14}$$

The first term in the left-hand side of equation (14) can be rewritten as

$$\rho \mathbb{E}_t \overline{V}_{t+1}(n, \mathcal{I}_{t+1}) = \sum_{s=t+1}^{t+k-1} \rho^{s-t} \mathbb{E}_t Q_s(n, \mathcal{I}_{t+1}) \Delta v(n)^\gamma + \sum_{s=t+k}^{\infty} \rho^{s-t} \mathbb{E}_t Q_s(n, \mathcal{I}_{t+1}) \Delta v(n)^\gamma,$$

where I have made explicit the dependence of the stock of electric vehicles on the installation date of station n. The second term in the left-hand size of equation (14) can be rewritten as

$$\rho^k \mathbb{E}_t \overline{V}_{t+k}(n, \mathcal{I}_{t+k}) = \sum_{s=t+k}^{\infty} \rho^{s-t} \mathbb{E}_t Q_s(n, \mathcal{I}_{t+k}) \Delta v(n)^{\gamma}.$$

The installed base of electric vehicle in both equations accumulate differently between period $t+1$ and $t+k-1$, since station n is installed in period $t+1$ in the first case and in $t+k$ in the second case. That is, we have that

$$\begin{aligned}\mathbb{E}_t Q_s(n, \mathcal{I}_{t+1}) &= (1-d)^{s-t} Q_t(n-1) + \sum_{\tau=t+1}^{t+k-1} (1-d)^{s-\tau} \mathbb{E}_t q_\tau(n) + \sum_{\tau=t+k}^{s} (1-d)^{s-\tau} \mathbb{E}_t q_\tau(n) \\ &= (1-d)^{s-t} Q_t(n-1) + \sum_{\tau=t+1}^{t+k-1} (1-d)^{s-\tau} (1+g_t)^{\tau-t} q_t(n) + \sum_{\tau=t+k}^{s} (1-d)^{s-\tau} (1+g_t)^{\tau-t} q_t(n),\end{aligned}$$

$$\begin{aligned}\mathbb{E}_t Q_s(n, \mathcal{I}_{t+k}) &= (1-d)^{s-t} Q_t(n-1) + \sum_{\tau=t+1}^{t+k-1} (1-d)^{s-\tau} \mathbb{E}_t q_\tau(n-1) + \sum_{\tau=t+k}^{s} (1-d)^{s-\tau} \mathbb{E}_t q_\tau(n) \\ &= (1-d)^{s-t} Q_t(n-1) + \sum_{\tau=t+1}^{t+k-1} (1-d)^{s-\tau} (1+g)^{\tau-t} q_t(n-1) + \sum_{\tau=t+k}^{s} (1-d)^{s-\tau} (1+g)^{\tau-t} q_t(n).\end{aligned}$$

where the second equality in each equation holds by Assumption **A2**. Combining these results, equation (14) can be rewritten as

$$\rho \mathbb{E}_t \overline{V}_{t+1}(n, \mathcal{I}_{t+1}) - \rho^k \mathbb{E}_t \overline{V}_{t+k}(n, \mathcal{I}_{t+k}) = \sum_{s=t+1}^{t+k-1} \rho^{s-t} \mathbb{E}_t Q_s(n, \mathcal{I}_{t+1}) \Delta v(n)^{\gamma} \tag{15}$$

$$+ \sum_{s=t+k}^{\infty} \rho^{s-t} \big(\mathbb{E}_t Q_s(n, \mathcal{I}_{t+1}) - \mathbb{E}_t Q_s(n, \mathcal{I}_{t+k}) \big) \Delta v(n)^{\gamma}. \tag{16}$$

Notice that the term in the right-hand side of (15) is greater or equal to zero since both $\mathbb{E}_t Q_s(\mathcal{I}_{t+1}) \geq 0$ and $\Delta v(n)^{\gamma} \geq 0$ by construction. The terms inside the sum in equation (16) can be rewritten as

$$\begin{aligned}\mathbb{E}_t Q_s(n, \mathcal{I}_{t+1}) - \mathbb{E}_t Q_s(n, \mathcal{I}_{t+k}) &= \sum_{\tau=t+1}^{t+k-1} (1-d)^{s-\tau} (1+g_t)^{\tau-t} \big(q_t(n) - q_t(n-1) \big) \\ &> 0,\end{aligned}$$

since $q_t(n) > q_t(n-1)$ by Assumption **A3**. Combining these results, we have that

$$\rho \mathbb{E}_t \overline{V}_{t+1}(n, \mathcal{I}_{t+1}) - \rho^k \mathbb{E}_t \overline{V}_{t+k}(n, \mathcal{I}_{t+k}) > 0, \quad \forall k > \ 1,$$

and we can choose $K(\rho)$ such that

$$K(\rho) = \min_{k>1} \left\{ \frac{\rho \mathbb{E}_t \overline{V}_{t+1}(n, \mathcal{I}_{t+1}) - \rho^k \mathbb{E}_t \overline{V}_{t+k}(n, \mathcal{I}_{t+k})}{a_k} \right\}$$

which completes the proof.[29]

$\square$

LEMMA 2. *Let $\rho \in [0,1)$ and define $\widetilde{\rho} = \rho(1-d)$. Then*

$$\rho \mathbb{E}_t \overline{V}_{t+1}(n, \mathcal{I}_t) - \rho \mathbb{E}_t \overline{V}_{t+1}(n, \mathcal{I}_{t+1}) = \frac{\widetilde{\rho}}{1-\widetilde{\rho}} \Delta v(n)^\gamma \big(q_t(n) - q_t(n-1)\big),$$

Proof. First, notice that Lemma 2 holds trivially for $\rho = 0$. For $\rho \in (0,1)$, we have that

$$\rho \mathbb{E}_t \overline{V}_{t+1}(n, \mathcal{I}_t) - \rho \mathbb{E}_t \overline{V}_{t+1}(n, \mathcal{I}_{t+1}) = \sum_{s=t+1}^{\infty} \rho^{s-t} \left(\mathbb{E}_t Q_s(n, \mathcal{I}_t) - \mathbb{E}_t Q_s(n, \mathcal{I}_{t+1}) \right) \Delta v(n)^\gamma,$$

where

$$\mathbb{E}_t Q_s(n, \mathcal{I}_t) = (1-d)^{s-t+1} Q_{t-1} + (1-d)^{s-t} q_t(n) + \sum_{\tau=t+1}^{s} (1-d)^{s-\tau} \mathbb{E}_t q_\tau(n),$$

and

$$\mathbb{E}_t Q_s(n, \mathcal{I}_{t+1}) = (1-d)^{s-t+1} Q_{t-1} + (1-d)^{s-t} q_t(n-1) + \sum_{\tau=t+1}^{s} (1-d)^{s-\tau} \mathbb{E}_t q_\tau(n).$$

Combining both equation, we have that

$$\mathbb{E}_t Q_s(n, \mathcal{I}_t) - \mathbb{E}_t Q_s(n, \mathcal{I}_{t+1}) = (1-d)^{s-t} \big(q_t(n) - q_t(n-1)\big), \quad \forall s > t.$$

Therefore,

$$\begin{aligned}
\rho \mathbb{E}_t V_{t+1}(n, \mathcal{I}_t) - \rho \mathbb{E}_t V_{t+1}(n, \mathcal{I}_{t+1}) &= \sum_{s=t+1}^{\infty} \rho^{s-t} (1-d)^{s-t} \big(q_t(n) - q_t(n-1)\big) \Delta v(n)^\gamma \\
&= \sum_{s=t+1}^{\infty} \widetilde{\rho}^{s-t} \big(q_t(n) - q_t(n-1)\big) \Delta v(n)^\gamma \\
&= \frac{\widetilde{\rho}}{1-\widetilde{\rho}} \Delta v(n)^\gamma \big(q_t(n) - q_t(n-1)\big).
\end{aligned}$$

[29]Notice than in the limit, we have $K(0) = \mathbb{E}_t \overline{V}_{t+1}(n, \mathcal{I}_{t+1}) \geq 0$.

□

E Computational Details

E.1 Details on the demand estimation

The estimation of the demand side parameters follows the best practices described in Conlon and Gortmaker (2020). I include two random coefficients to capture consumers heterogeneity. The random coefficient on prices captures differences in price sensitivity, while the random coefficients on the constant controls for the substitution between the inside good and the outside good. 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 concentrate out the linear parameters and focus the estimation on the 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[30] 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. List prices for cars are set at the Canadian level, hence assuming that manufacturers change prices in response to a local 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.

[30]See Varadhan and Roland (2008).

E.2 Details on the network supply estimation

My preferred specification for the indirect utility for charging $v(N, \theta_i)$ allows for some simplifications of the network supply problem. Recall that

$$v(N, \theta_i) = \theta_i \frac{(1+N)^\zeta - 1}{\zeta},$$

and

$$\Delta v(N) = \int \frac{\widetilde{r} v(N, \theta_i) - \widetilde{r} v(N-1, \theta_i)}{-\beta_i^{\mathbf{P}}} \, dF(\nu_i).$$

The curvature parameter does not depend on i, hence it can be taken outside of the integral. I rewrite

$$\begin{aligned} \Delta v(N) &= \frac{(1+N)^\zeta - N^\zeta}{\zeta} \cdot \widetilde{r} \cdot \int \frac{\theta_i}{-\beta_i^{\mathbf{P}}} \, dF(\nu_i), \\ &= \overline{\gamma}_{mt} f(N), \end{aligned}$$

where

$$\overline{\gamma}_{mt} = -\widetilde{r} \cdot \int \frac{\theta + \mathbf{D}_{mt} \Gamma^{\mathbf{N}} + \sigma^{\mathbf{N}} \nu_i^{\mathbf{N}}}{\beta^{\mathbf{P}} + \mathbf{D}_{mt} \Gamma^{\mathbf{P}} + \sigma^{\mathbf{P}} \nu_i^{\mathbf{P}}} \, dF(\nu_i) > 0$$

and

$$f(N) = \frac{(1+N)^\zeta - N^\zeta}{\zeta} > 0.$$

The network supply model is not estimated jointly with demand. Instead, I use the estimated parameters from the demand side to compute $\overline{\gamma}_{mt}$ prior to estimating the network supply model. Notice that the calibration of $\widetilde{r}$ does not matter as it is ultimately absorbed by fixed effects once I take the logarithm.[31] I now rewrite the estimating equation and the other structural functions in terms of the specific functional form for $\Delta v(N)$.

Conditional log-likelihood. The conditional log-likelihood becomes:

$$\begin{aligned} &\ell(\lambda \mid Q^{ev}_{m,t-1} \mathbf{D}_{mt}) \\ &\quad = \sum_m \sum_t \ln \Bigg[\Phi\bigg(\lambda^{\mathbf{N}} \ln \Big(\overline{\gamma}_{mt} f(N_{mt}) \Big) + \lambda^{\mathbf{Q}} \ln \Big(Q^{ev}_{mt}(N_{mt}) + \frac{\widetilde{\rho}}{1-\widetilde{\rho}} \Delta q^{ev}_{mt}(N_{mt}) \Big) + \mathbf{D}_{mt} \lambda^{\mathbf{D}} \bigg) \\ &\qquad\qquad - \Phi\bigg(\lambda^{\mathbf{N}} \ln \Big(\overline{\gamma}_{mt} f(N_{mt}+1) \Big) + \lambda^{\mathbf{Q}} \ln \Big(Q^{ev}_{mt}(N_{mt}+1) + \frac{\widetilde{\rho}}{1-\widetilde{\rho}} \Delta q^{ev}_{mt}(N_{mt}+1) \Big) + \mathbf{D}_{mt} \lambda^{\mathbf{D}} \bigg) \Bigg]. \end{aligned}$$

[31] In the analysis, I set $\widetilde{r} = \frac{1-0.871}{0.871}$, which is compatible with a discount factor of $\frac{1}{1+r} = 0.95$ and a scrapage rate of $d = 0.0832$.

Network supply. The supply function becomes:

$$N_{mt} = \sum_{n=1}^{S_{mt}-1} n \cdot \mathbb{1}\Big\{\lambda^{\mathbf{N}} \ln\Big(\overline{\gamma}_{mt} f(n)\Big) + \lambda^{\mathbf{Q}} \ln\Big(Q^{ev}_{mt}(n) + \frac{\widetilde{\rho}}{1-\widetilde{\rho}}\Delta q^{ev}_{mt}(n)\Big) + \mathbf{D}_{mt}\lambda^{\mathbf{D}} > \epsilon^{\mathbf{n}}_{mt}$$
$$\geq \lambda^{\mathbf{N}} \ln\Big(\overline{\gamma}_{mt} f(n+1)\Big) + \lambda^{\mathbf{Q}} \ln\Big(Q^{ev}_{mt}(n+1) + \frac{\widetilde{\rho}}{1-\widetilde{\rho}}\Delta q^{ev}_{mt}(n+1)\Big) + \mathbf{D}_{mt}\lambda^{\mathbf{D}}\Big\}$$
$$+ S_{mt} \cdot \mathbb{1}\Big\{\lambda^{\mathbf{N}} \ln\Big(\overline{\gamma}_{mt} f(S_{mt})\Big) + \lambda^{\mathbf{Q}} \ln\Big(Q^{ev}_{mt}(S_{mt}) + \frac{\widetilde{\rho}}{1-\widetilde{\rho}}\Delta q^{ev}_{mt}(S_{mt})\Big) + \mathbf{D}_{mt}\lambda^{\mathbf{D}} > \epsilon^{\mathbf{n}}_{mt}\Big\}.$$

Conditional expectation. The conditional expectation becomes:

$$\mathbb{E}_{\epsilon^{\mathbf{n}}}(N_{mt} \mid Q^{ev}_{m,t-1}, \mathbf{D}_{mt}) = \sum_{n=1}^{S_{mt}} \Phi\left(\lambda^{\mathbf{N}} \ln\Big(\overline{\gamma}_{mt} f(n)\Big) + \lambda^{\mathbf{Q}} \ln\Big(Q^{ev}_{mt}(n) + \frac{\widetilde{\rho}}{1-\widetilde{\rho}}\Delta q^{ev}_{mt}(n)\Big) + \mathbf{D}_{mt}\lambda^{\mathbf{D}}\right).$$

Marginal effect. Finally, the marginal effect becomes:

$$\frac{\partial N_{mt}}{\partial Q^{ev}_{mt}} = \sum_{n=1}^{S_{mt}} \phi\left(\lambda^{\mathbf{N}} \ln\Big(\overline{\gamma}_{mt} f(n)\Big) + \lambda^{\mathbf{Q}} \ln\Big(Q^{ev}_{mt}(n) + \frac{\widetilde{\rho}}{1-\widetilde{\rho}}\Delta q^{ev}_{mt}(n)\Big) + \mathbf{D}_{mt}\lambda^{D}\right) \cdot \frac{\lambda^{\mathbf{Q}}}{Q^{ev}_{mt}(n) + \frac{\widetilde{\rho}}{1-\widetilde{\rho}}\Delta q^{ev}_{mt}(n)}.$$

The general derivation of the marginal effect follows in the next section.

E.3 Elasticities

Elasticity of network supply and marginal effect. I first derive an expression for 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 $\frac{\partial N_{mt}}{\partial Q^{ev}_{mt}}$ is either zero or it is not differentiable. Following Blundell and Powell (2004), rewrite network supply as $N_{mt} = N(Q^{ev}_{m,t-1}, \epsilon^{\mathbf{n}}_{mt})$ to make the dependence on $Q^{ev}_{m,t-1}$ and $\epsilon^{\mathbf{n}}_{mt}$ explicit, and consider the average structural function,

$$\mathbb{E}_{\epsilon^{\mathbf{n}}}(N_{mt} \mid Q^{ev}_{m,t-1}) = \int N(Q^{ev}_{m,t-1}, \epsilon^{\mathbf{n}})\, dF(\epsilon^{\mathbf{n}}).$$

I can show that for $\epsilon^{\mathbf{n}}_{mt}$ distributed as standard normal, the average structural function can be written as

$$\mathbb{E}_{\epsilon^{\mathbf{n}}}(N_{mt} \mid Q^{ev}_{m,t-1}) = \sum_{n=1}^{S_{mt}} \Phi\left(\lambda^{\mathbf{N}} \ln\big(\Delta v(n)\big) + \lambda^{\mathbf{Q}} \ln\Big(Q^{ev}_{mt}(n) + \frac{\widetilde{\rho}}{1-\widetilde{\rho}}\Delta q^{ev}_{mt}(n)\Big)\right).$$

The partial effect can be recovered as the derivative of the average structural function, that is,

$$\frac{\partial N_{mt}}{\partial Q^{ev}_{mt}} = \sum_{n=1}^{S_{mt}} \phi\left(\lambda^{\mathbf{N}} \ln\left(\Delta v(n)\right) + \lambda^{\mathbf{Q}} \ln\left(Q^{ev}_{mt}(n) + \frac{\widetilde{\rho}}{1-\widetilde{\rho}}\Delta q^{ev}_{mt}(n)\right)\right) \cdot \frac{\lambda^{\mathbf{Q}}}{Q^{ev}_{mt}(n) + \frac{\widetilde{\rho}}{1-\widetilde{\rho}}\Delta q^{ev}_{mt}(n)}.$$

where $\Phi(\cdot)$ and $\phi(\cdot)$ represent the cummulative and probability distribution functions of the standard normal distribution.

Elasticity of demand. The elasticity to price can be computed using chain rule. We have that

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

where

$$\frac{\partial s_{jmt}(\mathbf{p}_t, N_{mt})}{\partial p_{kt}} = \frac{\partial s_{jmt}}{\partial p_{kt}} + \frac{\partial s_{jmt}}{\partial N_{mt}} \cdot \frac{\partial N_{mt}}{\partial Q^{ev}_{mt}} \cdot \frac{\partial Q^{ev}_{mt}}{\partial p_{kt}}. \tag{17}$$

It can be shown that the terms in (17) are

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

$$\frac{\partial s_{jmt}}{\partial N_{mt}} = \begin{cases} \int \theta_i (1+N_{mt})^{\zeta-1} \, s_{ijmt}\, \left(1 - \sum_{\ell \in EV} s_{i\ell mt}\right) \, dF(\nu_i) & \text{if } j \in EV \\ -\int \theta_i (1+N_{mt})^{\zeta-1} \, s_{ijmt}\, \sum_{\ell \in EV} s_{i\ell mt}\, dF(\nu_i) & \text{if } j \notin EV \end{cases},$$

$$\frac{\partial N_{mt}}{\partial Q^{ev}_{mt}} = \sum_{n=1}^{S_{mt}} \phi\left(\lambda^{\mathbf{N}} \ln\left(\Delta v(n)\right) + \lambda^{\mathbf{Q}} \ln\left(Q^{ev}_{mt}(n) + \frac{\widetilde{\rho}}{1-\widetilde{\rho}}\Delta q^{ev}_{mt}(n)\right) + \mathbf{D}_{mt}\lambda^{D}\right) \cdot \frac{\lambda^{\mathbf{Q}}}{Q^{ev}_{mt}(n) + \frac{\widetilde{\rho}}{1-\widetilde{\rho}}\Delta q^{ev}_{mt}(n)},$$

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

where L_{mt} is the market size.

Demand elasticities are useful to assess the quality of the estimation. Figure E.1 depicts the distribution of own price elasticities and Table E.1 reports the full elasticity matrix for selected battery electric and plug-in hybrid vehicles, in 2018.. The average over all vehicles is -3.27, which is comparable to other studies on the car market. Previous works find that the cross-price elasticities between electric vehicles are negative, suggesting that these products become complements once network effects are accounted for, see Springel (2021). I find the opposite: when network operators are forward-looking, all cross-price elasticities are positive, meaning that electric vehicles remain substitutes when I account for network effects. This follows from the fact that the marginal effects are very small on the network supply side, leading to weak network effects. Several cross-price elasticities become negative once we ignore the forward-looking behavior of local planners in favor of static network supply.

Figure E.1: Distribution of own-price elasticities

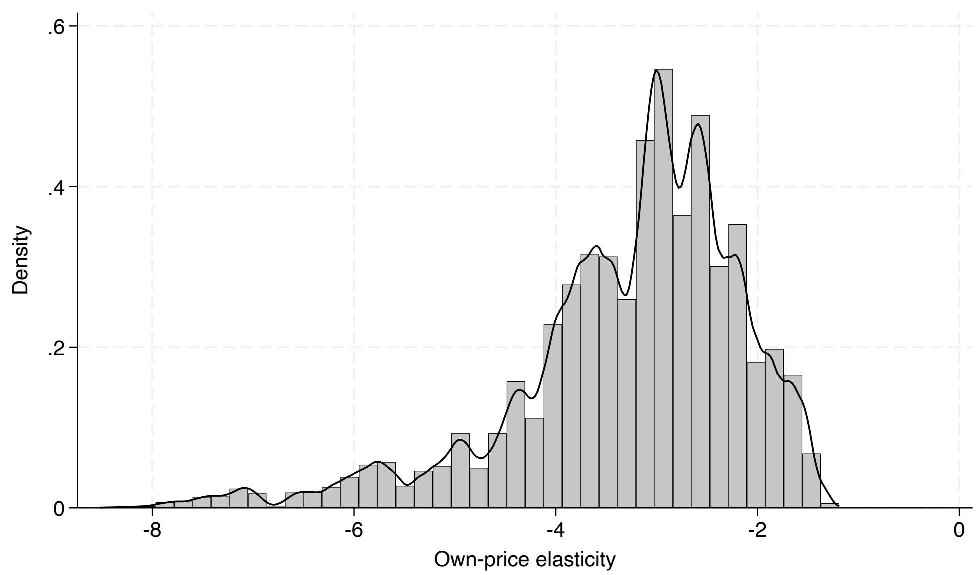


Table E.1: Average elasticities of electric vehicles, in 2018

	Bolt EV	Volt	Pacifica	C-Max	Fusion	Soul EV	Outlander	Leaf	Model 3	e-Golf
Panel A: Forward-looking network supply										
Chevrolet Bolt EV	**-2.953**	0.00189	0.00027	0.00009	0.00056	0.00030	0.00096	0.00205	0.00279	0.00046
Chevrolet Volt	0.00142	**-2.573**	0.00027	0.00011	0.00053	0.00036	0.00094	0.00220	0.00272	0.00052
Chrysler Pacifica	0.00108	0.00126	**-3.800**	0.00006	0.00052	0.00026	0.00134	0.00171	0.00345	0.00033
Ford C-Max	0.00156	0.00242	0.00035	**-2.205**	0.00074	0.00052	0.00173	0.00256	0.00328	0.00070
Ford Fusion	0.00130	0.00173	0.00027	0.00009	**-3.276**	0.00029	0.00101	0.00189	0.00295	0.00040
Kia Soul EV	0.00147	0.00230	0.00031	0.00012	0.00065	**-2.358**	0.00119	0.00251	0.00291	0.00060
Mitsubishi Outlander	0.00114	0.00146	0.00027	0.00007	0.00045	0.00022	**-3.581**	0.00169	0.00294	0.00034
Nissan Leaf	0.00145	0.00204	0.00026	0.00010	0.00053	0.00034	0.00105	**-2.803**	0.00284	0.00049
Tesla Model 3	0.00116	0.00129	0.00034	0.00006	0.00051	0.00022	0.00116	0.00152	**-4.208**	0.00026
Volkswagen e-Golf	0.00161	0.00245	0.00028	0.00012	0.00066	0.00044	0.00134	0.00252	0.00285	**-2.381**
Panel B: Static network supply										
Chevrolet Bolt EV	**-2.954**	-0.00029	-0.00004	0.00003	-0.00005	-0.00002	-0.00126	0.00002	0.00095	-0.00002
Chevrolet Volt	0.00022	**-2.575**	-0.00004	0.00004	-0.00011	0.00004	-0.00134	0.00018	0.00087	0.00004
Chrysler Pacifica	-0.00003	-0.00072	**-3.800**	0.00001	-0.00005	-0.00002	-0.00065	-0.00027	0.00158	-0.00014
Ford C-Max	0.00059	0.00080	0.00010	**-2.205**	0.00023	0.00029	0.00001	0.00086	0.00156	0.00029
Ford Fusion	0.00012	-0.00039	-0.00003	0.00002	**-3.277**	-0.00003	-0.00119	-0.00015	0.00111	-0.00008
Kia Soul EV	0.00035	0.00024	0.00005	0.00006	0.00005	**-2.358**	-0.00087	0.00043	0.00105	0.00013
Mitsubishi Outlander	-0.00006	-0.00072	-0.00004	0.00001	-0.00020	-0.00010	**-3.583**	-0.00034	0.00110	-0.00013
Nissan Leaf	0.00026	-0.00012	-0.00005	0.00004	-0.00010	0.00002	-0.00119	**-2.805**	0.00099	0.00001
Tesla Model 3	0.00001	-0.00083	0.00007	-0.00001	-0.00008	-0.00008	-0.00094	-0.00051	**-4.210**	-0.00022
Volkswagen e-Golf	0.00047	0.00041	-0.00001	0.00006	0.00008	0.00014	-0.00074	0.00047	0.00099	**-2.381**

E.4 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 $N_{mt} = N(Q^{ev}_{m,t-1}, \mathbf{D}_{mt}, \epsilon^{\mathbf{n}})$, with conditional expectation

$$\begin{aligned}\mathbb{E}_{\epsilon^{\mathbf{n}}}(N_{mt} \mid Q^{ev}_{m,t-1}, \mathbf{D}_{mt}) &= \int N(Q^{ev}_{m,t-1}, \mathbf{D}_{mt}, \epsilon^{\mathbf{n}})\, dF(\epsilon^{\mathbf{n}}), \\ &= \sum_{n=1}^{S_{mt}} \Phi\left(\lambda^{\mathbf{N}} \ln\left(\Delta v(n)\right) + \lambda^{\mathbf{Q}} \ln\left(Q^{ev}_{mt}(n) + \frac{\widetilde{\rho}}{1-\widetilde{\rho}}\Delta q^{ev}_{mt}(n)\right) + \mathbf{D}_{mt}\lambda^{\mathbf{D}}\right).\end{aligned}$$

Any structural function N_{mt} can be decomposed into its conditional expectation and a disturbance, that is,

$$N_{mt} = \mathbb{E}_{\epsilon^{\mathbf{n}}}(N_{mt} \mid Q^{ev}_{m,t-1}, \mathbf{D}_{mt}) + \epsilon_{mt}. \tag{18}$$

Notice that I can estimate $\widehat{\epsilon}_{mt}$ using parameter estimates $\widehat{\lambda}$ and the data, that is,

$$\widehat{\epsilon}_{mt} = N_{mt} - \mathbb{E}_{\epsilon^{\mathbf{n}}}(N_{mt} \mid Q^{ev}_{m,t-1}, \mathbf{D}_{mt}, \widehat{\lambda}). \tag{19}$$

With these estimates in hand, I can then compute counterfactual networks as

$$\widetilde{N}_{mt} = \mathbb{E}_{\epsilon^{\mathbf{n}}}(N_{mt} \mid \widetilde{Q}^{ev}_{m,t-1}, \mathbf{D}_{mt}, \widehat{\lambda}) + \widehat{\epsilon}_{mt}, \tag{20}$$

for any sequence of $\widetilde{Q}^{ev}_{m,t-1}$. Since the structural model takes as inputs the stock of electric vehicles and the stock of available charging stations, I need to solve counterfactuals recursively starting from $t = 1$. Let $\widetilde{Q}^{ev}_{m0} = Q^{ev}_{m0}$, $\widetilde{N}_{m0} = 0$, and consider counterfactual policy $\widetilde{\tau}$. The algorithm is as follows:

1. Start from $t = 1$;
2. For each county, the initial fleet of electric vehicles is $\widetilde{Q}^{ev}_{m,t-1}$;
3. Set initial network size $\widetilde{N}^0_{mt} = \widetilde{N}_{m,t-1}$;
4. Compute market shares $s_{jmt}(\widetilde{\tau}, \widetilde{N}^0_{mt})$;
5. Compute electric vehicle sales $\widetilde{q}^{ev}_{mt}(\widetilde{N}^0_{mt}) = L_{mt} \cdot \sum_{j \in EV} s_{jmt}(\widetilde{\tau}, \widetilde{N}^0_{mt})$;
6. Compute electric vehicle fleet $\widetilde{Q}^{ev}_{mt}(\widetilde{N}^0_{mt}) = \widetilde{Q}^{ev}_{m,t-1} + \widetilde{q}^{ev}_{mt}(\widetilde{N}^0_{mt})$;
7. Update network size $\widetilde{N}^1_{mt} = \mathbb{E}_{\epsilon^{\mathbf{n}}}(N_{mt} \mid \widetilde{Q}^{ev}_{m,t-1}, \mathbf{D}_{mt}, \widehat{\lambda}) + \widehat{\epsilon}_{mt}$;
8. Repeat steps 4-7 until convergence in $\widetilde{N}_{mt}$;
9. Update fleet variable $\widetilde{Q}^{ev}_{mt} = \widetilde{Q}^{ev}_{mt}(\widetilde{N}_{mt})$;
10. Repeat steps 2-9 recursively for $t = 2, 3, ..., T$.

F Aternative local planner objective

F.1 Setup

The main specification for the network supply model assumes that local planners install stations optimally to maximize consumers' utility of charging. In this section, I consider alternative objectives for the local planner.

First, I consider the case where the local planner installs chargers to mazimize the revenues for charging, following closely Springel (2021). Second, I consider the objective to maximize local electric vehicle adoption. While this doesn't correlate perfectly with emission reductions, this is a recurring objective stated by government to justify subsidies. Finally, I consider the objective to minimize local CO_2 emissions.

Table F.1: Alternative specifications for the local planner objective

Objective	$b(n)$	$Q(n)$	Fixed cost	Forward-looking
(1) Utility of charging	$\Delta v(n)^{\gamma}$	$Q^{ev}_{mt}(n)$	F_{mt}	Yes
(2) Revenues from charging	$\psi n^{\gamma-1}$	$Q^{ev}_{mt}(n)$	F_{mt}	Yes
(3) EV adoption	ψ	$\Delta q^{ev}_{mt}(n)$	$\kappa n^{\gamma}\overline{F}_{mt}$	No
(4) CO_2 emissions	ψ_t	$-\sum_j \Delta q_{jmt}(n)\, m_{jmt}\, e_{jt}$	$\kappa n^{\gamma}\overline{F}_{mt}$	No

In all cases, changing the objective of the local planners revolves around the specification of the benefit function and the specification of the fixed costs of installation. Recall that the contemporaneous benefits of installing station n can be written as

$$B_{mt}(n) = Q(n) \cdot b(n)$$

for some average benefit function $b(n)$ and market size function $Q(n)$. For example, by specifying $Q(n)$ to represent the emission reductions achieved from installing station n and $b(n)$ to represent the average value of these emissions, we can change the objective of the local planner to reducing carbon emissions.

For some of these alternative objective, the benefit function is not decreasing in n, which is a necessary condition to obtain an equilibrium. In this case, the benefits of adding more stations grow to surpass any constant fixed costs and local planners install additional stations without bounds, up to the saturation point. This is inconsistent with what I observe in the data. One way circumvent this issue and make the model consistent with the data is to specify the fixed costs of installation to grow with n, at a faster rate than the growth in benefits. It is not clear whether or not this assumption is reasonable in practice, however, it allows us to study these alternative objectives.

Table F.1 describe the average benefit function, the market size function, and the fixed costs associated with each local planner objective described above. I abstract from more complex problems which combines two or more objectives. I describe the solution to each of these new objectives in what follows and provide additional details in the following sections.

Note that the objectives that involve maximizing electric vehicle adoption or reducing fleet emissions are, by design, static objectives. The reason is that installing new stations doesn't generate additional benefits beyond current adopters (e.g., new stations cannot change past electric vehicle adoption). Therefore, there is no dynamic tradeoff in the installation decision: the local planner considers either current electric vehicle adoption (as opposed to the full fleet of electric vehicles) or the lifetime emissions associate to current sales, and there are no additional benefits that carry into the future.

F.2 Solution to the revenue maximizing problem

The solution to the local planner's problem under revenue maximization follows closely the methodology developed in Section 4.

The specification for revenues follows closely Springel (2021). She suggests that average revenues per station can be approximated by a nonlinear function of network size, $b(n) = \psi n^{\gamma-1}$, where $\psi > 0$ is a markup term (operators are price takers) and $0 < \gamma < 1$ captures decreasing returns from additional stations, which is consistent with the story that more profitable locations are opened first. This ensures that $b(n)$ is a decreasing function of n as the average revenues per station decreases mechanically with n (hence the $\gamma - 1$). It is worth mentioning that the linear parameter ψ, is not separately identified from fixed effects once we take the logarithm of $b(n)$.

F.3 Solution to the electric vehicle adoption problem

I derive the network supply for the electric vehicle adoption objective. In this case, the benefit function is

$$B_{mt}(n) = \psi \Delta q^{ev}_{mt}(n),$$

where $\Delta q^{ev}_{mt}(n) = q^{ev}_{mt}(n) - q^{ev}_{mt}(n-1)$ are the marginal electric vehicle sales in county m at time t, from opening station n, and ψ is a shadow price that converts these sales to dollars.

Note that this benefit function is not guaranteed to be decreasing in n. By strict monotonicity of consumers' preferences, Δq^{ev}_{mt} is guaranteed to be positive, but its derivative could be positive or negative over some range of n depending on the curvature of demand. Therefore, a model based on this specification of $B(n)$ is not guaranteed to have an interior solution (the problem described above). To solve this issue, I allow the fixed installation costs to be increasing in network size. This would occur if the local planner installs the most accessible sites first, which have low installation costs, then move on to more complex installations which are more costly.

Consider the following parametrization for fixed costs,

$$F_{mt}(n) = \kappa n^{\gamma} \widetilde{F}_{mt},$$

where $\kappa\ > 0$ and $\gamma > 0$ are parameters controling the complexity of the installation which scale up the fixed costs $\overline{F}_{mt}$. The lifetime value of installing station n is simply

$$V_{mt}(n) = -F_{mt}(n) + B_{mt}(n),$$

which does not depend on a continuation value. The model is static by construction and the local planner installs station as long as $V_{mt}(n) \geq 0$.

The optimal network size, N, has to satisfy the following two inequality conditions,

$$B_{mt}(N) \geq F_{mt}(N)$$

$$B_{mt}(N+1) < F_{mt}(N+1),$$

or

$$\frac{\psi}{\kappa} N^{-\gamma} \, \Delta q^{ev}_{mt}(N) \geq \overline{F}_{mt}$$

$$\frac{\psi}{\kappa} (N+1)^{-\gamma} \, \Delta q^{ev}_{mt}(N+1) < \overline{F}_{mt}.$$

Taking logs and reorganizing, the network supply equation is

$$\begin{aligned} N_{mt} = \sum_{n=1}^{S_{mt}-1} n \cdot \mathbb{1}\Big\{ & \lambda^{\mathbf{1}} + \lambda^{\mathbf{N}} \ln(n) + \lambda^{\mathbf{Q}} \ln\left(\Delta q^{ev}_{mt}(n)\right) \geq \epsilon^{\mathbf{n}}_{mt} \\ & > \lambda^{\mathbf{1}} + \lambda^{\mathbf{N}} \ln(n+1) + \lambda^{\mathbf{Q}} \ln\left(\Delta q^{ev}_{jmt}(n+1)\right) \Big\} \\ & + S_{mt} \cdot \mathbb{1}\Big\{ \lambda^{\mathbf{1}} + \lambda^{\mathbf{N}} \ln(S_{mt}) + \lambda^{\mathbf{Q}} \ln\left(\Delta q^{ev}_{mt}(S_{mt})\right) \geq \epsilon^{\mathbf{n}}_{mt} \Big\} \end{aligned}$$

where $\epsilon^{\mathbf{n}}_{mt} = \frac{1}{\omega} \ln(\overline{F}_{mt})$ is distributed as standard normal, $\lambda^{\mathbf{1}} = \frac{1}{\omega} \ln\left(\frac{\psi}{\kappa}\right)$, $\lambda^{\mathbf{N}} = -\frac{\gamma}{\omega}$, and $\lambda^{\mathbf{Q}} = \frac{1}{\omega}$.

F.4 Solution to the emission reduction problem

I derive the network supply for the emission reduction objective. In this case, the benefit function is simply the current emissions of the new electric vehicle sales multiplied by the value of these emissions, namely,

$$B_{mt}(n) = -\psi_t \sum_j \Delta q_{jmt}(n) \, m_{jmt} \, e_{jt},$$

where $\Delta q_{jmt}(n)$ are the marginal sales (including fuel and hybrid vehicles) of model j in county m at time t, due to the installation of station n, m_{jmt} is the average mileage of a driver of model j in county m at time t, e_{jt} are the emissions per kilometer of model j, and ψ_t is the value of emissions in period t (e.g., a carbon price).

Note that this specification suffers from two important problems. First, $B_{mt}(n)$ is not guaranteed to be positive. For example, increasing n can lead to substitution from the outside good to a plug-in hybrid with positive carbon emissions, increasing total emissions. Second, $B_{mt}(n)$ is not guaranteed to be decreasing in n. To solve these issues, I consider the same parametrization for the fixed costs as above and I exclude markets where $B_{mt}(n)$ is negative.

The lifetime value of installing station n is

$$\begin{aligned} V_{mt}(n) &= -F_{mt}(n) + \overline{V}_{mt}(n), \\ &= -\kappa n^{\gamma} \overline{F}_{mt} - \psi_t \sum_{s=t}^{t+T_j} \rho^{s-t} \sum_j \Delta q_{jmt}(n)\, \overline{m}\, e_{jt}, \end{aligned}$$

where T_j is the vehicles expected lifetime, ρ is the discount factor, and I have assumed that $\mathbb{E}_t(m_{jms}) = \overline{m}$ for all j, m, and t.[32] Notice that there are no dynamic considerations in this problem as installing stations do not change the environmental impact of past sales, hence the model is fully static, and local planners install stations as long as $V_{mt}(n) \geq 0$.

The optimal network size, N, has to satisfy the following two inequality conditions,

$$\overline{V}_{mt}(N) \geq F_{mt}(N)$$

$$\overline{V}_{mt}(N+1) < F_{mt}(N),$$

or

$$-\frac{\psi_t}{\kappa} N^{-\gamma} \sum_{s=t}^{t+T_j} \rho^{s-t} \sum_j \Delta q_{jmt}(N)\, \overline{m}\, e_{jt} \geq \overline{F}_{mt}$$

$$-\frac{\psi_t}{\kappa} (N+1)^{-\gamma} \sum_{s=t}^{t+T_j} \rho^{s-t} \sum_j \Delta q_{jmt}(N+1)\, \overline{m}\, e_{jt} < \overline{F}_{mt}.$$

Taking logs and reorganizing, the network supply equation is

$$\begin{aligned} N_{mt} = \sum_{n=1}^{S_{mt}-1} n \cdot \mathbb{1} \Bigg\{ & \lambda_t^{\mathbf{1}} + \lambda^{\mathbf{N}} \ln(n) + \lambda^{\mathbf{Q}} \ln\Big(-\sum_j \Delta q_{jmt}(n)\, \overline{m}\, e_{jt} \Big) \geq \epsilon_{mt}^{\mathbf{n}} \\ & > \lambda_t^{\mathbf{1}} + \lambda^{\mathbf{N}} \ln(n+1) + \lambda^{\mathbf{Q}} \ln\Big(-\sum_j \Delta q_{jmt}(n+1)\, \overline{m}\, e_{jt} \Big) \Bigg\} \\ & + S_{mt} \cdot \mathbb{1} \Bigg\{ \lambda_t^{\mathbf{1}} + \lambda^{\mathbf{N}} \ln(S_{mt}) + \lambda^{\mathbf{Q}} \ln\Big(-\sum_j \Delta q_{jmt}(S_{mt})\, \overline{m}\, e_{jt} \Big) \geq \epsilon_{mt}^{\mathbf{n}} \Bigg\} \end{aligned}$$

[32] I set $\rho = 0.95$, $\overline{m} = 22{,}083$km, and $T_j = 12.02$ years, see Section 6.

where $\epsilon^{\mathbf{n}}_{mt} = \frac{1}{\omega}\ln(\overline{F}_{mt})$ is distributed as standard normal, $\lambda^{\mathbf{1}}_t = \frac{1}{\omega}\ln\left(\frac{\psi_t}{\kappa}\cdot\frac{1-\rho^{T_j+1}}{1-\rho}\right)$, $\lambda^{\mathbf{N}} = -\frac{\gamma}{\omega}$, and $\lambda^{\mathbf{Q}} = \frac{1}{\omega}$.

F.5 Estimation and counterfactuals

I estimate the specification described in Table F.1. The results are presented in Table F.2 below. There are several interesting findings. First, maximing the network utility of consumers or the revenues from charging leads to network effects of similar magnitudes: the elasticity of network supply to the stock of electric vehicle is slightly higher under revenue maximization, 0.114 versus 0.108.

In both cases, the local planners install more stations in counties with a higher share of graduates (which captures environmental awareness) and in urban counties with fewer homeowners (which captures the potential for home charging). One interesting difference emerge. Under utility maximization, local planners install stations more in low-income counties, targetting vulnerable populations which may benefit more from additional local stations. The reverse is true when local planners maximize revenues: they install more chargers in counties where income is high, and the potential for revenues is high.

Second, mazimizing electric vehicle adoption or minimizing carbon emissions do not lead to network effects on the supply side (i.e., the elasticity of supply is zero). This happens mechanically as the objective function does not take into account changes to the stock of electric vehicles (through $Q^{ev}_{mt}(n)$ or $q^{ev}(n)$). Instead, the model depends on marginal adopters, $\Delta q^{ev}_{mt}(n)$, with $\partial\Delta q^{ev}/\partial q^{ev} = 0$, and the equilibrium is driven entirely by the increasing fixed costs. In other words, we could have that $\Delta q^{ev}(n)$ is constant in n, and we would still obtain an equilibrium from the increasing fixed costs, and network effects did not play any role.

It is difficult to compare the parameter values of the four specifications (beyond the sign), as they arise from different models. To assess whether or not the choice of the objective drives my results, I replicate the basic counterfactual simulations under these additional local planner objectives. The results are presented in Table F.3.

I find that the revenues maximizing objective predicts 1,107 additional electric vehicle sales and 90 additional charging stations over the utility maximizing objective. These slightly larger effects arise from the fact that the model predicts network effects that are slightly larger under that specification. These additional electric vehicle sales are associated to 741 fewer internal combustion and hybrid vehicles, which decrease emissions by an additional 0.027 million metric ton over the lifetime of vehicles. Overall, the difference in environmental outcomes between the two specifications remains small since electric vehicles

Table F.2: Network supply estimation for alternative local planner objectives

	(1) Network utility	(4) Revenues from charging	(2) EV adoption	(3) CO_2 emissions
$\lambda^{\mathbf{N}}$	2.376	-1.703	-1.539	-1.539
	(0.132)	(0.099)	(0.097)	(0.097)
$\lambda^{\mathbf{Q}}$	0.372	0.391	0.227	0.234
	(0.111)	(0.103)	(0.104)	(0.100)
Avg. income	-0.578	0.274	0.222	0.217
	(0.239)	(0.225)	(0.226)	(0.227)
Avg. age	1.857	0.725	0.654	0.670
	(0.560)	(0.482)	(0.500)	(0.495)
Avg. household size	-0.018	-0.990	-0.810	-0.823
	(1.504)	(1.458)	(1.441)	(1.445)
Share graduates	8.512	6.849	7.805	7.734
	(2.480)	(2.254)	(2.315)	(2.317)
Share homeowners	-6.099	-6.397	-6.825	-6.887
	(1.995)	(1.809)	(1.879)	(1.864)
Urban	0.426	0.362	0.502	0.487
	(0.328)	(0.309)	(0.311)	(0.311)
Elasticity to EV	0.108	0.114	0	0
EV for one additional station	75.71	70.52	n/a	n/a
Observations	830	830	814	813
Log-likelihood	-2,125.2	-2,131.4	-2,136.6	-2,134.5

Notes: Includes year fixed effects. Markets without electric vehicles in circulation are excluded from specifications (1) and (2). Markets without electric vehicles in the choice set are excluded from specification (3). Markets in which increasing network size increases emissions are excluded from specification (4). In this case, the local planner foregoes the installation of additional stations, and that observation does not contribute to the likelihood. Specifications (1) and (2) are estimated using a discount factor or $\widetilde{\rho} = 0.871$ and allow the local planners to be forward-looking. By construction, specifications (3) and (4) are static and the elasticity to the stock of EV is zero. Standard errors in parenthesis are clustered at the county level and are computed using 500 bootstrap replications.

do not substitute internal combustion engines one-to-one, and the difference in adoption is not large.

The results are different for the other two specifications, which focus on electric vehicle adoption and emission reductions. As stated above, there are no network effects on the network supply side for these specifications, hence the predicted growth in networks is less than halved: 184 additional stations under the electric vehicle adoption objective and 121 additional stations under the carbon emission objective. This translates to fewer electric vehicle sales, and worse environmental performance. This means that, interestingly, focusing on consumers' utility or revenues from charging leads to more adoption and fewer emissions

Table F.3: Counterfactual simulations for alternative local planner objectives

	Observed	Counterfactuals: No Subsidies			
	(1)	(2)	(3)	(4)	(5)
	Baseline	Network utility	Revenues from charging	EV adoption	CO_2 emissions
Key outcomes					
Δ Total sales	3,248,085	-14,219	-14,586	-13,551	-13,383
Δ Sales (fuel)	3,119,123	+27,430	+28,156	+26,114	+25,814
Δ Sales (electric)	84,174	-42,188	-43,295	-40,175	-39,702
Δ Sales (hybrid)	44,788	+539	+554	+511	+504
Δ Charging stations	2,811	-373	-463	-184	-121
Δ CO_2 emissions	141.46	+1.083	+1.110	+1.033	+1.021
Δ Consumer surplus	0	-576.4	-592.3	-547.4	-540.5
Δ Total cost	721.5	0	0	0	0
Implied abatement costs					
Avg. cost per ton CO_2	–	-666	-650	-699	-707
Avg. cost per electric vehicle	–	-17,102	-16,665	-17,959	-18,174

than focussing on adoption or emissions directly. This is a direct consequence of the positive network effects on the supply side that give rise to a positive feedback loop that increases adoption and station deployment.

I could not find evidence that the local planners in Quebec had emission targets or electric vehicle adoption targets. They are for the most part local county governments that invest in charging infrastructures to benefit their local population, in the same way as they develop public transports or other crucial infrastructures. This seems aligned with the network utility maximization objective.

I cannot rule out completely that some of these planners intend to raise public funds using stations, to cover for example the cost of installing future networks. Therefore, the true objective could include a mix of the network utility and revenues maximizing objectives. In this case, we should expect slightly larger network effects than I estimate, slightly more adoption, slightly lower emissions overall, and slightly lower abatement costs. However, since the two specifications yield very similar results, I am not concerned that the chosen specification produces misleading results.

G Cost-benefit analysis with future environmental gains

In this section, I describe how I incorporate future environmental gains to the cost-benefit analysis framework described in Section 6.

Setup. I consider the following policy implementation:

1. The policymaker offers subsidy τ, starting in period 1.
2. Electric vehicle adoption and investments in charging infrastructure occur in periods $t = 1, ..., T_1$, leading to $Q^{ev}_{T_1}(\tau)$ electric vehicles and $N_{T_1}(\tau)$ stations in period T_1.
3. Subsidies are phased out in period $T_1 + 1$.
4. Electric vehicle adoption and investment in charging infrastructures occur for an additional T_2 periods, leading to $Q^{ev}_{T_1+T_2}(N_{T_1}(\tau))$ electric vehicles and $N_{T_1+T_2}(Q^{ev}_{T_1}(\tau))$ stations.

To study the long term benefits of the policy, I then compare the environmental outcomes in period $T_1 + T_2$ between the policy implementation described above and a counterfactual where electric vehicles are never subsidized.

Forecasting demand. Solving for the counterfactual described above is only possible at the cost of additional assumptions, hence the results must be carefully interpreted with these caveats in mind. One difficulty arises from the fact that we need to forecast the demand for electric vehicles, yet we do not observe key features of the market in periods T_1+1 to T_1+T_2. For example, I do not observe the evolution of the choice set (e.g., new electric vehicles being introduced) or the evolution of the characteristics of existing models. As shown previously, new electric vehicles are being introduced every year and battery capacity is improving over time.

To forecast the demand for electric vehicles, I repeat the choice set that is available to consumers in 2020 to cover the period between 2021 and 2030. As shown in Section 6.4, electric vehicle adoption is essentially the same between 2021 and 2030 whether or not electric vehicles were initially subsidized (see panel (a) of Figure 4) and most of the environmental gains accrue from the period when subsidies were offered. In this context, I expect that the marginal abatement cost estimated from repeating the 2020 choice set is not far from the estimate I would get if I knew how the true evolution of the choice set and the characteristics of vehicles between 2021 and 2030.

Network supply. I forecast network supply in the same way, by repeating the county-level demographics from 2020 to cover the period between 2021 and 2030. There is very little variation over time in these average demographics at the county level.

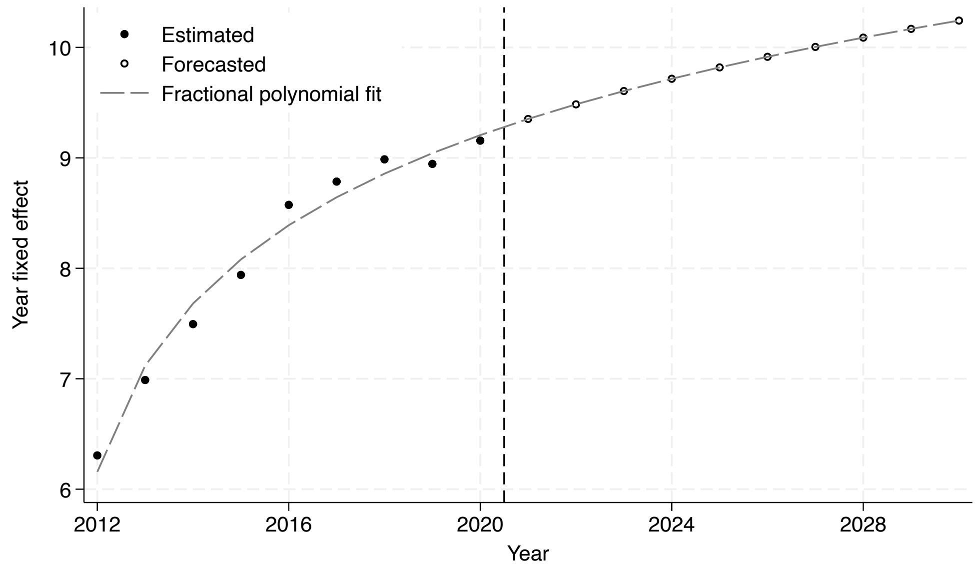
The network supply model includes time fixed effects. I observe a clear increasing pattern, partly driving the increase in network size. To avoid underestimating the growth in local network, I forecast these fixed effects in period 2021 to 2030 using a fractional polynomial fit on the estimated fixed effects from 2012 to 2020. The results of the regression are presented in Table F.4 and the forecasted values are presented in Figure F.1. The regression includes only 9 data points, so I use a polynomial of order 1 to estimate the model and produce the forecasted values.

Table F.4: Fractional polynomial regression for year fixed effects

	(1) Year fixed effect
Log of time trend	1.388***
	(0.073)
Constant	6.485***
	(0.127)
Observations	9
R-squared	0.978

Notes: This table presents the result from a fractional polynomial regression of the year fixed effects from the network supply model on a time trend. I restrict the polynomial to be of order 1. The functional form resulting from the estimation is the log of the time trend (i.e., power p = 0). Robust standard error in parenthesis. Significance: * < 0.10, ** < 0.05, *** < 0.01.

Figure F.1: Estimated and forecasted year fixed effects



Notes: This figure presents the forecasted values for the time fixed effects from the network supply model, using the results from the fractional polynomial fit in Table F.4.