Do Public Investments Crowd In or Out Private Investment? Insights from the EV Fast-Charging Network*

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Private Usage Data.
Please Do Not Circulate Publicly Without the Author's Authorization

Abstract

Public investment is known to crowd out private investments. However, this outcome may not hold in the presence of network externalities. I investigate this within the Electric Vehicle (EV) market, where adoption depends not only on the EV's technology but also on the availability of a fast-charging network. My focus is on Quebec, which stands out among its North American peers for tasking its state-owned utility with deploying a fast-charging network. By leveraging the network's concentric expansion, I implement a staggered difference-in-differences approach and find a statistically significant two-fold increase in EV adoption for newly connected cities. Given the durable nature of EVs, I extend the analysis using a dynamic treatment effect framework, revealing a monotonic increase in treatment effects over time, with no evidence of pre-treatment trends. I then develop a structural model to analyze the impact of charging station availability on EV adoption. The model employs a two-stage demand: in the first stage, consumers select EV models, and in the second, they derive utility from charging. The second stage captures a rich network topography by modeling utility derived from charging at desired stations (the intensive margin), but only from stations that are connected to the city (the extensive margin). I estimate the second stage by using high-quality private charging data at the consumer ID level. I then conduct various counterfactual analyses to provide policymakers with insights into the most cost-effective strategies for reducing GHG emissions. Preliminary results indicate that the "big push" policy has created a positive feedback loop in the two-sided EV market, particularly benefiting the public sector.

Keywords: Transportation, EV Adoption, Fast-Charging Network, GHG, Climate Justice, North America.

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1 Introduction

The urgency to address the climate crisis has spurred investments in novel technologies. However, as these technologies enter the market, they struggle to gain traction, facing powerful incumbents who benefit from decades of investment, leading to a lock-in of the carbon-intensive industry. The electric vehicle (EV) market is the perfect example as consumers value not solely the vehicles they purchase, but also the charging infrastructure, which need not be provided by the car manufacturer. The problem arises as these fast-charging stations are costly, offering minimal incentive to fast-charging firms to invest early on. Conversely, if the fast-charging network is sparse, consumers hesitate to purchase EVs that they cannot reliably charge. Tesla addressed this issue by making their incompatible network a feature of their vehicles. However, this approach leads to socially inefficient outcomes as it hampers EV adoption Li et al. (2019).

Instead, Quebec took a "big push" approach, tasking its state-owned utility with deploying the fast-charging network. This initiative led to the birth of the Electric Circuit, a *state-owned compatible* fast-charging network.

As soon as 2015, the public networks start connecting the main cities of Quebec through stations along the highways. The public agency has consistently expanded the network outward, connecting previously unconnected cities and increasing density in areas with higher road usage. On the other hand, the private sector responded seriously only in the early 2020s.

My first and main research question is: How do consumers respond to the availability of the charging network? To address this, I utilize transaction-level data from the public fast-charging network, which includes 100 million charges[1] at the consumer ID level. For each consumer, I have information on ZIP code, car models, and all charges made through the application between 2017 and 2024[2]. This dataset captures the *majority* of charges conducted in Quebec during this period[3], enabling me to identify key behaviors regarding charging station usage and understand how consumers interact with the network. This allows me to estimate the value of additional chargers and assess their impact on EV adoption across specific car models.

For policy-relevant insights, I cluster EV models into three groups: Tesla models, non-Tesla short-range models, and non-Tesla long-range models. This approach enables an evaluation of how the charging network affects these distinct vehicle groups. A critical assumption is that achieving widespread EV adoption, such as Canada's target of 100% EV sales by 2035, will depend on the success of cheaper, less mineral-intensive models[4].

The second part of this research project addresses: How has the public network influenced private investment and EV adoption? To explore this, I run a counterfactual model without public sector involvement, where only private firms provide the fast-charging network. This approach identifies (i) the contribution of the public network to EV adoption and (ii) the cost-per-ton of CO reduction achieved through public investment.

I further analyze the impact of a subsidy-based program on network deployment and EV adoption by re-running the model with USA-like subsidies to private firms. This comparison assesses whether the USA's approach is as efficient as Quebec's model, which emphasizes direct public involvement. Specifically, I investigate whether subsidies yield equivalent outcomes or if a publicly

[1] Including Level 2 (slow) and Level 3 (fast) charges

[2] This includes specific details such as charging power, coordinates, battery percentage at arrival and departure, duration of stay, and price paid.

[3] Tesla users remain prominent users of the network.

[4] This is especially relevant for the resale market, which will benefit lower-income households.

managed network offers superior results.

This paper makes several contributions to the literature. First, it adds to the growing body of research on electric vehicle markets. Notable contributions in this area include (Pavan, 2017; Li et al., 2019; Springel, 2021), who examine network effects in both alternative fuel and electric vehicle markets. Li et al. (2019) examines the impact of unifying competing standards for charging electric vehicles, focusing on cases where car manufacturers provide both the vehicles and the charging infrastructure.

I contribute by focusing on cases where charging stations are publicly provided by regional governments, ensuring that compatibility is not an issue. This distinguishes my work from studies that address the challenges of competing standards in privately provided networks.

Furthermore, I differentiate my approach from Fournel (2024) by utilizing transaction-level data to inform my model, enabling a simple yet comprehensive representation of the network's topography. A key feature of my model builds on Li and Springel (2024) by incorporating the extensive margins of the network. Specifically, more chargers availability provides utility, particularly in key locations, but only if the network is connected to these regions – which often requires unprofitable charging stations to bridge the gap.

Specifically, I employ a two-stage game: in the first stage, consumers select EV models; in the second stage, they derive utility from charging. This framework enables me to investigate how consumers make decisions regarding EV adoption based on individual preferences and city-specific characteristics. Crucially, the detailed micro-level usage data I possess allows me to capture charging preferences for each city.

Lastly, I contribute to the literature on estimating network effects and their influence on the adoption of novel technologies. This area of research spans various products, namely green cars (Pavan, 2017; Li et al., 2019; Springel, 2021). I extend this literature by examining cases where the complementary product, in this instance charging stations, is provided as a public good by forward-looking local planners.

My paper is divided as follows: Section 2 discusses institutional knowledge, such as the main policies impacting EV adoption. Section 3 briefly describes the datasets. Section 4 delves deeper into the network deployment by the public sector, followed by the private sector, along with key insights from the usage data that will feed into the modeling. Section 5 exploits the network's concentric expansion to offer a dynamic treatment effect. It also provides key insights into the network's profitability. Section 6 describes the models along with the identification strategy, and Section 7 concludes.

2 Institutional Knowledge

Global EV Policies and Adoption: An Overview

To highlight the uniqueness of the Quebec case, here lays an overview of other leading regions in EV adoption.

Norway

Norway is leading the EV race, with 90% of new cars sold being electric vehicles as of 2024. This high adoption rate is not by chance but is driven by two key policies. The first is the exemption from the 25% VAT (Value Added Tax), effectively providing a 25% subsidy on EVs, making them substantially cheaper than their ICE counterparts. The second is the allowance of free tolls for EVs on Norway's numerous roads and bridges, resulting in additional savings of up to USD 2,000 per year. With such broad fiscal incentives, it is no surprise that EV adoption has surged. By 2016, EV adoption had already reached 15-20%. Despite early government intervention through pilot projects, the fast-charging network expansion was largely driven by the private sector responding to surging demand, supported by government subsidies[5][6].

China

China has a 30-40% market share as of 2024, but more importantly, it is the largest EV market in the world. Policies such as direct subsidies and tax exemptions on EV purchases have been crucial in driving this adoption. Additionally, key stringent ones, such as license plate restrictions that limit which days one can drive, have further boosted EV adoption, as EVs are exempt from these restrictions. Another important contributing policy is the NEV Quota system, which regulations to ensure that automakers offer a certain percentage of their sales as NEVs. Similar to Norway, the government played a role in the early days of network deployment, but it was quickly taken over by the private sector.

Sweden

Sweden is making significant strides in EV adoption, with approximately 30% of new car sales being electric vehicles as of 2024. This growth is fueled by several key policies. The first is the Bonus-Malus system, which penalizes high-emission vehicles while providing bonuses for low-emission ones, offering significant financial incentives to EV buyers and narrowing the price gap between EVs and their ICE counterparts. The second key policy is the tax benefits offered for EVs used as company cars, which has been a strong driver of adoption in Sweden.

Germany

Germany is becoming a key player in the EV market, with EVs representing about 20-25% of new vehicle sales as of 2024. This growth has been driven by several important policies. The first is the substantial purchase subsidies offered by the government, which have significantly reduced the upfront cost of EVs, making them more affordable for consumers. The second major policy is the EU's stringent CO2 emissions regulations, which push automakers to increase their EV offerings to avoid hefty fines, thus incentivizing the production and sale of electric vehicles. Additionally, Germany has prioritized the expansion of its charging infrastructure, supported by both public and private investments, ensuring that charging availability is no longer a barrier to EV adoption.

[5]The Govt. also ensures compatibility by having multiple connectors such as CHAdeMO and CCS.

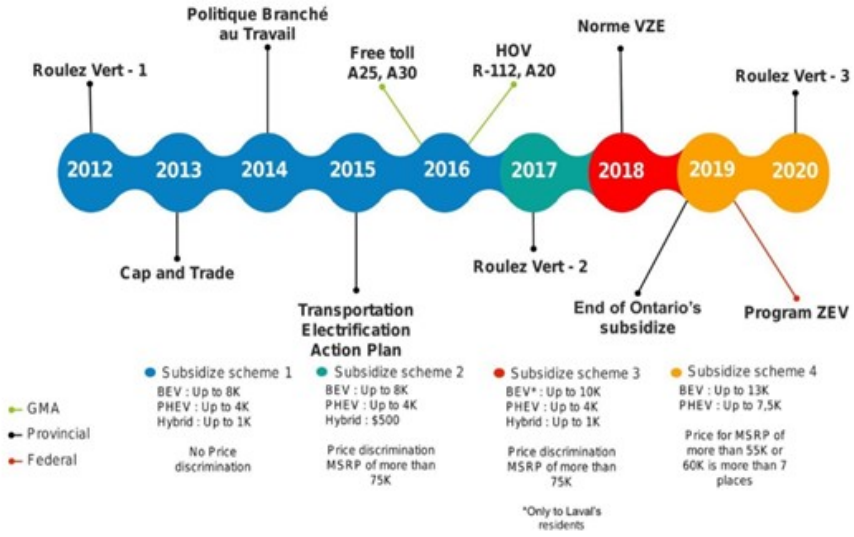
[6]Even in the early days when the state played a larger role in the charging network, it only had 300-400 fast-charging stations.

Quebec: Policies Insights

The striking difference between Quebec and other high EV adoption areas is the massive role the public fast-charging network plays, as it still provides 60% of all fast-charging stations.

In January 2012, the province of Quebec implemented the *Roulez Vert* program, offering purchase or rental rebates ranging from $500 to $8,000 to individuals, businesses, and municipalities purchasing a new EV. By November 2013, the rebates had been adjusted to between $4,500 and $8,000 for new EVs. In 2015, Hydro-Quebec – the state-owned utility – launched the Electric Circuit, Canada's largest charging network system. The province provided a rebate of up to $1,000 for the purchase and installation of private charging stations. The rebate amount varied depending on the vehicle's selling price, battery capacity, model, and year. Also, as of 2016, some HOV lanes were granted EVs access where carpooling is permitted (Cordeau et al., 2022)[7].

In 2017, Quebec reformed the *Roulez Vert* program, phasing out financial incentives for hybrid models before 2018, discontinuing subsidies for EVs with an MSRP above $125,000, and reducing subsidies for those priced between $75,000 and $125,000. In 2018, the government introduced the *Norme véhicules zéro émissions (VZE)* program to stimulate the supply of zero-emission vehicles. Between 2018 and 2019, the city of Laval also offered a $2,000 credit to buyers of BEVs. In 2019, the federal government launched the Zero Emission Vehicle (ZEV) program, providing an additional $5,000 in incentives for EV purchases. Finally, in 2020, Quebec reformed the *Roulez Vert* program again, limiting subsidies to EVs with an MSRP of $60,000 or less. Figure 2 summarizes all of the above.



3 Data

This study utilizes a comprehensive dataset that spans multiple dimensions of vehicle usage and charging infrastructure in Quebec. The key components of the dataset are as follows:

- **Vehicle Matriculation Data:** This dataset covers yearly vehicle registrations from 2011 to 2022 for over 1,000 cities in Quebec, encompassing approximately unique 10 million vehicles

[7]Still a working Paper

a year.

- **Public Charging Network Data:** The charging network data includes detailed records of 7,000 different charging stations operating from 2015 to 2022. Of these, 1,300 are fast charging stations, while the rest are slow chargers. For each station, the dataset includes the date of service, station ID, power output, and geographic coordinates (longitude and latitude).
  - **Charging Network Usage Data:** From 2017 to 2024, the dataset captures over 100 million charging sessions on the public charging network, of which 3 million are fast charges. The data includes specific consumer IDs, car models, and ZIP codes, providing nearly complete coverage of public charging behavior in Quebec during this period. Additionally, the dataset includes battery levels at the beginning and end of each charge, the exact kWh used, time spent charging, associated costs, and the date of charging.
- **Private Charging Network Data:** In addition to public charging data, I web-scraped the Chargehub website to obtain insights into the private charging network. This data includes user comments as a proxy for new station deployments, which I verified using both NRCan public data and other publicly available datasets.
- **Road Usage Data:** The Quebec government provides annual road usage data, which captures average traffic volumes on different road segments. This information is used to understand how road usage patterns correlate with vehicle matriculation and charging behavior.

EV Adoption

As I have matriculation data from every car in more than 1,000 cities across the province of Quebec from 2011 to 2022, we can observe that the transition from ICEs to EVs is substantial and accelerating, with market share reaching 30% in the summer of 2024. However, for simplicity, this paper focuses on the adoption of EVs relative to the vehicle fleet. Figure 1 illustrates the exponential growth in EV adoption, showing that EVs make up 3% of the total car fleet in 2022. Additionally, the data reveals a wide range of adoption rates, with EVs representing between 0.1% and 8% of the private car fleet in 2022 (See Figure 2). This variation is key to identifying how consumers respond to the fast-charging network, which varies by region.

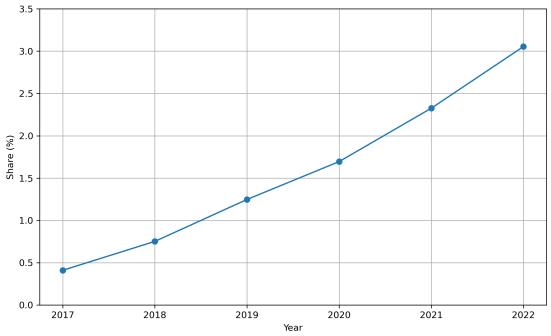


Figure 1: Provincial EV Share (2017-2022)

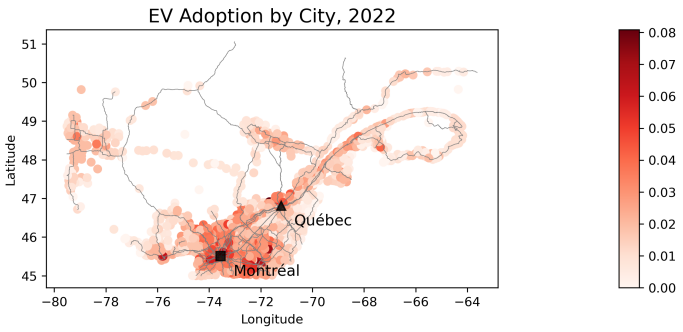


Figure 2: EV Adoption by City, 2022

4 Public Fast Charging Network

The public network was established to ensure that "any citizen can drive anywhere in Quebec with ease." To achieve this, the government permits Hydro-Québec to operate the network at a deficit during its expansion phase. In 2018, the government also allowed the utility to pass these deficits from charging network expansion onto other electricity market consumers, over which Hydro-Québec holds a monopoly[8]. In exchange, the state-owned utility is required to serve even more remote communities. Policies like these are commonly referred to as a "big push," aimed at fostering early EV adoption.

Moreover, the public fast-charging network addresses two key barriers: the early availability of chargers and compatibility issues. Each fast-charging station ensures the availability of both CCS[9] and CHAdeMO[10] connectors[11]. While Tesla continues to operate its proprietary network, Tesla owners can still use public charging stations with a CCS adapter[12][13].

This compatibility significantly impacts consumers, as it allows them to base decisions on car characteristics rather than the uncertainty of charging technologies (e.g., Nissan Leaf with CHAdeMO vs. Chevy Bolt with CCS). This dynamic is unique to Quebec. In other words, **my model captures preferences and trade-offs between charging coverage, battery autonomy, and price**, which previous studies could not address due to incompatible networks or data limitations.[14]

Network Deployment

Figure 3 shows the rapid expansion — and extensive coverage — of the public fast-charging network as early as 2016, and how this network continued to grow, becoming much denser by 2024. Interestingly, there has been a surge in private fast-charging providers. However, these networks differ from the public ones, as they are denser near urban centers — likely alleviating congestion. It remains unclear if this is a crowd-in or crowd out story.

[8] This is unlikely to distort market equilibrium, as consumer electricity prices in Quebec are exceptionally low—just a fraction of those in the Northeast corridor. Consequently, this indirect fee likely represents a Pareto improvement, as it narrows the gap between the marginal cost of electricity production and its price.

[9] CCS (Combined Charging System) is used by manufacturers such as Chevrolet, Hyundai, Kia, Volkswagen, BMW, Ford, and Audi.

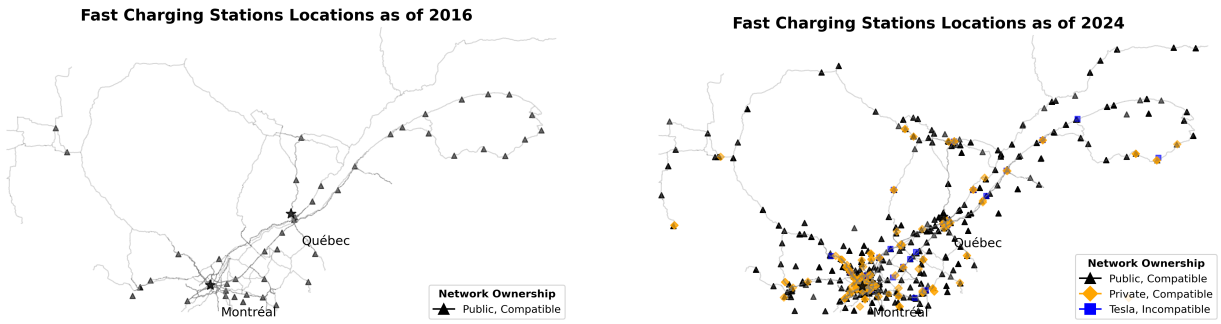
[10] CHAdeMO (Charge de Move) is used primarily by Nissan and Mitsubishi.

[11] Private charging stations in Quebec also offer both connector types.

[12] Tesla's technology is now the North American Charging Standard (NACS).

[13] Tesla began opening its network in 2024, but this is not reflected in the years currently covered by this study.

[14] My prior is that increased charging coverage primarily benefits the adoption of lower-end EV models with shorter ranges and lower prices. This has dual benefits: it mitigates environmental concerns about battery mining—an issue for environmentalists—and addresses affordability challenges for lower-income households.



(a) Public Fast-Charging Network: 2016

(b) EV Network Location 2023

Figure 3: Comparison of Public Fast-Charging Network (2016) and EV Network Location (2024)

Identification: Station-location Decision

What makes the public fast-charging network particularly noteworthy is that its deployment is exogenous to EV adoption. Documentations clearly state that decisions regarding station locations were not driven by existing EV adoption but by a mandate to connect the entire province. Thus road ridership is a much better proxy for charging deployment than latent endogenous demand. It's important to remember that the public network does not need to be profitable, as it can offset losses by adjusting electricity prices. Therefore, the public network's primary objective is to ensure continuous connectivity, particularly along major roads. As a result, regions with higher road ridership were prioritized for charging stations, but locations with relatively low charging infrastructure relative to road usage also received stations.[15]

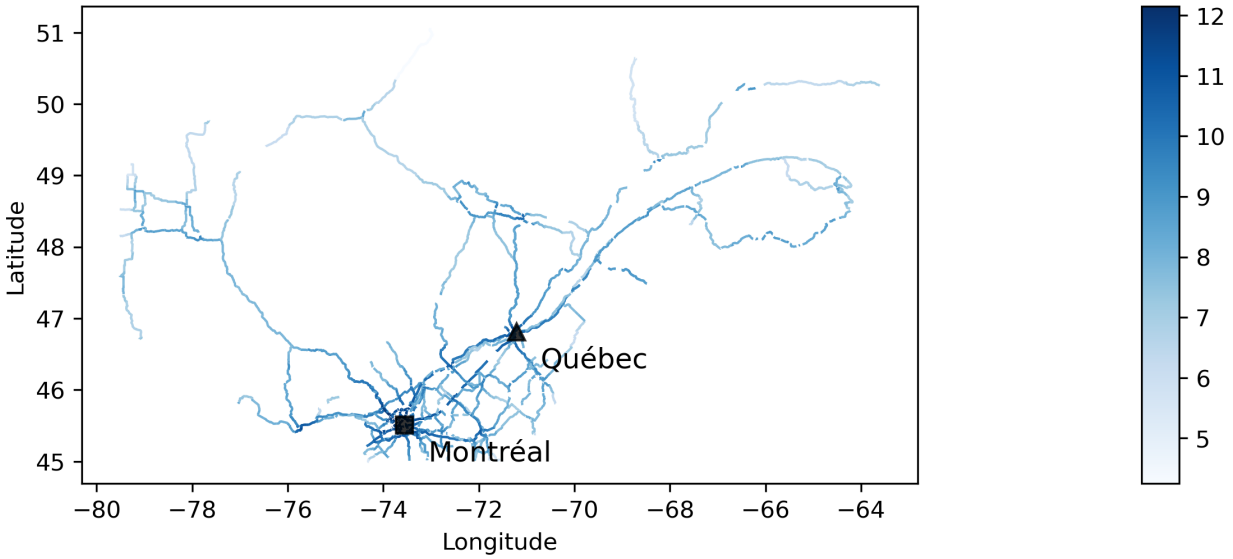


Figure 4: Road Usage (log), 2019

[15]To be done: Adding charging stations onto the figure across numerous years.

Network Profitability

A main concern is the possibility that the charging stations are selected based on their potential to generate profits. Although I previously argued that the government, as the shareholder, tasked the operator with deploying the network for broader coverage, providing additional evidence to support this claim could strengthen the argument.

To address this concern — and as a useful consideration before proceeding with the modeling — I analyze which stations are profitable and which operate at a loss (for robustness see Figure 11). Specifically, the value of a station is calculated as follows:

$$\text{Asset Value}(T, g, r)_i = \sum_{t=0}^{T} (1-r)^t (1+g)^t \left(\text{Revenues}_{i,t} - \text{Exploitation Costs}_{i,t} \right),$$

where T represents the asset's time horizon, g is the annual growth rate, and r is the discount rate. The expected profit of a station is then defined as:

$$\text{Expected Profit}(T, g, r)_i = \text{Asset Value}_i - \text{CAPEX}_i,$$

where CAPEX_i denotes the station's capital expenditures.

By assuming $T = 15$, $g = 0.15$, and $r = 0.06$, we generate Figure 9, where each dot represents a charging station, with red indicating deficits and green indicating profits. While most charging stations are profitable (see Figure 11), it is evident that profitability is concentrated in the network's core, whereas the peripheral stations operate at a deficit.

This figure supports two key points: (i) the expansion of the remote network is not driven by endogenous factors, and (ii) the private sector would have likely avoided investing in these deficit-generating areas, as their unprofitability was apparent prior to the build-out. Put succinctly, if remote areas and network connectivity prove to be important for consumer adoption, the specific impact of the public sector on EV adoption is likely to be important but remains unknown.

The next section delves into my model, which addresses this question in detail.

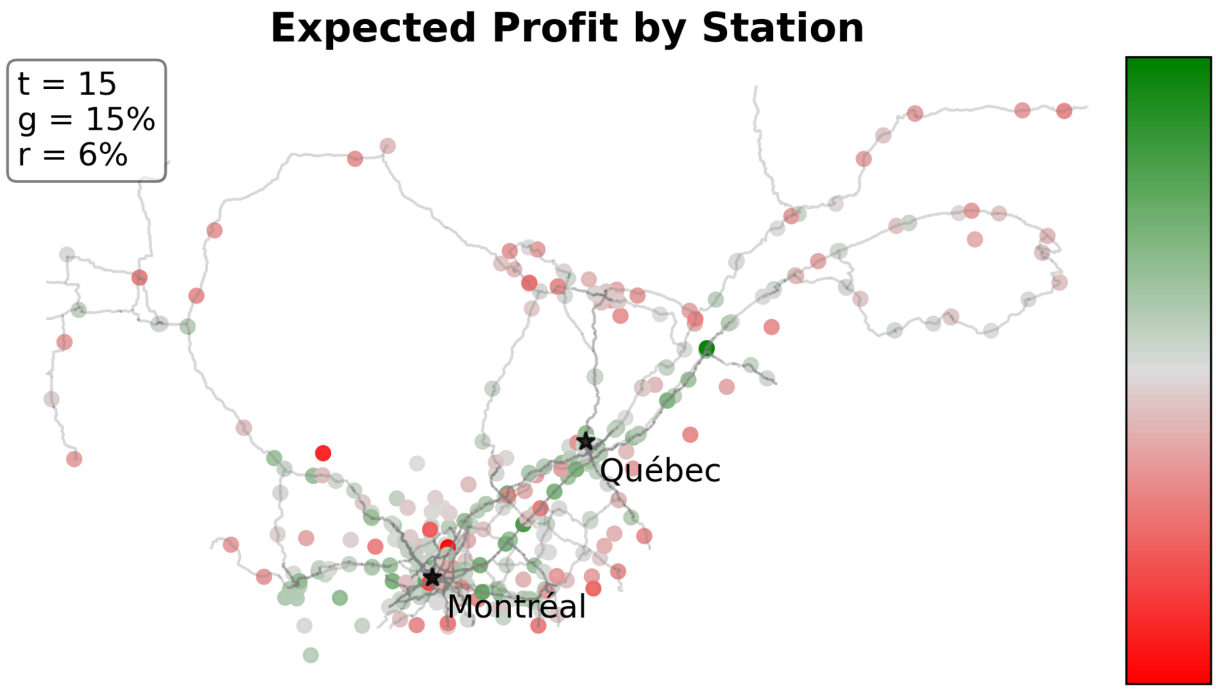


Figure 5: Expected Profits by Charging Station

Network usage

This section focuses on the fast-charging network usage, which is critical to our modeling. With access to Consumer IDs, zip codes, and car models, we can examine consumer behavior in each city in response to the existing charging network.

A case study

For visualization purposes, let's select two cities: one with high EV adoption (Bromont, 8%) and one with lower EV adoption (Val-d'Or, 1%) as of 2022. This exercise aims to examine whether individuals in regions with high EV adoption rates use or have access to a different charging network.

In Figure 6 (7), the left panel displays a heatmap of fast-charging usage, conditional on residing in Bromont (Val-d'Or). Red indicates the most frequently used *fast-charging* stations by residents of Bromont (Val-d'Or), while light grey represents all the chargers used at least once between 2017 and 2022[16]. The right-hand panel shows two kernel density distributions that illustrate the distances between the EV owner's ZIP code and the charging stations they used. The blue line represents the weighted usage, which for Bromont should be interpreted as "most charges are performed within the first 200 km of the EV owner's location." The green line provides complementary information by representing the extensive margin of the network usage, equally weighting each charging station. For Bromont, this should be read as "chargers located beyond 400 km from the

[16]The evolution of these two networks across the years can be found in the annex.

owner's location have a very low likelihood of being used even once."[17] Montréal and Québec City are included in the map to assist the reader, as the majority of Quebec's population resides in the corridor between these two cities.

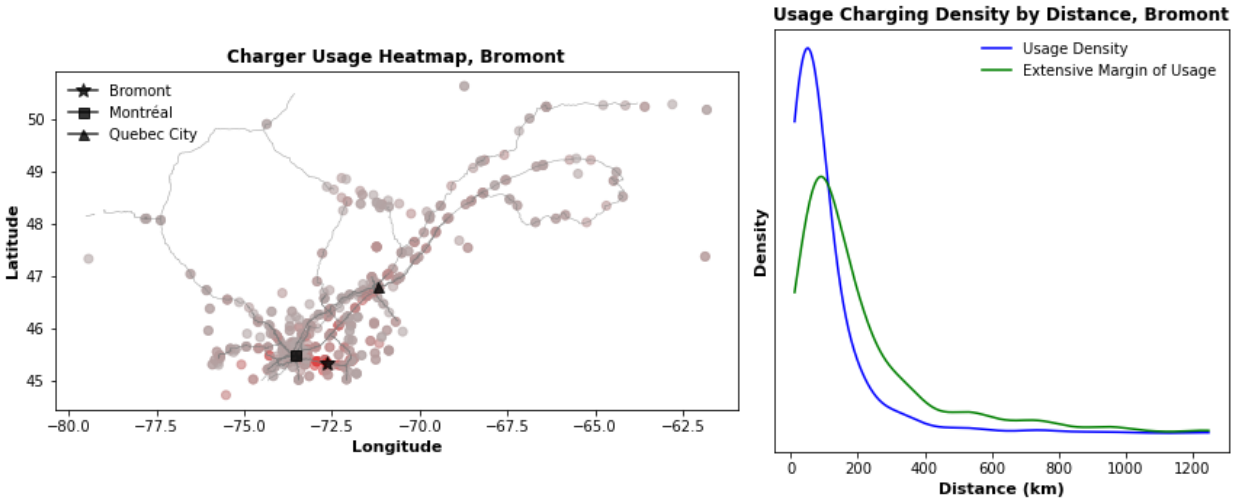


Figure 6: Charger Usage in Bromont

From Figure 6, one can observe the usage (in blue) is skewed to the left of the extensive margin (in green), indicating that consumers are more likely to value charging stations most when they are around 100 km away, with usage declining sharply after 200 km. On the other hand, Val d'Or (Figure 7) exhibits different behavior, with heavy usage of charging stations located far from one's home. The city's rural nature is indeed a contributing factor — something that a routing algorithm could address — but it also highlights the coarse location choice. This limited availability is negatively impacting the consumer experience, as the few stations may be far apart, forcing additional charging stops or even causing congestion during periods of high demand. The complexity of these behaviors underscores the necessity for a rich network topography, which our demand model effectively captures.

[17] To be verified: This could simply be due to the fact that there are fewer charging stations at that distance. The line should be adjusted by dividing it by the available network at that distance.

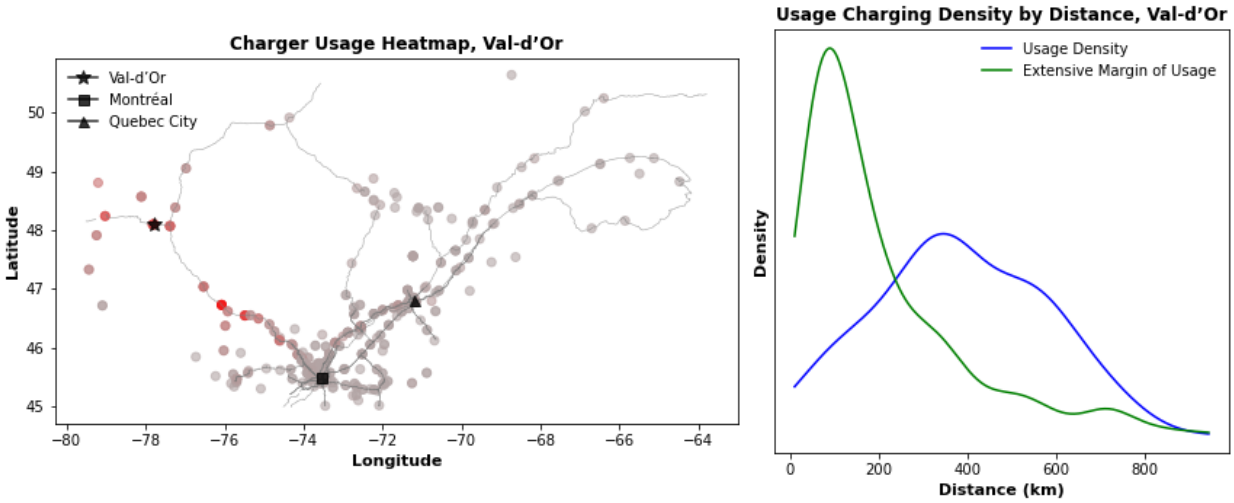


Figure 7: Charger Usage in Val-d'Or

5 Reduced Form

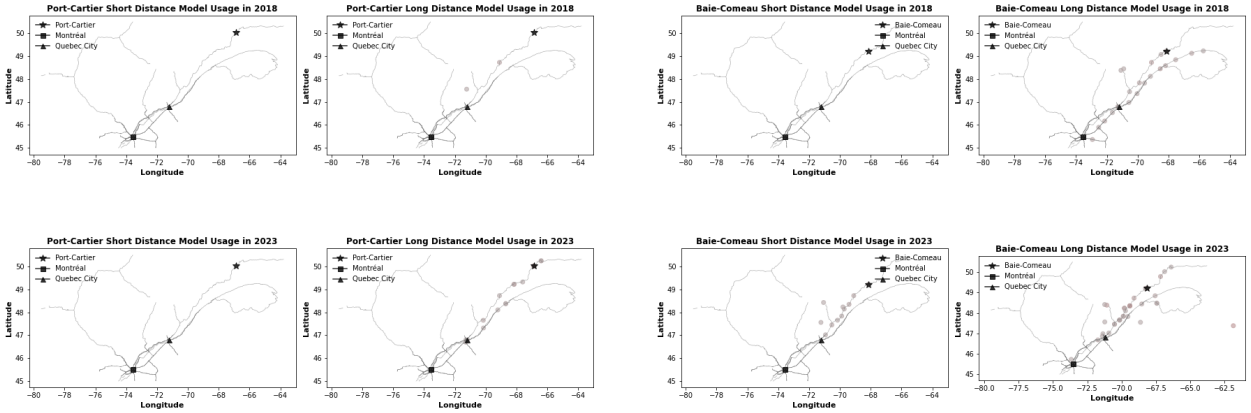
In this section, I formalize the role of network connectivity in driving EV adoption. Specifically, I analyze the impact of connecting cities sufficiently north of the network core to be considered disconnected[18]. To do so, I exploit the concentric expansion (south to north) of the public fast-charging network, focusing on Route 138, located north of Quebec City.

This setting provides an ideal case study due to the gradual northward expansion of the network between 2016 and 2022. Importantly, the bulk of the population resides south of Quebec City, creating a natural staggered rollout suitable for a difference-in-differences (diff-in-diff) framework. Thus, a city is considered treated when there is a charging station at most 50km from them.

Akin to the previous figure, Figure 8, each dot represents a charging station, with its color indicating usage intensity, where red denotes the highest usage. The figure highlights the differing charging behaviors between the two cities, particularly before Baie-Comeau's connection to the network. Port-Cartier was connected in 2020, while Baie-Comeau was connected in 2018.

The data show that by 2022, the two cities exhibit similar charging patterns, but their usage differs significantly prior to 2018. This suggests that disconnection fails to mitigate range and charge anxiety. If network connectivity indeed plays a critical role, we should observe a robust treatment effect in our analysis.

[18]See Appendix for the year-by-year netowkr expansion.



(a) Charger Usage: Port-Cartier (2018–2023)

(b) Charger Usage: Baie-Comeau (2018–2023)

Figure 8: Charger Usage Comparison in Port-Cartier and Baie-Comeau (2018–2023)

Dynamic Treatment Effects Model

I estimate the following specifications to evaluate the impact of treatment on EV market share:

$$\log(MS_{c,t}) = \beta_0 + \sum_{k \neq -1} \delta_k \cdot D_k^{(c,t)} + \alpha_c + \gamma_t + \epsilon_{c,t},$$

where $MS_{c,t}$ denotes the EV market share in city c at time t. The term $D_k^{(c,t)}$ is an indicator variable equal to 1 if city c is k periods away from its treatment at time t. Pre-treatment periods are represented by $k < 0$ (leading effects), while $k > 0$ corresponds to post-treatment periods (lagged effects). The coefficients δ_k capture the average treatment effect (ATE) for period k, relative to the baseline period $k = -1$.

City-specific fixed effects, α_c, control for time-invariant heterogeneity across cities, and time-fixed effects, γ_t, capture common shocks affecting all cities. The error term, $\epsilon_{c,t}$, accounts for idiosyncratic factors.

Result

I find an Average Treatment Effect on the Treated (ATT) of 1 with a standard deviation of 0.39, indicating a significant increase of $\exp(1)$ (≈ 2.72) fold increase in EV adoption relative to the non-connection scenario. It is important to note that EV adoption was relatively low before the connection. As a result, while the observed increase in the logarithmic scale is substantial, the corresponding increase in absolute terms is modest. However, given the durable nature of EVs, it would be unreasonable to expect the effect to manifest instantaneously. For this reason, Figure 9 presents the Dynamic Treatment Effects, capturing the evolution of the impact over time.

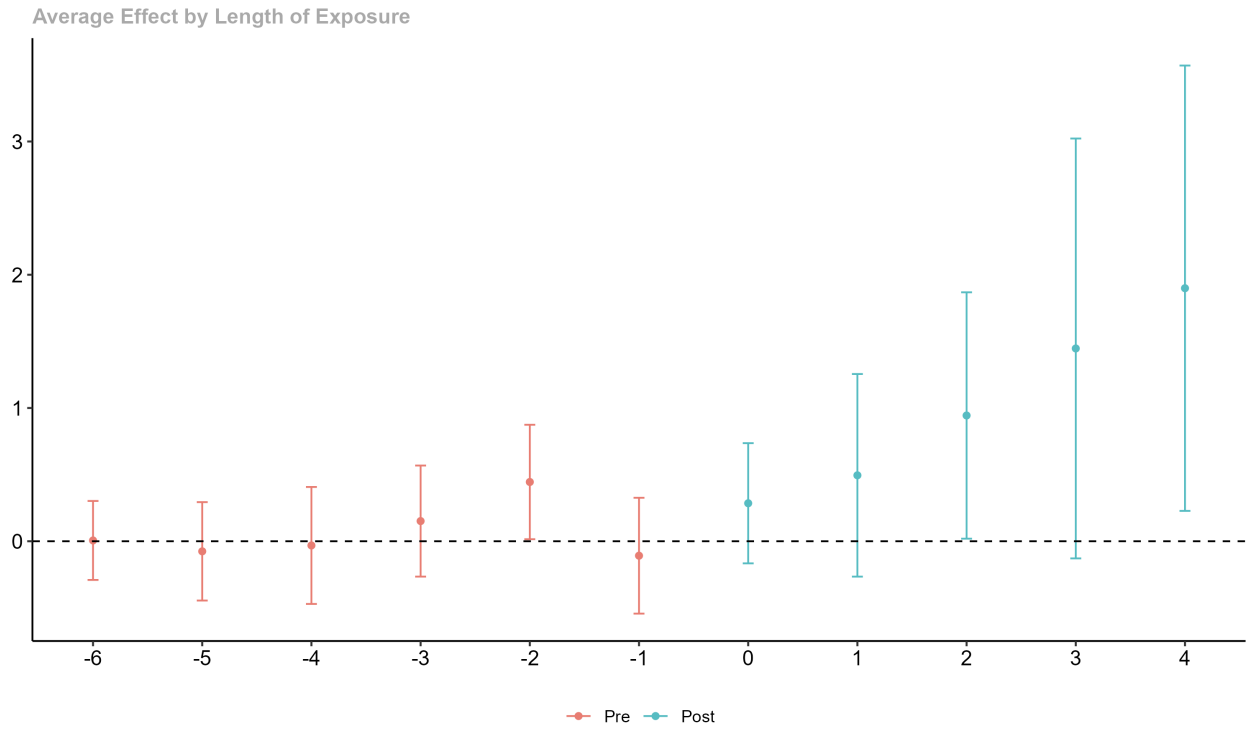


Figure 9: Dynamic Treatment Effects of Charging Network Connection on EV Adoption

The figure highlights two key observations: minimal to no pre-trend prior to treatment and a significant uptick in EV adoption in the post-treatment period, with the treatment effect exhibiting a monotonic increase over time. However, the post-treatment effect remains noisy, with only the second and fourth periods showing a statistically significant difference from zero.

It is important to emphasize that the figure is not intended to establish the causal effect of network connections but rather to provide evidence supporting the association between network connections and higher EV adoption. This evidence serves as a validation of a key assumption underlying my model, namely, that the charging network leads to EV adoption.

6 Model

This section presents a model of the EV market that captures the role of fast-charging networks in consumers' vehicle choices. The game is a series of static ones.

Setting. Prior to the game, consumers receive their unobserved preference over car models and charging stations. They also receive exogenous route frequencies to certain destinations, which are integrated into the model via charging demand on specific road segments. This information is publicly available.

Before the game begins, the public agency receives a deployment strategy, which specifies the location choices for each period, independent of EV adoption and private charging locations. These are known to private operators and unknown to the consumer until a year after their real-

ization. Consumers do not form expectations about the future state of the charging network[19]. At every period new vehicle models enters from an exogenous process.

Demand. Consumers perform two-stage games. First, they choose their car models; second, they charge their vehicles on specific road segments based on the exogenous route frequencies to specific destinations. Their charging and adoption are publicly known.

Supply. The supply sector operates as a two-stage game. In the first stage, the public sector determines the locations of fast-charging stations based on the deployment strategy. In the second stage, private charging providers observe the existing charging network and make entry decisions regarding a discrete set of locations.

Consumer Demand

Consumer vehicle demand follows the discrete-choice framework of Berry et al. (1993)[20]. In each period and city c, consumers arrive to purchase a vehicle. Consumer i's conditional indirect utility from choosing EV model m depends on the consumer's attributes and vehicle characteristics. It is given by:

$$U_{icm} = \delta x_m - \alpha p_m + \beta q_{cm} + \epsilon_{icm}$$

where U_{icm} is the utility for consumer i in city c choosing model m. x_m is a vector of vehicle characteristics and control variables, while p_m represents the price of model m. The charging network quality measures, q_{cm}, capture the attractiveness of the charging network for EV model m for a consumer living in city c.[21] The consumer-vehicle-specific taste shock, ϵ_{icm}, represents unobserved factors affecting utility, assumed to be i.i.d. Type-I extreme value distributed. The outside option is choosing a non-EV, with its indirect utility normalized to $U_{ic0} = \epsilon_{ic0}$. The charging network quality measures are described in detail below. Consumer i chooses vehicle m if $U_{icm} \geq U_{icm'}$ for all m'. The market share for vehicle m is given by the closed-form expression:

$$S_{cm} = \frac{\exp(\delta x_m - \alpha p_m + \beta q_{cm})}{\sum_{m'} \exp(\delta x_{m'} - \alpha p_{m'} + \beta q_{cm'})}.$$

Demand is estimated in two stages. In the first stage, matriculation data is used to estimate the EV adoption parameters. In the second stage, micro-level charging usage data is used to estimate the charging parameters. The parameters to be estimated in the first stage of the demand model are $\theta = (\alpha, \beta, \delta)$. [22]

Charging network quality. The quality of the network is summarized in, q_{cm}, and is defined as follows:

$$q_{cm} = \sum_{r \in R} I_{r|cm} \cdot \left(f_{r|c} \cdot \lambda_r \cdot \ln \left(\sum_{s \in S_r^m} \exp \left(\frac{V_{cms}}{\lambda_r} \right) \right) \right)$$

With

$$I_{r|cm} = \begin{cases} 1 & \text{if } r \text{ is accessible by model } m \text{ from city } c, \\ 0 & \text{otherwise.} \end{cases}$$

[19]The argument is that if some (marginal) consumers adopt EV because of their expectations about next year's network, they will wait an additional year.

[20]Currently doing multinominal logit

[21]Unobserved vehicle-specific attributes and demand shocks are represented by ξ_{cm}.

[22]The unobserved ξ_{cm} can be inferred from the model as a function of parameters θ. A strong argument can be made to have ξ_{cm} as ar AR(1) model. Namely, $\eta_{icmt}(\theta) = \epsilon_{icmt}(\theta) - \rho$
$xi_{icm,t-1}(\theta)$. Where η_{icmt} are mean-zero and independent across products m, city c, and time periods t

Here, q_{cm} represents the expected utility of the entire charging station network for a consumer in city c with model m[23]. The term $f_{r|c}$ indicates the relative importance of charging availability in road segment $r \in R$ for residents of city c, where R is the set of road segments (hereafter referred to as "road")[24]. The set S_r^m represents the available charging stations for model m on road r, with Tesla models having access to additional stations. The parameter λ_r represents the within-nest elasticity among charging stations on road r[25]. Thus, the expected maximum utility across the road r is given by:

$$\overline{V_{cmr}} = \lambda_r \cdot \ln\left(\sum_{s \in S_r^m} \exp\left(\frac{V_{cms}}{\lambda_r}\right)\right),$$

and is weighted by $f_{r|c}$ for residents of city c, but only if road r is accessible by model m from city c. Otherwise, it is 0. As shown by Li & Springel (2024), a route is considered connected for a short-range EV if there is no gap in the network greater than 50 miles (80 km), while for long-range EV models, the threshold is 100 miles (160

The term $f_{r|c}$ is exogenous and represents the share of individuals from city c who want to charge in road r. It is defined as the ratio of $\text{freq}_{r|c}$, the charges road r by residents of city c, to freq_c, the total number of charges from city c. These frequencies are estimated using 2022-2024 data, assuming the network covers all potential trips by then[26].

$$f_{r|c} = \frac{\text{freq}_{r|c}}{\text{freq}_c}$$

The utility obtained when charging at station s by a consumer from city c, driving vehicle model m , is expressed as:

$$V_{cms} = \gamma_0 \cdot Z_s + f(\gamma_1 \cdot d_{cs}) + \mu_{cms}$$

where Z_s is a vector of characteristics, such as charging speed and availability. The function $f(\gamma_1 \cdot d_{cs})$ is a cubic polynomial that represents the non-linear effect of distance on utility, specified as $f(\gamma_1 \cdot d_{cs}) = \gamma_1^{(1)} \cdot d_{cs} + \gamma_1^{(2)} \cdot d_{cs}^2 + \gamma_1^{(3)} \cdot d_{cs}^3$. Here, d_{cs} represents the distance between station s and city c, while γ_1 is a 3×1 vector $(\gamma_1^{(1)}, \gamma_1^{(2)}, \gamma_1^{(3)})$, containing the coefficients for the linear, quadratic, and cubic terms, which reflect the sensitivity to distance d_{cs}. The term μ_{cms} is the unobserved utility component, assumed to be i.i.d. Gumbel.

The choice probability for selecting station s on road r, conditional on the consumer being on road r, is given by:

$$P(s \mid c, m, r) = \frac{\exp\left(\frac{V_{cms}}{\lambda_r}\right)}{\sum_{s' \in S_r^m} \exp\left(\frac{V_{cms'}}{\lambda_r}\right)}$$

[23] q_{cm} will be parametrically inferred and incorporated into the first stage of the game to estimate β, using results derived from the second-stage estimations. These estimations involve two succinct steps: the first employs a multinomial logit or BLP framework with the EV matriculation data, while the second uses a nested logit model in the spirit of Ho et al. (2011) to obtain the key variable for the charger's choice section.

[24] $\{R : r \in \text{Roads x RCM}\}$, where RCM stands for Regional County Municipality. They represent 87 key regional municipal counties. Its interaction with roads ensures the relevance of each area is appropriately captured.

[25] As of now, λ_r is estimated by obtaining the correlation between charges within the same nest. A new modeling approach uses the HHM framework to obtain within-nest elasticities. Trial and error will determine which approach is most suitable.

[26] As my paper primarily focuses on incumbent users, this should not be an issue. I will compare the 2023 equilibrium adoption across various scenarios. Thus, the next marginal users are likely to have similar demand system patterns.

where λ is a $R \times 1$ vector, containing the within-nest elasticities λ_r.

The parameters to be estimated in the second stage of the demand model are $\tilde{\theta} = (\gamma_0, \gamma_1)$.

Price

Consumers pay a purchase price p_{jmt}, which is equal to the MSRP minus government subsidies:

$$p_{jmt} = \text{MSRP}_{jt} - \text{Province Subsidy}_{jmt} - \text{Federal Subsidy}_{j}.$$

MSRP and manufacturer discounts are the same across all markets and vary only by vehicle models and time. Provincial subsidies vary across vehicle models, provinces, and time, while federal subsidies vary across vehicle models but remain constant over time during the study period[27].

Instrumental Variable - Price

Production Cost Shifters are effective instruments for vehicle prices as they introduce exogenous variation in production costs that are unrelated to local consumer demand. Key inputs, such as steel, aluminum, and plastics, directly influence the marginal cost of producing vehicles, with their fluctuations driven by global commodity markets rather than regional market dynamics. By constructing a weighted composite price index of these inputs, this instrument captures industry-wide cost changes that affect manufacturers' pricing decisions while remaining uncorrelated with unobservable factors influencing consumer demand.

Exchange Rate Fluctuations provide a reliable source of exogenous price variation due to changes in the cost of imported vehicles. Exchange rates impact the production and transportation costs for automakers operating internationally, subsequently influencing vehicle prices. Since these fluctuations are determined by macroeconomic factors, they are unlikely to be correlated with unobservable consumer preferences or regional market shocks.

Instrumental Variable - Charging Station Location

Road Usage serves as the primary instrument to explain the location of public-sector charging stations. The intensity of road usage provides an exogenous measure of demand for infrastructure, reflecting traffic patterns that influence public-sector decisions while remaining uncorrelated with unobservable factors driving EV adoption. This instrument ensures that the estimated effect of charging stations on EV adoption is not confounded by endogenous placement decisions tied to local demand.

[27] This definition of purchase price assumes full pass-through of subsidies, consistent with prior findings in the literature (Muehlegger and Rapson, 2022; Sallee, 2011; Busse et al., 2006). Instrumental variables help identify the price coefficient, with the identifying assumption being that instruments are uncorrelated with unobservables, such as measurement error from not observing the transacted price.

7 Conclusion

In conclusion, this research highlights the critical role of charging infrastructure in driving EV adoption and reducing greenhouse gas emissions. By analyzing Quebec's publicly managed fast-charging network, I demonstrate the effectiveness of the "big push" approach in overcoming market failures and creating a positive feedback loop in the EV market. The counterfactual analyses provide valuable insights into the contribution of public networks to EV adoption and the cost-effectiveness of alternative subsidy-based strategies.

These findings underline the importance of coordinated public investment in addressing the two-sided nature of the EV market, where consumer adoption and private-sector investment are mutually dependent. As policymakers worldwide strive to meet ambitious decarbonization targets, this study offers evidence to guide decisions on infrastructure deployment and strategies to accelerate the transition to a low-carbon economy.

References

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Annex

8 Model

The demand model is as follows:

1. Consumers receive a taste shock over their car preferences.
2. Given their preferences, they choose a car model.
3. Consumers obtain, exogenously, the route frequency to certain destinations.
4. Consumers observe their taste preferences over charging stations (distance, number of stations).
5. Given their route frequency and preferences over charging stations, they choose a charging station on the road segment.
6. Utility from charging with model m for a resident of city c is received.
7. Utility from having model m in city c is received.

Market Participants

- **Consumers:** Choose their car models[28], namely ICE vehicles or EVs such as Tesla, Non-Tesla long and short range.
- **Charging Station Operators:** The fast-charging network deployment is then considered exogenous; the focus is on EV adoption given the existing network deployment. A later stage of the project will examine private sector location choices in response to public charging stations and EV adoption.

[28] Model availability and characteristics are considered to be exogenous as Quebec Quebec is too small of a market to influence EV manufacturers.

EV Adoption

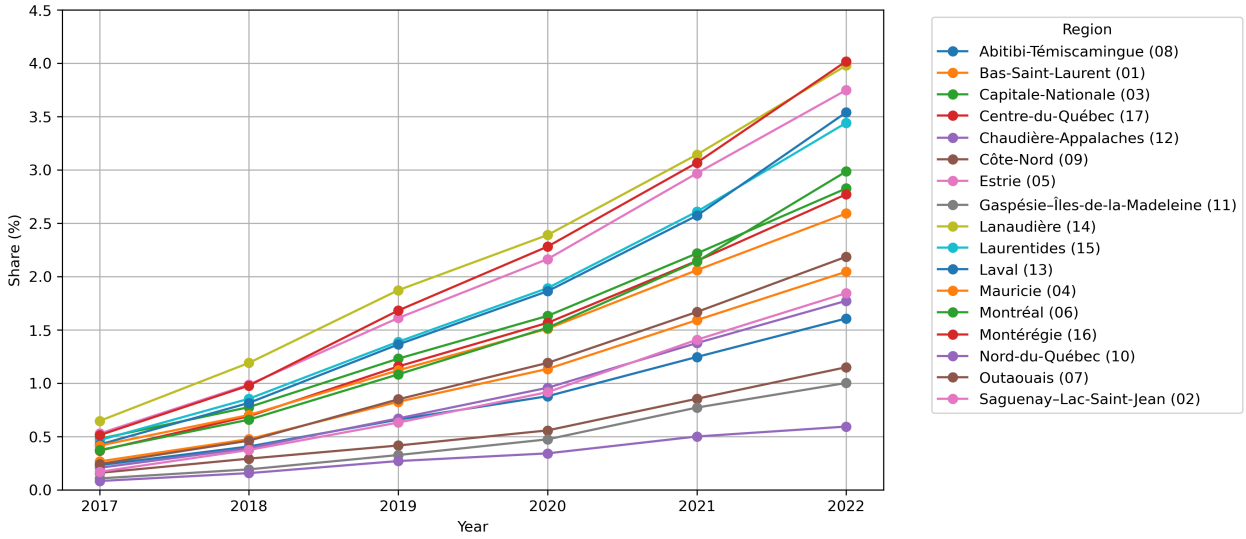


Figure 10: Provincial EV Share (2017-2022)

Network Deployment

A more comprehensive analysis is provided in Table 1, which examines network deployment by year. Specifically, each year, these three network providers choose station locations that are relative to the existing charging infrastructure Placing stations farther from the existing network improves coverage, whereas building them closer to existing stations alleviates congestion[29].

Starting with the first column (Public), one can observe the average distance at which new stations were built relative to the existing network each year. For example, in 2015, the new public stations were, on average, 175 km[30] from the existing charging network, and this distance decreased to 81 km in 2016, 44 km in 2017, and so on. A clear characteristic of the public network is its strategy to increase coverage year over year by halving the distance between stations, thereby improving the charging experience while also expanding coverage beyond the main urban areas. They accomplished this by offering charging stations along the main roads, regardless of the level of EV adoption in those areas; documentation shows that road ridership has been their primary metric.

In contrast, private charging stations tend to be closer to the existing network, a pattern that is consistent across most years, as seen in the second column under Private Universal. Another key characteristic is the deployment of the Tesla network, the third column. Before 2018, Tesla expanded its network to increase user coverage, but after that, it appeared to co-locate with the public network. This shift suggests that the public network had already provided substantial coverage, leading Tesla to focus on high-usage areas to alleviate congestion.

[29] Or perform business stealing.

[30] birf flight

Year	Public	Private Universal	Tesla Network
2015	176.43	65.78	
2016	81.92	6.94	45.37
2017	44.24		62.03
2018	31.80	2.27	
2019	26.06		0.14
2020			
2021	20.55	10.09	0.00
2022	16.41	7.41	8.11
2023	9.89	6.64	4.63

Table 1: Average Distance of the New Fast-Charging Stations to the Existing Network

Table 2 makes the argument formal by analyzing how each network provider impact the coverage, which we represent by the distance between the nearest fast-charging stations. Namely, the first column should be read as follows: assuming the charging network was only deserved by the public, 50 % of the charging station would be at less than 5 km and 1% would be located at more than 70 km of the nearest station. On the other hand, if we include the private network into the analysis – that is column 2 –, the median distance to the nearest station would be 2 km and the 99th percentile would be almost identical at 65 km. This means the private is heavily skewed into the densification of the network – below the median –, instead of decreasing the high distance between the charging stations, which would be beneficial to improve coverage. In the third column, we do the same, but with Tesla and it leaves these estimates seemingly unchanged; in Table 3 we show that it is because Tesla co-locates with the public network with more than 50% of the fast-chargers being within 500 meters of a public stations[31].

Table 2: Minimal distance between Charging Station by Network, 2023

	Public	Public & Private	Public & Tesla	All
Median	4.68	1.58	3.45	1.33
Mean	11.64	8.18	10.43	7.58
75th Percentile	14.25	9.11	13.50	7.76
90th Percentile	30.93	20.77	27.63	20.64
99th Percentile	71.05	65.12	69.99	64.43

Table 3: Distance of public charging station by type, 2023

	Public	Public-Private	Public-Tesla
Median	4.68	1.33	0.52
Mean	11.64	4.42	1.31
75th Percentile	14.25	3.02	1.54
90th Percentile	30.93	7.38	2.65
99th Percentile	71.05	16.91	10.47

[31] Need to add more details

Charging Distance by City Ownership

Type	year	Average (km)	Median	Sd	90th p.	Unique Chargers
Long Distance	2017	125	125	180	472	14
	2018	119	121	160	408	25
	2019	119	121	150	368	53
	2020	156	123	164	400	28
	2021	151	130	164	402	68
	2022	151	133	163	404	82
	2023	143	129	148	367	82
Short Distance	2017	96	101	190	469	16
	2018	86	101	156	356	30
	2019	78	92	138	294	66
	2020	80	74	125	242	48
	2021	81	82	130	271	91
	2022	81	81	132	257	112
	2023	76	77	124	240	102

Serial Charges

Table 4: Percentage of Serial Charges Across Models

Main Models	Percentage	Distance-Type	Range (km)
Model S	36	Long	595
Model 3	41	Long	518
E-Golf	43	Short	201
Bolt EV	43	Long	383
Kona Electric	43	Long	415
Leaf	45	Short	241
Ioniq Electric	45	Short	274
Model X	48	Long	475
i3	50	Short	246
Spark EV	50	Short	132
Soul EV	50	Short	179
Focus Electric	52	Short	185
i-MiEV	54	Short	100

Serial Charges

One of the main challenges of EVs is not charging itself, but the need for multiple charges on a single trip, referred to as *serial charges*. If network expansion improves the consumer experience, we should expect a reduction in the rate of serial charges.

To verify this, I used the main EV models and examined how serial charging behavior changed over time for both long-distance and short-distance EV models[32]. To conduct the analysis, I restricted my attention to fast charges; if two or more charges occurred on the same day, they were classified as serial charges.

Surprisingly, a significant share of fast charges were serial, with around 50% in 2017 and 40% in 2024, for both long- and short-distance models. This suggests that the network's expansion has contributed to its improvement. To ensure this is not due to the EV market composition, I performed a regression controlling for car models and still observed a 2% annual reduction in serial charges (see Table 5b). Moreover, another key indicator supporting this trend is the average use of unique fast-charging stations, which increased six-fold between 2017 and 2024 (see Table 8). Specifically, Short (Long) Distance models averaged 16 (14) unique chargers in 2017, compared to 102 (82) in 2024.

Table 5: Serial Charges Across Years and Network's Impact

Year	Long Distance Models	Short Distance Models
2017	51	52
2018	46	46
2019	42	46
2020	40	47
2021	44	47
2022	43	48
2023	40	45
2024	41	42

(a) Percentage of Serial Charges by Year and Distance

	(1)	(2)	(3)
Year	-0.02***	-0.02***	-0.03***
	(0.00)	(0.00)	(0.00)
Short Distance		0.14***	-40.71***
		(0.01)	(5.73)
Year X Short Distance			0.02***
			(0.00)
Model FEs	Yes	No	No
Observations	607,842	607,842	607,842

Note: *p<0.1; **p<0.05; ***p<0.01

(b) Logit Regression: Network's Expansion Impact on Serial Charges

Battery Level

Another key feature is that a denser network can help minimize range anxiety and perhaps allow individuals to be less cautious, as they know there will be a next station whenever they feel the need. To investigate this, we examine the battery levels at the start and end of charging between 2020 and 2024[33]. As shown in the left-hand panel of Table 6, both short- and long-distance models begin charging, on average, at 30%, but they diverge at the end of charging, with short-distance models stopping at around 70%.

What is even more striking is the right-hand panel, where we see the remaining kilometers in the battery. Short-distance models take a much bigger risk to reach 30% battery, as 70 km may seem like a lot, but in many areas outside Quebec, the next charging station is often 50 km to 100 km away. Fortunately, Quebec's network is much denser, allowing short-distance models to charge with peace of mind. We believe this is key to Quebec's relatively high EV market share, as it greatly enhances the user experience of more affordable models, such as the shorter-distance and non-Tesla vehicles. That said, they still charge their cars quite fully, typically stopping at around 70%[34].

[32] See Table 4 for further details on the EV models.

[33] There are fewer observations, as the battery data starts in 2020

[34] The charging speed dramatically decreases as the battery approaches 100%; an 80% charge is commonly the app

Table 6: Remaining Battery and Distance at Start and End of Charge by Model

Type	Start	End
Long Distance	32	62
Short Distance	32	71

(a) Battery Level (%)

Type	Start	End
Long Distance	133	257
Short Distance	72	160

(b) Distance Remaining (km)

Again, while these descriptive statistics are valuable, how does the deployment of the fast-charging network impact the start and end charge levels? As argued earlier, the greater availability of charging stations helps reduce serial charges[35], primarily by enabling strategic charging locations to minimize double and triple charges during a trip. If this is true, we should expect charging behavior to change over time.

This is precisely what Table 7 shows. The dependent variable is the percentage of battery charge, while the independent variables are years (to capture network evolution) and has a Short Distance Models dummy. The results show that Short Distance Models, indeed, take bigger risks by starting charges 6% lower than Long Distance models but also end with a battery 16% fuller. Finally, the network's improvement appears to slightly reduce range anxiety, as consumers charge 1% less fully per year.

Table 7: The Network's Expansion Impact on Charging Level at the Start and End of Charging

	Start	End
Year	0.00	-0.01***
	(0.00)	(0.00)
Short Distance	-0.06***	0.16***
	(0.00)	(0.00)
Observations	391,582	391,582
R^2	0.00	0.04
Adjusted R^2	0.00	0.04
Note:	*p<0.1; **p<0.05; ***p<0.01	

Network Profitability

In Figure 11, I first show that the results are quite robust to the choice of T, g, and r. Across nearly all scenarios, most stations are profitable, with only a left-hand tail representing stations operating at a deficit.

In the subsequent figure (Figure 12), I illustrate where Tesla chose to locate its stations compared to the public sector's profitability distribution. It is evident that Tesla has largely confined

notification and recommendation.

[35]Even though it might induce others due to marginal EV trips that would not have been undertaken or would have been done by ICEs instead

its network to the core, specifically in areas where charging stations remain highly lucrative. This aligns with expectations, as Tesla operates with a profit-driven model and targets areas with high charging demand.

The final figure (Figure 13) shows similar results for other private operators, with an even higher concentration of stations in the Greater Montreal area. This is consistent with the economic incentives for private firms, as they sell charging services and must prioritize profitability.

These findings align with the rationale behind Quebec's "big push" policy. While the entrance of private firms into the charging market could be interpreted as a validation of this policy, it also underscores the challenge of ensuring private investment in unprofitable, remote areas. Without public sector intervention, these regions would likely remain underserved, highlighting the importance of a coordinated public effort.

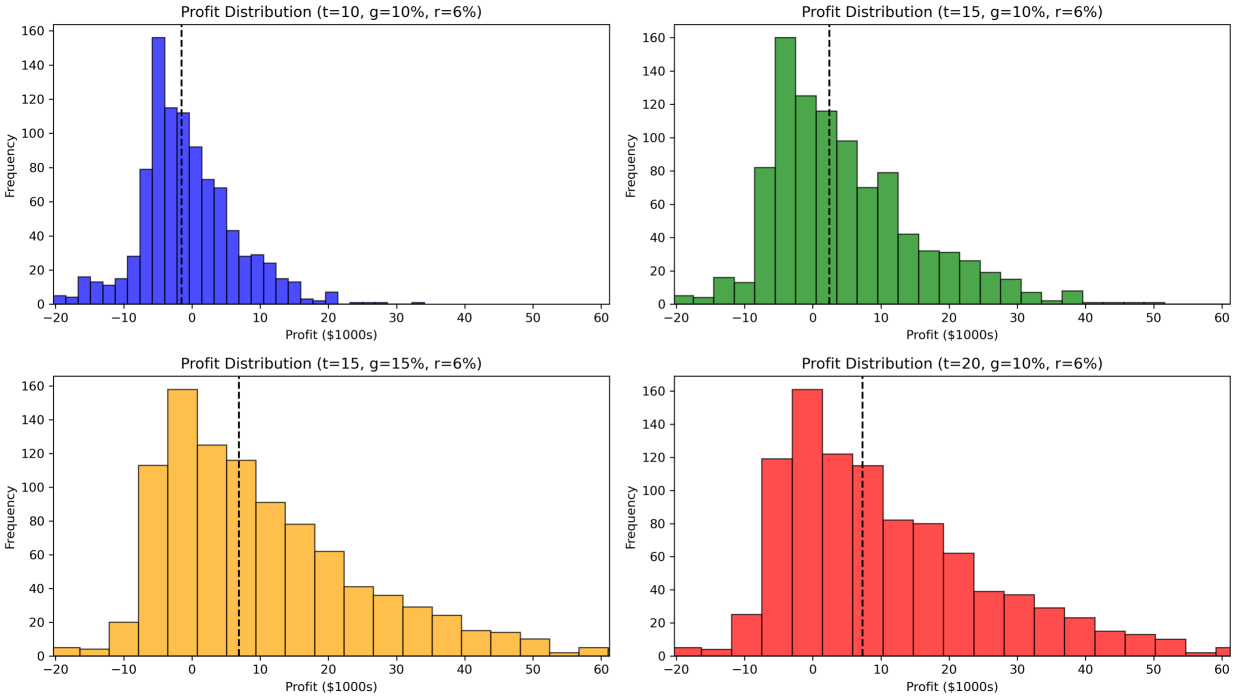


Figure 11: Profit Distribution of Public Charging Stations

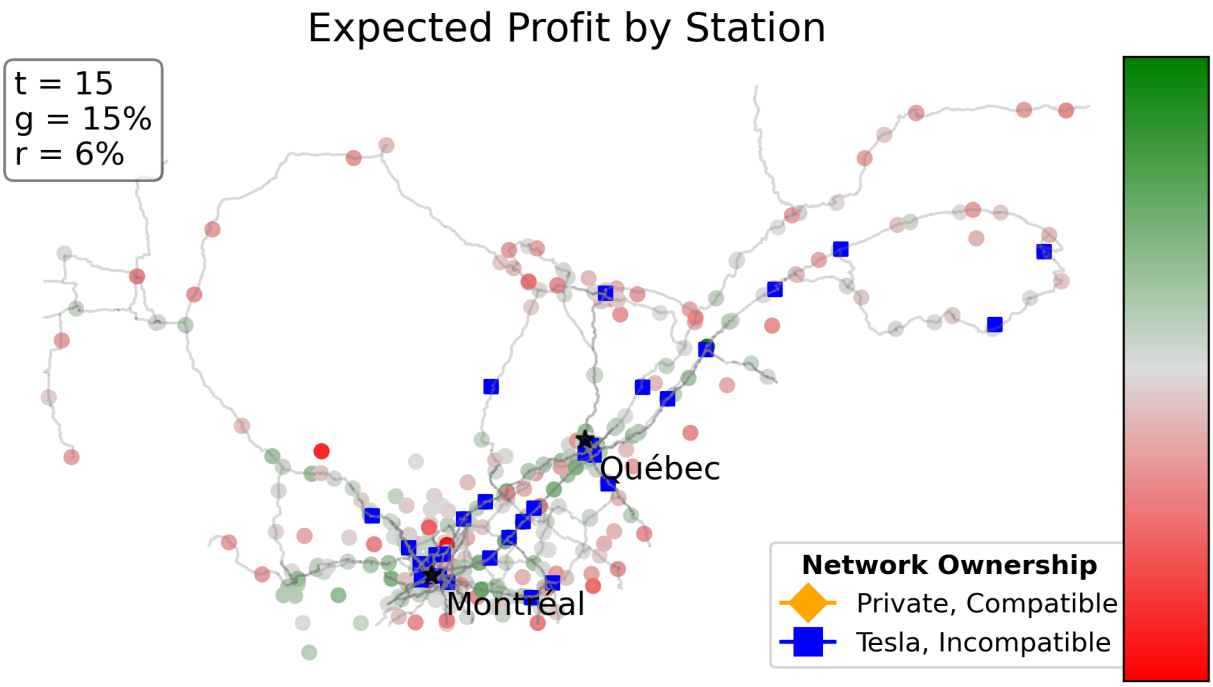


Figure 12: Tesla Charging Station Locations and Public Sector Profitability

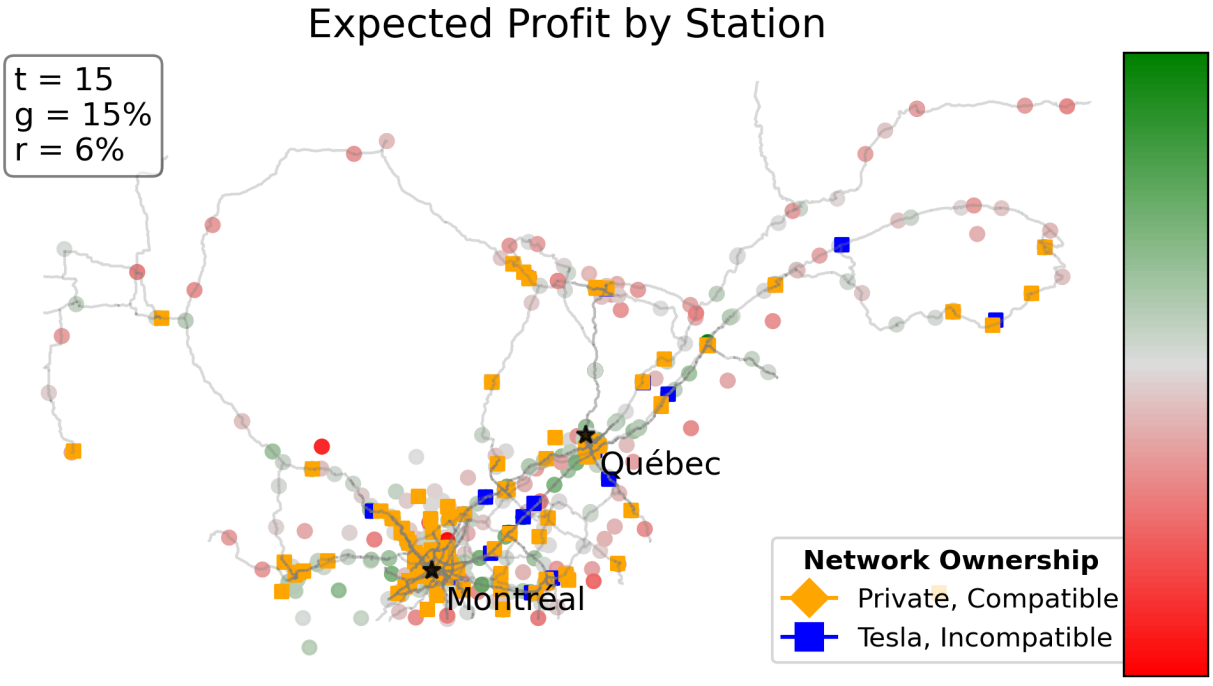


Figure 13: Private Charging Station Locations and Profitability Concentration