Spatio-temporal Analysis of Electric Vehicle Adoption in Quebec

Philippe Barla [Ψ] Jean Dubé [φ] Benoit Gagne [ξ] Luis Miranda-Moreno [τ]

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Summary

We analyze how spatial characteristics, socio-economic factors, travel patterns, and gasoline prices have influenced the adoption dynamics of Electric Vehicles (EVs) across 410 regions in Quebec, Canada, from 2012 to 2018. The average exponential growth rate was 66% with a range of 33% to 86% across different regions. We find that higher population density and a greater prevalence of individual houses experienced greater growth of EVs. Additionally, a higher proportion of self-employed workers, a larger number of children, and a higher median income are also associated with increased EVs adoption rates. Conversely, larger household sizes are linked to a decrease in EVs adoption rates. In terms of travel patterns, regions with a higher proportion of households with a home-to-work commute exceeding 45 minutes show a positive correlation with EVs adoption. Our analysis reveals that spatial factors account for 38% of the variation in adoption trends across regions, socio-demographic factors explain another 38% and travel patterns 24%. Furthermore, we observe a significant impact of gasoline prices, with an elasticity of 2.9. However, further analysis is needed to fully understand this relationship.

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[Ψ] Department of Economics, Université Laval, philippe.barla@ecn.ulaval.ca

[φ] Graduate School of Land Use Planning and Regional Development, Université Laval, jean.dube@esad.ulaval.ca

[ξ] Department of Economics, Université Laval, benoit.gagne.3@ulaval.ca

[τ] Department of Civil Engineering, Mc Gill, luis.miranda-moreno@mcgill.ca

1. Introduction

As the impacts of climate change become increasingly evident, there is an urgent need to transition towards a decarbonized global economy. One critical area for action is the transportation sector, which contributes approximately one fifth of global CO_2 emissions. Moreover, emissions from this sector have risen by more than 71% between 1990 and 2022 (IEA, nd). Among various modes of transportation, road passenger transport stands out as the leading emitter, responsible for over 45% of the sector's emissions and 15% of total emissions. To tackle this challenge, public authorities are increasingly advocating for the adoption of zero-emission vehicles (ZEVs) as a pivotal strategy to reduce the carbon footprint associated with road passenger transport.

Zero-emission vehicles (ZEVs) are vehicles that can operate without producing any tailpipe emissions.[1] Currently, ZEVs are predominantly represented by electric vehicles (EVs), with fuel cell and hydrogen-powered vehicles being relatively scarce. Electric vehicles can be broadly categorized into two types: battery-powered electric vehicles (BEVs), which operate solely on electricity, and plug-in hybrid vehicles (PHVs), which feature both a conventional internal combustion engine and a rechargeable battery that can be plugged into an external power source.

The transition to electric vehicles (EVs) started relatively recently, with the first plug-in hybrid electric vehicles entering the global market in 2008-2009, followed by the introduction of the first mass-produced lithium-ion battery electric vehicle, the Mitsubishi i-MiEV, in 2009. By 2022, EVs represented 14% of global new vehicle sales, marking a tenfold increase compared to 2017 (IEA, 2023).[2] China and Europe are leading this shift, with respective market shares of 29% and 25% in 2022, while Canada and the United States are behind the global average, at 9% and 8% respectively.

Based on analyses conducted by the International Energy Agency (IEA, 20023), electric vehicles (EVs) would need to account for 60% of global vehicle sales by 2030 to attain carbon neutrality by 2050. However, the IEA's projections indicate that, given existing policies and announced initiatives, EVs are expected to achieve only a 35% market share by 2030.

To accelerate the shift towards electric vehicles, it is essential to comprehend the factors that influence motorists' decisions to adopt these vehicles. Early empirical research in this area predates the commercial availability of EVs and relied on stated preference data, where respondents were asked to hypothetically choose between

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[1]This definition is used in both Canada and the United States. In Europe, however, vehicles must have a CO2 emission rate of less than 50g/km to be classified as Zero-Emission Vehicles.
[2]Naturally, the share of electric vehicles in the overall vehicle fleet is notably lower, standing at just over 1%.

different types of vehicles. In contrast, more recent studies utilize revealed preference data, which is based on actual sales or registrations of EVs.

In this article, we contribute to this evolving research by conducting a spatio-temporal analysis of the adoption of EVs among newly registered vehicles in Quebec. Our analysis aims to understand the factors contributing to regional variations in EV market share and its evolution from 2012 to 2018. Our analysis delves into the influence of spatial, socio-demographic, and travel profile characteristics of the regions, along with the annual fluctuations in gasoline prices.

The analysis of the Quebec context is particularly compelling due to its status as one of the leading jurisdictions in North America for the adoption of EVs, alongside California and British Columbia. Since 2012, the Quebec government has established ambitious goals and implemented substantial measures to promote EV adoption. These efforts include a generous subsidy program for EV purchases and the widespread installation of private and public charging stations.

By the end of 2020, Quebec was nearing its target of 100,000 registered EVs, which accounted for 1.9% of its total vehicle fleet. In terms of new vehicle registrations, the share of EVs in Quebec reached around 9% in 2021, trailing behind British Columbia at 11.6% but significantly surpassing the Canadian average of 5.2% (Statistics Canada, 2022). For comparison, California achieved a 12.2% share of EVs in new registrations in 2021 (California Energy Commission, nd). As of October 2023, the total number of EV has risen to 250 000, representing nearly 42% of all registered EVs in Canada—far exceeding its population share of 22% (AVEQ, nd). The share of EVs in sale is now close to 23% (Léveillé, 2023).

The Quebec context stands out from California or British Columbia due to its harsh winters, which can significantly impact the range of EVs. Despite this challenge, Quebec enjoys a unique advantage in that 97% of its electricity is generated from hydroelectric power. This results in a particularly favorable environmental balance for EVs.

Our research makes serval contributions to this topic. Firstly, it addresses a notable gap in the literature by focusing on the determinants of EVs adoption specifically within the context of Quebec. While much of the existing research centers on the United States, particularly California, and Europe, there is relatively little analysis of EV adoption in Quebec.[3]

Secondly, our analysis offers a high level of spatial granularity, utilizing Forward Sortation Areas (FSAs) or postal districts to divide Quebec into more than 400 zones. This detailed approach increases the variability and precision of our findings.

[3] One exception is Fournel (2022), which examines the impact of the Quebec subsidy for EVs.

Additionally, our dataset covers a relatively long and recent period, providing a more comprehensive view of the evolution of EVs.

Thirdly, our research extends beyond examining the influence of explanatory factors on the overall adoption rate. We delve into how these factors contribute to regional variations in adoption dynamics. To achieve this, we utilize a model that incorporates interaction terms between the trend and regional characteristics. This methodology not only enables us to explain differences in regional trends but also to assess whether the effects of regional determinants have evolved over time alongside the increasing adoption of EVs. Moreover, our model also enables us to identify potential catch-up effects or, conversely, a widening divergence in adoption trends among regions.

Our findings reveal a significant surge in the proportion of EVs among new registrations, with an average exponential growth rate of 66%. While there are disparities between regions, all have witnessed substantial increases, ranging from 33% to 86%. Regions with lower population density exhibit lower adoption trends compared to those with intermediate or high density. The prevalence of single-family homes also emerges as a crucial favorable factor. Both spatial factors collectively explaining up to 38% of the regional variation in trends.

Regarding socio-demographic attributes, household size notably hinders the adoption rate, whereas the presence of self-employed workers, higher numbers of children per adult, and increased income levels stimulate adoption. Gender, the proportion of university graduates, immigrants, and the region's age structure show no significant impact. Variations in these socio-demographic characteristics account for an additional 38% of the regional differences.

The travel profile, as indicated by the proportion of households with commutes exceeding 45 minutes by car, favors adoption and explains 24% of the regional variation. Lastly, the price of gasoline appears to exert a notable influence, with an elasticity of 2.9. However, this effect warrants careful analysis due to the limitations of our dataset.

This article is organized as follows. In Section 2, we provide an overview of the current state of knowledge. Section 3 outlines the data sources, provides descriptive statistics, and describes the Quebec public policy context. The methodology is detailed in Section 4 while Section 5 discusses the results. Section 6 describes robustness checks, and Section 7 discusses the conclusions and policy implications.

2. Literature overview

There is a vast and continuously expanding body of empirical literature investigating the adoption process of EVs. As proposed by Liao et al. (2017), the decision-making process between a BEV, PHVs, or a conventional vehicle (CV) can be analyzed within the framework depicted in Figure 1. This decision is influenced by individual consumer characteristics, including their level of openness and knowledge regarding innovation, as well as the attributes of the available choices. Moreover, the interaction between these factors could also play a crucial role in shaping the decision-making process.

Existing studies on this topic vary in terms of the type of data used, which can include hypothetical scenarios or real choices made by consumers. Additionally, studies differ in the level of data aggregation, with some analyzing individual or household-level data, while others aggregate data by geographic units. Furthermore, these studies examine a wide range of characteristics and attributes that can influence the adoption of electric vehicles.

Early studies in this field relied on survey data that presented respondents with hypothetical choices, which were then analyzed using discrete-choice statistical models. These studies allowed for a detailed analysis of the trade-offs between different attributes of choices at a disaggregated level, showing how these trade-offs varied according to the characteristics of the respondents. However, a key limitation of these studies is the hypothetical nature of the choices analyzed, which can introduce biases into the results.

A review by Liao et al. (2017) examined 26 such studies published between 2005 and 2015, drawing several conclusions from this body of research:

- Financial aspects, such as purchase price and operating costs, significantly impact the adoption of electric vehicles. Wealthier households may be less sensitive to these aspects.
- Technical factors, including range and charging times, also play a significant role. Longer ranges and shorter charging times are associated with higher adoption rates, while performance attributes like acceleration and power are viewed favorably.
- The availability of charging stations is a key factor that promotes the adoption of electric vehicles.
- The impact of public policies on adoption varies depending on the type of measure. Tax reductions tend to have a positive effect, while local measures like access to parking or reserved lanes may not always be effective.
- The influence of socio-economic characteristics on adoption is diverse and not always statistically significant. Factors such as age, income, gender, education level, and family composition have varying effects across studies.
- Some studies suggest a positive influence of social norms on the adoption of electric vehicles.

In Canada, several recent studies (Axsen & Wolinetz, 2018; Melton et al., 2020; Miele et al., 2020; and Bhardwaj et al., 2021) have conducted simulations of the evolution of EV sales and vehicle stock up to 2030. These forecasting models incorporate a demand module based on discrete choice analysis results derived from declared preference data. To capture consumer heterogeneity, these models use latent class classification models.

According to Miele et al. (2020), the adoption of EVs between 2020 and 2030 in Canada would be minimally influenced by the availability of charging infrastructure. Instead, policies aimed at increasing consumer information and improving the availability of EVs in the market would be more effective in driving adoption.

Hardman et al. (2017) conducted a comprehensive review of the impact of monetary incentive programs on the adoption of EVs. Their review focused on 35 studies published between 2008 and 2016, encompassing developed countries. The findings revealed that over 90% of the studies demonstrated that monetary incentives have a significant positive impact on EV adoption. Furthermore, programs that directly reduce the purchase price of EVs appeared to have a more pronounced effect compared to programs based on tax rebates.

Nevertheless, several studies have raised concerns about the efficiency of these programs, suggesting that their costs may outweigh their benefits. For instance, Clinton and Steinberg (2019) estimated that the federal incentive program in the United States incurs a cost of $36,000 per additional EV when factoring in the rate of opportunism. Additionally, they found that the cost per ton of CO_2 avoided is approximately $450, indicating a high cost-effectiveness ratio. Li et al. (2017) arrived at similar conclusions, reporting that 70% of EV purchases under the federal tax credit program would have occurred even without the incentive. Moreover, these studies observed that the EVs acquired through these programs often replace vehicles that would have been relatively fuel-efficient regardless.

The impact of incentive programs also seems to differ based on the characteristics of the buyers and vehicles involved. Certain studies indicate that these incentives may have a reduced impact on wealthy buyers. Considering this, Hardman et al. (2017) recommend that incentives be more targeted toward vehicles that offer the most significant environmental advantages, rather than being accessible to luxury EVs.

In their 2018 review, Hardman et al. examined approximately fifty studies on the impact of charging infrastructure for EVs. Their findings revealed that the primary location for EV charging is at home, followed by workplaces and public charging terminals. Consequently, the availability of private charging facilities at residences is considered a crucial factor. Additionally, while public charging terminals have been shown to have a positive impact on EV adoption, there is currently no clear evidence regarding the optimal number or spatial distribution of these terminals.

More recent studies have shifted towards using EV registration or sales data. For example, Li et al. (2017) analyzed the evolution of EV sales on a quarterly basis across

353 metropolitan areas in the United States from 2011 to 2013. Their objective was to assess the impact of the number of charging stations on EV sales, considering the bidirectional relationship between these two variables.

The study's findings highlighted the presence of network effects: a 10% increase in the number of public charging terminals in a region led to an 8.4% increase in new EV sales. Conversely, a 10% increase in EV stock in a region resulted in a 1.2% increase in the number of charging stations. The demand for EVs was found to be slightly elastic, as a 10% drop in price led to a 12% increase in sales. Furthermore, an increase in the price of gasoline was found to positively influence EV sales, with an elasticity of 0.42, as well as an increase in income, with an elasticity of 0.11.

In a study more closely related to our analysis, Morton et al. (2018) examined the factors influencing the rate of EV adoption across 320 regions in the UK in 2016. Their analysis focused on the impact of socio-economic factors, such as the population's educational attainment and employment status, as well as transport characteristics, including the availability of charging stations. The statistical analysis accounted for spatial autocorrelation in the data by using a spatial Durbin model.

The study's results revealed moderate spatial autocorrelation, with a notable cluster of high EV adoption rates in central London. Several factors were found to have a positive and statistically significant impact on EV adoption, including the percentage of the population with a university degree, the percentage of the population who are self-employed, median income, the percentage of the population living in semi-detached dwellings, and the number of charging stations. Conversely, household size was found to have a negative impact on adoption. The spatial effects analysis indicated that regions with a higher presence of EVs, charging stations, or higher population density in neighboring areas were more likely to experience increased EV adoption rates.

In a study by Springel (2021), the adoption of BEVs in Norway between 2010 and 2015 was analyzed at a local level. The research aimed to identify the effect of charging station networks on BEV adoption rates. The study's findings revealed that subsidies for the installation of charging stations initially had a significantly greater impact on BEV adoption compared to EV price rebate programs, with twice the effect. However, as the number of charging stations increased, this difference in impact decreased rapidly. The price elasticity of demand for BEVs was found to vary between -2 and -1.5 depending on the specific model, indicating a relatively elastic demand for these vehicles.

In a study by Bushnell et al. (2022), the relative impact of electricity and gasoline prices on EV adoption in California was examined. The analysis leveraged local price variations in California between 2014 and 2017. The study's findings revealed that changes in gasoline prices had a significantly larger impact, ranging from four to six times greater in magnitude, on EV adoption compared to changes in electricity prices. This substantial difference in impact was attributed to the greater salience of gasoline prices relative to electricity prices among motorists, suggesting that consumers may be more responsive to fluctuations in gasoline costs when making decisions about EV adoption.

In a study by Rostad Sæther (2022), the evolution of the share of electric vehicles (EVs) in 32 European countries from 2009 to 2019 was examined using a panel-type model with fixed effects. The study aimed to identify the factors influencing the adoption of EVs in these countries. The results of the analysis indicated that public charging infrastructures, particularly fast charging terminals, played a crucial role in driving the adoption of EVs. In contrast, demand-side policies had a comparatively lesser impact on adoption. This suggests that the availability and accessibility of charging infrastructure, especially fast terminals, were significant drivers of EV adoption across the European countries studied.

In addition to the specific studies on EVs, there is a vast multidisciplinary literature on the diffusion of new technologies (Rogers, 2003). One of the most well-known aspects of this literature is the concept of the S-shaped adoption process, characterized by an initial phase of slow adoption followed by a period of rapid diffusion until reaching a point of market saturation where the adoption rate slows down considerably. This pattern of diffusion can be attributed to various factors, including an epidemic-type information diffusion process or variations in the costs and benefits of adoption for different agents (Geroski, 2000).

Rogers proposed a classification of agents into five categories based on their adoption behavior and a normal distribution: innovators (about 2.5% of agents) who adopt new technologies first, followed by early adopters (13.5%), the early majority (34%), the late majority (16%), and finally the laggards. Given that EV adoption rates are still relatively low, most empirical evidence including ours relates most likely to the adoption pattern of innovators and early adopters.

3. Data, Descriptive Analysis and Policy Context

The registration data for the entire vehicle fleet at the end of each year from 2011 to 2018 were obtained from the Société de l'Assurance Automobile du Québec (SAAQ). By utilizing the initial registration date and the model year of each vehicle, we were able to identify new vehicles entering the fleet each year. The dataset includes information about the type of fuel used by the vehicles. However, to ensure accuracy and completeness in the classification of vehicles, it was necessary to cross-reference this information with Natural Resources Canada's Energy Consumption Guide and car guides.

In our spatial analysis, we utilize the Forward Sortation Areas (FSAs), which are derived from the first three characters of the postal code. The first character denotes a specific part of the province, while the second character is a numeric value. For rural areas, the second character is 0, whereas for urban areas, it ranges from 1 to 9. When combined, these three characters delineate areas of varying sizes, depending on the urban or rural context (refer to Figure 2 for details).

It's important to note that we have excluded the administrative region of Northern Quebec from our econometric analysis. This decision was based on the region's sparse population and unsuitability for electric vehicles. Our dataset encompasses a total of 410 distinct areas.

The spatial, socio-demographic, and mobility pattern variables used in our analysis are sourced from the 2016 Statistics Canada census. It's important to note that we did not utilize the 2011 census data due to its unreliable nature, as the participation rate was low since responding was optional. These variables are calculated at the level of the Forward Sortation Areas (FSAs) but remain constant over time.

As for gasoline prices, they are obtained from the Régie de l'énergie. These prices represent an annual average calculated at the level of the 16 administrative regions of Quebec, as they are not available at the FSA level. It's worth noting that the regional variability of gasoline prices is relatively low compared to temporal variability, accounting for less than 5% of the total variance.

Provincial trends

The evolution of the number of new PHVs and BEVs registered in Quebec, as well as the resulting adoption rates, are depicted in Figure 3 and 4, respectively. Commencing our analysis before 2011 would not be fruitful, as the number and proportion of EVs were already very low in 2011 with 150 new EVs representing an adoption rate of 0.03%. Additionally, our sample concludes in 2018, not only due to data availability but also because supply shortages emerged as a significant issue in 2019, leading to lengthy waiting periods for new EVs. These supply shortages were exacerbated by the onset of the pandemic. Consequently, registration figures after 2018 are less likely to accurately reflect demand growth.

The growth in new EV registrations is closely linked to the increasing number of available EV models. In 2018, the registration data included 38 different EV models, a substantial increase from the mere 4 models in 2011. However, despite this expansion, a handful of leading models maintained significant control over the EV market, as demonstrated in Table 1 through cumulative registrations from 2011 to 2018. Even in 2018, the seven leading EV models collectively held a commanding market share of 70%.

Public policies have played a significant role in driving these trends. As early as 2012, the Government of Quebec introduced the Roulez Electrique program, which later became Roulez Vert, aimed at promoting the adoption of EVs primarily through purchase incentives. Until 2022, the program offered an $8,000 rebate for the purchase of a Battery Electric Vehicle (BEV) and a variable amount ranging from $4,000 to $8,000 for a Plug-in Hybrid Electric Vehicle (PHEV) depending on the battery capacity.[4] Additionally, the program included a $600 grant for the installation of a home charging station.

Concurrently, the government corporation Hydro-Québec, in collaboration with various partners such as municipalities and private companies, initiated the development of a network of public charging stations known as the "electric circuit." The number of charging points in this network expanded significantly, growing from 150 standard stations in 2012 to 1,669 standard stations and 168 fast-charging stations by 2018. In addition to this network, several smaller alternative charging networks in Quebec have been developed by private companies. Moreover, there is a network of super-charging stations specifically designed for Tesla owners. These combined efforts have contributed to the infrastructure necessary to support the growing EV market in Quebec.[5]

Spatial Variations in Adoption Rates

While most of the variability in adoption rates occurs over time (87% of the total variance), there are also noticeable variations across different areas (constituting 13% of the total variance). In 2018, Figure 2 illustrates the distribution of EV adoption rates across the province, which range from 0% to over 13% for both PHEVs and BEVs combined. As expected, the standard deviation across areas has increased over time, growing from 0.1% in 2011 to 2.3% in 2018. Figure 2 suggests that adoption rates are stronger in the outskirts of the Montreal Metropolitan Area and, to a lesser extent, in the Quebec City Area.

4. The Empirical Strategy

In this section, we begin by offering a general overview of our empirical strategy. Following this, we present our model along with a description of the variables used.

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[4]As of 2022, the rebate amount for BEVs has been reduced to $7,000 and is now limited to vehicles priced under $60,000. Additionally, the rebate for PHEVs has been capped at a maximum of $5,000. It's worth noting that since 2019, the federal government has also introduced a financial incentive for the purchase of ZEVs.

[5] Additionally, it's important to note that since January 11, 2018, the Quebec government has implemented a zero-emission vehicle standard applicable to the 2020 model year, with a plan for progressive strengthening up to 2025. The aim of this standard is to incentivize the development and accessibility of ZEV options in Quebec.

Finally, we conclude this section by discussing certain econometric issues that are pertinent to our analysis.

Overview of the Empirical Strategy

Figure 5 depicts our general empirical approach. The adoption rates of EVs fluctuate both temporally and across regions. Our model addresses temporal variations through trends and gasoline prices, while differences in EV adoption rates across areas are explained by socio-demographic, spatial, and commuting characteristics. Additionally, our model incorporates interaction terms between the trends and the area's characteristics. These terms help to explain spatial variations in trends and to analyze how an area's characteristics' impact on adoption evolves over time. We revisit this aspect later below. Furthermore, our model accounts for correlation across observations resulting from unobservable time and area determinants.

It's important to note that we have adopted a reduced form rather than a structural model. This means that our model does not include endogenous explanatory factors such as the number of charging stations or the prices of vehicles. Instead, we assume that these endogenous factors are functions of the exogenous factors included in our model, which are in turn substituted to provide a reduced form. Consequently, the estimated coefficients capture both the direct effect of exogenous determinants on the rate of adoption of EVs and the indirect effects via their impacts on these other endogenous factors.

For instance, low adoption rates in low population density areas may be due to a lower level of interest in EVs by households living in rural areas or limited access to public charging stations. We have opted for a reduced form primarily because data on prices are unavailable. Additionally, structural models often require relatively stringent identification conditions.

Importantly, our model does not explicitly measure the impact of the provincial subsidies program designed to promote the adoption of EVs. This omission is due to the fact that the impact of the program cannot be identified, given that the program has remained unchanged over the period from 2012 to 2018, and there have been no regional disparities in its implementation. Nevertheless, it is likely that this program is affecting the intercepts and trends of our model in some way, but we are unable to quantify its specific impact.

Model and variables

Our approach involves estimating a mixed model comprising a fixed component with coefficients denoted as β's, alongside a random component denoted by α's. The model takes the following functional form:

$$Ln\left(Rate\_EV_{r,t}\right) = \beta_0 + \beta_1\, Trend + \beta_2 Ln(P\_Gasoline_t) + \beta_3\, Ln(X_r) + \beta_4 Ln(X_r)\; x\; Trend + \alpha_{1r} + \alpha_{2t} + \alpha_{3r} Trend + \epsilon_{r,t} \qquad [4.1]$$

The endogenous variable in our model is the adoption rate of EVs, denoted as **Rate_EV**. This variable represents the percentage of new vehicles registered that are electric (combining VEB and PHEV) relative to the total number of new vehicles registered in area r during year t.

The fixed part of the model incorporates a common exponential **Trend** (β_1) to account for the overall progression of EVs during the 2011-2018 period. Changes in the price of gasoline (**P_Gasoline**) may cause deviations from this general trend. The parameter β_2 measures the elasticity of the adoption rate with respect to the price of gasoline, which is expected to be positive. According to theoretical expectations, a relative increase in the price of gasoline should promote the adoption of EVs by enhancing the private profitability of this investment. Additionally, as suggested by the findings of Bushnell and al. (2022), the price of gasoline is a particularly salient factor for drivers, potentially strengthening its impact.

The adoption rate is further explained by a set of area-specific variables ($\boldsymbol{X_r}$), encompassing socio-demographic, spatial, and travel profile characteristics. As previously mentioned, the inclusion of interaction terms with the trend allows the impacts of these area characteristics to vary over time. The elasticities of the EV adoption rate with respect to $\boldsymbol{X_r}$ are measured by:

$$\frac{\partial Ln\left(Rate\_EV_{r,t}\right)}{\partial Ln(X_r)} = \beta_3 + \beta_4 Trend.$$

Alternatively, the interaction terms also imply that X_r may influence the dynamics in an area, as the elasticity of adoption with respect to the trend is given by:

$$\frac{\partial Ln\left(Rate\_EV_{r,t}\right)}{\partial Trend} = \beta_1 + \beta_4\, X_r.$$

The socio-demographic variables in our model encompass various factors. These include the median total household income of the area in 2015 (**MED_INCOME**) and the percentage of households with a total income over $150,000 (**%150k+**). Existing empirical evidence suggests that adoption of EVs tends to occur first among the wealthiest households.

Additionally, these variables include the percentage of men (**%MEN**), the share of the adult population between 19 and 40 years old (**%AGE19-40**), the number of children per adult (**CHILDREN**), the average household size (**SIZE**), the share of the population with a university degree (**%UNIVERSITY**), and the proportion of self-employed workers (**%SELF**). While these factors have been identified in other studies as influential, there is no consensus on the importance or even the direction of their impacts.

Furthermore, we incorporate the share of the immigrant population (**%IMMIGRANTS**) into our model, as immigrants might have different perceptions of new technologies compared to the local population.

In terms of the spatial characteristics of an area, our model incorporates the percentage of dwellings in the area that are single detached houses **(%SINGLE**). We anticipate a positive impact on adoption from this variable, as single-family homes facilitate the installation of private charging stations.

To account for population density's impact, we classify areas into three categories. Low-density areas belong to the first quartile of the distribution (**Low_DENSITY**), intermediate-density areas fall in the second or third quartile (**Medium_DENSITY**), and high-density areas are in the top quartile (**High_DENSITY**). This simplified specification mitigates multicollinearity issues with other variables while allowing for a nonlinear effect. Specifically, we expect that low density might hinder adoption due to rural environments with long travel distances and limited charging infrastructure. Conversely, overly dense environments might also hinder adoption due to challenges in accessing residential charging facilities.

To describe the commuting profile, we incorporate the percentage of people in the area whose usual travel time between home and work is more than 45 minutes (**%LONG**). Longer commutes might incentivize adoption by making investments in electric vehicles more financially appealing. However, it's worth noting that longer commutes could also raise concerns about the range of electric vehicles and their ability to cover such distances without recharging.

The random component of our model encompasses several elements. Firstly, there's an area-specific effect α_{1r}, which accommodates omitted variables that may create correlations between observations related to the same area. Secondly, a year-specific random effect, α_{2t} allows for correlations between observations stemming from annual specific unobservable factors. Thirdly, the model incorporates a random coefficient for the trend variable, α_{3r}, which accounts for correlations arising from area-specific unobservable factors influencing the trend.

These random effects are assumed to be normally distributed, with respective variances σ_{a1}^2, σ_{a2}^2 and σ_{a3}^2. The model also allows for an arbitrary covariance between α_{1r} and α_{3r}. A negative covariance would indicate a catching-up effect: an area with an initially low adoption rate (low α_{1r}) would experience a stronger trend (high α_{3r}). Conversely, a positive covariance would suggest a decoupling effect, where areas with a low initial adoption rate also experience a lower trend.

Finally, our model includes $\epsilon_{r,t}$, which represents the traditional independent and identically distributed random error term.

Table 2 provides the definition and data sources of each variable. Table 3 presents some descriptive statistics.

Econometric Issues

Our model poses some econometric issues. First, our dependent variable, Rate_EV, represents a rate and is therefore bounded between 0% and 100%. Additionally, in 2011, Rate_EV is equal to 0% for 81% of areas, but this decreases to only 1% of areas by 2018. Specification [4.1] does not account for these aspects, which could potentially affect the validity of our inference.[6] It is important to note, however, that none of our model's predicted values fall outside of these bounds. Moreover, we reassess to this issue in our robustness analysis.

Second, our model uses random effects instead of fixed effects. This approach is required to be able to identify the coefficients. Indeed, while our data exhibit a panel structure, our explanatory variables predominantly vary along a single dimension (either spatial or temporal). The socio-demographic and geographic variables do not change over time, and the price of gasoline varies minimally across areas.

Employing random effects assumes an absence of correlation between unobservable factors and the included variables, which can be a restrictive assumption. If this assumption does not hold, the estimated coefficients may be biased. Consequently, we must exercise caution when interpreting our results. We also return to this issue in our robustness analysis.

Third, given our assumed log-log functional form (except for the trend), the coefficients can be interpreted as elasticities. Additionally, to enhance the interpretability of the coefficients in the presence of interactions, X_r is centered around its mean (i.e., $Ln(X_r/\bar{X})$). Consequently, the coefficients β_3 represent the elasticities' values in 2011 when t=0. Moreover, β_1 denotes the trend for an average area, where $X_r = \bar{X}$. Regarding the trend, we would have liked to accommodate for a S-shaped pattern, as this shape typically characterizes the diffusion of new technology. However, since the adoption of EVs is still in an early phase of exponential growth, it is currently impossible to empirically detect inflection points.

Finally, the model is estimated by maximum likelihood using the Expectation-Maximization Algorithm.[7]

5. The results

[6] Another technical challenge arises from the fact that the Log function is undefined when the EV_rate is zero. To address this issue, we resolve it by adding 0.1 to zero adoption rates.

[7]The estimation is performed with the mixed procedure of Stata 17.

Table 4 presents the estimated coefficients of model [4.1]. The variances of the random effects are statistically significant. Additionally, there is a negative correlation between α_{1r} and α_{3r}, suggesting a catch-up effect where areas with a low adoption rate at the beginning of the period experience relatively higher growth rates. However, as we will show below, α_{3r} has a limited impact on determining the trend of an area, diminishing the relevance of the catch-up effect. Maximum likelihood tests reject the hypotheses of the absence of random effects or of interaction effects of the variables with the trend.

Regarding the explanatory performance of our model, we observe that the fixed part of our model explains 68.4% of the total variance, while the random component accounts for 4.1%.[8] Since 87% of the variance in our dependent variable occurs within areas, it is unsurprising that the time-varying determinants (such as the trend, gasoline price, and time-specific random effects) explain a significant portion of the total variance (over 62%). However, area-specific determinants (including the interaction terms) explain 40% of the variability between areas.

The general trend shows an exponential growth rate of 64%, which is roughly equivalent to a geometric growth rate of 90% per year. In simpler terms, the adoption rate nearly doubles every year. Table 5 provides statistics that depict the distribution of the estimated trend values across different areas. All areas have experienced a substantial increase in adoption rates, with the lowest exponential growth rate recorded at 33% and the highest at 86%. The observable factors explain most of the variability in the trend between areas, while the influence of the unobservable factors represented by α_{3r} is rather limited.[9]

The temporal shocks common to all areas (α_{2t}) are negative in 2011 (-62% of the predicted share), in 2017 (-24%) and 2018 (-15%) and positive in 2012 (26%), 2013 (3 %) 2014 (19%) 2015 (12%) and 2016 (14%). However, these shocks typically contribute less than one percentage point of the estimated adoption rate.

The elasticity of the adoption rate concerning the price of gasoline (P_Gasoline) is 2.4, meaning that a 10% increase in gasoline prices leads to an approximately 24% increase in the adoption rate. This impact is notably higher than the elasticity of 0.25 reported by Rostad Sæther (2022) in the European context. The divergence in these findings could be attributed to differences in the analytical context and methodology.

[8] These figures are obtained using the method proposed by Nakagawa & Schielzeth (2013). The first value corresponds to the marginal R^2, i.e., the variance of the predicted values based on the fixed part of the model divided by the variance of the endogenous variable. The second value, the conditional R^2 is the ratio of the variance of the predicted values including the random effects on the total variance.

[9] The variance of α_{3r} is quite weak and the BLUP of α_{3r} represents less than 10% of the trend for 95% of the areas.

Rostad Sæther (2022) employed a country-by-year fixed-effects model, where the influence of gasoline prices is inferred solely from country-specific time variations. Consequently, variations linked to changes in oil prices, which are common across all countries, are not considered, limiting the effective variability of the price variable. In contrast, our analysis captures the impact of gasoline prices through their temporal fluctuations.

However, there is a risk of correlation between the price of gasoline and unobservable factors, potentially leading to bias from omitted variables. Hopefully, the inclusion of the trend variable in our analysis should somewhat mitigate this issue.

While not directly comparable, it's worth noting that Li et al. (2017) obtained an elasticity of the quantity demanded for Battery Electric Vehicles (BEVs) and Plug-in Hybrid Electric Vehicles (PHEVs) with respect to gasoline prices ranging from 0.49 to 1.9. Additionally, Bushnell et al. (2022) reported an elasticity of approximately 1.5 for the number of BEV sales per capita.

To emphasize the significance of the gasoline price impact, the first panel of Figure 6 depicts the model's prediction of the effect of a one standard deviation increase in gasoline price, from 130 cents per liter to 145 cents (+11%), on the temporal progression of EV adoption. According to the model, this price increase would lead to an approximate 1.4 percentage point increase in the share of EVs in 2018.[10] This finding suggests that gasoline prices indeed play a crucial role in influencing the adoption of EVs. Once again, it's important to exercise caution in interpreting this result due to the possibility that it may be capturing unobservable factors.

Regarding the impact of area characteristics, our analysis examines both the variations of these impacts over time and their influence on area dynamics. Table 6 provides the elasticities of adoption concerning area characteristics computed for the years 2011, 2014, and 2017. To demonstrate how each area characteristic affects the trend, we simulate the impact of a one standard deviation increase in the value of a characteristic on the progression dynamics.[11] Figure 6 illustrates these results, showcasing the effect of each area characteristic on the trend.

Turning to the impact of income, the results reveal that the share of high-income households (%150k+) initially has a positive and statistically significant effect, with an elasticity of 0.59 in 2011. However, this effect diminishes over time and becomes statistically insignificant, dropping to an elasticity of 0.13 in 2018. Conversely, the median income variable (MED_INCOME) shows no significant impact in 2011 but becomes positive and significant at 0.7 in 2018. This shift could be attributed to a

[10]The difference is statistically significant, even if the confidence intervals increase.
[11]We calculate this adjustment for each observation and then determine the average across all observations.

change in the buyer profile, transitioning from initially high-income innovators to early adopters with more diverse income levels.

For comparison, Morton et al. (2018) report income elasticities ranging from 0.7 to 1.18 in the United Kingdom, while Rostad Sæther (2022) identifies negative income elasticities in the European context. In the United States, Narassimhan & Johnson (2018) find a short-run income elasticity of 0.34 and a long-run elasticity of 1.2.

As shown in panels two and three of Figure 6, a one standard deviation increase in MED_INCOME results in a one percentage point higher adoption rate in 2018, with a significant effect at 10%. In contrast, the effect of %150k+ is negligible when statistically significant.

The elasticity of the adoption rate with respect to the percentage of the male population (%MEN) is initially positive at 2.8 but later becomes insignificant. As noted in the literature review, evidence regarding the impact of gender is highly varied. The simulation indicates a barely perceptible (and non-significant) positive impact on the trend following a one standard deviation increase in %MEN (Figure 6). It's worth noting that the variability between areas for this variable (%MEN) is relatively limited, with a coefficient of variation of only 3.4%, which could explain the challenge in capturing the gender impact effectively.

On the other hand, the increased presence of people in the 19 to 40 age group (%AGES_19-40) appears to favor adoption, with an elasticity of 0.5 that slightly increases over time. However, Morton (2018) and Clinton & Steinberg (2019) report a non-significant age effect. The impact of a one standard deviation increase in %AGES_19-40 from 32% to 40% on the trend is small and not statistically significant.

The ratio of children per adult (CHILDREN) initially has no impact but becomes a favorable factor over time, with an elasticity of 0.72 in 2018. The simulation demonstrates that an increase in this ratio from 0.21 to 0.27 leads to a one percentage point higher adoption rate in 2018. This result is somewhat unexpected, considering the limited availability of EVs suitable for families with children. However, it's plausible that this variable is correlated with the presence of a second vehicle, which might be more likely to be electric.

In contrast, household size (SIZE) initially has an insignificant effect but becomes significant and negative over time, with an elasticity of -2.2 over the period and -4.1 in 2018. Morton (2018) finds elasticities ranging from -3.5 to 1.4 depending on the models used. The simulation indicates that an increase in household size from 2.28 to 2.59 is associated with a significant reduction in the progression dynamics over the period, leading to a 2.3 percentage point drop in the adoption rate in 2018. This effect is quite noticeable.

The presence of university graduates in an area (%UNIVERSITY) initially has a negative impact on adoption, but this effect diminishes and becomes insignificant by the end of the period. In contrast, Morton et al. (2018) and Clinton & Steinberg (2019) report positive impacts from this variable. The trend simulation indicates a barely perceptible and statistically insignificant impact (panel 8 of Figure 6).

Conversely, the presence of self-employed workers (%SELF) promotes adoption, and this effect strengthens over time, with the elasticity increasing from 0.38 to 1.1. This finding aligns with Morton (2018), who obtains an elasticity of around 0.3 with data from 2016. The trend simulation reveals that an increase in the percentage of self-employed workers in an area from 11.7% to 15.5% supports the momentum of adoption, resulting in a 2-percentage-point increase in the adoption rate in 2018. This effect is noteworthy and does not seem to be tied to a specific tax treatment for this category of workers during the study period.[12] Instead, entrepreneurial characteristics, travel profiles, or impacts on brand image could explain this relationship.

The share of the immigrant population in an area (%IMMIGRANTS) does not significantly affect the adoption rate. While there is a positive elasticity, it is minimal and statistically significant only at the 10% level at the beginning of the period.

The presence of detached houses (%DETACHED) fosters adoption, and this effect becomes more pronounced over time, with the elasticity increasing from 0.13 to 0.31. Morton (2018) reports a similar elasticity of 0.2. Simulation of this variable's impact on the trend reveals a significant positive effect, leading to a 2.5 percentage point increase in the adoption rate in 2018 when the percentage of single-family homes increases from 47% to 74%. This substantial impact likely underscores the importance of being able to install a private charging station in the decision to adopt EVs.

Compared to areas with low population density, areas with intermediate density (DENSITY_medium) exhibit higher adoption rates. Morton (2018) finds no significant impact of population density in the UK, while Rostad Sæther (2022) shows that the share of the population in urban areas positively impacts adoption in Europe. Intermediate density also favors a more robust adoption dynamic over time, with a 3.86 percentage point increase in 2018. A similar impact is observed for regions with high density (DENSITY_high), albeit slightly more limited, with a 2.85 percentage point increase in 2018. In contrast, the adoption of EVs in rural areas appears to be much slower, likely due to issues with vehicle suitability, range, and the scarcity of charging stations in these areas. It's interesting to note that there doesn't seem to be a weaker trend in high-density areas, although we control for housing type, which determines the possibility of installing private charging terminals.

[12] The Federal government introduced favorable tax rules for ZEVs, but only in 2019.

The increase in the percentage of people with home-to-work trips lasting more than 45 minutes (%LONG) has a positive and increasing impact over time, with the elasticity rising from 0.06 to 0.3. This variable also significantly favors the adoption trend, resulting in a 1 percentage point increase in the adoption rate in 2018 when %LONG increases from 16% to 25%. This aligns with the notion that EV adoption becomes more economically viable for owners when annual mileage is sufficient.

To better understand the relative influence of different categories of factors, we analyze how they contribute to the variation between areas with the weakest and strongest adoption dynamics. These two groups are defined based on their adoption rates in 2018, with areas in the 5th percentile and those in the 95th percentile, respectively. Figure 7 depicts the simulated adoption rate evolution for these two groups based on the model results. The estimated share of EVs in 2018 is 1.44% for the first group and 9.02% for the second group.

To evaluate the role of explanatory factors in this difference, we re-simulate the adoption rate progression for the first group while adjusting the values of spatial determinants (DENSITY and %INDIVIDUAL) to match the average values of the second group. For instance, we increase the %INDIVIDUALS variable from 48% to 68%. This adjustment has a substantial impact (illustrated as the "spatial" simulation on the graph), increasing the adoption rate in 2018 from 1.44% to 4.3%, accounting for 38% of the difference between the adoption rates of the two groups in 2018.

Next, we simulate the impact of adjusting socio-economic characteristics to match the average values of the areas with the highest adoption rates. This additional change increases the adoption rate from 4.3% to 7.22% in 2018, also explaining 38% of the difference in 2018 between the two groups.

Finally, we adjust the travel profile characteristics, further increasing the adoption rate from 7.22% to 9.02%, which aligns with the adoption rate profile of the 95th percentile areas. This factor accounts for 24% of the difference in the adoption rate.

In summary, the analysis reveals that spatial determinants initially play a significant role, followed by socio-economic characteristics, and finally, travel profile characteristics, in explaining the variation in adoption rates between different areas.

6. Robustness Analysis

We begin the robustness analysis of model [4.1] by evaluating its performance using the adoption rate of BEVs only (Rate_BEV). The general trend exhibits slightly weaker growth, with an exponential growth rate of 58% compared to 66% in the case of both BEVs and PHEVs combined. Table 7 presents the estimated elasticities for 2011, 2014, and 2018. Some differences from the baseline analysis are observed, possibly due to the more recent development of BEV supply. The elasticity of gasoline price is slightly lower at 1.57. The impact of median income or income share over 150k is not statistically significant except marginally in 2014. Initially, household size appears to have a positive impact but becomes negative over time. The share of the immigrant population has a favorable effect at the beginning of the period. The commuting profile variable initially has a negative impact but becomes positive over time, possibly due to the increasing autonomy of BEVs. Overall, however, the results are quite comparable.

Since our dependent variable is bounded between 0 and 1, and many areas start with a rate of zero, we also estimate a logistic fractional model to address this characteristic. However, these models do not accommodate random effects. Instead, we consider the possible correlation of observations from the same areas in estimating the variance-covariance matrix. With this model, the coefficient on the trend is slightly lower at 55% compared to 66%. Table 8 presents the elasticities obtained from this model for 2011, 2014, and 2018. The price elasticity of gasoline is also slightly lower at 2.25 in 2018. The effect of MED_INCOME is not significant in this specification, but the effect of %150k+ is comparable to that obtained in the base model. Some socio-demographic characteristics show slightly weaker effects, such as household size. The density effect is also weaker in 2018. Simulations comparing areas in the 5th percentile and 95th percentile indicate a more limited impact of socio-demographic characteristics (20% of the difference compared to 38% in the basic model see Figure 8). It's important to note that this model overestimates the average adoption rates achieved in 2018 for the first group and underestimates them for the second.

Specification [4.1] assumes that unobservable factors are captured by random effects, which assumes no correlation between these unobservable variables and the explanatory variables. While it's not possible to estimate the model with area fixed effects due to insufficient variation in the explanatory variables across the two dimensions, we can include fixed effects at the level of the 16 administrative regions. Each region comprises between 6 and 97 FSA areas. We allow these fixed effects that have an impact on both the intercept and the trend. The trend corresponds to an exponential growth rate of 59%, and Table 9 presents the elasticities obtained with this specification. The results are quite comparable, although there is a weaker impact of spatial variables (particularly density), which can be explained by the reduced variability of these variables with the introduction of fixed effects.

6. Conclusions and Implications

Between 2011 and 2018, all regions of Quebec experienced a significant increase in the share of Electric Vehicles (EVs) in new registrations. The overall trend indicates an exponential growth rate of approximately 66%, with notable deviations in certain years such as 2011 and 2017. Regional differences are evident, with growth rates ranging from 33% to 86%. Spatial factors, including population density and housing type, play a significant role in determining regional progression dynamics. Regions with intermediate or high population density and a higher percentage of detached houses exhibit stronger progression. Socio-demographic factors also impact EV progression, with household size having an adverse effect, while the proportion of self-employed workers, the number of children per adult, and income have a positive impact. Other socio-demographic factors such as gender, age, level of university education, or the share of the immigrant population have negligible effects in our analysis. The length of work-home journeys also contributes to the growth, with longer journeys associated with more sustained EV adoption.

The price of gasoline appears to be a key factor in adoption, with an elasticity of 2.9. However, this result should be interpreted cautiously, as this variable may capture other unaccounted elements.

It's important to note that our data covers a period when adoption rates remain relatively low, primarily among innovators and early adopters. As EV technology becomes more widespread, the impact of explanatory factors may change. However, adoption in low population density or multi-dwelling environments is expected to be delayed due to challenges related to autonomy and recharging. Developing EV models tailored to rural areas, such as pick-ups, could accelerate adoption in these regions. The negative impact of household size may diminish as larger electric vehicles become available.

In terms of public policies, if the impact of gasoline prices on adoption is confirmed in future research, it underscores the importance of carbon pricing to promote the transition to EVs. Conversely, a potential drop in global oil prices could reduce demand for EVs. However, our research has limitations. We did not study the role of purchase subsidies, which are known to impact adoption but were uniform and unchanged in our study period. Similarly, we did not measure the specific impact of public charging station availability or policies imposing minimum Zero-Emission Vehicle (ZEV) quotas, which can be decisive in a supply-constrained context.

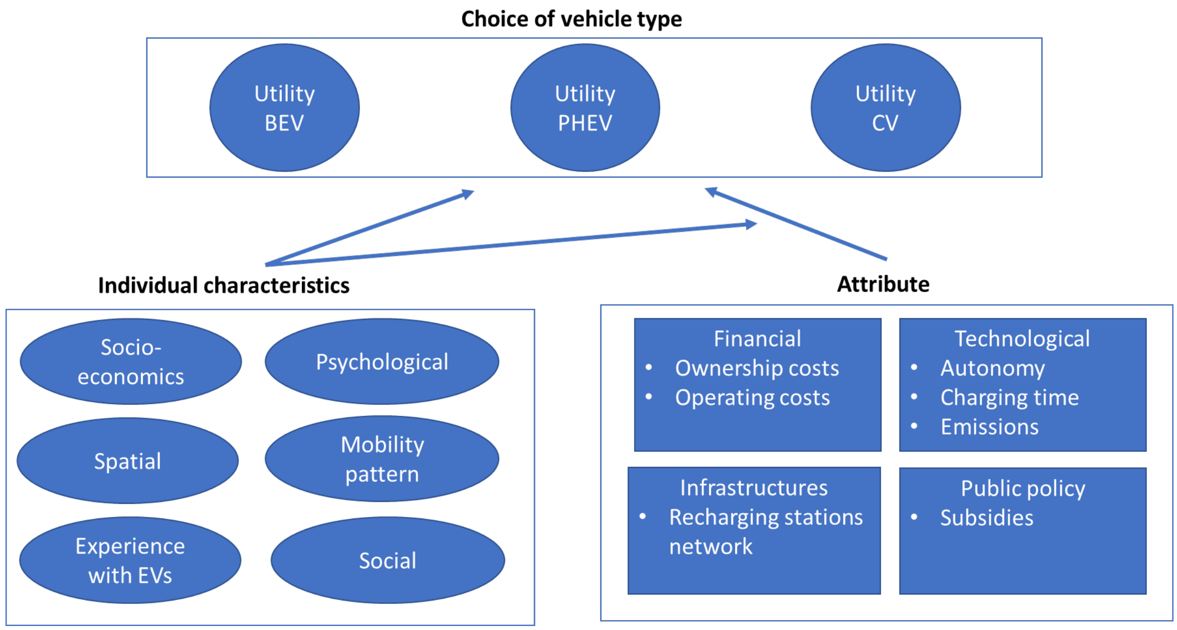


Figure 1. Framework for analyzing the choice of engine type.

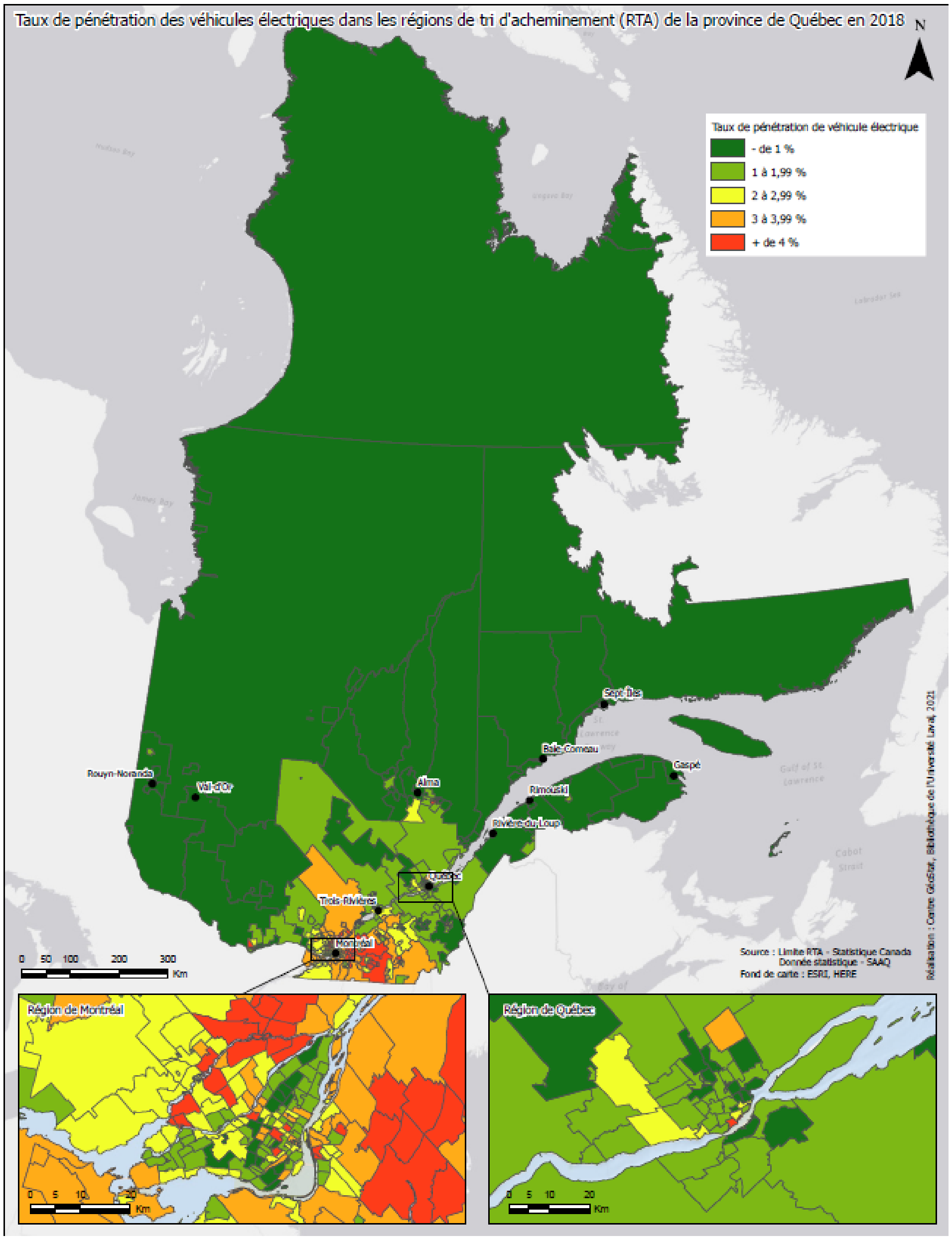


Figure 2. 2018 EV Adoption Rate by Forward Sortation Area

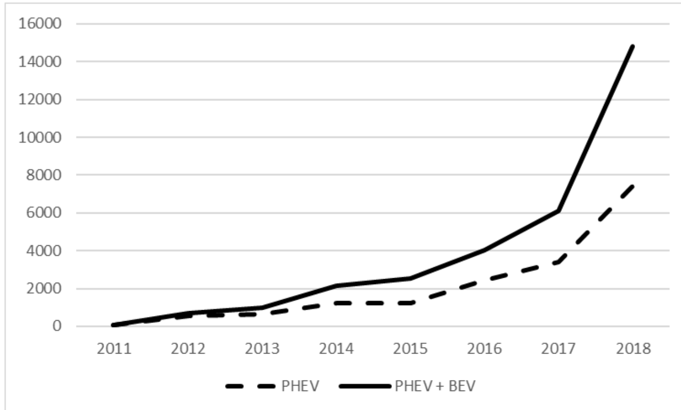


Figure 3. Temporal variation in the number of new PHEV and BEV registration

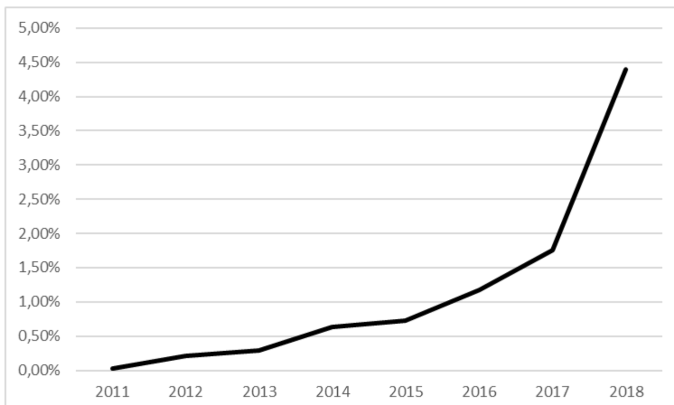


Figure 4. Temporal variation in adoption rate of EV in new vehicle registrations

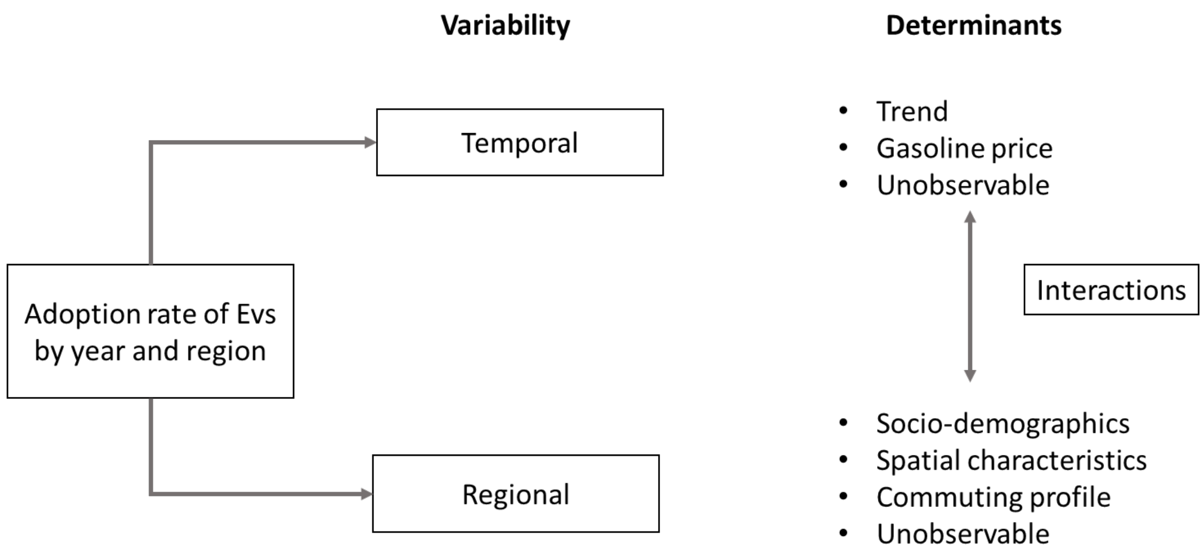
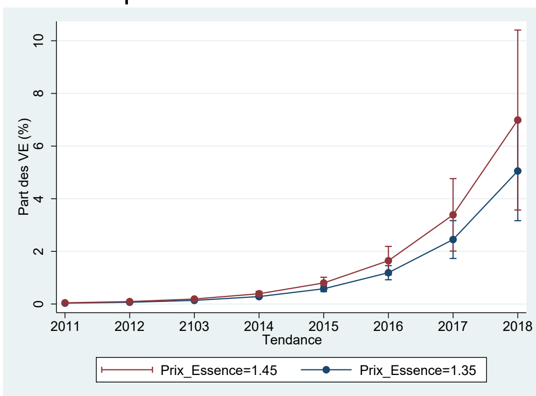


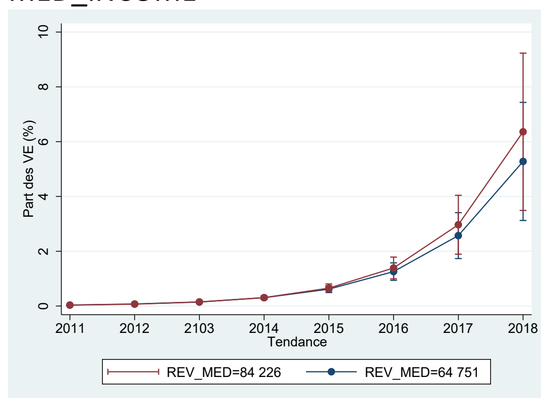
Figure 5. Empirical strategy

Year on the horizontal and simulated share on the vertical axis

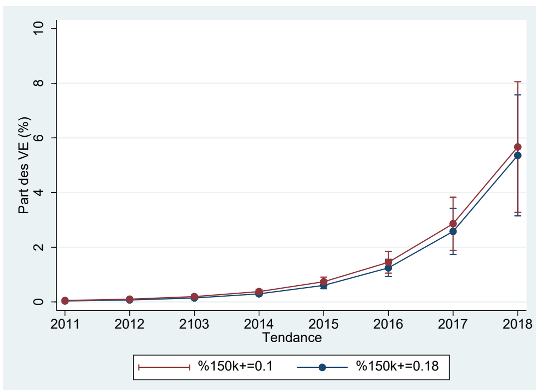
Gasoline price



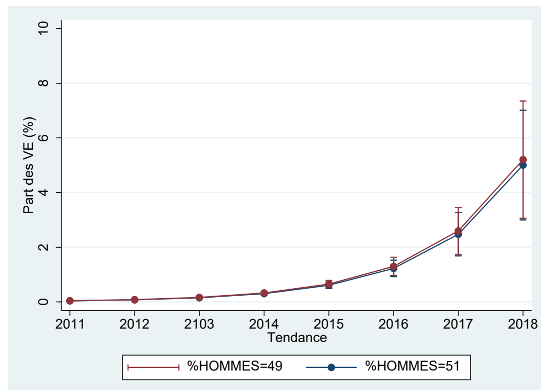
MED_INCOME



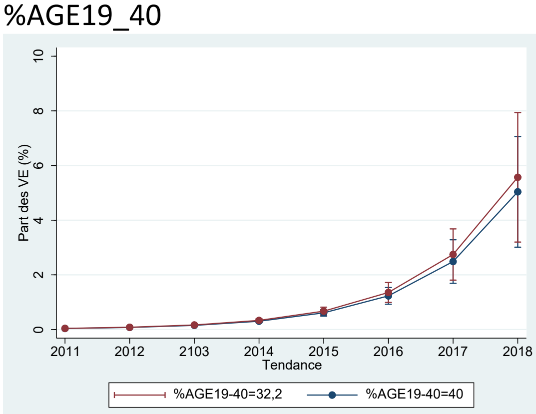
%150k



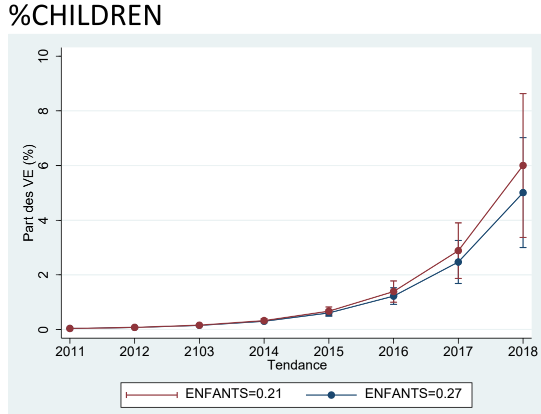
%MEN



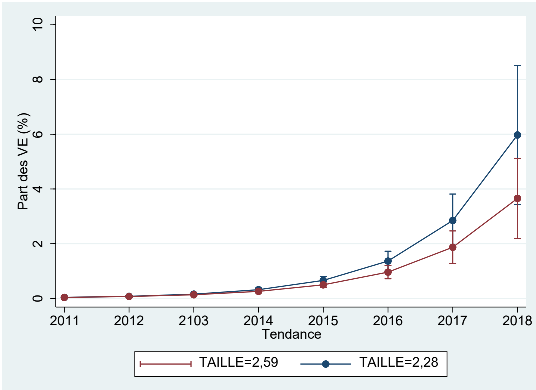
%AGE19_40



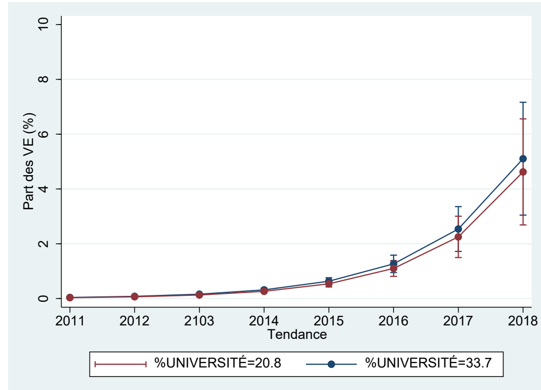
%CHILDREN



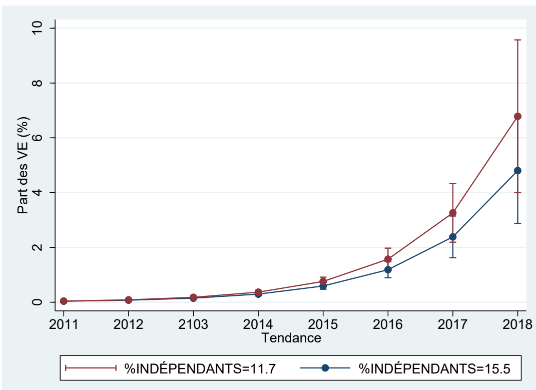
SIZE



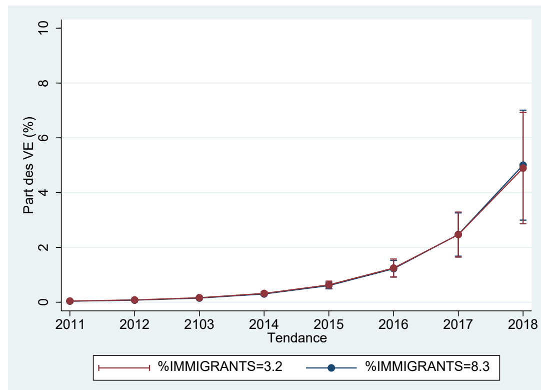
%UNIVERSITY



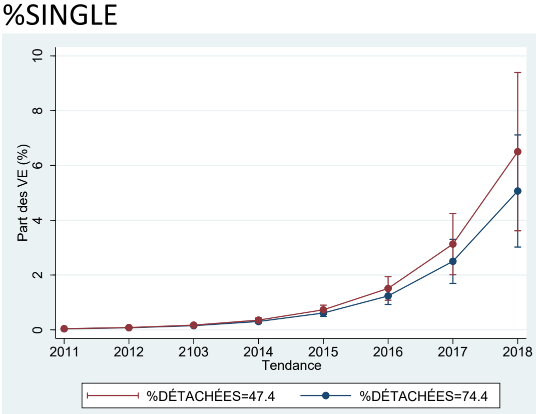
%SELF



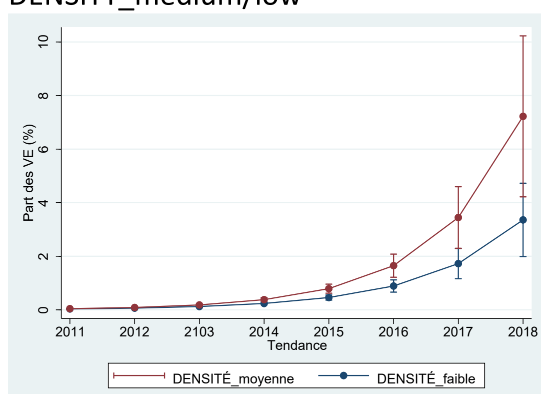
%IMMIGRANT



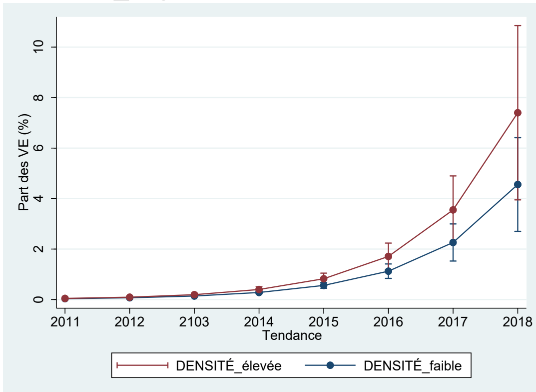
%SINGLE



DENSITY_medium/low



DENSITY_High/low



%LONG

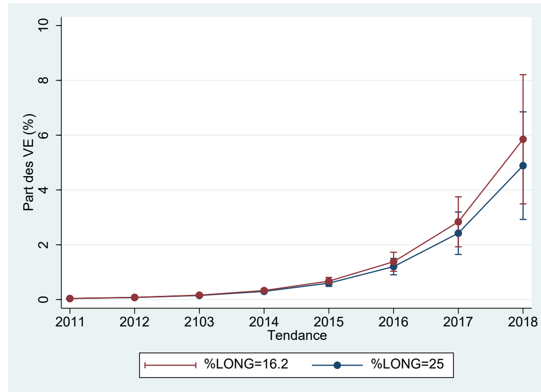
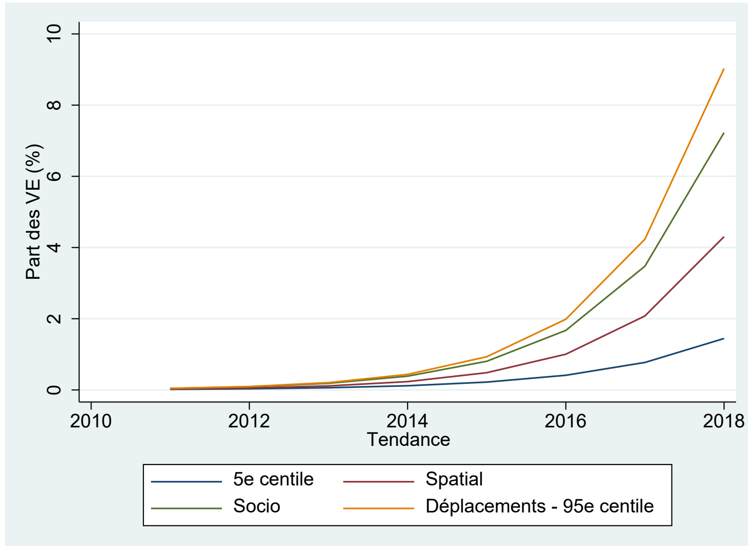
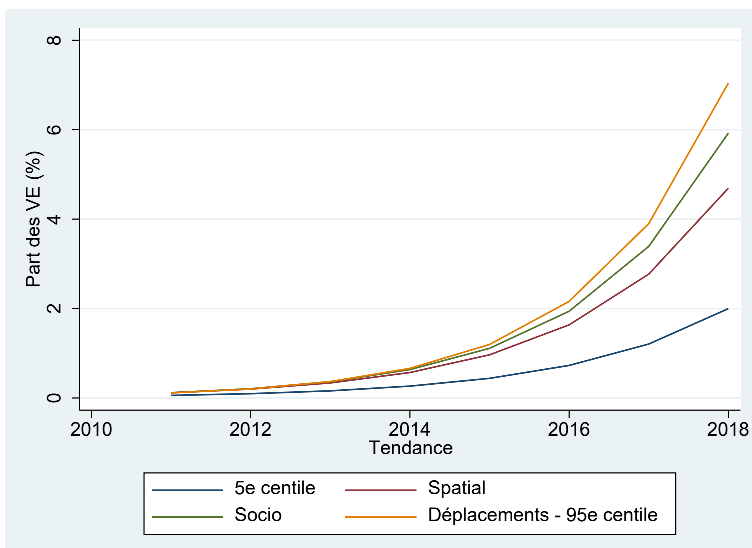


Figure 6. Average of the impact of a one standard deviation change in the explanatory variables.



Year on the horizontal axis and simulated RATE_EV on the vertical axis

Figure 7. Simulation of the gradual transformation of FSA characteristics from the 95th percentile to the characteristics of the 5th percentile in terms of RATE_VE of 2018 (base model).



Year on the horizontal axis and simulated RATE_EV on the vertical axis

Figure 8. Simulation of the progressive transformation of the characteristics of the FSAs from the 95th percentile towards the characteristics of the 5th percentile in terms of RATE_VE of 2018 (fractional model).

Table 1. Leading* EV models in Quebec over the 2011-2018 period

Make-Model	Category	Start**	Generations	End	Cumulative registration
		PHEV			
Chevrolet Volt	Compact	2010	2015	2019	8898
Toyota Prius Prime	Mid-size	2012	2016, 2023		2213
Mitsubishi Outlander	Small SUV	2018	2021		1773
		BEV			
Nissan Leaf	Mid-size	2011			4728
Chevrolet Bolt	Small Station Wagon	2017			2168
Tesla Model 3	Mid-size	2018	2021		1466
Tesla Model S	Full-size	2012	2016, 2021		1328
Kia Soul E	Small station wagon	2014		2023	1107

* This includes models that have sold at least 1000 units over the period

** First year of appearance in the registration data

Table 2. Definition and sources of variables

Variable (sources of variation)	Definition	Sources
Rate_EV (FSA, Year)	Number of new battery electric vehicles or plug-in hybrids divided by the total number of new vehicles registered x 100	SAAQ, Consumer Guides and Car Guides
Rate_BEV (FSA, Year)	Number of new battery electric vehicles divided by the total number of new vehicles registered x 100	SAAQ, Consumer Guides and Car Guides
P_Gasoline (RA, Year)	Annual average gasoline price	Quebec Energy Board
MED_Income (FSA)	Median total gross household income	Statistics Canada
%150k+ (FSA)	Percentage of households with an annual gross income of 150k or more	Statistics Canada
%MEN (FSA)	Percentage of male population	Statistics Canada
%AGE_19-40 (FSA)	Percentage of population in the age group 19 to 40	Statistics Canada
%CHILDREN	Ratio of the number of children (under 15) to the number of adults (over 18)	Statistics Canada
SIZE (FSA)	Average household size	Statistics Canada
%SELF (FSA)	Percentage of self-employed in the population aged 15 and over	Statistics Canada
%UNIVERSITY (FSA)	Percentage of population with a university degree	Statistics Canada
%IMMIGRANTS (FSA)	Percentage of population that immigrated to Canada	Statistics Canada
%DETACHED (FSA)	Percentage of dwellings that are detached houses	Statistics Canada
DENSITY_low	Population density is equal to or less than 81.43 persons/km2	Statistics Canada
DENSITY_medium	Population density is greater than 81.43 persons/km2 and less than or equal to 2832.39	
DENSITY_high	Population density is greater than 2832.39 people/km2	
%LONG (FSA)	Percentage of working population commuting for more than 45 minutes	Statistics Canada

Table 3. Descriptive statistics

Variable	Mean (standard deviation)	Min-Max
Rate_EV (%)	1.13 (1.59)	0 - 13.5
$P_{Gasoline}$ (cents)	132.2 (14.13)	103.8 - 158.8
MED_INCOME ($)	64,751 (19,475)	24,864 - 223,744
%150k+	10.3 (7.7)	0 - 63
%MEN	49.2 (1.7)	44 - 58
AGE_19-40	32.2 (7.82)	16.6 – 65
CHILDREN	0.21 (0.06)	0.04-0.52
SIZE	2.28 (0.31)	1.5-3.2
%UNIVERSITY	20.8 (12.9)	3.7-67
%SELF	11.7 (3.8)	3-32
%IMMIGRANTS	3.2 (5.1)	0.1-39
%DETACHED	47.4 (27)	0-96
DENSITY_low	0.26 (0.43)	0 – 1
DENSITY_medium	0.5 (0.5)	0 – 1
DENSITY_high	0.24 (0.43)	0 – 1
%LONG	16.2 (8.8)	2-38

Table 4: Model results (4.1)

	Coefficient [Min-Max] (Standard Deviation)	
Ln[$P_{Gasoline}$]	2.392	***
	(0.83)	
Tendency	0.642	***
	(0.05)	
Ln[MED_INCOME]	-0.371	
	(0.39)	
Ln[%150k+]	0.591	***
	(0.15)	
Ln[%MEN]	2.985	*
	(1.59)	
Ln[%AGES_19-40]	0.395	
	(0.31)	
Ln[CHILDREN]	-0.016	
	(0.28)	
Ln[SIZE]	-0.009	
	(0.80)	
Ln[%UNIVERSITY]	-0.414	**
	(0.18)	
Ln[%SELF]	0.397	**
	(0.16)	
Ln[%IMMIGRANTS]	0.071	
	(0.05)	
Ln[%DETACHED]	0.033	
	(0.04)	
DENSITY_medium	0.246	*
	(0.13)	
DENSITY_high	0.253	
	(0.20)	
Ln[%LONG]	0.049	
	(0.08)	
Trend # Log(MED_INCOME)	0.154	**
	(0.07)	
Trend # Ln[%150k+]	-0.065	**
	(0.03)	
Trend # Ln[%MEN]	-0.269	
	(0.30)	
Trend # Ln[%AGES_19-40]	0.008	
	(0.06)	
Trend # Ln[CHILDREN]	0.083	
	(0.05)	
Trend # Ln[SIZE]	-0.505	***
	(0.15)	
Trend # Ln[%UNIVERSITY]	0.035	
	(0.03)	
Trend # Ln[%SELF]	0.107	***
	(0.03)	
Trend # Ln[%IMMIGRANTS]	-0.012	
	(0.01)	
Trend # Ln[%DETACHED]	0.011	*
	(0.01)	
DENSITY_medium # Trend	0.074	***
	(0.02)	
DENSITY_high # Trend	0.033	

	(0.04)	
Trend # Ln[%LONG]	0.034	**
	(0.01)	
Intercept	-15.213	***
	(4.15)	
$\sigma^2_{\alpha 1}$	0.280 [0.20-0.38]	
	(0.044)	
$\sigma^2_{\alpha 2}$	0.062 [0.02-0.17]	
	(0.032)	
	0.002 [0.000-0.008]	
$\sigma^2_{\alpha 3}$	(0.001)	
$cov(\alpha 1, \alpha 3)$	-0.025 [-0.04—0.01]	
	(0.007)	
σ^2_{ϵ}	0.804 [0.76-0.85]	
	0.022	
Number of observations	3280	

***p<0.01, **p<0.05, *p<0.1

Table 5. Descriptive statistics on variations in trends between areas

Statistical	**Estimated trend***	**BLUP(α_{3r})****
Minimum	0.33	-0.12
10th percentile	0.61	-0.04
50th percentile	0.69	0
90th percentile	0.76	0.04
Maximum	0.86	0.10

* The estimated trend includes the fixed part (the interaction effects) and the best unbiased linear prediction ofα_{3r}

** Best unbiased linear prediction ofα_{3r}

Table 6. Basic model elasticities

	2011		2014		2018	
$P_{Gasoline}$	2.392	***	2.392	***	2.392	***
	(0.83)		(0.83)		(0.83)	
MED_INCOME	-0.371		0.169		0.708	**
	(0.39)		(0.24)		(0.31)	
%150k+	0.591	***	0.363	***	0.135	
	(0.15)		(0.09)		(0.12)	
%MEN	2.985	*	2.043	**	1.102	
	(1.59)		(0.98)		(1.25)	
%AGES_19-40	0.395		0.424	**	0.452	*
	(0.31)		(0.19)		(0.25)	
CHILDREN	-0.016		0.274		0.563	**
	(0.28)		(0.17)		(0.22)	
SIZE	-0.009		-1.775	***	-3.542	***
	(0.80)		(0.50)		(0.64)	
%UNIVERSITY	-0.414	**	-0.291	***	-0.167	
	(0.18)		(0.11)		(0.14)	
%SELF	0.397	**	0.770	***	1.143	***
	(0.16)		(0.10)		(0.13)	
%IMMIGRANTS	0.071		0.029		-0.013	
	(0.05)		(0.03)		(0.04)	
%DETACHED	0.033		0.072	***	0.110	***
	(0.04)		(0.02)		(0.03)	
DENSITY_medium	0.246	*	0.506	***	0.766	***
	(0.13)		(0.08)		(0.10)	
DENSITY_high	0.253		0.369	***	0.485	***
	(0.20)		(0.12)		(0.16)	
%LONG	0.049		0.167	***	0.285	***
	(0.08)		(0.05)		(0.06)	
Number of observations	3280		3280		3280	

***p<.01, **p<.05, *p<.1

Table 7. Elasticities for battery-only vehicles

	2011		2014		2018	
$P_{Gasoline}$	1.568	**	1.568	**	1.568	**
	(0.65)		(0.65)		(0.65)	
MED_INCOME	-0.191		0.186		0.563	
	(0.41)		(0.28)		(0.40)	
%150k+	0.236		0.200	*	0.164	
	(0.16)		(0.11)		(0.16)	
%MEN	2.072		1,780		1.487	
	(1.68)		(1.12)		(1.61)	
%AGES_19-40	0.191		0.466	**	0.741	**
	(0.33)		(0.22)		(0.32)	
CHILDREN	-0.439		0.037		0.514	*
	(0.30)		(0.20)		(0.29)	
SIZE	2.137	**	-0.458		-3.052	***
	(0.84)		(0.57)		(0.81)	
%UNIVERSITY	-0.223		-0.064		0.095	
	(0.19)		(0.13)		(0.18)	
%SELF	0.355	**	0.981	***	1.608	***
	(0.17)		(0.11)		(0.16)	
%IMMIGRANTS	0.106	**	0.074	**	0.042	
	(0.05)		(0.03)		(0.05)	
%DETACHED	-0.027		0.067	***	0.162	***
	(0.04)		(0.03)		(0.04)	
DENSITY_medium	0.141		0.488	***	0.835	***
	(0.14)		(0.09)		(0.13)	
DENSITY_high	0.308		0.364	***	0.420	**
	(0.21)		(0.14)		(0.20)	
%LONG	-0.236	***	0.081		0.399	***
	(0.08)		(0.06)		(0.08)	

***p<.01, **p<.05, *p<.1

Table 8. Elasticities with the logistic fractional model

	2011		2014		2018	
$P_{Gasoline}$	2.362	***	2.348	***	2.257	***
	(0.14)		(0.14)		(0.13)	
MED_INCOME	-0.687		-0.272		0.133	
	(0.49)		(0.24)		(0.21)	
%150k+	0.451	**	0.278	**	0.104	
	(0.20)		(0.12)		(0.12)	
%MEN	0.803		0.319		-0.154	
	(1.93)		(1.10)		(0.88)	
%AGES_19-40	0.126		0.377	**	0.606	***
	(0.29)		(0.18)		(0.16)	
CHILDREN	0.270		0.343	*	0.402	**
	(0.36)		(0.19)		(0.18)	
SIZE	-0.292		-1.266	***	-2.155	***
	(0.73)		(0.48)		(0.49)	
%UNIVERSITY	-0.210		-0.168	*	-0.122	
	(0.14)		(0.10)		(0.10)	
%AUTONOMOUS	0.487	***	0.630	***	0.745	***
	(0.17)		(0.10)		(0.09)	
%IMMIGRANTS	0.072		-0.000		-0.070	**
	(0.04)		(0.03)		(0.03)	
%DETACHED	0.300	*	0.359	***	0.402	***
	(0.16)		(0.09)		(0.08)	
DENSITY_medium	0.415	***	0.492	***	0.549	***
	(0.17)		(0.09)		(0.07)	
DENSITY_ high	0.364		0.422	***	0.465	***
	(0.23)		(0.13)		(0.11)	
%LONG	-0.083		0.085		0.242	***
	(0.09)		(0.05)		(0.05)	

***p<.01, **p<.05, *p<.1

Table 9. Elasticities of the model with fixed effects by administrative regions

	2011		2014		2018	
$P_{Gasoline}$	2.251	**	2.251	**	2.251	**
	(1.09)		(1.09)		(1.09)	
MED_INCOME	-0.449		0.240		0.929	***
	(0.40)		(0.22)		(0.30)	
%150k+	0.723	***	0.442	***	0.160	
	(0.17)		(0.09)		(0.13)	
%MEN	2.968	*	2.591	***	2.213	*
	(1.60)		(0.85)		(1.20)	
%AGES_19-40	0.296		0.214		0.133	
	(0.33)		(0.17)		(0.25)	
CHILDREN	-0.269		0.113		0.494	**
	(0.29)		(0.16)		(0.22)	
SIZE	0.732		-1.448	***	-3.627	***
	(0.87)		(0.46)		(0.65)	
%UNIVERSITY	-0.394	**	-0.127		0.141	
	(0.20)		(0.11)		(0.15)	
%SELF	0.076		0.236	**	0.397	**
	(0.21)		(0.11)		(0.16)	
%IMMIGRANTS	0.097	**	0.034		-0.029	
	(0.05)		(0.03)		(0.04)	
%DETACHED	-0.015		0.030		0.076	***
	(0.04)		(0.02)		(0.03)	
DENSITY_medium	0.079		0.223	***	0.366	***
	(0.14)		(0.07)		(0.10)	
DENSITY_high	0.256		0.266	**	0.275	*
	(0.20)		(0.11)		(0.15)	
%LONG	0.184		0.219	***	0.254	***
	(0.12)		(0.07)		(0.09)	

***p<.01, **p<.05, *p<.1

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