Speeding Up Electric Vehicle Adoption: Evidence from France

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While transportation accounts for 32% of the French greenhouse gas emissions, electrifying the car fleet has become a crucial lever in order to decarbonize the sector and deliver on the French and EU commitment to cut their greenhouse gas emissions by 55% by 2030. France is aiming for 15% of the private car fleet to be made up of electric vehicles by 2030, as compared to 1.2% today.

Yet, since EVs suffer from limited range and slow charging, as compared to internal combustion engines (ICEs), it generates range anxiety among drivers. Consequently, the willingness to buy an EV depends on the existence and accessibility of charging infrastructure. Consequently, a "chicken-and-egg" problem arises: is the rise in demand for EVs at the origin of charging infrastructures development or is the deployment of charging stations first the cause of EV demand? EV adoption is thus characterized by indirect network effects, which can slow down the electrification of the car fleet. Such characteristics have implications in terms of public policy: subsidies should indeed be tailored to be efficient in such a context. Therefore, building on the "chicken-and-egg" literature, I investigate whether, in France, from 2011 to 2022, building charging infrastructure had more impact on EV adoption than EV adoption on the deployment of charging infrastructure. I also investigate whether the effect is heterogeneous across time, space (rural v. urban areas) and level of income of an area.

Working on comprehensive French data at the EPCI ("Etablissement Public de Coopération Intercommunale") level, which is seen since the 2019-"Loi d'Orientation des Mobilités" (LOM) as the relevant entity to organize transportation services, I construct a panel dataset containing quarterly EV registrations and the number of charging stations available by each quarter at the EPCI level. To bypass the risk of having an endogeneity bias due to simultaneity, I use a 2SLS approach. To quantify the effect of charging stations on EV demand, I construct an instrument *à la* Bartik by interacting the number of supermarkets in an EPCI with the number of charging stations in all EPCIs but the observed EPCI. To quantify the impact of the size of the EV fleet on the deployment of charging stations, I use a set of past and current gasoline prices as instruments.

I find that, on average, a 10% increase in the number of charging stations led to a 11.8% rise in quarterly EV registrations. Yet, I find this effect to be heterogeneous, as it is smaller in rural areas: this suggests that rural drivers are less reliant on public infrastructure as they can more easily recharge at home since they tend to live in houses, instead of apartments, as compared with urban drivers. The effect is also smaller in low-income areas, suggesting that the budget constraint may be the main limitation when it comes to buying an EV in these territories. Reversely, I find no effect of EV adoption on the deployment of charging stations, suggesting that the building of charging stations depends much more on local political willingness to subsidize such infrastructure than on the local EV fleet.

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Abstract

While transportation accounts for 32% of the French greenhouse gas emissions, electrifying the car fleet has become a crucial lever in order to decarbonize the sector and deliver on the French and EU commitment to cut their greenhouse gas emissions by 55% by 2030. Yet, since EVs suffer from limited range and slow charging, as compared to internal combustion engines (ICEs), it generates range anxiety among drivers. EV adoption is thus characterized by indirect network effects, which can slow down the electrification of the car fleet. Therefore, building on the "chicken-and-egg" literature, I investigate whether, in France, from 2011 to 2022, building charging infrastructure had more impact on EV adoption than EV adoption on the deployment of charging infrastructure. I find that, on average, a 10% increase in the number of charging stations led to a 11.8% rise in quarterly EV registrations. Yet, I find this effect to be heterogeneous, as it is smaller in rural and low-income territories. Reversely, I find no effect of EV adoption on the deployment of charging stations.

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Contents

1 Introduction

While transportation accounts for 32% of the French greenhouse gas emissions, road transportation represents the vast majority of them (94%)[1]. More specifically, 54% of road transportation emissions originate from passenger cars. As France aims to cut its greenhouse gas emissions by 55% by 2030, in line with the European Union "Fit for 55" package, speeding up the energy transition of the transportation sector appears to be crucial: the program entitled "France Nation Verte" intends to reduce greenhouse gas emissions stemming from road transportation by 28 $MtCO_2eq$ by 2030, as compared to 2019.

To achieve such ambitious goals, electrifying the car fleet has become a central lever: the Secrétériat Général à la Planification Ecologique is aiming for 15% of the private car fleet to be made up of electric vehicles by 2030, as compared to 1.2% today. Yet, this issue calls for a more fundamental question: how can EV adoption be quickly sped up?

Subsidies on EV purchases are the most widespread instrument used by policymakers throughout the globe, which explains why a large part of the economic literature has been focusing on them. The rationale behind their implementation (Rapson and Muehlegger, 2021) is not only that there exist positive environmental externalities from driving an EV rather than a conventional vehicle, but also that EVs exhibit higher upfront costs, which could discourage purchases, and that consumers underestimate future fuel savings costs (Allcott et al., 2014).

Nevertheless, subsidising the deployment of both public and private charging infrastructure has gained traction over the recent years. These tools have started to become studied by the latest developments of the economic literature. The research question the latter tries to answer boils down to a chicken-and-egg problem: is the deployment of charging points the source or the consequence of EV adoption? Indeed, the EV market is fundamentally two-sided and exhibits indirect network effects (Li et al., 2017; Meunier and Ponssard, 2020; Springel, 2021; Hagem et al., 2023). As a consequence, subsidies on EV purchases should be evaluated with regards to their complementarity

[1] All the figures used in this section are those communicated by the Secrétariat Général à la Planification Ecologique (French General Secretary for Ecological Planning) in 2023 : "La planification écologique dans les transports".

with subsidies on charging stations. This literature stresses the magnitude of range anxiety among car buyers: it mostly finds that it is more effective to subsidize charging infrastructure deployment first - which makes it possible to reduce range anxiety, and thus to speed up adoption - and only then to complement them with subsidies on EV purchases, since subsidies on charging infrastructure suffer from decreasing marginal returns.

Yet, this literature suffers from several limitations. First, since the boom of the EV market is very recent, very few papers have investigated recent and on-going trends. This also explains why articles from this literature often study plug-in hybrids and not EVs (Gallagher and Muehlegger, 2011), even though these two types of vehicles exhibit different dynamics. Secondly, to our knowledge, no causal study on indirect network effects has been carried out on French data. Last but not least, spatial heterogeneity has generally been overlooked, whereas rural dwellers' response may differ from that of urban consumers. One key factor which should be of interest when wondering whether to subsidize chargers or EVs first in rural areas, is the fact that, as country dwellers tend to live in houses rather than apartments, they tend to have private parking space. Consequently, they may favor charging at home rather than relying on public infrastructure[2]. In such a scenario, the standard result of the literature - subsidizing chargers first - could fail.

That is why, using French data on charging stations and EVs from 2010 to 2022, I wish to answer the following issues: what is the relative impact of deploying charging stations on EV adoption, and of adopting EVs on the deployment of charging stations in France? Are these effects heterogeneous across time, space and economic characteristics?

Section 2 reviews existing policies aimed at speeding up EV adoption in France. Section 3 offers a comprehensive review of the existing literature on EV-oriented policies. Section 4 describes the data used. Section 5 presents the identification strategy used to tackle the "chicken-and-egg" problem arising because of indirect network effects. Section 6 displays the results of the analysis and Section 7 concludes.

[2]In all the following analysis, "public infrastructure" must be understood as charging infrastructure open to the public. For instance, supermarket parking lots, though privately owned, are open to the public: thus they are included in the definition.

2 Policy background

Several national incentive schemes have been created to support EV adoption. As this study focuses on the market of new electric passenger cars, only the relevant policy background is presented.

First, there exists a wide range of subsidies on EV purchases, i.e. oriented towards the demand side.

As the outcome of the "Grenelle de l'environnement" in October 2007, a bonus-malus scheme was introduced: from 2008 to 2016, EVs were eligible to a purchase bonus up to €6,300, while ICEs (internal combustion engines) emitting less than 130g of CO_2 per kilometer were eligible to a small purchase bonus. Reversely, cars emitting more than 160g of CO_2 per kilometer were subject to a small penalty. In 2016, the scheme became stricter: diesel cars were excluded from the bonus scheme and hybrid vehicles as well as plug-in hybrid cars experienced a drop in the purchase subsidies offered. The goal of such a policy was to quickly and clearly redirect subsidies towards EV purchases. Throughout the years, the bonus-malus scheme has evolved to include other characteristics which have an impact on CO_2 emissions: roof rack, weight, etc. In 2022, the closing year of the period studied in this paper, the so-called "bonus écologique" ("ecological bonus") could go up to €6,000 (capped at 27% of the purchase price), depending on the vehicle characteristics (price, model, etc.).

In addition to this bonus-malus scheme, another well-known incentive device exists since 2015: a "cash for clunkers" scheme ("prime à la conversion" also known as "prime à la casse"). In 2022, drivers who wished to change from an ICE[3] to an EV could get up to €5,000, depending on the type of car bought and on their income.

More recently, in January 2024, the government launched a new program focused on low-income households : the "electric social leasing" program. It enables low-income households to rent an EV on a long-term contract basis for only €100 per month.

[3]In 2022, only diesel cars registered before 2011 and gasoline cars registered before 2006 were eligible.

Secondly, even if they are less well-known from the general public, there exist subsidies on the deployment of both public and private charging infrastructure. The national program entitled "Advenir", launched in 2016, delivers subsidies on the installation of charging stations. The amount granted depends on the status of who is calling for the installation (citizens or firms for instance), where it is installed and under which conditions[4]. In addition, installing charging points can be eligible to tax credits. It is also subject to a reduced value added tax rate (5.5%) since 2014.

Finally, it is worth noting that only national subsidy programs were presented in this section. Yet, there also exists a variety of local subsidies offered by some French regions, departments and intercommunalities[5]. As they greatly differ across territories, summing them up here is impossible.

3 Literature Review

A large part of the literature regarding the EV market has been focusing on policies targeting demand, since they are the most widespread. Yet, a part of it has also focused on the supply-side of the market, by investigating for example the role of standards. Nevertheless, the most recent papers have been focusing on the interactions between these two types of policies, especially regarding the presence of indirect network effects in the EV market and its impacts on the design of optimal policy.

3.1 Demand-Side Policies

Most existing EV incentives today are directed towards demand, under the form of subsidies. The rationale behind them (Rapson and Muehlegger, 2021) is not only that there exist positive

[4]For instance, the amount granted is higher when an association of co-owners installs a shared charging point than when a driver living in a multi-unit building installs a private, individual one.

[5]An intercommunality is a form of cooperation between nearby municipalities deciding to delegate some of their powers to this new public entity, officially called "établissement public de coopération intercommunale" (EPCI). Following several laws (MAPTAM law in 2014, NOTRe law in 2015 and LOM law in 2019), the powers of EPCIs have been strengthened and extended. Notably, most EPCIs are now in charge of organizing local public transportation. That is why the analysis is conducted in this paper at the EPCI level.

environmental externalities from driving an EV rather than an ICE, but also that EVs exhibit higher upfront costs which could discourage purchases, and that consumers underestimate future fuel savings costs (Alcott et al., 2014). Thus, even acknowledging that implementing optimal Pigouvian taxes on electricity and fuels was feasible, consumers would under-adopt EVs anyway because of cognitive bias. Moreover, from a cost-effectiveness perspective, one would prefer concentrating subsidies on agents who would not have bought an EV absent the reform, and not on those who would have anyway.

3.1.1 Efficiency

Testing for a causal and positive impact of fuel-alternative subsidies on adoption is a research question which has expanded in the 2010s and has been approached through three different perspectives: do consumers respond to incentives? Does the design of the subsidy influence consumers' response? Does the price of gasoline have an impact on the decision to buy an alternative-fuel vehicle and is this impact more or less large than that of subsidies?

Albeit focused on hybrid cars and not EVs, the first seminal paper regarding this issue (Gallagher and Muehlegger, 2011) uses quarterly, state-level sales data for eleven hybrid car models sold in the U.S. from 2000 to 2006, to estimate a time- and state-model fixed effects, which shows that monetary incentives have a positive impact on hybrid sales, albeit of unequal magnitude, conditional on their design: sales tax waivers are ten times as effective as income tax credits and, on average, gasoline prices have no significant effect.

This contradicts Diamond's findings (2009) over the exact same period: while incentives have poor impacts, a 10% rise in gasoline prices is estimated to lead to a 72% increase in state hybrid market share. This opposition being essentially driven by the use of different data sources, Diamond doesn't rule out the possibility for efficient subsidies, since he attributes this lack of significant impact to the time a consumer has to wait to get back the tax credit.

De facto, more recent studies claiming to build on Diamond's work have demonstrated the efficiency of such tax incentives. Jenn et al. (2018) take advantage of much more precise data to estimate three different specifications and find a significant and positive impact of incentives on EV sales in the U.S., in line with Gallagher and Muehlegger (2011). They also add to the literature by their third specification, a lagged-dependent model, which addresses simultaneity, the main weakness of EV literature: do EV sales increase thanks to state subsidies or does the increasing demand for EVs in some states encourage these states to implement incentives?

Yet, the jury is still out considering cost-effectiveness. Chen *et al.* (2021) put forth an overlooked mechanism of the literature. Adopting a difference-in-difference setting in China, they highlight that, if at first sight, subsidies boost EV sales, the policy actually generates a substitution effect from highly fuel-efficient vehicles towards EVs: this mechanism raises the cost of the policy since only the agents who already adopted satisfying vehicles actually choose to move to an EV. The authors thus conclude that the program reduces social welfare.

3.1.2 Distributional Effects

Nonetheless, properly assessing any consumer subsidy program also requires a distributional analysis. A consensus has arisen in the literature: uniform subsidy policies tend to be unfair.

In line with Allcott et al. (2015) who find that energy efficiency subsidies are first and foremost taken up by wealthier and better informed agents, Borenstein and Davis (2016) show this result holds for EV subsidies: the top income quintile received 90% of the EV tax credit scheme studied.

In line with these findings, Fournel (2023) estimates a structural model and conducts a cost-benefit analysis on a Canadian subsidy program: even if it led to a 93% increase in EV adoption, half of the subsidies is captured by agents who would have bought an EV even absent the program. Those agents being wealthier on average, Fournel envisions targeting such policies under a certain income threshold. Nevertheless, in this case, efficiency and equity are not aligned: he finds that a “cash for clunkers” program would be more effective to speed up EV adoption at a lower cost.

However, if structural estimation can be useful to estimate the impacts of one-size-fits-all subsidy policies, quasi-experimental approaches seem more appropriate to estimate the effects of income-targeted subsidies: indeed, very few articles exist on this issue in the literature, thus little is known about the demand elasticity of low- and middle-income consumers. Yet, it has become a very active field of research since the landmark paper written by Muehlegger and Rapson (2022). Taking advantage of a quasi-experimental setting in California following the implementation of an EV subsidy program specifically targeting the low- and middle-income consumers, they conduct a matched difference-in-difference and a triple-difference: this state-of-the-art econometric approach enables them to find the first precise estimates of EV subsidy responsiveness of households ranked at the bottom of the income distribution. The authors show that, surprisingly, they are quite responsive: a subsidy decreasing the buy-price of EVs by 10% increases demand by 21%.

3.1.3 When Efficiency and Equity Meet

Yet, Muehlegger and Rapson (2022) don't delve into the issue of cost-effectiveness. Thus, considering Fournel's results, does that mean efficiency and equity are irreconcilable?

Being increasingly studied in these last few years, the recent answers given are a clear "no". Estimating a vehicle choice model based on representative American car buyers in 2015, Sheldon and Dua (2019) show that cost-effectiveness could actually be doubled if subsidies were targeting the consumers who wouldn't have bought an EV absent the incentives: low-income or rural car buyers for instance. Reconciling efficiency and equity, they also underline that it could increase social and political acceptability of EVs. Similar results are found by Xing et al. (2021) who conclude that current federal tax credit program increased EV sales but that 70% of them were captured by consumers who would have bought an EV anyway, whereas providing larger subsidies to low-income households would have been both more cost effective and more progressive. This leads Joshua Linn (2022) to conclude that there is no trade-off between efficiency and equity, conditional on targeting low-income households and taking into account interactions of subsidies with other policies: income-based subsidy is found to be 40% more effective than other schemes.

3.2 Supply-Side policies

If the majority of policies implemented are oriented towards demand, through subsidy programs, speeding up EV adoption entails to use all available levers, including those affecting supply constituted of car manufacturing and charging infrastructures. Interestingly, the main supply-oriented policies implemented by governments - and studied by the literature - are based on standards.

3.2.1 Standards

Non-monetary incentives have been widely used by governments to act on carmakers, may it be directly or indirectly. In the US, two main supply-side efficiency standards exist: the Zero Emission Vehicle (ZEV) and the Corporate Average Fuel Economy (CAFE) (Rapson and Muehlegger, 2021). ZEV sets manufacturer-level targets for ZEV sales while CAFE sets fuel-efficiency norms.

However, the effects of such standards have been challenged by the economic literature from the start, as economists usually consider price instruments to be more efficient and less costly. In line with Austin and Dinan (2005) who find gasoline taxes would have saved more gasoline and at a lower cost, Jacobsen (2013), using a representative car producer, concludes that CAFE exhibits poor cost-effectiveness and, more importantly, raises equity issues from two standpoints: (1) because of heterogeneity between firms, some being exempted, the costs are mainly supported by domestic firms; (2) because it also increases car prices on the secondary market (used cars), low-income households are largely negatively impacted.

If standards ought to be considered carefully for efficiency and equity reasons, the particular case of EVs though makes them more useful than in the standard economic theory. Estimating a structural model, Jing Li (2023) shows that unifying incompatible charging standards into a uniform standard would lead to a 4.3% increase in EV sales in the US between 2011 and 2015 while also considerably increasing consumer surplus.

3.2.2 Carmaking Innovation

The rationale for supply-side policies is partly based on the acknowledgment that demand subsidies aren't efficient enough in quickly speeding up EV adoption: predicting the future market share of EVs in the U.S. from 2020 to 2035, Archsmith et al. (2021) highlight that "the first $500 billion in cumulative nationwide EV subsidies is associated with a 7-10% increase in EV market share in 2035" only, in addition to having decreasing returns. The authors stress that non-monetary factors, such as car quality and range limitation, are crucial in stimulating demand, reinforcing the need for technology improvement. Since then, this idea has been empirically documented: Forsythe et al. (2023) demonstrate that technology improvement is *the* force which has driven the increase in EV share in the US in recent years, in particular the improvement in range limitation (the average range of BEVs has increased by 200%), fast-charging capabilities and operating costs. The authors show that innovation made possible to compensate EVs perceived flaws from the consumer perspective and predict that expected innovation should lead consumers to be willing to pay up to a $8,000 price premium to buy an EV over a conventional car.

Those conclusions identify an important driving force of EV adoption but don't state how to efficiently support innovation in this type of industry. A less recent literature has addressed this issue by working more generally on energy-saving technological change and showed that such innovation was encouraged by higher fossil energy prices and stricter standards (Newell et al., 1999). Building on it but focusing on EVs, Knittel (2012) finds a significant positive relation between rising prices and rising CAFE standards and annual technological progress for cars. Klier and Linn (2016) go further by using cross-sectional variations in the stringency of the standards and fixed effects to control for confounding factors: increasing stringency led to a faster rate of adoption of new technologies by car manufacturers.

3.2.3 Charging Infrastructure Development

The other side of supply on the EV market, charging infrastructure, has been shown to be the most crucial dimension of supply to speed up EV adoption because of the extent of drivers' range anxiety (Springel, 2021). The extensive analysis of Schulz and Rode (2022) conducted between 2009 and 2019 in Norway, a country where 90% of the annual sales are made up by EVs, both shows that developing a wide network of chargers is *efficient* in stimulating demand and can respond to *equity* concerns. Using an event study setting, they use a difference-in-difference approach following the state-of-the-art method of Callaway and Sant'Anna (2021) to estimate the effect of a municipality getting its first charger on EV adoption. They find a robust, significant and strong positive effect on local electric vehicle ownership rate, which increases by 200% over five years. An interesting complement to this analysis is that of Neaimeh et al. (2017) which underlines, in the US and UK contexts, that the type of charger also matters much: fast chargers have a stronger effect.

3.3 Policies Interactions

So far, we have shown that demand- and supply-side policies could be, depending on their design and on the context, both efficient and equitable in speeding up EV adoption. The latest developments in the literature have focused on the interactions between these different policies. Taking them into account can greatly change the outcome.

3.3.1 The Need for Studies of Policies Interactions

The need for studying interactions stems from both efficiency and equity concerns.

From an efficiency standpoint, Gillingham et al. (2021) give an important example of issues arising when policies interact with each other. Studying the interaction between carbon pricing and EV adoption policies, the authors show that in the U.S., under moderate carbon prices, the benefits from carbon emissions reduction thanks to EV adoption would be reduced. Indeed, in a country such as the U.S. where electricity generation is highly based on fossils, a larger adoption of EVs would lead to an increase in electricity demand which, under moderate carbon pricing, would be met by coal generation pushed up to the margin. This would also lead to slowing coal plants retirements. Using historical data, the authors demonstrate that such mechanisms actually occurred in several regions. Surprisingly, this means that benefits from EV adoption would be higher under no carbon price or high carbon price than under a moderate carbon price.

From an equity perspective, interactions between EV subsidy programs and other policies, especially standards, change the trade-off between equity and effectiveness. Linn (2022) demonstrates that income-based subsidies make it possible to preserve the progressivity of the system overall, even when interacted with ZEV standards: while the latter is likely to be regressive because it decreases prices of EVs when high-income individuals are more likely to buy EV, income-based subsidies make it possible to counteract this effect.

3.3.2 The "Chicken-and-Egg" Issue

Even if there have been few studies on policies interactions until then, one specific interaction has been particularly investigated: subsidies to EV consumers v. subsidies to charging infrastructure development. The EV market is a two-sided market with important indirect network effects: the willingness to buy an EV depends on the existence and accessibility of charging infrastructure. Consequently, a "chicken-and-egg" problem arises: is the increased demand for EVs at the origin of charging infrastructures development or is the deployment of charging stations first the cause of EV demand? What should be subsidized first and foremost?

The theoretical building blocks of the study of these policies interactions can be found in Meunier and Ponssard (2020) who consider a static partial equilibrium model with indirect network effects. They conclude that the optimal policy would be to subsidize both charging stations and EVs because the existence of indirect network effects can lead to getting stuck in the Pareto-dominated market equilibrium.

These theoretical findings have since then been empirically investigated. The very first seminal paper doing so (Li et al., 2017) finds evidence of pretty large indirect network effects and recommends to subsidize charging infrastructure deployment first as it is more cost-effective: a 10% increase in the number of public charging stations (respectively, in the stock of EV) would lead to an 8% increase in EV sales (respectively, a 6% increase in charging station deployment).

Since then, recent papers have built on this landmark study. For instance, Springel (2021), whose study has become a reference, addresses the same research question but adds to the literature by estimating a structural model based on a simultaneous-move game where, in each period, consumers and stations make decisions under complete information. Applying the study to comprehensive Norwegian data, she confirms Li et al.'s (2017) results: station subsidies were more than twice as effective as price subsidies in Norway between 2010 and 2015. Yet, she also adds to the literature by showing that such subsidies exhibit decreasing marginal gains, hence the need for demand subsidies thereafter. Those results are now getting traction within the literature: Hagem et al. (2023), by calibrating and estimating a numerical model for Norwegian abatement policies, also highlight that governments should start by subsidizing stations even if they exhibit higher marginal abatement costs because such a policy increases EV adoption in the long run and not only in the few following years.

3.4 Ramifications

This review has exhibited too main take-aways regarding how to speed up EV adoption. First, whereas EV incentives are usually divided by policymakers into incentives targeting *either* demand *or* supply, an efficient policy should act on both of them, by taking into account their interaction, which is all the more important on the EV market as it exhibits indirect network effects. Secondly, EV incentives are not neutral: their distributional effects should always be carefully monitored, even more so if policymakers aim to increase the acceptability of energy transition policies.

Yet, this review has also shown how small the empirical literature on the "chicken-and-egg" issue regarding the EV market is. Indeed, it is mainly the U.S. and Norwegian contexts which have been studied until then. Moreover, papers have studied distant periods which correspond to the beginning of car fleet electrification. Hence, as Glachant (2021) puts it: "Many consumers purchasing EVs during that period are likely to be early adopters who are less price sensitive than the general car-buying population. The extent to which these estimates scale and their applicability in other market contexts is an area that would benefit from addition empirical research". This is what the following analysis tries to accomplish, regarding the French context.

4 Data

Building on this "chicken-and-egg" literature, we aim to address some of its limitations. First, to our knowledge, no paper has ever studied this issue in the French context. Secondly, many papers in this literature study plug-in hybrids instead of EVs, whereas these two types of vehicles have different dynamics. Finally, Li et al.'s seminal paper (2017) uses U.S. data from 2011 to 2013 : not only is it a short period, but also the situation has evolved a lot and very quickly since 2013, with an increase in both the number of charging stations and of EV sales. In addition, the paper delivers an analysis at the Metropolitan statistical Area (MSA) level : this is a large and urban aggregate - e.g. the New York MSA encompasses more than 12,000 km^2 and 20 million inhabitants. Thus, this may not be the most relevant aggregate to study consumers' behavior and geographical heterogeneity.

Consequently, I work on comprehensive French data from 2011 to 2022 at the EPCI ("Etablissement Public de Coopération Intercommunale") level, which is seen since the 2019-"Loi d'Orientation des Mobilités" (LOM) as the relevant entity to organize transportation services.

4.1 Data Sources

I use two main data bases to construct a panel dataset containing quarterly EV registrations and the number of charging stations available by each quarter at the EPCI level, from 2011 to 2022, in hexagonal France (i.e. France without Corsica and overseas territories). The final panel dataset consists of 987 EPCIs, out of the 1213 EPCIs existing in hexagonal France in 2022, due to lacking data regarding charging stations in some EPCIs.

The first dataset, built upon data from the "Ministère de la Transition Ecologique et de la Cohésion des Territoires"[6] which are based on data from the "Agence Nationale des Titres Sécurisés" (ANTS[7]), contains the number of quarterly registrations of new cars, including electric passenger cars, in each French municipality from 2011 to 2022. It also gives the number and nature

[6]French Ministry for the Green Transition and Territorial Cohesion.

[7]The ANTS is a French administration taking care of the edition of official papers, such as passports and car registration documents.

of the cars making up the fleet, yearly. To run the regressions, I only keep electric passenger cars used by private individuals (as opposed to professionals[8]). Based on the Insee[9] municipality code[10] and the EPCI code, I am able to match municipalities to the EPCI they were attached to on January 1, 2022, thanks to the table of correspondence offered by BANATIC[11].

The second dataset used is an open data base displaying information about available public charging stations in France : the "répertoire national des Infrastructures de Recharge pour les Véhicules Electriques" (IRVE). It is published by transports.data.gouv, a "State startup" ("startup d'Etat") created on the initiative of the interministerial direction of digital technology (DINUM, "Direction interministérielle du numérique") and placed under the supervision of the "Ministère de la Transition Ecologique et de la Cohésion des Territoires".

As it is an open dataset, it requires much data cleaning. Using the version published on March 9, 2024, it first displays 90,177 stations. Yet, the commissioning date is often missing, while necessary to pursue the analysis: thus, filtering out observations without proper date, 63,618 stations are left. Some dates are outliers (e.g. year 1920 or 1970 for the building of a station). In addition, since the risk of having errors in the dates before 2010 is high and since the number of such observations is negligible, I remove stations built before 2010. Moreover, since the analysis runs from 2011 to 2022, I remove stations built after 2022. Then, as it is difficult to assign charging stations built on highways to a specific municipality (and thus, to an EPCI) and since it is unlikely that drivers pay the highway toll to get their EV charged on a daily basis, I remove such stations. Filtering for all of this, there are 37,139 stations left. However, many of these observations are actually duplicates: thanks to their address, I remove such duplicates. In the end, there are 11,824 stations

[8]I exclude electric cars bought by professionals because they may adopt different behaviors: for instance, it is very likely that they charge their car on their workplace, with chargers not being open to the general public. They may even leave their car there at night. These different behaviors could have biased the results.

[9]"Institut national des statistiques et des études économiques" (French national statistics institute).

[10]The Insee municipality code is different from the zip code. It is uniquely attached to each municipality, while several municipalities can have the same zip code.

[11]BANATIC, "Base nationale sur l'intercommunalité", is the national information system collecting data regarding intercommunalities (EPCIs), developed by the "Direction générale des collectivités territoriales" (DGCL), a department of the French Ministry of Internal Affairs ("Ministère de l'intérieur"). URL: https://www.banatic.interieur.gouv.fr/V5/a_propos/banatic.php.

registered which can be worked on. Out of these 11,824 stations, 3,823 observations display an unchecked Insee municipality code or location. Therefore, I extract for each of these addresses the string which is the most likely to correspond to the municipality name. Then, I check by hand the names (orthography, homonyms, etc.), which then enables me to match these previously unchecked stations to EPCIs. In the end, I work on 11,824 stations spanning 987 EPCIs.

Note that all the following analysis is run at the charging station level, not at the charging point level. Indeed, it appears in the data that the registered number for charging points is not standardized. Some service providers seem to understand it as the number of charging terminals within a station, while others register the total number of plugs there are on the charging terminals of the station. Moreover, several typing errors can be identified in the number of charging points registered: the number is sometimes artificially high even in very small towns. It seems also that the error is non-random as some regions are more subject to it. Checking such high numbers on specialized websites such as "Chargemap", it appears that they are indeed mistakes. Consequently, to avoid both of these issues, I work on a more robust indicator : the number of stations per EPCI. For several reasons, I suspect the results would not be very different if one used clean charging points data.

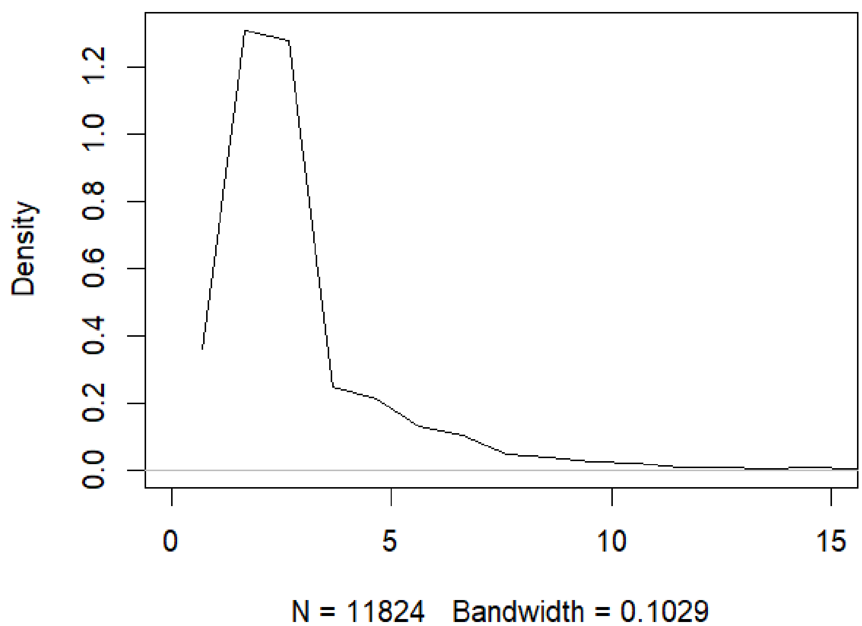
First, if the charging points data set I have is not *too* distorted, one can see on Figure 1 that most stations have the same number of charging points : two or three. The distribution is indeed right skewed. This would be coherent with the numbers communicated by Avere-France ("Association nationale pour le développement de la mobilité électrique")[12]: the association concluded that at the end of 2022, there were 30,352 charging stations and 82,107 charging points in France, which gives a mean of 2.7 charging points per station[13].

[12] Avere-France is the National Association for the Development of Electric Mobility, created in 1978 to gather and represent professionals working in this sector. The numbers published by the association each month are considered as very reliable and are regularly used by officials and newspapers.

[13] Avere-France, January 2023, "Baromètre national des infrastructures de recharge ouvertes au public", URL: https://www.avere-france.org/publication/barometre-82-107-points-de-recharge-ouverts-au-public-fin-decembre-2022/.

Secondly, it can be argued that what drives a local upsurge in EV sales is really the change stemming from having no charging point installed at all to getting one charging point installed. To put it differently, the first charging point is the one generating the main effect: recent literature (Springel, 2021) has shown that charging points exhibit decreasing marginal returns. In addition, seeing suddenly a charging point installed in public space is likely to acculturate drivers to EVs, as well as to reduce their range anxiety, and thus to convince them to take the plunge and buy an EV.

Figure 1: Density of the number of charging points according to the dataset used



Notes: This graph draws the density of the number of charging points per station in 2022 in the data set used. Note that descriptive statistics give that the minimum is equal to 1, the first quarter and median to 2, the third quartile to 3 and the maximum to 505. The mean is equal to 3.289.

Finally, in the EV demand equation, the number of supermarkets is needed to construct the instrumental variable *à la* Bartik. I find such data thanks to OpenStreetMap.

4.2 Descriptive Statistics

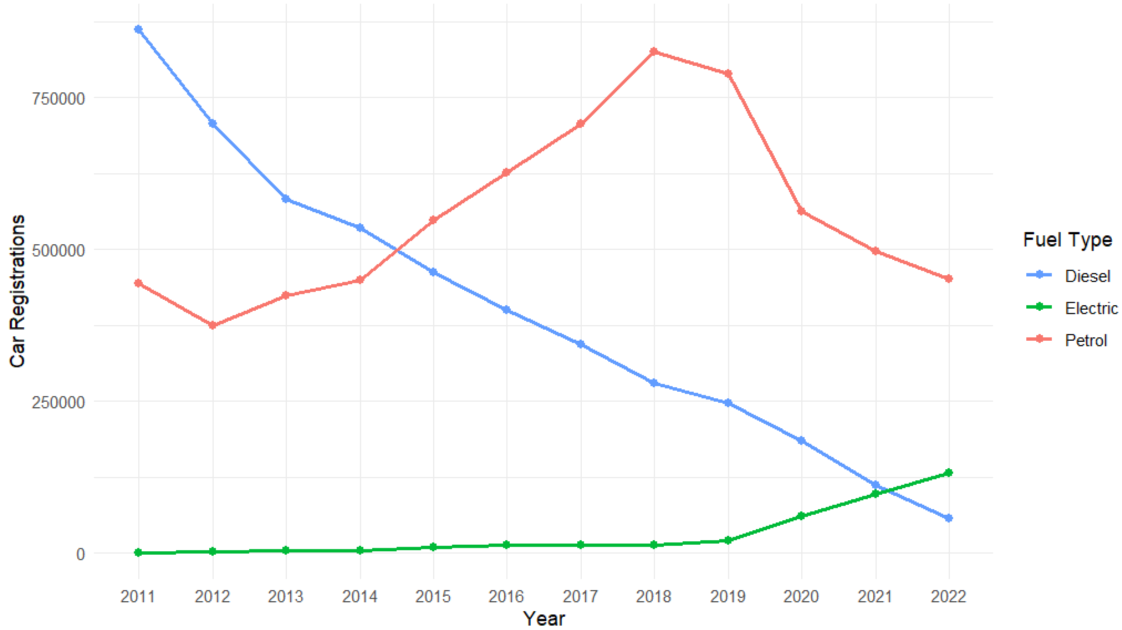
Figure 2 depicts the evolution of the number of new passenger cars registrations between 2011 and 2022. First, the constant decline of diesel-powered cars since 2011 is absolutely striking:

in 2022, there were fewer registrations of diesel cars than of EVs. This drop is partly due to the introduction of stricter environmental standards[14], improvement of petrol-powered cars, and scandals, such as the "Dieselgate" in 2015 with Volkswagen. Secondly, one can see on the graph that petrol cars may have benefited from the drop in diesel cars at the beginning, as the number of registrations went up until 2018. Thereafter, as of 2019, registrations of petrol-powered cars started falling sharply. Thirdly, if the important drop in 2020 was partly driven by the global Covid-19 pandemic, the graph shows an interesting pattern: the number of EV registrations increased significantly as of 2020, the very same year as the pandemic, and kept increasing thereafter. Thus, this first graph seems to suggest a new trend in consumers' behaviors.

If the share of EVs in the total car fleet remains very small (Figure 3) as the surge in EV sales is quite recent, Figure 4 shows that the increasing trend of EV ownership has closely followed the shape of the upward trend of the number of charging stations installed.

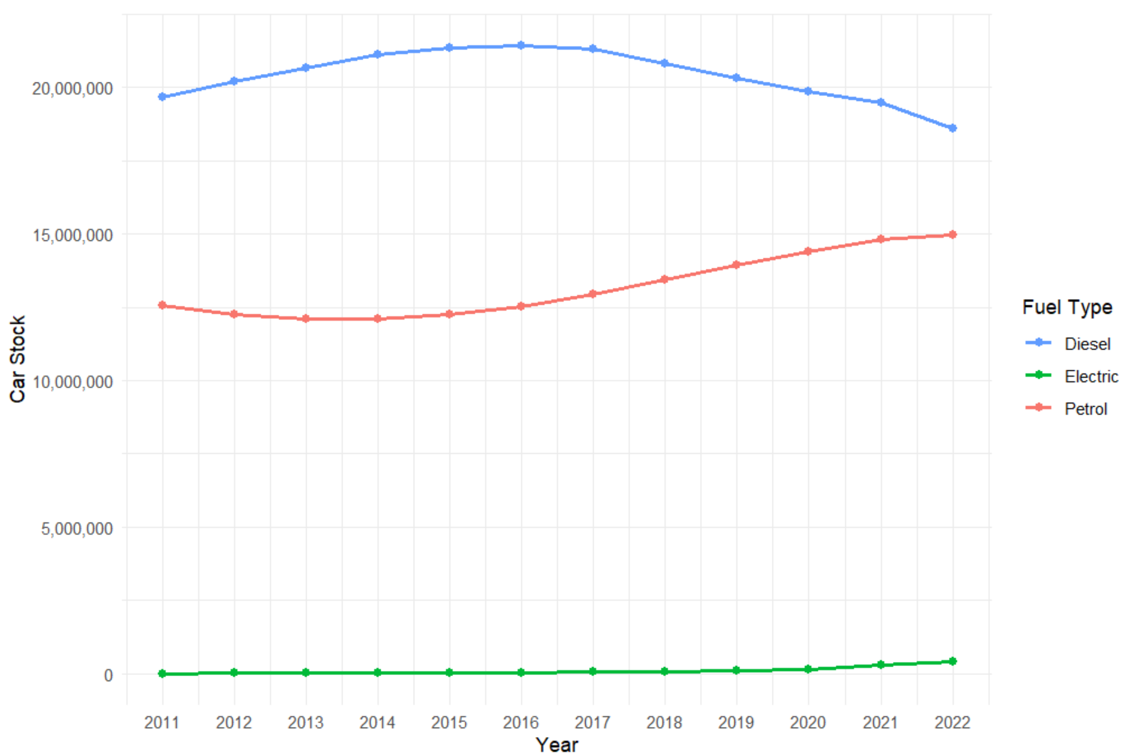
[14]Recently, such environmental standards have consisted in, for instance, the EU announcement of a ban on ICEs as of 2035 and the introduction of low-emission zones. In France, in 2019, the LOM act made it compulsory for EPCIs with air quality higher than the official norms to introduce low-emission zones ("Zones à Faibles Emissions"). Although the schedule has been modified several times, it was made clear that old diesel cars would eventually be forbidden in city centers. URL: https://www.ecologie.gouv.fr/politiques-publiques/zones-faibles-emissions-zfe.

Figure 2: Evolution of New Passenger Car Registrations from 2011 to 2022 in France



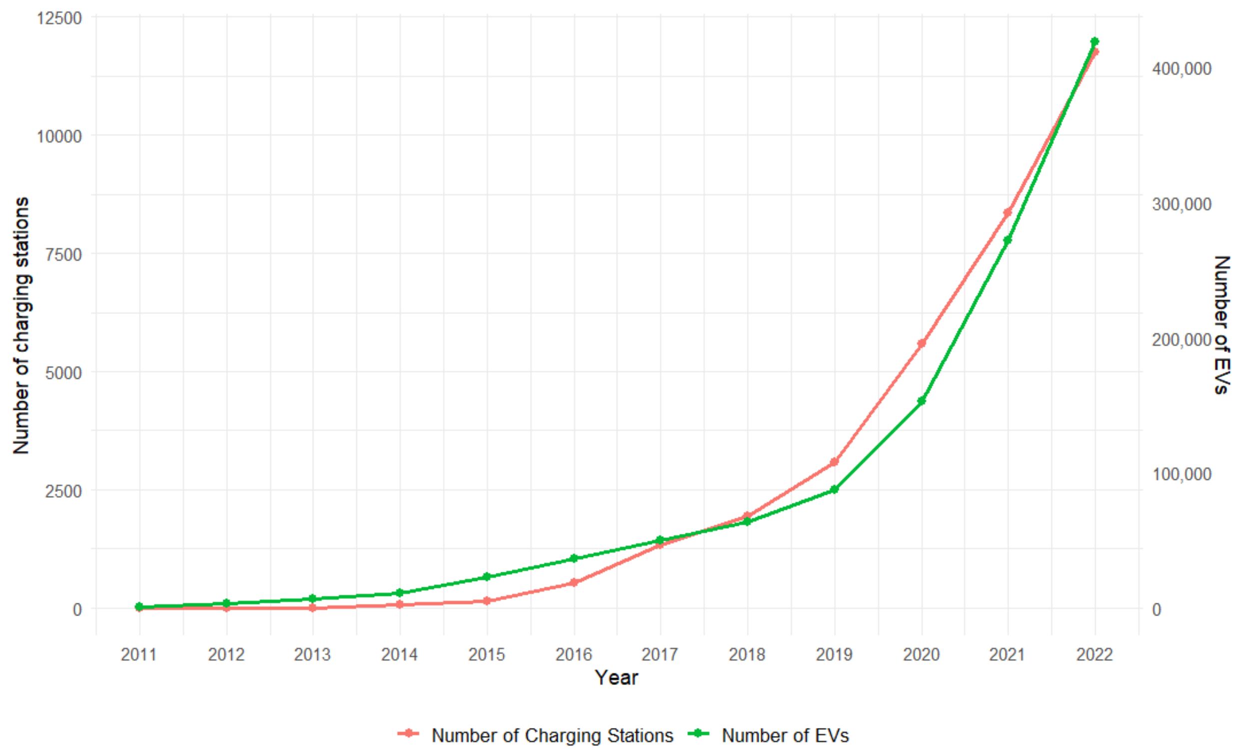
Notes: This graph draws the number of registrations of new passenger cars used by private individuals from 2011 to 2022, in hexagonal France (without Corsica and overseas territories). Only diesel- and petrol-powered cars, as well as electric cars, are depicted. In the Appendix, Figure 11 draws the number of registrations of new passenger cars used by private individuals *and* professionals, in France, including Corsica and overseas territories.

Figure 3: Evolution of the Passenger Cars Fleet from 2011 to 2022 in France



Notes: This graph draws the evolution of the passenger car fleet (used by private individuals) from 2011 to 2022, in hexagonal France (without Corsica and overseas territories). The number of cars given for each year corresponds to the number of cars in the French fleet on December 31 of each year.

Figure 4: Evolution of the Passenger Electric Car Fleet and of Charging Station Infrastructure from 2011 to 2022 in France



Notes: This graph draws the evolution of the electric passenger car fleet (used by private individuals) along that of the installed base of charging stations, from 2011 to 2022, in hexagonal France (without Corsica and overseas territories). The number of cars given for each year corresponds to the number of cars in the French fleet on December 31 each year.

Table 1 and Table 2 present summary statistics for variables either used in the regressions or relevant to describe the structure of the 987 EPCIs included in the dataset. All the variables, except the car and EV stock and the number of supermarkets, are taken from Insee 2021-census data.

Note that the EPCI having both the smallest amount and share of electric passenger cars in 2022 was the CC[15] Pays Gentiane, an EPCI located in Cantal, Auvergne-Rhône-Alpes: this EPCI can be considered as very rural, as there were only 6,572 inhabitants and 14.3 people per km^2 in 2021, according to Insee.

In contrast, the Métropole du Grand Paris, the EPCI gathering together Paris with its 130 suburban municipalities, is the EPCI with the largest EV fleet, with 11,427 electric passenger cars, used by private individuals. Yet, the share of EVs there is only 0.5%: this is not surprising as the

[15]"Communauté de communes": it is one of the possible forms taken by EPCIs, along with "Communauté d'agglomérations" or "Métropoles" which are bigger entities.

capital city area is where the number of cars is also the largest.

In the EV demand equation and the supply equation, the EPCI with the highest share of EVs (2.7%) in 2022 was the CC Gally Mauldre, in Yvelines, Île-de-France. It is much less densely populated than the Métropole du Grand Paris but much more densely populated than CC Pays Gentiane, with 235.5 people per km^2 and 22,336 inhabitants.

To get a quick overview of the correlation between the variables selected in the summary statistics tables and the share of EVs in 2022, I run a naive OLS on the data of that year. I estimate:

$$share_e^{EV} = ln(D_e) + ln(I_e) + ln(S_e) + \varepsilon_e$$

where $share_e^{EV}$ is the share of EVs in the total car fleet in 2022 in EPCI e, D_e is the population density in EPCI e, I_e is the median equivalized disposable income in EPCI e and S_e is the total number of charging stations existing in EPCI e in 2022. Table 3 underlines that a higher population density, median equivalized disposable income and total number of stations, are correlated with a higher share of EVs: hence, according to this naive regression, a typical EPCI with a high share of EVs would be an urban, rich and well-equipped EPCI. These patterns are thus investigated geographically in Section 4.3.

Table 1: Summary Statistics for Relevant Variables regarding the EV Demand Equation

	Min.	Q1	Median	Mean	Q3	Max.
Population	3,983	16,953	28,124	64,554	54,387	7,144,932
Population density	6.30	36.64	75.16	178.45	154.85	8,703.35
Car stock by 2022	2,659	11,084	17,748	35,332	34,425	1,944,629
EV stock by 2022	7	60	124	256.9	253	11,427
Number of charging stations by 2022	0	2	5	10.58	11	1,097
Median equivalized disposable income	17,560	21,340	22,310	22,759	23,450	40,320
Share of houses in principal residences	13.01%	69.15%	82.40%	77.59%	90.65%	98.22%
Number of supermarkets	1	3	6	12.37	12	906

Notes: This table provides summary statistics for variables which are relevant regarding the EV demand equation. The statistics include the minimum (Min.), first quartile (Q1), median, mean, third quartile (Q3), and maximum (Max.) values for each variable. All variables are measured at the EPCI level. These statistics are calculated from observations used in the EV demand regression, whose results are available in Section 6.1: thus, these statistics are calculated over 45,167 observations.

Table 2: Summary Statistics for Relevant Variables regarding the Charging Station Equation

	Min.	Q1	Median	Mean	Q3	Max.
Mean fuel price in the last quarter	0.9825	1.2883	1.4187	1.4118	1.4806	2.2189
Mean fuel price in current quarter	0.9825	1.2885	1.4226	1.4206	1.4860	2.2189
Mean fuel price one year ago	1.067	1.275	1.400	1.372	1.467	1.834
Mean fuel price two years ago	1.046	1.247	1.348	1.344	1.453	1.738
Mean fuel price three years ago	1.046	1.240	1.347	1.340	1.453	1.738
Population	4,870	17,597	28,316	65,635	55,202	7,144,932
Population density	6.30	37,44	75.81	181,26	157.09	8,703.35
Car stock by 2022	2,659	11,084	17,748	35,332	34,425	1,944,629
EV stock by 2022	7	63	127	261.2	258	11,427
Number of charging stations by 2022	0	2	5	10.73	11	1,097
Median equivalized disposable income	17,560	21,360	22,330	22,762	23,450	40,320
Number of supermarkets	1	3	6	12.37	12	906

Notes: This table provides summary statistics for variables which are relevant regarding the charging station equation. The statistics include the minimum (Min.), first quartile (Q1), median, mean, third quartile (Q3), and maximum (Max.) values for each variable. All variables are measured at the EPCI level. These statistics are calculated from observations used in specification (3) of the charging station equation, whose results are available in Section 6.2: thus, these statistics are calculated over 43,861 observations.

Table 3: Naive OLS on data of the year 2022

	Dependent variable:
	Share of EVs
log(population density)	0.0004***
	(0.0001)
log(median equivalized disposable income)	0.029***
	(0.001)
log(total number of stations)	0.0004***
	(0.0001)
Constant	−0.281***
	(0.010)
Observations	987
R^2	0.542
Adjusted R^2	0.540
Residual Std. Error	0.003 (df = 983)
F-statistic	387.4 (df = 3; 983)

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Clustered (EPCI) standard-errors in parentheses.

4.3 Geographical Patterns

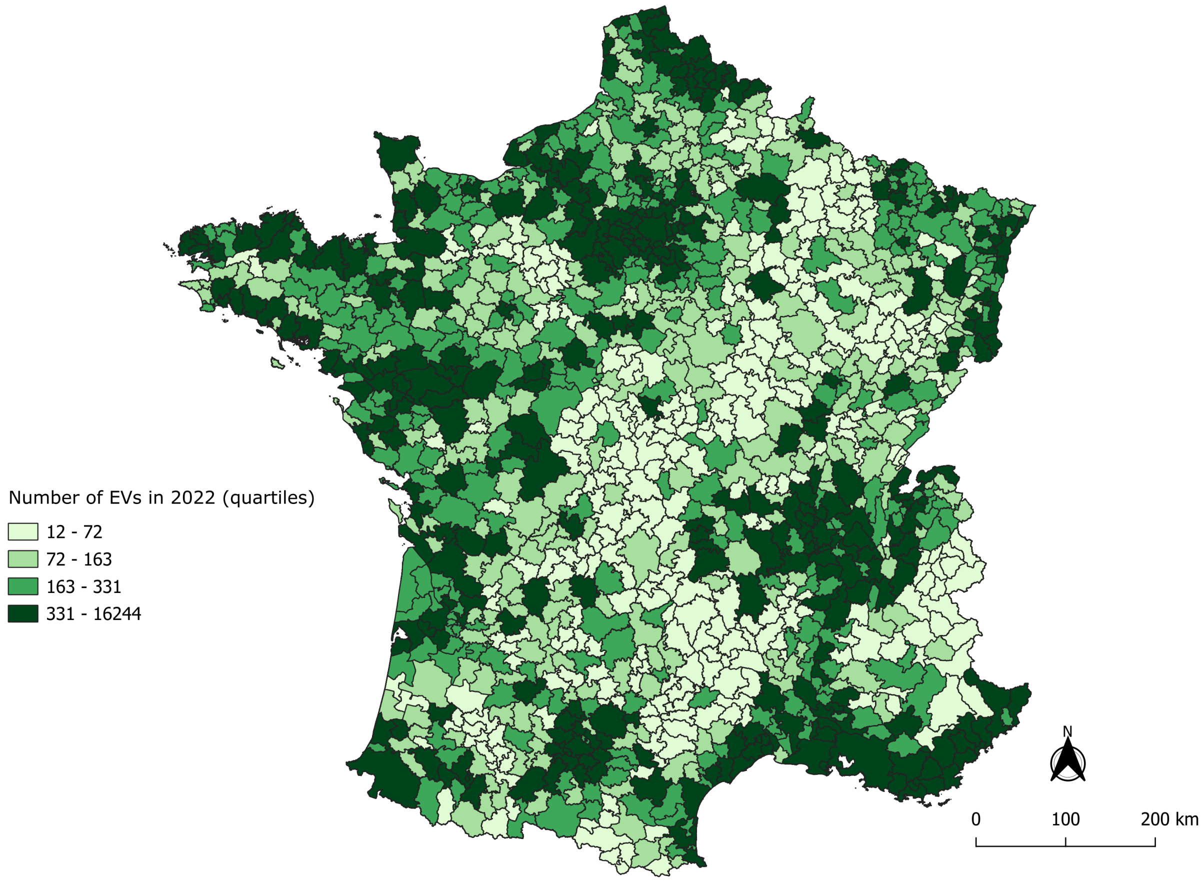
Figure 5 tends to show that the EV fleet is unequally distributed on the French territory. Of course, comparing only the installed base can be misleading because of the difference in population across EPCIs. Yet, Figure 7 seems to confirm this assessment. The share of EVs tends to be higher around large urban areas, like Marseille, Toulouse, Lyon and Strasbourg. Interestingly, the Métropole du Grand Paris has the largest installed base of EVs but is "only" in the third quartile. Its suburbs though tend to be in the fourth quartile: it could likely be due to commuters driving their car to work inside Paris while living outside the metropolis.

In addition, Figure 6 shows that, according to the open dataset used in this study, there is an unequal coverage in charging stations in France, urban areas hosting a larger number of charging stations. This goes into the direction of the existence of a positive correlation between the number of charging stations and the number (and share) of EVs.

To dig this question a bit deeper, Figure 8 creates a metric to assess the availability of charging infrastructure in the EPCIs studied: dividing the EV fleet of each EPCI by the number of existing charging stations there, one gets the number of EVs per station. The higher this number, the fewer charging stations are available. Interestingly, while urban areas like Paris or Toulouse seem to have a high degree of station availability *and* a high share of EVs (Figure 7), it looks like some rural areas have a small share of EVs, despite being rather well equipped. This raises the issue of spatial heterogeneity: does building a charging station in a rural and urban areas have the same effect?

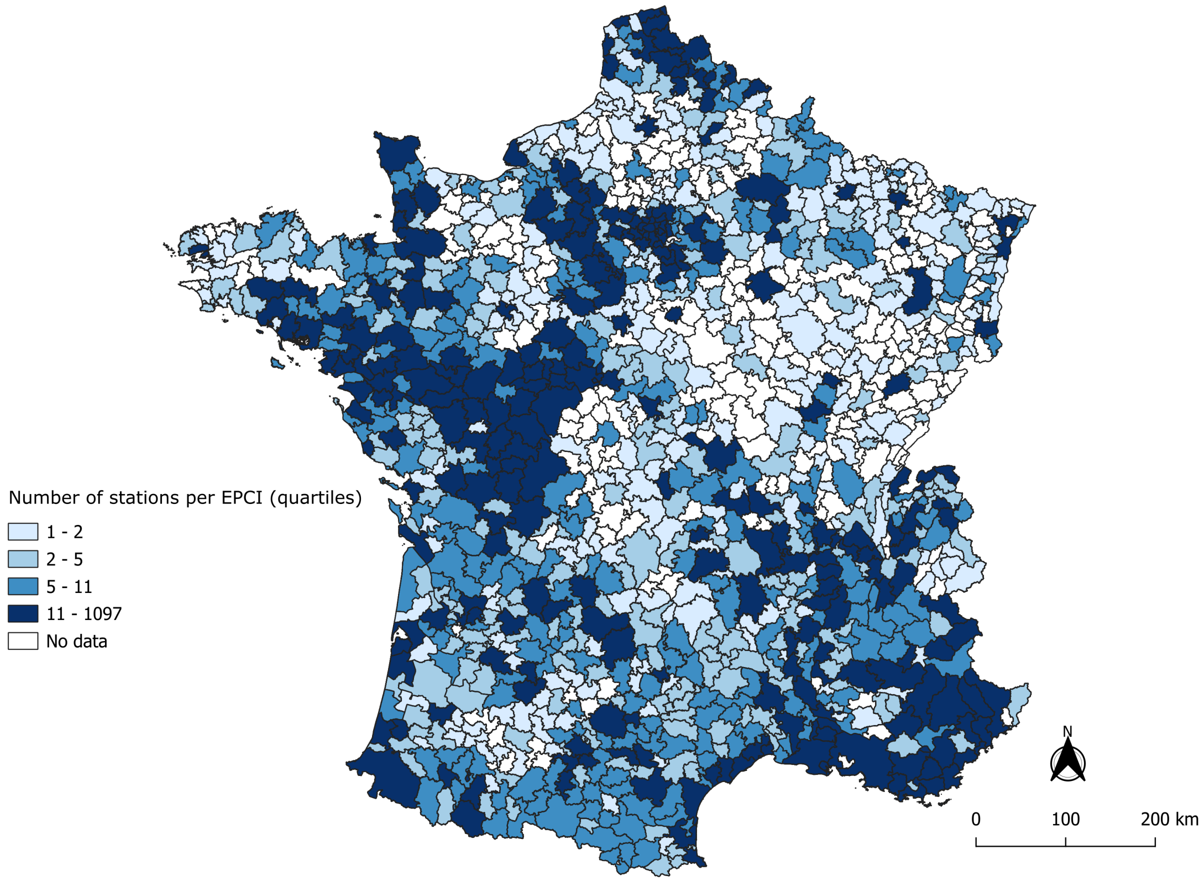
Finally, Figure 9 and Figure 10 point out the spatial pattern of the deployment of charging stations and of EV sales from 2011 to 2022. First, before 2017, the number of charging points was very low; secondly, charging stations were initially deployed around big cities, like Paris and Marseille, and in Poitou-Charentes as a consequence of the voluntaristic policies implemented by the politicians of the time in this region. The EV sales seem to follow the same pattern, with sales being first driven by cities.

Figure 5: Geographical Distribution of the Installed Base of EVs in 2022



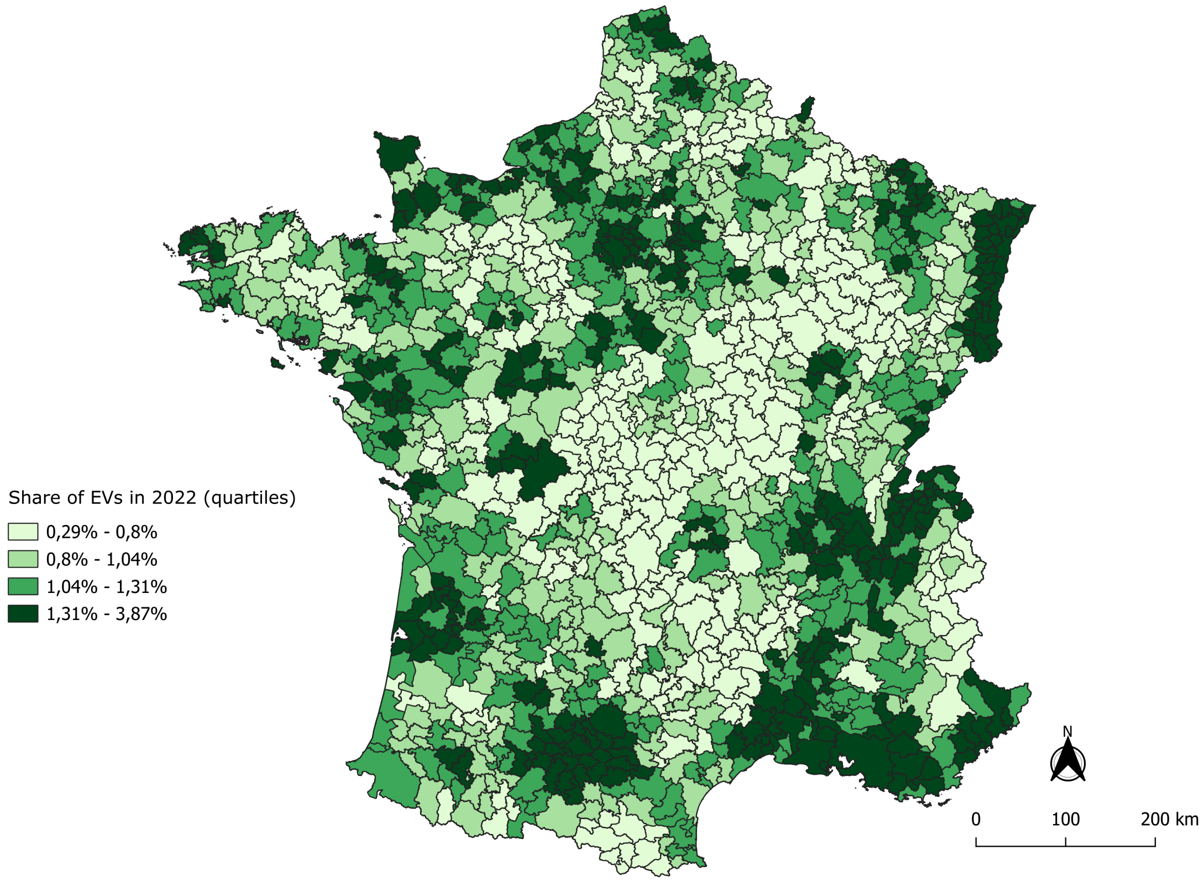
Notes: This map represents the installed base (stock) of electric passenger cars used by private individuals (EPCI level), on December 31, 2022. It is not restricted to the 987 EPCI used in the regressions.

Figure 6: Geographical Distribution of the Installed Base of Charging Stations in 2022



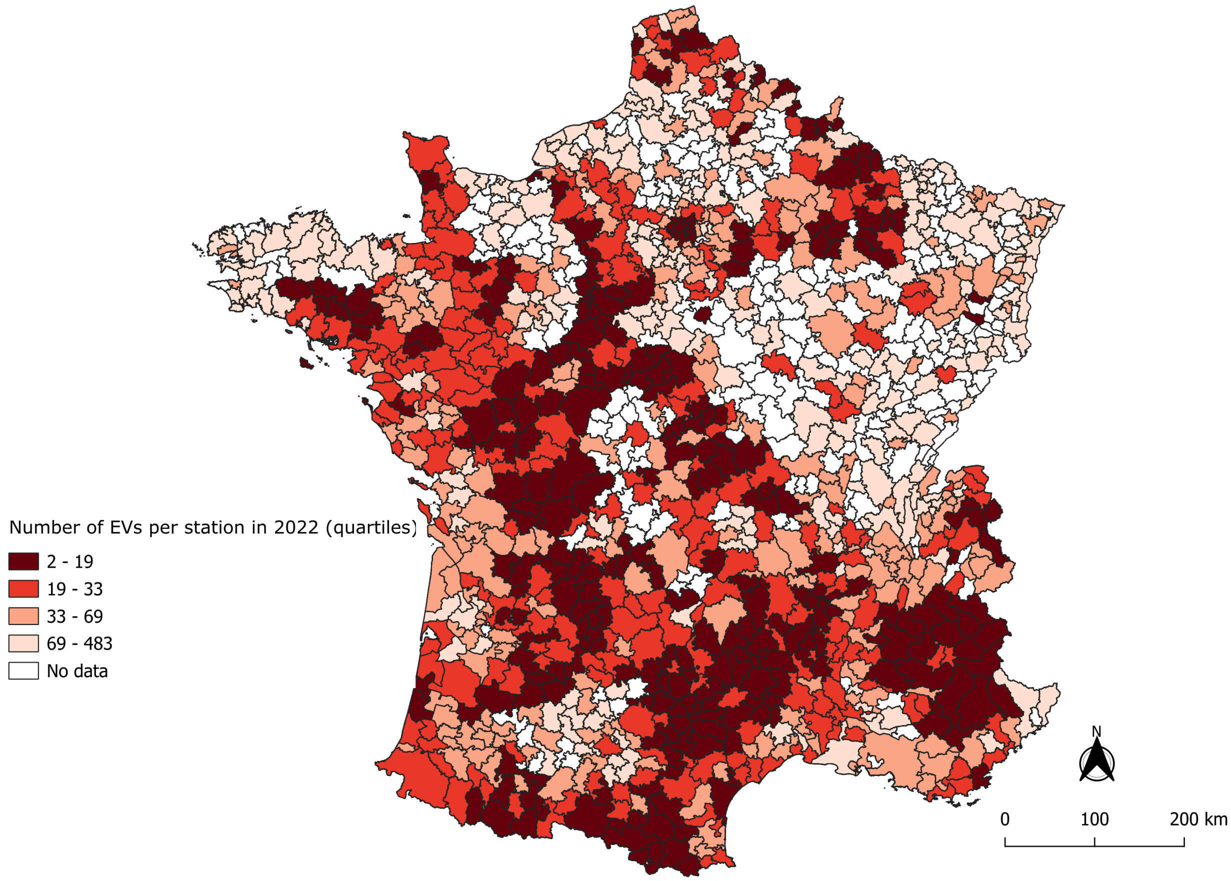
Notes: This map represents the installed base (stock) of charging stations (EPCI level), which are registered in our database after data cleaning, on December 31, 2022.

Figure 7: Share of EVs in the Total Car Fleet in 2022



Notes: This map represents the share of electric passenger cars, used by private individuals, in the total passenger car fleet, used by private individuals in France (on December 31, 2022, EPCI level). It is not restricted to the 987 EPCI used in the regressions.

Figure 8: Number of EVs per Charging Station in 2022



Notes: This map represents the number of electric passenger cars used by private individuals per charging station (on December 31, 2022, EPCI level). When the indicator gets higher, the number of cars per charging station grows. Thus, it can be seen as a measure of the availability of charging stations: the higher the indicator, the fewer charging stations are available.

Figure 9: Geographical Evolution of Charging Stations Installation from 2011 to 2022

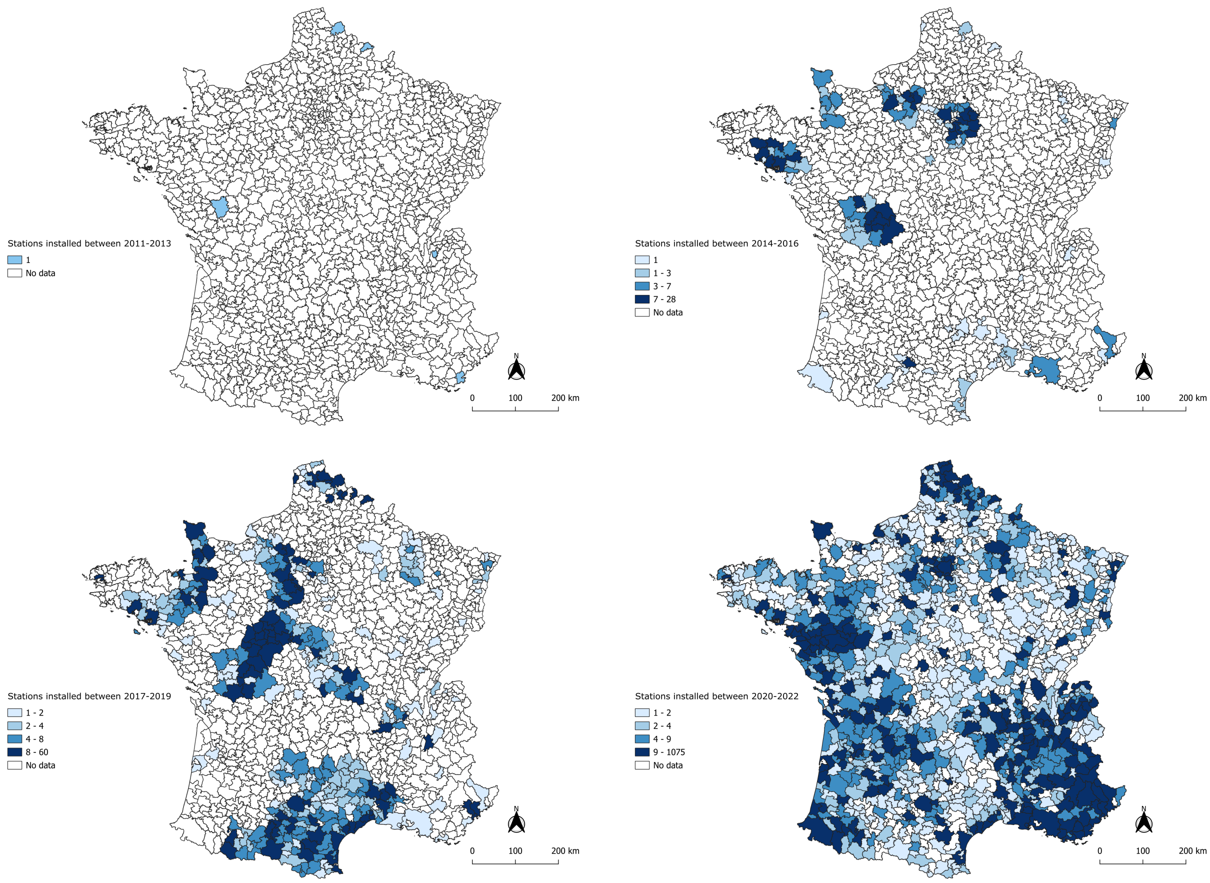
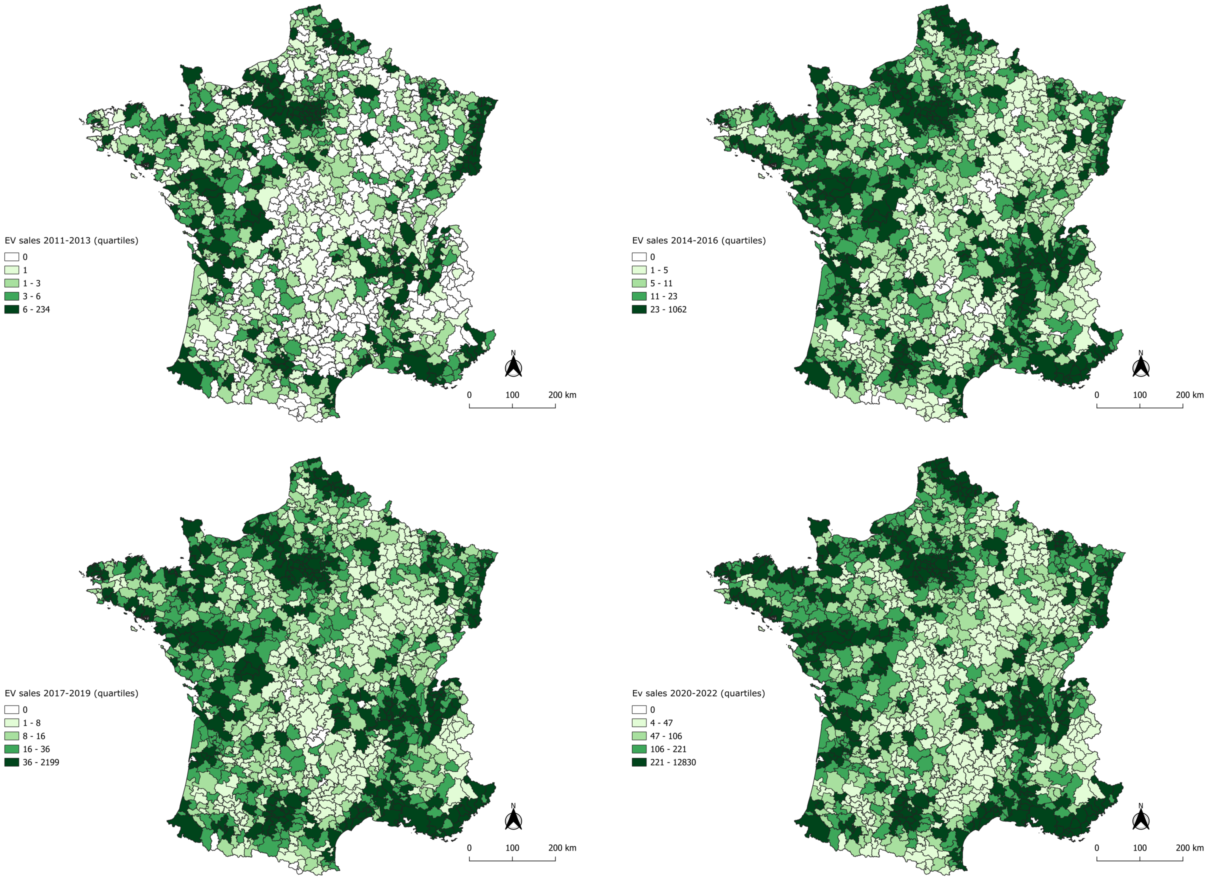


Figure 10: Geographical Evolution of EV Registrations from 2011 to 2022



5 Empirical Strategy

Because of its structure, the EV market can be seen as a two-sided market exhibiting network externalities. These network effects are indirect: because of limited range and slow charging, the marginal utility derived from driving an EV depends on the availability of public charging stations. The existence of positive indirect network effects is precisely what creates a "chicken-and-egg" issue and thus may slow down EV adoption. Indeed, on the one hand, if the number of charging stations increases, range anxiety reduces, leading to more EV purchases: drivers value the existence of public charging infrastructure. On the other hand, building charging infrastructure requires massive financial investments, which can only be amortized if the EV fleet gets large enough. Therefore, building more charging stations can stimulate demand for EVs *but* increasing the share of EVs in the car fleet can stimulate the building of charging stations.

Then, the immediate question arising is: which effect is bigger? Indeed, it has policy ramifications: which side should be subsidized first or more heavily? This entails to quantify the intensity of the network effects on both sides of the market. Yet, this issue becomes non-trivial when it comes to econometrics: the "chicken-and-egg" problem leads to a simultaneity or reverse causality issue, hence an endogeneity bias in absence of a proper identification strategy.

Building on Li et al. (2017), I perform a reduced form estimation using an instrumental variable (IV) strategy for each side of the market. On the one hand, the "EV demand equation" aims to capture the intensity of the indirect network effects from charging infrastructure on EV demand. On the other hand, the "charging station equation" identifies the effect of the size of the EV fleet on the building of charging stations.

5.1 EV Demand Equation

Using quarterly electric passenger car registrations data from 2011 to 2022 and denoting e the EPCI in which the EV is registered and t the year and quarter, the demand equation writes:

$$\ln(r_{et}^{EV}) = \beta_0 + \beta_1 \ln(N_{et}) + T_t + \delta_e + \varepsilon_{et}$$

where r_{et}^{EV} stands for the registrations of electric cars in EPCI e and year-quarter t, N_{et} represents the number of public charging stations built in EPCI e by year-quarter t. T_t denotes year-quarter fixed effects, controlling for time-varying national trends, i.e. shocks being common to all the EPCIs studied, such as, for instance, the development of environmental information aimed at the consumers. The fixed effect δ_e controls for time-invariant EPCI characteristics, such as its geographical situation (e.g. a mountainous situation, which could have an impact on the willingness to buy an EV). ε_{et} recovers the unobserved variations.

Yet, simply estimating this equation would not settle the issue of reverse causality: N_{et} is still endogenous as it could be correlated with ε_{et} due to simultaneity. To purge the results from any endogeneity bias, I use an IV strategy. It requires to find a variable correlated with the number of public charging stations N_{et} (relevance condition) but not with EV registrations r_{et} (exclusion restriction).

Consequently, following Li et al. (2017), I choose an instrument *à la* Bartik. Coming from the literature of labor economics, an instrument *à la* Bartik consists in interacting two variables: one captures national shocks, the other is a local variable manifesting the fact that territories[16]

[16] In the original book (Bartik, 1991), the local variable is the local industry employment shares, while the national

have a differential exposure to these national shocks. In the present case, I interact the number of supermarkets in each EPCI S_e with the number of charging stations in all EPCIs but EPCI e, lagged by a quarter : $S_e \times N_{-e,\,t-1}$. Indeed, grocery stores tend to install charging points in order to attract new consumers (Arlt et Astier, 2023). Therefore, the two variables should be correlated. Reversely, considering the set of fixed effects included in the equation, there is no credible mechanism through which the number of supermarkets would impact the consumer decision to buy an EV. Since such a variable doesn't include any variation, I introduce time variation by interacting it with the lagged number of charging stations in all EPCIs but the one in which the studied grocery stores are located. To put it in a nutshell, this instrument *à la* Bartik is built upon the following idea: the lagged number of charging stations captures the national trend in charging infrastructure development (namely, a national policy aiming to expand the charging infrastructure) but this trend has a stronger effect on EPCIs where there are more supermarkets, since grocery stores are willing to install charging stations to attract more consumers. The supermarket variable thus captures the local exposure to the national shock.

5.2 Charging Station Equation

Using similar notations, the supply equation writes:

$$\ln(N_{et}) = \gamma_0 + \gamma_1 \ln(R_{et}^{EV}) + \gamma_2' Z_{et} + \lambda_y + \rho_q + \nu_e + \mu_{et}$$

where R_{et}^{EV} denotes the size of the EV fleet in EPCI e by year-quarter t, Z_{et} stands for the instrument of the EV demand equation used as a control variable here, λ_y is a year fixed effect, ρ_q a quarter fixed effect, and ν_e an EPCI fixed effect. μ_{et} captures the unobserved variations (error term).

To rule out simultaneity, following Li et al. (2017), I instrument the existing stock of registered EVs R_{et}^{EV} by current and past gasoline prices. Indeed, the higher the gasoline prices, the higher the incentive to buy an EV, as potential fuel cost savings increase. Thus, in EPCIs where the cost of gasoline is higher, drivers should be more likely to buy an electric car. Reversely, there doesn't seem to be a clear mechanism which would lead gasoline prices to impact the stock of charging stations, other than through the EV sales channel. Consequently, this instrument should satisfy both the relevance condition and the exclusion restriction.

Note that this time I use year and quarter fixed effects to control for time-varying shocks and

trend is the national industry employment growth rates.

seasonality, instead of year-quarter fixed effects, because introducing year-quarter fixed effects along the EPCI fixed effects would have left too few variations to exploit. Indeed, the price of gasoline varies across EPCIs in France, but not as much as in a federal government like the U.S.

5.3 Heterogeneity on the Demand Side

So far, the use of the IV strategy has made it possible to disentangle the indirect network effects existing on this two-sided market: thanks to this analysis, one will be able to conclude whether *on average*, the supply effect is stronger or weaker than the demand effect, resulting in different policy recommendations.

However, the charging infrastructure is likely to exhibit decreasing returns to additional stations: the first station in an EPCI is likely to have a strong impact, while each station after that is likely to have a smaller one as the total equipment improves. This could especially be the case as the car fleet takes some time to renew and considering that consumers could be subject to a form of acculturation due to the public display of the new technology. Consequently, the magnitude of the effect of charging stations on EV sales may vary through time: thus, I check whether this effect decreases between 2011 and 2022. To do so, I investigate the shape of the curvature in order to check whether there exist decreasing marginal returns: I run the 2SLS regression with a first stage in which I regress the log-number of stations and the squared log-number of stations on the log-instrument and the squared log-instrument.

Moreover, the literature on EVs has mainly been focused on *average* effects only, not looking deeper into the possibility of heterogeneous effects. Yet, the dynamics of mobility are likely to be very different between rural and urban areas: country dwellers, who are much more dependent on passenger cars to move around and tend to live in stand-alone houses, are likely to install private chargers at home, since they have some private parking space at home, thus making them less reliant on public infrastructure. In such a case, country dwellers' decision to buy an EV would be much more dependent on the level of EV purchase subsidies or subsidies on private chargers, rather than on the availability of public stations nearby. Such a conclusion highlights how important taking into account geographical heterogeneity is, since it leads to very different public policy recommendations. To assess whether there are heterogeneous effects between rural and urban areas, I exploit population density: I create quintiles of population density to categorize EPCIs and I interact them with the instrument to finally run the 2SLS regression.

In addition, income inequality across territories could also lead to heterogeneous effects. Indeed, if some EPCIs concentrate low-income households, it is possible that building charging stations will have a minor impact on EV sales, as the budget constraint would be too binding for households anyway to be able to buy an electric car. To assess the impact of such socioeconomic disparity, I construct quintiles of median equivalized disposable income to categorize EPCIs, interact them with the instrument and run the 2SLS analysis.

6 Results

I first present the results for the EV demand equation and the charging station equation. I then discuss heterogeneity.

6.1 Results for the EV Demand Equation

Table 4 and Table 5 present the results for the EV demand equation when a log-transformation is applied to the number of stations and EV registrations. The log-transformation is not only useful to standardize data but also to interpret the results: as both sides are log-specified, the point estimate of interest can be interpreted as an elasticity.

While Section 5 explained why the instrument chosen satisfies the orthogonality condition, the first-stage result (Table 4) tends to confirm, in addition, the relevance of the instrumental variable chosen: the F-statistic is much larger than the value of reference for weak instruments and the coefficient is indeed highly significant, at the 1% level.

Table 5 delivers the expected result as the positive and significant point estimate on the charging infrastructure variable pinpoints the existence of indirect network effects: indeed, on average, a 10% increase in the installed base of charging stations leads to a 11.81% increase in the number of quarterly EV registrations, this coefficient being significant at the 1% level. This is a large effect, slightly higher than the 8.4% found by Li et al. (2017). This difference could be due to a different "car culture" between the U.S. and France but possibly also to the geographical aggregates chosen: as MSAs are large aggregates, capturing the very local effect of charging infrastructure investment is more difficult.

Table 4: EV demand equation - first-stage of the 2SLS

	log(stations built by quarter t in EPCI e)
Supermarkets × log(lagged national stations)	0.0011***
	(0.0004)
Observations	45,167
R^2	0.61621
Within R^2	0.04914
Year-quarter fixed effects	Yes
EPCI fixed effects	Yes
F-statistic	2,331.7

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Clustered (EPCI) standard-errors in parentheses.

Table 5: EV Demand Equation - second-stage of the 2SLS

	log(quarterly EV registrations by EPCI)
log(stations built by quarter t in EPCI e)	1.181***
	(0.1609)
Observations	45,167
R^2	0.60157
Within R^2	-0.93925
Year-quarter fixed effects	Yes
EPCI fixed effects	Yes

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Clustered (EPCI) standard-errors in parentheses.

Note that to perform the log-transformation, each time a zero appears in the needed chargers or EV variables, I have to add one, i.e. I replace the null value with $log(0 + 1) = 0$. As the dataset includes many zeros at the beginning of the period, especially regarding the number of charging stations, I check this transformation doesn't affect the estimation too much by dropping such observations. In the Appendix, Table 11 presents the results when all the observations for which the number of charging stations installed by time t equals 0 are dropped. Table 13 adds to this result, by also dropping observations for which quarterly EV sales are null. The first- and second-stage coefficients are still highly significant (at least at the 5% level) and positive. The second-stage coefficient is smaller than before though: a 10% increase in charging stations would generate a 2.95% increase in quarterly EV registrations.

Moreover, I check the significance and direction of the indirect network effect by running the 2SLS without any functional transformation. Table 15 and Table 16, in the Appendix, display highly significant and positive coefficients, in accordance with the log-transformed results.

6.2 Results for the Charging Stations Equation

Table 6 and Table 7 present the results for the charging station equation when a log-transformation is applied to the number of stations, EV registrations and fuel prices. Again, to perform the log-transformation, I add one when the registered value is null. In the Appendix, Table 17 and Table 18 present the results when all the null observations are dropped (for both EV and stations related variables). As before, I also perform the regression with no functional transformation (Table 19 and Table 20 in the Appendix). For all these methods, I test four specifications with different combinations for the instrumental variables: I use alternatively combinations made of the fuel price in the last quarter, in the current quarter, one year ago, two years ago and three years ago.

In Table 6, the F-statistic is higher than the reference value for weak instruments, hence the instruments chosen should satisfy the relevance condition. Interestingly, the direction of the coefficient is not the one which was expected. Indeed, one would have expected that a higher fuel price would have given incentives to buy an EV rather than an ICE. Then, explaining this negative coefficient is a bit tedious: one explanation could be that a surge in fuel prices can greatly impact consumers' budget, thus reducing their financial capacity to buy EVs, whose upfront cost is high.

Moreover, unlike Li et al. (2017), Table 7 unveils no significant effect from the EV fleet on the building of charging stations : standard errors are all the more very large. The coefficients are also insignificant in all the other specifications (Table 18 and Table 20). Several reasons could explain this finding. First, the few papers which studied this issue found the effect of building charging stations on EV demand to be stronger than the other way around (Li et al., 2017 ; Springel, 2021). As such, finding no significant effect and having point estimates very close to 0 points into this direction: the main channel to speed up EV adoption is to increase the number of charging stations, at least at the beginning since they might suffer from decreasing marginal returns afterwards. Secondly, it could be due to the structure of the deployment of charging stations: indeed, if it is not the local demand for charging stations (i.e. the EV fleet) which creates incentives to build stations, it is likely that stations are eventually built according to the way subsidies are designed. For instance, it is likely that the building of charging stations depends much more on local political willingness to subsidize such infrastructure than on the local EV fleet. Such political effects are highlighted by the case of Poitou-Charentes in Figure 9, a region which intended to become a pioneer in electric mobility as of 2012. Consequently, since building charging stations is partly subject to local political considerations, what is at stake is to make sure local authorities design their subsidies efficiently enough to speed up EV adoption quickly: that is why, in its latest report on the charging infrastructure, the French Competition Authority (2024) recommends to make it compulsory for local authorities to draw up master plans for the development of charging stations (SDIRVE, "schémas directeurs de développement des IRVE") on their territory. Finally, from a purely methodological viewpoint, it would be interesting to see if the results stay identical when using other instrumental variables: indeed, with such EPCI, year and quarter fixed effects, it is likely that few variations are left to exploit when working with fuel prices in France. Indeed, contrary to the U.S., variations in fuel prices across the country remain quite small.

Also, the second-stage results (Table 7) interestingly highlight that the EV demand equation instrument is highly significant and positive, i.e. it has a positive impact on the building of stations, which further confirms that it satisfies the relevance condition needed to use it as an instrumental variable in the EV demand equation.

Table 6: Charging Station Equation - first-stage of the 2SLS

	log(quarterly EV fleet by EPCI)			
	(1)	(2)	(3)	(4)
log(fuel price in current quarter)	-0.5039***		-0.4274***	-0.4267***
	(0.0474)		(0.0431)	(0.0573)
log(fuel price in the last quarter)		-0.2962***	-0.1344***	-0.1394***
		(0.0269)	(0.0152)	(0.0277)
log(fuel price one year ago)	0.2031	0.1260	0.2602	
	(0.3490)	(0.3571)	(0.3501)	
log(fuel price two years ago)	-0.3016	-0.3006	-0.3164	
	(0.2688)	(0.2738)	(0.2737)	
log(fuel price three years ago)	-1.367***	-1.356***	-1.386***	
	(0.3957)	(0.3970)	(0.3969)	
EV demand equation instrument (log)	0.0003	0.0003	0.0003	0.0004
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Observations	43,889	43,861	43,861	44,097
R^2	0.94829	0.94825	0.94830	0.94776
Within R^2	0.01180	0.01104	0.01196	0.00998
Year fixed effects	Yes	Yes	Yes	Yes
Quarter fixed effects	Yes	Yes	Yes	Yes
EPCI fixed effects	Yes	Yes	Yes	Yes
F-statistic	43.1	34.6	35.9	40.6

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Clustered (EPCI) standard-errors in parentheses. As the dataset used only contains the number of EVs making up the EV fleet *yearly* but gives *quarterly* sales, I am able to construct the EV fleet *quarterly* by creating a correction factor. I compute the number of EVs going out of service every year and, assuming that these removals are equally distributed between the four quarters, I can allocate them to each quarter and, using quarterly EV sales, I finally obtain the quarterly EV fleet.

Table 7: Charging Station Equation - second-stage of the 2SLS

	log(stations built by quarter t in EPCI e)			
	(1)	(2)	(3)	(4)
log(quarterly EV fleet by EPCI)	-0.0172	-0.0874	-0.0375	0.0300
	(0.2628)	(0.3210)	(0.2570)	(0.1881)
EV demand equation instrument (log)	0.0011^{***}	0.0011^{**}	0.0011^{***}	0.0011^{***}
	(0.0004)	(0.0004)	(0.0004)	(0.0004)
Observations	43,889	43,861	43,861	44,097
R^2	0.61418	0.60942	0.61301	0.61532
Within R^2	0.04607	0.03442	0.04330	0.05105
Year fixed effects	Yes	Yes	Yes	Yes
Quarter fixed effects	Yes	Yes	Yes	Yes
EPCI fixed effects	Yes	Yes	Yes	Yes

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Clustered (EPCI) standard-errors in parentheses.

6.3 Heterogeneous Effects on the Demand Side

To achieve a quick electrification of the car fleet, tailoring public policy is crucial. Hence, the need to investigate potential heterogeneous effects. Thus, I investigate whether the effects from building stations on EV sales are heterogeneous across time, space and income.

6.3.1 Heterogeneity over Time

To study heterogeneity over time, I use a polynomial specification to check whether the point estimate on the squared of the log number of stations is negative.

Table 8 exhibits a significant negative coefficient on the squared log-number of charging stations, suggesting the existence of decreasing marginal returns on charging infrastructure. Consequently, it suggests the charging infrastructure exhibits decreasing returns to additional stations.

Table 8: Time heterogeneity - second-stage (2SLS)

	log(quarterly EV registrations by EPCI)
log(stations)	2.383***
	(0.2597)
log(stations)^2	-0.2358***
	(0.0372)
Observations	45,167
R^2	0.29020
Within R^2	-2.4548
Year-quarter fixed effects	Yes
EPCI fixed effects	Yes

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Clustered (EPCI) standard-errors in parentheses.

6.3.2 Spatial heterogeneity

As explained in Section 5, it is likely that rural areas experience different dynamics, as compared to urban areas, since country dwellers tend to live in stand-alone houses, making it easier to charge at home rather than with public infrastructure.

The results presented in Table 9 display a clear gradient: the more densely populated an area is, the greater the effect. For instance, in an EPCI categorized in the fifth quintile, i.e. in an EPCI exhibiting a density of at least 182.17 people per km^2, a 10% increase in the number of charging stations would lead to a 9.9% increase in the number of EV registrations. Reversely, the effect is not even significant for the first quintile, in which the population density is inferior to 30.26 people per km^2; for the second quintile, in which the population density is smaller than 56.72 people per km^2, a 10% increase in charging stations would lead to a 4% increase only in EV registrations.

These results go into the direction of a smaller effect of public charging stations on EV sales in rural areas. This is a hint that rural drivers may be less reliant on public charging infrastructure than urban drivers as they can more easily charge at home. This is not surprising as the French Competition Authority (2024) notices that "home charging is easily accessible in stand-alone houses, but particularly complex for households living in multi-unit housing. [...] The level of equipment in condominiums remains very low, with only 2% of them equipped with charging infrastructure".

Yet, as seen in Section 4, rural EPCIs tend to have a lower share of EVs in their car fleet. Thus, the smaller effect in rural EPCIs doesn't mean that subsidies on public charging infrastructure should be stopped (the effect is still positive!) but rather that it should be supplemented, for instance, by subsidies on EV purchases and on private chargers.

Table 9: Spatial heterogeneity - second-stage (2SLS)

	log(quarterly EV registrations by EPCI)
log(stations) × Q1(density)	-0.1010
	(0.1586)
log(stations) × Q2(density)	0.4044***
	(0.1187)
log(stations) × Q3(density)	0.8660***
	(0.1345)
log(stations) × Q4(density)	0.9994***
	(0.1077)
log(stations) × Q5(density)	0.9932***
	(0.1224)
Observations	45,167
R^2	0.73526
Within R^2	-0.28858
Year-quarter fixed effects	Yes
EPCI fixed effects	Yes

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Clustered (EPCI) standard-errors in parentheses. Q1(density) to Q5(density) categorize EPCIs in quintiles, depending on their population density.

6.3.3 Income heterogeneity

As explained in Section 5, it is likely that EPCI with the highest concentration of low-income households are less responsive to the building of charging stations, as the budget constraint may be too binding anyway for these consumers to buy EVs.

This is confirmed by data: Table 10 highlights that a 10% increase in the number of charging stations would lead to a 9% increase in the number of EV registrations in the EPCIs whose median equivalized income is smaller than €21,082, compared with 11% in the EPCIs whose median equivalized income is higher than €23,998[17].

These results underline the need for multi-dimensional public policies, particularly in the areas most in need. Supporting only the building of charging infrastructure is likely to be insufficient in territories gathering low-income households if no EV purchase policy is conducted. This is all the more true given that the "poorest" EPCIs are often also the most rural: indeed, in our dataset, comparing the EPCIs making up the bottom 40% in population density and in median equivalized income, 248 out of 395 combine both characteristics. Thus, roughly 63% of the most rural EPCIs are also the poorest.

Table 10: Income heterogeneity - second-stage (2SLS)

	log(quarterly EV registrations by EPCI)
log(stations) × Q1(income)	0.9191***
	(0.0964)
log(stations) × Q2(income)	1.014***
	(0.1375)
log(stations) × Q3(income)	1.224***
	(0.1412)
log(stations) × Q4(income)	1.254***
	(0.1000)
log(stations) × Q5(income)	1.112***
	(0.2287)
Observations	45,167
R^2	0.62797
Within R^2	-0.81076
Year-quarter fixed effects	Yes
EPCI fixed effects	Yes

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Clustered (EPCI) standard-errors in parentheses. Q1(income) to Q5(income) categorize EPCIs in quintiles, depending on their median equivalized disposable income.

[17]Table 10 shows a maximal effect on the fourth quintile, while the fifth quintile experiences a smaller effect. It could be because high-income households can buy EV models which have a better range, thus making them less range anxious and less sensitive to charging stations. It would be interesting, in the future, to check this hypothesis by getting more extensive data which would include personal income as well as the model of the EV bought.

7 Conclusion

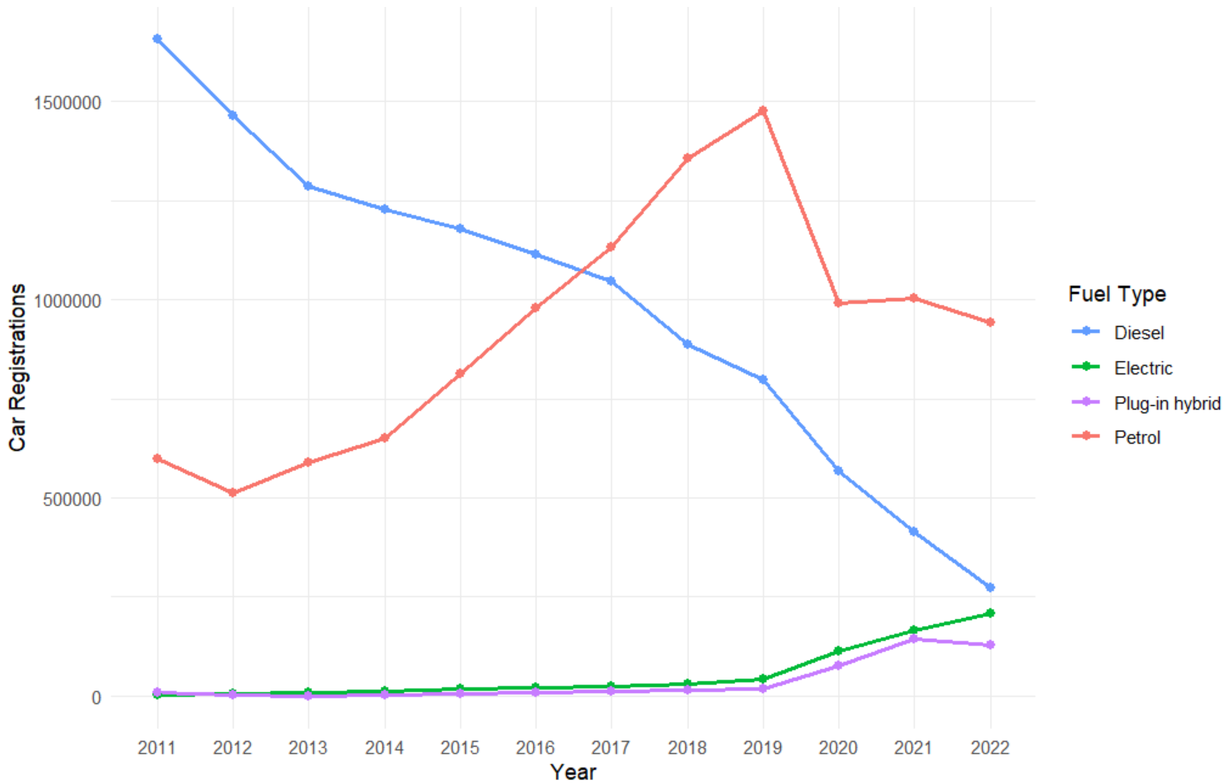
As transportation represents a third of French greenhouse gas emissions, electrifying the car fleet has been made a national priority by successive governments. Often described as two-sided, the EV market is said to exhibit indirect network effects. Hence, a significant debate exists today to determine which tools should be used to quickly speed up EV adoption. In particular, there exist two main types of subsidies: subsidies on EV purchases and subsidies on the charging infrastructure. Should one of them be prioritized? Which one? This depends on the magnitude of the effect of building charging stations on EV adoption and reversely.

Therefore, building on the "chicken-and-egg" literature and Li et al. (2017), I quantify the intensity of these two effects, working on comprehensive French EV and station data from 2011 to 2022. Adopting a 2SLS approach, I find that, on average, a 10% increase in the number of charging stations led to a 11.8% rise in EV registrations throughout this period. On the contrary, I find no significant effect of EV adoption on the building of charging stations. First, this is in line with Li et al.'s (2017) results as they conclude that the effect of the charging infrastructure on EV adoption is much larger than the converse effect. Secondly, this absence of effect may perhaps be a sign that the building of charging stations is much more determined by the local political will to subsidize it, rather than by a law of supply and demand. Thus, this could mean that the charging infrastructure is not always deployed where it is the most needed at a given moment. However, this shouldn't be seen only as a form of inefficient dynamics. Indeed, another major feature of EV adoption in France nowadays is its unequal distribution across the territory: rural and low-income territories tend to have a lower share of EVs in their car fleet. Consequently, a voluntaristic policy consisting in deploying charging infrastructure even where there are few EVs makes sense if one seeks to stimulate EV adoption in such territories. Yet, this analysis has also shown that the positive impact of building stations on EV adoption is much smaller in these areas: country dwellers may be less reliant on public infrastructure as they can more easily charge at home and low-income households may have a budget constraint too binding anyway to be able to buy an EV. As a consequence, the support to the deployment of charging stations in the public space is likely to achieve its goal only if other types of support are implemented too, such as EV purchase subsidies.

Much is still to investigate and discover regarding the EV market. This study made it possible to study a more recent period and a new context (the French one), as compared to more distant periods and the U.S. and Norwegian contexts, which have traditionally been analyzed. Yet, this analysis has shown the need for an improvement in the quality of data on charging stations in France: the charging station dataset used, which is an open dataset, has been extremely useful but it included many duplicates, measurement and location errors or missing information, especially regarding the commissioning date of charging stations and the number of available charging terminals within stations. This issue creates a risk of selection bias for this analysis, but also for all the institutional studies conducted in France on this topic. The number of such analyses can only grow in the future, as the jury is still out regarding many issues: what is the relative impact of fast chargers, as compared to slow charging terminals? What is the impact of having several coexisting norms of price display (price per minute, price per kWh, etc.)? For all these challenges, data will be key: hence the recommendation of the French Competition Authority (2024) to make the improvement of such data a priority.

Appendix

Figure 11: Evolution of New Passenger Car Registrations from 2011 to 2022 in France



Notes: This graph draws the number of registrations of new passenger cars used by private individuals *and* professionals, in France, including Corsica and overseas territories.

Table 11: EV Demand Equation - first-stage of the 2SLS with null observations of charging stations removed

	log(stations built by quarter t in EPCI e)
Supermarkets × log(lagged national stations)	0.0009**
	(0.0004)
Observations	11,773
R^2	0.82055
Within R^2	0.02992
Year-quarter fixed effects	Yes
EPCI fixed effects	Yes
F-statistic	361.8

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Clustered (EPCI) standard-errors in parentheses. All observations exhibiting zeros for the charging stations variable were removed.

Table 12: EV Demand Equation - second-stage of the 2SLS with null observations of charging stations removed

	log(quarterly EV registrations by EPCI)
log(stations built by quarter t in EPCI e)	0.2953***
	(0.0959)
Observations	11,773
R^2	0.89739
Within R^2	-0.05397
Year-quarter fixed effects	Yes
EPCI fixed effects	Yes

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Clustered (EPCI) standard-errors in parentheses. All observations exhibiting zeros for the charging stations variable were removed.

Table 13: EV Demand Equation - first-stage of the 2SLS with null observations of charging stations and EVs removed

	log(stations built by quarter t in EPCI e)
Supermarkets × log(lagged national stations)	0.0008**
	(0.0004)
Observations	10,703
R^2	0.81844
Within R^2	0.02848
Year-quarter fixed effects	Yes
EPCI fixed effects	Yes
F-statistic	312.6

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Clustered (EPCI) standard-errors in parentheses. All observations exhibiting zeros for the charging stations and the EV registrations variables were removed.

Table 14: EV Demand Equation - second-stage of the 2SLS with null observations of charging stations and EVs removed

	log(quarterly EV registrations by EPCI)
log(stations built by quarter t in EPCI e)	0.2041**
	(0.0924)
Observations	10,703
R^2	0.89925
Within R^2	-0.02854
Year-quarter fixed effects	Yes
EPCI fixed effects	Yes

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Clustered (EPCI) standard-errors in parentheses. All observations exhibiting zeros for the charging stations and the EV registrations variables were removed.

Table 15: EV Demand Equation - first-stage of the 2SLS, without log-transformation

	Stations built by quarter t in EPCI e
Supermarkets × lagged national stations	$9.63 \times 10^{-5***}$
	(7.33×10^{-6})
Observations	45,167
R^2	0.78809
Within R^2	0.71124
Year-quarter fixed effects	Yes
EPCI fixed effects	Yes
F-statistic	111,132.8

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Clustered (EPCI) standard-errors in parentheses.

Table 16: EV Demand Equation - second-stage of the 2SLS, without log-transformation

	Quarterly EV registrations by EPCI
Stations built by quarter t in EPCI e	2.598^{***}
	(0.6336)
Observations	45,167
R^2	0.65478
Within R^2	0.42632
Year-quarter fixed effects	Yes
EPCI fixed effects	Yes

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Clustered (EPCI) standard-errors in parentheses.

Table 17: Charging Station Equation - first-stage of the 2SLS with null observations removed

	log(quarterly EV stock by EPCI)			
	(1)	(2)	(3)	(4)
log(fuel price in the last quarter)		-0.0685***	-0.0683***	-0.0732***
		(0.0156)	(0.0138)	(0.0144)
log(fuel price in current quarter)	-0.0466*		-0.0006	-0.0024
	(0.0270)		(0.0259)	(0.0281)
log(fuel price one year ago)	-0.5996	-0.6217	-0.6216	
	(0.3788)	(0.3826)	(0.3814)	
log(fuel price two years ago)	-0.1628	-0.1233	-0.1234	
	(0.2724)	(0.2789)	(0.2788)	
log(fuel price three years ago)	-0.5851	-0.5812	-0.5813	
	(0.4115)	(0.4135)	(0.4135)	
EV demand equation instrument (log)	1.87×10^{-5}	1.81×10^{-5}	1.81×10^{-5}	6.16×10^{-6}
	(3.49×10^{-5})	(3.48×10^{-5})	(3.48×10^{-5})	(3.57×10^{-5})
Observations	12,475	12,467	12,467	12,503
R^2	0.98985	0.98985	0.98985	0.98981
Within R^2	0.00511	0.00556	0.00556	0.00091
Year fixed effects	Yes	Yes	Yes	Yes
Quarter fixed effects	Yes	Yes	Yes	Yes
EPCI fixed effects	Yes	Yes	Yes	Yes
F-statistic	15.9	17.3	13.9	5.58

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Clustered (EPCI) standard-errors in parentheses. All null observations were removed. The observations span 987 different EPCIs.

Table 18: Charging Station Equation - second-stage of the 2SLS with null observations removed

	log(stations built by quarter t in EPCI e)			
	(1)	(2)	(3)	(4)
log(quarterly EV stock by EPCI)	-1.659	-1.681	-1.679	0.0949
	(1.609)	(1.457)	(1.457)	(1.037)
EV demand equation instrument (log)	0.0007*	0.0007*	0.0007*	0.0007**
	(0.0004)	(0.0004)	(0.0004)	(0.0003)
Observations	12,475	12,467	12,467	12,503
R^2	0.75520	0.75402	0.75413	0.80431
Within R^2	-0.22385	-0.22965	-0.22912	0.02035
Year fixed effects	Yes	Yes	Yes	Yes
Quarter fixed effects	Yes	Yes	Yes	Yes
EPCI fixed effects	Yes	Yes	Yes	Yes

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Clustered (EPCI) standard-errors in parentheses. All null observations were removed. The observations span 987 different EPCIs.

Table 19: Charging Station Equation - first-stage of the 2SLS without log-transformation

	Quarterly EV stock by EPCI			
	(1)	(2)	(3)	(4)
Fuel price in the last quarter		71.36***	78.75***	78.62***
		(7.574)	(5.500)	(5.701)
Fuel price in current quarter	21.52*		-21.72**	-21.97*
	(12.01)		(10.60)	(13.08)
Fuel price one year ago	17.53	-18.97	-11.48	
	(64.99)	(68.14)	(66.23)	
Fuel price two years ago	36.17	37.74	37.56	
	(34.95)	(35.13)	(35.21)	
Fuel price three years ago	38.21	43.11	40.99	
	(61.34)	(61.43)	(61.93)	
EV demand equation instrument	0.0021***	0.0021***	0.0021***	0.0021***
	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Observations	43,889	43,861	43,861	44,097
R^2	0.90451	0.90470	0.90470	0.90464
Within R^2	0.83261	0.83293	0.83294	0.83292
Year fixed effects	Yes	Yes	Yes	Yes
Quarter fixed effects	Yes	Yes	Yes	Yes
EPCI fixed effects	Yes	Yes	Yes	Yes
F-statistic	3.82	24.9	20.8	48.3

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Clustered (EPCI) standard-errors in parentheses.

Table 20: Charging Station Equation - second-stage of the 2SLS without log-transformation

	Stations built by quarter t in EPCI e			
	(1)	(2)	(3)	(4)
Quarterly EV stock by EPCI	-0.0996	-0.0100	-0.0045	-0.0011
	(0.1131)	(0.0074)	(0.0067)	(0.0043)
EV demand equation instrument	0.0003	0.0001***	0.0001***	9.86×10^{-5}***
	(0.0002)	(1.87×10^{-5})	(1.83×10^{-5})	(1.41×10^{-5})
Observations	43,889	43,861	43,861	44,097
R^2	0.19013	0.77436	0.78318	0.78712
Within R^2	-0.10294	0.69271	0.70472	0.71017
Year fixed effects	Yes	Yes	Yes	Yes
Quarter fixed effects	Yes	Yes	Yes	Yes
EPCI fixed effects	Yes	Yes	Yes	Yes

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Clustered (EPCI) standard-errors in parentheses.

Table 21: Time heterogeneity - first-stage (2SLS)

	log(stations)	log(stations)^2
log-instrument	0.0024***	0.0090***
	(0.0004)	(0.0023)
log-instrument^2	-2.19×10^{-7}***	-5.68×10^{-7}**
	(4.93×10^{-8})	(2.62×10^{-7})
Observations	45,167	45,167
R^2	0.62646	0.57640
Within R^2	0.07453	0.13949
Year-quarter fixed effects	Yes	Yes
EPCI fixed effects	Yes	Yes
F-statistic	1,816.8	3,656.7

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Clustered (EPCI) standard-errors in parentheses.

Table 22: Spatial heterogeneity - first-stage (2SLS) with population density

	log(stations) × Q1(density)	log(stations) × Q2(density)	log(stations) × Q3(density)	log(stations) × Q4(density)	log(stations) × Q5(density)
log-instrument × Q1(density)	0.0208***	-0.0019***	-0.0025***	-0.0018***	-0.0118***
	(0.0027)	(0.0004)	(0.0005)	(0.0006)	(0.0019)
log-instrument × Q2(density)	-0.0012***	0.0163***	-0.0016***	-0.0012***	-0.0077***
	(0.0003)	(0.0012)	(0.0003)	(0.0004)	(0.0011)
log-instrument × Q3(density)	-0.0010***	-0.0010***	0.0123***	-0.0009***	-0.0061***
	(0.0002)	(0.0002)	(0.0012)	(0.0003)	(0.0009)
log-instrument × Q4(density)	-0.0005***	-0.0005***	-0.0007***	0.0097***	-0.0034***
	(0.0001)	(0.0001)	(0.0002)	(0.0010)	(0.0006)
log-instrument × Q5(density)	-4.95×10^{-5}*	-5×10^{-5}*	-6.66×10^{-5}*	-4.88×10^{-5}	0.0013***
	(2.92×10^{-5})	(2.86×10^{-5})	(3.77×10^{-5})	(3.09×10^{-5})	(0.0005)
Observations	45,167	45,167	45,167	45,167	45,167
R^2	0.51428	0.58486	0.56481	0.57373	0.55134
Within R^2	0.21330	0.26366	0.22417	0.28849	0.20199
Year-quarter fixed effects	Yes	Yes	Yes	Yes	Yes
EPCI fixed effects	Yes	Yes	Yes	Yes	Yes
F-statistic	2,446.5	3,230.8	2,607.1	3,658.4	2,283.9

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Clustered (EPCI) standard-errors in parentheses. Q1(density) to Q5(density) categorize EPCIs in quintiles, depending on their population density.

Table 23: Income heterogeneity - first-stage (2SLS)

	log(stations) × Q1(income)	log(stations) × Q2(income)	log(stations) × Q3(income)	log(stations) × Q4(income)	log(stations) × Q5(income)
log-instrument × Q1(income)	0.0085***	-0.0005***	-0.0009***	-0.0010***	-0.0013***
	(0.0008)	(0.0001)	(0.0002)	(0.0002)	(0.0002)
log-instrument × Q2(income)	-0.0009***	0.0089***	-0.0012***	-0.0014***	-0.0018***
	(0.0002)	(0.0012)	(0.0003)	(0.0003)	(0.0003)
log-instrument × Q3(income)	-0.0003***	-0.0003***	0.0041***	-0.0005***	-0.0007***
	(0.0001)	(9.66×10^{-5})	(0.0008)	(0.0002)	(0.0002)
log-instrument × Q4(income)	-0.0002***	-0.0001***	-0.0002***	0.0028***	-0.0004***
	(6.37×10^{-5})	(5.61×10^{-5})	(9.3×10^{-5})	(0.0007)	(0.0001)
log-instrument × Q5(income)	-4.8×10^{-5}	-4.13×10^{-5}	-6.97×10^{-5}	-8.09×10^{-5}	0.0009***
	(3.05×10^{-5})	(2.64×10^{-5})	(4.44×10^{-5})	(5.14×10^{-5})	(0.0003)
Observations	45,167	45,167	45,167	45,167	45,167
R^2	0.58562	0.54389	0.52580	0.53656	0.46323
Within R^2	0.27247	0.21567	0.18263	0.18561	0.09702
Year-quarter fixed effects	Yes	Yes	Yes	Yes	Yes
EPCI fixed effects	Yes	Yes	Yes	Yes	Yes
F-statistic	3,379.2	2,481.1	2,016.1	2,056.4	969.5

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Clustered (EPCI) standard-errors in parentheses. Q1(income) to Q5(income) categorize EPCIs in quintiles, depending on their median equivalized disposable income.

References

Allcott, H., & Wozny, N. (2014). Gasoline prices, fuel economy, and the energy paradox. *Review of Economics and Statistics*, 96(5), 779–795. https://doi.org/10.1162/REST_a_00419

Allcott, H., Knittel, C., & Taubinsky, D. (2015). Tagging and targeting of energy efficiency subsidies. *American Economic Review*, 105(5), 187-191. https://doi.org/10.1257/aer.p20151008

Archsmith, J., Muehlegger, E., & Rapson, D. S. (2021). Future paths of electric vehicle adoption in the United States: Predictable determinants, obstacles, and opportunities. *NBER Working Papers 28933*, National Bureau of Economic Research, Inc. http://www.nber.org/papers/w28933

Arlt, M.-L., & Astier, N. (2023). Do retail businesses have efficient incentives to invest in public charging stations for electric vehicles? *Energy Economics*, 124. https://doi.org/10.1016/j.eneco.2023.106777

Austin, D., & Dinan, T. (2005). Clearing the air: The costs and consequences of higher CAFE standards and increased gasoline taxes. *Journal of Environmental Economics and Management*, 50(3), 562-582. https://doi.org/10.1016/j.jeem.2005.05.001

Autorité de la concurrence. (2024). *Avis 24-A-03 du 30 mai 2024 relatif au secteur des infrastructures de recharge pour véhicules électriques*. https://www.autoritedelaconcurrence.fr/

Bartik, T. (1991). *Who benefits from state and local economic development policies?* W.E. Upjohn Institute.

Borenstein, S., & Davis, L. W. (2016). The distributional effects of U.S. clean energy tax credits. *Tax Policy and the Economy*, 30(1), 191-234. https://doi.org/10.1086/685597

Callaway, B. & Sant'Anna, P. (2021). Difference-in-differences with multiple time periods. *Journal of Econometrics*, 225(2), 200-230. https://doi.org/10.1016/j.jeconom.2020.12.001

Chen, C.-W., Hu, W.-M., & Knittel, C. R. (2021). Subsidizing fuel-efficient cars: Evidence from China's automobile industry. *American Economic Journal: Economic Policy*, 13(4), 152-184. https://doi.org/10.1257/pol.20170098

Davis, L., Li, J., & Springel, K. (2023). Political ideology and U.S. electric vehicle adoption. Energy Institute Working Paper 342, October. https://haas.berkeley.edu/wp-content/uploads/WP342.pdf

Diamond, D. (2009). The impact of government incentives for hybrid-electric vehicles: Evidence from US states. *Energy Policy*, 37(3), 972-983. https://doi.org/10.1016/j.enpol.2008.09.094

Forsythe, C., Michalek, J., & Whitefoot, K. (2023). Technology advancement is driving electric vehicle adoption. *Proceedings of the National Academy of Sciences*, 120(23). https://doi.org/10.1073/pnas.2219396120

Fournel, J.-F. (2023). Electric vehicle subsidies: Cost-effectiveness and emission reductions. TSE Working Paper 23-1465, September. https://www.tse-fr.eu/publications/electric-vehicle-subsidies-cost-effectiveness-and-emission-reductions

Gallagher, K. S., & Muehlegger, E. (2011). Giving green to get green? Incentives and consumer adoption of hybrid vehicle technology. *Journal of Environmental Economics and Management*, 61(1), 1–15. https://doi.org/10.1016/j.jeem.2010.05.004

Gillingham, K., Ovaere, M., & Weber, S. M. (2021). Carbon policy and the emissions implications of electric vehicles. *NBER Working Papers 28620*, National Bureau of Economic Research, Inc. https://doi.org/10.3386/w28620

Glachant, J.-M., Joskow, P. L., & Pollitt, M. G. (2021). (Eds.). *Handbook on electricity markets*. Edward Elgar Publishing.

Hagem, C., Kverndokk, S., Naevdal, E., & Rosendahl, K. E. (2023). Policies for electrification of cars in the short and long run. *Transportation Research Part D: Transport and Environment*, 117. https://doi.org/10.1016/j.trd.2023.103606

Hidrue, M. K., Parsons, G. R., Kempton, W., & Gardner, M. P. (2011). Willingness to pay for electric vehicles and their attributes. *Resource and Energy Economics*, 33(3), 686-705. https://doi.org/10.1016/j.reseneeco.2011.02.002

Holland, S. P., Mansur, E. T., & Yates, A. J. (2021). The electric vehicle transition and the economics of banning gasoline vehicles. *American Economic Journal: Economic Policy*, 13(3), 316-344. https://doi.org/10.1257/pol.20200120

Jacobsen, M. R. (2013). Evaluating US fuel economy standards in a model with producer and household heterogeneity. *American Economic Journal: Economic Policy*, 5(2), 148-187. https://doi.org/10.1257/pol.5.2.148

Jenn, A., Springel, K., & Gopal, A. R. (2018). Effectiveness of electric vehicle incentives in the United States. *Energy Policy*, 119, 349-356. https://doi.org/10.1016/j.enpol.2018.04.065

Kempton, W. (2016). Electric vehicles: Driving range. *Nature Energy*, 1(9), 1-2. https://doi.org/10.1038/nenergy.2016.131

Klier, T., & Linn, J. (2016). The effect of vehicle fuel economy standards on technology adoption. *Journal of Public Economics*, 133(C), 41-63. https://doi.org/10.1016/j.jpubeco.2015.11.002

Knittel, C. R. (2011). Automobiles on steroids: Product attribute trade-offs and technological progress in the automobile sector. *American Economic Review*, 101(7), 3368-3399. https://doi.org/10.1257/aer.101.7.3368

Li, J. (2017). Compatibility and investment in the U.S. electric vehicle market. Working paper, October. https://www.haas.berkeley.edu/wp-content/uploads/J.-Li.pdf

Li, S., Tong, L., Xing, J., & Zhou, Y. (2017). The market for electric vehicles: Indirect network effects and policy design. *Journal of the Association of Environmental and Resource Economists*, 4(1), 89-133. https://doi.org/10.1086/689702

Linn, J. (2022). Is there a trade-off between equity and effectiveness for electric vehicle subsidies? Working Paper 22-7, University of Maryland and Resources for the Future. https://media.rff.org/documents/WP_22-7.pdf

Meunier, G., & Ponssard, J.-P. (2020). Optimal policy and network effects for the deployment of zero emission vehicles. *European Economic Review*, 126(C). https://doi.org/10.1016/j.euroecorev.2020.103449

Muehlegger, E., & Rapson, D. S. (2022). Subsidizing low- and middle-income adoption of electric vehicles: Quasi-experimental evidence from California. *Journal of Public Economics*, 216(C). https://doi.org/10.1016/j.jpubeco.2022.104752

Neaimeh, M., Salisbury, S. D., Hill, G. A., Blythe, P. T., Scoffield, D. R., & Francfort, J. E. (2017). Analysing the usage and evidencing the importance of fast chargers for the adoption of battery electric vehicles. *Energy Policy*, 108(C), 474-486. https://doi.org/10.1016/j.enpol.2017.06.033

Needell, Z. A., McNerney, J., Chang, M. T., & Trancik, J. E. (2016). Potential for widespread electrification of personal vehicle travel in the United States. *Nature Energy*, 1(9), 1-7. https://doi.org/10.1038/nenergy.2016.112

Newell, R. G., Jaffe, A. B., & Stavins, R. N. (1999). The induced innovation hypothesis and energy-saving technological change. *The Quarterly Journal of Economics*, 114(3), 941-975. https://doi.org/10.1162/003355399556188

Rapson, D. S., & Muehlegger, E. (2021). The economics of electric vehicles. *NBER Working Papers 29093*, National Bureau of Economic Research, Inc. https://doi.org/10.3386/w29093

Schulz, F., & Rode, J. (2022). Public charging infrastructure and electric vehicles in Norway. *Energy Policy*, 160(C), 1-15. https://doi.org/10.1016/j.enpol.2021.112660

Sheldon, T. L., & Dua, R. (2019). Measuring the cost-effectiveness of electric vehicle subsidies. *Energy Economics*, 84(C). https://doi.org/10.1016/j.eneco.2019.104545

Springel, K. (2021). Network externality and subsidy structure in two-sided markets: Evidence from electric vehicle incentives. *American Economic Journal: Economic Policy*, 13(4), 393-432. https://doi.org/10.1257/pol.20190131

Xing, J., Leard, B., & Li, S. (2021). What does an electric vehicle replace? *Journal of Environmental Economics and Management*, 107(C). https://doi.org/10.1016/j.jeem.2021.102432