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Master's Thesis

FACTORS OF ELECTRIC VEHICLES MARKET ADOPTION: FRANCE

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EMIN MASTER

Master's Thesis

FACTORS OF ELECTRIC VEHICLES MARKET ADOPTION: FRANCE

By Aleksandr Matveev

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Under the esteemed guidance of:
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Best wishes,

Aleksandr

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LIST OF SUPPORTING MATERIALS

ACCRONYMS

AVERE	The European Association for Battery, Hybrid and Fuel Cell Electric Vehicles
ACF/PACF	Autocorrelation / partial autocorrelation function
BEV	Battery electric vehicle
CV	Conventional vehicle
DW	Durbin-Watson test
EV	Electric vehicle
FD	First differences
OLS	Ordinary least squares
PHEV	Plug-in hybrid
SS	Sum of squares
SD	Second differences
VIF	Variance inflation factor

CHAPTER 1. PROBLEM STATEMENT

1.1 Introduction

The prospects of EVs eventually replacing conventional cars may still seem far-fetched. After all, the internal combustion engine has been the standard technology for transportation roughly for the last 2 centuries. However, one needs to know that initially it was only one out of several options. Steam and electricity used to compete on equal footing with oil whose advantages as a primary energy source were not that obvious at the time.

The prevalence of oil-fueled cars accounts for *sometime* cheapness of oil. It is no longer the case, which however cannot bring immediate readjustments. The hydrocarbon society is tailored by its infrastructure, attitudes and inertia to exploit fossil fuels. It results in global warming, pollution and ever more frequent temperature anomalies. Over and above, the need for oil causes dependency on foreign suppliers who may prove unreliable.

Whatever advantages conventional fuels might have, they are still unreliable in the long run due to their limitation. And the transition towards a more sustainable alternative has already begun. High officials all around the globe are taking commitment to green innovations. Enormous amounts of investments are being put into the creation of a new energy framework. It is also worth mentioning the Paris agreement uniting the efforts of many nations towards this goal. Special attention is given to the transportation sector as one of the biggest contributors to CO_2 emissions.

That is why EVs are attracting so much attention. It is no longer a matter of scientific speculation, but rather that of huge practical importance. Upon EV development, to a large extent, depends the resolution of exacerbating ecological and geopolitical issues. It represents an eco-friendlier mode of transportation. And although most of electricity still comes from fossil fuels, power facilities produce much less emissions thanks to advanced filtration. Apart from that, achieving balanced electricity consumption reduces the idle running of generators and improves overall energy use.

Another reason why the topic is becoming so popular is rapid technological progress. It finally makes EVs commercially viable and investment attractive. Just recently they seemed outlandish, economically and technologically unfeasible. Now, they are getting a common sight in the streets, along with growing charging infrastructure. More and more companies are launching R&D projects aimed at improving energy storage capacities. The notorious range anxiety is being addressed, both on local and international levels: Paris, Amsterdam, Berlin as many other cities have established extensive charging systems. By now, EVs have already reached a much higher efficiency ratio (energy to power at the wheels): 60 % as compared to only 20 % of CV **[US Department of Energy, 2017].** Moreover, EVs produce less noise, having better acceleration and maintenance characteristics. Driving range, recharge time and costs have been also consistently improving over the past years. For instance, the new Tesla model can be on the move for up to 250 miles on a single battery. Given all this, it becomes no surprise that Bloomberg predicts production cost parity between EVs and CVs already by 2022 [**Randal, T. (2016)**].

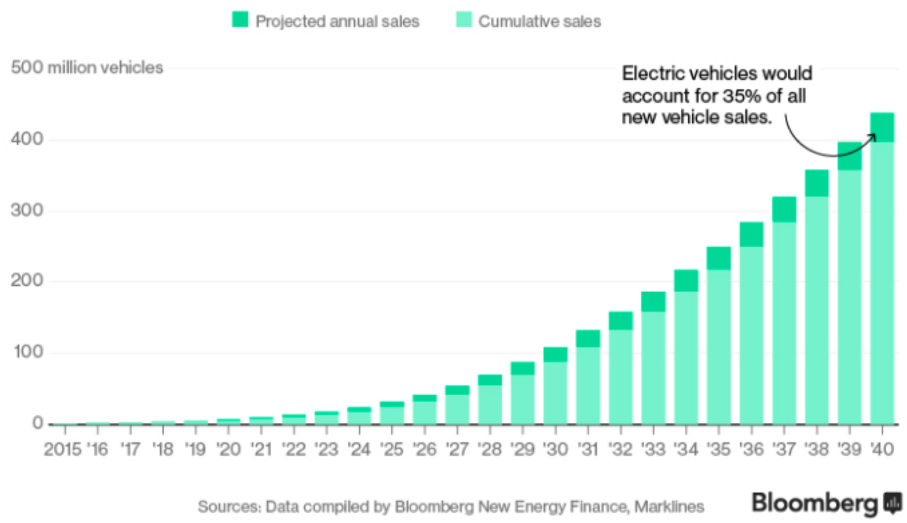

Figure 1. Bloomberg EV sales projections

The growing EV segment arises many questions: what, when and how to finance; what role should government assume and to which extent is the technology self-reliant. Answering those defines the vector of the industry's development and the framework by which it will be bound for many years to come. Potential mistakes at the beginning stage may be all the more detrimental.

Particular attention in this regard must be paid to charging infrastructure. It serves as a prerequisite of EV widespread market adoption, one of whose main concerns still remains "range anxiety". Apart from economic and technological, this involves social, political, town planning and many other considerations. That is why it is of such great relevance to rely upon a thorough research of current socio-economic trends as well as on appropriate optimization and modelling techniques.

1.2 Literature review

Although first EVs came about as early as in the 19th century (52 years before CV), their employment was negligible until very recently [**Paul Wolfram et al, 2016, p. 2**]. This explains the erstwhile lack of literature and oversimplication of the topic. It used to deal primarily with experimental prototypes' performance which due to limited interest and financial resources were hardly able to test the technology's potential. Now, it has profoundly changed. Having become a topic of high practical importance, EV attracted the attention of governments, research institutions and investors.

There appears an ever increasing volume of articles dedicated to different aspects of the topic; starting from technical specifications and ending with factors of market adoption. Let us briefly outline a list of the most important publications. They can be classified in several categories including those based on statistical analysis **[Lutsey, N. et al. (2015a)]**, **[Sierzchula, W. et al. (2014)]**, **[Greene, D. et al. (2014)]**, **[Clinton, B. et al. (2014)]** as well as on surveys **[Hardman, S. et al. (2016)]**, **[Krupa, J. et al. (2014)]**, **[Helveston, J. et al. (2015)]**. Some scientists prefer modelling and simulation techniques (MATLAB/Simulink) due to their robustness: **[Mesrane et al. (2015)], [Lin, C. et al. (2001)], [Hofmman et al. (2004)], [Wipke, K.B. et al. (1999)]**. Others rely on personal experience and qualitative judgments: **[Dougherty et al. (2014)], [Lutsey, N. (2015b)], [Coplon-Newfield, G. (2016)]**.

To begin with, **[Dougherty et al. (2014)]** focused on various barriers preventing EV from gaining widespread use. Among those, the authors specifically point out range anxiety. In large part, it accounts for insufficient charging infrastructure. Particularly, this conclusion relates to a low density of charging points and their limited access along the way on distant trips. One of the arguments was that these problems are resulting from financial uncertainty investors face. And the government must promote various investment tools including leasing arrangements and securitization schemes.

[Nic Lutsey (2015)] also made an inquiry into the topic of charging infrastructure as one of the crucial factors of EV deployment. He showed that provided its insufficiency, stimulating measures (financial incentives and tax reductions) have a little positive impact. This was proven the case in the New York City and in a number of European countries. A special emphasis was placed on making clear to customers how to use this infrastructure. Charging points location as well as instructions on their utilization should be readily available on the internet and in other outlets.

The above conclusions are consistent with the findings of [**Clinton, B. et al. (2014)**]. Applying regression analysis, the authors found a positive relationship between charging infrastructure (size & density) and EV sales during 2011-2013 in different American states. Other factors such as rebates and access to special lanes on the road, although with positive coefficients, turned out to be less significant. The study suggests that those incentives on their own are not effective, serving its purpose only being complementary to a highly developed charging infrastructure. Yet again, it was given priority in defining the industry's evolution.

[Lin, C. et al. (2001)] applied advanced modelling techniques simulating CV and EV performance under similar driving conditions. The cars' architecture has been emulated as complex input-output systems. Among the elements, engines, motors, battery, power control modules, transmission links were considered in their dynamic relationships. This virtual experiment, amazingly enough, replicates physical reality, making actual car prototypes unnecessary. This in turn reduces manifold the time, costs and efforts which had been a significant obstacle in studying EVs for a long period before. According to the obtained results, the EV has demonstrated a much higher efficiency and reliability. Over and above, the authors proposed a dynamic programming model (algorithm) describing the principles of an efficient power management.

[Sierzchula, W. et al. (2014)] examined the factors of EVs market adoption by using multiple linear regression analysis. It was determined what impact the average level of income, charging stations density, financial incentives, fuel economy and EV price have on each particular producer's market share. One of the main conclusions was that charging infrastructure played the most important role in EV promotion. Financial incentives and the local presence of branches of companies also showed a positive correlation with the dependent variable. Therefore, the recommendations were that the government must maintain its support of both, producers (in the form of co-financing charge infrastructure development) and end-consumers (subsidies and tax reductions).

The aforementioned papers along with many others were thoroughly studied in order to collect sufficient materials and statistics. This allowed to draw on the research of ones of the most prominent specialists in the field. And their findings were used as a reference when elaborating the thesis' methodology and hypotheses. Consequently, the obtained results were tested as applied to France.

1.3 Goal and tasks

The goal of the thesis is to determine the factors of EV market adoption and the most efficient ways of its promotion; to analyze current trends in the industry and their implications in a broader socio-economic context. The obtained results may hopefully be used for improving related regulatory policies and facilitating the industry's development. In order to accomplish this goal, a number of tasks will be performed, namely:

- A review of charging technologies: types, stations, their limitations, advantages and drawbacks;
- Analysis of the French charging infrastructure: usage, standards, long-term strategies;
- Revising different kinds of public policies aimed at encouraging green innovations: subsidies, tax allowances, special privileges in traffic, financial support of EV producers;
- Finding out to which extent charging infrastructure serves as a factor of EV market adoption;
- An estimation of synergistic benefits associated with the growing number of EVs: alleviation of electricity network congestions, unit commitment optimization, abatement of harmful emissions;
- A discussion of possible regulatory framework improvements, both on local and international levels and addressing various issues around EV in economic, technological, social and political contexts.

1.4 Subject and scope

The subject of the study is the French EV industry including such relevant elements as: EV brands, design and technical characteristics; charging infrastructure and supportive networks; national legal and economic framework (technological standards, special support schemes, international collaboration).

The scope is complex relationships involved in designing, operating, supervising and improving the French EV industry. A special focus will be placed on charging infrastructure which is believed to be one of the main factors of the industry's development. Particular attention is paid to its network nature being subject to various externalities. Associated market failures imply government intervention which is indeed widely present. Given this specificity, the subject is viewed primarily from the regulator's standpoint.

1.5 Hypotheses

The main assumption is that monthly EV sales can be explained through a set of variables. The hypotheses relate to different factors of EV adoption, signs and values of their contributions. First and foremost, a suggestion is made as to what are the main elements to be taken into account. Given the multifaceted nature of EV, as many of them as possible were considered. Among those, EV price and range, cost of electricity, battery specifications, government subsidies, total cars sales and GDP growth rate have been assumed potentially significant.

Secondly, the nature of their influence on the resulting variable, both quantitative and qualitative, was analyzed. To name a few, EV prices, battery production cost, electricity tariffs were deemed to have a negative correlation with EV sales; whereas EV range, oil quotation, subsidies, number of charging points – a positive one. Among them, EV range and charging infrastructure appear crucial, having to do with the notorious "range anxiety". Although less relevant, EV and electricity prices are also believed to make sizable contributions to the dependent variable. All the rest factors follow next in importance.

1.6 Methodology

The methodology applied is regression analysis using a number of software tools such as STATA, Gretl and Matlab. It involved several steps: hypothesis proposal, data collection, modelling, quality control checks, statistical tests interpretation and eventually analysis of the obtained results. Given the technical specificities of the subject, the thesis draws on a wide array of information including basic engineering, statistics and economics. Therefore, the topic concerned lies in the interdisciplinary field of data analysis, mathematical statistics, econometrics, marketing and management of the electric power industry.

1.7 Scientific novelty

The scientific novelty of the research consists of applying regression analysis to the French EV market. Based on an extensive literature review, there has been created a model explaining the factors of EV adoption. Their impact has been quantitatively and qualitatively estimated, which allowed to measure the efficiency of the current regulatory policies. Proceeding from that, some of them were deemed advisable to continue while others - to change. The approach used differs in a number of ways from existing researches, some of whose limitations are believed to be overcome. This permitted obtaining more accurate results, implying different kinds of policies and areas of focus of the government, business and the public.

The author compiled an extensive database encompassing various statistical sources. For obtaining some of those, a respective public agency has been contacted directly. The array of indicators concerns many aspects of the topic: economic, social, governmental and attitudinal. To mention a few: monthly EV sales in France, weighted EV range and price, amount of subsidies, the number of charging stations and so on. In efforts to ensure data homogeneity, their individual characteristics were thoroughly analyzed and subjected to a set of certain standards.

The practical importance of the research is that it provides an insight into establishing an efficient regulatory framework for stimulating EV deployment. The obtained conclusions may facilitate setting right policy priorities, be it promoting investment into charging infrastructure or EV range enhancement, subsidizing end consumers or producers and the like. Additionally, this kind of research helps establish green incentive programs (e.g. clean transportation). Hopefully, it will usefully contribute to the ongoing debates about the EV outlook.

1.8 Structure

Apart from the introduction and conclusion, the thesis includes three chapters. The first one covers the problem statement, literature review and the latest developments in the industry. The second one deals with the research methodology, namely a description of the regression techniques employed; variables and their suggested contributions as well as necessary steps to ensure results robustness. The final chapter is concerned with interpreting the obtained coefficients, both as regards separate variables and the model as a whole; and analyzing the substance behind them. Based on that, possible improvements to the current French government policies will be proposed and the industry's outlook will be examined.

CHAPTER 2. METHODOLOGY AND DATA COLLECTION

2.1 Peculiarity of regression analysis

An important aspect of regression analysis[1] is that it examines variables *taken together*. That is, individual factors depend on their particular combination and functional form. A given variable may be significant when coupled with another, but not - otherwise. When a variable is added to or omitted from an equation, the signs and coefficients of other factors change. Therefore, decisions on specific variables should not be made based solely on their individual significance.

Suppose two opposite forces define the outcome. Let it be, for instance, prices and income as factors of spending. Other conditions equal, the price has a negative contribution to spending, while income – positive. Assume that only 1 out of the 2 factors is accounted for in the model. Then, the only factor will take upon itself the total explicative power which otherwise would have been shared between the two. As a result, the sign and value of this single factor would be distorted, swaying either towards positive or negative, depending on the ratio between the two forces. If the positive contribution of income (omitted) exceeds the negative one of the price (included), then the accumulative contribution is positive. So a higher price turns out to encourage higher spending, which is contradictive.

Although omitted, factors still exercise an implicit influence over the resulting variable. Therefore, the explicative power of the equation may be compromised. Before jumping to conclusions, one needs to make sure that the residuals scatter plot has no recognizable trend. Otherwise, it has to be extracted by factoring missing variables in. In this way, the implicit influence would become explicit, which will straighten all the signs up.

For example, the residuals scatter plot below contains seasonality. Depending on a problem examined, one must figure out what this seasonality stands for. It may have to do with economic, temperature, social and other kinds of factors. In the case of EV sales, such seasonality might be due to the seasonal nature of car sales in general. Since the EV segment represents only a small fraction of total sales, its inclusion into the model supposedly would not cause any endogeneity

[1]Regression analysis is a particular type of statistical analysis expressing one variable as a linear combination of the others. This is performed by the OLS. It consists of summing up and then minimizing the squares of vertical differences between actual and estimated observations. The higher the result, the bigger the deviations. Below are the sum of squares (SS) formulas: f_i fitted values, y_i actual observations, e – “errors”.

$SS_{residuals} = \sum_i (y_i - f_i)^2 = \sum_i e_i^2 \quad SS_{regression} = \sum_i (f_i - y_{mean})^2 \quad SS_{total} = \sum_i (y_i - y_{mean})^2$

issues. The implicit influence of seasonality would be revealed, thereby setting other coefficient to right values.

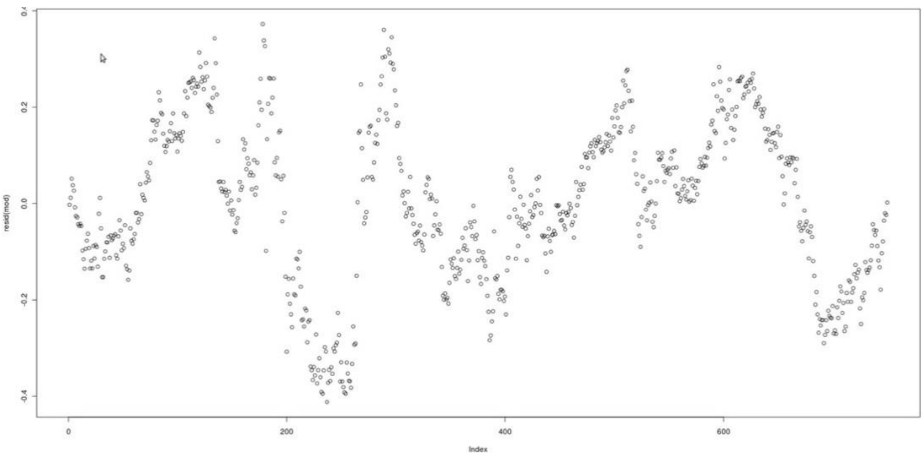

Figure 2. A residuals scatter plot with seasonality

2.2 Reliability requirements

Apart from the inclusion of all important factors, a model has to be ensured against a number of potential issues: multicollinearity, heteroskedasticity, endogeneity, autocorrelation and non-stationarity. Let us briefly go over each of those.

MULTICOLLINEARITY

A high correlation does not necessarily imply significance, which is particularly the case when regressors duplicate each other. A twin variable not only brings no new information, but also it spoils model quality by creating numerous solutions[2]. It results in wider confidence intervals and decreasing precision. Multicollinearity may be detected using the variance inflation factor (VIF) [**Penstate Eberly College, 2017]** or covariance matrix **[Cohen, J. (1988)]**.

ENDOGENEITY

Endogeneity arises when a variable is modelled on its very twin. Rather than an equation, an identity is obtained not broken down into elements. As opposed to multicollinearity, endogeneity affects the functional form of the equation obscuring cause and effect relations between the resulting and explanatory variables: e.g. was it economic growth that stimulates employment or

[2] Assume an equation: $b=x_1 + x_2 + x_3$, where $x_1 = x_2 + x_3$. Adding "a" to x_1 and deducting it from $(x_2 + x_3)$ does not affect the result. $b = [[(\beta)]_1 + a)x_1 + [[(\beta)]_2 - a)x_2 + [[(\beta)]_3 - a)x_3 = \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + a(x_1 - x_2 - x_3) = \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3$

the other way around. The most popular way of testing endogeneity is the Durbin Watson test[3]. It is applicable only to time series, which is why spatial models have to be preliminary modified by adding an artificial time variable.

STATIONARITY

Up until now there has been much of scientific debates around the consequences of differencing. Although cognizant of non-stationarity issues[4], **[Brooks, C. (2008, p. 292)]** conceded that differencing is not always advisable. That is because examined relationships may become obscured throwing away meaningful information about the long-term time-series trend. Likewise, [**Sims, C. (1980, p. 4)]** made an argument against "artificial constraints" distorting original data. He went on to suggest not to remove indiscriminately all instances of non-stationarity. Of the same opinion are James H. Stock, Mark W. Watson **[Sims, C. et al. (1990), p. 114]**, Gianni Amisano and Carlo Giannini **[Amisano, G. et al. (1996)]**. The fact of the matter is that non-stationary variables may cancel each other (co-integration) and allow for obtaining efficient estimates. On the other hand, should one of those be removed, the equation at large may be imbalanced.

A differenced variable is not an equivalent to its original, but rather a derivative. And the higher the degree of differencing, the farther away the derivative moves from its original. This adversely affects results interpretation: it will be no longer obvious what the increment stands for and how

[3] Should the d-statistics be lower than the *lower* bound of the interval of critical values, then H_1 claiming endogeneity is accepted. If the d-statistics exceeds the *upper* bound of the interval, H_1 is rejected. Being within the interval makes the DW test inconclusive. The authors of the test proposed using a beta-distribution in case of inconclusiveness. However, it has limited applicability **[Harlow, A.A. (1962), p. 57]**: only big models of no less than 40 degrees of freedom. The Breusch-Godfrey and Durbin alternative tests allow for a lagged version of the dependent variable, which is incompatible with endogeneity identification.
[**Pratschke, J.L. (1971, p. 500)], [Pratschke, J.L. (1969)]** has summarized the findings of the most prominent specialists in the field, by experimenting with four kinds of tests for endogeneity: 1) "tau test" by R.C. Geary, 2) "runs test" by A. Wald & J. Wolfowitz and F.C. Swed & C. Eisenhart, 3) "chi-squared test" by Z. Griliches and 4) "exact test" by R.A. Fisher. The results were discarded: a 50 % level of error. The attempts by **Theil, H. and Nagar, A.** similarly failed **[Jeong, J. et al. (2001)]**. [**Harrison, M.J. (1972, p. 42)]**; **[Miller, G.J. et al (2007, p. 480)]** made an argument that, there are neither suitable methods of overcoming inconclusiveness nor an adequate alternative to the DW test. Using other tools requires to significantly modify original data or involves non-reliable estimations. Therefore, interpreting the inconclusive range as no endogeneity is quite common.

[4] Stationarity implies a constant mean, variance and probability distribution **[Perron, P. (1988)]**. Otherwise, variables' dynamics may be obscured by a trend. Should it be the case, they appear correlated due to the influence of some common circumstances (e.g. inflation) rather than mutual relationship. A non-stationarity can be removed by differencing **[Iordanova, T. (2007)]**: chain subtraction of each observation from the previous one. This makes a variable flatter removing the trend and making its fluctuations more pronounced. In some cases, differencing stands out as the only option. Although obscuring variables' interpretation, it still ensures model reliability requirements.

obtained conclusions relate to actual parameters. Therefore, excessive differencing is strongly undesirable, especially in the case of relatively small observation sets. Rather a comprehensible approach has to be adopted, weighing pros and cons of leaving weakly stationary variables in the model.

HETEROSKEDASTICITY

As Paul Allison put it [**Williams, R. (2015), p. 3**], heteroskedasticity makes the OLS suboptimal because it treats all observations equally, while they are not. Those with a lower variance are more predictable and therefore informative. As a result, (although coefficients would likely remain unbiased) standard errors along with P-values become unreliable. In order to overcome the issue, an equation needs to be divided by or stripped of the affected factors. As a result, the heteroskedastic variable becomes constant, while the others are supposed to "absorb" the negative effect.

AUTOCORRELATION

Autocorrelation is a backward chain-link relationship among observations [**Pindur, D. (2009), p. 176**]. There are distinguished two types: positive and negative[5]. It creates numerous solutions and affects model precision. While coefficients remain intact, standard errors increase. The most common solution is factoring a lagged version of the dependent variable in. In this way the implicit influence becomes explicit straightening coefficients up. Upon doing it, the Durbin alternative and Breush-Godfrey tests will be carried out. If inconclusive, the Newey-West approach is due to be applied. Being compatible with autocorrelation, multicollinearity and heteroskedasticity, it yields robust standard errors. Should the factors remain significant, then an autocorrelation is deemed negligible and the model – reliable enough.

[5] Positive autocorrelation is a kind of inertia which prevents a process from sharply changing its direction (a train unable to be stopped or accelerated instantaneously due to its huge mass). A negative autocorrelation implies regular volatility when a positive value is followed by a negative one like pendulum (financial markets). The former is more likely to appear in a time-series. Be it sales, economic growth, birthrates or any other evolutionary process – all of them, to some extent, are distinguished by an inertial interdependence across observations.
Another important aspect is that autocorrelation links only observations at the same interval. Apart from that, partial autocorrelation **[Quality America Inc., 2017]** examines all possible cross relationships. For illustration, let us assume that "a" is a linear combination of ("b" and "c") and "z" is that of ("x" and "y"). In this case, autocorrelation is concerned only with the relationship between "a" and "z", while partial autocorrelation also examines how their components relate: "b", "c", "x", "y".

2.3 Database collection

Table 1. List of variables

monthly Jan 2011-Dec 2016 (72 obs), France (compiled by the author)

VARIABLE	DESCRIPTION	UNIT	SOURCE
Registration	EVs registered per month	Item	[Automobile Propre, 2017]
Stations	Cumulative number of stations	Item	[Global EV Outlook, 2016, p. 38]
Battery	Average battery production cost	$/kWh	[Global EV Outlook, 2016, p. 5]
Total_sales	Total car sales (incl. EV) per month	Item	[INSEE, 2017]
Subsidy	Lump sum per EV purchase	M€	[Beretta, J. (2015), p. 12] [EV Research, 2012]
Electricity	Electricity tariffs, MV	€/MWh	[Eurostat, 2017]
Price	Price, top 10 EV weighted by sales	M€	[EVobsession.com, 2017]
Socket	Cumulative number of sockets	Item	[Chargemap.com, 2017]
Oil	Oil price	$/bbl	[Macrotrends.net, 2017]
Range	Range, top 10 weighted by sales	Mile	(individual for each car)[6]
EVshare	EV share in total sales per month	%	[Global EV Outlook, 2016, p. 37]
EVstock	Cumulative EV number	Item	[Global EV Outlook, 2016, p. 35]
GDP	GDP of France, chain-linked 2010	MM€	[FRED, 2017]

DIFFERENCING

Since the ensuing modelling requires stationarity, let us firstly check the variables' suitability using the Dicky-Fuller test (refer to Annex A). As a result, some of them have had to be differenced, namely: d2_range, d_stations, d_subsidy and d_price. The newly obtained variables were denoted d_ and d2_, depending on the degree of differencing applied: first or second.

The author relies on the scientists cited in the "stationarity" part **Chris Brooks (2008), Chris Sims (1980/90), James H. Stock & Mark W. Watson (1990), Gianni Amisano & Carlo Giannini (1996)** in deciding to retain one weakly stationary variable, d_stations. Further differencing is deemed excessive due to the limited observation set size and the significant reduction of non-stationarity by taking first differences. The P-value has dropped from 1 down to 0,198. Since the dependent

[6] [Avere, 2017c], [Krome, C. (2017)], [Electric on wheels, 2008], [Glotfelty, D. (2013)], [Straubel, J.B. (2008)], [Straubel, J.B. (2014)], [Autocar, 2016a|b], [Kia.com, 2017], [Oliveira, J. (2016)], [Wikipedia, 2017a-g].

variable is stationarity, there is no substantial risk of spurious significance between the two. Proceeding from the designation “d2_”, the range was differenced twice. This is because the level of non-stationarity remained quite high upon the first attempt of differencing (new Dicky-Fuller test value 0,97).

2.4 Variables description

Having obtained a set of variables, let us move on to their description. Particular attention will be paid to the underlying assumptions, as they strongly affect the time series. For instance, the EV price may be average or weighted, with or without accounting for inflation, that of top 5, 10 or all brands in the market. The same holds, for instance, with respect to EV range. Electricity prices in turn require picking up a representative voltage level. There are no universal rules on which to hold to when determining the most appropriate variables’ characteristics. This was done relying on an extensive literature review, so as to adapt existing approaches to the examined problem.

REGISTRATIONS

The monthly EV registrations is the dependent variable whose behavior is going to be explained by all the others. It was obtained in full and ready-assembled; so room for making additional assumptions was limited. Displayed in the graph below is a pronounced seasonality accompanying an upward trend. Towards the right, the variance seems to slightly increase, which however was not confirmed by statistical tests for stationarity. The fluctuations may have to do with production cycles or a particular shipment regularity, characteristic of the automobile industry. Indeed, the pattern has been found similar to that of total car sales (the next section).

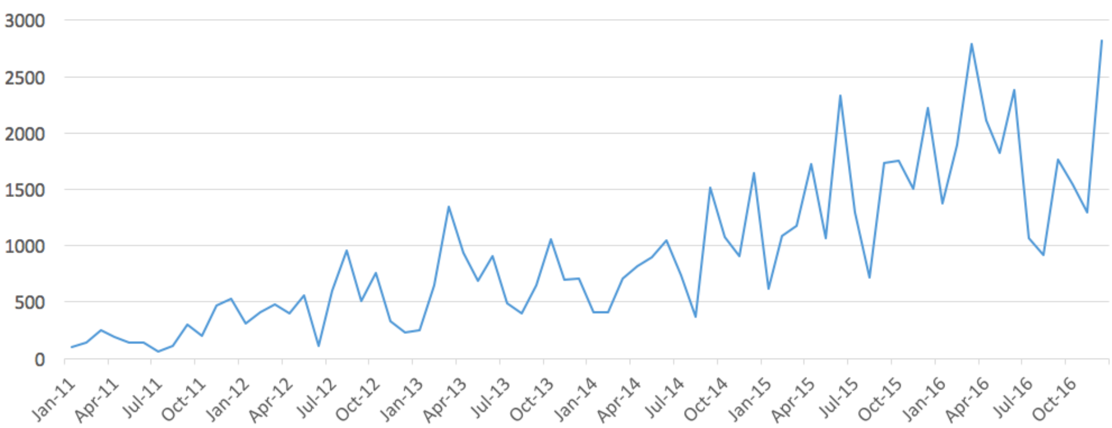

Figure 3. Monthly EV registrations

TOTAL CAR SALES

Total car sales need to be accounted for, so as to remove seasonality from the dependent variable. Said differently, the implicit impact must be exposed cleaning up the residuals of the trend and bringing the coefficients into right proportions. This should not cause problems of endogeneity, given a small fraction of EV in total sales.

As the picture shows, the EV registrations and total sales fluctuation patterns are quite similar. The former, being just a small portion of the latter, is compelled to following general macroeconomic conjuncture. And as the EV number grows, it becomes of yet more regularity in terms of the underlying factors of the industry. That is why the lines tend to converge. This results in a variation which has no direct relationship with the factors of EV market adoption. Therefore, its further break down falls beyond the goal of the thesis.

Total car sales are assumed to have a positive correlation with EV registrations (pro-cyclical). In other words, general sales growth signifies favorable conditions in the industry, which in turn encourages EV sales. Given no grounds to do otherwise, no additional modifications were applied to the variable.

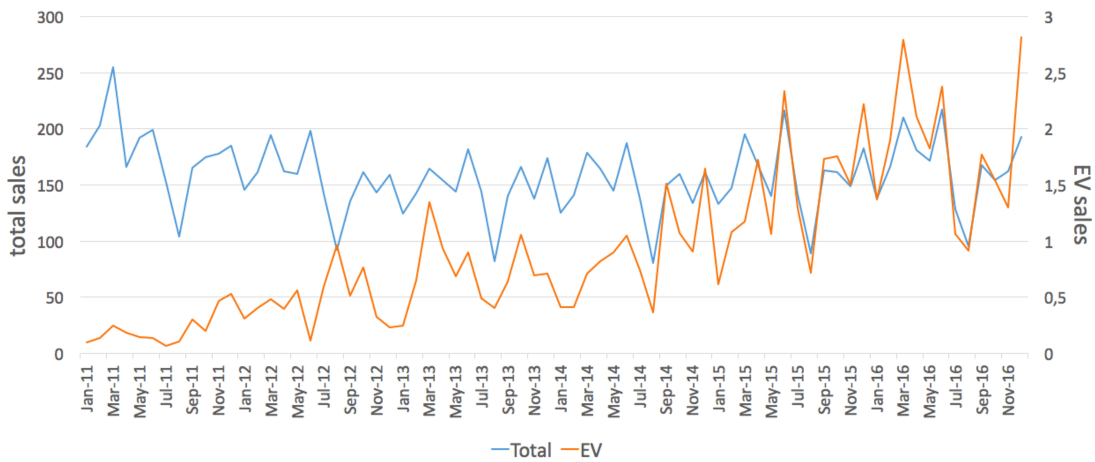

Figure 4. EV and total sales (scales 1:1000)

RANGE

Range limit is possibly the strongest stumbling block on the way to wide EV market adoption. This is so much so that the problem was even labeled “range anxiety” which is currently attracting ever more attention [**Salah, K. et al (2016)**], [**Bulut, E. et al (2017)**]. Potential buyers demand excessive range capabilities which are unlikely to be used. A peculiarity of this issue is that it is by no means limited only to practical inconveniences, but rather it involves a kind of superstitious precaution against the technology.

A UK consultancy firm Deloitte analyzed the discrepancies between expected and actual EV characteristics, particularly range [**Deloitte, 2011a, p. 6-7**]. Target groups in several countries have been asked about the minimum range below which they would not consider buying or leasing an EV. The results were a surprise: whereas around 80+% of drivers cover no more than 50 miles a day, this very range is acceptable only for about 5 % on average. In France this contrast appeared even more so: 83 to 2 %, while as much as 33 % have indicated 400 miles (640 km) as the bare minimum acceptable.

These estimations are somewhat unrealistic and speak for insufficient public awareness of the EV technology. Because of that, additional assurances in the form of a super high range are demanded. The survey was conducted back in 2011 when the EV surge had just began. Since then, charging infrastructure has been growing intensely, which to some extent alleviated range anxiety. However, it still persists: according to the recent survey by the National Renewable Energy Laboratory (USA, 2016) [**Singer, M. (2016), p. 19**], only 55 % of respondents were satisfied with a range of 375-400 miles. The majority asks for a significant margin, atop what they normally drive.

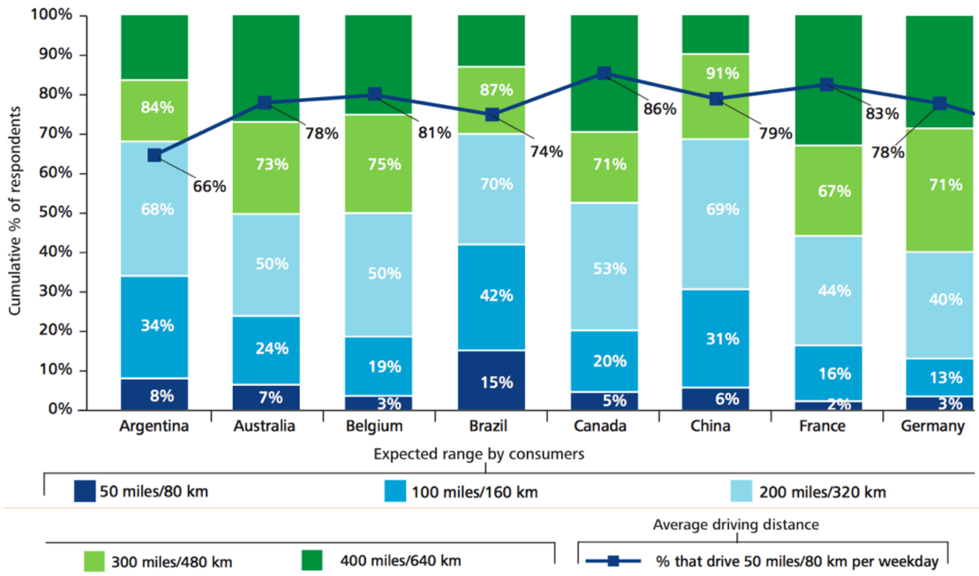

Figure 5. Range expectations & distance traveled

That is why Tesla having addressed this strong urge by first introducing a 250+ miles range EV is believed to contribute most to EV development and popularity. The latest Tesla is capable of being on the move for more than 350 miles without recharging. IBM, Apple along with other companies are increasingly joining the competition. The aim now is reportedly 500 miles per charge [**Shahan, Z. (2016)**].

One of the primary issues while collecting data was ensuring consistency. The fact of the matter is that battery behavior very much depends on the elements: temperature, humidity level and mode of driving (high-way or city). Moreover, the approaches to measuring range by various agencies significantly differ, so do their estimations. Yet worse, they tested different cars which have had to be compiled into a single series. Range also varies depending on car configuration: trim level (basic) and additional accessories. Some cars require battery leasing, while others do not. Last but not least, most sources afforded only the latest range specifications, while their dynamics over the last 6 years was needed (same EV models of different years of issue may have different ranges).

To avoid selection biases, the following principles have been followed. First of all, the number of sources referred to was kept to a minimum as far as possible. The main one is the EPA (US Environmental Protection Agency) whose portfolio of tested cars was found most extensive. Another aspect is comparing only among basic configurations with the exception of BMW i3. This one has a too big difference between ranges in the lowest and highest configurations, so the middle has been settled on. City driving as more widespread among EVs was preferred over highway driving. Finally, the range enhancement of a car along the years has been taken into account.

The resulting variable is obtained by weighting by sales the ranges of the top 10 most sold EVs annually. This indicator appears representative enough for the following reasons. To begin with, it reflects the demand for a particular range, which an average value would not do. Apart from that, the latter would be biased in favor of the leader in range - Tesla which however, still captures a relatively small market share. The decision was made to limit the number of brands up to 10, because those beyond that account for only a negligible amount of sales.

Let us proceed to analyzing the range's dynamics (blue line) and its second differences (orange) depicted in the next graph. As shown, the variable has a stable upward trend; having more than doubled during the considered period: from 94 to 190 miles. The biggest contributor to that is Tesla having rolled out in 2014 the model S with almost twice the range of then the leader in sales, Renault ZOE. It had shocked the market quite a bit encouraging other producers to double down on battery enhancement.

As for the statistical aspect, it is crucial to point out some similarities between the upward trends of the range and EV registrations. This potentially creates a spurious significance which may inadequately reflect the actual relationships. That is why second differencing had to be taken imparting onto the graph a peculiar saw-like shape. It inherits the “upward trend” in the form of explosive fluctuations. The initial hypothesis is that the range has a positive influence over EV sales.

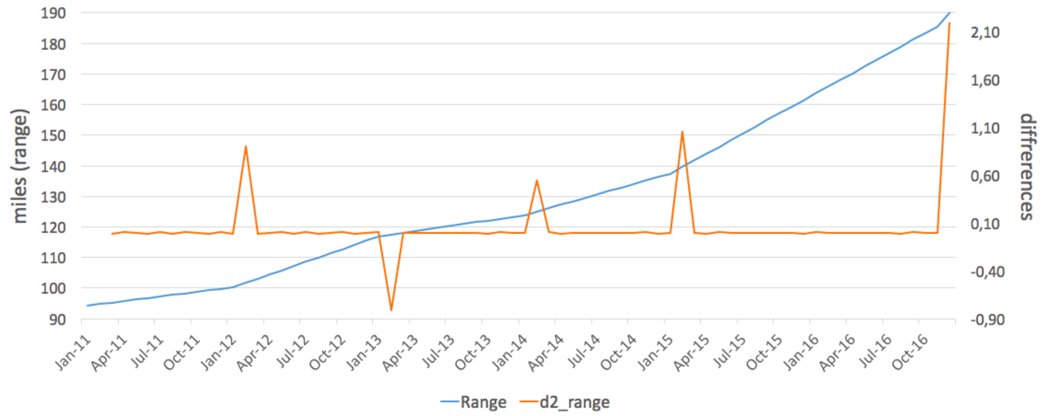

Figure 6. Range and d2_range

STATIONS

As EV technology continues to reinforce itself as a future substitute for gasoline cars, more companies are joining the efforts in developing charging infrastructure. The business is gradually loosing its negative image as a risky enterprise with likely sunk costs. So much so that since 2011, global charge stations deployment has increased from less than 100.000 to nearly 12,5 mln [**Kosior, K. (2015)**].

The number of stations is supposed to reflect the level of charge infrastructure development. The choice of the variable was, to a large extent, dictated by non-existence of relevant data (according to the AVERE and Chargemap.com statistics portal, covered in the “Factors discarded” part). Otherwise, much more parameters would have been considered such as the number of sockets (total and per station), their geographical distribution (stations in cities and along highways; only partial information: **[McKinsey, 2014, p. 34], [Masson, L.J. (2013)], [Blue2bGreen, 2016]**). Additionally, shares of different kinds of chargers would have been taken into account: slow, fast and superfast. Information about stations’ workload as well as charging tariffs (for private stations) might also be useful. Last but not least, it would be instructive to know the approximate share of EV drivers charging their vehicles from household outlets (only non-residential are available).

Despite limited options, the chosen variable appears suitable. Although yearly rather than monthly, this time-series completely covers the period of interest as opposed to the number of charging sockets ("Factors Discarded" section). Furthermore, it is reported by a single source and therefore more consistent. Over and above, no monthly data breakdown poses no serious problem, given the long-term nature of the indicator. Involving thorough governmental planning and high capital intensity, it is not prone to monthly volatility.

The available yearly data will be used as a set of turning points defining the vector of overall development. The gaps between them are to be filled in with extrapolated data assumed to be evenly distributed. The approach validity is partially confirmed by the available statistics of charging sockets. During the period 2013-2016, their number gradually increases without any fluctuation noise **[Chargemap.com, 2017].**

Of particular importance is the relationship between range anxiety and charge infrastructure. The latter provides ever more opportunities for feeding EVs, both in residential and office areas. Surprisingly enough however, the number of stations and the persistent need for more range appear somehow delinked. Apart from range anxiety, there seems to be a kind of "stations anxiety". The impact of their increasing number falls short of expectations. Yet worse, many people underestimate the time required for full recharge [**Deloitte, 2011b, p. 5**]. All this results in extra stations representing a costly redundancy, a price of overcoming public skepticism. As the learning curve unfolds and more EVs hit the road, the excess of charging stations may be probably "absorbed".

To examine the 2 anxieties, it was decided not to bundle the variables of range and stations up. Given their different periodicity, it might add up noise to the measurements. Additional modifications were also deemed impractical, contrary to some researchers. For example, [**Vergis, S. et al (2014)**], [**Bil, G. (2015)]; [DeShazo, J. et al. (2015), p. 15**] consider the number of stations per 1000 of population. It seems unjustified because only a small fraction of population represents EV drivers. Similar ideas are put forth with respect to EV drivers as well [**Tietge, U. et al (2016), p. 14**], so as to somewhat account for an average station's workload. Nevertheless, given the excess of charging capacities, this restriction cannot be binding.

It would be desirable to follow the approach of **[Xydas, E. et al. (2016)**] who used detailed information about the time, duration and load of charging cycles at each station (UK). Apart from that, [**Chen, D. (2013)]** analyzed the local demographic structure (Seattle, USA) and the daily routine timetable of an average resident (time in traffic, in parking lots, at home). This allowed to adjust the charging infrastructure by intensity of utilization, which however is inapplicable in the present case due to lack of data.

The graph below shows the stations and its first differences. The trend is quite similar to the previous case except for a steeper angle. Indeed, the growth (in both absolute and relative values) is much bigger, especially starting from the year 2015. The number of charge stations has multiplied manifold, particularly following the introduction of the CORRI-DOOR project [**EU Directive, 2013**]. The government made it one of its top priorities not only to increase inner-city charge stations density, but also to link them with superchargers along main long-distance highways. This applies to international travel as well, Spain-France-Germany as major EV hubs. As expected, the stations should exercise a positive force in the resulting variable and be highly significant.

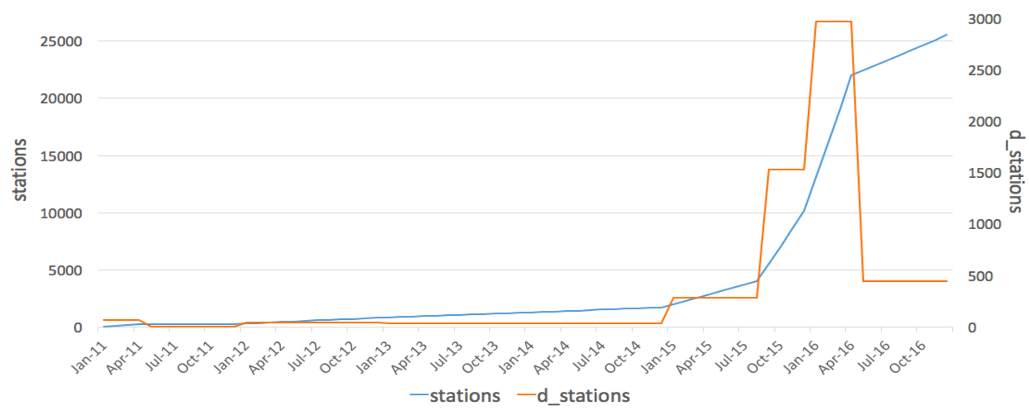

Figure 7. Stations and d_stations

EV PRICE

EV floor prices exceed those of CV, which is interpreted by many researchers [**Fitzgerald, G. et al. (2017)]; [Ajanovic, A. (2015)**] as a serious impediment towards wide EV market adoption. On the other hand, **[Lambert, F. (2017)], [Inderbitzin, A. et al. (2015)]** emphasize that numerous indirect EV benefits excessively compensate for the unfavorable price difference. Among those are free charge stations, special privileges in traffic and tax exemptions, let alone the French government bonus of up to 10.000 euros per EV purchase. So EVs become cheaper than CVs in overall cost (price & service) already in the first years of utilization. And the main impediment has actually to do mostly with insufficient public awareness. Probably because of that, most potential buyers are so reluctant to pay the EV price premium, even provided a significant reduction of expenditures on fuel and maintenance. This is illustrated by the next diagram [**Singer, M. (2016), p. 22]**: 22 % of respondents do not consider paying any extra for an EV, despite a fuel cost reduction by one-third (along the horizontal axis – fair price premiums as perceived by the buyer).

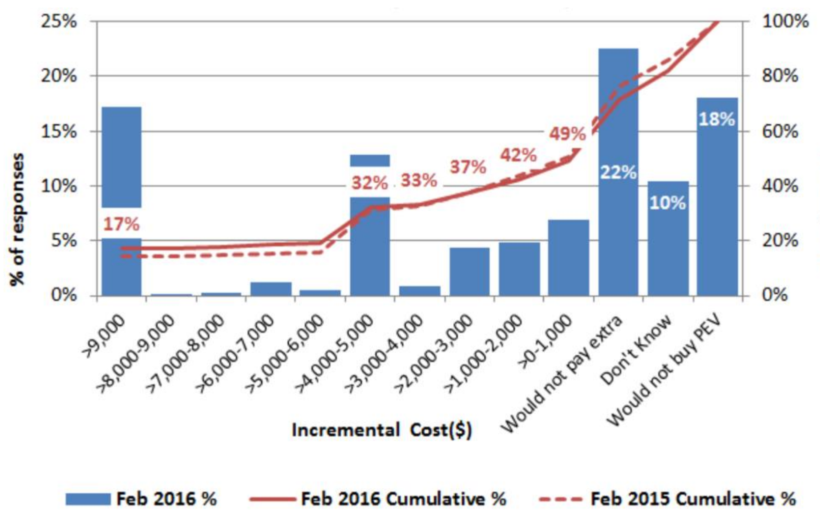

Figure 8. Willingness to pay the EV price premium.

As for possible variable modifications, [**Uller, G.B. et al. (1993), p. 7], [Martens, J. (2015), p. 14**] factor in a ratio of the weighted EV price to that of CVs. In doing so, they account for relative price dynamics. On the other hand, [**Cheng, J. (2016), p. 8], [Wang, N. et al. (2015), p. 12**] include the EV price independently. That is because the 2 categories are not directly comparable. EVs encompass various car classes starting from "economy" (MIA, Citroen C-Zero, Bollore BlueCar) and "SUV" (BMW X5 xdrive40e) and ending with "Luxury" (Tesla model S) and "Sport" (Tesla Roadster). And that subgroups have a price segmentation differing from CV. Therefore, it is not clear how to ensure homogeneity when determining the weighted prices.

Moreover, the price ratio takes no account of qualitative differences between the two car types. It is as if assuming a potential buyer of a Bollore BlueCar (€ 22.000) to necessarily consider as an alternative an economy class CV; or the other way around. In fact, EV adopters have somewhat different preferences, less conservative and tech-savvy leaning [**Anadiotis, P. (2012), p. 64**]. They may be specifically interested in familiarizing themselves with an innovative product; or be strongly committed to the environment. At the same time, they may prefer an expensive CV.

Last but not least, the ratio seems redundant, at least because of CV prices stability. Dividing by it hardly affects the result. Even in case of price fluctuations, they are mostly caused by macroeconomic factors equally affecting both groups of cars.

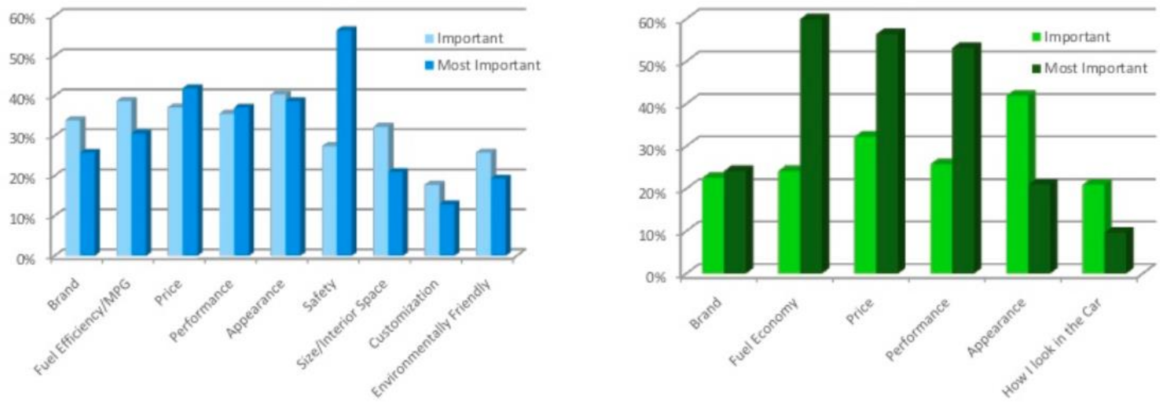

Figure 9. Preferences of CV (left) and EV buyers (right)

As opposed to range subjected to different interpretations, the price is more definitive. Despite some variations depending on the country and car configuration, EV prices appear generally homogenous. As for the French market, it is currently dominated by relatively cheap economy-class cars, in descending order [**EVobsession.com, 2016**]: Renault Zoe, Nissan Leaf, Peugeot iOn, Bollore Blue Car and Kia Soul EV. To the credit of French car manufacturers, they are steadily leading the ranking. Apart from the mentioned ones, Citroen C-zero has been quite popular during the last 6 years. And this is so despite the non-discriminatory approach of the government in affording per-purchase subsidies.

Figure 10. The top 5 selling BEV (left) and PHEV (right)

Prices were included without subsidies which will be accounted for by a separate variable. Otherwise, it would be impossible to split the effects of the two factors apart. Prices of cars requiring a regular battery change (or monthly leasing payments) have been recalculated as follows: an initial price plus the sum of payments for 3 years[7]. American EV prices (Tesla) were converted to euros by average yearly exchange rates of the corresponding years. As for calculating the aggregate indicator, the same logic was followed as in the case of EV range: top 10 EV sold weighted by sales.

The decision was also made to take account of inflation. In a technological context it may be interpreted as the depreciation rate of know-hows. To put it simply, innovative products tend to loose in price along the time, be it iPhone, satellite broadcast, solar panels or EV battery. By the analogy with inflation as a function of money supply, technological depreciation accompanies the unfolding of a learning curve. A possible argument is that this depreciation should be already reflected in price. In fact, the prices of the same cars have mostly remained constant. Therefore, neither regular inflation, nor "technological" one has been evaluated.

There was a number of options to factor this in: consecutive yearly increments or splitting the data series apart. The latter has been chosen based on some important events occurred in the industry. The leading company in EV transportation and battery technology, Tesla announced in 2014 that it discloses all its patents [**Musk, E. (2014)**]. Moreover, it welcomed everybody to using them for free with a promise of no judicial or other kinds of claims. As a result, the know-hows became widely accessible, which is considered a major factor of EV technological depreciation. The time series has been divided into two equal parts 2011-13 and 2014-16. Whereas the latter period retains actual EV prices, the former has all of them increased by 5 %. Years of issue have not been taken into account as supposedly having a negligible effect.

The price dynamics and its first differences are shown in the next picture. Despite the assumed technological depreciation, the graph has an upward trend. This is because of the recent introduction of a series of expensive EVs: Tesla (€69.000), BMW i3 (€34.950), KIA Soul EV (€34.745). They are several times more expensive than earlier EVs. Having addressed the acutely standing issue of range anxiety, these brands have managed to take a significant market share, notwithstanding their higher prices.

[7] **[EVobsession, 2017]** BLUECAR 18.400 + 80 per month (3 years) = 21.280; Renault ZOE 21.362 + 68,33 per month (3 years) = 23.821; Renault Fluenza ZE 26.300 + 82 per month (3 years) = 29.252. | **[Autoblog.com, 2016]** Citroen E-Mehari 24.000 + 72 per month = 26.592 | **[Glotfelty, D. (2013)]** | **[Olivier Marie, P., 2016].**

The differenced variable to be used in the model has neither definitive direction nor clear interpretation. Proceeding from its relatively stagnant profile, the price variable is supposed to have a limited contribution to EV sales.

Figure 11. Price and d_price

BATTERY COST

The battery constitutes the bulk of the EV price. Therefore, the downward trend is potentially translatable into cheaper EVs, which would alleviate one the strongest barriers to their further proliferation. Nevertheless, most EV producers, as shown above, preferred to improve range characteristics rather than to cut down on prices. But as soon as the technology achieves an appropriate level of development, there may be a huge down spiral in prices.

From a regression standpoint, the downward trend imposes an opposite effect onto the resulting variable as compared to the previous cases. Thus, the hypothesis is that the battery coefficient is likely to be negative and significant. This will be a balancing force, without which the positive impacts of range, stations and total sales may be underestimated. Although having some convexity, the graph still leans towards a linear rather than exponential relationship. Therefore, no logarithm or square have been applied.

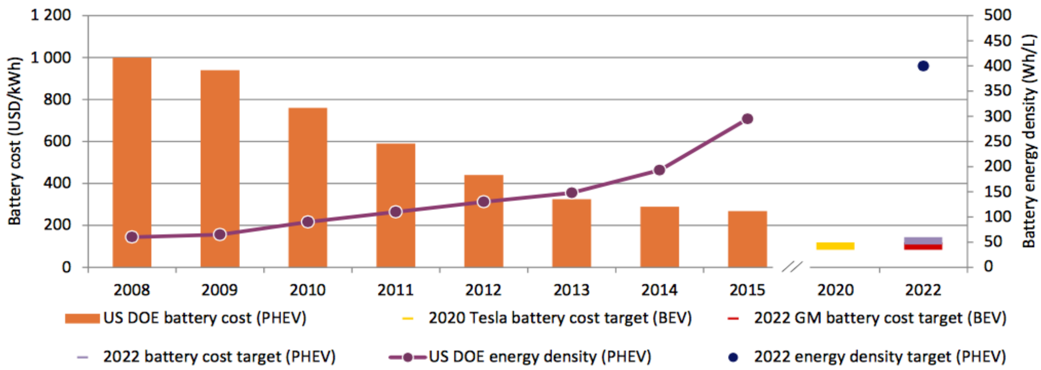

Figure 12. Battery cost and energy density

SUBSIDY

So far public support was considered an absolute prerequisite for EV development. The main assumption behind that is EV insufficient maturity for competing with conventional cars. Keeping in mind significant social benefits of the technology, the government is willing to share in its promotion. Therefore at least at the initial stages, market adoption must be facilitated by virtue of different incentives. Among them, there are both monetary (direct bonuses, tax exemptions, special rebates) and non-monetary (access to public transport lanes, waiver of traffic restrictions on foggy days, priority parking).

In the case of France, probably the biggest incentive is the EV per purchase subsidy. Its amount has been fluctuating over the past years: €5.000 before 2012, then €7.000 with the following adjustment to €6.300 [**Amiot, M. (2013)**]. As of now it makes up for up to €10.000 (but no more than one-third of the EV price including VAT) provided that an old car is given away for scrap metal. This potentially renders all the issues associated with unfavorable EV prices pretty much irrelevant. This subsidy based on non-discriminatory principles is afforded to buyers of both domestic and foreign brands. And as many experts believe, such a significant discount on EV prices cannot but give a strong push to their sales.

With respect to modelling, per purchase subsidies have another advantage of being easily accounted for. It is a net gain EV owners receive depending neither on horsepower nor car dimensions. In contrast with hybrids, the absence of CO_2 emissions serves to further simplification. On the opposite, tax exemptions involve calculation of payments based on average exhaust, grams per km [**Bucco-Lechat, C. (2014)**]. This in turn is contingent upon a particular car and mode of driving. So in order to evaluate these benefits, one needs to determine CV opportunity costs (how much taxes would be spared if switching over to an EV). This involves too much of assumptions and thus likely errors, but with no obvious gains. So the decision was made to settle on the lump-sum subsidy as a consolidated indicator of government stimulating policies.

The variable along with its first differences is depicted in the next graph. Apart from a peculiarly broken shape, it is characterized by an upward trend. Not counting the small recess from October 2013 to April 2015, there are three consecutive step-ups: 5, 7 and 10 thousand euros. From a regression sense, the variable's positive influence over EV sales would be principally the same as that of other factors with ascending trends.

The variable's nonstationarity resulting from a level shift (nonconstant mean) prevents it from being used in the model. In spite of that, its first differences will be. They do not succumb to interpretation, having no clear trend. As a derivative of such an important factor as subsidies however, it is supposed to be highly significant. The contribution is presumably positive: the bigger the subsidy or its first differences, the stronger the stimulus EV sales receive.

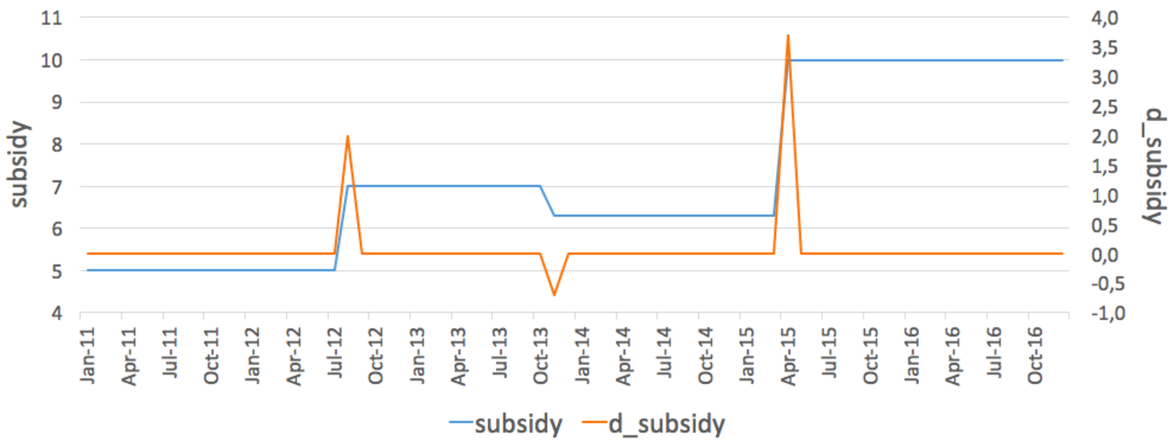

Figure 13. EV per purchase subsidy and FD

LAGGED VARIABLE

An auxiliary variable had to be added in order to address the issue of autocorrelation. It represents a lagged version (with a step of 6) of the dependent variable. In other words, the latter has been moved forward by 6 periods, so it starts from the 6th observation. In all other respects, it has the similar characteristics as EV registrations covered above. The rationale behind this modification will be explained in the "3.3. Quality control tests" section ("Autocorrelation").

FACTORS DISCARDED

Not all of the variables ended up in the model. Among those is "oil" which was initially expected to be positively correlated with EV sales. That is because high oil prices make CV utilization more expensive. Nevertheless, petroleum market volatility coupled with statistical insignificance led to the variable's removal. Whereas in the long run, oil prices would most likely be relevant, their short term impact appears rather obscure.

The EV share in total monthly sales and the EV cumulative number (EVshare and EVstock respectively) have not been factored in either. Initially, they were supposed to represent the increasing level of EV market penetration, attracting late adopters. However, due to their predominantly flat profile, they exercised a limited influence over the resulting variable. For the same reason, GDP (along with its derivatives: real and rate chain-linked) has been also turned down. This is no wonder given a relatively stable macroeconomic situation during the period in question.

Despite its high relevance, the number of charging points has been discarded due to lack of data. Thanks to an extensive search, the figures of 2016, 2014 and partially 2013 have been obtained from open sources. In order to fill in the gaps, a number of agencies were contacted directly, including the AVERE (the French regulator of charging infrastructure) and Chargemap.com statistics portal. Both of them replied to the inquiry communicating that only the most recent numbers are available, but not their dynamics over the last years. There might be occasionally only some reports having referred to old figures.


historical data charging points, France Inbox x

Aleksandr Matveev [redacted] Jan 17
to marie.castelli

Chère madame Castelli,

Pourriez-vous s'il vous plaît me recommander où je peux trouver le nombre de points de facturation en France au cours des années 2011-2016. Idéalement, ce serait des données mensuelles. Tout le site ne donne que les derniers chiffres, mais pas les séries historiques.

Merci beaucoup d'avance! Je serai impatient de votre réponse,
Sincèrement vôtre, Alexander

marie castelli [redacted] Jan 18
to me

French > English Translate message Turn off for: Frenc

Bonjour

Malheureusement ces données n'existent pas à ma connaissance.

Cordialement

Marie Castelli

Figure 14. The AVERE reply to the request for statistics (Jan 17, 2017) [8]

Yet worse, there is a significant discrepancy among different statistical agencies. For instance, the French government registration office reports only 1.200 public charging outlets (as of October 2015) [**French government registrar (2017)**]. On the other hand, the Ministry of Ecology, Sustainable Development and Energy [**Green Growth Act (2015)**] indicates a figure of more than 10.000 for the same period. A popular source of charge infrastructure statistics, "**Chargemap.com**" refers to much higher orders of magnitude, around 20.000. [**Tietge, U. et al. (2016), p. 32**] argue that the second source mentioned (the Ministry) is the most reliable, while its disadvantage is that it does not collect spatial data for regional analysis.

[8] Translation from French.
Author: Could you please recommend where to find the number of charge points in France over the years 2011-2016 (monthly time series). **Marie Castelli, AVERE:** Unfortunately, this data does not exist to my knowledge.

In view of the above, an extrapolation of the available data was deemed unreliable. And the number of charging stations has been used instead, as the indicator of charging infrastructure. Despite that, the socket variable has been tried in the model for informational purposes. Extrapolating the average rate of growth 2014-16 onto the period 2011-2013 proved the variable insignificant. Consequently, the trend was assumed exponential, which indeed yielded positive results.

The electricity price variable, apart from being insignificant, did not fit because most EV owners reside in cities, in multi-storey buildings, where a household plug cannot be used for EV charging. Therefore, charge stations (as of now mostly free in France) serve as an alternative, which makes electricity tariffs irrelevant for the driver. Despite all this, electricity being the EV’s “fuel” is by all means an important factor and will be statistically confirmed as such, once necessary payment infrastructure and government willingness are in place.

CHAPTER 3. QUALITY CONTROL AND RESULTS INTERPRETATION

3.1 Descriptive statistics

Let us analyze the descriptive statistics of the chosen variables contained in the next table. First of all, the default number of observations is 72 (number of months in 6 years). Since each differencing reduces the set by 1, the variables differenced once have 71 observations (d_stations, d_subsidy and d_price); while those differenced twice – 70 observations (d2_range). Since lag6 is the registration variable starting from the 6^{th} period, the number of its observations equals 66 (=72-6).

Table 2. Descriptive statistics

VARIABLE	OBS	MEAN	STD. DEV.	MIN	MAX
Registration	72	925,78	678,95	64	2.819
D2_range	70	0,0554	0,3292	-0,81	2,19
D_stations	71	359,25	734,56	4,12	2.969,5
Battery	72	405,83	183,06	240	900
Total_sales	72	158.492,4	31.907,81	80.669	255.009
D_subsidy	71	0,0704	0,5047	-0,7	3,7
D_price	71	0,0262	0,2008	-0,78	1,27
Lag6	66	867,32	652,44	64	2.794

Of interest are the two last columns providing the minimum and maximum values of each factor. The biggest gap is that of EV registrations: 64 against 2.819. These extremes correspond to the opposite ends of the considered time interval. So the increase in EV sales during the past 6 years has been truly large. Although not as much as that, total car sales have also shown a considerable min-max variation: roughly 1:3. However, it was not due to growth, but rather - due to strong market fluctuations. The cost of battery production has significantly dropped from 900 down to 240. As for the differenced variables, their interpretation, as mentioned earlier, appears limited. These "proxy" figures imply a moderate variability of the subsidies, prices and range, while that of the number of stations is fairly high.

The mean also helps get a sense of variables' general dynamics. Should it be closer to the middle of the min-max range, then the trend tends to be smoother. The closer the mean to the minimum value, the sharper its increase to the maximum one (and the other way around). Proceeding from that, the battery production cost and total sales demonstrate quite a gradual change, while that of EV sales is much sharper. Among the differenced factors, the range is of the sharpest trend.

Last but not least, standard deviations characterize factors' variability qualifying their significance. Its degree will be estimated by the software in the following sections. Having reviewed all the variables, let us move on to the model's specification and control tests necessary for ensuring results reliability.

3.2 Model specification

Table 3. Model specification

VARIABLE	COEFFICIENT	P > |T|
D2_range	270,61	0,009***
D_stations	0,2482	0,000***
Battery	-1,60	0,000***
Total_sales	0,0067	0,000***
D_subsidy	187,74	0,005***
D_price	-338,65	0,045***
Lag6	0,3445	0,000***
_constant	132,88	0,561
R-squared	0,85	
R-squared adj	0,84	
Prob > F	0,000	

3.3 Quality control tests

SIGNIFICANCE INDICATORS

Before results interpretation, let us ensure their reliability based on the obtained significance indicators. First of all, the R^2 equals 0,85 (R^2 adjusted 0,84), which means that 85 % of the EV sales dynamics has been explained by the regressors. The rest (unexplained variation) may account either for missing variables or random walk. All the variables are significant at the strictest 1 % level, besides the constant. According to the "Prob > F" statistics, the equations as a whole is of the highest level of significance as well.

R^2 alone is insufficient for judging the model's quality however. Precautions should be taken against spurious significance potentially caused by miscalculations, erroneous hypotheses or regression issues: multicollinearity, endogeneity, heteroskedasticity, non-stationarity and autocorrelation. In order to rule this out, a set of quality control checks needs to be conducted next.

AUTOCORRELATION

To begin with, let us examine the autocorrelation and partial autocorrelation functions of the model **excluding lag6** (refer to Annex B). The 4 columns (left figure) sticking out from the confidence band (grey area) suggest an autocorrelative pattern of up to the 3rd lag, plus the 6th lag. This means that each EV sales observation is affected by its 3 preceding observations and the previous 6th observation. The 3rd and 6th columns are longest supposing the corresponding lags to have the biggest influence over the variable. Also worth mentioning is that all the 4 columns belong to the upper half of the coordinate system, indicating a positive autocorrelation.

The exponential decay of the columns confirms the stationarity of the "EV registrations" variable [**Keshvani, A. (2013)**]. (Otherwise, they would have been of around the same height). Another aspect to pay attention to is the level of the supposed autocorrelation, indicated along the vertical axis. The highest column reaches 60 %, which represents a medium autocorrelation. The prominence of the 6th lag may be traceable to the so-called propagation force [**Nau, R. (2017)**] when first lags pass part of their autocorrelative effect onto the following ones. If so, the 6th lag may be only a derivative of the previous lags and not the actual source of autocorrelation. This will be established based on the partial autocorrelation function (right figure).

The second graph has more columns beyond the confidence band revealing previously hidden cross-relationships. To be interpreted as a partial autocorrelation, their distribution should be of some regularity **[CrossValidated, 2013]**. However, the order of the columns sticking out (1, 2, 3, 6, 12, 18, 19, 28, 29, 30, 31, 32, 34) fits no regular pattern. Therefore, no additional conclusions are made. Just for curiosity, let us point out that the 6^{th} column's overshoot in the left graph indeed accounts, to some extent, for the propagation effect of lags 1, 2 and 3.

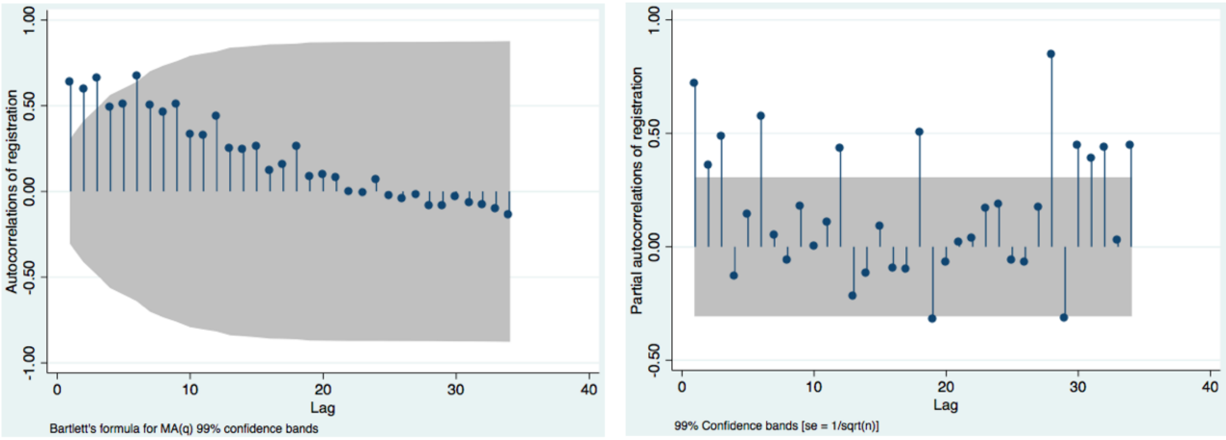

Figure 15. Autocorrelation (left) and partial autocorrelation (right) correlograms

The above conclusions are partially consistent with the Durbin's alternative and Breusch-Godfrey tests. In both cases, the obtained P-values exceed the 5 % level (refer to Annex D: Breusch-Godfrey Prob > chi2 = 0,0736 ∊ [0,05; 0,1]; Durbin's alternative Prob > chi2 = 0,0847 ∊ [0,05; 0,1]). This is the second strictest level of precision, meaning that an autocorrelation cannot be ruled out in 5 % of the cases. Let us try to improve the result by following the principle of making an implicit influence explicit. For this purpose, several lagged versions of the dependent variable have been tested (in accordance with the correlograms, lags 1, 2, 3 and 6).

Upon adding lag3, the tests have not improved. All the rest lags turned much better (refer to Annex D: Durbin's alternative and Breusch-Godfrey respectively: lag1 [0,29; 0,32], lag2 [0,24; 0,27] and lag6 [0,25; 0,28]. Lag6 has been settled on because it provides a high significance of the variable. The risk of autocorrelation has been completely dismissed. For curiosity, let us mention that dividing the dependent variable by the total sales failed to reduce the autocorrelation.

MULTICOLLINEARITY

The test for multicollinearity has been carried out using the VIF [**O'Brien, R. (2007), p. 674**]. Its cumulative value equals 2,33 (refer to Annex C) which falls short of the threshold (2,5) under the strictest criterion [**Allison, P. (2012)**]. This means that the factors' variance increases only slightly when taken together qualifying them for regression purposes.

ENDOGENEITY

Endogeneity was checked with the Durbin-Watson test **[Gross, J. (2003), p. 321]**. The obtained result is 1,71 (refer to Annex C); while the interval of critical values (8 variables incl. the intercept, 66 observations and 1 % significance level): [1,23; 1,68] [**Stanford, 2017**]. The d-statistics exceeds the upper bound of the interval (1,71 > 1,68), therefore the hypothesis of the presence of endogeneity is rejected.

HETEROSKEDASTICITY

The test for heteroskedasticity was performed, using the methodology of Breusch-Pagan and Cook-Weisberg. The obtained P-value "Prob > chi2" equals 0,44 (refer to Annex D) which way exceeds the threshold of 10 %. That is, the variance is assumed to be uniformly distributed (no heteroskedasticity).

NEWEY-WEST ESTIMATOR

Table 4. Newey-West standard errors

VARIABLE	COEFFICIENT	P > |T|
D2_range	270,61	0,006***
D_stations	0,2482	0,000***
Battery	-1,60	0,000***
Total_sales	0,0067	0,001***
D_subsidy	187,74	0,015***
D_price	-338,65	0,001***
Lag6	0,3445	0,000***
_constant	132,88	0,569
Prob > F	0,000	

For when regression issues cannot be removed, there was devised the Newey-West estimator. Despite autocorrelation, heteroskedasticity and multicollinearity, it allows for obtaining reliable estimates [**Mueller, U.K. (2014)], [Eviews User's Guide (2016)**]. Should they be significant, the model is deemed reliable enough. Let us double check the obtained conclusions under this approach. In accordance with the correlograms (Figure 15), 6 is selected as the maximum number of lags.

The table contains the results where the changes in errors are marked out in grey. The equation as a whole and all the variables besides the constant are of the highest significance. The logic behind the signs and coefficients holds as well. Therefore, the Newey-West estimator speaks up for the model's validity.

3.4 Results interpretation

Before proceeding to results interpretation, let us briefly outline the rules applied. First differences represent a set of increments from one observation to another. Thus, an increment in first differences either widens or narrows the gaps. The outcome depends on the one hand, on the sign of an increment in differences and on the other – on the variable's trend.

A positive increment in differences would enhance the increasing parts of the trend and curb the decreasing ones (and the other way around). Consequently, the trend would be straightened out, making accompanying fluctuations less pronounced. It will also be rotated either clockwise (positive increment in differences) or anticlockwise (negative).

Another point is that an increment in first differences **progressively** changes the gaps. Let us assume the following set of numbers: (1, 3, 2, 8 and 15). Should a unit increment be added to each of those gaps as taken separately, only the first one will change: [(1-3) => **(1-4)**]; [(3-2) => **(3-3)**]; [(2-8) => **(2-9)**]; [(8-15) => **(8-16)**]. The result: (1; 4; 3; 9; 16). Therefore, it represents an increment in the variable rather than in first differences. As a result, the graph will retain its proportions being shifted up- or down in parallel.

It should be done as follows. In the first iteration, the time-series moves upward by a unit increment: (1; 4; 3; 9; 16). In order to widen the second gap, one needs to move the time series up again, starting from the 3rd observation: (1; 4; 4; 10; 17). Repeating the same algorithm, one obtains at the 3rd step: (1; 4; 4; 11; 18) and finally: (1; 4; 4; 11; 19). Let us compare the gaps of the initial and the newly obtained sets: (2; -1; 6; 7) against (3, 0, 7, 8). Each of them increased by one: the goal has been achieved.

SUBSIDY

The graph below illustrates the impact of a unit increment in first differences on the variable. It is not uniform across the period: the increasing parts became sharper, while decreasing ones - more obtuse. Therefore, the step-ups progressively accumulate towards the right. The upward trend became more consistent: the recess from Nov 2013 to Mar 2015 has disappeared.

A unit increment in first differences of the subsidy variable causes EV sales to rise by about 187,74 cars. The difference between the means of the new and initial subsidies is €1.560 (=€8.740-€7.180). Therefore, the relationship could be conditionally paraphrased as follows: **A €1.560 increment in subsidies causes on average an increase in EV sales by about 187,74 cars monthly** (€1000 per 120 cars)**.**

Complying with the initial hypotheses, subsidies exercise a positive influence over EV sales. The absolute contribution is one of the highest among the factors, qualifying it as crucial in EV market adoption. It is no surprise, given the problem of high EV prices whose negative impact is partially mitigated by subsidies. As the EV segment develops, subsidies are expected to play an ever lessening role in stimulating EV sales. Therefore, the corresponding variable may cease being significant in the coming years.

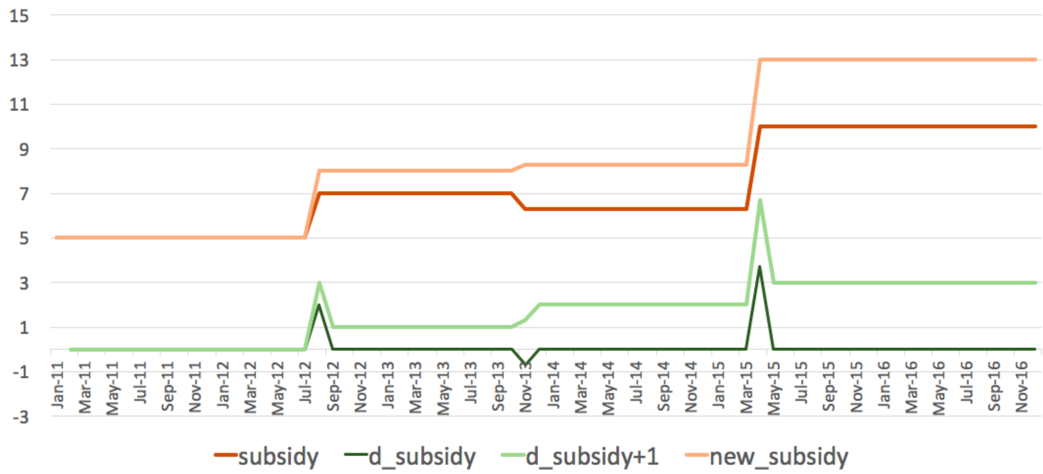

Figure 16. Changes in subsidies in response to a unit increment in FD

PRICE

EV prices are in many ways the flip side of subsidies having the opposite influence on EV sales. A unit increment in first differences of the weighted price, on average, reduces EV sales by 338,65 cars. The difference between the means of the new and initial prices equals €2.560 (=€28.830-€26.270). Therefore, the interpretation is conditionally paraphrased as follows: **An increment of €2.560 in the weighted EV price reduces EV sales by about 338,65 cars monthly (€1.000 per 132 cars).**

The absolute contribution (338,65) is highest among the variables, representing (depending on the month) from 10 to 30 % of total EV sales in 2016. This presumably makes the factor most important in determining EV sales. Another observation is that, despite high prices, EVs have already passed the break-even point. A price increase of €1.000 would mean a very large drop in EV sales in 2011 (average monthly sales 219 against [-132]). In 2016 however, they reached several thousands, which excessively overrides the negative effect of rising prices. It would be also instructive to consider the impact of prices and subsidies combined. This is around -12 cars (=120–132) per a €1.000 increment in the aggregated variable.

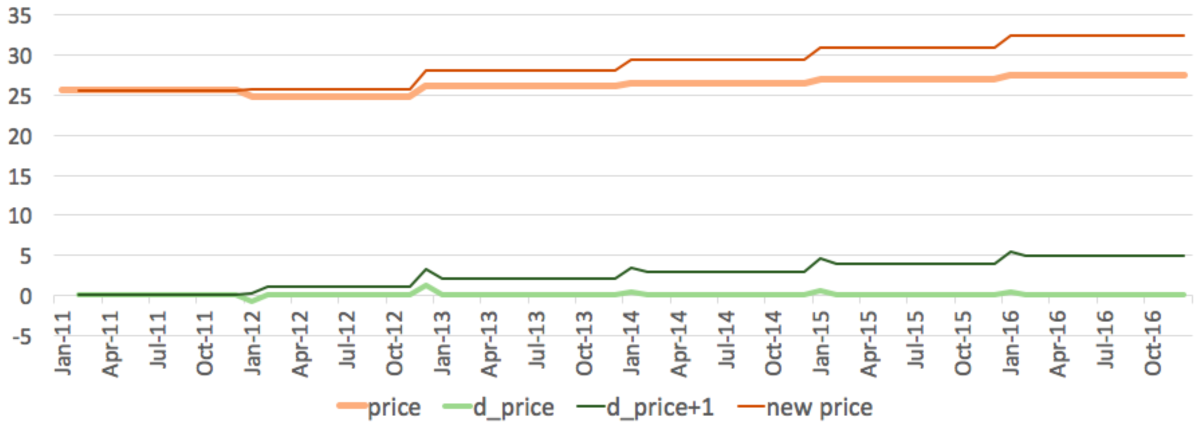

Figure 17. Changes in price as a result of a unit increment in FD

CHARGING STATIONS

A unit increment in first differences of the number of charge stations would increase EV sales by 0,2482 cars. First differences have a negligible effect on the stations' variable, given its much higher order of magnitude (up to 26.000). This is why, as shown below, the graphs mostly superimpose each other. Therefore, the impact of an increment in first differences roughly equals that of an increment in the variable. The above interpretation can be conditionally read as follows: <u>**an additional charging station, on average, encourages an EV sales increase of about 0,25 cars (4 stations per car).**</u>

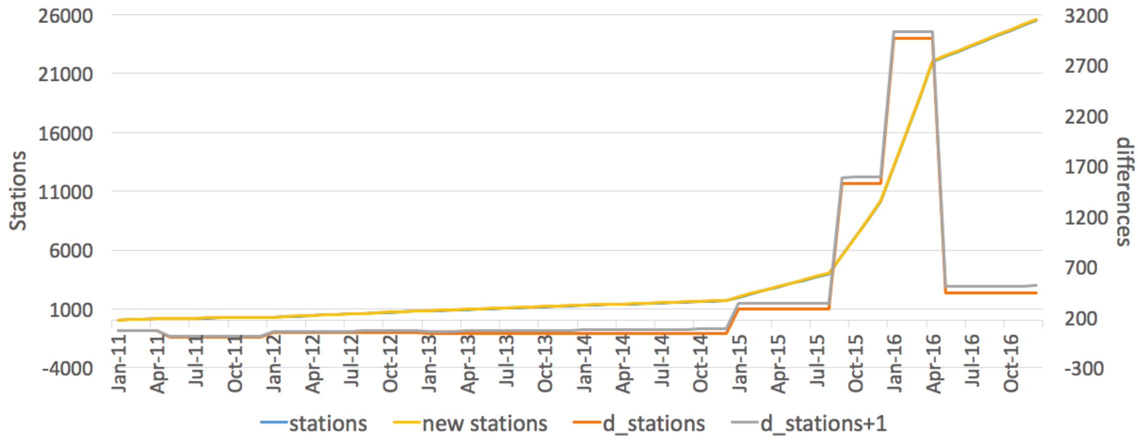

Figure 18. Changes in stations in response to a unit increment in FD

Such a low contribution is primarily attributable to the ongoing explosive growth in the number of stations: only 26 in 2010, while roughly 10.120 (!) by 2015 (390 times more) **[Global EV Outlook, 2016, p. 38]**. It is so much so that France became the European leader with a significant margin by the amount of both stations and plugs (diagram below [**Chargemap.com, 2017**]).

Another problem is a highly unequal geographical distribution of charging infrastructure. The Paris area concentrates about 2.600 stations while an average region in the rest of the country accounts for 180-200 [**Chargemap.com, 2017**]. Neighboring Germany, for example, enjoys a much better position in this respect. In spite of a single huge hub, there are many of them: Berlin (384 stations), Stuttgart (706), Frankfurt (408), Munich (496), Dortmund (497) [**Chargemap.com, 2017**]. Therefore, an average German charging station may be expected to have a higher useful workload and bigger marginal utility, as compared to France. The need for a more even distribution is further emphasized by the fact that France, due to its vast territory, holds a low rank in terms of the number of charging points per km: 0,005 as opposed to 0,065 in Norway, 0,05 in the Netherlands, 0,018 in Austria **[I-CVUE, 2017, p. 9].**

Despite persisting range anxiety, the marginal utility of an additional station tends to diminish. It represents slightly more comfort rather than a necessity. Therefore, the factor is expected to be getting less important as a contributor to EV sales. This will be further emphasized, as the French charging infrastructure achieves an optimal level of development. As of now, it supposedly has not done it yet.

Figure 19. Charging points distribution per country,

RANGE

A unit increment in second differences of the range makes up for an increase of 270,61 EVs in sales. To relate this coefficient to the range variable, let us check with the graph below. The green lines represent the second differences, while the red ones – the variable of range. The effect of an increment in second differences has been firstly translated into the first differences and, then into the variable itself. So as not to encumber graph interpretation, the first differences are omitted.

The difference between the means of the new and initial ranges is 36,6 (=166,6 – 130) miles. Hence, the above interpretation can be conditionally put as follows: **An increment of 36,6 miles in range provides on average an increase in EV sales of up to 270,61 cars monthly (1 mile per 7,4 cars).** The ratio may seem too high. Miles, however, are not bough separately, but rather in bunches representing qualitative leaps in range (e.g. 50-100-250 miles). This contains a high price premium due to range anxiety and resulting from it heightened expectations covered above.

The ratio 1:7,4 may also imply an exponential rather than linear relationship between EV sales and *the range variable*. If so, each additional mile of range would be given higher importance at lower levels of range (and the other way around). Thus, 7,4 cars per mile may well be an average of, let's say, 12 cars per mile within a range of up to 40 miles; 6 cars per mile – within a range of [40-100] miles and so on. This is only general reasoning, while the specific thresholds cannot be determined from the available information.

The strong direct relationship between EV sales and range confirms yet again the presence of range anxiety. That is why most EV producers have been focusing their efforts on improving battery characteristics rather than discounting prices. As a result, the weighted range in the last half of the period increased by 40 % (43,5 miles) as compared to the first half. In terms of sales, this attracts around 321 new clients on the monthly basis (43,5*7,4).

By the example of stations, range supposedly has some optimal levels, beyond which further improvement would be commercially and technologically unjustifiable. Apart from general efficiency, these levels take into account range anxiety and other subjective factors. Therefore, the variable is believed to have a falling payoff which would eventually result in a lasting convergence on some value. An additional mile of range would be irrelevant, which in turn will be driving the significance level down.

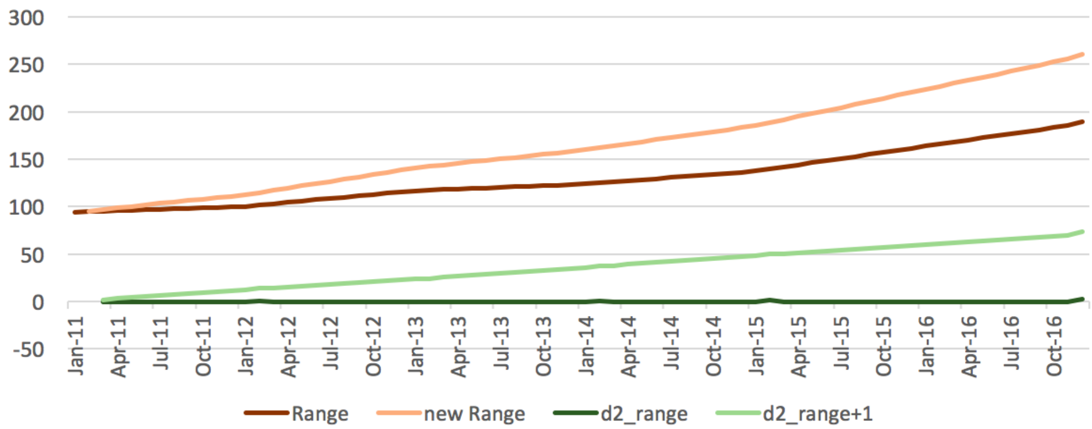

Figure 20. Changes in range as a result of a unit increment in SD

BATTERY COST

An additional $/kWh in the cost of battery production brings about on average a reduction in EV sales of about 2 cars (1,6). 1 $/kWh represented 0,125 %, while 2 cars – 2 % of their respective totals at the beginning of 2011. At the end of 2016, it was respectively: 0,4 % against 0,1 %. So, there is some exhaustion of scale in relative terms. At the initial stages of development, a little improvement in battery technology used to yield a much bigger increment in EV sales. This may imply that EV manufacturers' incentives to further reduce battery cost would tend to diminish along the time. This is partly confirmed by the graph convexity (Figure 12). By the magnitude of contribution, the battery variable exceeds the coefficients of total sales and stations. Therefore, its position falls somewhere in the middle in terms of importance for the buyer. As the battery becomes cheaper, its marginal contribution to EV sales is expected to diminish.

TOTAL SALES

On average, an additional car in total sales encourages an EV sales increase of 0,0067. Such a negligible contribution is no surprise: the variable has been included in order to mitigate the effect of seasonality rather than to explain EV sales. Total sales have a positive impact, which is consistent with the initial hypothesis of EV sales being of procyclical nature. That is, the overall industry growth stimulates in particular EV adoption. As soon as the EV market share achieves significant proportions, the use of total sales in the regression would be inappropriate. This is because of the aforementioned multicollinearity and endogeneity issues. Because of those, EV sales would be explained by their twin variable exposing the model to spurious significance.

CONSTANT

A constant is automatically added by the software, so as to allow for the fixed element of the resulting variable. That is, the one that does not depend on regressors. Graphically, it stands for the intercept with the vertical axis. In many instances however, even a significant constant appears meaningless [**Roberts, M.R. (2009), p. 67**]. This is particularly because of the fact that some regressors cannot be set to zero by definition (e.g. person's height, weight). Over and above, many of them have high base values. It becomes even more complex when considering an interplay of a number of such variables.

This is the case here. First of all, battery cost and EV price may not be zero. Assigning zero to range capacities, total car sales, number of stations, although theoretically possible, also raises doubts. Subsidies is the only factor whose potential zero value complies with common sense. In view of the above, it is natural that the constant appears contradictive. Formally it says that absent any charging infrastructure, subsidies, total car sales and range, there will be still 132,88 EVs sold monthly.

It may probably be suggested that the positive impact of zero EV prices overrides the negative one of the other factors. It is so much so that even zero range could not be an impediment. These assumptions are only of conditional value.

THE LAG

A unit increment in the previous 6th observation, on average, causes a given observation of EV sales to increase by 0,3445 cars. As already discussed, this represents a sort of inertia which is so characteristic of sales. In essence, it stands for a byproduct of market uncertainty causing flows of goods and services to fluctuate in search for dynamic equilibrium. To put it simply, not knowing public demand and preferences, sellers tend either to over- or undershoot the needed volumes of production. Upon finding out that they have missed the trend, they return to it with a delay, again and again. By introducing this variable into the model, its covert impact (which was initially embedded in the other coefficients) has been revealed. And potential autocorrelation has been completely ruled out enhancing model robustness.

Table 5. FD & SD contributions approximation

FACTOR	MODEL	FD/SD adjusted
Range	270,61	7,4
Stations	0,2482	0,2481999..
Battery	-1,60	-1,60
Total sales	0,0067	0,0067
Subsidy	187,74	120
Price	-338,65	-132
Lag6	0,3445	0,3445
_constant	132,88	132,88

3.5 Regulatory policy recommendations

MANTAINING SUBSIDIES

The first recommendation would be to continue actively addressing the issue of high EV prices. Per purchase subsidies proved effective in doing that. Therefore, the French government should maintain their amount at the current levels and consider increasing them further.

Reaching up to one third of the EV price, subsidies are believed to account for much of the recent EV sales boom. Given that during many months of 2011, EV sales were less than the marginal contribution of subsidies (120 cars); they have played all the more critical role in EV promotion. Since then, their relative impact has been diminishing due to the raising amount of sales. And as the technology develops, this trend is expected to continue. Upon reaching a point where the contribution of subsidies is small enough, the government may consider reducing its support. It may well be in the year 2022 which according to Bloomberg **[Randal, T., 2016]** will mark production cost parity between EV and CV.

In this regard battery cost plays a significant role. Despite its considerable reduction, EV prices have slightly increased. This is because most EV producers preferred to reinvest the surplus into further improving range characteristics rather than cutting down on prices. The fact of the matter is that EV technology so far continues to face strong skepticism in the form of range anxiety and heightened expectations. And for many buyers the question is still not how good is it, but rather is it really usable. Upon reaching solid technical characteristics, the accumulated potential for price reduction will be released.

As regards improving EV range characteristics, the role of government is more limited. Business takes the lead in that. Nevertheless, promotion of relevant R&D projects would be of great importance. Additionally, direct financial support and quotas proved useful in some countries, particularly in the USA. Surprisingly enough, Tesla had been demonstrating net losses for 13 consecutive quarters as of August 2016 [**Tharakan, A.G. (2016)**]. And one of the decisive factors that kept the company from bankruptcy was the US government's participation. Mandatory quotas for EVs in a number of states including California were of much value. This practice may be well adopted in France.

RAISING PUBLIC AWARENESS

Although much has already been achieved in this regard (42 % of American respondents believe that EVs are just as good or better than CVs, (Figure below) **[Mark Singer (2016), p. 14]**), low public awareness around the topic remains quite an issue. In large part, this is what conditions such a big negative impact of prices rather than their high level as such. It was discussed above that EVs offer numerous indirect benefits which already in the first years make their overall cost of usage lower than that of a CV. However, many potential buyers have no knowledge of that. As a result, they are so reluctant to pay a reasonable EV price premium, expecting on the opposite a high "risk premium" in the form of tax reductions, subsidies and price discounts.

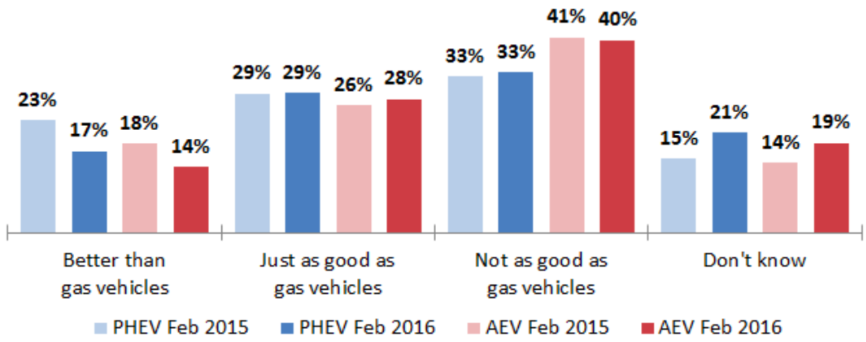

Figure 21. The general US public opinion of the EV, 2016

Therefore, EV advantages should be broadly conveyed to the public. Particularly, reports devoted to irrational behavior caused by range anxiety would be of great importance. As said, while 80 % of drivers cover much less than 50 miles a day, only 5 % find it an acceptable range [**Deloitte, 2011a, p. 6-7**]. Being pointed to this inconsistency may hopefully allow people to readjust their heightened expectations to more realistic targets.

Much of these responsibilities rests with EV producers who are interested in making the advantages of their product clear to customers. Tesla, for instance, issues advertisements and organizes numerous events where the capabilities of their cars are laid out for the public. The government, however, is also urged to participate in such activities simply by virtue of its huge stake in the investments. It could facilitate, for example, distribution of guidelines explaining the utilization of charging stations **[Nic Lutsey (2015)]**. Apart from that, it is of crucial significance to make it clear to customers what the conditions are for receiving subsidies and qualifying for tax reductions. Accounting for only a small fraction of aggregate expenditures, this activity may define the success or failure of the whole enterprise.

It is also worth noting that there is a number of specialized governmental bodies (regulatory, supervisory, legislative, research and environmental) whose functions concern, to some extent, the topic of EVs. Among those AVERE, INSEE, French Ministry of Ecology and many others could be mentioned. So their active involvement in studying and popularizing various aspects of EVs would encourage their market adoption. Additionally, they are called upon to facilitate complex relationship among numerous parties: public in general, EV buyers and manufactures, electricity generators, town planners and many others. Over and above, technical aspects such as technology standardization and logistics are to be addressed.

FOCUSING ON INTERCITY CHARGING INFRASTRUCTURE

Given a limited effectiveness of the number of charging stations in EV promotion; the French government is advised to reconsider its policies. As said above, charging infrastructure has been rapidly developing. With the amount of EV sales growing year by year, a bigger client's base is being captured. It is so much so that despite a plenty of available free stations in France, private ones (Bolloré, Renault) demonstrate revenues. On the other hand, formerly free stations are starting to charge their customers. According to Tesla's recent policy, vehicles issued after 2015 no longer enjoy free superchargers [**Stewart, J. (2016)**].

It seems that the sector is close to becoming mature enough for gradual government withdrawal. It is certainly true with respect to stabilizing the number of stations within the Paris area. Consequently, payment infrastructure may be introduced for public charging points, so as to make this sector commercially viable and to create room for competition **[Deloitte, 2013, p. 7]**.

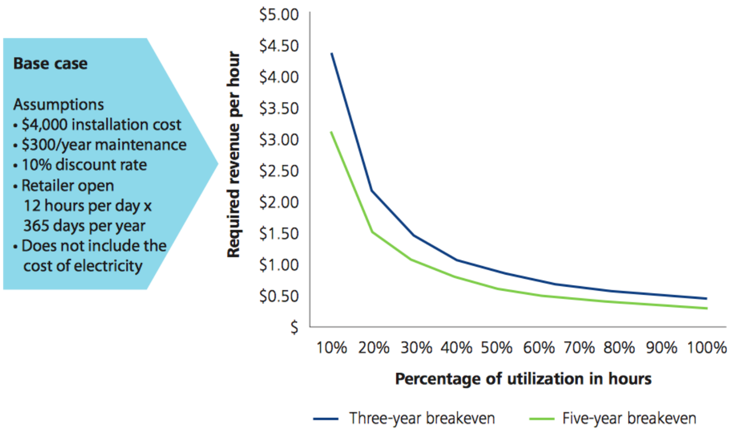

Figure 22. Break-even points in charge stations business

This might appear contradictive, given the issues of high EV prices and the need for maintaining per purchase subsidies. Nevertheless, the elasticities associated with EV purchase and its usage are believed to be different. In other words, EV drivers presumably have more tolerance towards regular payments for charging as opposed to a high price payable upfront. This will be further emphasized as oil prices start to go up making electricity relatively cheaper.

Coupled with the above measures, the focus should be reinforced on interregional and international charging infrastructure. Much of its development is currently being promoted within the framework of the Corri-Door pilot project [**Morganti, E. et al. (2015), p. 7**]. It has been proposed in 2014 in order to connect big cities of France (Paris - Caen, Paris - Lille, Lyon - Marseille) by a chain of 200 superchargers, at an interval of 80 km. The European Commission provided 50 % of the funds, while a number of private investors - the rest: Sodetrel, VW, BWM, Renault, Nissan and others **[TEN-T, 2015, p. 4]**. Consistent with the proposal for liberalization, the service will be paid: from €1,5 to 3,5 for 15 min of charging **[France electrique tour, 2016, p. 14]**. Upon construction completion, there will be needed several years for receiving and analyzing the feedback. Depending on the results, the French government will have, if necessary, to readjust the degree of its involvement into the project. If it turns out not profitable enough, additional public funds might be required.

3.6 Limitations

There are some potential limitations worth mentioning. First of all, the size of the observation set may not be viewed ideal from a strict econometrics sense. However, this was conditioned, among other things, by non-existence of relevant data. As said earlier, EV have started receiving more or less significant attention only recently. Before 2011, the industry can be well characterized as stagnant, with most of the parameters of interest roughly constant. Yet worse, the earlier the period, the less data is available. According to the AVERE (the French regulator of charging infrastructure) and the popular Chargemap.com information portal, the official statistics of the year-by-year number of charging points in France does not exist (refer to the AVERE's reply, Figure 14).

Another aspect is more of qualitative nature. The model combines short-, medium- and long-term processes. Whereas EV sales, oil and electricity prices are highly volatile across months, the average cost of battery production, EV range and volume of government subsidies – are not so much. This is all the more true as regards establishing nation-wide charging infrastructure. Therefore, there are considerable differences in the variables' variability: monthly, quarterly, semi-yearly, yearly and longer.

Nevertheless, all those variables have been brought to the common denominator, months. The gaps in the variables with a lesser variability were filled in with extrapolated data (e.g. stations). This provided a gradual transition from one turning point to another, with a constant step. These gradual transitions were, however, consequently removed when differencing. Their values became equal to the rate at which the transitions went on, the aforementioned step.

In view of the above, the relationships among some of the variables are stepwise. For example, a specific number of charging stations or a level of battery cost production will equally influence EV sales over a number of months. Electricity would do the same with an interval of half a year. On the other hand, the monthly series of total sales and oil are more sensitive, varying synchronously with EV sales. It cannot be positively concluded however that different variability interferes with model precision.

CONCLUSION

The present research is believed to have achieved its goals. A considerable volume of statistical and factual data regarding factors of EV market adoption has been thoroughly analyzed. Although not all, but most of the initial hypotheses were confirmed by empirical data. And all this has been done by following a rigorous scientific approach involving a number of quality control checks.

Among others, tests on stationarity, multicollinearity, endogeneity, heteroskedasticity and autocorrelation have been carried out. Their interpretation involved generalizing a large amount of literature on potential statistical inconsistencies and their solutions. The econometrics model obtained has indicated high levels of significance, both of the equation as a whole and of its individual variables. Their coefficients and degrees of precision have been interpreted, both statistically and substantively.

The process of EV adoption has been successfully broken down into its elements. Their separate as well as aggregate contributions were ranked in order of importance. Furthermore, a general forecast has been made, as to how these factors are going to evolve in the near future. It provides a valuable insight into what needs to be primarily focused on when dealing with the industry. Therefore, it may be of useful application in marketing of EVs and conducting regulatory policies. In this regard, it is worth mentioning that a number of recommendations has also been offered. They are concerned with employing the most efficient tools in promotion of EV deployment.

Among other conclusions was that the French government subsidies are demonstrating a remarkable performance. They address to a large extent the issue of EV costliness, thereby relieving one of the most persisting obstacles towards their wider adoption. Based on the high relevance of the problem, this instrument was suggested to remain in place at least until EVs reach the parity in price with CVs (around 2022, Bloomberg **[Randal, T., 2016]**).

On the other hand, the sector of charging infrastructure has been said to reach a certain level of maturity. Even despite the availability of free stations, private ones already seem to reach their break-even point. It is consistent with the low contribution of the corresponding variable. Therefore, the government should gradually embark on the sector’s liberalization, reducing its investments into charging infrastructure (at least in cities). Apart from that, the focus should be placed on developing interregional and international charging infrastructure, which is all the more important in the case of the vast territory of France. Payment infrastructure needs to be gradually introduced for city public charging points following the example of “Corri-Door” superchargers.

Range has been shown to exercise a considerable influence over EV sales. On average, a mile increment in range brings about an increase of 7,4 EVs in sales. This is yet another confirmation of the effect of notorious range anxiety. Hence, the decision of most EV’s manufacturers to exploit the drop in battery production cost in order to enhance range capabilities is quite understandable. During the 6 years considered, a qualitative leap in range has been made, further reinforcing the EV’s position on the market.

To wrap up, the obtained conclusions will hopefully contribute to the ongoing discussions about EVs and possible ways of their promotion.

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ANNEXES

ANNEX A. DICKY-FULLER TEST (STATA)

Registration: P-value = 0,0296 < 0,05 => Ho cannot be accepted at 5 % level: H_1 (variable stationary)

Dickey-Fuller test for unit root — Number of obs = 71

	Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value
		Interpolated Dickey-Fuller		
Z(t)	-3.061	-3.551	-2.913	-2.592

MacKinnon approximate p-value for Z(t) = 0.0296

Battery: P-value = 0,0000 < 0,01 => Ho cannot be accepted at 1 % level: H_1 (variable stationary)

Dickey-Fuller test for unit root — Number of obs = 71

	Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value
		Interpolated Dickey-Fuller		
Z(t)	-34.760	-3.551	-2.913	-2.592

MacKinnon approximate p-value for Z(t) = 0.0000

Total_sales: P-value = 0,0000 < 0,01 => Ho cannot be accepted at 1 % level: H_1 (variable stationary)

Dickey-Fuller test for unit root — Number of obs = 71

	Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value
		Interpolated Dickey-Fuller		
Z(t)	-6.883	-3.551	-2.913	-2.592

MacKinnon approximate p-value for Z(t) = 0.0000

d2_range: P-value = 0,0000 < 0,01 => Ho cannot be accepted at 1 % level: H_1 (variable stationary)

Dickey-Fuller test for unit root — Number of obs = 69

	Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value
		Interpolated Dickey-Fuller		
Z(t)	-5.269	-3.553	-2.915	-2.592

MacKinnon approximate p-value for Z(t) = 0.0000

d_stations: P-value = 0,1980 > 0,1 => assumed weakly stationary, H_1

Dickey-Fuller test for unit root — Number of obs = 70

	Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value
		Interpolated Dickey-Fuller		
Z(t)	-2.223	-3.552	-2.914	-2.592

MacKinnon approximate p-value for Z(t) = 0.1980

d_subsidy: P-value = 0,0000 < 0,01 => Ho cannot be accepted at 1 % level: H_1 (variable stationary)

Dickey-Fuller test for unit root — Number of obs = 70

	Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value
		Interpolated Dickey-Fuller		
Z(t)	-8.413	-3.552	-2.914	-2.592

MacKinnon approximate p-value for Z(t) = 0.0000

d_price: P-value = 0,0000 < 0,01 => Ho cannot be accepted at 1 % level: H_1 stationary

Dickey-Fuller test for unit root — Number of obs = 70

	Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value
		Interpolated Dickey-Fuller		
Z(t)	-8.392	-3.552	-2.914	-2.592

MacKinnon approximate p-value for Z(t) = 0.0000

ANNEX B. MODEL WITH NO LAGGED VARIABLE (STATA)

Source	SS	df	MS
Model	25545141.6	6	4257523.61
Residual	5840932.92	63	92713.221
Total	31386074.6	69	454870.646

Number of obs	=	70
F(6, 63)	=	45.92
Prob > F	=	0.0000
R-squared	=	0.8139
Adj R-squared	=	0.7962
Root MSE	=	304.49

registration	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
d2_range	303.0682	113.1156	2.68	0.009	77.02458	529.1117
d_stations	.2992836	.0559045	5.35	0.000	.1875674	.4109998
battery	-2.580505	.2540989	-10.16	0.000	-3.088281	-2.072729
tot_sales	.0080107	.001235	6.49	0.000	.0055427	.0104787
d_subsidy	186.9024	72.41325	2.58	0.012	42.19603	331.6087
d_price	-464.4072	182.9064	-2.54	0.014	-829.9164	-98.89786
_cons	572.5415	194.3646	2.95	0.005	184.1349	960.9482

ANNEX C. VIF TEST FOR MULTICOLLINEARITY (STATA)

```
. vif

    Variable |       VIF       1/VIF
-------------+----------------------
        lag6 |      2.33    0.428405
     battery |      2.18    0.458412
  d_stations |      1.33    0.754554
   tot_sales |      1.18    0.844741
     d_price |      1.05    0.950010
    d2_range |      1.04    0.965925
   d_subsidy |      1.01    0.992882
-------------+----------------------
    Mean VIF |      1.45
```

ANNEX C. DURBIN-WATSON TEST FOR ENDOGENEITY (STATA)

```
. dwstat

Durbin-Watson d-statistic(  8,    66) =  1.708709
```

ANNEX D. BREUSCH-GODFREY AND DURBIN'S ALTERNATIVE TESTS (STATA)

Prob > chi2 = 0,0736 ∈ [0,05; 0,1], H_O claiming the absence of autocorrelation is adopted at the 5 % level of significance; and refused at the 10 % level of significance.

```
Breusch-Godfrey LM test for autocorrelation

    lags(p)  |          chi2               df                 Prob > chi2
-------------+-------------------------------------------------------------
       1     |          3.202               1                   0.0736

                        H0: no serial correlation
```

Prob > chi2 = 0,0847 ∈ [0,05; 0,1], H_O claiming the absence of autocorrelation is adopted at the 5 % level of significance; and refused at the 10 % level of significance.

```
Durbin's alternative test for autocorrelation

    lags(p)  |          chi2               df                 Prob > chi2
-------------+-------------------------------------------------------------
       1     |          2.972               1                   0.0847

                        H0: no serial correlation
```

Prob > chi2 = 0,25 > 0,1, H_O claiming the absence of autocorrelation is adopted at the 1 % level of significance.

```
Breusch-Godfrey LM test for autocorrelation

    lags(p)  |          chi2               df                 Prob > chi2
-------------+-------------------------------------------------------------
       1     |          1.337               1                   0.2476

                        H0: no serial correlation
```

Prob > chi2 = 0,28 > 0,1, H_O claiming the absence of autocorrelation is adopted at the 1 % level of significance.

```
Durbin's alternative test for autocorrelation

    lags(p)  |          chi2               df                 Prob > chi2
-------------+-------------------------------------------------------------
       1     |          1.179               1                   0.2776

                        H0: no serial correlation
```

ANNEX D. BREUSCH-PAGAN TEST FOR HETEROSKEDASTICITY (STATA)

```
Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
         Ho: Constant variance
         Variables: d2_range d_stations battery tot_sales d_subsidy d_price lag6

         chi2(7)      =     6.87
         Prob > chi2  =   0.4427
```