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Predicting the Diffusion of the Electric Vehicle: A Dynamic Approach to Model the Impact of Imitation and Experience

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Abstract: Driven by environmental awareness and new regulations for fuel efficiency, electric vehicles (EVs) have significantly evolved in the last decade, though their market share is still much lower than expected. Besides understanding the reasons for this slow market penetration, it is crucial to have appropriate models to predict the right diffusion of these innovative automobiles. Recent studies predicting the evolution of the market for EVs combine substitution with diffusion models. In these models advanced discrete choice models are used to measure the substitution effect among alternative vehicle's engines, while Bass-type methods are used to account for the diffusion effect of innovation. However, the most recent substitution/diffusion models are not explicitly dynamic, nor measure the fact that innovation is communicated through certain channels over time among members of a social system. In this paper, we extend these substitution/diffusion models by including explicitly the dynamic effect. This dimension makes the EV demand in a given period dependent on the EV sold in a previous period. In this modeling scheme, we also account for and measure, for the first time, some of the effects of social conformity on individuals' choices. The model also includes the impact of policy incentives, in particular in the availability of parking spaces and parking cost strategies. We illustrate our model for the Danish EV market using data for the period 2013-2017. Results show an initial slow penetration of the EV in the market, that progressively increases in the 2050 horizon.

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1. Introduction

The number of cities in Europe and the U.S. that have implemented traffic restrictions due to pollution is considerable. In many cases, these policies are accompanied by other pro electric vehicle (EV) measures, such as allowing drivers to park free of charge in regulated areas, drive in High Occupancy Lanes, or access locations that other more polluting vehicles are not allowed to. These benefits, along with the prospect of savings —given current fuel costs, present an economic incentive for users to adopt the EV technology. The European market experienced a substantial surge with more than one million PHEV reached in 2018, experiencing 42% Year over Year growth (Pontes, 2019), with some countries nearly doubling sales in the first half of 2018 (Denmark, Finland, Portugal, Netherlands, and Spain). Likewise, 360,800 plug-in hybrid electric vehicles (PHEV) were sold in the U.S. in 2018 (Irle et al., 2019), representing 81% market growth. Backed by this growing attention on the part of users, the interest of the automobile industry in promoting the EV has increased, too. Producers are making significant investments both to expand their catalogs and to improve the models that they already offer. Finally, public administrations, from local to national, have been adjusting their regulations on EVs in recent years to promote their acquisition and use. Most of these modifications have to do with fees, public utilities, and infrastructure; and their particularities are, overall, similar among the European countries and American states (Lutsey, 2017; Tietge et al., 2016).

Altogether, these factors place the EV market in a unique and interesting situation, albeit fraught with uncertainty. Thus, the need for reliable information on the future of EVs is greater than ever, as solid predictions are the basis for both industry strategic decisions and proper policymaking. Hence, great efforts have been made in the last decade to predict EV market penetration and the evolution of its sales. Unfortunately, the forecasts published so far —in academia or other spheres— have differed substantially from the actual trends taking place thereafter, falling short in some cases, and being too optimistic in others. Some of the reasons we identify for this are methodological, while others have to do with how the topic has been approached. For instance, Discrete Choice Models (DCM) have been a popular tool in some fields such as marketing and transportation for predicting demand. However, DCM rely on the responses provided in hypothetical scenarios, i.e. Stated Preferences (SP) data. Thus, when these models are used for prediction, they need to be calibrated to reflect the unobserved factors present in real markets, which can be quite particular in the case of innovative products. A second main reason that may explain the divergence between predictions and actual market evolution is the neglect of the dynamism of the demand. Although classic diffusion models such as Bass (Bass, 1969) or Gompertz (Gompertz, 1862) have been applied to model the particular adoption behavior of new technology —slow introduction until critical mass is reached, they have had limited success. Finally, diffusion is a process that occurs through social channels. In the words of Rogers (Rogers, Someya, & Huang, 2010), "*the diffusion process is defined as that by which an innovation is communicated through certain channels over time among members of a social system*". The behavioral assumption is that an innovation is first adopted by a small segment of *innovators*, and then later embraced by an increasing number of *customers*, the imitators, who are influenced by the number of adoptions that have already occurred. This conception corresponds to what in the psychological literature is defined as Social Conformity (SC). Friends, family, and acquaintances influence our behavior. Even people who we do not know personally may indirectly influence our decisions. SC can occur because one wants to be accepted by the members of a certain group (Normative Conformity), or because they want to act like it is supposedly right (then they consult members of their group to obtain information, which is called Informational Conformity) (Asch, 1961; Crutchfield, 1955; Sherif, 1935). Therefore, conformity is a type of social influence involving a change in attitudes, beliefs, and behaviors to fit in a group, matching the group's norms and beliefs (Cialdini & Goldstein, 2004).

In summary, although these three aspects (model specification, dynamism, and social conformity) are considered in some works, they have not always been properly addressed and, certainly, not considered jointly, as the literature review in the next section shows. Our study aims to do so, by articulating in a single methodology these elements. This will fill the gap in the existing literature regarding new methodologies for predicting the diffusion of new technologies. Especially, the consideration of social elements is an area not too much explored, at a general level, and particularly in the case of electric vehicle diffusion. For this purpose, we use a combined substitution-diffusion model that explicitly includes SC. Our objective is to provide an accurate prediction that can serve as the basis on which stakeholders (industry, public agencies, consumers, and practitioners) can make informed decisions.

This paper is organized as follows: Section 2 describes the efforts made in the field to combine DCM and diffusion models, as well as Diffusion and social influence. Section 3 fully describes the data collection and the methodology; while results and conclusions are presented in Sections 4 and 5, respectively.

2. Literature Review

2.1. Discrete Choice and Diffusion Models

Several studies have been aimed to predict the evolution of the EV market in the last decade, mainly through three approaches; i) Discrete Choice models (Ben-Akiva et al., 1999; Train, 2009), to provide a quantification of the willingness to purchase an EV; ii) Diffusion-type models (Bass, 1969), to predict the evolution of sales over time and; iii) a combination of these two to take advantage of the benefits of both types. Regarding the DCM approach, two of the best attempts were those of Eppstein et al. (2011) and Kieckhäfer, Volling, and Spengler (2014). The first used an agent-based choice model where the purchasing decision of customers was affected by media coverage and social network activity, while the latter estimated a disaggregate demand model that was integrated into a dynamic simulation to analyze the effect of the evolution of EV characteristics. However, neither of these two papers accounted for the diffusion effect. Thus, authors, in general, have been leaning towards other specifications in which time and the evolution of sales play a major role. Ayyadi and Maaroufi (2018) Ayyadi and Maaroufi (2018) used a Generalized Bass diffusion model to evaluate the interaction between accumulated sales of EVs and the battery price. Among its main results, they showed that the Moroccan market reached the maximum sales of EV after 14 years and that the cost of the battery had a significant effect in accelerating the diffusion. Redondo and Cagigas (2015) performed a forecast of EV sales in Spain until the year 2040, using a version of the Bass model that allowed to consider different product generations, as well as the *jump* phenomenon (switch to a different generation). Similarly, Becker, Sidhu, and Tenderich (2009) adopted a Bass model to forecast sales using as inputs: market size of the new technology, a parameter that captured the percentage of buyers whose purchase decision was not influenced by the purchasing behavior of others, and a metric that captured the likelihood that additional consumers would adopt the technology in response to the buying experience of others. Jiang and Jain (2012) proposed a Generalized Bass Model in which marketing mix variables were also incorporated, which offered better overall performance than other specifications, both in terms of fit and forecast performance. In a recent study, Gnann et al. (2017) conducted a thorough analysis of 40 research articles that developed diffusion models as well as other approaches to the adoption of EV. They aimed to study the similarities among the models to offer recommendations for their implementation. Also, Massiani and Gohs (2015) studied the potential of Bass models to evaluate the policies to promote the diffusion of the EV market in Germany. They questioned the varying values of the parameters of these models found in the literature, highlighting the uncertainty faced by researchers when developing further research upon them. Finally, Klasen and Neumann (2011), also concluded that the Bass model is not easily parameterized when there is no available market data. However, the most recent and advanced studies combine substitution and diffusion models. For instance, Shepherd, Bonsall, and Harrison (2012) (based on Struben and Sterman (2008)) proposed a simulation system that integrated disaggregate demand and system dynamic models, including the diffusion effect. However, the parameters were exogenously defined rather than estimated. de Santa-Eulalia et al. (2011) in their research, presented a Bass model and a DCM with a dynamic perspective to assess how consumer preferences and social forces influence the introduction of EV on the market. The model estimated both time and market share and was flexible regarding the number of products and attributes, without the need for any market data. From their part, Higgins et al. (2012) developed a diffusion specification that incorporated multicriteria analysis and choice models, focusing on the geographical uptake of EV and the effect of policy incentives. More recently, Jensen et al. (2017) suggested a method that combined diffusion, as typically estimated in the marketing literature, with advanced DCM. All the parameters of the joint substitution/diffusion model were estimated jointly, with the disaggregated model estimated with SP being was adjusted to the real market endogenously in the diffusion process. However, this extension only included innovation through one single term, whose effect on the probability of choosing EV varies over time linearly. Moreover, imitation was left aside since it was dependent on the number of individuals that had adopted the product already.

2.2. Diffusion and Social Influence

Although SC, as described in the previous sections, has been extensively researched in psychology, (Ash & Woodward, 1989; Cialdini, 2007; Cialdini & Goldstein, 2004; Goldstein & Cialdini, 2007; Schultz, Khazian, & Zaleski, 2008), for just a few examples), it has also been the object of study in other disciplines, including the two on which this work focuses: Economics/Business and Transportation. Regarding the former, efforts have focused mainly on unveiling the consumer decision-making process. In this line, Baddeley (2010) advocated for considering the incidence of social influence and not exclusively the rational cost-benefit approach when evaluating this process, since it is rooted in psychological and social motivations. Cecere, Le Guel, and Rochelandet (2017) studied what people consider when making small investments in prosocial projects, to create more effective crowdfunding campaigns. Consumer behavior is also to some extent related to so-called *herd behavior,* a phenomenon by which individuals act as part of a group, making decisions that they would not make as an individual. This conduct has been reviewed by Biel et al. (2010) in the context of stock markets, where quick decisions are made, sometimes led by what the majority does.

Regarding the field of transportation, Pike and Lubell (2018), as well as Sherwin, Chatterjee, and Jain (2014), conducted research to test the hypothesis that certain factors condition social influence in the adoption of bicycles. They concluded that social influence played a vital role in promoting cycling, although its degree of leverage depended on specific aspects of the trip such as distance. Kormos, Gifford, and Brown (2015) evaluated the impact of the opinion of others in a person's choice of private vehicle use. Goetzke et al. (2015) studied the relationship between the choice of an EV made by an individual and the choice made by others. Axsen and Kurani (2012) used the personal network and the experiences of individuals with a hybrid vehicle to study the effect of interpersonal influence in the adoption of this technology. TyreeHageman, Kurani, and Caperello (2014) described EV buyers and their relationships with EV communities, finding that early drivers used forums to gather information about the EV characteristics. However, the number of works that directly measure the effect of social influence as an attribute in the stated preference experiment is reduced, but two of them deserve special attention. The first is Kuwano, Chikaraishi, and FUJIWARA (2014), who included the market share of EV in the choice tasks. The second, Rasouli and Timmermans (2013), extended this methodology, dividing the market of EV into four reference groups. They also added an attribute measuring a positive/negative overview of the EV.

Concerning how social influence in general, and SC, in particular, affect Diffusion, there are remarkable contributions. Pyo et al. (2023) focused on the role of the social network in the diffusion process, paying particular attention to the imitation component. They proposed an extension of the Bass model to make the social network a function of the number of customers who adopted the product. Smaldino (2022) looked at the role of social identity and how the diffusion of a product in society is affected by identity signaling. They also extended a Bass model, assuming that the probability of adoption is influenced by three factors: a background ratio of spontaneous adoption, social influence from one's group members, and social influence from members of the outgroup. Morvinski, Amir, and Muller (2017) found that information about a large number of previous adopters positively influences adoption only if those previous adopters were described as similar to the potential ones. Finally, Cherchi (2017) measured the effect of both Informational and Normative conformity in the preference for EV. She found the social conformity effects highly significant, and also that their impact on the overall utility could be large enough to compensate for major differences in the characteristics of EV and Internal Combustion Vehicles (ICV).

3. Data collection and Methodology

This paper builds on the work by Jensen et al. (2017), improving it by considering intrinsic innovation and imitation in a diffusion-substitution model. The specification is also dynamic since the demand of EV in time *t* is dependent on the number of EVs sold in time *t-1*. In doing so, we avoid the conceptual and methodological pitfalls mentioned above. This procedure can be described in two steps:

1. Estimation of a disaggregated DCM to account for the substitution effect that occurs when individuals substitute another means of transportation, especially a car with a different type of engine, by an EV. This formulation includes social influence and social conformity so that the effect of the influence of others' behavior on that of the individual making the choice is also considered. Information of previous periods is also included to gather the dynamic effect.
2. Projection of the actual data into the future and estimation of a diffusion-substitution model in which the coefficients of the DCM are integrated, to forecast EV sales.

3.1. Data

The data used in this research comes from different sources. The vehicle characteristics, as well as the Danish EV monthly sales, have been computed by the Danish Energy Agency (Statistics, 2016) until the year 2018. The coefficients interacting with these characteristics in the diffusion model proceed from Jensen et al. (2016). As for the social conformity parameters, they are derived from a survey performed in Denmark in the period between December 2014 and January 2015 (Cherchi, 2017) and are indicated in Table 1.

Table 1: Social conformity parameters from (Cherchi, 2017).

Coefficient	Value
Number EV sold t-1	0.067
Negative information on the need to change activities	-0.339
Negative information on range and activities	-0.437

1. The survey was built specifically to study the effect of parking policies on the choice of EV versus ICVs, as well as the role played by social conformity on this choice. It consisted of five sections:
2. Detailed information about the last parking activity, vehicle ownership and use, most likely future vehicle purchase, and whether a new EV car would be an additional vehicle in the household or if it would replace an existing one. Users were also asked to indicate the degree of influence that they had in the decision about the type of car.
3. A Stated Choice Experiment, pivoted around the values collected in the first section. It included attributes related to the car characteristics and to the parking options, plus attributes that allow measuring the effect of conformity.
4. The third section was dedicated to gathering socioeconomic and residential information.
5. Individuals' attitude and perception towards several aspects related to EV, injunctive social norms, affections, and values in life. Injunctive norms define when the individual's behavior is affected by what other people think of them doing something. In this case, the norm is measured by asking respondents about the level of agreement to the following statements:

a. *People who are important to me (friends, family) would approve of me using an electric vehicle instead of my conventional car.*

b. *People who are important to me (friends, family) think that using an EV instead of my conventional car is appropriate.*

c. *People who are important to me (friends, family) think that more people should use an EV instead of their conventional car.*

6. Finally, information about personal and family income was asked.

The sample was gathered from a list of individuals who had signed up to participate in a real-life experiment in 2010 in which they could use an EV for three months. 39% of the participants had already heard and been informed about EV. 73% of the users were males and the average age was 47. Regarding vehicle ownership, 52% of the users lived in a household with one car, while 46% lived in a household with more than one car. Additionally, 76% of the interviewees stated that the next purchase of a vehicle would replace an old one. Interestingly, the average daily distance traveled was about 55km. A table illustrating other characteristics of the complete sample is presented in Appendix A[1].

Regarding the forecast exercise, it was necessary to make assumptions about the evolution of the EV attributes. In this case, we designed a scenario in which the EV characteristics experience gradual improvements thanks to technological progress. Table 2 provides these values, which we consider realistic since, as stated above, they are based on reliable sources (a description of the variables is provided in Appendix B).

Table 2: Forecasting Scenario 2018 - 2050.

MONTH	YEAR	CTY_SL	SHO_SL	CTY_FA	SHO_FA	PP_EV	PP_GAS	FU_EV	FU_GAS	RA_EV	RA_GAS	CO2_EV	CO2_GAS
3	2018	0.2	0.2	0.2	0.2	262,032.1	212,573.2	0.3	0.7	220.5	852.8	41.9	140.9
4	2018	0.2	0.2	0.2	0.2	262,032.1	212,573.2	0.3	0.7	220.5	852.8	41.9	140.9
5	2018	0.2	0.2	0.2	0.2	262,032.1	212,573.2	0.3	0.7	220.5	852.8	41.9	140.9
6	2018	0.2	0.2	0.2	0.2	262,032.1	212,573.2	0.3	0.7	220.5	852.8	41.9	140.9
7	2018	0.2	0.2	0.2	0.2	262,032.1	212,573.2	0.3	0.7	220.5	852.8	41.9	140.9
8	2018	0.2	0.2	0.2	0.2	262,032.1	212,573.2	0.3	0.7	220.5	852.8	41.9	140.9
9	2018	0.2	0.2	0.2	0.2	262,032.1	212,573.2	0.3	0.7	220.5	852.8	41.9	140.9
...	...	...	...	...	...	...	...	...	...	...	...	...	...
5	2050	1	1	1	1	1417,96.5	194,178.3	0.3	0.6	373.7	852.8	0	108.8
6	2050	1	1	1	1	141,796.5	194,178.3	0.3	0.6	373.7	852.8	0	108.8
7	2050	1	1	1	1	141,796.5	194,178.3	0.3	0.6	373.7	852.8	0	108.8
8	2050	1	1	1	1	141,796.5	194,178.3	0.3	0.6	373.7	852.8	0	108.8
9	2050	1	1	1	1	141,796.5	194,178.3	0.3	0.6	373.7	852.8	0	108.8
10	2050	1	1	1	1	141,796.5	194,178.3	0.3	0.6	373.7	852.8	0	108.8
11	2050	1	1	1	1	141,796.5	194,178.3	0.3	0.6	373.7	852.8	0	108.8
12	2050	1	1	1	1	141,796.5	194,178.3	0.3	0.6	373.7	852.8	0	108.8

Finally, the potential market (*M* in Equations (5) and (6) below), is defined as 877,000, half of the car-owning families in Denmark. More complex assumptions could have been made, but they would have been difficult to validate, while this one seemed to us simple yet good enough.

3.2. Model Specification

The model of reference follows Jensen et al. (2) which, in turn, is based on the diffusion model that accounts for substitution effect developed by Jun and Park (1999).

[1] It is worth mentioning that although the sample presents an imbalance in some of the socioeconomic variables, those were not included in any model and, therefore, had no influence on the estimates.

Concretely, Jun & Park (1999) included the diffusion effect into the utility $V_t^{i,k}$ of technical new technology k at time t.

$$V_t^{i,k} = q^{i,k}(t - \tau^k + 1) + \beta^{i,k} x^{i,k} (1)$$

where $x^{(i,k)}$ is a vector of the technology attributes, $\beta^{(i,k)}$ its corresponding coefficients, $q^{(i,k)}$ the time-dependent diff effect, and τ^k is the period of the introduction of this technology in the market. The superindex (i,k) refers to the case of an individual owning a technology i who switches to k. The probability of purchasing a product of generation k is

$$P_t^{i,k} = \frac{exp(V_t^{i,k})}{exp(c)+\sum_j exp(V_t^{i,j})} \qquad i,j \le k (2)$$

Considering M_t the potential market at time t, and Y_{t-1} the total number of units of a product at time $t-1$, the number of sales in each period is:

$$S_t^k = (M_t - Y_{t-1}) \cdot P_t^k$$
$$= (M_t - Y_{t-1}) \cdot \frac{exp(V_t^{i,k})}{exp(c)+\sum_j exp(V_t^{i,j})} (3)$$

From here, Jensen et al. (2016) defined their model as

$$S_t^{EV} = (M^{EV} - Y_t^{EV}) \cdot P(EV_t)$$
$$= (M^{EV} - Y_{t-1}^{EV}) \cdot$$
$$\cdot \frac{exp\left(ASC^{EV} + q^{EV}(t - \tau^{EV} + 1) + \lambda(\hat{\beta}^{EV} x_T^{EV})\right)}{exp(\lambda(ASC^{ICV} + \hat{\beta}^{ICV} x_T^{ICV})) + exp\left(ASC^{EV} + q^{EV}(t - \tau^{EV} + 1) + \lambda(\hat{\beta}^{EV} x_T^{EV})\right)}$$
(4)

Where $\hat{\beta}^{EV}$ and $\hat{\beta}^{ICV}$ were estimated using SP data and fixed in the diffusion process. The three parameters estimated are the EV Alternative Specific Constant, $ASC^{EV} (since\ ASC^{ICV}\ is\ fixed)$, q, and λ, which represented the alternative specific constant, the *diffusion* parameter, and a scaling coefficient, respectively.

That said, the research presented here brings several improvements to the methodology. In order to consider the effect of social influence on the individual choices, two elements are included; the number of EV sold in the previous period $t-1$, which makes the model dynamic; and the type of information that the potential customer receives about specific characteristics of the EV. This information that other users report on is related to parking spaces reserved to EV, EV range, and the need to change activities due to low battery life. We compiled all three into one dummy variable named *Info*, which equals 1 when the feedback is negative. Moreover, we consider it equal to 1 for all periods until the penetration of the charging infrastructure reaches 33% and the EV range also reaches 33% of the ICV range. At that point, it is assumed that the negative feedback about parking spaces, range, and need to change activities becomes positive and, therefore, *Info* takes the value 0 onwards. The reason for considering this variable in negative terms is due to the *negativity bias* effect. This refers to the understanding that "negative information tends to influence evaluation stronger than comparably extreme positive information" (Ito et al., 1998). Cherchi (2017) showed in her study that only negative feedback is significant.

On the other hand, the preliminary data analysis showed a peak in sales in December 2015. This was caused by the Danish government announcement that the registration tax for EV would be increased. Instead of considering this information as an outlier, a dummy variable was defined to model the anticipation to this policy.

Considering all these aspects, the utility function that is the base of our model specification is:

$$V_t^{EV} = ASC^{EV} + q^{EV}(t - \tau^{EV} + 1) + \lambda(\hat{\beta} \cdot \ln N_{t-1}^{EVsold} + \hat{\beta} \cdot Info_{t-1} + \hat{\beta} X_t^{EV}) + \alpha \cdot Tax_t \ (5)$$

The elements common to Jensen et al. (2017) maintain their meaning, while *Info* and *Tax* stand for the concepts discussed above about information received and anticipation to tax policy, respectively. λ is the substitution parameter, which reflects the overall effect of vehicle attributes, information received, and number of EV sold. It is worth mentioning that this last element is considered in logarithms since the relation of this variable with its lags is clearly not linear. Equation 5 leads to a number of sales in each period equal to:

$$S_t^{EV} = (M^{EV} - Y_t^{EV}) \cdot P(EV_t)$$
$$= (M^{EV} - Y_t^{EV}) \cdot \frac{exp(V_t^{EV})}{exp(V_t^{ICV})+exp(V_t^{EV})} (6)$$

4. Results

This section provides the results of the estimation of the model described above as well as those obtained with the specification of Jensen et al. (2017), for comparison purposes. shows these results. Model 1 is the original specification from Jensen et al. (2016), estimated with the new data we count with. Model 2 is the model proposed in (3.6) and (3.7), but in which the variable *Info* (feedback provided by others) has not been included. Finally, Model 3 is the full model proposed in (3.6) and (3.7). In brief, Model 1 does not include any social element, while Model 2 includes SC (EV sales), and Model 3 includes Social Conformity and Social Influence (*Info*). This distinction is made in order to quantify separately the impact of these elements in the prediction.

Table 3: Estimation Results.

	Model 1 Jensen et al. (2016)		Model 2 Social Conformity		Model 3 Social conformityand Social Influence	
	Value	p-value	Value	p-value	Value	p-value
ASC EV	−13.26	0.0001	−12.78	0.0001	−11.38	0.0001
q	0.94	0.03**	0.83	0.06*	0.58	0.05**
λ	0.05	0.81	0.14	0.52	0.12	0.59
Tax	2.64	0.0001***	2.61	0.0001***	2.59	0.0001***
R2	0.707		0.707		0.711	

*significant at 10%, ** significant at 5%, ***significant at 1%

For the full model, the values of both ASC and *q* are in line with the finds of Jensen et al. (2016), although in the lowest bound of the confidence interval in the case of the later. They obtained a range of (-17.99, -6.98) for the *ASC*, and (0.83, 2.57) for *q*. The diffusion parameter, *q*, is significant at the 95% level in models 1 and 3, and significant at the 90% in model 2; which evidences that considering the effect of diffusion allows a more realistic forecast of the EV spread. On the other hand, λ is not significant in any of the models, reflecting that substitution plays a minor role in choice. The variable that gathers the tax effect of December 2015 is highly significant, revealing the consumer's rush to take advantage of lower final prices. It is worth mentioning that Model 1, being simpler than the others, yields the highest value of the parameter q; that is, a more intense effect on the diffusion due solely to the passage of time. A possible reason for that may be that the elimination of both the social conformity and social influence variables causes the entire explanatory power to fall on this effect. More interesting is the forecast obtained for the period 2018 – 2050, shown in Figure 1. It presents, for the three models, forecasted EV monthly sales, and the cumulative number of EV sold expressed as a percentage of the total.

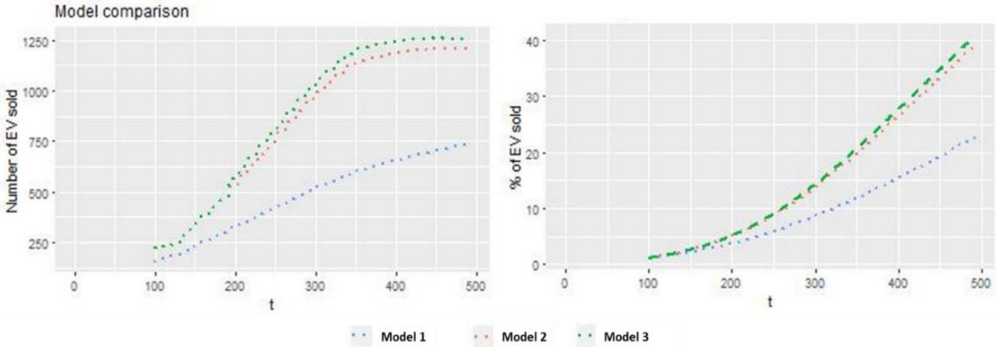

Figure 1: Actual, fitted, and forecast sales. Cumulative number and percentage of EV sold.

The classic S-shape that characterizes the introduction of a new technology can be appreciated, with low market penetration in the early stages, and later progressive increase once the product is more established in the market. In Model 2 and Model 3 the share of EV evolves from just 2% at the beginning of 2018 to around 40% by 2050. On the contrary, Model 1 (which does not include social elements) reaches a more conservative final market share. These results conform the main finding of this work: explicitly considering elements of social conformity in the substitution model represents both a qualitative and a quantitative leap in predicting the development of the EV market since models 2 and 3 prediction of EV sold by 2050 is about 66% higher than model 1 predictions (1,250/750 * 100). It especially helps to predict the shift in market shares from the initial phase to the sharp increase in sales that occurs after reaching critical mass. This evolution is not due to an improvement of the vehicle characteristics, but exclusively to the inclusion of these social elements, as our methodology reveals. As soon as the feedback about the use of the EV turns positive, a significant inclination towards this type of vehicle occurs. Relying on the abundant literature on social conformity (Baddeley, 2010; Cialdini, 2007; Cialdini & Goldstein, 2004; Kormos, Gifford, & Brown, 2015), the rationale behind this phenomenon is that individuals change their attitudes, beliefs, and behaviors because they want to fit in with a group, because they need help in making a decision, or because they simply want to do what is supposed to be right.

5. Conclusions and Discussion

This paper proposes a methodology that aims to overcome the problems that are commonly incurred in forecasting EV sales. These shortcomings have to do with the use of methodologies that are not the most convenient for that task (DCM or Bass-type models, only), the lack of dynamism, and the neglection of social elements. We suggest a method that combines a substitution model estimated with real disaggregated data, with a diffusion model based on a realistic projection of the variables involved. We pay particular attention to the role of Social Conformity, which is considered in psychology (and increasingly in other fields) capital in the decision-making process of individuals. Thus, our approach considers richer information than previous work, and integrates the concepts of substitution and diffusion into a single methodological paradigm.

Our results lead to several conclusions. Explicitly considering elements of social conformity in the substitution model represents a qualitative leap in predicting the development of the EV market. It especially helps to predict the shift in market shares from the initial phase to the sharp increase in sales that occurs after reaching critical mass. This evolution is not due to an improvement of the vehicle characteristics, but exclusively to the inclusion of these social elements, as shown by the comparison of the predictions of Model 1 with those of Models 2 and 3. Relying on the abundant literature on conformity (Baddeley, 2010; Cialdini, 2007; Cialdini & Goldstein, 2004; Kormos, Gifford, & Brown, 2015) the reason is that individuals change their behaviors because they want to fit in with a group, because they need help in making a decision, or because they want to do what is supposed to be right. Therefore, when we succeed in capturing these effects, we can achieve a better understanding of the process through which a technology diffuses in society. Concretely, we can now understand that the negative information about the EV that individuals may have received until recently may have been, in part, behind the slowdown experienced in the market. In our models, the variable capturing the effect of informational conformity gathered relevant aspects regarding the flexibility in one´s activity plans or schedule when using an EV. Although these aspects are clearly related to EV attributes (range, charging time, etc.), they are in fact difficult to evaluate intuitively when someone is considering the purchase of such a vehicle and is presented with a range figure. However, it is much easier to value the opinion of a close relative or friend, who gives trusty feedback on these aspects.

Therefore, an effective policy to promote the use or purchase of vehicles would involve allowing individuals to participate in trial tests. Although it would be difficult for a significant number of individuals to have access to these tests, our results show that the participation of some of them would be reflected in the feedback they give to others, boosting the expansion of the EV if it were positive. On the other hand, in light of these results, other policies to promote the EV should consist of expanding and improving the charging infrastructure. A denser network that provides shorter charging times would be crucial in the diffusion of EVs, since part of the weight of the spread of this technology still falls on the characteristics of the vehicle itself. Finally, although less related to the background of this work, public and private investment dedicated to the improvement of vehicle characteristics (such as the investment in research for new generations of batteries to increase autonomy, or public subsidies to reduce the final purchasing price), could provide the final boost, in conjunction with the other aforementioned aspects, to the acquisition of this technology. In any case, it is necessary to emphasize the importance of other aspects of social conformity not addressed in this study such as social-signaling —for which we refer the reader to Cherchi (2017), which any policy, to be truly effective, must combine. In this line, it is worth mentioning that, if we take for good the hypothesis of technology diffusion through social channels, such diffusion will of course be dependent on the scenarios designed to make the predictions. This is the reason why we relied on reliable sources to elaborate a design that would reflect a realistic evolution of all elements involved in the model estimation and forecast exercise.

In any case, we are confident that our methodology can, on the one hand, improve the diffusion models used in the industry. On the other hand, we also hope that they can be used as an evaluation tool for public agents, who may make use of a tool that provide more reliable predictions on EV technology deployment. A tool on which they can leverage to carry out more accurate and successful policies.

Finally, there are some improvements that could enhance this study, although the one that could have the greatest impact would be a better collection of the social information. That is, to know in greater detail the composition of the social network of each individual in the sample, as well as to improve the Stated Choice Experiment so that it could capture even better the elements of Normative and Informational Conformity. This, in fact, is a work that is already being developed by the authors of this article (Bas, Cirillo, & Cherchi, 2021).

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Authors Contributions

Javier Bas: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Writing. **Elisabetta Cherchi:** Conceptualization, Investigation, Methodology, Review & editing, Supervision. **Cinzia Cirillo**: Funding acquisition, Review & editing, Supervision.

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APPENDIX A – Sample sociodemographics. Source (Cherchi, 2017)

Number of individuals	2363	
Gender:		
Female	628	27%
Male	1735	73%
Profession:		
Employed	1847	78%
Freelance	187	8%
Pensioners, early retirement	211	9%
Other	118	5%
Job with fixed hours	998	42%
Age (average)	47	
N. of members in the household (average)	3.12	
N. of cars available in your household (average)	1.52	
Daily km travelled (average)	54.62 km	
N. of families with:		
One car	1228	52%
More than one car	1087	46%
Missed information	48	2%
Type of replacement:		
Replace an old car	1803	76%
Acquire additional one	265	11%
Not considering acquiring any car	295	12%
Car class in the intended purchase:		
Mini	294	12%
Small	532	23%
Medium 1	613	26%
Medium 2	426	18%
Large	132	6%
MPV	268	11%
Other	98	4%
% of influence in the decision	86%	
Parking location:		
On the street	836	35%
Other (e.g. multi-storey car park)	1527	65%
Time to find a parking space (average)	10 min	
Strategy for parking choice:		
The first one available	1455	62%
The one closest to destination	785	33%
Reserved	28	
Other	95	4%
N. of activities performed after parking:		
All purposes	1.52	
Work related	0.27	
Business	0.24	
Shopping	0.65	
Leisure	0.19	
Other	0.18	
Walking time from the parking space to the first destination (average)	5.7 min	
Duration of the parking (average)	2 h 35 min	
Frequency of the parking in the same zone and same time of the day:		
Every day	240	10%
Between 2 and 4 times a week	193	8%
Once a week	324	14%
Once every 2 weeks	288	12%
Less than twice a month	1318	56%

Appendix B - Table 2 variables' description.

MONTH	YEAR	CTY_SL	SHO_SL	CTY_FA	SHO_FA	PP_EV	PP_GAS	FU_EV	FU_GAS	RA_EV	RA_GAS	CO2_EV	CO2_GAS
3	2018	0.2	0.2	0.2	0.2	262,032.1	212,573.2	0.3	0.7	220.5	852.8	41.9	140.9
4	2018	0.2	0.2	0.2	0.2	262,032.1	212,573.2	0.3	0.7	220.5	852.8	41.9	140.9
5	2018	0.2	0.2	0.2	0.2	262,032.1	212,573.2	0.3	0.7	220.5	852.8	41.9	140.9
6	2018	0.2	0.2	0.2	0.2	262,032.1	212,573.2	0.3	0.7	220.5	852.8	41.9	140.9
7	2018	0.2	0.2	0.2	0.2	262,032.1	212,573.2	0.3	0.7	220.5	852.8	41.9	140.9
8	2018	0.2	0.2	0.2	0.2	262,032.1	212,573.2	0.3	0.7	220.5	852.8	41.9	140.9
9	2018	0.2	0.2	0.2	0.2	262,032.1	212,573.2	0.3	0.7	220.5	852.8	41.9	140.9
...	...	...	...	...	...	...	...	...	...	...	...	...	...
5	2050	1	1	1	1	1417,96.5	194,178.3	0.3	0.6	373.7	852.8	0	108.8
6	2050	1	1	1	1	141,796.5	194,178.3	0.3	0.6	373.7	852.8	0	108.8
7	2050	1	1	1	1	141,796.5	194,178.3	0.3	0.6	373.7	852.8	0	108.8
8	2050	1	1	1	1	141,796.5	194,178.3	0.3	0.6	373.7	852.8	0	108.8
9	2050	1	1	1	1	141,796.5	194,178.3	0.3	0.6	373.7	852.8	0	108.8
10	2050	1	1	1	1	141,796.5	194,178.3	0.3	0.6	373.7	852.8	0	108.8
11	2050	1	1	1	1	141,796.5	194,178.3	0.3	0.6	373.7	852.8	0	108.8
12	2050	1	1	1	1	141,796.5	194,178.3	0.3	0.6	373.7	852.8	0	108.8

CTY_SL: Percentage of penetration of slow-charging stations in city centers.
SHO_SL: Percentage of penetration of slow-charging stations in shopping malls.
CTY_FA: Percentage of penetration of fast-charging stations in city centers.
SHO_FA: Percentage of penetration of fast-charging stations in shopping malls.
PP_EV: Purchasing price of the electric vehicle.
PP_GAS: Purchasing price of the gasoline vehicle.
FU_EV: Fuel cost of the electric vehicle.
FU_GAS: Fuel cost of the gasoline vehicle.
RA_EV: Driving range of the electric vehicle.
RA_GAS: Driving range of the gasoline vehicle.
CO2_EV: CO2 emissions of the electric vehicle.
CO2_GAS: CO2 emissions of the gasoline vehicle.