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# Modeling the diffusion of Electric Vehicles by a robust explanation of the Bass diffusion model: An application to Pan-European Policy Analysis

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ABSTRACT

Accurate prediction of the diffusion of new transportation technologies such as electric vehicles (EVs) is critical for defining policy, infrastructure planning, and anticipating impacts on energy, emissions, and mobility systems. The Bass diffusion model is widely used to forecast technology adoption, but its parameters traditionally do not explicitly account for market-specific factors driving diffusion. This research proposes a generalized Bass model incorporating the effects of policy, economic, technological, and social variables derived from expert surveys. However, limited survey sample sizes introduce uncertainty that must be addressed. We develop a novel approach using extreme value theory to robustly estimate the Bass parameters while accounting for errors from imperfect survey data. Our approach links forecasting models with market factors from multiple data sources while rigorously handling uncertainties, supporting the design, evaluation, and impact assessment of transportation policies. The methodology is applied to forecast the adoption of regional electric vehicles throughout Europe in different policy scenarios related to factors such as charging infrastructure, purchase incentives, battery costs, and environmental awareness.

## 1. Introduction

In recent years, the transportation sector has increasingly embraced technological innovations to enhance the efficiency and effectiveness of transport systems. The diffusion of new technologies, products, and services in transportation has garnered significant attention, with forecasting models playing a critical role in shaping policy decisions. In the context of transportation policy, understanding the diffusion of innovations is essential for developing effective strategies that address key concerns such as safety, efficiency, environmental sustainability, and equity.

A widely recognized model for understanding the adoption and diffusion of innovations is the Bass Model (BM) (Bass, 1969). Initially developed to forecast the adoption of new consumer products, the BM has been extensively applied across various industries to predict innovation growth trajectories. Applying the Bass Model to transport innovations enables policymakers to anticipate adoption rates and design strategies that promote the successful integration of these technologies. This paper examines the relevance of the Bass Model in the transport sector, exploring how its application can inform policy decisions aimed at enhancing the adoption of innovative solutions across various transportation modes.

The Bass model is known for its compact and elegant representation of the innovation diffusion and the presence of only three parameters to tune, which are market-agnostic (Peres et al., 2010; Bass, 2004). However, once these parameters are tuned, policymakers must link them to market-specific variables, which is a complex task. It requires the derivation of a new mathematical model and the addition of new market-specific variables.

The primary contributions of this paper are threefold:

- A Generalized Bass Model Framework. This research proposes a generalized Bass Model that explicitly incorporates the effects of market-specific explanatory variables (e.g., policy, economic, social, and technological factors) derived from expert surveys (Cosguner and Seetharaman, 2022), without altering the model's fundamental structure. This provides a direct and flexible link between market-agnostic diffusion parameters and actionable policy levers.
- A novel and robust estimation method to incorporate market-specific explanatory variables. Since expert survey data are often limited in sample size, they introduce uncertainty and potential biases (Micklewright et al., 2012; Burzio et al., 2009; Giusti

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et al., 2019). To address this challenge, we develop a novel approach using extreme value theory to robustly estimate the Bass Model parameters, accounting for errors and fluctuations arising from imperfect survey information. The proposed framework fills a critical gap in quantitative policy analysis by linking forecasting models to specific market factors derived from multiple information sources, while rigorously handling the uncertainty associated with limited data samples. This research is particularly relevant for the design and evaluation of transport policies, infrastructure planning, manufacturing to meet future mobility demands, and managing the technological, economic, and environmental impacts of transport systems. This approach rigorously addresses the uncertainty and potential errors stemming from limited or imperfect information, as that arising from small-sample expert surveys. The new method is qualified by applying it to well-known innovation curves used in the literature as standard benchmarks.

- Application to Pan-European EV Policy Analysis. We apply the proposed methodology to forecast the adoption of electric vehicles in Europe. We use survey data on factors such as charging infrastructure availability, purchase incentives, battery costs, and environmental awareness, all derived within the context of INCIT-EV, the flagship European project for managing electric charging stations (INCIT-EV Consortium, 2019). The generalized Bass Model enables simulations of different policy scenarios, analyzing their impacts on transition timelines and peak EV adoption levels across markets, thus providing valuable decision support for policies aimed at accelerating sustainable mobility transitions. By simulating various policy scenarios, our model provides valuable, data-driven insights for policymakers on the differential impacts of incentives, infrastructure development, and other factors across different markets and time horizons.

The paper is organized as follows. Section 2 gives an overview of the relevant literature. Section 3 defines the problem setting and generalizes the Bass Model by incorporating market-specific explanatory variables, approximating their random oscillations. Extensive tests and analyses are reported in Section 4. Section 5 discusses the implications for the EV market and forecasts for the European market. Finally, Section 6 summarizes the results and suggests avenues for future research and development.

## 2. Literature review

Our paper deals with three main issues: the limitation of the oscillations due to the expert-based surveys measurement of market explanatory variables, their introduction in a general growth model in order to obtain a market-specific growth model that can be used by policy-makers and practitioners to elaborate business strategies and public policies, and finally the application to the Bass model. Hence, in this section, we highlight the main results and gaps in the related literature along these axes.

Survey observations are affected by measurement errors that may be caused by interviewers, bias of the respondents, data processors, and other survey personnel. Measurement errors are often hidden in the data and are only revealed when the measurement process is repeated or responses are compared to error-free measurements. Many analytical techniques can be used to account for measurement errors in data analysis and inference, such as structural equation modeling instrumental variables and errors-in-variables modeling. These techniques usually need a quite large number of observations in order to evaluate some characteristics of the error as standard deviation and covariance (Biemer, 2009). In expert-based surveys, the sample is normally quite limited and the usage of such methods might give unreliable outcomes. In other cases, as in peer group measurements, the process is repeated several times in order to obtain a better sample of the entire peer group (Walters, 2021; Micklewright et al., 2012; Burzio et al., 2009). Even this approach is not suitable in expert-based surveys for market analysis, due to the limited availability of the experts themselves. To mitigate these oscillations in expert-based surveys, various strategies have been proposed. These include calibrating expert assessments, employing interval-valued response modes, and applying advanced statistical techniques to manage biases and uncertainties (Perälä et al., 2020; Ellerby et al., 2022). However, such methods typically necessitate substantial adjustments to the survey structure and involve an extensive tuning phase, which is generally incompatible with experts' limited availability.

The BM, first proposed by Bass (1969), is the best-known new product growth and diffusion model in the marketing literature. It was used for the forecast of new product sales in thousands of industrial applications over the past 50 years. The appealing aspect of the BM is its parsimony. It considers just three parameters: the innovation coefficient (p), the imitation coefficient (q) and the market size (M). It then considers two influences on the market adoption of the new product: the effects of external media and interpersonal communications (or "word of mouth"). It is often used for the development of optimal marketing policies for new products (Peres et al., 2010). On the other hand, the BM must incorporate the effects of marketing variables on new product diffusion. The literature mainly focused on the introduction of dynamic pricing (Cosguner and Seetharaman, 2022). The method requires a modification of the model and is parameter-specific (as in the case of the price).

Regarding the use of the BM for EV forecasting, the existing literature is relatively limited. Bitencourt et al. 2021 apply the Bass diffusion model to evaluate the impact of policies on the adoption of EV through a structured three-stage approach: evaluation of public policies, economic analysis, and market analysis. Additionally, Maybury et al. 2022 utilize the Bass model to illustrate various market diffusion scenarios by systematically examining different combinations of the Bass parameters $p$ and $q$. Furthermore, the Bass diffusion model is confirmed to provide robust forecasting performance in the context of EV market penetration and to fit better than Gompertz and Logistic models (Ayyadi and Maaroufi, 2018; Rietmann et al., 2020; Dhakal and Min, 2021).

From the literature analysis emerges how a more general approach is required not only for the BM but, more in general, for deriving market-specific models from generic growth models. Thus, we need an approach that effectively reduces errors arising from small expert groups while minimally impacting the survey administration process. In this context, we derive analytical expressions that eliminate the need for precise knowledge of error probabilities, accurate estimations of distribution parameters (such as standard deviation or covariance), or extensive survey modifications.

## 3. Generalizing the Bass model by incorporating market-specific explanatory variables

According to Bass (1969), the BM in market size of $M$ consumers for a new product, the likelihood that a consumer will adopt the new product at time t, given that the consumer has not yet adopted, is given by the following equation:

$$\frac{f(t)}{1-F(t)} = p + qF(t), \tag{1}$$

where $p$ and $q$ are the imitation and innovation parameters of the market, respectively, $t$ is the time of the customer's adoption of the product, $f(t)$ is the Probability Density Function (PDF) characterizing the random variable $t$ and $F(t)$ is the Cumulative Distribution Function CDF. By solving the differential equation (1), one obtains the CDF as:

$$F(t) = \frac{1-e^{-(p+q)t}}{1+\frac{q}{p}e^{-(p+q)t}}. \tag{2}$$

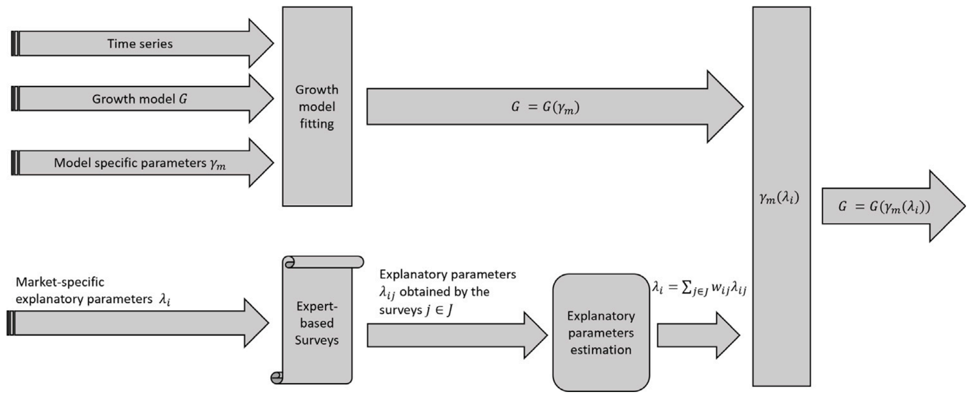


**Fig. 1.** Growth model estimation incorporating market explanatory variables.

The curve parameters are usually estimated by nonlinear least-squares procedures (Srinivasan and Mason, 1986) by minimizing the functional

$$SSE = \sum_{t=1}^{T} \left[\tilde{N}(t) - N(t)\right]^2, \tag{3}$$

where $T$ is the total number of periods in which the sales are available, $N(t)$, are the actual sales and the $\tilde{N}(t)$ are the predicted ones computed as

$$\tilde{N}(t) = M\left[F(t) - F(t-1)\right]. \tag{4}$$

The parameters $p$, $q$, and $M$ are then estimated from (3), while the peak adoption time can be computed as:

$$peak = \frac{\ln p - \ln q}{p+q} \tag{5}$$

Given this growth model, an interesting question arises concerning the explanability and the relation of the market-agnostic parameters $\gamma_m$, $m \in \mathcal{M} = \{p, q, M\}$ with market-specific explanatory variables $\lambda_i$, $i \in I$ (see Fig. 1 for a description of the process).

Traditionally, estimating these market-specific factors has relied on expert-based surveys, often based on limited sample data, which introduces uncertainty (Micklewright et al., 2012; Burzio et al., 2009; Giusti et al., 2019). This uncertainty stems from two primary factors: converting qualitative information into quantitative values and potential biases in the survey responses. Statistical methods typically depend on estimating the distribution of the sample data and associated errors. Unfortunately, due to the limited sample size inherent in expert-based surveys, these methods are not applicable (Micklewright et al., 2012). This problem is widely recognized when estimating explanatory parameters based on expert-based surveys. If the survey design only observes a random sample of experts for each parameter, any summary statistic derived from the survey data and used as an explanatory variable in regression analysis is subject to sampling variation. This creates measurement errors similar to errors-in-variables. Unfortunately, in the case of expert-based surveys, the expert group is typically small, making a proper analysis of the error difficult. Furthermore, the uncertainty resulting from sampling errors in expert-based surveys cannot be adequately measured or represented by a known probability distribution. As a result, incorporating this uncertainty into the definition of Bass model parameters using market and business factors becomes challenging.

Linking the market-agnostic parameters with market-specific explanatory variables can be done in two main ways: either by modifying the original Bass model to introduce market-specific explanatory variables or by establishing a connection between the market-agnostic parameters and the market-specific explanatory variables. The first approach is quite difficult to apply in practice, as it requires redefining the Bass model and deriving a new closed form for the model. This must be done for every change, even minor, in the list of explanatory variables. The second method is more straightforward and has the advantage of being more general and it is in general the most used by practitioners. A common way to perform the second method is by a regression in the form

$$\gamma_m = \gamma_{0m} + \sum_{i\in I} \gamma_{im}\lambda_i, \tag{6}$$

where $\gamma_{0m}, \gamma_{im}$ are the outcome of the regression.

Being the market-specific parameters quite sensitive to the specific knowledge of the market, $\lambda_i$ are usually estimated by expert-based surveys. Let be $j \in J$ a single survey, then $\lambda_{ij}$ is the value of the parameter $\lambda_i$ estimated through the survey $j$. A quite common way to compute $\lambda_i$ is to combine the values $\lambda_{ij}$ in a linear combination. For example, $\lambda_i$ can be a mean (weighted or not) of the values $\lambda_{ij}$ over the survey's data $j \in J$.

**Hypothesis 1** (*H*1). $\lambda_i$ are obtained as a linear combination of the values $\lambda_{ij}$ which are reference values for the explanatory variable $i$ in survey $j$ (e.g., the value of a Likert scale). Therefore,

$$\lambda_i = \sum_{j\in J} w_{ij}\lambda_{ij} \tag{7}$$

where $w_{ij}$ are the weights of the convex combination defining $\lambda_i$.

If, on the one hand, experts are an excellent source of information, on the other hand, the number of the surveyed experts is quite limited and its composition is heavily affected by their availability. This means that the survey data can vary while varying sampling and selection criteria and, consequently, the values of the explanatory variables are subject to uncertainty due to biases of the responders and their limited number. Moreover, there is quite limited knowledge of this uncertainty in value and distribution which depends on the sample scenario. Let $l \in L$ be the specific sample scenario, i.e., the specific subset of experts surveyed, and $\theta_j^l$ its random error, we can assume that the $\lambda_{ij}$ in the sample scenario $l$ are stochastic and affected by an error $\theta_j^l$.

In the following, we will prove how under mild assumptions of the distribution of the probability of $\theta_j^l$ and without explicit knowledge of this distribution we can derive a closed form of (6) able to incorporate the effect of the uncertain error $\theta_j^l$.

We assume the following:

**Hypothesis 2** (*H*2). $\theta_j^l$ are i.i.d. stochastic variables with the same unknown probability distribution.

**Hypothesis 3** (*H*3). $\theta_j^l$ have an exponential left tail.

Although the independence assumption could seem unrealistic, it is frequent to ignore dependency when little is known about the real probability distribution of the data, which is also the case for market sampling or expert-based surveys (Giusti et al., 2019; Burzio et al., 2009). Moreover, we will show in the computational results, obtained by using empirical data, that we can obtain very good results even with dependent errors. The quite stringent assumption of identical distributions of the oscillations is mitigated by the fact that the only common property required for these distributions is to be asymptotically exponential in their left tail. This is a very mild assumption as we observe that many probability distributions show such behavior, among them the widely used distributions Exponential, Normal, Lognormal, Gamma, Gumbel, Laplace, and Logistic. Also in this case, our computational results show that, even with different probability distributions for the oscillation errors, our approach is very accurate.

Under the previous assumptions, our goal is to estimate the growth model parameters $\gamma_m$ under the assumption that $\lambda_{ij}$ are affected by random oscillations $\theta_j^l$. In particular, we assume that we can represent the stochastic variable $\tilde{\lambda}_{ij}$ as a deterministic constant $\bar{\lambda}_{ij}$ plus the effect of $\theta_j$ that is the minimum of the random error oscillation $\theta_j^l$ of explanatory variable $j \in J$ across the alternative sample scenarios $l \in L$.

$$\tilde{\lambda}_{ij}(\theta_j) = \bar{\lambda}_{ij} + \theta_j = \bar{\lambda}_{ij} + \min_{l \in L} \theta_j^l \qquad \forall i \in I, \forall j \in J \tag{8}$$

Notice that even if $\theta_j^l$ can be either negative and positive, we assume that they are such that $\tilde{\lambda}_{ij}(\theta_j)$ are always positive. □

**Proposition 1** (*P*1). *Under the hypothesis H2, if $F_j(x) = Pr\{\theta_j^l \geq x\}$ is the cumulative right distribution function of $\theta_j^l$, the cumulative right distribution function of $\theta_j$, $B_j(x) = \Pr\{\theta_j \geq x\}$ becomes*

$$B_j(x) = \prod_{l \in L} \Pr\left\{\theta_j^l \geq x\right\} = \prod_{l \in L} F_j(x) = \left[F_j(x)\right]^{|L|} \tag{9}$$

*since $\theta_j \geq x \Longleftrightarrow \theta_j^l \geq x$, $\forall l \in L$.* □

To minimize the effects of the oscillations, we need to solve, for every explanatory variable $i \in I$, the following optimization problem:

$$\min \mathbb{E}_{\theta_j}[\sum_{j \in J} \tilde{\lambda}_{ij}(\theta_j) w_{ij}] \tag{10}$$

*s.t.*

$$\sum_{j \in J} w_{ij} = 1 \tag{11}$$

$$w_{ij} \geq 0 \tag{12}$$

where the constraint (11) imposes the convex combination of the surveys' data. For each $i$, we observe that the optimal solution can be obtained by fixing variables $w_{ij}$ in the following way.

$$w_{ij} = \begin{cases} 1 & \text{if } j = j^* \\ 0 & \text{otherwise} \end{cases} \tag{13}$$

where

$$j^* = arg\, min_{j \in J} \tilde{\lambda}_{ij}(\theta_j). \tag{14}$$

For the sake of simplicity, we assume that $j^*$ is unique. Then, the objective function (10) becomes

$$\min_j \mathbb{E}_{\theta_j}\left[\sum_{j \in J} \tilde{\lambda}_{ij}(\theta_j) w_{ij}\right] = \mathbb{E}_{\theta_{j^*}^l}\left[\tilde{\lambda}_{ij^*}(\theta_{j^*})\right] = \mathbb{E}_{\theta_j}\left[\min_{j \in J} \tilde{\lambda}_{ij}(\theta_j)\right] = \hat{\lambda}_i \tag{15}$$

**Proposition 2** (*P*2). *Under the hypothesis H2, the cumulative right distribution function of $\hat{\lambda}_i$, becomes*

$$\begin{aligned} G_i(x, |L|) &= Pr\left\{\min_{j \in J} \tilde{\lambda}_{ij}(\theta_j) \geq x\right\} = \prod_{j \in J} Pr\left\{\tilde{\lambda}_{ij}(\theta_j) \geq x\right\} \\ &= \prod_{j \in J} Pr\left\{\tilde{\theta}_j \geq x - \bar{\lambda}_{ij}\right\} = \prod_{j \in J} B_j\left(x - \bar{\lambda}_{ij}\right) \\ &\prod_{j \in J} \left[F_j\left(x - \bar{\lambda}_{ij}\right)\right]^{|L|} \end{aligned} \tag{16}$$

*In fact, given an $i \in I$ $\min_{j \in J} \tilde{\lambda}_{ij}(\theta_j) \geq x \iff \tilde{\lambda}_{ij}(\theta_j) \geq x$ $\forall j \in J$ and $\tilde{\lambda}_{ij}(\theta_j)$ are independent over $j \in J$.*

Now, let us assume that $|L|$ is large enough to use the asymptotic approximation $\lim_{|L| \to +\infty} G_i(x, |L|)$ as a good approximation of $G_i(x)$, i.e.

$$G_i(x) = \lim_{|L| \to +\infty} G_i(x, |L|) \tag{17}$$

We prove now that under a mild assumption on the shape of the unknown probability distribution $F_j(.)$, the limit in (17) tends to a Gumbel probability distribution (Gumbel, 1958).

**Theorem 1.** *Under hypothesis H3 the probability distribution $G_i(x)$ becomes*

$$G_i(x) = \lim_{|L| \to +\infty} G_i(x, |L|) = \exp\left(-A_i e^{\beta x}\right) \quad i \in I \tag{18}$$

*where $\beta > 0$ is a parameter to be calibrated and*

$$A_i = \sum_{j \in J} e^{-\beta \bar{\lambda}_{ij}} \tag{19}$$

*is the accessibility, in the sense of Hansen (1959).*

**Proof.** If a constant is added or subtracted to $\tilde{\theta}_j$, the solution of problem (10)–(12) does not change. Thus we can fix that constant $a_L$ root of

$$1 - F_j(a_L) = \frac{1}{|L|}$$

. Now, replacing $\lambda_{ij}$ with $\lambda_{ij} + a_L$ one obtains

$$G_i(x, |L|) = \lim_{|L| \to +\infty} = \prod_{j \in J} \left[F_j\left(x - \bar{\lambda}_{ij} - a_L\right)\right]^{|L|} \tag{20}$$

By (16) we have

$$\begin{aligned} G_i(x) &= \lim_{|L| \to +\infty} G_i(x, |L|) = \\ &= \lim_{|L| \to +\infty} \prod_{j \in J} \left[F_j\left(x - \bar{\lambda}_{ij} - a_L\right)\right]^{|L|} \\ &= \prod_{j \in J} \lim_{|L| \to +\infty} \left[F_j\left(x - \bar{\lambda}_{ij} - a_L\right)\right]^{|L|} \end{aligned} \tag{21}$$

By hypothesis H3 we have that

$$\lim_{y \to +\infty} \frac{1 - F_j(x - y)}{1 - F_j(-y)} = e^{\beta x}. \tag{22}$$

Thus

$$\lim_{|L| \to +\infty} \frac{1 - F_j(x - \bar{\lambda}_{ij} - a_L)}{1 - F_j(-a_L)} = e^{\beta(x - \bar{\lambda}_{ij})} \tag{23}$$

By (21) and $\lim_{|L| \to +\infty} a_L = +\infty$ we then obtain

$$\begin{aligned} G_i(x) &= \prod_{j \in J} \lim_{|L| \to +\infty} \left[F_j\left(x - \bar{\lambda}_{ij} - a_L\right)\right]^{|L|} = \\ &= \prod_{j \in J} \lim_{|L| \to +\infty} \left[1 - (1 - F_j(-a_L)) e^{\beta(x - \bar{\lambda}_{ij})}\right]^{|L|} = \\ &= \prod_{j \in J} \lim_{|L| \to +\infty} \left[1 - \frac{e^{\beta(x - \bar{\lambda}_{ij})}}{|L|}\right]^{|L|} \end{aligned}$$

Recalling that $\lim_{n \to +\infty}(1 + \frac{x}{n})^n = e^x$ we have

$$\begin{aligned} G_i(x) &= \prod_{j \in J} \lim_{|L| \to +\infty} \left[1 - \frac{e^{\beta(x - \lambda_{ij})}}{|L|}\right]^{|L|} = \\ &= \prod_{j \in J} exp(-e^{\beta(x - \bar{\lambda}_{ij})}) = \\ &= exp(-A_i e^{\beta x}) \end{aligned} \tag{24}$$

where

$$A_i = \sum_{j \in J} e^{-\beta \bar{\lambda}_{ij}}. \quad \square \tag{25}$$

Using the probability distribution $G_i(x)$ given by (18) and substituting for $t = A_i e^{\beta x}$, after some manipulations, $\hat{\lambda}_j$ in (15) becomes

$$\hat{\lambda}_i = -\int_{-\infty}^{+\infty} x dG_i(x) = -\int_{-\infty}^{+\infty} x \exp\left(-A_i e^{\beta x}\right) A_i e^{\beta x} \beta dx =$$
$$= -\frac{1}{\beta}(\ln A_i + \gamma) \tag{26}$$

where $\gamma \simeq 0.5772$ is the Euler constant and $\beta$ is the parameter of a Gumbel distribution.

Considering (10)–(12), (6) becomes

$$\gamma_m = \gamma_{0m} + \sum_{i\in I} \gamma_{im}(\min \mathbb{E}_{\theta_j} \sum_{j\in J} w_{ij}\tilde{\lambda}_{ij}) = \tag{27}$$
$$= \gamma_{0m} - \sum_i \gamma_{im}\frac{\gamma}{\beta} - \sum_i (\frac{\gamma_{im}}{\beta} \ln A_i) \tag{28}$$
$$A_i = \sum_j e^{-\beta\tilde{\lambda}_{ij}} \tag{29}$$

From (29), it is interesting to observe that the expected minimum total oscillation is equivalent, neglecting the constant $\frac{1}{\beta}$, to the maximum of the logarithm of the total accessibility.

The deterministic approximation requires an appropriate value of the parameter $\beta$. This parameter describes the propensity of the model to choose among the set of explanatory variables. This calibration is performed as follows. Let us consider the standard Gumbel distribution $G(x) = \exp(e^{-x})$. If an approximation error of 2‰ is accepted, then $G(x) = 1 \Leftrightarrow x = 6.08$ and $G(x) = 0 \Leftrightarrow x = -1.76$. Let us consider the distribution range $[o, O]$. The following equations hold

$$\beta(o - \zeta) = -1.76 \tag{30}$$

$$\beta(O - \zeta) = 6.08 \tag{31}$$

where $\zeta$ is the mode of the Gumbel distribution $G(x) = \exp\left(e^{-\beta(x-\zeta)}\right)$.

By subtracting (30) from (31) one gets for $\beta$ the value

$$\beta = \frac{6.08 - (-1.76)}{O - o} = \frac{7.84}{O - o} = \frac{7.84}{5 - 1} = 1.96. \tag{32}$$

More sophisticated methods to calibrate $\beta$ can be found in Galambos et al. (1994).

Given a set $J$ of explanatory variables for the BM, we can rewrite $p$, $q$, and $M$ according to explanatory variables as in (29).

$$B(p(i), q(i), M(i)) \tag{33}$$
$$p = p_0 - \sum_i p_i \frac{\gamma}{\beta} - \sum_i (\frac{p_j}{\beta} lnA_i) \tag{34}$$
$$q = q_0 - \sum_j q_i \frac{\gamma}{\beta} - \sum_i (\frac{q_i}{\beta} lnA_i) \tag{35}$$
$$M = M_0 - \sum_i M_i \frac{\gamma}{\beta} - \sum_i (\frac{M_i}{\beta} lnA_i) \tag{36}$$
$$A_i = \sum_j e^{-\beta\tilde{\lambda}_{ij}} \tag{37}$$

## 4. Model validation

In this section, to validate our model, we focus on a set of already tuned Bass curves. We perform two different kinds of experiments. In the first one, we generate surveys with identical distributed random oscillations; in the second one, we introduce correlation among the different random variables. In order to test our approach we develop a Monte Carlo simulation–optimization algorithm performing the following steps (Fig. 2 provides a schematic overview of the validation process):

- Consider a set of Bass curves $B$, a set of explanatory variables $I$, and a set of surveys $J$.
- The Monte Carlo simulation module repeats the following process for a given number $|Q|$ of iterations.
  - Consider a Bass curve in $B$ defined by its parameters $p, q, M$.
  - For each explanatory variable $i \in I$, randomly generate (according to a given distribution) a set of survey data values $\lambda_{ij}, \forall j \in J$ over a Likert scale.
  - Take the number of periods and their discretization from the literature. Let $t$ the index of the time periods.
  - Explain the parameters $p$, $q$, and $M$ by a regression $R^O$ according to (6), by considering as values of the $\lambda_i$ the mean of the values $\lambda_{ij}$ over the surveys and compute the Bass CDF and PDF, namely $BCDF^O$, $BPDF^O$.
  - Explain the parameters $p$, $q$, and $M$ by a regression $R^A$ according to (34)–(37), by considering the values $\lambda_{ij}$ in the surveys, and compute the approximated Bass CDF and PDF, namely $BCDF^A$, $BPDF^A$.
  - For $k = 1 \dots |L|$ perturb the surveys according to a given distribution, obtaining a new survey set $s$.
    * Given the new survey, consider it as the true evaluation of the explanatory variables. Explain the parameters $p$, $q$, and $M$ by a regression $R^T$ according to (6), by considering the values of the new surveys. Compute the Bass CDF and PDF, namely $BCDF^T$, $BPDF^T$.
    * Compute the new values of $p$, $q$, and $M$ according to the regression $R^O$, but applying the values $s$. In this way, we simulate the fact that the new surveys are seen as a perturbation of the system and not as the true evaluation of the explanatory variables. Compute the Bass CDF and PDF, namely $BCDF^O$, $BPDF^O$.
    * Compute the new values of $p$, $q$, and $M$ according to the regression $R^A$, but applying the values $s$. In this way, we simulate the fact that the new surveys are seen as a perturbation of the system and not as the true evaluation of the explanatory variables. Compute the Bass CDF and PDF, namely $BCDF^A$, $BPDF^A$.
    * Compute $eMax^O$, i.e., the difference between the cumulative distributions $BCDF^T$ and $BCDF^O$ in the last time period as
    $$eMax_k^O = \frac{|BCDF^T(t) - BCDF^O(t)|}{BCDF^T(t)}$$
    at repetition $k$.
    * Compute $eMax^A$, i.e., the difference between the cumulative distributions $BCDF^T$ and $BCDF^A$ in the last time period as
    $$eMax_k^A = \frac{|BCDF^T(t) - BCDF^A(t)|}{BCDF^T(t)}$$
    at repetition $k$.
    * Compute $\Delta Peak^O$, i.e., the difference between the peak time periods of the user adoption computed by (5) over the cumulative distributions $BCDF^T$ and $BCDF^O$ as
    $$\Delta Peak_k^O = Peak^T(t) - Peak^O(t)$$
    at repetition $k$.
    * Compute $\Delta Peak^A$, i.e., the difference between the peak time periods of the user adoption computed by (5) over the cumulative distributions $BCDF^T$ and $BCDF^A$ as
    $$\Delta Peak_k^A = Peak^T(t) - Peak^A(t)$$
    at repetition $k$.
    * Return $eMax_k^O$, $eMax_k^A$, $\Delta Peak_k^O$, and $\Delta Peak_k^A$.
- Compute the mean and the standard deviation of $eMax^O$ and $eMax^A$, as the mean and the standard deviation over all the

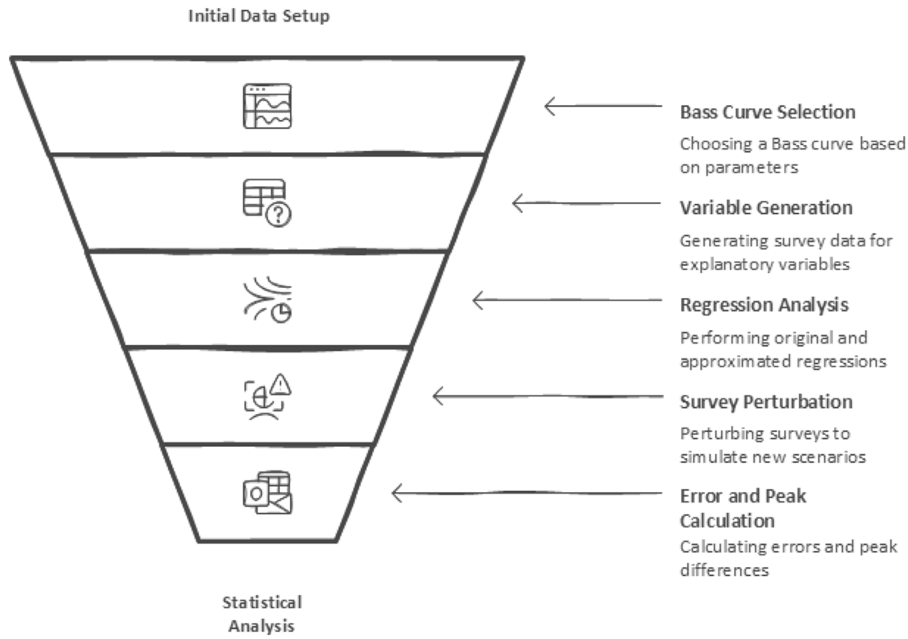


**Fig. 2.** Methodological framework of the study, illustrating the workflow from data collection and initial calibration to robust parameter estimation using extreme value theory and application in policy scenario analysis.

iterations of the Monte Carlo and the repetitions in each single Monte Carlo iteration. Compute the mean $\Delta Peak^{O}$, and $\Delta Peak^{A}$ as the mean value of the peak period over all the iterations of the Monte Carlo and the repetitions in each single Monte Carlo iteration.

We consider two distributions for the oscillations, the Uniform and the Gumbel. The reason for this choice is that the Gumbel represents the most favorable case for our approximation because we approximate a Gumbel distribution with a Gumbel-based approximation and it represents the minimum error we can have. The Uniform, on the contrary, is the opposite, being one of the few distributions violating the hypothesis H3. The oscillations can be independent or correlated. In the independent tests, the oscillations are i.i.d.. In the correlated ones, we group the variables in clusters of up to 3 variables (the size is randomly generated). Then, for each cluster $c$, the oscillation is computed as $\theta_{ij} = \theta_c + \theta_{cij}$, where both $\theta_c$ and $\theta_{cij}$ are extracted by the same distribution of probability assigned to the Monte Carlo simulation. Given the mean of the Monte Carlo simulation with i.i.d. oscillations $\mu$, the means of $\theta_c$ and $\theta_{cij}$ are set to $\mu_c = \alpha\mu$ and $\mu_{cij} = (1-\alpha)\mu$, $\alpha \in (0,1)$. We set $\mu = 2$ for both distributions.

Other parameters for the simulation are as follows:

- Number of surveys: $|J|$=4, 10, and 20.
- Number of explanatory variables: $|I|$=3, 10, and 30.
- Iterations of the Monte Carlo simulation: $|Q|$=1000.
- Number of repetitions: $|L|$=100.
- Tested values for $\alpha$= 0.3, 0.5 and 0.7.

The parameters for the simulation are chosen to ensure the statistical validity and convergence of the results. A total of $|Q| = 1000$ iterations for the Monte Carlo simulation are set to guarantee that the mean and standard deviation of our key performance metrics stabilized, which is a common practice for achieving reliable estimates in such experiments. The number of inner-loop repetitions is set to $|L| = 100$ to sufficiently model the effects of sampling variability from different potential expert groups (sample scenarios) while maintaining a reasonable computational runtime.

To demonstrate the effectiveness of the proposed methodologies, it is essential to adopt benchmark load curves from the literature. For this reason, we adopt widely recognized benchmarks, Color TV and Air Conditioner, because they are the most commonly used in the literature and thus allow for direct comparison with the majority of published studies (Cosguner and Seetharaman, 2022). Furthermore, we introduce a third curve drawn from the electric-vehicle domain, specifically the historical EV penetration in Germany, to capture dynamics more representative of the transportation sector (Brdulak et al., 2021). Table 1 presents the tests for the case of the independent distributions. The columns are organized as follows. For each market (EV in Germany, Color TV, and Air Conditioner) a separate subtable is presented. Each subtable presents the same structure. Columns 1 and 2 give the number of explanatory variables and the number of surveys, respectively. Then, the aggregated results for the case in which the oscillation is Uniform and Gumbel are presented.

According to the numerical results, it is clear how our approximation outperforms the standard method of the linear combination of the explanatory variables. The latter method has a mean error in the estimation of the market size of more than 10% and a high variance. On the contrary, our extreme value approximation reduced it by more than 50% in the worst case (the uniform distribution). We have in fact to consider that it is an unlikely case to have a uniform distribution of the oscillations, in particular, if they are related to biases in the evaluation. Thus, in a practical application, we expect to have a behavior more similar to the Gumbel one, with a very low loss both in terms of mean and deviation compared to the real curve. The extreme theory approximation presents an even better behavior if we consider the error in the peak period. The standard method shows a mean error of about 1 period of time, with a maximum of 1.5. In contrast, our approximation has an error of 0.3 in the worst case. The results just discussed are related to the case in which the variables are i.i.d. as required by our hypotheses. Table 1 shows the effect of a correlation among the explanatory variables. Both the classic and the extreme value methods take advantage of the correlation. This reduces the effect of uncertainty. Unfortunately, this effect is quite limited, and thus our approximation is still required and by far the best choice. Thus, it becomes clear how, by using a quite compact reformulation of the linear combination of explanatory variables it is possible to obtain a very accurate approximation of the original Bass curve while considering at the same time the effects of under-sampling of the set of the experts and biases in their evaluation.

Focusing on the EV market in Germany it is clear how our approximation outperforms the classical regression method, which exhibits a mean error in estimating the final market adoption $eMax^O$ of over 10% with significant variance. In contrast, our extreme value approximation reduces this error by more than 50% even in the worst-case test, i.e., a Uniform distribution. Again, given that real-world survey biases are unlikely to be uniformly distributed, we expect practical performance to be closer to the Gumbel case, which shows an error reduction of nearly 80% as shown in the Gumbel case. The improvement is even more important when considering the error in forecasting the peak adoption period ($\Delta Peak$). The standard method shows a mean error of approximately −1.5 periods (years), suggesting a significant premature forecast. From a managerial standpoint, this is a crucial flaw. An error of one year could lead to producing peak-level inventory that remains unsold, triggering costly stock reduction measures and disrupting production planning for the subsequent (actual) peak year. In contrast, our approximation reduces this peak-timing error to a few months (−0.31 periods in the Gumbel case), allowing for far more accurate strategic and operational planning within the same fiscal year (see Table 2).

## 5. Application to the Electric Vehicle market

We discuss a real application of our approach for the creation of a decision support system for public stakeholders in the European market of Electric Vehicles. The methodology has been tested in INCIT-EV (INCIT-EV Consortium, 2019), a H2020 framework project with the objective of demonstrating an innovative set of charging infrastructures, technologies, and associated business models, to improve the EV users' experience beyond early adopters, thus fostering the EV market share in the EU. The innovative charging solutions developed in the project are tested in five pilot cities: Paris (France), Saragossa (Spain), Amsterdam (Holland), Tallinn (Estonia), and Turin (Italy). These use cases have been conceived pursuing innovative upgrades in the current charging solutions as well as their seamless integration into the existing transport, grid, ICT and civil infrastructures. Moreover, with the aim of improving the users' experience and engaging them in sustainable mobility solutions, a very important outcome of the project will be a digital platform to empower the users with applications enabling interoperable direct payment, charging points location, availability and reservation, and smart charging. In this paper, we consider the Holland use case. In particular, the application of the model within the project is aimed at forecasting the EVs' adoption in the pilot cities, based on sales data from the past years, and on a questionnaire representing the main factors affecting the EVs market. The application of the model allows policy makers and decision-makers to evaluate the effects of policies and incentives to foster the penetration of EVs in the market, by simulating different scenarios (see Fig. 3 for a resume of the methodology and the data sources).

The parameters of the Bass model were calibrated from market data (EV registration by year from 2016 to 2021) (Statista, 2023). The explanatory variables are taken from an expert-based survey. In business analysis, PEST analysis describes a framework of macro-environmental factors used in the environmental scanning component of strategic management (Aguilar, 1967). It is a strategic tool for understanding market growth or decline, business position, potential and direction for operations. Its name comes from the four categories in which the factors influencing the market are classified, i.e., political, economic, socio-cultural and technological.

The first calibration of $p$, $q$ and $M$ has been done starting from market data (EV registration by year from 2016 to 2021). These calibrations can be done directly from (2) by nonlinear least square techniques (Schmittlein and Mahajan, 1982; Srinivasan and Mason, 1986), for instance. Following Srinivasan and Mason (1986) we opted for the usage of the nonlinear least square technique based on a Python script.

The assessment of the PEST factors i.e., P (political), E (economic), S (socio-cultural), and T (technological) was performed gathering expert judgment of professionals with relevant domain knowledge. The survey was conducted using a Computer-Assisted Telephone Interviewing (CATI) approach with English as the official language. Before doing the survey, each survey respondent received a list of the factors and a brief description of the literature definitions and evidences for his/her country. This method ensured consistency and reliability in data collection while facilitating expert participation across multiple countries in a standardized and efficient manner. The CATI system also allowed immediate data validation and reduced interviewer bias. Then, for each factor its definition was read and then the respondent was asked to give its score to it (see Table 3 for the full list of the factors). Data can be retrieved in the Annex A of INCIT-EV's Deliverable D9.2 "Demand Scenarios (Roadmap) for the different use cases through PESTEL and estimation of penetration curves" (INCIT-EV Consortium, 2023). Each expert was asked to rate each factor using a five-level Likert scale, reflecting its expected impact in the given city and target year (2025, 2030, and 2035). The scale was defined as follows:

- Strongly negative effect;
- Moderately negative effect;
- Neutral;
- Moderately positive effect;
- Strongly positive effect.

30 experts per country were selected, ensuring adequate representation and diversity of perspectives. Experts were drawn from the stakeholder groups identified in the INCIT-EV Deliverables (INCIT-EV Consortium, 2022, 2023):

- EV rental and sharing companies;
- Delivery service companies;
- Electromobility associations;
- ICT and technology providers;
- Energy utilities;
- Charging station manufacturers;
- Regional, national, and local public authorities;
- Public transport operators;
- Environmental and civil society organizations.

These experts were identified based on their involvement and influence in the electromobility ecosystem, ensuring a comprehensive and informed evaluation of the factors under study.

The Bass model parameters $p$, $q$, and $M$ can be then explained according to these variables.

After the calibration of the Bass parameters and the application of our approximation, the resulting values are:

- p = 0.00000103;
- q = 0.84752372;
- M = 6,816,565.

The Mean Absolute Percentage Error (MAPE) is extremely low (less than $10^{-4}\%$), indicating that the estimated adopters curve closely matches the S-curve (see Fig. 4).

Once performed the second calibration, it is possible to forecast the number of circulating EVs in Holland in three different time horizons:

- 2,258,556 in 2025;
- 6,787,572 in 2030;
- 6,816,563 in 2035.

Considering these values as reference values, it is possible to simulate the impacts of their variation on the EVs market. The first analysis has been made considering each macro-factor (Political, Economic, Social, and Technological) separately, and simulating a precautionary

**Table 1**
Comparison of the original formula and the approximation with different distributions of the oscillation: number of adopters and change in the peak period.

Electric Vehicles in Germany (Brdulak et al., 2021)

| Vars | Surveys | Uniform | | | | | | Gumbel | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | Orig | | | Approx | | | Orig | | | Approx | | |
| | | $eMax^O$ Mean (%) | $eMax^O$ Std (%) | $\Delta Peak^O$ Mean (periods) | $eMax^A$ Mean (%) | $eMax^A$ Std (%) | $\Delta Peak^A$ Mean (periods) | $eMax^O$ Mean (%) | $eMax^O$ Std (%) | $\Delta Peak^O$ Mean (periods) | $eMax^A$ Mean (%) | $eMax^A$ Std (%) | $\Delta Peak^A$ Mean (periods) |
| 3 | 4 | 12.04 | 3.47 | −1.45 | 4.19 | 2.21 | −0.40 | 10.89 | 2.51 | −1.32 | 2.76 | 1.45 | −0.21 |
| | 10 | 12.16 | 3.50 | −1.47 | 3.50 | 1.51 | −0.42 | 10.36 | 1.52 | −1.25 | 1.90 | 0.93 | −0.19 |
| | 20 | 12.00 | 3.15 | −1.45 | 3.15 | 1.13 | −0.42 | 10.60 | 1.10 | −1.28 | 1.72 | 0.73 | −0.22 |
| 10 | 4 | 13.13 | 5.66 | −1.59 | 5.66 | 2.00 | −0.72 | 10.94 | 1.36 | −1.32 | 2.82 | 1.23 | −0.33 |
| | 10 | 12.41 | 5.08 | −1.50 | 5.08 | 1.30 | −0.68 | 10.42 | 0.83 | −1.26 | 2.71 | 0.82 | −0.36 |
| | 20 | 12.41 | 5.07 | −1.50 | 5.07 | 0.93 | −0.68 | 10.63 | 0.60 | −1.29 | 2.49 | 0.60 | −0.34 |
| 30 | 4 | 13.71 | 5.30 | −1.66 | 5.30 | 1.18 | −0.70 | 11.03 | 0.79 | −1.33 | 2.87 | 0.76 | −0.38 |
| | 10 | 12.92 | 5.57 | −1.56 | 5.57 | 0.73 | −0.75 | 10.46 | 0.48 | −1.26 | 2.91 | 0.48 | −0.39 |
| | 20 | 12.54 | 5.48 | −1.52 | 5.48 | 0.51 | −0.74 | 10.66 | 0.34 | −1.29 | 2.83 | 0.34 | −0.38 |
| Tot | | 12.59 | 4.70 | −1.52 | 4.78 | 1.28 | −0.61 | 10.66 | 1.06 | −1.29 | 2.56 | 0.82 | −0.31 |

TV color (Cosguner and Seetharaman, 2022)

| Vars | Surveys | Uniform | | | | | | Gumbel | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | Orig | | | Approx | | | Orig | | | Approx | | |
| | | $eMax^O$ Mean (%) | $eMax^O$ Std (%) | $\Delta Peak^O$ Mean (periods) | $eMax^A$ Mean (%) | $eMax^A$ Std (%) | $\Delta Peak^A$ Mean (periods) | $eMax^O$ Mean (%) | $eMax^O$ Std (%) | $\Delta Peak^O$ Mean (periods) | $eMax^A$ Mean (%) | $eMax^A$ Std (%) | $\Delta Peak^A$ Mean (periods) |
| 3 | 4 | 9.79 | 3.07 | −0.66 | 3.88 | 2.06 | −0.18 | 8.75 | 2.20 | −0.60 | 2.28 | 1.29 | −0.08 |
| | 10 | 9.83 | 3.25 | −0.67 | 3.25 | 1.42 | −0.19 | 8.20 | 1.33 | −0.57 | 1.79 | 0.86 | −0.10 |
| | 20 | 9.65 | 2.93 | −0.66 | 2.93 | 1.07 | −0.19 | 8.34 | 0.95 | −0.58 | 1.68 | 0.66 | −0.11 |
| 10 | 4 | 10.72 | 5.34 | −0.72 | 5.34 | 1.90 | −0.33 | 8.75 | 1.20 | −0.60 | 2.57 | 1.09 | −0.15 |
| | 10 | 10.03 | 4.77 | −0.68 | 4.77 | 1.23 | −0.31 | 8.25 | 0.73 | −0.57 | 2.41 | 0.74 | −0.16 |
| | 20 | 10.00 | 4.76 | −0.69 | 4.76 | 0.89 | −0.31 | 8.40 | 0.52 | −0.58 | 2.23 | 0.55 | −0.15 |
| 30 | 4 | 11.23 | 5.02 | −0.76 | 5.02 | 1.11 | −0.32 | 8.74 | 0.69 | −0.60 | 2.68 | 0.70 | −0.18 |
| | 10 | 10.47 | 5.26 | −0.71 | 5.26 | 0.69 | −0.34 | 8.23 | 0.42 | −0.57 | 2.65 | 0.44 | −0.18 |
| | 20 | 10.11 | 5.16 | −0.69 | 5.16 | 0.48 | −0.34 | 8.44 | 0.30 | −0.59 | 2.59 | 0.31 | −0.18 |
| Tot | | 10.20 | 4.40 | −0.69 | 4.49 | 1.21 | −0.28 | 8.46 | 0.93 | −0.59 | 2.32 | 0.74 | −0.14 |

Air conditioner (Cosguner and Seetharaman, 2022)

| Vars | Surveys | Uniform | | | | | | Gumbel | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | Orig | | | Approx | | | Orig | | | Approx | | |
| | | $eMax^O$ Mean (%) | $eMax^O$ Std (%) | $\Delta Peak^O$ Mean (periods) | $eMax^A$ Mean (%) | $eMax^A$ Std (%) | $\Delta Peak^A$ Mean (periods) | $eMax^O$ Mean (%) | $eMax^O$ Std (%) | $\Delta Peak^O$ Mean (periods) | $eMax^A$ Mean (%) | $eMax^A$ Std (%) | $\Delta Peak^A$ Mean (periods) |
| 3 | 4 | 10.54 | 3.25 | −0.85 | 4.06 | 2.15 | −0.23 | 9.31 | 2.31 | −0.76 | 2.59 | 1.37 | −0.11 |
| | 10 | 10.60 | 3.40 | −0.86 | 3.40 | 1.48 | −0.25 | 8.87 | 1.42 | −0.73 | 1.94 | 0.92 | −0.14 |
| | 20 | 10.42 | 3.07 | −0.85 | 3.07 | 1.12 | −0.24 | 8.98 | 1.01 | −0.74 | 1.65 | 0.69 | −0.13 |
| 10 | 4 | 11.54 | 5.56 | −0.93 | 5.56 | 1.97 | −0.42 | 9.42 | 1.28 | −0.77 | 2.71 | 1.19 | −0.20 |
| | 10 | 10.82 | 4.98 | −0.88 | 4.98 | 1.28 | −0.40 | 8.91 | 0.77 | −0.73 | 2.57 | 0.79 | −0.21 |
| | 20 | 10.80 | 4.98 | −0.88 | 4.98 | 0.92 | −0.40 | 9.12 | 0.56 | −0.75 | 2.38 | 0.58 | −0.20 |
| 30 | 4 | 12.08 | 5.22 | −0.97 | 5.22 | 1.16 | −0.41 | 9.48 | 0.74 | −0.78 | 2.67 | 0.73 | −0.22 |
| | 10 | 11.28 | 5.48 | −0.92 | 5.48 | 0.72 | −0.44 | 8.96 | 0.45 | −0.74 | 2.70 | 0.46 | −0.22 |
| | 20 | 10.91 | 5.39 | −0.89 | 5.39 | 0.50 | −0.43 | 9.12 | 0.32 | −0.75 | 2.80 | 0.33 | −0.23 |
| Tot | | 11.00 | 4.59 | −0.89 | 4.68 | 1.26 | −0.36 | 9.13 | 0.98 | −0.75 | 2.44 | 0.78 | −0.18 |

scenario (each macro-factor increases by 1), and an optimistic scenario (each macro-factor is set at 5, the maximum value). Macro-factors values changed one at a time. The results are shown in Table 4.

As a first observation, we notice that the main effects on the market in Holland are in the short term (2025), while the positive effects decrease in the medium-long term. In practice, the effects of political, economic, social, and technological improvements are mainly concentrated in the short term, after that the market starts to saturate and new EVs sales start to decrease. This is mainly due to the fact that in Holland (as generally in North-European countries) citizens are already quite familiar with EVs, and the transition towards sustainable mobility appears to be easier than in other countries. The second observation is that the most effective factors for the market penetration of EVs are the economic and social ones, while the increase of the political factors has a marginal impact on the market.

To draw better insights, in a second simulation we consider three different scenarios:

- In the first scenario, we analyze the effects of political incentives to foster the market penetration of EVs, assuming that the increase of the values of the political factors will positively affect also some economic and social factors (as shown in Table 5). We assume that increasing all the political factors at the maximum value (5), the other affected factors increase by 1.5 points.
- The second scenario analyzes the effects of technological improvements, assuming that the increase of the technological factors will affect also some economic aspects (as shown in Table 6). Also in this case, we assume that increasing the technological factors at the maximum level (5) will increase the other affected factors by 1.5 points.
- In the third scenario, we analyze the stability of the market characteristics ($p$ and $q$) with respect to fluctuations in the market size $M$. Specifically, we keep $p$ and $q$ fixed, vary the value of $M$ by certain percentages, and then calculate the Mean Absolute Percentage Error (MAPE) for each adjusted market size. We

**Table 2**
Comparison of the original formula and the approximation with different values of correlation.

| Curve | Distribution | Independent case | | | |
|---|---|---|---|---|---|
| | | $eMax^O$ | $eMax^A$ | $\Delta Peak^O$ | $\Delta Peak^A$ |
| Germany | Uniform | 12.59 | 4.78 | −1.52 | −0.61 |
| | Gumbel | 10.66 | 2.56 | −1.29 | −0.31 |
| TV Color | Uniform | 10.20 | 4.49 | −0.69 | −0.28 |
| | Gumbel | 8.46 | 2.32 | −0.59 | −0.14 |
| Air Conditioner | Uniform | 11.00 | 4.68 | −0.89 | −0.36 |
| | Gumbel | 9.13 | 2.44 | −0.75 | −0.18 |

| Curve | Distribution | Dependent with $\alpha = 0.3$ | | | | Dependent with $\alpha = 0.5$ | | | | Dependent with $\alpha = 0.7$ | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | $eMax^O$ | $eMax^A$ | $\Delta Peak^O$ | $\Delta Peak^A$ | $eMax^O$ | $eMax^A$ | $\Delta Peak^O$ | $\Delta Peak^A$ | $eMax^O$ | $eMax^A$ | $\Delta Peak^O$ | $\Delta Peak^A$ |
| Germany | Uniform | 11.97 | 2.40 | −1.45 | 0.23 | 10.87 | 2.25 | −1.31 | 0.22 | 11.16 | 2.21 | −1.35 | 0.22 |
| | Gumbel | 8.88 | 1.93 | −1.07 | 0.02 | 8.54 | 1.88 | −1.02 | 0.02 | 8.02 | 1.90 | −0.97 | 0.02 |
| TV Color | Uniform | 8.71 | 4.20 | −0.63 | −0.23 | 7.91 | 3.92 | −0.57 | −0.23 | 7.38 | 3.61 | −0.53 | −0.22 |
| | Gumbel | 8.23 | 2.28 | −0.50 | −0.14 | 7.92 | 2.22 | −0.48 | −0.14 | 7.15 | 2.19 | −0.44 | −0.13 |
| Air Conditioner | Uniform | 9.39 | 4.37 | −0.81 | −0.30 | 8.53 | 4.09 | −0.74 | −0.29 | 7.95 | 3.76 | −0.69 | −0.28 |
| | Gumbel | 7.79 | 2.28 | −0.68 | −0.15 | 7.08 | 2.13 | −0.62 | −0.14 | 6.60 | 1.96 | −0.58 | −0.14 |

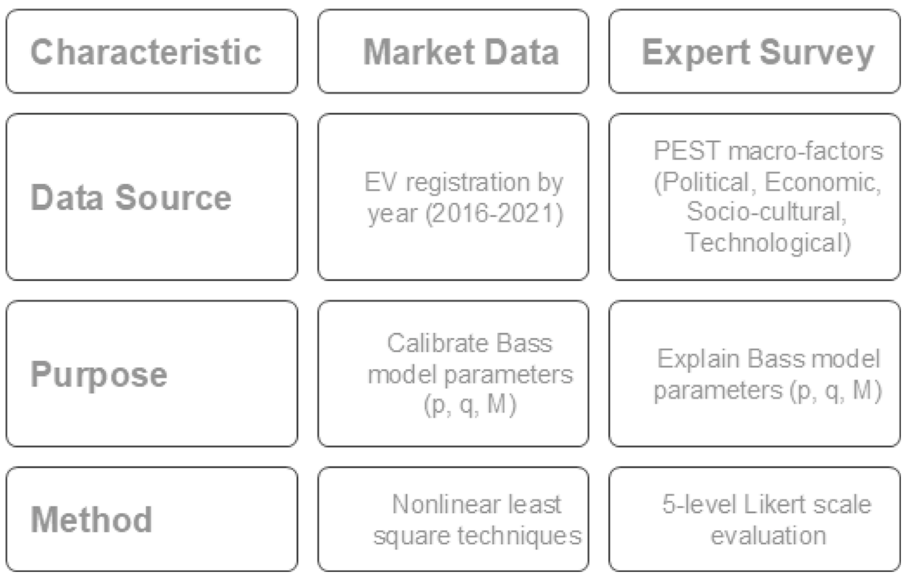


**Fig. 3.** Resume of the adoption analysis.

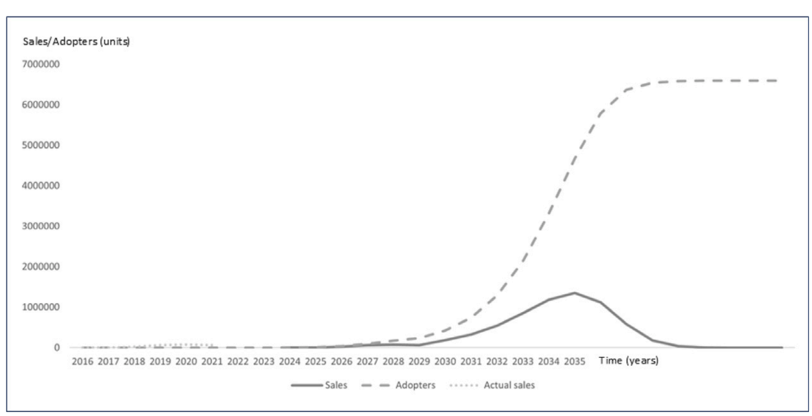


**Fig. 4.** Plot of the estimated S-Curve (broken line), the actual adopters used for the first calibration of the Bass model (dotted line), and the adopters (continuous line). The graph reports the time reported in years in the horizontal axis and the number of sales/adopters on the vertical axis (as in the standard Bass model, we assume one sale equal to one adopter). Please note that for sales the curves report the cumulative, while for the adopters the number of new adopters in one year.

**Table 3**
Factors affecting EVs market penetration.

| Factor type | Factor | Mean value |
|---|---|---|
| Political | Charging points availability | 3.5 |
| Political | Policy regulations and government incentives for EV in terms of tax policy, legal regulations | 3.5 |
| Political | Grants and funding initiatives for additional governmental investments in infrastructure | 3.5 |
| Economic | Savings in operational costs | 3.0 |
| Economic | Savings in maintenance costs | 3.0 |
| Economic | Improved efficiency | 2.5 |
| Economic | Initial cost | 3.0 |
| Economic | Installation costs for private charging points | 3.0 |
| Economic | Charging cost | 3.0 |
| Economic | Innovation index | 2.5 |
| Economic | Battery price for EVs | 2.5 |
| Economic | Electricity price | 3.0 |
| Social | Quietness | 3.0 |
| Social | Reduction of pollution | 3.5 |
| Social | Environmental awareness | 3.0 |
| Social | Population-GDP | 3.0 |
| Social | Cars per household | 3.0 |
| Technological | Duration of the batteries | 3.0 |
| Technological | Autonomy | 3.0 |
| Technological | Charging speed | 3.0 |

**Table 4**
Impact on the EVs market considering each category of factors independent.

| Factor type | Approach | EV stock variation (2025) | EV stock variation (2030) | EV stock variation (2035) |
|---|---|---|---|---|
| Political | Precautionary | 6.3% | 3.8% | 3.6% |
| Political | Optimistic | 6.3% | 3.8% | 3.6% |
| Economic | Precautionary | 11.9% | 6.9% | 6.6% |
| Economic | Optimistic | 12.2% | 7.1% | 6.8% |
| Social | Precautionary | 10.1% | 6.0% | 5.7% |
| Social | Optimistic | 10.8% | 6.4% | 6.1% |
| Technological | Precautionary | 7.9% | 4.7% | 4.4% |
| Technological | Optimistic | 8.3% | 4.9% | 4.7% |

**Table 5**
Increased values for Scenario 1.

| Factor type | Approach | Initial value | Increased value |
|---|---|---|---|
| Political | Charging points availability | 3.5 | 5.0 |
| Political | Policy regulations and government incentives for EV in terms of tax policy, legal regulations | 3.5 | 5.0 |
| Political | Grants and funding initiatives for additional governmental investments in infrastructure | 3.5 | 5.0 |
| Economic | Initial cost | 3.0 | 4.5 |
| Economic | Installation costs for private charging points | 3.0 | 4.5 |
| Economic | Charging cost | 3.0 | 4.5 |
| Economic | Electricity price | 3.0 | 4.5 |
| Social | Reduction of pollution | 3.5 | 5.0 |
| Social | Environmental awareness | 3.0 | 4.5 |

then compare these new MAPE values to the original MAPE obtained without variation. We consider the percentage change in $M$ acceptable if the difference between the MAPE computed with variation and the original MAPE is within 1%.

To test the geographical variation of the effects of these scenarios in Europe, we also performed this simulation in Italy, to analyze how the same incentives lead to different outcomes in countries with different levels of EVs adoption.

The results of this simulation in Holland (Table 7) confirm that, in this country, for both scenarios, the main effect on the EVs market is in the short term (2025). The policy-driven scenario, in which we consider the effects of the political incentives on the other factors (economic and social), highlights the importance of these type of incentives in fostering the market penetration of EVs. On the contrary, the technology-driven scenario has a weaker effect on the market penetration of the EVs.

**Table 6**
Increased values for Scenario 2.

| Factor type | Approach | Initial value | Increased value |
|---|---|---|---|
| Technological | Duration of the batteries | 3.0 | 5.0 |
| Technological | Autonomy | 3.0 | 5.0 |
| Technological | Charging speed | 3.0 | 5.0 |
| Economic | Improved efficiency | 2.5 | 4.0 |
| Economic | Battery price for EVs | 2.5 | 4.0 |

Considering the Italian market (Table 8), it is possible to note that the main effects of the different scenarios are in the medium term (2030), and also in this case the policy-driven scenario has a stronger effects than the technology-driven one. The importance of the correct estimation of the time horizon in which the incentives will have their higher impact relies on the need for the technological and automotive sectors to foresee the sales volumes, and thus to plan the production of

**Table 7**
Results of scenario simulations in Holland.

| Scenario | EV stock variation (2025) | EV stock variation (2030) | EV stock variation (2035) |
|---|---|---|---|
| Political incentives | 22.0% | 12.3% | 11.9% |
| Technology improvement | 10.6% | 6.2% | 5.9% |

**Table 8**
Results of scenario simulations in Italy.

| Scenario | EV stock variation (2025) | EV stock variation (2030) | EV stock variation (2035) |
|---|---|---|---|
| Political incentives | 21.5% | 41.9% | 12.9% |
| Technology improvement | 10.4% | 19.8% | 6.6% |

vehicles and implementation of the necessary activities. For the same reason, it is important to estimate the time horizon of these impacts for the development of the charging infrastructures.

A comparative analysis of the results from Holland and Italy shows clear differences in the context-dependent nature of EV diffusion. In Holland, a relatively mature EV market with established infrastructure and higher consumer awareness, the primary impact of incentives appears in the short term (2025), accelerating adoption among the remaining pool of potential buyers as the market approaches saturation. In mature markets, where much of the early adoption has already taken place, incentives tend to produce immediate but diminishing effects, mainly supporting uptake among late adopters and facilitating fleet renewal.

In contrast, Italy, which represents an emerging EV market, exhibits the most significant impact in the medium term (2030). This delayed effect suggests that in less mature markets, where consumers face more substantial barriers, such as limited public charging infrastructure, lower awareness of EV benefits, and higher perceived risks, policy and technological improvements require more time to influence mainstream consumer behavior. Overcoming initial obstacles like infrastructure anxiety, range concerns, and higher upfront vehicle costs takes longer, and incentives alone may not be sufficient in the short term without complementary investments in enabling conditions.

This temporal difference has implications for stakeholders. For policymakers, it underlines the need to plan not only immediate incentive schemes, but also sustained, long-term investments in infrastructure, education, and supporting services, so that early policy efforts translate into consistent market growth. For manufacturers, it suggests the importance of aligning production and marketing strategies with geographically varied demand trajectories, focusing supply and promotional campaigns in mature markets where short-term gains are possible, while adopting a more gradual approach in emerging markets as structural barriers are addressed.

We also performed a sensitivity analysis of the estimated values of the market characteristics in the case of a change in the market size. We then consider the effects of the change of the market size on the more distant (and thus more effected) forecast, i.e., 2035. The calibration of the Bass model parameters remains stable within a range of percentage variations in the market size $M$, specifically between −20% and +30%. Within this interval, the variations in the estimated values of the market characteristics, represented by parameters $p$ and $q$, produce only minor deviations. This indicates that the forecasts based on these parameters are robust against errors arising from inaccuracies or fluctuations in estimating the total market potential.

This stability is particularly important considering the evolving transportation sector, where potential decreases in market size might occur due to increased adoption of alternative mobility solutions. In particular, the growing use of Mobility-as-a-Service (MaaS) offerings and car-sharing platforms could significantly impact the traditional market for car sales. Such trends, extensively documented in the existing literature (Perboli et al., 2018; Ferrero et al., 2018), highlight a scenario where owning a car becomes less common, shifting consumer behavior towards shared or on-demand transportation services.

Therefore, the demonstrated stability of the Bass model parameters ($p$ and $q$) against market size uncertainties reinforces the reliability of the model in forecasting adoption patterns, even under significant market shifts driven by innovative mobility solutions.

## 6. Conclusions and future developments

In this paper, we have faced the issue of linking the market-agnostic parameters of the Bass model to market-specific factors, estimated through expert-based surveys. The uncertainty resulting from sampling errors caused by limited sample sizes is incorporated into the definition of the Bass model parameters and efficiently addressed by using the extreme value theory. The flexibility of the model allows policy-makers and decision-makers to perform a more detailed calibration of the parameters by designing and conducting customized surveys.

The application to a use case of the INCIT-EV project has shown that the model is effective in forecasting the market penetration of EVs based on the users' perception of the political, economic, social and technological environment. From the application of the model to the use case in Holland it emerges that technological advancements of EVs alone will not be enough to promote a deep decarbonization of the automotive sector. Political and economic policies can instead accelerate the EVs market penetration in the short term (by 2025). The insights provided by the model are also useful to show the differences between countries in which the penetration of EVs and the development of the infrastructures are at different stages. The correct estimation of the time horizon in which the policies will have their higher impact is valuable in every sector, but crucial for the automotive sector to plan production, as well as for the policymakers, to develop the appropriate infrastructure. The proposed generalized Bass diffusion model, though specifically applied to the European context within this manuscript, inherently offers significant potential for broader application and generalizability to other geographical contexts, including regions with different infrastructural or socio-economic constraints. By employing a PEST (Political, Economic, Social, and Technological) analysis framework, our methodological approach inherently ensures adaptability. Specifically, the factors identified within each PEST category can readily be modified or expanded to reflect region-specific characteristics, making the model universally replicable. For instance, regions with emerging electric vehicle (EV) markets or those facing distinct socio-economic barriers can apply our proposed methodology by conducting tailored expert surveys, thus identifying and quantifying region-specific variables. By adjusting the explanatory variables derived from these surveys, policy recommendations can then be customized to address local conditions effectively. Consequently, this flexibility enhances the model's global relevance, allowing policymakers and stakeholders from various markets to leverage it for tailored strategic planning and infrastructure development. Therefore, the robustness and adaptability of the proposed framework underscore its applicability across diverse markets, making it an effective tool for international policymakers aiming to foster the diffusion of electric vehicles globally.

Despite the promising results, the methodology has some limitations. First, while our model robustly handles uncertainty from small-sample expert surveys, it remains reliant on the quality and potential inherent biases of the expert opinions themselves. Future work could explore integrating consumer-level survey data to complement experts' data. Second, our theoretical framework relies on certain statistical assumptions, such as the i.i.d. nature of random errors and the exponential tail behavior of their distributions (Hypothesis H2 and H3). Although our model showed robustness in validation tests, further research could focus on developing non-parametric approaches or models that relax these assumptions. Finally, the Bass model, even in its generalized form, is primarily a diffusion model and may not capture the effects of sudden, disruptive external shocks, such as severe economic crises or unexpected policy reversals. Integrating agent-based modeling could provide a more granular view of such complex system dynamics.

## CRediT authorship contribution statement

**Maria Elena Bruni:** Writing – review & editing, Writing – original draft, Methodology, Investigation, Formal analysis. **Stefano Musso:** Writing – review & editing, Writing – original draft, Data curation. **Guido Perboli:** Writing – review & editing, Writing – original draft, Validation, Supervision, Project administration, Methodology, Formal analysis, Data curation, Conceptualization.

## Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Perboli Guido reports financial support was provided by European Commission. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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## Data availability

Data will be made available on request.

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