Forecasting the demand of new energy vehicles in China — Bass model based on real world data

In order to deal with climate change, it is imperative to develop and deploy new energy vehicles (NEVs). This article uses the Bass model to estimate the diffusion pattern and market potential of Chinese NEVs, and employs the Generalized Bass model to estimate the impact of government subsidies on the diffusion of NEVs. Through the established Bass model, we can predict that the market for NEVs will saturate in about 6 years. The model results and the sensitivity analysis on the innovation coefficient and imitation coefficient show that our estimated diffusion curve is robust. The important innovation of this paper is comes from the real world NEV sales data, and the estimation of the Bass model based on it, which makes our conclusions more credible.

Table of Contents

1. Introduction............................................................................................................................................1
2. Literature review........................................................................................................................................5
3. Model specification....................................................................................................................................8
4. Models estimation...................................................................................................................................11
   4.1 Basic Bass model...........................................................................................................................11
   4.2 Generalized Bass model...............................................................................................................15
Conclusions..............................................................................................................................................18
1. Introduction

Nowadays, among the public grows a stronger concern about energy conservation as well as global warming. While the NEVs can reduce not merely petroleum consumption, but also greenhouse gas (GHG) emissions. Consequently, NEV has been regraded as one of the most promising technologies in the mobility sector, and have successfully drawn considerable attention of multiple countries including China. Due to the significant role NEVs play in government’s decision-making process, enterprise’s capacity expansion, and charging infrastructure construction, scholars have been working on the prediction of the diffusion of NEVs from various aspects since 2000 (see Al-Alawi and Bradley, 2013).

![Flow Chart](image)

*Figure 1: Flow Chart*
Among all the countries, China has been the world’s best-selling NEVs market for three consecutive years since 2015 (Cobb, Jeff, 2016, 2017; Jose Pontes, 2018), with the largest ownership of light-duty NEVs by the end of 2017 (Jose Pontes, 2018). Figure 2 shows the stacked bar chart of different types of NEVs’ production and sales volume in terms of months, while Figure 3 illustrates the stacked area chart of cumulative sales volume of various NEVs. And in order to reduce the dependency on fossil fuels, to strengthen energy security, to reduce carbon emissions and to fulfill its promise of eliminating haze, Chinese government has been keen to assist its consumers in a further adoption of NEV (Lixian Qian, Didier Soopramanien, 2014). More details are in “The Guidance of the General Office of the State Council on Accelerating the Popularization and Application of New Energy Vehicles”, 2014. Hence, it is of utmost importance to predict the market penetration, market potential of China's NEVs, and to determine and quantify the effect of external variables such as (subsidy) policy options.
The term NEVs in this paper includes plug-in hybrid electric vehicles (PHEVs) and battery electric vehicles (BEVs) according to Ministry of Industry and Information Technology, National Development and Reform Commission, and Ministry of Finance of the People’s Republic of China. This definition of NEVs is congruent with our NEVs’ sales data as well as our subsidy data. In this study, following the methodology of Park, Kim, and Lee (2011), we choose the Bass diffusion model and Generalized Bass diffusion model to forecast NEV’s market penetration path. Because Bass model is most widely used and acknowledged for its simple structure (a S-shape penetration curve) with meaningful interpretation of the estimated parameters (Bass, 1969; Mahajan et al., 1990; Nigel and Towhidul, 2006; Till Gnann et al., 2015). But we employ real world historical sales data for parameter estimation, as opposed to some researches adjusting the parameter estimated from outside market in lack of early sales data (see Park, Kim, and Lee, 2011; Yingqi et al. 2016).

![Production and Sales Data of NEVs](figure2.png)

*Figure 2: Production and Sales Data of NEVs*
More specifically, we estimate the basic Bass model with NEVs’ sales data in the CSMAR database, from April 2007 to October 2017 in terms of every 9 months. This basic Bass model gives us the estimated values of the three core parameters m, p, q (represents potential market size, innovation factor, and imitation factor respectively). Then, given these three estimated parameters, we use monthly sales volume of NEVs and the amount of vehicle subsidies from 2005 to 2017 to estimate the coefficient of the vehicle subsidy policy via the Generalized Bass model. All of our estimates are significant and in line with our expectations. The basic Bass model shows that the number of users of NEVs in China will continue to increase, and monthly sales volume of NEVs will reach the maximum in the first half of 2018 (about 160,000 per month). Hereafter, sales will gradually decline. The estimated market potential of NEVs is around 10 million, and the market will be saturated after about 6 years. In addition, the Generalized Bass model demonstrates that the vehicle subsidy amount has a significant positive impact on the market penetration rate of NEVs: for every one-percentage-point decrease in the vehicle subsidy, the market penetration rate of NEVs also decreases by about one percentage point. The sensitivity analysis of the parameters shows that our predicted diffusion curve is robust enough.
2. Literature review

Since 2000, many scholars throughout the world have employed various NEVs market penetration forecasting models. The literature in this field is therefore quite rich, as Al-Alawi and Bradley (2013), Rezvani, Zeinab, Johan Jansson, and Jan Bodin (2015) and T Gnann, P Plötz (2015) provided detailed literature reviews of the modeling approaches of alternative fuel vehicles (may includes hybrid, plug-in hybrid, battery electric vehicles, fuel cell electric vehicles and liquefied petroleum gas vehicles). As for the forecast of NEVs in China, Wang, Shanyong, et al. (2016) predict Chinese consumers’ intention to adopt HEVs through an extended model of the theory of planned behavior. Qian, L., & Soopramanien, D. (2014) compare multiple models (namely, Gompertz, logistic, Bass model, extended specifications of the Gompertz and logistic models) with ownership data on cars in China. Qian and Soopramanien (2015) adopt segment-specific discrete choice models, incorporating heterogeneity to predict the demand of NEVs in China.

As shown in Figure 4, there are different classification methods concerning NEVs penetration forecasting models. As is well-acknowledged by many literature (Y. Wind, 1981; Geroski, 2000; Qian and Soopramanien, 2015; C Liu, Z Lin, 2017), there are at least two main types of approaches to model the market diffusion. Geroski (2000) categorizes them as population models and probit models; while Y. Wind (1981) and Qian and Soopramanien (2015) describe these two groups of models as diffusion models and individual behavior-based choice models. Fleiter et al. (2011) and T Gnann, P Plötz (2015),
classify relevant approaches into two model philosophies: bottom-up and top-down models. Briefly, top-down models are based on a series of assumptions about individuals’ behaviors; while bottom-up models treat them as a group, and reply on some macro-level assumptions to study the aggregate behave directly. A more sophisticated classification methodology can be found in T Gnann, P Plötz (2015). Whereas, Al-Alawi and Bradley (2013) classified modeling techniques in the NEVs market forecasting literature into three types: agent-based models, consumer choice models, and diffusion and time series models.

We choose to follow the classification of Y. Wind (1981) and Qian and Soopramanien (2015), comparing diffusion modeling with individual behavior-based choice models. Many scholars have discussed the strength and weakness of these two model philosophies comprehensively (Qian and Soopramanien 2015; T Gnann, P Plötz 2015, Gnann, Till, et al. 2015). Compared with individual behavior-based models, diffusion models have many drawbacks such as the lack of consideration of within-market diversity of products or adopters’ preference heterogeneity. Therefore, to explicitly contains adopter heterogeneity in driving behavior and purchase preferences, Higgins, Andrew, et al. (2012) and Qian and Soopramanien (2015) employ discrete choice models to study the demand for NEVs respectively. Moreover, individual behavior-based choice models have a strong ability of containing multiple external variables. T Gnann, P Plötz (2015) propose 10 factors which ought be taken into account when dealing with the diffusion of NEVs and their refueling infrastructure models, and this could only be achieved by individual behavior-based choice models.

Additionally, we can see a significant tendency of the combination of different models. As in recent researches, consumer choice models (usually consist of discrete choice models and logit models) are almost always integrated with agent based computer simulation or system dynamics simulation, in order to analyze market penetration paths under different scenarios. For example, Tanaka, Makoto, et al. (2014) had to perform simulations to estimate an error component multinomial logit (ECML) model, since ECML choice probability is not in a closed form. Another example is that Y Lee, C Kim, J Shin (2016) combined system dynamics with consumer choice models to identify the optimal policy portfolio. Moreover, to understand the NEVs market uncertainty, C Liu, Z Lin (2017) incorporate nested multinomial logit consumer choice model into Monte Carlo simulation.

However, in this paper, neither do we employ individual behavior-based choice models, nor do we combine our Bass diffusion model with simulations of complex scenarios. Consumer choice model is not adopted because consumer choice models almost always rely on interview, survey, or conjoint experiment data (Table 1 in Rezvani, Zeinab, Johan Jansson, and Jan Bodin 2015 provides an overview of relevant studies and results using different kinds of surveys). Models with micro-foundations is certainly desirable, but being exposed to total survey error (TSE) builds these solid forecast models on a somewhat fragile foundation (Alwin, Duane F. 2007; Weisberg, Herbert F. 2009; Saris, Willem E., and Irmtraud N. Gallhofer, 2014; Lyberg, Lars E., and Herbert F. Weisberg 2016). Therefore, NEVs’ diffusion curve is calibrated to the historical sales data in China via Bass model and Generalized Bass
model (Bass, Krishnan, and Jain, 1994), instead of consumer choice model along with experiment data. Furthermore, the simulation under complex scenarios is deprecated as well, since the more factors scholars take into consideration, the higher uncertainty the simulation model tend to reveal. Till Gnann et al. (2015), Benvenutti, L. M. M., Ribeiro, A. B., & Uriona, M. (2017) and C Liu, Z Lin (2017) have admitted and thereby studied the high uncertainty of the prediction of NEVs resulted from complicated assumptions about policy and infrastructure etc. A straightforward and effective Bass diffusion model is enough to shed light on the forecast of NEVs in China (Li, Yushan, Gangyi Ma, and Lefei Li 2017).

Bass diffusion model (Bass, 1969) as well as Generalized Bass model (Bass et al., 1994) have been widely adopted to forecast the diffusion pattern of NEVs (Lee, Duk Hee, et al., 2013). Researches on the diffusion of Chinese NEVs that are based on Bass model include Ming et al. (2013), Bin et al. (2013), Yingqi et al. (2016). However, when it comes to emerging market like China, forecasting the sales of NEVs via diffusion model becomes more difficult due to lack of early sales data (Lixian Qian, Didier Soopramanien, 2014). Thus, none of literature listed above uses real-world sales data to calibrate their Bass model, but rather they turn to sales data in other countries (Yingqi et al. 2016) or draw the coefficients by the general rule of thumb instead of estimation (Ming et al. 2013). Li, Shunxi, Hang Chen, and Guofang Zhang (2017) estimate coefficients of innovation and imitation in Bass model through the Chinese BEVs ownership data from Jan 2015 to Sep 2016. They identify that, though with simple structure, Bass model have a better prediction accuracy than Lotka-Volterra Model. But they estimate the coefficient of market potential via official plan issued by State Council of China, rather than Bass model, which limits the implication of this research. Li, Yushan, Gangyi Ma, and Lefei Li (2017) successfully estimate the corresponding parameters via Generalized Bass model on historical sales and charging station data. It is the first Bass model that manages to forecast Chinese NEVs market with real-world sales data. Furthermore, Generalized Bass model is employed to probe the relation between NEVs adoption and the infrastructure construction (i.e. charging stations). Nevertheless, Li, Yushan, Gangyi Ma, and Lefei Li (2017) haven’t explored the interaction between NEVs sales volume and the subsidy policy from Chinese government, which we consider to be extremely significant to the penetration of NEVs. According to Bass, Krishnan, and Jain, (1994), basic Bass model works quite well even without an external variables, especially when the omitted decision variables (X) is highly correlated with included variables (like t). Given the fact that the number of charging stations is strongly correlated with time, there’s no doubt that Li, Yushan, Gangyi Ma, and Lefei Li (2017) get a small $\beta$ (influence coefficient of decision variable) compared with our result. That’s why we choose another decision variable (subsidy) without obvious tendency. Many scholars have worked on the possible effect of policy and subsidy on the diffusion of NEVs. For example, Y Lee, C Kim, J Shin (2016) indicate that policy incentives such as tax credit and retirement subsidy have a better effect when they are used conjointly. While C Silvia, RM Krause (2016) shows that policies that increase the familiarity of electric vehicles are most effective via a agent based model. A Kangur et al. (2017) illustrates that effective policy requires a long-lasting implementation of a combination of monetary, structural and informational measures. Therefore, we calibrate basic Bass model to get the estimation of potential market size, innovation factor, and imitation factor, and then employ Generalized Bass diffusion model to probe the possible effect of the subsidy in China.
3. Model specification

Many theoretical and empirical literature has shown that the market diffusion process of new methods, new products, and new concepts can be successfully expressed by Bass model without decision variables (Bass and Krishnan, 1992), as Equation 1. Because the empirical value of external variables \((X)\) tend to be approximately linear to \(t\) (just like the number of charging stations in the study of Li, Yushan, Gangyi Ma, and Lefei Li, 2017), which leads to a reduction from Generalized Bass model to basic Bass model (Bass, Krishnan, and Jain, 1994).

\[
\frac{f(t)}{1 - F(t)} = p + qF(t) \quad \text{(Equation 1)}
\]

In Equation 1, \(F(t)\) is the number of adopters at time \(t\), while \(f(t)\) is its first order differential. Parameter \(p\) and \(q\) represent coefficients of innovation and imitation respectively (or external influence and internal influence by Lekvall and Wahlbin, 1973).

Assuming \(F(0) = 0\), then we have the solution of Equation 1:

\[
F(t) = \frac{1 - e^{-(p+q)t}}{1 + \frac{2}{p}e^{-(p+q)t}} \quad \text{(Equation 2)}
\]

And its density function:

\[
f(t) = \frac{(p + q)^2}{p} \frac{e^{-(p+q)t}}{(1 + \frac{2}{p}e^{-(p+q)t})^2} \quad \text{(Equation 3)}
\]

When calibrating with sales date, Equation 1 can be estimated by Equation 4:

\[S(t) = m \frac{(p + q)^2}{p} \frac{e^{-(p+q)t}}{(1 + \frac{2}{p}e^{-(p+q)t})^2} \quad \text{(Equation 4)}\]
Equation 4 is derived from the fact $S(t) = m \times f(t)$, where $S(t)$ is the rate of adoption (i.e. the increase of the number of NEVs users in $\Delta t$), and $m$ is the market potential (in terms of the numbers of adopters).

To fit Equation 4 in time domain, which has an obvious non-linear format, we need a non-linear estimation approach, usually non-linear least squares as demonstrated by Srinivasan and Mason (1986). Whereas, there’s another domain, cumulative sales domain, to estimate the parameters via OLS as presented in the original paper (Bass 1969):

$$S(t) = pm + (q - p) Y(t) - \frac{q}{m} Y(t)^2, \quad \text{where } Y(t) = mF(t) \quad (\text{Equation 5})$$

While the Bass model in both time domain and cumulative adoption domain ought to be equivalent without random disturbance. Hence, Equation 5 can be used to estimate a initial point from where non-linear least squares estimation iterates until convergence. Thereby we get estimation of three parameters (namely $m$, $p$, and $q$) through basic Bass model. Then we fix these three parameters and calibrate a Generalized Bass model (as Equation 6) with monthly sales data and the amount of subsidy, more specifically, Chinese central subsidy for a complete NEV, to find out the effect of subsidy policy on the diffusion of NEVs.

$$\frac{f(t)}{1 - F(t)} = (p + qF(t))x(t) \quad (\text{Equation 6})$$

Where $x(t)$ is mapping function which maps the carryover effects of subsidies (Bass, Krishnan, and Jain, 1994). Here we suggest:

$$x(t) = 1 + \beta_1 \frac{\text{sub}(t)}{\max(\text{sub}(t))} \quad (\text{Equation 7})$$

Where $\text{sub}(t)$ is the amount of subsidy for a complete NEVs determined by Chinese central government. According to the diminishing returns argument, mapping function $x(t)$ usually consist of a weighted change of decision variables, for example, $\frac{\Delta \text{sub}(t)}{\text{sub}(t - 1)}$ (as suggested by Bass, Krishnan, and Jain, 1994). Nonetheless, the amount of aforesaid subsidy for Chinese NEVs doesn’t change frequently.
Thus in the mapping function we suppose that the relative position of subsidy at time $t$, \( \frac{sub(t)}{\max(sub(t))} \), will lead to a better performance than \( \frac{\Delta sub(t)}{sub(t - 1)} \).

Scholars have been studying the influence of NEVs’ infrastructure (typically, the number of charging stations) on NEVs’ diffusion for a long time (Park, Kim, and Lee, 2011; Li, Yushan, Gangyi Ma, and Lefei Li, 2017). We should have incorporated this factor into our Generalized Bass model as well, however, charging stations or charging piles data are only accessible via China Electric Vehicle Charging Infrastructure Promotion Alliance (EVCIPA), which doesn’t provide adequate data for analysis. As Köhler et al. (2010) illustrate in their paper, only small subsidy needed for initial infrastructure and infrastructure is not a major barrier for vehicle diffusion. Therefore we focus on subsidy and ignore the charging stations data.

Equation 6 can be calibrated by the following equation:

\[
S(t) = m \times x(t) \frac{(p+q)^2}{p} e^{-(X(t) - X(0))(p+q)} \left( e^{-(X(t) - X(0))(p+q)} + 1 \right)^2
\]

(Equation 8)

Where \( S(t) = m \times f(t) \), and \( x(t) \) is defined by Equation 7.
4. Models estimation

4.1 Basic Bass model

The sales data of NEVs from 2005 to 2017 comes from the Production and Sales of NEVs table in CSMAR database, China industry research Series, New Energy sub-database. By assuming that sales of NEVs at this period of time are entirely attributable to the increase in the number of its users, i.e., there is no repeatedly purchasing concerning NEVs currently, we can equate NEV sales data with NEV user growth data.

Then the NEVs’ sales data from 2007 to 2017 is selected to fit the basic Bass model and get three core parameters m, p, and q. Our data starts in 2007 because the sales volume before 2007 is minuscule compared to the data after 2007. It stayed at a level close to zero for a long time and should not be seen as a start of proliferation of NEVs. And the outliers from 2005 to 2007 cause a non-convergence of the regression equation. In addition, the Bass model does not have any restriction on the length of the unit time period, therefore we choose a unit time period where the iterations converge: 9 months. Monthly sales of NEVs are summed up every 9 months, from April 2007 to October 2017, 14 sample points in total. It should be pointed out that the 14 sample points are not that small among the Bass model estimation practices. Park, Kim, and Lee (2011) only had 10 sample points to fit the three parameters of the Bass model, while Li, Yushan, Gangyi Ma, and Lefei Li (2017) have only 7 points to fit four parameters. For our 14 sample points, a simple least-squares is first performed using Equation 5 to obtain a preliminary estimate of m, p, and q:

|      | Estimate | Std. Error | t value | Pr(>|t|) |
|------|----------|------------|---------|----------|
| p m  | -4.627e+03 | 1.621e+04  | -0.286  | 0.78056  |
| q-p  | 6.789e-01 | 5.088e-02  | 13.343  | 3.88e-08 *** |
| -q/m | -7.405e-08 | 2.030e-08  | -3.647  | 0.00384 ** |

Signif. codes: 0 *** 0.001 ** 0.01 * 0.05
Residual standard error: 44400 on 11 degrees of freedom
Multiple R-squared: 0.9898, Adjusted R-squared: 0.988
F-statistic: 535.5 on 2 and 11 DF, p-value: 1.095e-11

The result of OLS estimation is significant with a R square of about 0.99. Then we calculate m, p, q (represents potential market size, innovation factor, and imitation factor respectively) from the above estimation: p = 0.0005049755, q = 0.6784197, m = 9162185, which are in turn used in the non-linear least square estimation of Equation 4:
|    | Estimate  | Std. Error | t value | Pr(>|t|)   |
|----|-----------|------------|---------|------------|
| M  | 9.818e+06 | 1.615e+06  | 6.079   | 7.98e−05 *** |
| P  | 7.366e−05 | 2.646e−05  | 2.783   | 0.0178 *   |
| Q  | 5.902e−01 | 4.531e−02  | 13.027  | 4.98e−08 *** |

Signif. codes: 0 *** 0.001 ** 0.01 * 0.05

Residual standard error: 31020 on 11 DF

Number of iterations to convergence: 13

Achieved convergence tolerance: 6.972e−06

The estimated values of m, p, q are almost the same as those obtained via OLS estimation, and all of them are significant. The result of these two models shows that our model selection is correct and the fitting result is credible. Based on the regression results, we can also plot the historical and the

**Figure 5: Number of New Adopters of NEVs in China**
predicted incremental adopters in Figure 2, along with the cumulative users in Figure 3. The scatters in the figures are the original sales data compiled from CSMAR database (which can also be regarded as the number of new users), and the curve is the distribution of the NEVs’ adoption over time. It can be seen clearly that the predicted diffusion path of NEVs is highly consistent with real sales data.

According to the findings of Lawrence and Lawton (1981), $p+q$ is usually between 0.3 and 0.7, which is also consistent with our results. However, if we consider them separately, the estimated coefficients $p$ and $q$ are still different from other existing studies (Mahajan, Muller, and Bass, 1995). And this pair of innovation coefficient $p$ and imitation coefficient $q$ that deviate slightly from the conventional ranges can give us much inspiration.

The value of the innovation coefficient $p$ is 0.00007, which is significant at a confidence level of 0.95, reflecting the characteristics of the new product or new technology itself (Bass, 1969). The low coefficient of innovation, $p$, means that the NEVs themselves are spreading slowly, probably because of their high prices, various infrastructure constraints, and the path dependence that drivers have when buying cars. This means that a typical consumer is less likely to be altered to purchase a NEV by

Figure 6: Number of Cumulative Adopters of NEVs in China
external media, government propaganda, or other external factors. Here external refers to the consumer group; on the contrary, the influence of other consumers’ choices is called internal factors. In the entire potential NEV user group, the innovators (who independently decides to purchase a NEV, whether or not the other individuals choose to do the same thing) only account for a very small portion. Compared with other related studies such as Sultan, Farley, and Lehmann (1990), our \( p \) is small. However, as Jeuland (1994) points out, the innovation coefficient \( p \) is by nature small, usually less than 0.01.

Similarly, the imitation coefficient \( q \) is approximately 0.6, which is significant at a confidence level of 0.999. The imitation coefficient \( q \) not only reflects the characteristics of new products or new technologies, but also reflects the characteristics of consumers (Bass, 1969). We estimate that the imitation coefficient \( q \) is larger than the common interval 0.3-0.5 presented by Jeuland (1994). The high imitation coefficient \( q \) means that the diffusion of NEVs largely depends on the consumer’s word-of-mouth effect, probably because the NEVs are highly durable goods, making potential consumers tend to ask for advice from friends who are already using NEVs before their purchase. And the opinions of friends (which should be mainly positive opinions from the results of the regression) remarkably facilitate the transition of potential consumers to adopters of NEVs. Of course, there may be other explanations. In fact, all influences from other individuals’ decisions in their social network, whether active or passive, are internal factors. And imitators are influenced by internal factors. They submit to the pressure from others in the same social network who purchase NEVs, and thus decide to purchase a NEV as well. Imitators have been dominating the entire potential NEVs user community.

Parameter \( m \) represents the market potential, that is, the total number of users of NEVs in the future. It is expected, according to the significant estimation of \( m \), that the total number of users of NEVs in the future will reach 10 million, which is a small proportion compared to 342 million (the statistics of Chinese Ministry of Public Security as of the end of 2017) of national automobile drivers, about 2.92%. However, this estimate is reasonable because it is very difficult for NEVs to permeate the whole car driver community: As of 2017, the market share of plug-in electric vehicles in the United States is only 1.13% (according to CSMAR Economic and Financial Research Database 2018).

According to our Bass model, the market potential of NEVs is limited and will soon saturate. But Bass model is actually used to study how the number of users adopting new products changes over time. Neither its parameters nor the model itself directly studies the sales of the product, but rather it predicts the sales of new products (e.g. NEVs) by forecasting the growth of new users. However, for a typical durable good such as a car, the growth of new users is usually in line with the expansion of new products. Therefore, in the initial stage of diffusion, to forecast the growth of new users is, theoretically, to forecast the sales of new products. However, when the number of new users reach steady state, it does not mean that the sales volume of NEVs will also stagnate. Because durable consumer goods (such as NEVs) have repeated purchases. Therefore, when the number of users no longer increases significantly, the sales of NEVs will still increase steadily.
4.2 Generalized Bass model

The basic Bass model does not take into account external factors that may affect NEVs’ diffusion, such as marketing and overall price reduction, nor does it take into account that innovation and imitation coefficients are affected by external factors over time.

As explained by Bass, Krishnan, and Jain (1994) and mentioned above, Bass model works well in prediction without external decision variables when external decision variables have a strong linear trend (and it is usually the cases empirically), and our basic Bass model confirms this. However, we still hope that we can consider the policy considerations in the model and explore the possible impact of vehicle subsidies on the diffusion of NEVs, because the amount of subsidy determined by Chinese central government doesn’t have an obvious tendency, instead, it fluctuates over years.

In order to use policy variables in the Generalized Bass model, we have collected relevant documents issued by the Ministry of Industry and Information Technology of the People's Republic of China and
related materials issued by the Ministry of Finance of the People's Republic of China. Most of the subsidy policies have distinguished different kinds of NEVs (such as pure electric vehicles, plug-in hybrid vehicles, fuel cell vehicles), and then differentiate its subsidy settings. In order to simplify the subsidy policies, we use the maximum subsidy for the pure electric passenger vehicles as the proxy for the subsidy of the NEVs.

Pursuant to the “Announcement on Launching a Subsidy Program for Private Purchase of NEVs” and the “Private Subsidy Pilot Project for NEVs Officially Launched”, from 2010 to 2013, the maximum subsidy for pure electric passenger vehicles was ¥60,000 per vehicle. According to the “Announcement on Continuing the Popularization and Application of NEVs”, pure electric passenger vehicles are still up to 60,000 yuan per vehicle, but in 2014 and 2015, the subsidies for various NEVs (including pure electric passenger vehicles, pure electric vehicles, plug-in hybrid passenger vehicles, and fuel cell vehicles) were reduced by 10% and 20% respectively on the basis of the 2013 standard. According to the “2016 NEV Promotion and Application Subsidy Standard”, the maximum subsidy for pure electric passenger cars rose to RMB 55,000 per vehicle in 2016. However, according to the “Announcement on Financial Support Policies for the Promotion and Application of NEVs 2016-2020”, the subsidy

![Figure 8: Sensitivity Analysis of Cumulative Adopters](image)

Figure 8: Sensitivity Analysis of Cumulative Adopters
standard for 2017 will be adjusted downwards by 20% on the basis of 2016. We get the subsidy data of pure electric passenger vehicles from 2010 to 2017 as \( \text{sub}(t) \) in Equation 7.

In addition, we use the monthly NEV sales data in CSMAR database from December 2010 to October 2017 as an agent for the growth of NEVs users. Then fix \( m, p, q \) in Equation 8, using the monthly NEV user growth \( S(t) \) and the pure electric passenger vehicle subsidy \( \text{sub}(t) \) for nonlinear least-squares regression, since Equation 8 has a non-linear form (Srinivasan and Mason, 1986). Fit four coefficients at the same time will lead to iterative divergence with no estimation results. It’s actually a common question when dealing with Generalized Bass model (Bass, Krishnan, and Jain, 1994), while it cannot provide any academic or policy implications by this means. Thus the variable \( \text{sub}(t) \) is fitted separately with fixed \( m, p, \) and \( q \):

| Estimate | Std. Error | t value | Pr(>|t|) |
|----------|------------|---------|---------|
| 5.1197   | 0.1046     | 48.96   | <2e-16 *** |

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05

Residual standard error: 675400 on 82 DF

Number of iterations to convergence: 15

Achieved convergence tolerance: 6.401e-06

The regression result is very significant, and both the direction and the absolute value are in line with our expectations.

By fixing \( m, p, q \) and calibrate the policy variable separately with sales volume, we obtain the estimated value of the Generalized Bass model \( \beta_1 = 5.1197 \). According to Equation 6 and Equation 8, we can get the economic implication of \( \beta_1 \): When vehicle subsidies fall by 10% from the highest standard, i.e., drop by 6,000 yuan for pure electric vehicles, the speed of diffusion \( f(t) \) will correspondingly decrease to 91.63%; when the vehicle subsidy is 20% lower than the highest standard, the diffusion speed of NEVs will drop to 83.27% of it before the decline. In other words, the decline in vehicle subsidies led to a similar rate of decline in the diffusion speed. This discovery not only highlights the active role Chinese government's subsidy policy plays in the promotion of NEVs, but also has quantified to what extent the government's subsidies can promote the spread of NEVs, or quantify how the subsidy withdrawal system has slowed down the proliferation of NEVs.

Figure 7 and Figure 8 show six additional trajectories for NEVs users growing when adding and subtracting one standard error from the fitted parameters \( m, p, \) and \( q \). As explained earlier, the diffusion of NEVs in China relies mainly on the imitators’ beliefs in word-of-mouth, rather than on the independent decision-making of innovators. Therefore, compared with the innovation coefficient \( p \), the change of the imitating coefficient \( q \) will lead to a larger fluctuation in both the incremental and the cumulative number of NEVs users. In the same way, we can also perform sensitivity analysis on the market potential parameter \( m \). The result is nothing more than an increase or decrease in proportion of the diffusion curve. In general, the diffusion curves obtained by our model are reliable because the parameters are estimated to be robust enough.
Conclusions

This paper uses two Bass models to study the diffusion of NEVs market in China. The basic Bass model shows that the number of users of China's NEVs will continue to rise and become saturated after about 6 years. The ultimate market potential is around 10 million users, most of which are imitators. In addition, sales of NEVs will reach a maximum value in the first half of 2018 (approximately 160,000 per month), and sales will gradually decline thereafter.

The Generalized Bass model shows that Chinese central government’s vehicle subsidy has a significant positive impact on the market penetration rate of NEVs: For every one percentage point decrease in the vehicle subsidy, the market penetration rate of NEVs also decreases by approximately one percentage point. To better promote NEVs and achieve government goals for energy conservation and emission reduction, there are several possible solutions:

1. Improve the innovation coefficient \( p \) and increase the number of innovative consumers. Public education through public service advertisements (PSAs) or commercial advertisements is helpful to encourage consumers to try new driving habits. It will be also beneficial to reduce the interest rate on car loans, to simplify car purchase procedures, to promote technological progress, and to reduce transaction costs and car purchase costs.

2. Improve the imitative coefficient \( q \) and increase the number of imitators. Through the establishment and regulation of active NEVs forums, websites, and other information exchange channels to increase the word-of-mouth effect and proliferation speed of NEVs, so that the purchase and use of NEVs will become a fashion.

3. Improve the subsidy policy. From the relevant announcements issued by the Ministry of Industry and Information Technology of the People's Republic of China and the Ministry of Finance of the People's Republic of China since 2010, it can be seen that the government’s subsidy policy has been gradually refined and improved. This structural optimization of the subsidy policy will undoubtedly increase the actual effect of government subsidies and promote the diffusion of NEVs.

Due to the poor nature of the data, we took a two-step regression of the Bass model. Although there are similar approaches before (Park, Kim, and Lee, 2011), but we have to admit that this workaround ignores possible external factors in the estimation of the three parameters of the basic Bass model. In fact, if we get all the parameters directly through the Generalized Bass model, then the estimation of \( m,p,q \) may be different. Meanwhile, we independently studied the market for NEVs, and did not consider the interaction of NEVs and their alternatives: traditional cars.

Moreover, this article uses the Generalized Bass model proposed by Bass, but as Bass said, the basic Bass model has many other kinds of extensions (Bass, Krishnan, and Jain, 1994). For example, it is worth considering that the market potential parameter \( m \) is also regarded as a function of external variables; because it is hard to believe that charging infrastructure, government subsidies and other factors will only affect the diffusion rate, without affecting the total number of potential consumers at all.
So, as Gnann, Plötz, Kühn, and Wietschel (2015) pointed out, there are many uncertainties in our results: First, the inherent uncertainty from the model design; Second, the parameters of the model may change over time and input data. Therefore, our forecast should be used carefully when formulating policies.