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Integrating Firm Theory and the Generalized Bass Diffusion Model: Predicting China's Electric Vehicle Market Sales Trends

Wei LI and Ke LI

Graduate School of Economics, Nihon University, 1-3-2 Misaki Cho, Chiyoda-ku, Tokyo 1010061 Japan

ecir24003@g.nihon-u.ac.jp; Li.Ke@nihon-u.ac.jp

Abstract

The Generalized Bass Diffusion Model (GBDM) offers a flexible way to forecast electric vehicle (EV) adoption in China. Unlike the traditional Bass model, which assumes a fixed market size and smooth growth, GBDM lets the market potential change over time as policies, charging infrastructure, and technology evolve. This is crucial in a fast-moving market shaped by shifting subsidies, expanding charging networks, and rapid battery improvements. By adjusting to these dynamics, GBDM can capture both rapid surges and temporary slowdowns, providing a closer fit to real sales data than models that assume steady growth. It also allows scenario testing under different policy conditions. Still, the model has limits: its changing parameters describe what happens but not always why. Factors like overcapacity, price competition, and declining product quality arise from firm-level behavior, which lies beyond the model's structure. For this reason, GBDM works better when combined with firm theory and behavioral analysis. Together, they connect overall market diffusion with company strategies and consumer attitudes, offering a more complete understanding of China's evolving EV market.

1. Introduction

Forecasting China's electric vehicle market is challenging because policy, technology, and infrastructure all change quickly. Traditional diffusion models, such as the Bass model, assume a stable market potential and uniform consumer behavior. These assumptions work in mature markets but fail to capture China's rapid shifts in subsidies, battery range, and charging networks. The GBDM addresses this problem by allowing market potential, m(t), to change over time. This flexibility makes it possible to model sudden policy changes, technology breakthroughs, or infrastructure expansion. As a result, GBDM provides more accurate and policy-sensitive forecasts than standard logistic or Gompertz models. However, diffusion patterns alone cannot explain everything. Firm-level behavior—such as capacity expansion, pricing competition, and quality issues—also affects adoption by shaping consumer trust and market stability. Integrating firm theory into GBDM helps explain these effects by linking market diffusion with company actions and consumer responses. This approach makes GBDM not only a forecasting tool but also a framework for understanding how technology, firms, and policy interact in China's evolving EV market.

2. Literature Review

Debates about the diffusion of electric vehicles (EVs) in China have been widely ranged, although the emphasis across studies has not always been consistent. Early contributions tended to privilege consumer-oriented explanations, highlighting concerns over driving range, government subsidies, and the convenience of charging (Rezvani et al., 2015; Liao et al., 2017). Over time, attentions shifted toward institutional and regulatory dynamics, with scholars examining how policy frameworks, subsidy phase-outs, and instruments such as carbon taxation reshape adoption trajectories (Chen et al., 2023; Liu et al., 2024; Tang et al., 2024). These suggest that neither consumer-oriented reasons nor government policies alone is sufficient. It might be the interaction between individual preferences and structural incentives appears to be essential.

Several research have been done to illustrate this hypothesis. One emphasized the importance of infrastructure, showing that the roll-out of charging networks not only complements but also alters consumer expectations of convenience and accessibility (Yue et al., 2021; Elahe et al., 2022). Another drew from political economy and industrial policy perspectives, emphasizes how coordinated government action, sector complementarities, and evolving demand structures have collectively shaped market (Gomes et al., 2023). Such accounts argue that the Chinese EV sector must be interpreted less as a simple aggregate of consumer choices than as part of a broader project of industrial strategy by involving government, OEMs and individuals.

However, only few studies have been done on diffusion models directly. Li et al. (2017), for example, modified the Bass model to include charging infrastructure growth, but their forecasts underestimated sales momentum after 2020. A more recent attempt by Fan et al. (2025) incorporated cost differentials and employed genetic algorithms; however, their framework still fell short in capturing the disruptive influence of policy shocks and the resilience of demand in the post-subsidy era. Other attempts to bypass this limitation have drawn on game theory approaches, which show the strategic interdependence of government, firms, and consumers. Work by Chen et al. (2023), Liu et al. (2024), and Tang et al. (2024) illustrates how coordinated or conflicting strategies among these actors can magnify or weaken policy effectiveness. Yet these models, while valuable for understanding incentives, often lack of the empirical tractability needed for long-term forecasting the EV sales volume when comparing with GBDM approaches.

Although diffusion models are widely used to study how EVs spread through the market, more advanced investigation of these models are still not enough. Moreover, these models often overlook how companies' actions affect EV adoption. In study, I try to address the gap by introducing a new approach, which a GBDM approach that includes two important factors—consumer anxiety and barriers created by firms. The aim is to combine data analysis with business theory to better understand and predict how EVs are adopted in China market.

3. Materials and Methods

3.1 Methodology

3.1.1 Diffusion Models in EV Forecasting

Diffusion models have long served as foundational tools for analyzing the spread of new technologies, offering a formalized structure to trace how innovations permeate social systems. Among these, the Bass model (Bass, 1969) remains particularly influential, often cited as a paradigmatic framework within the literature on innovation adoption, such as in China market EV sales. The model distinguishes between two principal mechanisms of diffusion: One is innovation effects, which capture the influence of external incentives such as government subsidies, number plate restrictions or market campaigns by car makers; the other is imitation effects, which reflect interpersonal dynamics including influence from observing and following the others' choices, benefits from fuel prices, and so on. Although the model itself is appealing because of its clear structure, its assumptions that have a fixed number of potential buyers and assuming all consumers behave the same ways, have been questioned especially in fast-increasing market such as the China's EV market. In this market, the adoption patterns are influenced not just by what consumers want, but also by strong government policies and business strategies by car makers. To improve the limitations of the Bass model, later studies have developed more flexible versions that let important factors change over time. These updated models aim to better match real world situations by including time-based factors. The GBDM is part of a wider effort to improve and update traditional models. It allows the market potential to change over time based external factors, such as improvement of technologies, expansion of charging stations and the removal of government subsidies. This makes GBDM a more flexible way to understand how people adopt EVs. In fast increasing markets like China EV, where rules and economic conditions can shift quickly, consumers' needs are adapting quickly, models that assume everything stays the same may miss important turning points in adoption trends.

However, despite its promise, GBDM remains underutilized in the mainstream EV adoption literature. Some scholars have raised concerns regarding its parameter complexity and data demands, while others argue that its integration of firm level dynamics, especially regarding strategic behaviors and market signals remains insufficient. These opinions brought a broader debate about the appropriate balance between model parsimony and empirical fidelity. So, it is necessary to find an appropriate GBDM to better understand such a broader behavioral and institutional framework, holds potentials not just for better forecasting, but for deeper explanatory insight.

3.1.2 Limitations of the Traditional Bass Model

The vanilla Bass model is not without merits, but its rigid assumptions hinder its adoption to the China EV market. Fixed market potential implies that eventual saturation is determined from the outset, ignoring the possibility that policy interventions, technological advances expand the scope of potential adopters over time. Moreover, the model treats consumers as homogeneous, disregarding heterogeneity in attitudes toward driving range, cost, technology improvement and brand reputation, etc. In constantly changing policy environments, these simplifications generate misleading predictions: adoption is either smoothed into gradual S-curves or fails to capture sudden surges induced by external factors mandates. Limitations include homogeneous assumptions, fixed parameters, lack of economic variables, and aggregate focus without micro-foundations, making it unsuitable for China's dynamic EV market.

3.1.3 Advantages of the Generalized Bass Diffusion Model (GBDM)

GBDM introduces several modifications to address these shortcomings. Market potential is dynamic, parameterized in ways that reflect infrastructure density, driving range, or government policies. The model also adapted itself to scenario analysis, allowing researchers to simulate optimistic, baseline, and pessimistic futures depending on policy or technological assumptions with parameters representing the phenomenon. Moreover, this flexibility preserves the interpretability of the Bass model framework while extending its empirical usage.

In this study, the GBDM is extended by adding an anxiety index to account for consumer concerns about driving range and the availability of charging stations. This index acts as a suppressive factor—reducing the likelihood of adoption when anxiety is high. By including this dimension, the model better reflects how consumer worries can slow the spread of EVs.

3.1.4 Parameter Definition and Implementation

To estimate the model's parameters, nonlinear least squares (NLS) was used, which is a common technique for fitting diffusion models. To improve accuracy and avoid getting stuck in local minimum, this method was supported by genetic algorithm (GA). The model is using data from 2015 to 2024, including EV sales (annual data), Cumulative EV sales, Cumulative Charging Infrastructure, and the Weighted Average Driving Range (achieved from top 20 best-selling models).

The Bass Model:

GBDM modifies the model as:

$$\frac{dF(t)}{dt} = [p + q \cdot F(t)][1 - F(t)] \cdot nomalized\ anxiety(t)$$

The anxiety index is defined as:

$$anxiety(t) = 500/range(t) + 1/density(t))$$

where *range(t)* denotes Weighed Average Driving Range and *density(t)* denotes cumulated charging infrastructure. This formulation reflects the intuition that both technological improvements and charging infrastructure density release consumer hesitation. Here the 500 used in the anxiety calculation is considering that the normal driving range of a gasoline vehicle is around 500km with full tank gas fueled. If the EV range can exceed 500km with full charged battery, it will release the consumer from anxiety of range. On the other hand, we can easily understand that the more density, the less consumer anxiety.

Normalized anxiety(t) constrains the index to values between 0 and 1, facilitating integration into the GBDM structure. Normalization is done according to below formula:

$$normalized\ \ anxiety(t) = \frac{anxiety(t) - \min(anxiety(t))}{\max(anxiety(t)) - \min(anxiety(t))}$$

Data sources include EV sales for each year, Cumulative EV sales, Cumulative Charging Infrastructure, and Weighted Average Driving Range (data from year 2015 - 2024). Mean squared error is minimized and genetic algorithms (GA) for robustness is used. Explanation of parameters:

- EV sales: Means the EV sold in that year
- Cumulative EV sales: denotes the cumulative EV sales volume until that year.
- Cumulative Charging Infrastructure: denotes the cumulative charging infrastructure until that year.
- The Weighted Average Driving Range (WADR) is defined as follows:

$$WADR_t = \frac{\sum_{i=1}^{n}(R_i \ \cdot \ S_i)}{\sum_{i=1}^{n} S_i}$$

Where,

$WADR_t$: the Weighted Average Driving Range in year t, here the range is considered only BEV (Battery Electric Vehicles), but not PHEV, although it is also calculated as NEV. t is from year 2015 to year 2024.

R_i: The range of model i (in km). This can be obtained from manufacturer specifications or test reports (such as the CLTC standard, commonly used in China).

S_i: The sales volume of model i (in units). This serves as the weight, ensuring that high-sales models dominate the average.

n=20 (top 20 models ranked by sales volume are used in the measurement).

The weighted average range was calculated by selecting the top 20 selling models in each year. This means that each year we will use the top 20 best-selling models' sales volume and driving range data to calculate the Weighted Average Driving Range. Therefore, it will ensure the dominant models exert appropriate influence in the measurement. Charging density data were obtained from national and industry reports, with verification against multiple statistical yearbooks to reduce the risk of measurement bias.

3.2 Materials

EV sales and Cumulative EV sales data are from marklines database. Cumulative Charging Infrastructure data is from national and industry reports. Weighted Average Driving Range data is calculated by the top20 best-selling vehicles each year. Raw data is from marklines database.

Year	EV Sales in units	Cumulative EV Sales in units	Cumulative Charging Infrastructure = density(t) in units	Weighted Average Driving Range in km	normalized Anxiety(t)
2015	209,416	296,999	115,000	172.53	1.0000
2016	485,825	782,824	275,000	234.79	0.6082
2017	679,179	1,462,003	445,700	197.41	0.8138
2018	1,222,682	2,684,685	777,000	272.76	0.4571
2019	1,256,657	3,941,342	1,219,000	394.71	0.1684
2020	1,484,449	5,425,791	1,681,000	425.87	0.1211
2021	3,952,969	9,378,760	2,617,000	429.71	0.1158
2022	7,465,252	16,844,012	5,222,000	462.93	0.0732
2023	9,973,610	26,817,622	8,950,000	533.91	0.0000
2024	13,241,038	40,058,600	12,818,000	528.43	0.0050

Table 1: Materials used in the analysis

4. Data Analysis

4. 1 GBDM Model Formula and Fitting

The discrete GBDM is:

$$n(t) = [p + q \cdot \frac{N(t-1)}{m(t)}] \cdot (m(t) - N(t-1)) \cdot (1 - \beta \cdot nomarlized\ \ anxiety(t))$$

approximately 800 EV models in China but the top 20 models ranked by sales volume are considered. Each parameter is defined as follows,

p is coefficient of innovation (external influence)

q is coefficient of imitation (internal influence)

m(t) is market potential at time t

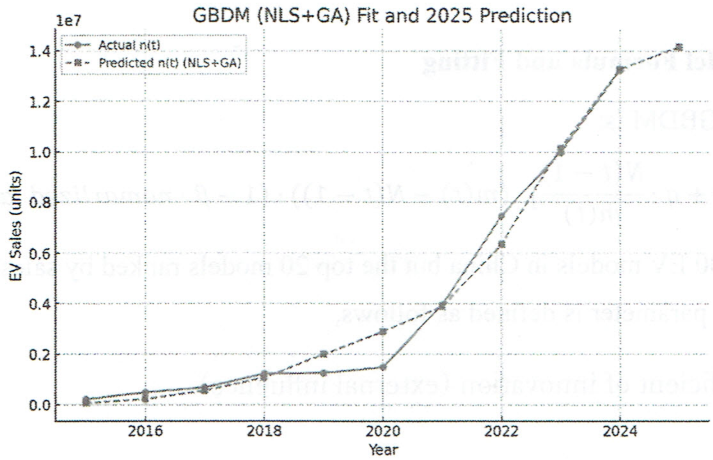
N(t-1) is cumulative adopters before t

$\beta \cdot normalized\ \ anxiety(t)$ is psychological resistance (reduces adoption)

$n(t)$ number of new adopters in year t

- By using NLS and GA method, we can calculate the p = 0.000001, q = 0.7828, β = 0.1072, m(t) = 72,694,383 units
- Fit Quality: $R^2 = 0.98$; RMSE(Root Mean Square Error) = 624,622 units

  which means that the model's annual prediction error for EV sales from 2015 to 2024, averaged about 620,000 units per year. Considering that the actual sales in 2024 exceeded 13 million vehicles, this error rate is less than 5%, indicating that the model's overall fit is very good.
- Based on the parameters achieved above, we can easily estimate n(t) of 2025, which is 14,147,802 units. By using this estimation, we can easily check the fittings with 2025 January to August, China market NEV sales volume is 9.62 million units, the whole year prediction is around it is quite aligning with GBDM prediction baseline.



5. Results and Discussion

The estimation results indicate that the Generalized Bass Diffusion Model (GBDM), when enhanced with a mileage anxiety index, captures the trajectory of EV adoption in China with a high degree of accuracy. The fitted parameters reveal a diffusion process that was initially constrained by consumer hesitation and policy uncertainty but subsequently accelerated through imitation effects once technological and infrastructural thresholds were crossed.

5.1 Key Findings

Several features of the results warrant attention. First, the low innovation coefficient, $p = 0.000001$, underscores that early adoption was not primarily driven by spontaneous consumer experimentation. Instead, it was highly dependent on external stimuli such as purchase subsidies, license plate restrictions, and favorable tax policies. This aligns with earlier observations by Ouyang et al. (2020) and Lu et al. (2020), who emphasized the catalytic role of government incentives in stimulating initial demand.

Second, the imitation coefficient, $q \approx 0.7828$, suggests a strong contagion effect, consistent with diffusion literature that highlights the importance of peer-to-peer influence once a product reaches critical visibility. In China's EV market, this dynamic appears to have been amplified by rising brand recognition and social signaling, as noted by Buhmann and Criado (2023), where EV ownership increasingly conveys status and alignment with environmental values.

The estimated anxiety coefficient ($\beta \approx 0.1072$) indicates that consumer concerns about range and charging access still had a noticeable slowing effect on electric vehicle adoption. Over time, as the average driving range improved and charging stations became more common, the normalized anxiety index fell from about 1.0 in 2015 to nearly zero by 2024. This steady decline suggests that technological progress and infrastructure investment have helped reduce psychological resistance among potential buyers. These results support what many policy reports have suggested: improving charging convenience and battery performance does more than make electric cars practical—it changes how people feel about them. Still, the link between anxiety and adoption should be interpreted with care. Social factors, media coverage, and government incentives may also shape how consumers perceive risk. In this sense, β reflects not a fixed psychological constant but a moving indicator of how confidence grows as technology and policy evolve together.

5.2 Policy Implications and Limitations

From a policy point of view, the results suggest that building and maintaining charging infrastructure is still the most effective way to support long-term growth. Better infrastructure directly lowers consumer anxiety and encourages more people to follow others in adopting electric vehicles. In addition, good quality control and clear information for consumers are just as important as financial subsidies for keeping public confidence high. Without these measures, price competition caused by overproduction and declining product quality could weaken trust and slow down market growth. The analysis is not without limitations. The anxiety index, while conceptually plausible, simplifies complex consumer perceptions into a single metric and relies on proxies such as average range and charging density. Furthermore, the model does not yet incorporate export markets, second-hand vehicle sales, or regional disparities, all of which may alter adoption dynamics in the medium term. These limitations suggest avenues for further refinement, including multi-level modeling that integrates regional heterogeneity or game-theoretic elements capturing firm-government interactions.

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Corresponding author: Wei LI
Graduate School of Economics, Nihon University
1-3-2 Misaki Cho, Chiyoda-ku, Tokyo 1010061 Japan
E-mail: ecir24003@g.nihon-u.ac.jp