Diffusion of Electric Vehicles in China (2010–2050): A Bass Model Perspective

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ABSTRACT

The diffusion of electric vehicles (EVs) is a central pillar of the transition toward low-carbon transport systems, with China representing the world's largest and most dynamic EV market. This paper analyzes the long-term diffusion of electric vehicles in China over the period 2010–2050 using the Bass diffusion model. The model captures technology adoption as the interaction of innovation-driven external influences and imitation-driven social contagion effects. Based on an analogy-based synthesis of existing empirical studies, representative innovation and imitation parameters are derived and applied to a projected market potential of 473 million vehicles (**link** to the model). The results indicate a pronounced S-shaped diffusion path with a rapid acceleration phase in the late 2020s and a peak in annual adoption around 2029, followed by gradual market saturation. Sensitivity analysis shows that diffusion outcomes are highly responsive to changes in the imitation parameter, underscoring the importance of social and network effects in large-scale EV adoption. A comparison with historical sales data suggests that the baseline model likely overestimates near-term diffusion, highlighting structural barriers and uncertainty in parameter calibration. Overall, the analysis illustrates both the usefulness and the limitations of the Bass model for assessing long-term EV diffusion under strong policy intervention.

INTRODUCTION

The diffusion of electric vehicles (EVs) is a key element in the transition toward low-carbon transportation systems. China represents the most important market for electric mobility worldwide, driven by strong government support, rapid infrastructure deployment, and large-scale urban transport electrification. Understanding how EVs diffuse over time is essential for evaluating long-term market development and the effectiveness of policy instruments. Technology adoption typically follows a non-linear pattern characterized by an initial slow uptake, followed by rapid growth and eventual market saturation. This paper analyzes the diffusion of EVs in China from 2010 to 2050 using the Bass diffusion model. The Bass model is a well-established framework for modeling technology adoption processes and distinguishes between innovation-driven and imitation-driven adoption [1]. By applying this model to the Chinese EV market, this study aims to capture the long-term diffusion dynamics.

TECHNOLOGY AND TIME CONTEXT OF EV DIFFUSION IN CHINA

EVs are vehicles powered by electric motors that use energy stored in onboard rechargeable batteries, without any internal combustion engines. A EV primarily consists of a high-voltage battery pack, an electric traction motor, power electronic converters, and an energy management system that controls power flow and vehicle operation. Lithium-ion batteries dominate current EV-designs due to their high energy density, efficiency, and comparatively long cycle life, making them suitable for automotive applications. Improvements in battery chemistry and thermal management have significantly increased driving range and reliability, addressing early technological limitations [2].

In China, EV diffusion since 2010 has been tightly coupled with rapid progress and scaling up in battery manufacturing, the expansion of charging infrastructure and sustained policy support [3–5].

From a technological perspective, the most influential improvements were declining battery costs and performance gains enabled by manufacturing scale and learning effects, combined with improved charging availability that reduced range anxiety and increased the operational feasibility of EVs [3–5].

Regarding the time context, China's EV deployment follows a multi-phase trajectory shaped by strong policy-driven innovation effects in the early stages and increasing imitation dynamics as the market matures. During the initial phase (2010–2012), EV adoption was largely confined to government-led pilot programs and public fleets. High vehicle costs, limited driving range, and insufficient charging infrastructure constrained consumer uptake. In diffusion-model terms, adoption in this phase was dominated by external influences, with policy incentives and industrial planning acting as the primary drivers rather than market-based demand [6]. Between 2013 and 2015, China entered a market formation phase characterized by expanded purchase subsidies and the introduction of non-monetary incentives, such as preferential license plates, access privileges, and early charging infrastructure deployment in major cities. These measures substantially lowered adoption barriers and increased the perceived utility of EVs [7]. A decisive structural shift occurred after 2016, when China gradually phased down direct subsidies and transitioned toward regulation-based market support. The introduction of the NEV (New Energy Vehicle) mandate and the dual-credit system in 2018 embedded EV production and sales into manufacturers compliance strategies, strengthening supply-side incentives. This policy transition coincided with rapid technological progress, including declining battery costs, increasing driving ranges, and accelerated charging infrastructure expansion [8]. The period from 2019 to 2022 represents the market breakthrough phase for EVs in China. Sales expanded exponentially, and EVs transitioned from a niche technology to a mass-market product. From a diffusion-model perspective, this phase reflects the dominance of imitation effects, as growing vehicle visibility, social acceptance, and improved usability reinforce adoption dynamics. China sold approximately 6.9 million electric vehicles in 2022, confirming the transition to a late growth phase of the S-shaped diffusion curve [9]. The subsequent period can be interpreted as a transition from rapid diffusion to market consolidation. Technological improvements and charging infrastructure expansion continued to reduce the total cost of ownership and usability constraints, sustaining diffusion primarily through social contagion and replacement demand rather than first-time adoption [3, 10]. Beyond 2030, EV diffusion in China is expected to enter a maturity phase in which policy intervention is likely to focus on long-term regulatory frameworks, grid integration, and decarbonization objectives, consistent with China's long-term NEV development strategy [10].

METHODOLOGY

Bass Diffusion Model

The diffusion of EVs is modeled using the Bass diffusion model, which describes the timing of the initial adoption of a technology. The model assumes that adoption is driven by two distinct mechanisms: innovation and imitation. Innovation-driven adoption represents external influences on potential adopters and is captured by the coefficient p. These influences are largely independent of the current number of adopters and include factors such as government policies, financial incentives, technological improvements, marketing activities, and information provided by manufacturers or public institutions. Innovators, therefore, adopt the technology without being influenced by the behavior of other users. Imitation-driven adoption, captured by the coefficient q, represents internal influences within the social system. Potential adopters are influenced by previous adopters through mechanisms such as word-of-mouth effects, social interaction, visibility of the technology, and the expansion of complementary infrastructure. As the number of adopters increases, imitation effects become stronger, accelerating the diffusion process over time. The probability of adoption at time t, denoted as $P(t)$, is defined as:

$$P(t) = p + \frac{q}{m} \cdot Y(t) \tag{1}$$

where:

- p is the coefficient of innovation,
- q is the coefficient of imitation (diffusion),
- m is the total market potential,
- $Y(t)$ is the cumulative number of adopters at time t.

The evolution of the total number of adopters over time is given by the following discrete-time formulation:

$$I_t = I_{t-1} + \left(p + \frac{q}{m} \cdot I_{t-1}\right) \cdot (m - I_{t-1}) \tag{2}$$

where I_t denotes the total volume of EVs in the market at time t, and $m - I_{t-1}$ represents the remaining market potential.
At the beginning of the diffusion process, adoption is mainly driven by innovation effects captured by p. Over time, imitation effects represented by q become increasingly important, leading to accelerated diffusion. This formulation results in an S-shaped diffusion curve, which is characteristic of the adoption of many energy and transport technologies. For many durable goods, studies suggest that p is usually small (around 0.03 on average) and q is larger (around 0.38 on average). A common orientation is that p + q often falls in the 0.3–0.5 range for successful product diffusions. The innovation coefficient p is often an order of magnitude smaller than q – reflecting that imitation (social diffusion) usually drives most of the S-curve once a critical mass is reached [1]. China's imitation coefficient q is observed to be very high relative to other countries, likely due to recent rapid uptake and strong peer effects [11].

Parameter Selection and Data Sources

Due to limited time-series data for China's EV market, the innovation (p) and imitation (q) coefficients were obtained via an analogy-based literature synthesis. Following established diffusion-modeling practice [12], we referenced three independent studies that applied the Bass model to the Chinese electric vehicle context. These studies provided a diverse range of adoption scenarios:

- Guo and Yan (2024) [1]: This study focuses on the "New Energy Vehicle" (NEV) sector, applying the Bass model to predict the broader development and diffusion trajectory of NEVs across the Chinese market.

- Zhu and Du (2018) [6]: This research narrows the scope to a regional level, forecasting the number of electric vehicles specifically in Beijing. Their findings offer coefficients that reflect adoption patterns in high-density urban environments where policy support is strong.

- Shi (2022) [13]: While primarily an analysis of raw material requirements, this study utilizes the Bass model to construct diffusion scenarios for automotive electrification in China to estimate future cobalt demand, providing coefficients based on long-term saturation goals.

The reported p and q values from these sources were extracted and their arithmetic means were calculated to serve as the model inputs.The market potential m is set at 473 million EVs, taken from a projection of car ownership in China for the year 2050 [14]. It is assumed that the market potential corresponds to 100% of the projected vehicle fleet in 2050, implying that the existing fossil-fuel-powered mobility stock has been entirely displaced from the market. This ensures consistency between long-term fleet projections and the diffusion ceiling of the Bass model.

Table 1. Reported Bass coefficients for China-related EV contexts (as cited)

Study	Context	p	q
[1]	Toyota HEVs (analogy to China NEVs)	0.000695	0.33460
[6]	EVs in Beijing	0.001045	0.38637
[13]	China EV market (three scenarios)	0.0005–0.0019	0.36–0.39

Averaging procedure. Let (p_i, q_i) denote the pair reported by study i. The representative coefficients are given by:

$$\bar{p} = \frac{1}{K}\sum_{i=1}^{K} p_i, \qquad \bar{q} = \frac{1}{K}\sum_{i=1}^{K} q_i, \quad K = 3.$$

Using the values from Table 1 (regarding the third study, the values $p = 0.001$ and $q = 0.37$ are taken from the baseline scenario [13]), this yields:

$$\bar{p} = 0.00091, \qquad \bar{q} = 0.3637.$$

These aggregated coefficients are used for the subsequent Bass model calibration. The model itself can be accessed via this **link**.

RESULTS

Diffusion Path of EVs in China (2010-2050)

Figure 1 illustrates the diffusion path of EVs in China based on the aggregated Bass model parameters, which are used to construct a representative baseline diffusion scenario. The upper panel displays the cumulative adoption of EVs, while the lower panel shows the corresponding number of new adopters per year. The cumulative adoption curve exhibits the characteristic S-shape of the Bass diffusion model, with slow initial growth followed by a strong acceleration around the late 2020s and eventual saturation approaching the assumed market potential of 473 million EVs. The inflection point occurs around 2029, after which the growth rate declines as the market nears full penetration. The yearly adoption curve follows a unimodal pattern, with new EV adopters rising sharply until a peak of roughly 43 million around 2029 before declining symmetrically as the market saturates. This peak reflects the transition from imitation-driven acceleration to saturation dynamics typical of Bass diffusion processes.

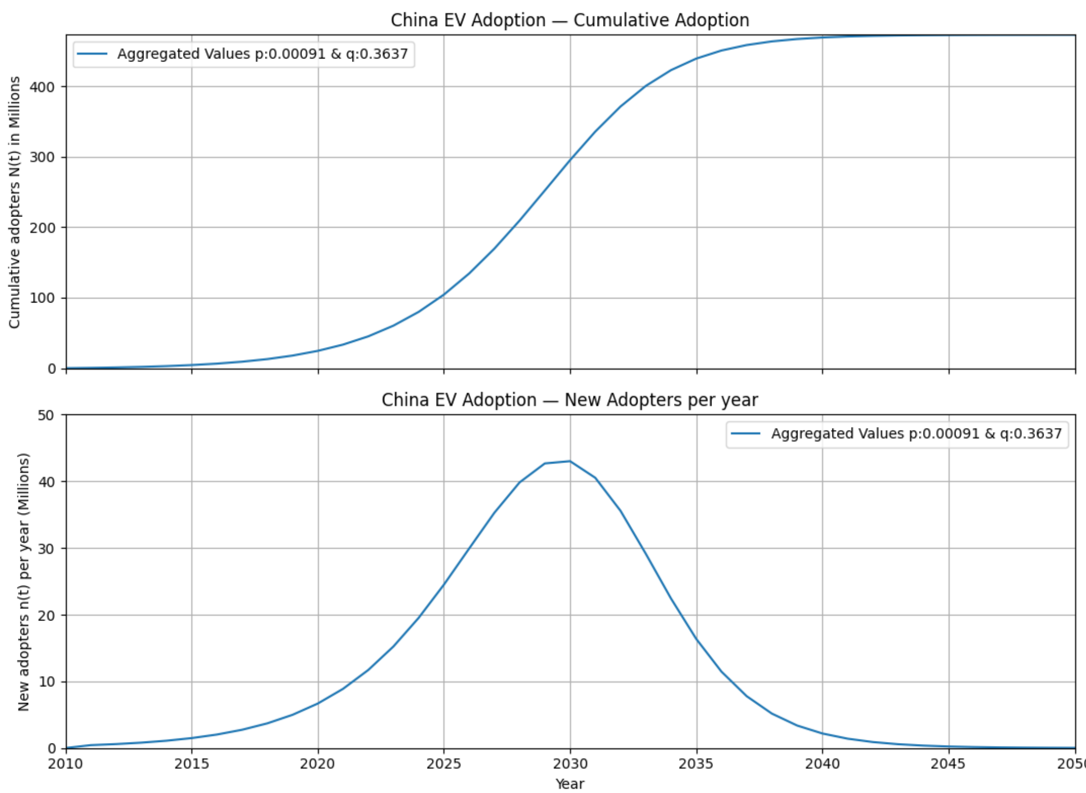

Figure 1. EV adoption in China: cumulative and annual values, 2010–2050

Sensitivity Analysis

The sensitivity analysis shows that variations in the imitation parameter q exert the strongest influence on the diffusion trajectory, substantially shifting both the timing and the magnitude of the adoption peak. An increase of q by 20% accelerates the diffusion process, yielding an earlier and higher maximum of yearly adopters and a faster convergence toward market saturation, whereas a decrease in q delays adoption and produces a noticeably flatter diffusion curve. Changes in the innovation parameter p affect the early growth phase but have comparatively limited impact on long-term adoption levels. Overall, the model behaves considerably more sensitively with respect to imitation-driven social contagion (q) than to external-influence mechanisms (p), which aligns with typical findings in Bass diffusion analyses.

Table 2. Parameter combinations used in the sensitivity analysis.

Model run	p	q
Baseline	0.00091	0.36370
$p-20\%$	0.000728	0.36370
$p+20\%$	0.001092	0.36370
$q-20\%$ (pessimistic)	0.00091	0.29096
$q+20\%$ (optimistic)	0.00091	0.43644

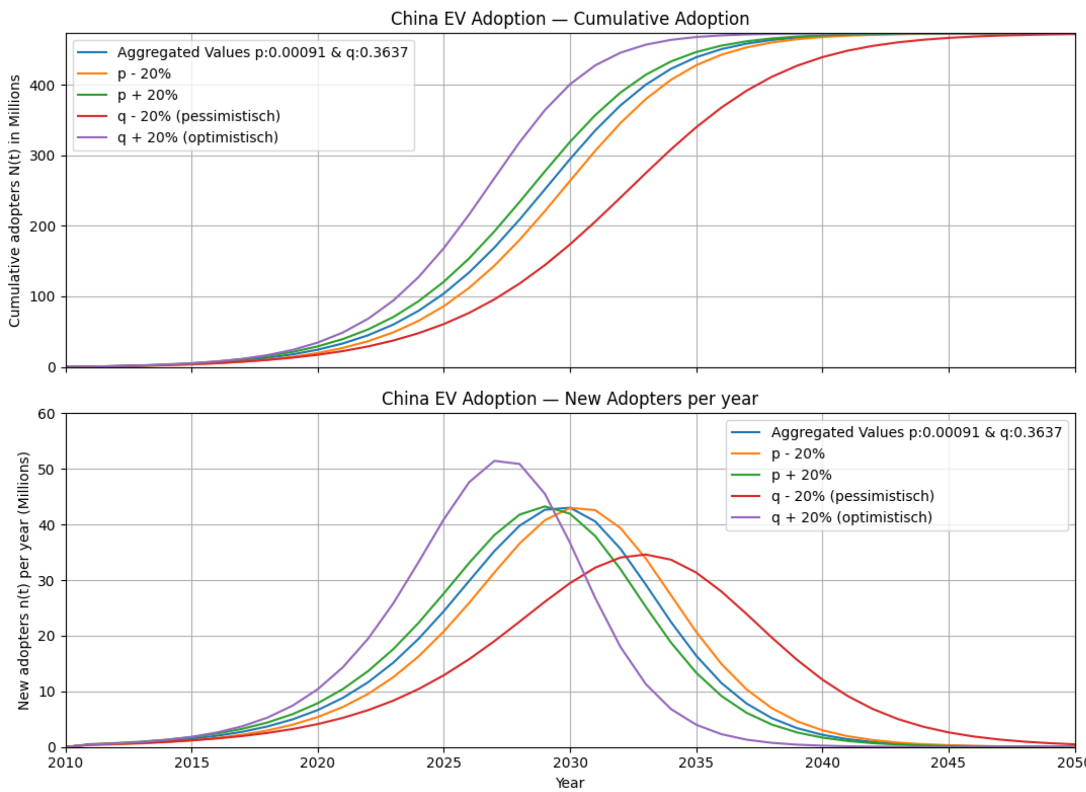

Figure 2. Sensitivity analysis of China's EV adoption dynamics using $\pm 20\%$ variations of the innovation parameter p and the imitation parameter q, illustrating their effects on cumulative adoption and yearly new adopters.

Comparison with Historical Adoption

Sales data are available up to the year 2024. By this point, technology adoption was still far from the assumed market potential of 473 million electric vehicles. Consequently, comparability is limited to roughly one third of the examined time horizon, corresponding to the early, left-hand segment of the S-curve. The slow and modest increase in EV adoption between 2010 and 2024 suggests a relatively low value of p, indicating that only a small share of consumers adopted the technology independently of social influence or market saturation effects. At the same time, the projection curves show a pronounced acceleration in adoption after 2024, implying that the applied models assume a comparatively high imitation coefficient q, where peer effects, visibility, and network dynamics are expected to drive rapid diffusion. However, the historical data lying consistently below all four model projections indicates that the chosen parameter values – particularly q – may be overestimated. The anticipated strong imitation-driven takeoff has not yet materialized in the empirical data, suggesting that real-world diffusion dynamics up to 2024 are weaker than assumed in the model calibrations.

The overestimation observed in the studies can be attributed to several factors. First, structural barriers such as limited charging infrastructure and regional disparities in adoption might have been underestimated. Second, the models seem to assume higher consumer readiness and stronger imitation effects than empirically observed, leading to inflated values of the Bass parameter q. Third, early calibration based on a short initial time series (2010–2024) amplifies the tendency to project an unrealistically steep acceleration in future adoption. Finally, the assumed market potential of 473 million EVs may itself be overstated, causing the diffusion curves to be stretched upward and reinforcing the overestimation bias.

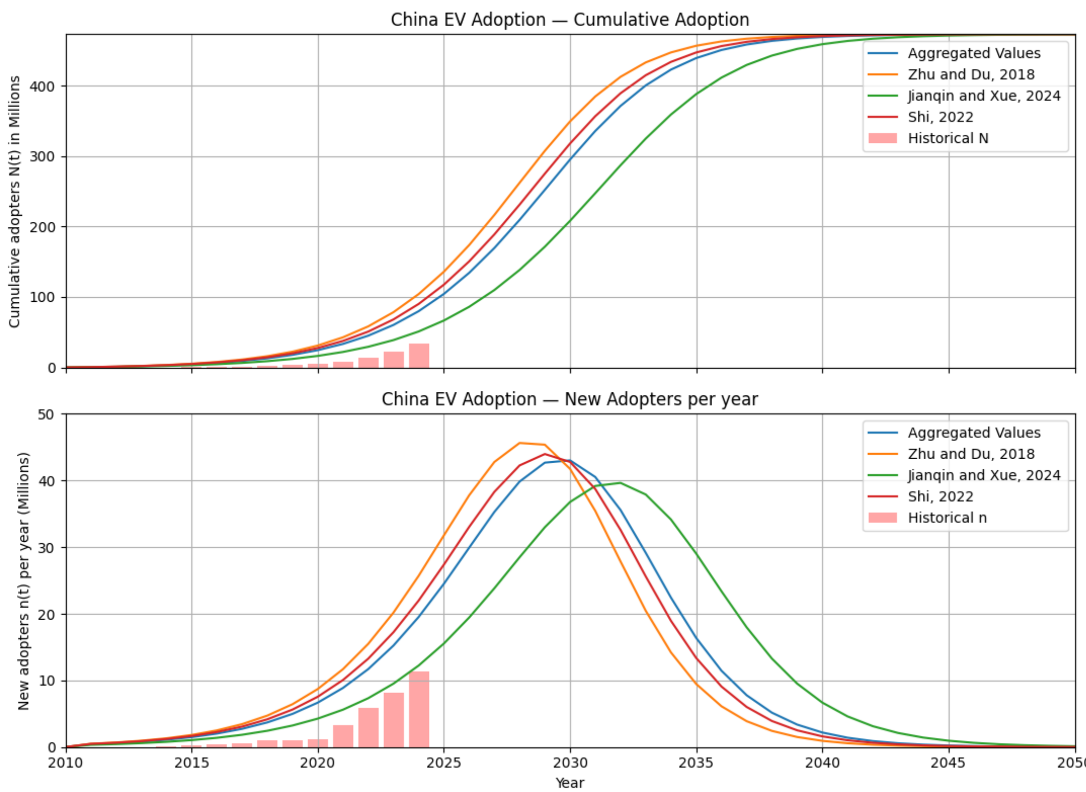

Figure 3. Comparison of historical EV sales in China with model simulations using aggregated Bass parameters and the parameter sets reported in Zhu and Du (2018), Jianqin and Xue (2024), and Shi (2022), shown for cumulative adoption (top) and yearly new adopters (bottom).

Limitations of the Model

A central limitation of the applied Bass model lies in the specification of the market potential, which represents a highly uncertain and difficult-to-estimate quantity. In addition, the market potential is treated as static, although it is in reality shaped by dynamic factors such as shifts in Chinese mobility policy, technological progress, and developments in global automotive markets. Beyond this, the Bass model imposes structural simplifications that restrict its explanatory power: it assumes homogeneous consumer behavior, neglects regional heterogeneity, and does not account for supply-side constraints such as charging infrastructure, production capacity, or regulatory interventions. Furthermore, the model presumes constant parameters p and q over time, even though innovation and imitation dynamics may evolve as the technology matures. These limitations imply that the model can capture general diffusion tendencies but may struggle to accurately reflect the complex and rapidly changing conditions of the Chinese EV market.

INSTRUMENTS FOR EV DIFFUSION IN CHINA

General Instruments Influencing Technology Diffusion

The diffusion of new technologies is largely determined by two key factors: the costs of adoption and the perceived benefits for users. Both policymakers and market participants have a range of instruments at their disposal to deliberately influence these determinants and thereby steer the diffusion process of technologies [15].

From the perspective of the Bass diffusion model, these influencing mechanisms can be interpreted as factors that either reinforce external or internal diffusion dynamics.

Policy Instruments

Regulation constitutes a central policy instrument through which the adoption of new technologies can be enforced or guided by increasing the costs of, or restricting, conventional technologies. Regulatory measures may target market structure, market access, as well as economic framework conditions in the form of taxes and charges [15]. Applied to electric vehicles, such instruments include, among others, production or sales quotas for EVs, restrictions on internal combustion engine vehicles, and differentiated taxation schemes favoring low-emission powertrains [16].

Another key instrument is subsidies, which facilitate the market entry of new technologies by reducing effective adoption costs. Subsidies can be applied on the demand side, for example, in the form of purchase incentives for consumers, as well as on the supply side, such as production or research and development (R&D) support for manufacturers, and can be designed in a targeted manner [15, 16].

Beyond this, governments can support the diffusion of systemic technologies through so-called state sponsorship. This includes the coordination of actors, the establishment of technical standards, the targeted development of complementary infrastructure, and the creation of public demand, for instance through public procurement [15].

In terms of the Bass diffusion model, such government interventions primarily act as external adoption incentives and are therefore suitable for amplifying innovation-driven diffusion effects.

Instruments of Market Participants

Market participants primarily influence the diffusion of new technologies through firm-level strategic decisions. Technological improvements and investments in R&D increase the quality, performance, and reliability of new products and thereby enhance their attractiveness [15]. At the same time, technological maturity and standardization can contribute to cost reductions and economies of scale [16].

Closely linked to this are cost and pricing strategies. Through economies of scale, process innovations, and learning curves, firms can reduce their production costs and pass these advantages on to consumers via lower prices, thereby improving the competitiveness of new technologies [15].

The availability of complementary inputs represents another important influencing factor. Firms can support the diffusion process by providing infrastructure, service networks, or specialised skills that enable the effective use of the technology [15]. In addition, product portfolio and supply strategies allow firms to actively shape diffusion dynamics, for example by expanding new product offerings while gradually withdrawing conventional alternatives [17].

These company-driven measures are particularly effective through social diffusion processes, as they increase visibility, user experience, and acceptance, thereby promoting imitation-driven dynamics.

Implementation of Diffusion Instruments in China

Policy Instruments Implemented

In line with the general policy instruments outlined above, China implemented a comprehensive policy mix consisting of regulation, subsidies, and state sponsorship.

At the regulatory level, market-structuring measures were introduced through the NEV quota and dual credit system (NEV + Corporate Average Fuel Consumption, CAFC) in force since 2018, which requires manufacturers to achieve a minimum share of NEVs in their fleets. Non-compliance is sanctioned through penalties or the purchase of NEV credits [18]. In addition, metropolitan areas such as Beijing and Shanghai apply registration restrictions to internal combustion engine vehicles, from which electric vehicles are exempt [18].

At the same time, China pursued an active opening of the EV market by allowing full foreign ownership of EV manufacturing facilities from 2018 onward, most prominently exemplified by the Tesla Gigafactory in Shanghai [4]. These measures were accompanied by extensive public investment in charging and energy infrastructure; by 2024, more than 8 million charging points had been installed nationwide, supported by national and local subsidy programs [18].
Economic regulation further includes the exemption of EVs from the 10% purchase tax introduced in 2014 and extended until at least 2027, as well as the introduction of CO_2-based charges on conventional vehicles [16, 18].
Subsidies formed another central pillar of policy: between 2009 and 2023, purchase subsidies for EVs amounting to approximately EUR 61 billion were granted, while cumulative state support for the NEV industry, including production and R&D funding, totaled around EUR 212 billion [18]. From 2018 onwards, these support instruments were also extended to foreign manufacturers [4].
In addition, China deliberately implemented non-monetary usage incentives, in particular exemptions from driving restrictions, preferential registration procedures, and traffic and parking privileges for EVs in large cities [18].

Instruments Implemented by Market Participants

Chinese market participants employed a combination of the firm-level influence mechanisms described above. A central element consisted of technological improvements, particularly in battery technology. China developed into the world's leading production location for EV batteries, accounting for approximately 60% of global battery production in 2022, supported by high levels of R&D investment and short innovation cycles [4, 19].
In addition, firms consistently pursued cost and scaling strategies. High production volumes, vertical integration, and locally integrated supply chains led to substantial cost reductions. As a result, average EV prices in China have been lower than those of internal combustion engine vehicles since 2018. In 2022, the average EV price amounted to approximately EUR 22,800 compared to EUR 23,800 for conventional vehicles [4].
Furthermore, market participants invested in complementary infrastructure. Companies such as NIO established proprietary charging and battery-swapping networks, thereby complementing public infrastructure programs. By 2024, more than 12.8 million charging points and over 4,400 battery-swapping stations had been installed nationwide [18].
In addition, manufacturers such as BYD and Geely employed product portfolio and supply strategies by introducing a broad range of EV models across different price segments at an early stage while simultaneously reducing the development of new internal combustion engine platforms [17, 18].

CONCLUSION

This paper applied the Bass diffusion model to analyze the long-term adoption dynamics of electric vehicles in China between 2010 and 2050. Using literature-based innovation and imitation parameters and an upper-bound estimate of future vehicle ownership, the model generates a characteristic S-shaped diffusion path with a rapid expansion phase in the late 2020s and eventual market saturation. The results highlight the dominant role of imitation-driven dynamics in shaping large-scale EV diffusion, consistent with China's strong peer effects, increasing visibility of EVs, and expanding charging infrastructure.
The sensitivity analysis demonstrates that diffusion outcomes are particularly sensitive to the imitation parameter, whereas changes in the innovation parameter mainly affect early adoption. This finding underscores the importance of social contagion, network effects, and complementary infrastructure in sustaining rapid EV uptake once a critical mass has been reached. At the same time, the comparison with historical sales data indicates that the calibrated model tends to overestimate near-term adoption.
From a policy perspective, the results support the view that China's comprehensive policy mix — combining regulation, subsidies, infrastructure investment, and industrial strategy — has been crucial in initiating EV diffusion and amplifying imitation effects.
Overall, while the Bass diffusion model provides a useful stylized representation of long-term adoption dynamics, its simplifying assumptions limit its ability to capture the complexity of China's EV market. Future research could extend this approach by incorporating time-varying parameters, regional heterogeneity, endogenous market potential, or hybrid models that explicitly account for infrastructure constraints and policy feedback mechanisms.

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USE OF ARTIFICIAL INTELLIGENCE

AI software (Chat-GPT-5 and Microsoft Copilot) was used to support the translation and summarization of the referenced papers as well as the formatting of the manuscript in LaTeX.