

Article

The Impact of Policy Thematic Differences on Industrial Development: An Empirical Study Based on China's Electric Vehicle Industry Policies at the Central and Local Levels

Zizheng Liu  and Tao Xie *

School of Economics, Shenyang University, Shenyang 110041, China; lzz0528@163.com

* Correspondence: syu_pdr_xie@syu.edu.cn

Abstract: Since the 21st century, the electric vehicle (EV) industry has become a key driver of global transformation, with increasing emphasis on the study and evaluation of industrial policies across nations. However, traditional frameworks struggle to capture the dynamic interactions between policies at different government levels or effectively analyze large volumes of policy texts. This study adopted a central–local policy interaction perspective, employing the BERT deep semantic learning model and a threshold regression model to investigate the impact of policy differences on industrial development. The findings reveal an inverted U-shaped relationship between central–local policy thematic similarity and EV market penetration, with the optimal similarity shifting as policy volume increases. This suggests the necessity of dynamically allocating central and local policies to balance national consistency with regional flexibility and promote synergy among regions. Recommendations include optimizing multi-level coordination, maintaining a balance between uniformity and specialization, strengthening policy error tolerance mechanisms, and fostering innovation. By integrating text analysis with econometric modeling, this study offers a novel framework aligned with China's political system, providing insights into central–local policy interactions and serving as a reference for other countries seeking to refine their industrial strategies.



Citation: Liu, Z.; Xie, T. The Impact of Policy Thematic Differences on Industrial Development: An Empirical Study Based on China's Electric Vehicle Industry Policies at the Central and Local Levels. *Energies* **2024**, *17*, 5805. <https://doi.org/10.3390/en17225805>

Academic Editor: Giovanni Lutzemberger

Received: 14 October 2024

Revised: 12 November 2024

Accepted: 15 November 2024

Published: 20 November 2024



Copyright: © 2024 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (<https://creativecommons.org/licenses/by/4.0/>).

Keywords: electric vehicles; thematic similarity; BERT; threshold effect

1. Introduction

The electric vehicle (EV) industry has emerged as a critical focus globally, as nations strive to reduce carbon emissions and advance sustainable development. Since China identified EVs as a strategic emerging industry in 2009, it has rapidly ascended to become the world's largest EV market, accounting for over 60% of global production and sales by 2023 [1]. While this national-level success is remarkable, significant regional disparities in EV adoption persist, which cannot be readily explained by traditional factors such as economic strength or infrastructure development [2]. Paradoxically, economically less developed regions such as Guangxi and Hainan exhibit higher EV market penetration than more affluent regions like Guangzhou and Zhejiang, despite sharing similar geographic conditions and climates. Conventionally, wealthier regions with robust industrial foundations and advanced infrastructure would be expected to lead in EV adoption [3]. This counterintuitive pattern raises a critical question: why are economically disadvantaged regions outperforming their wealthier counterparts in EV adoption, despite having fewer resources and industrial capacity?

These unexpected regional disparities suggest that factors beyond economic and infrastructural conditions may be influencing EV adoption. A pivotal factor is the divergence between the central government's strategic planning and the policy design implemented by local governments [4]. While the central government establishes broad national goals—such as promoting green technologies and accelerating EV adoption—local governments

are granted considerable autonomy in interpreting and adapting these directives to fit regional contexts. This special policy framework allows local governments to tailor national policies to regional needs, but it also introduces substantial variations in policy emphasis and execution, creating gaps between central objectives and local implementation [5].

Such discrepancies provide critical insights into the unbalanced development of the EV industry across regions. Central and local governments often adopt differing policy priorities, with central policies emphasizing national objectives such as market expansion and technological leadership, while local governments focus on region-specific goals like infrastructure development, consumer subsidies, or support for local industries [6]. These differences in policy design and implementation can significantly influence regional industrial development. This study systematically examines the impact of central–local policy misalignments on the development trajectory of the EV industry, with particular attention to their effects on regional industrial development. Furthermore, it seeks to identify the optimal degree of policy divergence that, while ensuring alignment with national strategic objectives, enables regional flexibility and innovation to maximize the sustainable development of the industry [7].

This research addresses these gaps by examining the impact of central–local policy divergence on the development of the EV industry. While existing research primarily focuses on technical, market, and economic drivers of EV adoption, it has largely overlooked the influence of policy variation across different administrative levels. Utilizing the BERT (Bidirectional Encoder Representations from Transformers), a deep learning-based semantic analysis model (details are provided in Section 4), this study quantitatively assessed the thematic similarities between central and local EV policies [8]. These quantifications were then incorporated into a threshold effect model (a statistical analysis method that divides regression intervals based on specific threshold values), which will be detailed in Section 5, to explore the nonlinear relationship between policy alignment and EV market penetration, determining whether an optimal degree of policy coherence exists that maximizes industrial growth while accommodating regional flexibility.

This research makes several key contributions to the existing literature. Theoretically, it extends the dual principal–agent theory by integrating it with policy research, offering a new framework to analyze the interactions between central and local governments in industrial policy implementation. Methodologically, it combines advanced natural language processing techniques, leveraging BERT-based semantic analysis, with econometric models like the threshold effect model, providing a more rigorous and quantitative evaluation of policy differences. Practically, this study delivers recommendations for balancing national consistency and regional flexibility in policy design, supporting the sustainable development of China’s EV industry while offering insights for similar industries globally.

The structure of this paper is as follows: Section 2 provides a literature review, analyzing the current research on electric vehicle industry policies and identifying gaps in the literature. Section 3 introduces the theoretical framework and research methodology, with a focus on applying the “dual principal–agent” theory to the electric vehicle industry. Section 4 details the measurement of policy thematic similarity using the BERT model, including data selection and text preprocessing procedures. Section 5 constructs a threshold effect model with policy quantity as the threshold variable, systematically exploring the impact of policy differences on electric vehicle market penetration. Section 6 discusses the contributions and limitations of the study. Finally, Section 7 presents the conclusion and policy recommendations, summarizing the findings and offering relevant policy suggestions.

2. Literature Review

2.1. Current Research on the New Energy Vehicle Industry

In recent years, the electric vehicle industry has received extensive attention from academia as an essential driving force for global economic transformation and sustainable development. A comprehensive review of the existing literature reveals that scholars have

primarily discussed the development of the electric vehicle industry from three perspectives: influencing factors, policy effects, and industry development. In terms of influencing factors, Wang [9] and Li et al. [10] analyzed the considerations in the adoption of electric vehicles from the perspectives of consumers and enterprises, respectively, and found that environmental awareness, economic advantages, and technological progress are the main driving forces. Another group of scholars approached the issue from a macro perspective, examining the mechanism of public policies on industrial development. For example, Chen [11] and Lin [12] emphasized the importance of economic incentives and infrastructure construction for the promotion of electric vehicles. Sun et al. [13] demonstrated the interplay between environmental regulations and technological innovation. Focusing on the current state of industrial development in China, Hu et al. [14] assessed the potential impact of subsidy phase-out on the industry and pointed out the development direction of China's electric vehicle industry in the post-subsidy era. Xie et al. [15] analyzed the impact of changes in consumer preferences on the marketization process of electric vehicles under the dual-credit policy. Additionally, a small number of scholars have devoted their efforts to regional comparative analyses of electric vehicle policies. For instance, Ma et al. [16] constructed an AHP (Analytic Hierarchy Process) model to conduct a comprehensive evaluation of the electric vehicle industry policies in China, Japan, the United States, and Germany, aiming to identify the optimal policy path suitable for the development of electric vehicles.

However, existing research still has limitations. On the one hand, the foreign literature focuses more on economic, climatic, and technological factors, with relatively weak analysis of policy impacts. On the other hand, domestic research, although incorporating policy perspectives, primarily employs qualitative methods and lacks theoretical analysis and empirical testing combined with local realities. Moreover, the existing literature pays little attention to the potential differences in policy effects brought about by China's unique "dual principal-agent" (which will be explained in detail in Section 3.1) administrative model. Under this model, whether the intentions of central policies can be effectively transmitted to local levels and subsequently influence industrial development remains to be further explored. Therefore, future research should further expand the analytical perspective, combine policy factors with other influencing factors, innovate research methods, strengthen theoretical construction and empirical testing in the local context, and particularly focus on China's "dual principal-agent" administrative system to discuss the effects and mechanisms of industrial policies, with the aim of providing more comprehensive, in-depth insights that align with the national conditions for the high-quality development of the electric vehicle industry.

2.2. Current Research on Text Quantification Methods

With the advent of the big data era and the improvement of computational capabilities, text quantification methods have been widely applied in social science research. A comprehensive review of the existing literature revealed that scholars have primarily discussed text quantification methods from two perspectives: technical paths and application fields. In terms of technical paths, the word2vec model proposed by Mikolov et al. [17] and the BERT model developed by Devlin et al. [18] have provided important tools for calculating text similarity from the perspectives of word embedding and text representation learning, respectively. The GloVe model proposed by Pennington et al. [19] learns word vectors through a global word co-occurrence matrix, further enriching word embedding methods. In terms of application fields, Linder et al. [20] used topic models to analyze the policy texts of the European Commission and studied the evolution and interaction of policy issues. Gentzkow et al. [21] combined word embedding and machine learning methods to examine the dynamic changes in ideology in U.S. Supreme Court cases, expanding a new perspective of judicial research. Hansen et al. [22] employed text analysis methods to study the uncertainty of policy statements by the Federal Open Market Committee (FOMC)

and found that monetary policy uncertainty has a significant impact on asset prices and macroeconomic activities.

Theoretical research on text analysis methods currently surpasses practical applications. Most existing studies rely on qualitative approaches, with limited quantitative analysis, making it difficult to capture text content features accurately. Additionally, research tends to focus on text analysis techniques themselves, with little integration into econometric models, limiting the potential of text quantification in empirical research. This study addressed these gaps by using the BERT model to calculate thematic similarity in policy texts and incorporating it. It also established a nonlinear regression model based on threshold effects to quantitatively analyze the intrinsic relationship between policy differences and industrial development. This approach offers new interdisciplinary insights, highlighting the potential for integrating text analysis with econometric modeling and advancing social science research paradigms.

3. Research Framework and Theoretical Foundation

3.1. Dual Principal–Agent Administrative Framework

In the current international framework, China possesses three major characteristics: a large economic scale, a large population base, and rapid development speed. The coexistence of development potential and risks in this unique development context compelled China to construct an industrial policy system with higher administrative efficiency and stronger constraining capabilities to ensure industrial security and sustainable development [23].

Under China’s political and economic background, the design and implementation process of its industrial policies can be regarded as the transfer of policy intentions between the formulators and the implementers, presenting a typical dual principal–agent relationship [24]. The central government, as the controller of the development direction, formulates long-term industrial development strategies and requires local governments to refine and implement policies according to local conditions. In this process, the central government acts as the principal, and local governments act as the agents, constituting the first layer of the principal–agent relationship. Subsequently, local governments design specific policy tools based on the requirements of the central government, promoting local industrial development through a series of industrial policies such as subsidies, taxation, regulation, and service policies [25]. Enterprises, as the main recipients of these policies, complete production and operations according to specific policy requirements [26]. In this process, local governments act as the principals, and enterprises become the agents, forming the second layer of the principal–agent relationship (see Figure 1).

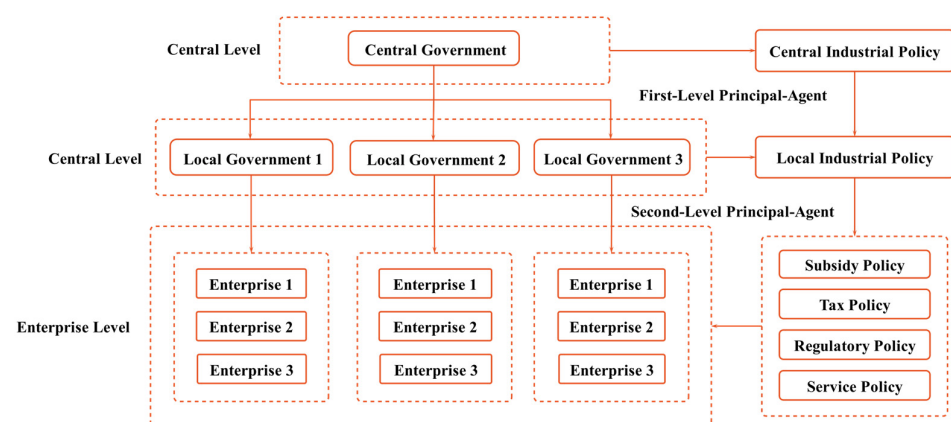


Figure 1. Dual principal–agent model of China’s new energy vehicle industry policy system.

In the dual principal–agent relationship, differences in policy objectives and information asymmetry between the central and local governments lead to inevitable variations in

the formulation and implementation of policies for the electric vehicle (EV) industry. On one hand, these differences allow local governments the flexibility to tailor policies to their specific regional conditions, such as subsidies for charging infrastructure, tax incentives for EV manufacturers, and consumer purchase incentives. This flexibility can stimulate local innovation and adaptation, fostering a more dynamic industrial environment [27]. However, excessive policy divergence may cause local governments to stray from the broader national strategy, resulting in fragmented industrial development, inefficient resource allocation, and even unhealthy regional competition [28]. In such cases, the lack of coordination can undermine the overall effectiveness of policy measures designed to promote EV adoption. Conversely, overly rigid alignment with central policies might suppress local governments' autonomy, limiting their ability to address region-specific challenges and opportunities [29].

3.2. Theoretical Foundation

The relationship between policy thematic similarity and the development of the EV industry is complex and can be explained by a blend of policy consistency theory and local autonomy in policy innovation. These two theoretical frameworks provide a foundation for understanding both the linear and non-linear dynamics between central–local policy alignment and industrial growth.

1. Policy Consistency Theory

Policy consistency, or alignment between central and local government policies, is often viewed as a key driver of efficient policy implementation. The central government, in its role as a strategic planner, sets national objectives such as promoting green technologies and accelerating EV adoption as part of its sustainable development goals. When local governments align their policies closely with these national goals, the resulting consistency minimizes miscommunication and friction in the policy implementation process [30]. Theoretically, this alignment enables resources to be more effectively allocated, reduces uncertainty for market participants (such as manufacturers and consumers), and strengthens the signal to investors that the EV sector is a stable and growing industry [31].

In a linear relationship, high thematic similarity between central and local policies implies stronger coordination. This reduces transaction costs, such as the time and effort required for local governments to interpret and adjust central directives [32]. It also leads to smoother execution of national priorities at the local level, thus fostering industrial growth. For instance, when a local government adopts central policies without significant modification, it benefits from clearer policy guidelines, greater political support, and increased financial incentives from the central government. The consistency between policy objectives across government levels can thus amplify the effectiveness of subsidies, tax incentives, and infrastructure investment programs that are critical for EV development [33].

2. Local Autonomy and Policy Innovation Theory

However, policy consistency alone does not always guarantee optimal industrial outcomes. The theory of local autonomy in policy innovation highlights the importance of regional flexibility. Local governments, faced with distinct regional challenges such as varying levels of infrastructure, economic development, and consumer preferences, often need to adapt national policies to local conditions. This flexibility is crucial because a one-size-fits-all approach may not address the specific needs of different regions [34]. For example, a policy designed to promote charging infrastructure in densely populated urban areas like Guangzhou may not be as effective in rural or less economically developed regions like Guangxi, where transportation infrastructure or energy capacity may differ significantly.

When local governments exercise discretion to tailor national policies, they are able to innovate and implement more regionally effective strategies. This adaptability introduces a non-linear dynamic into the relationship between policy similarity and EV industry development. Too much alignment between central and local policies might stifle local

innovation, preventing local governments from responding effectively to unique challenges [35]. Conversely, too much divergence could lead to fragmentation, where local policies deviate so far from national objectives that they become ineffective or incompatible with the central government's broader goals.

3.3. Mechanism of Impact

The impact of policy thematic similarity on EV development operates through two main mechanisms. First, a high degree of policy alignment between the central and local governments facilitates efficient information transmission and reduces the communication costs associated with policy implementation. This coordination ensures that local governments can effectively execute central policies, leading to smoother industrial development. Consequently, a positive linear relationship between policy similarity and industrial growth may emerge [36].

However, if local governments merely replicate central policies without adapting them to local circumstances, the effectiveness of these policies may be diminished. Regions with different economic structures or infrastructure capabilities may require tailored approaches to national EV policies to better suit local conditions. Excessive policy alignment can lead to rigid implementation, hindering necessary local innovations and, in turn, impeding industrial growth [37]. This scenario suggests a non-linear relationship: moderate thematic similarity allows for local flexibility and innovation, maximizing the potential for EV development, while too much or too little alignment results in suboptimal outcomes [38].

In this context, achieving a balance of moderate thematic similarity becomes ideal. Local governments benefit from the strategic direction and resources provided by the central government while retaining sufficient flexibility to innovate and address region-specific needs [39]. This balance fosters optimal conditions for EV industry growth, as regions can implement targeted policies—such as consumer subsidies tailored to local economic conditions or infrastructure investments suited to regional needs—while still aligning with national objectives.

Accordingly, discussing the specific impact of these differences on industrial development, determining the optimal range of difference control, and identifying the appropriate degree of policy autonomy that local governments should enjoy are of great significance for promoting high-quality industrial development. This study employed the BERT model to analyze the thematic differences in electric vehicle industry policies between the central government and 31 provincial-level administrative units. It also utilized the random forest model to establish a nonlinear regression equation, quantitatively analyzing the intrinsic relationship between policy differences and industrial development. The findings provide a scientific basis and theoretical support for formulating an efficient and coordinated “central–local” industrial policy system.

4. Policy Thematic Distance Measurement Based on the BERT Model

4.1. Policy Selection

A total of 2427 electric vehicle-related policies in China were collected, including 290 central policies and 2237 local policies. The policies were screened according to the policy classification method proposed by Luo Qian [40]. The results include policy documents or excerpts from policy documents related to electric vehicles at both the central and local levels, such as strategic plans, guiding opinions, management measures, implementation methods, enforcement regulations, and industry regulations. Finally, 142 central industrial policy documents and 726 local industrial policy documents were selected. Based on this policy sample, a dataset containing multi-level policy texts was constructed. Data preprocessing included text segmentation, removal of non-text elements, and formatting the text into an input format acceptable to the BERT model. The ultimately selected central and some local electric vehicle policies were used to generate the dataset.

A total of 2427 electric vehicle-related policies in China were collected, including 290 central policies and 2237 local policies. These policies were sourced from official

government portals at various levels in China [41], the Peking University Legal Information Network [42], the China Association of Automobile Manufacturers [43], and other relevant platforms. The policies were screened according to the classification method proposed by Luo Qian [40]. The resulting dataset includes policy documents or excerpts related to electric vehicles at both central and local levels, such as strategic plans, guiding opinions, management measures, implementation methods, enforcement regulations, and industry regulations. Ultimately, 142 central industrial policy documents and 726 local industrial policy documents were selected. Based on this policy sample, a dataset containing multi-level policy texts was constructed. Data preprocessing involved text segmentation, removal of non-text elements, and formatting the text into an input format compatible with the BERT model. The vehicle industrial policies are shown in Tables 1 and 2.

Table 1. China’s new energy vehicle industry policies at the central level (excerpts).

Year	Policy Name	Policy Number
2009	Announcement on the Release of Access Management Rules for New Energy Vehicle Manufacturers and Products	No. 44 [2009] of the Ministry of Industry and Information Technology
.....		
2023	Guiding Opinions on Further Strengthening the Construction of Safety Systems for New Energy Vehicle Enterprises	No. 10 [2022] of the General Office of the Ministry of Industry and Information Technology

Table 2. China’s new energy vehicle industry policies at the local level (Shanghai).

Year	Policy Name	Policy Number
2009	Several Policy Provisions on Promoting the Development of New Energy Vehicle Industry in Shanghai	No. 55 [2009] of the General Office of the People’s Government of Shanghai Municipality
.....		
2023	Shanghai’s Implementation Plan for Accelerating the Development of New Energy Vehicle Industry (2021–2025)	No. 10 [2021] of the General Office of the People’s Government of Shanghai Municipality

4.2. BERT Model Parameter Settings

Policy thematic distance research differs from general text analysis, as it not only requires accurate identification of policy themes but also quantification of abstract text data. The analysis process involves complex policy expressions and highly specialized technical terms, necessitating the selection of tools capable of understanding the deep meaning of the text. Traditional text analysis methods such as TF-IDF and Word2Vec can perform word frequency statistics and importance calculations but lack an understanding of the overall theme and deep logic of the text.

In 2018, Devlin released the BERT model, marking a new stage of development in the field of natural language processing (NLP) [18]. The architecture of BERT is based on the Transformer and employs a bidirectional pre-training mechanism to learn language representations from large-scale corpora, enabling it to capture the complex semantic relationships of vocabulary in different contexts and more accurately understand the language habits and design logic of different policy entities [44]. Moreover, the fine-tuning capability of the BERT model allows for customized optimization on specific policy analysis tasks, enabling it to reveal subtle differences between policies and further improve the accuracy and depth of the research. BERT processes input tokens, including *CLS* for sentence-level tasks, individual words, and *SEP* for separating sentences, by converting them into embeddings. These embeddings are then passed through multiple bidirectional Transformer layers to generate contextualized representations. Finally, the outputs are fed

into a dense layer to perform task-specific predictions, such as classification or labeling (see Figure 2).

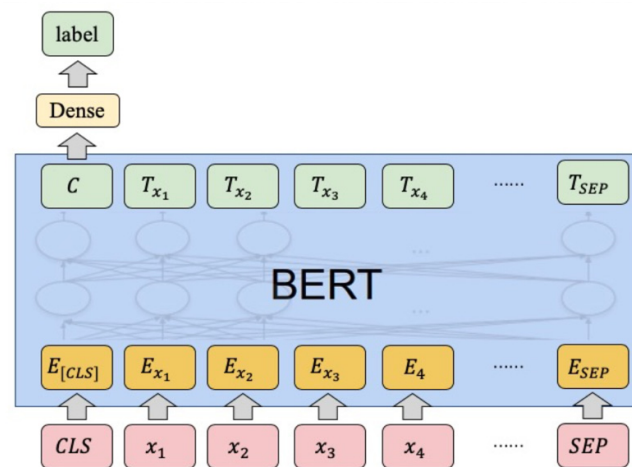


Figure 2. BERT model operation mechanism.

To quantify the policy distance between China’s central and local new energy vehicle industry policies, a fine-tuned BERT model was employed. Built upon the pre-trained BERT-based-Chinese model, the fine-tuning process included a custom fully connected layer added to BERT’s output layer. This additional layer converted the high-dimensional feature vectors generated by BERT into compact vector representations, tailored for calculating policy text distances. This structure allowed the model to represent subtle distinctions and potential semantic relationships in policy texts effectively. The computational tasks were conducted using an NVIDIA Tesla V100 GPU. Training the model on the complete policy dataset required approximately 8 h, and the average inference time per policy document was 20 milliseconds. To ensure reliability and accuracy, the model’s parameters and architecture were systematically configured to address the specific requirements of policy text analysis.

1. Parameter Settings

The BERT model employed in this study features a 12-layer architecture, with each layer containing 768-dimensional hidden units and 12 attention heads. The total parameter count is approximately 110 million. To balance the model convergence speed and stability, the learning rate was set to 2×10^{-5} , which ensures a steady optimization process. The batch size was configured as 16 to efficiently utilize GPU memory without sacrificing computational speed. Additionally, the model was trained for three epochs to achieve sufficient learning of the data features while mitigating overfitting risks. These parameter settings were validated through multiple experiments, ensuring an optimal balance between training efficiency and model performance, thereby laying a solid foundation for subsequent policy similarity analysis.

2. Activation Function and Loss Function

To enhance the model’s capability in capturing semantic features, this study employed the Gaussian Error Linear Unit (GELU) as the activation function in the hidden layers. GELU applies a smooth nonlinear transformation that improves training stability and model adaptability to complex semantic structures. The mathematical expression for GELU is shown in Equation (1):

$$GELU(x) = 0.5 \times (1 + \tanh(\sqrt{\frac{2}{\pi}}(x + 0.044715x^3))) \quad (1)$$

Compared to the traditional ReLU activation function, GELU is more effective in handling the diverse and complex semantic features inherent in policy texts.

The optimization of the model relies on the Cross-Entropy Loss function, which measures the discrepancy between predicted values and ground truth labels, as shown in Equation (2):

$$L = -\frac{1}{N} \sum_{i=1}^N [y_i \log(\hat{y}_i) + (1 - y_i) \log(1 - \hat{y}_i)] \quad (2)$$

where y_i represents the true label, and $\hat{y}$ denotes the predicted probability for the i instance. The term L represents the average loss across all N instances in the dataset. By minimizing this loss function, the model iteratively optimizes its parameters during training, thereby improving its performance in classification and similarity tasks.

3. Data Preprocessing and Similarity Calculation

Preprocessing the input data is a crucial step for ensuring consistent and effective model training. In this study, raw policy texts were preprocessed systematically. First, the BERT tokenizer was used to segment the texts into tokens. To standardize input lengths, all tokenized sequences were either padded or truncated to a maximum length of 512 tokens. Additionally, non-textual elements, such as special characters and unnecessary whitespace, were removed to ensure the cleanliness of the input data.

Subsequently, using the fine-tuned BERT model, each policy document in the dataset was encoded, obtaining vector representations for each document. By calculating the cosine similarity between these vectors, we quantified the deep semantic distance between central and local new energy vehicle industry policies, which represents the thematic similarity between policies. This is shown in Equation (3).

$$\text{Cos}(\theta) = \frac{\sum_{i=1}^n C_i L_i}{\sqrt{\sum_{i=1}^n C_i^2 \sum_{i=1}^n L_i^2}} \quad (3)$$

where $\text{Cos}(\theta)$ represents the cosine similarity between the two texts, while C_i and L_i represent the central and local text vector features generated by the BERT model, respectively.

4.3. Model Evaluation and Conclusions

To comprehensively evaluate the performance of the fine-tuned BERT model in policy text classification tasks, this study employed metrics such as classification accuracy, precision, recall, and F1 score. Classification accuracy measures the model's overall ability to correctly classify samples in the test set, while precision and recall reflect the model's accuracy in predicting positive samples and its ability to capture relevant samples, respectively. The F1 score, as a harmonic mean of precision and recall, assesses the model's robustness under imbalanced class distributions. Macro-averaging was used to calculate these metrics, ensuring that class frequency differences did not disproportionately affect the evaluation results.

The evaluation results indicate that the fine-tuned BERT model achieved an overall classification accuracy of 92.7%, with macro-averaged precision of 91.3%, recall of 93.1%, and an F1 score of 92.2%. These results demonstrate that the model exhibits high classification precision across most categories and effectively captures samples from each class. The high recall score highlights the model's strong ability to identify positive samples, while the slightly lower precision may be attributed to semantic overlap between certain categories or insufficiently distinct sample features. However, this does not significantly affect the study's primary objective, as the core task of policy text analysis focuses on identifying semantic similarities and differences rather than achieving strict categorical classification. Moreover, the balanced F1 score underscores the model's robustness and its ability to maintain consistent performance across imbalanced categories.

Figure 3 is a four-dimensional bubble chart composed of policy thematic similarity, regional names, electric vehicle penetration rate, and policy quantity. The horizontal axis

represents the thematic similarity of electric vehicle policies, while the vertical axis shows the names of provincial-level regions in China. Color depth indicates the electric vehicle penetration rate, and bubble size reflects the number of policies. The purpose of this chart is to preliminarily integrate commonly used research variables in the electric vehicle field, laying a foundation for subsequent econometric model development.

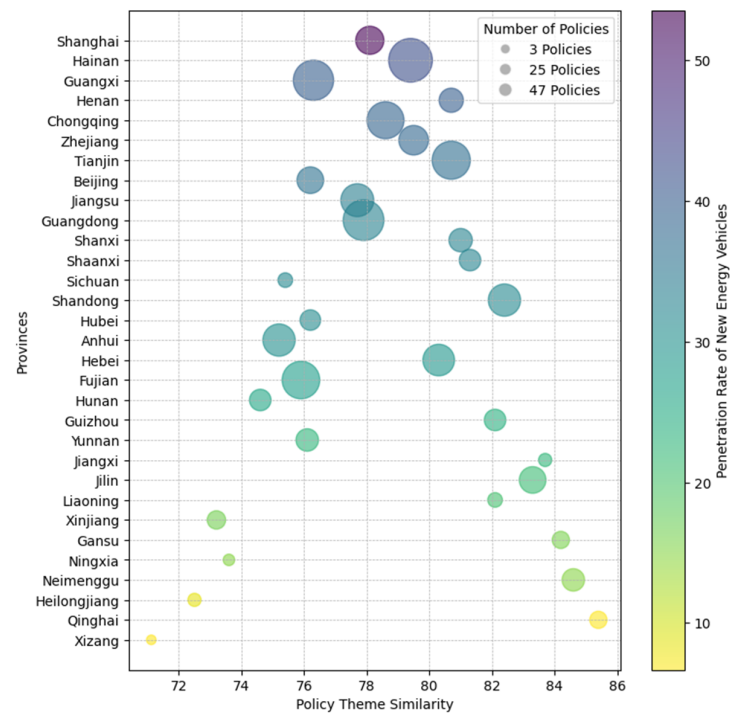


Figure 3. Three-dimensional relationship between policy thematic similarity, policy quantity, and new energy vehicle penetration rate.

Through systematic observation of the scatter plot distribution characteristics, it can be found that there exists a nonlinear association pattern between policy thematic similarity and new energy vehicle penetration rate [45]. When the policy thematic similarity is low, the new energy vehicle penetration rate increases rapidly with the improvement of similarity. However, when the similarity exceeds a certain threshold, the growth rate of penetration gradually slows down and even shows a downward trend. This phenomenon indicates that policy thematic similarity has a “threshold effect” on the promotion of new energy vehicles [46,47]: moderate policy differences are conducive to adapting to local conditions and promoting industrial development, while excessive differences may lead to policy deviation and reduced implementation efficiency, affecting the industrial process. Therefore, finding the “optimal interval” for central–local policy matching is key to achieving healthy development of the new energy vehicle industry.

The policy text quantity and new energy vehicle penetration rate show a significant positive relationship, revealing the important role of active policy supply by local governments in promoting industrial development [48]. However, it is worth noting that in some regions with higher penetration rates, there is a clear “breakpoint” phenomenon in the scatter plot, reflecting that relying solely on “quantitative” policy supply is difficult to fundamentally promote industrial upgrading, and more attention needs to be paid to improving policy quality and targeting [49]. Furthermore, policy quantity may influence policy thematic similarity. In regions with a large number of policies, the policy thematic similarity of the scatter points shows a greater degree of dispersion, implying that a large number of policy texts may increase the diversity of policy themes, to some extent weakening the consistency with central policies. Therefore, while pursuing the quantity of policy supply, it is also necessary to strengthen top-level design and systematic planning,

focusing on the logical coordination and internal coupling of various policies to enhance the systematic and scientific basis of the overall policy [50].

5. The Impact of “Central–Local” Policy Differences on New Energy Vehicle Penetration Rate

To further explore the influencing mechanism of policy effects, a threshold effect model was constructed. The potentially nonlinear relationship between the policy quantity, policy thematic similarity, and new energy vehicle penetration rate laid the foundation for introducing a threshold effect model. The “breakpoint” phenomenon in the scatter plot distribution indicates that there may be a certain “critical point” in the policy quantity, causing the relationship between policy thematic similarity and new energy vehicle penetration rate to exhibit significant differences within different policy quantity intervals, requiring an interval division to process variables within different ranges. The threshold regression model can describe the nonlinear impact of independent variables on dependent variables and reveal the differentiated characteristics of variable relationships in different regions [51], providing a suitable econometric analysis framework for analyzing structural mutations in policy effects [52]. In view of this, the next section of this study constructed a threshold regression model with policy quantity as the threshold variable, policy thematic similarity as the core explanatory variable, and new energy vehicle penetration rate as the explained variable. With the help of econometric empirical methods, the nonlinear association between variables was systematically tested, aiming to reveal the structural characteristics of policy transmission under the “dual principal–agent” framework and provide precise and detailed decision-making references for optimizing new energy vehicle industry policies.

5.1. Selection of Indicators and Data

Referring to the indicator selection methods of scholars [53–55], the new energy vehicle penetration rate was selected as the explained variable of the model, policy thematic similarity as the key explanatory variable, policy quantity as the threshold variable, and public charging pile quantity, average temperature, air quality index, population density, education level, and per capita disposable income as control variables.

The choice of the new energy vehicle penetration rate as a proxy for the development status of new energy vehicles is grounded in its comprehensive reflection of market adoption and diffusion dynamics. This rate, representing the proportion of new energy vehicle sales to total vehicle sales within the same period, encapsulates not only consumer acceptance levels but also the effectiveness of policy measures and infrastructural support in promoting new energy vehicles. According to the diffusion of innovation theory, the penetration rate serves as a critical metric for assessing the adoption lifecycle of new technologies [56]. It integrates various market factors such as technological readiness, economic feasibility, and societal acceptance, thus providing a holistic indicator of the industry’s developmental trajectory. Furthermore, utilizing the penetration rate allows for temporal and spatial comparisons, facilitating a nuanced analysis of how new energy vehicles are progressing toward mainstream acceptance across different regions and periods.

The new energy vehicle penetration rate came from the China Association of Automobile Manufacturers, representing the ratio of new energy vehicle sales to total vehicle sales in the same period; policy thematic similarity was derived from the calculation results of the BERT model in the previous section; policy quantity was sourced from the portals of various government agencies in China; public charging pile quantity was obtained from the China Electric Vehicle Charging Infrastructure Promotion Alliance; average temperature and air quality index were sourced from meteorological observation stations of the China Meteorological Administration; population density was derived from the China Statistical Yearbook, representing the ratio of regional population to regional area; per capita disposable income was obtained from the China Statistical Yearbook. The symbol representation and descriptive statistics of the variables are shown in Table 3.

Table 3. Descriptive statistics of model variables.

Variable Name	Variable Symbol	Unit	Minimum Value	Maximum Value	Mean	Standard Deviation
New Energy Vehicle Market Penetration	NEP	%	6.67	53.53	27.77	10.98
Policy Thematic Similarity Index	SIM	%	71.1	85.40	78.69	3.78
Number of Policies	NUM	count	3	47	18.23	12.14
Public EV Charging Infrastructure	CPL	10,000 units	0.0557	38.30	5.79	7.1034
Average Temperature	TEMP	°C	3.6	24.8	14.0	5.41
Air Quality Index	AQI	µg/m ²	5.4	46.00	29.67	9.10
Population Density	POP	Persons/km ²	3	3950	474.58	707.52
Educational Attainment	EDU	%	4.75	28.60	8.43	4.90
Per Capita Disposable Income	COL	10,000 CNY	2.32731	7.96	3.66	1.37043

5.2. Benchmark Model of Policy Similarity on New Energy Vehicle Penetration Rate

Given the use of panel data and the inclusion of numerous variables, this study employed a fixed-effects model to address potential endogeneity concerns. Endogeneity is a critical issue in empirical research, as it can compromise the validity of causal inferences and lead to biased or inconsistent estimations. In the context of this study, the potential for endogeneity arises from several factors. Reverse causality may occur if the development of the electric vehicle (EV) industry influences the formulation and implementation of policy measures, rather than being solely a consequence of such policies. Additionally, omitted variable bias could result from unobserved regional characteristics or macroeconomic conditions that simultaneously affect both policy measures and EV industry growth. Measurement errors in key variables, such as the intensity of policy implementation or industry performance indicators, could further exacerbate endogeneity issues.

The fixed-effects approach addresses these concerns by controlling for unobserved heterogeneity across regions and over time, thereby isolating the within-region and over-time variations to estimate the relationship between policy measures and EV industry development. This methodological choice reduces the risk of biased estimations and ensures that the analysis captures more reliable and causal effects of policy measures.

Before constructing the threshold effect model, a benchmark model of the impact of policy thematic similarity on the new energy vehicle penetration rate was constructed to test the rationality of the different model structures and control variables, as shown in Equation (4).

$$NEP_{it} = \alpha_0 + \alpha_1 SIM_{it} + \alpha_2 SIM_{it}^2 + \sum_{j=1}^{n=6} a_{j+6} X_{it} + \zeta_i + \mu_t + \varepsilon_{it} \quad (4)$$

where NEP_i represents the new energy vehicle penetration rate; SIM_i represents the thematic similarity between central and local government policies; X_i represents the control variables; ζ_i is the individual fixed effect; μ_i is the time fixed effects, controlling for macro-level influencing factors such as changes in the international situation, COVID-19 pandemic, and technological innovation commonly experienced by different provinces; and ε_i is the random error term, representing unobserved demand changes in each province, etc. The regression results of the benchmark model are shown in Table 4.

The regression results in Table 3 show that the benchmark group has the highest goodness of fit, with an R^2 of 0.8298, significantly outperforming the three control groups. This indicates that after introducing control variables, the relationship between policy thematic similarity and new energy vehicle penetration rate can be more accurately described. In contrast, control group 1 excluded all control variables, resulting in a significant decrease in the explanatory power of the regression results. Although control groups 2 and 3 employed different functional forms, their fitting effects were still inferior to the benchmark group. The estimation results of the benchmark model validate the rationality of the settings for

each variable, providing a reliable foundation for further exploring the threshold effect of policy thematic similarity.

Table 4. Benchmark model regression results.

Variable	Basic Group	Control Group 1	Control Group 2	Control Group 3
α_0	−9.6490 *** (0.000)	−6.653 (0.392)	−9.5640 ** (0.031)	−9.6131 * (0.979)
SIM	−0.2253 *** (0.008)	−0.1292 (0.141)		
SIM^2	36.2431 *** (0.000)	13.6509 * (0.152)		
$\ln SIM$			1.790 (0.121)	3.914 (0.149)
$(\ln SIM)^2$			3.590 * (0.087)	4.275 (0.101)
N	31	31	31	31
R^2	0.8298	0.2289	0.5928	0.5012
SSE	519.5843	694.5287	558.3571	600.8154
RMSE	4.3868	9.3427	5.743	5.219
Control variables included	Yes	No	Yes	No

Note: The asterisks represent the significance level of the coefficients: *** $p < 0.01$ (highly significant), ** $p < 0.05$ (significant), * $p < 0.10$ (weakly significant). Numbers in parentheses are p -values indicating the statistical significance of the coefficients.

As shown in Figure 4, the benchmark model fitting image intuitively presents the non-linear relationship between policy thematic similarity and new energy vehicle penetration rate. The scatter plot distribution exhibits a clear quadratic function feature, i.e., the new energy vehicle penetration rate shows a trend of first increasing and then decreasing as policy thematic similarity improves. The shape of the fitted curve is consistent with the theoretical analysis: when policy thematic similarity is low, the penetration rate grows rapidly with similarity; however, when the similarity exceeds a critical value, the growth rate of penetration gradually slows down, showing a trend of marginal diminishing returns.

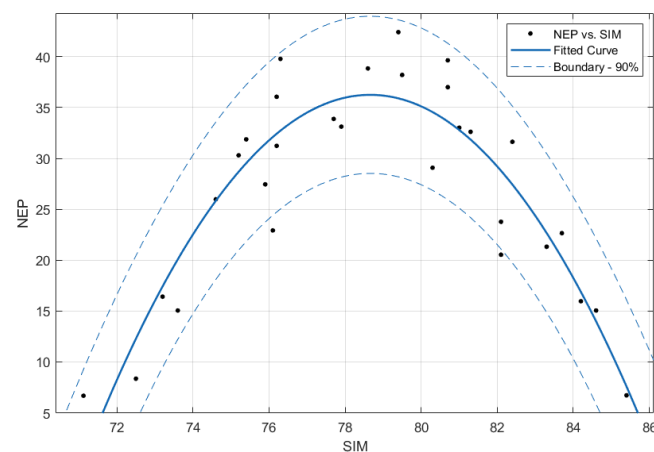


Figure 4. Benchmark model fitting image.

Combining the above analysis, the model structure setting meets the standards for establishing a threshold effect model. On the one hand, the benchmark model test results confirm the effectiveness of the control variable selection, with significant estimated coefficients for each variable. On the other hand, the nonlinear relationship revealed by the fitted image provides a basis for the model form when introducing the threshold effect model. Hence, the policy quantity threshold variable is formally introduced, and the threshold regression model is employed to deeply analyze the structural relationship between policy thematic similarity and new energy vehicle penetration rate, aiming to obtain more accurate and comprehensive conclusions and provide decision-making references for optimizing new energy vehicle industry policy supply.

5.3. Threshold Effect Model of Policy Similarity on New Energy Vehicle Penetration Rate

The choice of policy quantity as the threshold variable, rather than using the independent variable of new energy vehicle (NEV) penetration rate, is deliberate and grounded in theoretical and empirical considerations. The progression of policy quantity often reflects the increasing intensity and scope of governmental intervention in the development of the NEV industry [57]. Early-stage policies typically focus on foundational support, such as subsidies and infrastructure development, while more mature stages witness a rise in policy complexity and diversity. By employing policy quantity as the threshold variable, we aim to identify a “tipping point” where the marginal impact of additional policies on industry growth may undergo significant changes. At lower levels of policy quantity, the effect on NEV development tends to be more pronounced; however, as the number of policies reaches a certain threshold, the marginal returns may diminish. In some cases, the increasing complexity and coordination challenges of policy implementation could lead to reduced effectiveness or even counterproductive outcomes [58,59].

While policy thematic similarity remains the key independent variable, capturing the degree of alignment between central and local government policies, it does not fully account for the intensity of policy intervention. Moreover, using NEV penetration rate as a threshold variable could introduce endogeneity issues and blur the causal relationships under investigation. By contrast, introducing policy quantity as the threshold variable not only reveals dynamic changes in policy intensity over time but also addresses, to a certain extent, the limitations of thematic similarity in explaining the effects of policy intervention [60]. This approach provides a more comprehensive understanding of how varying levels of policy intensity influence the growth of the NEV industry, particularly in identifying potential nonlinear effects when policy interventions become either excessive or insufficient. This dual methodology allows for a nuanced analysis that captures both the consistency of policy content and the overall strength of policy interventions, thereby offering deeper insights into the effectiveness of governmental policies.

To determine the number of thresholds and threshold values in the threshold effect model, the Bootstrap method was used for testing. The Bootstrap method simulates the sample distribution through self-sampling, effectively overcoming problems such as heteroscedasticity and non-independence, and improving the robustness of threshold effect estimation [51]. Alternative scenarios with 1 to 4 thresholds were set, and 350 Bootstrap samplings were performed for each scenario as shown in Table 5.

Table 5. BS sampling results.

Threshold Quantity	BS Sample Size	F-Statistic	p-Value
1	350	7.89	0.159
2	350	13.38	0.009
3	350	8.91	0.151
4	350	6.25	0.242

The F-statistic of the double threshold model reached 13.38, rejecting the null hypothesis of the number of thresholds equal to 1 at the 1% significance level, and was significantly higher than the other alternative scenarios. In comparison, the F-statistics of the triple threshold and quadruple threshold models were relatively small and did not pass the significance test. Therefore, the double threshold model was ultimately selected as the optimal model setting.

After selecting the double threshold effect model, the likelihood ratio test was further used to estimate the threshold values [52]. Figure 5 presents the relationship between the likelihood ratio statistic and the threshold estimate. The likelihood ratio statistic reached the minimum value at the first threshold $\phi_1 = 12$ and the second smallest value at the second threshold $\phi_2 = 26$, both passing the 1% significance level test. This indicates that when the policy quantity reaches 12 and 26, respectively, the relationship between

policy thematic similarity and new energy vehicle penetration rate will undergo significant changes, exhibiting structural mutation characteristics based on policy quantity.

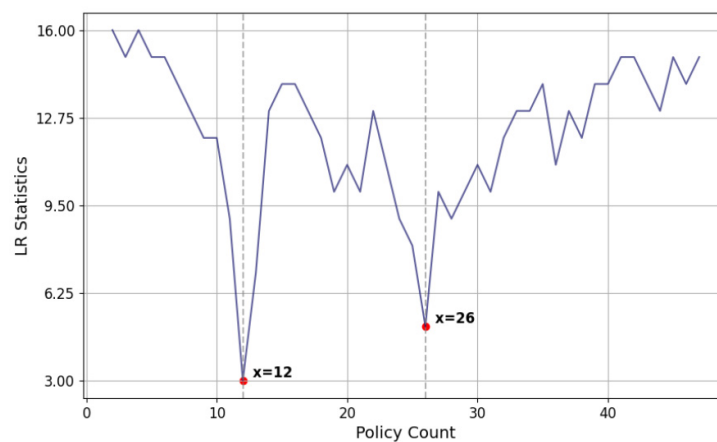


Figure 5. LR statistic distribution.

Based on the Bootstrap test and the distribution of LR statistics, a policy quantity double threshold effect model was constructed to deeply investigate the impact of new energy vehicle industry policy thematic similarity on new energy vehicle penetration rate within different policy quantity ranges as shown in Equation (5).

$$NEP_{it} = \alpha_0 + \alpha_1 SIM_{it} \cdot I(NUM_{it} < \phi_1) + \alpha_2 SIM_{it}^2 \cdot I(NUM_{it} < \phi_1) + \alpha_3 SIM_{it} \cdot I(\phi_1 \leq NUM_{it} < \phi_2) + \alpha_4 SIM_{it}^2 \cdot I(\phi_1 \leq NUM_{it} < \phi_2) + \alpha_5 SIM_{it} \cdot I(NUM_{it} \geq \phi_2) + \alpha_6 SIM_{it}^2 \cdot I(NUM_{it} \geq \phi_2) + \beta_1 NEP_{it-1} + \sum_{j=1}^{n=6} a_{j+6} X_{it} + \varepsilon_{it} \quad (5)$$

where I represents the indicator function, which takes the value of 1 when the condition holds and 0 otherwise; ϕ represents the threshold value; NEP_{it-1} represents the lagged new energy vehicle penetration rate; β_1 represents the regression parameter of the lagged term; and ε_{it} is the random disturbance term. The model regression results are shown in Table 6.

Table 6. Threshold effect model regression results.

Indicator	NUM < ϕ_1	$\phi_1 \leq$ NUM < ϕ_2	NUM $\geq \phi_2$
α_0	−2233.6577 *** (0.000)	−3477.4708 *** (0.007)	−1960.2629 *** (0.009)
SIM	54.6759 *** (0.009)	89.1656 *** (0.001)	52.5481 *** (0.000)
SIM ²	−0.3307 *** (0.000)	−0.5657 *** (0.010)	−0.3456 *** (0.003)
F-statistic	5.261 (0.000)	4.029 (0.000)	3.905 (0.000)
Jarque–Bera	0.315 (0.8543)	0.437 (0.0788)	0.5624 (0.7549)
Breusch–Pagan	1.6788 (0.432)	0.6022 (0.74)	1.5869 (0.4523)
White	1.8387 (0.7654)	1.2087 (0.8767)	3.7518 (0.4406)
α_0 VIF	9.7542	9.7868	9.9174
SIM VIF	6.7959	6.9173	5.7317
SIM ² VIF	7.7315	7.5322	9.6424
Durbin–Watson	1.85	1.775	1.678
N	434	434	434
R ²	0.801	0.765	0.721

Note: The asterisks represent the significance level of the coefficients: *** $p < 0.01$ (highly significant) Numbers in parentheses are p -values indicating the statistical significance of the coefficients.

This study provides multiple test indicators to assess the effectiveness of the model. First, the R^2 values within the three threshold ranges were all greater than 0.7, indicating that the overall model results were effective. The F-statistics were all greater than 3.9, and the p -values were all less than 0.01, indicating that the model is significant and has a

good fit. Second, the VIF values were all less than 10, suggesting that there is no serious multicollinearity problem. This study also conducted the Jarque–Bera, Breusch–Pagan, and White tests to evaluate the statistical properties of the residuals. The Jarque–Bera test examines whether the residuals follow a normal distribution by analyzing skewness and kurtosis, while the Breusch–Pagan and White tests are used to detect heteroscedasticity by assessing whether the variance of residuals remains constant across observations. The p -values for all three tests were greater than 0.05, indicating that the residuals are normally distributed and that there are no issues of heteroscedasticity or serial correlation. Finally, the Durbin–Watson values were close to 2, also indicating that there was no obvious autocorrelation. Combining the above test results, it can be considered that the double threshold model is effective and robust and can accurately describe the threshold effect of policy thematic similarity on the new energy vehicle penetration rate.

Figure 6 presents the three fitted curves, each corresponding to different policy quantity intervals, depicting the complex impact of policy differences between central and local governments on the development of the new energy vehicle industry. Although all three curves exhibit the basic form of a quadratic function, their nonlinear characteristics and evolutionary patterns show significant differences, producing multiple “consistency–specificity” equilibrium points. These points represent the balanced degree of similarity between central and local industrial policies where policy combination efficiency is highest (visually represented by the peak positions of the curves). The migration of these equilibrium points across different development stages reflects the dynamic effects and structural contradictions of industrial policies.

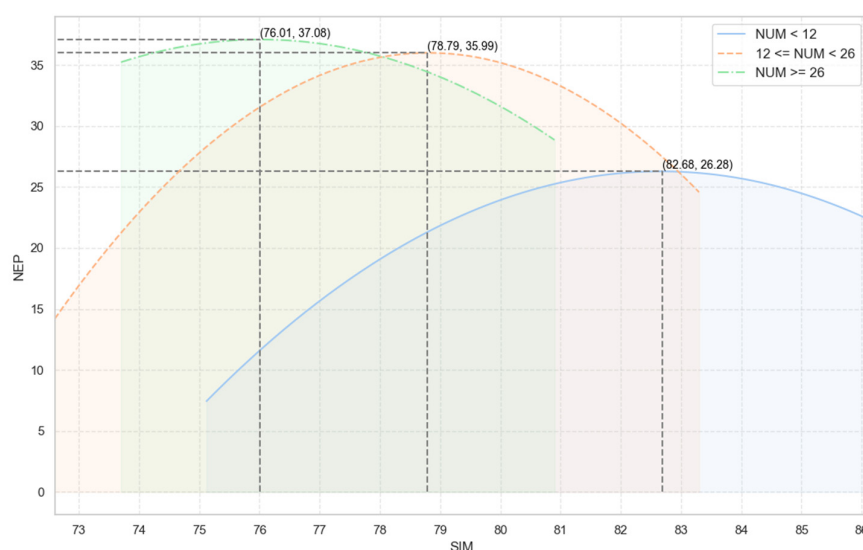


Figure 6. Threshold effect model fitting image.

When the policy quantity is at a low level (less than 12), the penetration rate exhibits nonlinear characteristics with changes in policy thematic similarity, and the overall function curve shifts to the right. The equilibrium point of the penetration rate (i.e., the similarity corresponding to the peak of the curve) is close to 83%, indicating that industrial development requires higher policy consistency at this stage, and “central–local” policies need to maintain a higher degree of convergence to form a joint force. This may be because, in the context of relatively scarce regional policy supply, excessively dispersed policy orientations make it difficult to concentrate resources and form a unified industrial development atmosphere, and the authority and overall planning of central policies become particularly crucial.

When the policy quantity rises to the moderate interval of 12–26, the curve shifts significantly upward as a whole, and the penetration rate level increases substantially at each similarity point, indicating that the enrichment and systematization of policies have a positive impact on accelerating industrial development. At the same time, the curvature of

the curve also increases significantly, showing a typical inverted U-shape, reaching a peak near the equilibrium point of around 80% similarity. This implies that, within this policy quantity interval, the development of the new energy vehicle industry is more sensitive to the balance of “coherence–specificity”, and the requirement for balancing both increases substantially [61]. If policies are too convergent (similarity significantly higher than 80%), it may inhibit local enthusiasm; if they are too dispersed (similarity significantly lower than 80%), it is difficult to form policy synergy. Both deviations will have a clear negative impact on the penetration rate [62]. Therefore, in the future, while adhering to the leading role of central policies, appropriate exploration space should be left for localities, guiding them to formulate differentiated strategies based on regional endowments so as to realize the precise control of policy effectiveness in the dynamic game.

As the policy quantity further increases (exceeding 26), the curve undergoes significant changes again, but with clear differences from the change path of the previous interval. On the one hand, although the overall shape remains an inverted U, the vertical displacement of the curve decreases, and the penetration rate level shows a slight decline at most similarity points, indicating that the marginal effect of policy quantity is diminishing, and its driving force for industrial development has weakened to some extent. On the other hand, the curve shifts to the left as a whole, with the equilibrium point decreasing from around 80% to 76%, indicating that as the policy system at the regional level becomes increasingly perfect, the requirement for local government autonomy in industrial development further increases [63]. When policy supply is already abundant, further strengthening consistency yields diminishing marginal returns and may instead suppress regional innovation vitality, leading to a “convergence trap” [64].

In summary, the dynamic evolution patterns reflected by the three fitted curves have important implications for optimizing the “central–local” policy game and promoting high-quality development of the new energy vehicle industry. In the initial stage of industrial development, the focus should be on leveraging the leading role of central policies, controlling the degree of local decentralization, and strengthening consistency to concentrate resources and expand the industry. As the industry enters the growth stage, appropriate decentralization should be implemented under the central policy framework, encouraging localities to engage in differentiated exploration and seeking a dynamic balance between “consistency and specificity”. When the industry reaches maturity, government control should be appropriately reduced, market vitality should be released, and local autonomy should be further expanded to maximize the stimulation of regional endogenous dynamism. It can be seen that the key to achieving dynamic optimization of industrial policy effectiveness lies in accurately identifying the stage changes of the “equilibrium point”, dynamically adjusting control intensity based on the law of diminishing effectiveness, and cyclically switching between centralization and decentralization to precisely match the needs of industrial development [65]. In the future, top-level design should be further strengthened, and the local policy fault tolerance and correction mechanism should be improved to provide an institutionalized channel for policy gaming, continuously pushing the new energy vehicle industry to a higher level with more precise and pragmatic policy combinations.

5.4. Robustness Test

To verify the robustness and address potential endogeneity concerns in the model results, this paper adopted the method of replacing the explained variable for testing. Specifically, the new energy vehicle ownership ratio [66] was used to replace the new energy vehicle penetration rate, and the threshold effect regression was performed again to examine whether the core conclusions still hold. The new energy vehicle ownership ratio reflects the proportion of new energy vehicle stock in the total vehicle stock, representing the overall level of new energy vehicle popularization and application in a region [13], and can serve as a reasonable alternative indicator to the penetration rate.

The results of the robustness test (see Table 7) are highly consistent with the benchmark model in terms of both the division of threshold intervals and the estimation of threshold

values. In the three different policy quantity intervals, the policy thematic similarity and the new energy vehicle ownership ratio consistently exhibit a significant inverted U-shaped relationship, and the “equilibrium point” presents a nonlinear evolution feature of first moving to the right and then to the left as the policy quantity increases. This indicates that the main conclusions drawn in this paper based on the penetration rate indicator have strong robustness and are not affected by the specific indicator selection.

Table 7. Robustness test.

Indicator	NUM < $\varphi 1$	$\varphi 1 \leq \text{NUM} < \varphi 2$	NUM $\geq \varphi 2$
α_0	−2455.8537 *** (0.000)	−3410.8366 *** (0.007)	−1895.8356 *** (0.004)
SIM	56.9377 *** (0.029)	90.8572 *** (0.000)	51.9266 *** (0.005)
SIM ²	−0.3963 *** (0.000)	−0.5924 *** (0.010)	−0.3128 *** (0.007)

Note: The asterisks represent the significance level of the coefficients: *** $p < 0.01$ (highly significant). Numbers in parentheses are p -values indicating the statistical significance of the coefficients.

It is worth noting that the significance level of the impact coefficient of policy thematic similarity slightly decreases in the robustness test. This may be because, compared to the penetration rate, the ownership ratio responds relatively sluggishly to short-term policy shocks, thus weakening the statistical test power of the impact of policy differences on it. However, overall, the robustness test further verifies the nonlinear impact of “central–local” policy differences on the development of the new energy vehicle industry and the necessity of dynamically adjusting control intensity based on policy quantity. In the future, the indicator system should be further enriched, and robustness tests should be conducted using more dimensions of industrial development indicators to provide more comprehensive and precise empirical support for improving the identification of policy “equilibrium points” and optimizing the dynamic control of policy effectiveness.

6. Conclusions and Policy Implications

This study, based on the “dual principal–agent” theoretical perspective and utilizing the BERT model and threshold regression method, examined the impact of differences in new energy vehicle industry policies between China’s central and local governments on industrial development. This research found a significant inverted U-shaped relationship between policy thematic similarity and new energy vehicle market penetration. As the number of policies increases, the optimal policy interval for this relationship exhibits a dynamic evolutionary characteristic of first shifting right and then left. Therefore, in the process of industrial development across different regions, both centralized and decentralized decision-making models have emerged to varying degrees. While both models may have played a role in promoting industrial growth, any tendency toward extremity in either model could lead to adverse effects.

Centralizing policy decision-making in emerging sectors, such as the new energy vehicle industry, can introduce certain risks, particularly regarding its potential impact on innovation and regional adaptability. While centralized policies promote consistency and alignment with national strategies, they may limit the flexibility and responsiveness of local governments. This limitation is especially problematic in rapidly evolving industries, where localized experimentation, tailored approaches, and quick adaptation to technological and market changes are critical for fostering innovation. Such restrictions may impede technological advancements and slow the industry’s ability to respond to dynamic conditions.

On the other hand, excessive decentralization in policy decision-making may bring certain risks to emerging sectors. Decentralized policies can result in fragmented strategies and uneven implementation across regions, making it difficult to achieve coherent national objectives. For strategic industries that rely on significant state-level investment, overly decentralized decisions during the early stages of development may hinder resource coordination and collaborative efforts. Moreover, inconsistent local policies can create

regulatory uncertainty and delay the standardization of technologies, further affecting industry growth.

This suggests that the allocation of new energy vehicle industry policies between central and local governments should be dynamically adjusted at different stages of industrial development to enhance policy effectiveness and address evolving sectoral needs. Based on these findings, this paper proposes the following policy recommendations:

1. Optimize Multi-Level Policy Coordination within Current Administrative Structure

In the initial stage of industrial development, due to the limited number of policies, a more regulatory and less autonomous policy mode is preferable for industrial development. At this time, efforts should focus on strengthening the leading role of central policies, enhancing guidance and supervision of local policy formulation, improving the consistency of vertical policies between central and local governments, and rapidly expanding the industry scale by concentrating limited resources and factors [67]. As policy supply gradually increases and the industry enters a growth phase, the optimal policy interval gradually shifts left, and local governments' demand for policy design autonomy expands. During this stage, while maintaining central macro-guidance, policy-making autonomy should be moderately delegated, encouraging localities to innovate policies based on regional development realities, adjusting policy content in real-time, seeking a dynamic balance between central and local policy content, and ensuring precise adaptation to the pace of industrial development. When the industry enters maturity and the policy system becomes more refined, the balance point further shifts left. At this point, efforts should be made to expand the boundaries of local policy autonomy, promoting differentiated and characteristic policy innovations, and fully stimulating the endogenous motivation of local governments to drive industrial development. Simultaneously, the boundaries of rights and responsibilities between central and local governments in industrial development should be further clarified, improving and perfecting the vertical transmission mechanism of policies, facilitating information exchange channels between government levels, strengthening interest coordination, and continuously enhancing the overall effectiveness of policy supply through multi-level policy synergy [68].

2. Balancing Consistency and Specificity for Enhanced Policy Precision

This empirical study shows that both excessive policy differences and high policy convergence between central and local governments can, to some extent, weaken the endogenous driving force of new energy vehicle industry development. On the one hand, when local policies deviate excessively from central policy objectives, it can easily lead to disorderly competition among regions, resulting in chaotic industrial layout and incomplete industrial chains, which is unfavorable for forming a policy synergy to promote industrial development. On the other hand, blindly pursuing high policy convergence may trigger regional homogeneous competition, suppressing local policy innovation vitality, and even leading to policy decisions unfavorable to local industrial development. Therefore, future efforts should further strengthen the top-level design of industrial development strategies, clarifying phased goals and key tasks for industrial development at the national level, while reserving necessary exploration space for localities to formulate differentiated policies based on local conditions. Localities should be encouraged to leverage their resource endowments, industrial foundations, and locational advantages to highlight regional characteristics, conducting differentiated explorations within the national policy framework to form a regional industrial pattern of complementary advantages and staggered development [69]. Concurrently, mechanisms for coordinating and dialoguing on inter-regional industrial policies should be further established and improved, enhancing cross-regional policy information sharing and interest coordination, promoting optimal resource allocation, and achieving regional collaborative development amid differences. Additionally, third-party evaluation mechanisms should be actively introduced to dynamically assess policy implementation effectiveness from an objective and neutral perspective, providing customized policy consulting services to local governments, and offering scientific decision-

making references for optimizing and adjusting policy combinations between central and local levels based on specific development levels [70,71].

3. Strategic Policy Adaptation: A Global Perspective

In terms of policy frameworks, the Chinese political system exhibits significant strengths due to its top-down enforcement capabilities and efficient policy adjustment processes, which are particularly evident in the rapid implementation of central policies at the local level. However, this centralized execution mechanism, while ensuring swift policy implementation, also harbors risks: flaws in strategic policy design can quickly magnify errors, extensively impacting the entire industry [39]. Therefore, when other nations consider adopting similar policy frameworks, they must first evaluate whether such models are compatible with their own political and administrative systems. It is advisable for these countries to establish flexible mechanisms for policy feedback and adjustment to enhance adaptability and sustainability, ensuring long-term effectiveness and the capacity to dynamically respond to complex situations [58].

At the industry development level, this research underscores the necessity of phase-specific policy adjustments and the adaptability of local government policies, offering significant insights for other countries in formulating policies to support new energy vehicles and other strategic emerging industries. It is recommended that nations, in their policy-making processes, should thoroughly consider the specific conditions and characteristics of local contexts, allowing local governments the scope within national policy frameworks to make necessary adjustments and innovations [61]. Additionally, by strengthening policy coordination and resource integration across different regions, policy fragmentation during implementation can be more effectively prevented, facilitating the optimal allocation of industrial resources and balanced industrial development. This approach will assist countries in designing more effective and adaptable policy systems based on their unique circumstances, supporting sustained innovation and growth in their industries.

7. Discussion

This study makes significant contributions to the field of China's new energy vehicle industry policy. It introduces an innovative "dual principal-agent" theoretical perspective, combined with advanced text mining techniques and threshold regression methods. This research provides new analytical insights and empirical evidence for policy process theory and differentiated policy management. By examining the interactive relationships between policies at different levels, it aligns closely with the actual interactions between central and local governments in China's unique political system. This study proposes seeking a dynamic balance between central and local policies, emphasizing the importance of adjusting policy differences based on the industry's development stage. This approach breaks through the traditional binary opposition of centralization and decentralization, enriching the theoretical understanding of differentiated policy management. The findings offer valuable insights for developing precise and effective multi-level policy coordination mechanisms, contributing to both theoretical advancement and practical optimization of new energy vehicle industry policies in China and potentially worldwide.

To evaluate the applicability of the analytical framework, this study selected Japan and the United States as case examples. These two countries represent distinct governance systems and industrial contexts: Japan's centralized administrative structure contrasts sharply with the decentralized federal system of the United States. Additionally, both nations have mature EV industries and significant policy experience, making them ideal for testing the adaptability of the framework across varying governance and economic conditions.

Japan's governance structure is highly vertical, with centralized control over policy formulation and limited local government autonomy. Local governments primarily serve as executors of national policies, resulting in a hierarchical administrative system. To adapt the framework to this context, additional layers are necessary to reflect the interactions between central ministries and local implementers. These adjustments enable the framework

to account for centralized processes while addressing regional disparities, such as uneven EV infrastructure development. The United States, in contrast, operates under a decentralized federal system characterized by significant delegation of authority to states. This flat governance structure, combined with substantial economic and administrative diversity among states, requires the framework to emphasize differentiation mechanisms. Specifically, it should incorporate quantitative methods capable of addressing the heterogeneity of state-level conditions, such as hierarchical modeling or multi-level regression approaches, which allow for simultaneous analysis of national trends and state-specific dynamics.

Specifically, future research should focus on the following aspects for further expansion:

1. Extend the research to more industrial fields, conduct comprehensive comparative analyses across industries and regions, construct a multi-dimensional indicator system for measuring policy differences, and further test the universality of the “dual principal-agent” analytical framework.
2. Incorporate more explanatory variables such as industrial development stages and regional innovation environments, introduce theoretical tools like evolutionary economics and game theory, and deeply explore the dynamic evolution mechanism of central-local policy interactions.
3. Strengthen comparative studies with cutting-edge research in related fields abroad, expand the international perspective of China’s industrial policy research, absorb the advantages of industrial policies from various countries, and gradually improve the industrial policy evaluation system.

Author Contributions: Data curation, Z.L.; Formal analysis, Z.L.; Funding acquisition, T.X.; Methodology, Z.L.; Project administration, T.X.; Software, Z.L.; Supervision, T.X.; Validation, Z.L.; Visualization, T.X.; Writing—original draft, Z.L.; Writing—review and editing, T.X. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the Liaoning Provincial Social Science Planning Fund Key Project “Analysis on the Focus Change and Path Evolution of New Energy Vehicle Industry Policies”, grant number L23AJL001”.

Data Availability Statement: The authors are willing to provide necessary data to other scholars. The original contributions presented in the study are included in the article; further inquiries can be directed to the corresponding author.

Conflicts of Interest: The authors declare no conflicts of interest.

References

1. China Association of Automobile Manufacturers. China Association of Automobile Manufacturers Information Conference. Available online: http://www.caam.org.cn/chn/4/cate_39/con_5236359.html (accessed on 27 April 2024).
2. National Development and Reform Commission. Decision of the State Council on Accelerating the Cultivation and Development of Strategic Emerging Industries [National Development and Reform Commission [2010] No. 32]. Available online: https://www.gov.cn/zwggk/2010-10/18/content_1724848.htm (accessed on 27 April 2024).
3. Wang, N.; Tang, L.; Zhang, W.; Guo, J. How to Face the Challenges Caused by the Abolishment of Subsidies for Electric Vehicles in China? *Energy* **2019**, *166*, 359–372. [CrossRef]
4. Lains, P. Convergence, Divergence and Policy: Portugal in the European Union. *West Eur. Politics* **2019**, *42*, 1094–1114. [CrossRef]
5. Peng, J.; Liu, Y.; Wang, Q.; Tu, G.; Huang, X. The Impact of New Urbanization Policy on in Situ Urbanization-Policy Test Based on Difference-in-Differences Model. *Land* **2021**, *10*, 178. [CrossRef]
6. Curran, D.; Mahmalat, M. Policy Divergence across Crises of a Similar Nature: The Role of Ideas in Shaping 19th Century Famine Relief Policies. *Rev. Int. Political Econ.* **2021**, *28*, 712–738. [CrossRef]
7. Chong, Z.; Wang, Q.; Wang, L. Is the Photovoltaic Power Generation Policy Effective in China? A Quantitative Analysis of Policy Synergy Based on Text Mining. *Technol. Forecast. Soc. Change* **2023**, *195*, 122770. [CrossRef]
8. Zhang, Z.; Sheng, N.; Zhao, D.; Cai, K.; Yang, G.; Song, Q. Are Residents More Willing to Buy and Pay for Electric Vehicles under the “Carbon Neutrality”? *Energy Rep.* **2023**, *9*, 510–521. [CrossRef]
9. Wang, S.; Li, J.; Zhao, D. The Impact of Policy Measures on Consumer Intention to Adopt Electric Vehicles: Evidence from China. *Transp. Res. Part A* **2017**, *105*, 14–26. [CrossRef]

10. Li, J.; Li, J.; Wu, Y. Product R&D Strategy of New Energy Vehicle Enterprises Embedded with Technical Services Under the Subsidy Threshold. *J. Knowl. Econ.* **2024**, 1–28. [\[CrossRef\]](#)
11. Chen, K.; Zhao, F.; Hao, H.; Liu, Z. Synergistic Impacts of China's Subsidy Policy and New Energy Vehicle Credit Regulation on the Technological Development of Battery Electric Vehicles. *Energies* **2018**, *11*, 3193. [\[CrossRef\]](#)
12. Lin, B.; Wu, W. The Impact of Electric Vehicle Penetration: A Recursive Dynamic CGE Analysis of China. *Energy Econ.* **2021**, *94*, 105086. [\[CrossRef\]](#)
13. Sun, J.; Tian, M.; Zhang, W.; Ning, J. Government Subsidies and Innovation in New Energy Vehicle Companies: An Empirical Study of New Energy Vehicle Listed Companies Based on Shanghai and Shenzhen A-Shares. *PLoS ONE* **2023**, *18*, e0284693. [\[CrossRef\]](#) [\[PubMed\]](#)
14. Hu, Y.; Yin, H.; Zhao, L. Subsidy Phase-Out and Consumer Demand Dynamics: Evidence from the Battery Electric Vehicle Market in China. *Rev. Econ. Stat.* **2023**, 1–50. [\[CrossRef\]](#)
15. Xie, Y.; Wu, J.; Zhou, X.; Sheng, Y. The Impact of Consumer Preferences on the Evolution of Competition in China's Automobile Market under the Dual Credit Policy—A Density Game Based Perspective. *PLoS ONE* **2024**, *19*, e0295947. [\[CrossRef\]](#) [\[PubMed\]](#)
16. Ma, Y.; Shi, T.; Zhang, W.; Hao, Y.; Huang, J.; Lin, Y. Comprehensive Policy Evaluation of NEV Development in China, Japan, the United States, and Germany Based on the AHP-EW Model. *J. Clean. Prod.* **2019**, *214*, 389–402. [\[CrossRef\]](#)
17. Mikolov, T.; Sutskever, I.; Chen, K.; Corrado, G.; Dean, J. Distributed Representations of Words and Phrases and Their Compositionality. *arXiv* **2013**, arXiv:1310.4546.
18. Devlin, J.; Chang, M.-W.; Lee, K.; Toutanova, K. BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding. Available online: <https://arxiv.org/abs/1810.04805v2> (accessed on 9 April 2024).
19. Pennington, J.; Socher, R.; Manning, C. Glove: Global Vectors for Word Representation. In Proceedings of the 2014 Conference on Empirical Methods in Natural Language Processing (EMNLP), Doha, Qatar, 25–29 October 2014; Association for Computational Linguistics: Doha, Qatar, 2014; pp. 1532–1543.
20. Linder, F.; Desmarais, B.; Burgess, M.; Giraudy, E. Text as Policy: Measuring Policy Similarity through Bill Text Reuse. *Policy Stud. J.* **2020**, *48*, 546–574. [\[CrossRef\]](#)
21. Gentzkow, M.; Shapiro, J.M.; Taddy, M. Measuring Group Differences in High-Dimensional Choices: Method and Application to Congressional Speech. *ECTA* **2019**, *87*, 1307–1340. [\[CrossRef\]](#)
22. Hansen, S.; McMahon, M.; Prat, A. Transparency and Deliberation Within the FOMC: A Computational Linguistics Approach. *Q. J. Econ.* **2018**, *133*, 801–870. [\[CrossRef\]](#)
23. Wei, J. Thoughts on the Adjustment of China's Industrial Policy in the New Era. *J. Beijing Jiaotong Univ. (Soc. Sci. Ed.)* **2019**, *18*, 1–9. [\[CrossRef\]](#)
24. Yu, B.; Zhou, X. Urban Administrative Hierarchy and Urban Land Use Efficiency: Evidence from Chinese Cities. *Int. Rev. Econ. Financ.* **2023**, *88*, 178–195. [\[CrossRef\]](#)
25. Landry, P.F.; Lu, X.; Duan, H. Does Performance Matter? Evaluating Political Selection along the Chinese Administrative Ladder. *Comp. Political Stud.* **2018**, *51*, 1074–1105. [\[CrossRef\]](#)
26. Lu, L.; Huang, H.; Wei, J.; Xu, J. Safety Regulations and the Uncertainty of Work-Related Road Accident Loss: The Triple Identity of Chinese Local Governments under Principal-Agent Framework. *Risk Anal.* **2020**, *40*, 1168–1182. [\[CrossRef\]](#) [\[PubMed\]](#)
27. Shen, Q.; Feng, K.; Zhang, X. Divergent Technological Strategies among Leading Electric Vehicle Firms in China: Multiplicity of Institutional Logics and Responses of Firms. *Sci. Public Policy* **2016**, *43*, 492–504. [\[CrossRef\]](#)
28. Huang, H. The Mechanism for Joint and Individual Accountability Based on the Multilayered “principal-Agent” Relationships: Taking the Implementing of “Peaceful Zhejiang” as an Example. *J. Chin. Gov.* **2017**, *2*, 292–306. [\[CrossRef\]](#)
29. Aguirre, I.; Beitia, A. Modelling Countervailing Incentives in Adverse Selection Models: A Synthesis. *Econ. Model.* **2017**, *62*, 82–89. [\[CrossRef\]](#)
30. Sabatier, P.; Mazmanian, D. The Implementation of Public Policy: A Framework of Analysis. *Policy Stud. J.* **1980**, *8*, 538–560. [\[CrossRef\]](#)
31. Li, L.; Wang, Z.; Wang, Q. Do Policy Mix Characteristics Matter for Electric Vehicle Adoption? A Survey-Based Exploration. *Transp. Res. Part D-Transp. Environ.* **2020**, *87*, 102488. [\[CrossRef\]](#)
32. van Geet, M.T.; Verweij, S.; Busscher, T.; Arts, J. The Importance of Policy Design Fit for Effectiveness: A Qualitative Comparative Analysis of Policy Integration in Regional Transport Planning. *Policy Sci.* **2021**, *54*, 629–662. [\[CrossRef\]](#)
33. Wildavsky, A.; Pressman, J.L. *Implementation: How Great Expectations in Washington Are Dashed in Oakland; or, Why It's Amazing That Federal Programs Work at All, This Being a Saga... Who Seek to Build Morals on a Foundation*; University of California Press: Berkeley, CA, USA, 1984; ISBN 978-0-520-05331-1.
34. Ostrom, V.; Tiebout, C.M.; Warren, R. The Organization of Government in Metropolitan Areas: A Theoretical Inquiry. *Am. Political Sci. Rev.* **1961**, *55*, 831–842. [\[CrossRef\]](#)
35. Zhao, C.; Feng, F.; Chen, Y.; Li, X. Local Government Competition and Regional Innovation Efficiency: From the Perspective of China-Style Fiscal Federalism. *Sci. Publ. Policy* **2021**, *48*, 488–489. [\[CrossRef\]](#)
36. Li, J.; Guo, Y. The Impact of Energy Use Rights Trading Policy on Industrial Companies' Green Investments –Evidence from a Quasi-Natural Experiment in China. *Energy Rep.* **2024**, *12*, 329–340. [\[CrossRef\]](#)
37. Yang, F.; Gan, Q. Effect of Energy Poverty Alleviation on High-Quality Economic Development: An Empirical Study Based on China. *Energies* **2024**, *17*, 5085. [\[CrossRef\]](#)

38. Tuckerman, L.; Nelles, J.; Walsh, K.; Vorley, T. Sustainable Innovation Policy: Examining the Discourse of UK Innovation Policy. *Environ. Sci. Policy* **2023**, *145*, 286–297. [CrossRef]
39. Ran, R. Perverse Incentive Structure and Policy Implementation Gap in China's Local Environmental Politics. *J. Environ. Plan. Policy Manag.* **2013**, *15*, 17–39. [CrossRef]
40. Luo, X.; Wang, H.; Kang, Z. Research on the policy changes of China's integrated circuit industry. *Stud. Sci. Sci.* **2023**, *41*, 413.
41. The Website of the Central People's Government of the PRC. Available online: <https://www.gov.cn/> (accessed on 11 August 2024).
42. Peking University Legal Information Network. Available online: <https://www.pkulaw.com/> (accessed on 11 August 2024).
43. China Association of Automobile Manufacturers. Available online: <http://www.caam.org.cn/> (accessed on 11 August 2024).
44. Vaswani, A.; Shazeer, N.M.; Parmar, N.; Uszkoreit, J.; Jones, L.; Gomez, A.N.; Kaiser, L.; Polosukhin, I. Attention Is All You Need. In Proceedings of the Neural Information Processing Systems, Long Beach, CA, USA, 4–9 December 2017.
45. Elmaslar Özbaş, E.; Akin, Ö.; Güneysu, S.; Özcan, H.K.; Öngen, A. Changes Occurring in Consumption Habits of People during COVID-19 Pandemic and the Water Footprint. *Environ. Dev. Sustain.* **2022**, *24*, 8504–8520. [CrossRef]
46. Deng, Q.S.; Alvarado, R.; Cheng, F.N.; Cuesta, L.; Wang, C.B.; Pinzón, S. Long-Run Mechanism for House Price Regulation in China: Real Estate Tax, Monetary Policy or Macro-Prudential Policy? *Econ. Anal. Policy* **2023**, *77*, 174–186. [CrossRef]
47. Wang, Q.; Sun, J.; Li, R.; Korkut Pata, U. Linking Trade Openness to Load Capacity Factor: The Threshold Effects of Natural Resource Rent and Corruption Control. *Gondwana Res.* **2024**, *129*, 371–380. [CrossRef]
48. Huang, X.; Wang, X.; Ge, P. Selective Industrial Policy and Innovation Resource Misallocation. *Econ. Anal. Policy* **2024**, *82*, 124–146. [CrossRef]
49. Li, H.; Qi, H.; Cao, H.; Yuan, L. Industrial Policy and Technological Innovation of New Energy Vehicle Industry in China. *Energies* **2022**, *15*, 9264. [CrossRef]
50. Binetti, M.N. Rebuilding Energy Infrastructures and the Manufacturing Sector in Post-Conflict Countries. *Energy Policy* **2023**, *172*, 113298. [CrossRef]
51. Hansen, B.E. Sample Splitting and Threshold Estimation. *Econometrica* **2000**, *68*, 575–603. [CrossRef]
52. Caner, M.; Hansen, B.E. Instrumental Variable Estimation of a Threshold Model. *Econ. Theory* **2004**, *20*, 813–843. [CrossRef]
53. Haustein, S.; Jensen, A.F.; Cherchi, E. Battery Electric Vehicle Adoption in Denmark and Sweden: Recent Changes, Related Factors and Policy Implications. *Energy Policy* **2021**, *149*, 112096. [CrossRef]
54. Wenig, J.; Sodenkamp, M.; Staake, T. Battery versus Infrastructure: Tradeoffs between Battery Capacity and Charging Infrastructure for Plug-in Hybrid Electric Vehicles. *Appl. Energy* **2019**, *255*, 113787. [CrossRef]
55. Singh, V.; Singh, V.; Vaibhav, S. A Review and Simple Meta-Analysis of Factors Influencing Adoption of Electric Vehicles. *Transp. Res. Part D Transp. Environ.* **2020**, *86*, 102436. [CrossRef]
56. Rogers, E.M. *Diffusion of Innovations*, 5th ed.; Free Press: New York, NY, USA.; London, UK; Toronto, ON, Canada; Sydney, Australia, 2003; ISBN 978-0-7432-2209-9.
57. Jiang, Z.; Xu, C. Policy Incentives, Government Subsidies, and Technological Innovation in New Energy Vehicle Enterprises: Evidence from China. *Energy Policy* **2023**, *177*, 113527. [CrossRef]
58. Noda, K. Institutional Economics as Theory of Policy Change: Impact of Past Policy Failures on Present Policy. *J. Econ. Issues* **2018**, *52*, 117–135. [CrossRef]
59. Wang, X.; Zhang, J. Beyond the Quantity-Quality Tradeoff: Population Control Policy and Human Capital Investment. *J. Dev. Econ.* **2018**, *135*, 222–234. [CrossRef]
60. Gao, X. The Comparative Impact of Solar Policies on Entrepreneurship in the US Solar Photovoltaic Installation Industry. *Energy Policy* **2021**, *156*, 112389. [CrossRef]
61. Mao, N.; Ma, J.; Chen, Y.; Xie, J.; Yu, Q.; Liu, J. Forecasting Motor Vehicle Ownership and Energy Demand Considering Electric Vehicle Penetration. *Energies* **2024**, *17*, 5094. [CrossRef]
62. Xia, L.; Gao, S.; Wei, J.; Ding, Q. Government Subsidy and Corporate Green Innovation—Does Board Governance Play a Role? *Energy Policy* **2022**, *161*, 112720, Corrigendum in *Energy Policy* **2022**, *168*, 113115. [CrossRef]
63. Banna, S.; Ottesen, A.; Alzougool, B. Reasons Why Only Kuwaiti Citizens Drive Electric Vehicles despite Being Only a Quarter of the Population. *World Electr. Veh. J.* **2023**, *14*, 287. [CrossRef]
64. Acheampong, A.O.; Opoku, E.E.O.; Dogah, K.E. The Political Economy of Energy Transition: The Role of Globalization and Governance in the Adoption of Clean Cooking Fuels and Technologies. *Technol. Forecast. Soc. Change* **2023**, *186*, 122156. [CrossRef]
65. Ali, I.; Naushad, M. A Study to Investigate What Tempts Consumers to Adopt Electric Vehicles. *World Electr. Veh. J.* **2022**, *13*, 26. [CrossRef]
66. Lucchi, E. Integration between Photovoltaic Systems and Cultural Heritage: A Socio-Technical Comparison of International Policies, Design Criteria, Applications, and Innovation Developments. *Energy Policy* **2022**, *171*, 113303. [CrossRef]
67. Elmallah, S.; Hoen, B.; Fujita, K.S.; Robson, D.; Brunner, E. Shedding Light on Large-Scale Solar Impacts: An Analysis of Property Values and Proximity to Photovoltaics across Six U.S. States. *Energy Policy* **2023**, *175*, 113425. [CrossRef]
68. Afrifa, G.A.; Tingbani, I.; Adesina, O.O. Stochastic Frontier Modelling of Working Capital Efficiency across Europe. *Technol. Forecast. Soc. Change* **2022**, *184*, 122012. [CrossRef]
69. Cheng, X.; Wu, P.; Liao, S.S.; Wang, X. An Integrated Model for Crude Oil Forecasting: Causality Assessment and Technical Efficiency. *Energy Econ.* **2023**, *117*, 106467. [CrossRef]

-
70. Wu, Y.; Lau, Y.-Y.; Wu, J.-A. Integration of Electric Vehicles into Microgrids: Policy Implication for the Industrial Application of Carbon Neutralisation in China. *World Electr. Veh. J.* **2022**, *13*, 96. [[CrossRef](#)]
 71. Ma, T.; Cao, X. FDI, Technological Progress, and Green Total Factor Energy Productivity: Evidence from 281 Prefecture Cities in China. *Environ. Dev. Sustain.* **2022**, *24*, 11058–11088. [[CrossRef](#)]

Disclaimer/Publisher’s Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.