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Impact of the latent topics of policy documents on the promotion of new energy vehicles: Empirical evidence from Chinese cities

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ABSTRACT

As an important strategic emerging industry to promote sustainable economic development, new energy vehicles (NEVs) play multiple vital roles in energy saving and emission reduction and promote the transformation and upgrading of the automobile industry. China's government has formulated abundant policies to support the NEV industry. Existing studies do not pay enough attention to the latent information from NEV policy documents. This paper explores the latent topics of numerous NEV policy documents and their impact on promoting NEVs at the city level by combining the Latent Dirichlet Allocation (LDA) topic model and the econometric method. The results show that the latent topics of NEV policy documents can be categorized into charging infrastructure operation, promotion subsidy, and production support. The prevalence of the promotion subsidy topic is the strongest among the three types of topics. Total topic prevalences significantly promote NEV sales. The 2013 year is a turning point in policy preferences, and this change boosts NEV sales. The prevalence of promotion subsidy topic has an inverted U-shaped effect on NEV sales. The NEV sales will increase by 19% when the prevalence of production support topic increases by 1. Under the COVID-19, although the promotion subsidy policy is still dominant, the production support policy has been paid more attention. Finally, combining the development of China's NEV industry under the COVID-19 epidemic, the paper puts forward pertinent policy suggestions.

1. Introduction

Currently, China is facing a severe resource and environmental situation (Fan et al., 2019; Wei et al., 2020; Gao et al., 2019). In particular, the transportation industry's rapid development is one of the main reasons for increasing energy consumption and carbon dioxide emissions (He et al., 2017; Zhang et al., 2020). By the end of 2020, the number of motor vehicles in China has reached 372 million, of which 281 million are automobiles. The use of motor vehicles is an essential part of urban energy demand and the primary source of urban air pollution (He and Jiang, 2021). The automobile industry's fuel consumption accounts for about 60% of the total oil consumption (Lin and Du, 2017). With the increase of automobile ownership, the proportion of oil consumption in the automobile industry will increase (Du et al., 2019b). China is now the world's largest automobile market, and the growth in automobile ownership shows no sign of abating (Lin and Wu, 2021). With the high-quality development of China's economy, the improvement of people's living standards, and the acceleration of urbanization, automobile demand will continue to grow for a long time in the future, and the resulting energy shortage and environmental pollution will become more prominent.

On September 22, 2020, during the 75th UN General Assembly, China proposed to take more effective policies and measures. Carbon dioxide emissions strive to reach the peak by 2030 and endeavor to achieve carbon neutralization by 2060 years, putting forward higher requirements for carbon emission reduction. Compared to conventional fuel vehicles, new energy vehicles (NEVs) not only have the potential for energy saving and emission reduction but also contribute to better air quality, climate and health benefits (Liang et al., 2019; Xu et al., 2021). As a promising way to solve energy and environmental problems, NEV is highly valued by the government and has been listed as a strategic emerging industry. The Chinese government has issued various policies to support the NEV industry's development, the most important of which is monetary policy. Fig. 1 shows the major NEV economic policies for 2016–2020. For example, in 2017, the Ministry of Finance, the General Administration of Taxation, the Ministry of Industry and Information Technology, and the Ministry of Science and Technology issued the "Announcement on Tax Exemption on the Purchase of New Energy Vehicles," proposing an exemption from vehicle pur-

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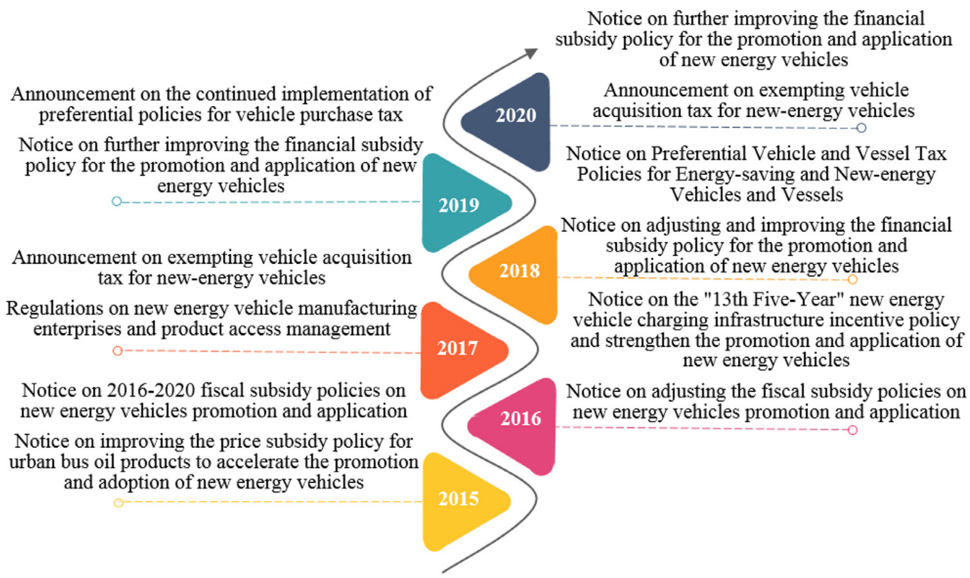

Fig. 1. Major New energy vehicle policies for 2016–2020.

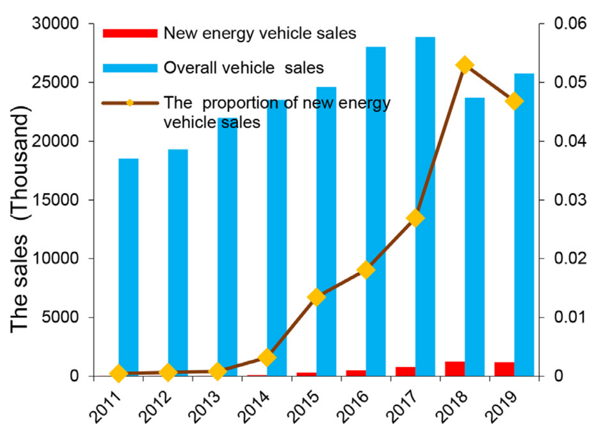

Fig. 2. The sales of new energy vehicles from 2011 to 2019 CAAM (2020).

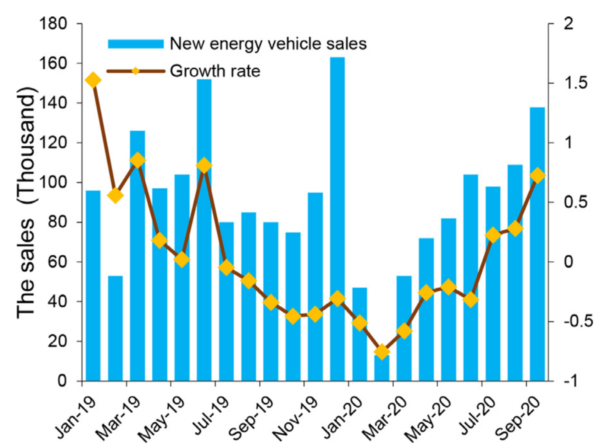

Fig. 3. The per month sales and growth rate of new energy vehicles CAAM (2020).

chase tax for NEVs from January 1, 2008, to December 31, 2020. In 2020, the Ministry of Finance, the Ministry of Industry and Information Technology, the Ministry of Science and Technology, and the Development and Reform Commission issued the "Notice on Further Perfecting the Policy of Financial Subsidies for the Promotion and Application of New Energy Vehicles," pointing out that the current technical index system framework and threshold requirements for purchase subsidies will remain unchanged in 2021. In addition to economic policy, non-economic policies such as road priority and new energy unlimited licensing also play a key role.

Since 2015, China has become the world's largest NEV producer and marketer for five consecutive years under economic and non-economic multiple policy support. As shown in Fig. 2, the sales volume of NEVs has continued to rise in the past nine years, and the proportion of NEVs in total vehicle sales in 2011 was only 0.07% and increased to 5.3% in 2018. However, in 2019, affected by the decline of subsidies, the annual sales volume of NEVs and the proportion in the total sales volume of vehicles declined for the first time. Significantly, the NEV industry has been further hit since the COVID-19 outbreak in early 2020. From the monthly sales of NEVs from January 2019 to September 2020 shown in Fig. 3, it can be found that from July 2019, the year-on-year growth rate of NEV sales has been negative for twelve consecutive months. In the first three months of 2020, the year-on-year growth rate dropped by more than 50%. Under the impact of COVID-19, stabilizing bulk consumption such as automobiles has become a top priority for the government. As shown in Fig. 4, after President Xi Jinping explicitly proposed on February 15 to encourage local purchase restriction areas to increase automobile license plate quota appropriately, the government has launched a series of policies and measures favoring the NEV industry. Under the influence of stimulus policies such as extending subsidies and exempting purchase tax, NEV sales increased for the first time since July 2020. It can be seen that the government will learn and adjust the NEV policy according to the changes in the external social environment. Furthermore, there are differences in the response of the NEV market to different types of policies. Government issue policies are in text form. The same policy topic may be distributed in various policy texts, and a policy text may have multiple policy topics. Through the analysis of policy topics, it is conducive for policymakers to grasp the characteristics of policy evolution of NEVs, enhancing the understanding of the development of NEVs.

Text mining can effectively deal with unstructured information, objectively understand policy topic changes that policymakers are mainly concerned about in the vast policy documents, and grasp the policy development process. The topic model is a commonly used text mining method to discover potential topics based on a

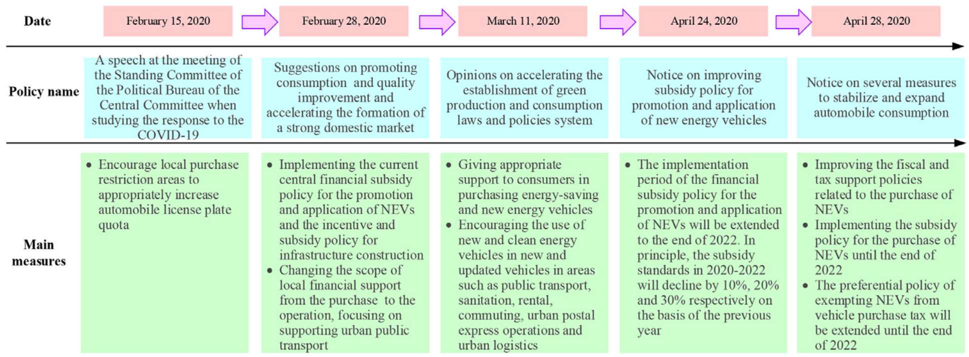

Fig. 4. NEV policies under the background of COVID-19.

series of documents. An important reason for the rapid popularity of topic models in recent years is that the extracted topic words are easy to understand, which achieves a good compromise between complexity and interpretability (Zhang et al., 2021). Some scholars have tried to use topic models to analyze the latent topics of policy texts, including climate policy texts (Hsu et al., 2020), environmental protection policies (Du et al., 2019a), low-carbon city policies (Wu et al., 2021), bridge management policy (Wen et al., 2019), COVID-19 policies (Goyal and Howlett, 2021), etc. However, few studies use the topic model to mine the latent topics of NEV policies and apply it to quantitative analysis.

To bridge this research gap, this paper aims to use text mining methods exploring latent topics from numerous NEV policy texts and empirically demonstrate the impact mechanisms of different latent topics on the development of NEVs. This paper is interested in the following questions. First, what are the topics implied in a large number of NEV policy documents? How do you identify these topics? Second, what is the impact mechanism of different policy topics on the development of the NEVs industry?

The main innovations are as follows. (1) Policy documents imply various measures and means for policymakers to achieve goals and solve problems. To the best of my knowledge, this is the first paper to apply the LDA topic model to determine the latent topics in a large number of NEV policy documents. (2) We further analyze the influence mechanism of different policy topics on promoting NEVs and provide implications for decision-makers to guide the NEVs industry's development. (3) The pilot cities have promoted the demonstration and promotion of NEVs. This paper analyzes the differences in NEVs sales from the city level using panel data by combining NEV policy topics with digital variables.

The rest is organized as follows: Section 2 is a literature review, including NEV policy and policy text analysis. Section 3 introduces variable selection, data source introduction, the Latent Dirichlet Allocation (LDA) topic model, and the regression analysis method. Section 4 presents the impact analysis of the latent topic of the policy documents on the promotion of NEVs. Section 5 is a related discussion. The conclusions and policy implications are given in Section 6.

2. Literature review

2.1. NEV policy

The existing scholars' research on NEV policy mainly focuses on two aspects: policy effect analysis and the impact of policy on consumers' purchase intention. In terms of policy effect analysis, Li et al. (2019a) use a complex network evolutionary game method to study government policies' dynamic impact on electric vehicle diffusion in different scale networks. Based on the system dynamics model, Liu and Xiao (2018) establish the scenario analysis and analyze China's electric vehicles' development under the policy incentive. By a consumer complex network decision-making model, Li et al. (2020a) discuss the impact of economic policy and information policy on the adoption rate of electric vehicles. These studies are mainly based on simulation methods, and few scholars have conducted empirical research on policy effects. For example, Zhao et al. (2019) have proved that China's relevant industrial policies in 2009 can significantly improve the number of invention patent applications of China's NEV industry through the double-difference method. Liu et al. (2020b) also use the double-difference method to reveal that electric vehicles' deployment in the public sector can effectively stimulate individuals to purchase electric vehicles.

Researchers primarily use questionnaires to analyze the impact of NEV policies on consumers' purchase intentions. For example, through the investigation and analysis of four first-tier cities in China (Beijing, Shanghai, Guangzhou, Shenzhen), Lin and Wu (2018) find that price acceptability, government subsidies, vehicle performance have a significant impact on respondents' willingness to purchase electric vehicles (Lin and Wu, 2018). Based on a survey of more than 1000 respondents from different cities in China, Qian et al. (2019) find that in addition to government subsidies, the free license policy of electric vehicles is desirable to consumers compared with the license-plate lottery of traditional gasoline vehicles. Li et al. (2020b) research indicate that for young consumers, almost all incentives to reduce operating costs or increase convenience can increase their adoption of electric vehicles. Based on the extended theory of planned behavior, Li et al. (2020c) explore the relationship between psychological factors, policy portfolio characteristics, and electric vehicles' purchase intention. However, these studies are based on consumers' willingness to adopt, which is difficult to reflect consumers' actual purchase behavior. Besides, the questionnaire survey coverage is usually one or several cities, which is challenging to cover the purchase of NEVs of different levels of cities.

Although electric vehicles' incentive policies in some pilot cities are the same, the effect of local incentive policies may be different. It is of considerable significance to discuss incentive policies' effectiveness on NEV sales from the cities' perspective. A few scholars have explored the factors affecting NEV sales from the city level, but the sample period is short. For example, based on the data of pilot cities for two years, Qiu et al. (2019) and Wang et al. (2017) explore the effectiveness of urban NEV policy. Zhang et al. (2016) explain the rapid growth of electric vehicle sales in China using the data set of 88 pilot cities for three years. Guo et al. (2020) using data from 20 major cities in 4 years to investigate the relationship between $PM_{2.5}$ concentration and electric vehicle sales. Most of the information (over 80%) is stored as text (Gupta and Lehal, 2009). However, these studies focus on quantitative indicators and lack attention to the latent information in a large number of policy documents.

2.2. Policy text analysis

Policy text analysis focuses on content analysis and comparative analysis of NEV policies. Some scholars use content analysis to score and sort out the policy types of NEV policy documents. For example, Zhang et al. (2017) systematically collect and sort out electric vehicle policies. Dong and Liu (2020) score and summarize the policies according to the publishing agency and the text's effectiveness level to derive the strength of different types of policy tools. Liu et al. (2020a) applied a similar method to analyze the NEV policy intensities issued by the Chinese central government between 2006 and 2018. However, the strength of many policies cannot be simply expressed with or without. A policy document usually involves more than one theme but several aspects of the NEV industry's development. Besides, in the era of big data, documents issued by governments at all levels are constantly updated.

To understand latent information of policies more efficiently and quickly, it is necessary to use the text mining method to identify the information carried by policies. Text mining technology enables researchers to synthesize information from many unstructured text data and identify policy topic trends. A topic model is a crucial tool for text mining. The topic model is beneficial to organize, understand, research, and summarize a large amount of text information, which is difficult for human annotation to achieve (Benites-Lazaro et al., 2018). LDA is the most widely used algorithm among topic models (Blei et al., 2003). LDA model extracts a series of topics related to all documents from the corpus, provides a way to quantify the research topics, and monitors the evolution of topics, and portrays the similarity between documents. Notably, the LDA model can be best applied to documents dealing with multiple topics (Moro et al., 2019). The NEV policy promulgated by the government usually contains several key points. That is, the text of the NEV policy has multiple topics. This proves that it is reasonable to adopt the LDA model in this paper.

LDA model has been widely used in literature (Lamb et al., 2019; Moro et al., 2019),patent (Jeong et al., 2019),news (Wang et al., 2020),newspaper (Benites-Lazaro et al., 2018; de Oliveira Capela and Ramirez-Marquez, 2019),microblog (Ibrahim and Wang, 2019; Wang et al., 2019b),consumer review platforms (Lang et al., 2020) and other text analysis. The policy text is different from the former, which shows strong preciseness, scientificity, standardization, and authority (Du et al., 2019a). At present, there are few studies on using the LDA model to analyze latent themes in policy texts. Altaweel et al. (2019) apply a topic model to investigate policy responses to ecological disturbances. Kim et al. (2019) find that the topics detected based on the Korea policy research database are pretty consistent with the future drivers selected by the experts. Few scholars employ LDA topic modeling to explore the latent topics of NEV policies and analyze them quantitatively.

With the development of natural language processing technology, it is an inevitable trend to combine text data with quantitative data. To extract the factors promoting NEV sales, structured data such as the economic development and population sizes of different regions should be considered. The unstructured text data implied in a large number of policy documents also should be used. However, few studies combine text themes with quantitative indicators, and almost no energy policies are involved. For example, Chen et al. (2018) combine LDA and ontology to classify and judge merchants' reputations in the secondary trading market. Dybowski and Adämmer (2018) comprehensively combine a probabilistic topic model with a dictionary based on sentiment analysis to build a time series that shows when and how the president of the United States (positive or negative) communicates tax policy messages to the public. Korfiatis et al. (2019) use the structured topic model to combine the topic extracted from airline passengers online comments with digital features and find that it can improve the prediction of passengers' satisfaction. These studies have laid the foundation for analyzing the impact of latent policy topics on NEV sales.

In summary, many studies use questionnaire surveys or interviews to study the impact of policies on consumers' willingness to purchase NEVs. Still, the data used for analysis is subjective. Some scholars empirically analyzed the impact of policies on the actual sales of NEVs but did not consider the information of text type data. To fill in the above research gaps, this paper combines text data and quantitative data, using LDA topic modeling and econometric regression methods to explore the latent topics of numerous policy documents and their role in promoting NEVs from the city level.

3. Method

3.1. Data and variables

3.1.1. Dependent variable

Sales refer to the annual sales of NEVs of the cities studied during the study period. The data comes from the energy saving and new energy vehicle yearbook.

3.1.2. Independent variables

Pol refers to the total topic prevalences in each city's NEV policy during the research period, expressed by the number of NEV policies. In China, NEVs refer to vehicles that use new power systems and are entirely or mainly driven by new energy sources, including pure electric vehicles, plug-in hybrid vehicles, and fuel cell vehicles SC (2012). According to this definition, we use the keywords "new energy vehicles," "electric vehicles," "plug-in hybrid vehicles," "fuel cell vehicles" from the energy saving and new energy vehicle yearbooks, municipal government websites and pkulaw website, automobile industry association, wanfang database, cnki database to collect 721 NEV policies. Numerous scholars have used these databases for policy analysis (Wen et al., 2019; Xu et al., 2019; Yao and Zhang, 2018).

We use the following standard screening policies. First, it is highly related to the development of NEVs, which are only mentioned in general and will not be adopted. Second, policy documents are mainly law and regulations, planning, methods, notices, opinions, etc. Some informal decision-making documents, such as approval and reply, will not be adopted.

Topic^k is the prevalence of topic k in each city's NEV policy during the research period, expressed by the score of policy topic k.

3.1.3. Control variables

Tp refers to the technological progress of the cities studied during the study period, expressed in the number of NEV patent applications (including invention patents, utility model patents, design patents). We used the keyword = (new energy vehicles OR electric vehicles OR plug-in hybrid vehicles OR fuel cell vehicles) from the website of the National Intellectual Property Administration to collect the NEV patents. Ma et al. (2017) find that technological progress has a more significant impact on the diffusion of NEVs than economic subsidy policies.

Pop refers to the population density of the cities studied during the study period. The population density is an essential factor in NEV adoption.

Di refers to the per capita disposable income of urban residents of the cities studied during the study period. Consumers with

Table 1
Variables and data source.

Types	Name	Definition	Source
Dependent variable	$Sale_{it}$	The new energy vehicle sales of the city i in year t	Energy Saving and New Energy Vehicle Yearbook
Independent variable	Pol_{it}	The total topic prevalences of the city i in year t	Pkulaw website China Association of Automobile Manufacturers Wanfang database Cnki database Municipal government websites Energy Saving and New Energy Vehicle Yearbook
	$Topic_{it}^{k}$	The prevalence of topic k of the i city's new energy vehicle policy in year t	Authors calculating
Control variables	Tp_{it}	The technological progress of city i in year t	National Intellectual Property Administration
	Pop_{it}	The population density of the city i in year t	National Bureau of Statistics China Urban Statistical Yearbook
	Di_{it}	The per capita disposable income of urban residents of the city i in year t	Statistical Yearbook of each city Statistics Bulletin on National Economy and Social Development
	Cha_{it}	The number of charging piles of the city i in year t	Energy Saving and New Energy Vehicle Yearbook

higher purchasing power are more likely to buy NEVs (Guo et al., 2020).

Cha refers to the number of charging piles of the cities studied during the study period. A sufficient number of charging piles can reduce consumers' anxiety about NEV charging and conductive to purchase NEVs (Egner and Trosvik, 2018).

This paper collects data from 36 NEV promotion and application cities from 2011 to 2019 to construct a panel regression model. 36 cities are Beijing, Tianjin, Dalian, Shanghai, Ningbo, Hefei, Wuhu, Zhengzhou, Xinxiang, Wuhan, Xiangyang, Changsha, Guangzhou, Shenzhen, Haikou, Chengdu, Chongqing, Kunming, Xi'an, Tangshan, Hangzhou, Jinhua, Shaoxing, Huzhou, Xiamen, Nanchang, Dongguan, Shenyang, Changchun, Nanjing, Suzhou, Nantong, Yancheng, Yangzhou, Guiyang, Zunyi. The reasons for choosing these 36 cities as sample cities are as follows. According to the application of new energy vehicle promotion and application programs in each city, the Ministry of Finance, the Ministry of Science and Technology, the Ministry of Industry and Information Technology, and the Development and Reform Commission issued two batches of new energy vehicle promotion and application cities in November 2013 and January 2014 respectively, with a total of 88 cities listed as NEV promotion and application cities. We collect data based on the 88 pilot cities. In this process, we find that some cities have insufficient data. If cities lack too much data, they are excluded from our sample. If a small amount of data is missing, we use interpolation to supplement it. In the end, we found that data for 36 cities were available and were included in the sample.

We paid attention to this period because the "Ten Cities and Thousands of Vehicles" project started to promote the adoption of electric vehicles by consumers, and the main incentives for the project were launched in 2011. Before 2011, few incentive policies in each city. There is no need to include data before 2011 (Li et al., 2019b). Besides, the latest statistical yearbook is the 2020 version. Since the statistical yearbook is based on the previous year's data, we can get the latest data from each city by 2019.

We assume that all variables can promote NEV sales. The specific variables definition is shown in Table 1.

3.2. Latent Dirichlet allocation model

LDA is a document topic generation model known as a three-tier bayesian probability model, which includes a three-tier structure of words, topics, and documents. As an unsupervised machine learning technique, the LDA topic model can identify the latent topics in large document sets or corpora. It uses the bag of words method to convert each document as a word frequency vector. Consequently, the unstructured text can be transformed into digital data, which is easy to model. Combining the research of Song and Suh (2019) and Altaweel et al. (2019), as shown in Fig. 5, given a set of policy documents, the LDA topic model can be used to get the topic distribution of each policy document and the word distribution of each topic.

Based on the obtained NEV policy documents, we use the Jieba package to segment words by Python 3.7 software. For useless words such as "of," "is," and punctuation, we cleaned them up by adding the stop words list. We correct some wrong segmentation results by custom dictionary. Afterward, we use the Gensim package to construct the LDA topic model. A common problem in the practical application of the LDA topic model is to select the appropriate topic number. Too few categories lead to too broad topics (Abuhay et al., 2018), while too many categories will lead to many highly similar topics (Valencia and Cardona, 2014). There is no consensus on how to determine the parameter. Many scholars have determined the number of topics based on historical experience (De Clercq et al., 2019; Zhang et al., 2021). It can be seen from Table 2 that, according to existing studies, most scholars classify NEV policies into three categories. Therefore, this paper refers to the current literature on the NEV policy categories and finally determines the topic number is 3. Besides, we display the top 10 keywords with the highest probability of each topic.

3.3. Econometric model

We use the F test to determine whether to use a mixed OLS regression or variable intercept model and use the Hausman test to decide whether or not it is a fixed effect model or a random effect model. The p-value of the F test is far less than 0.01. Therefore, we reject the null hypothesis and accept the alternative hypothesis. That is, we choose the variable intercept model. The p-value of the Hausman test is 0.0000, far less than 0.01. Therefore, we choose the fixed effect model as the final model.

Formula (1) and (2) respectively present the panel data model to study the relationship between the total and different types of topic prevalences and NEV sales. α is the intercept term.$\beta$is the coefficient of the independent variable.$\gamma_1, \gamma_2, \gamma_3, \gamma_4$is the coefficient of the control variable.$\mu_i$and$\varphi_t$are the fixed effect of the city and time, respectively.$\varepsilon_{it}$is an error disturbance term.

$$\ln Salse_{it} = \alpha + \beta Pol_{it} + \gamma_1 \ln Tp_{it} + \gamma_2 \ln Pop_{it} + \gamma_3 \ln Di_{it} + \gamma_4 \ln Cha_{it} + \mu_i + \varphi_t + \varepsilon_{it} \tag{1}$$

$$\ln Salse_{it} = \alpha + \beta Topic_{it}^{k} + \gamma_1 \ln Tp_{it} + \gamma_2 \ln Pop_{it} + \gamma_3 \ln Di_{it} + \gamma_4 \ln Cha_{it} + \mu_i + \varphi_t + \varepsilon_{it} \tag{2}$$

4. Result

4.1. The result of the latent Dirichlet allocation model

Table 3 presents a list of top words for each topic and the probability distribution of top words. From the first line, we can see

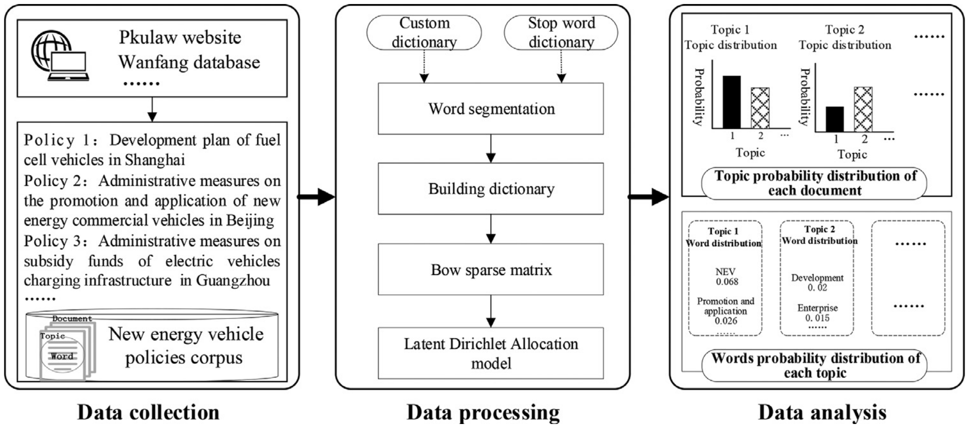

Fig. 5. Latent Dirichlet Allocation model diagram.

Table 2
The category of new energy vehicle policies.

Number	Category name	Reference
2	1) Supply-side policies 2) Demand-side policies	Qiu et al., 2019a; Wang et al., 2019a
3	1) Research and development (R&D) 2) Charging infrastructure and service equipment investments 3) Vehicle tax credits or rebates	Green et al., 2014
3	1) Strategy and investment policies 2) Market incentive policies 3) Regulations and standards	Li et al., 2016
3	1) Finance policies 2) Infrastructure promotion 3) R&D investment	Zhang et al., 2017
3	1) Supply-side policies 2) Demand-side policies 3) Environment policies	Lu et al., 2017; Ma et al., 2019
3	1) Guiding policies 2) Supporting policies 3) Normative policies	Dong and Liu, 2020
4	1) Production 2) Purchase 3) Use 4) Charging infrastructures	Wang et al., 2017
4	1) New energy vehicle purchases (Traditional subsidies or tax exemptions) 2) Industrialization and R&D policies 3) Charging infrastructures 4) Accompanying costs reduction (Free parking and low-cost charging)	Hemmati et al., 2017
5	1) Pilot policies 2) Infrastructure promotion policies 3) Financial subsidies 4) Tax policies 5) Research and development investment	Zhang et al., 2014

Table 3
The top words for different topics.

Topic	Topic 1 (170)	Topic 2 (263)	Topic 3 (288)
Top words with high probability	Development (0.022)	Construction (0.030)	New energy vehicle (0.056)
	Enterprise (0.017)	Charging (0.023)	Promotion and application (0.026)
	Industry (0.011)	Infrastructure (0.021)	Vehicle (0.025)
	Automobile (0.011)	Electric vehicle (0.016)	Enterprise (0.023)
	key point (0.010)	Charging infrastructure (0.014)	Capital (0.029)
	Construction (0.010)	Planning (0.011)	Subsidy (0.017)
	Support (0.009)	Charging pile (0.008)	Allowance (0.015)
	New energy vehicle (0.008)	Department (0.008)	Production (0.014)
	Project (0.007)	Parking lot (0.007)	Department (0.009)
	Accelerating (0.007)	Public transport (0.007)	Finance bureau (0.009)
Policy orientation	Production support	Charging infrastructure operation	Promotion subsidy

that 170 policy documents having the highest probability in topic 1, 263 policy documents for topic 2, and 288 policy documents for topic 3. That is, the possible topics for about 40% of the policy documents are promotion subsidies.

From the results of the LDA topic model, we can obtain the probability that each policy document belongs to the three topics (Du et al., 2019a). Taking Beijing as an example, we calculate the topic prevalences of different NEV policies in 2014. As shown in Table 4, Beijing city promulgated 5 NEV policies in 2014, and the sum of each policy's probability on the three topics is 1. In 2014, the sum of the five policy documents' probability on topics 1 to 3 was 0.30243, 1.558643 and 3.138927, respectively. That is, the prevalence of production support topic in 2014 is 0.30243, for charging infrastructure operation topic is 1.558643, and for promotion subsidy topic is 3.138927. The total topic prevalences are the sum of the prevalence of three types of topics. The sum of all topic prevalences for Beijing city's NEV policies in 2014 is the number of policies issued (i.e., 5).

From the prevalence change of three types of topics shown in Fig. 6, the prevalence of promotion subsidy topic is the strongest generally, which suggests that the primary incentive measures of NEV pilot cities are purchase incentives from the demand side, such as purchase subsidy, vehicle purchase tax exemption, government procurement, etc. Nevertheless, the overall prevalences of charging infrastructure operation topic and production support topic are rising, and the gap with the prevalence of promotion subsidy topic has gradually narrowed. This reveals that pilot cities' policy focus has shifted from financial subsidies and demonstration promotion to supporting infrastructure operation and upgrading the core technology of NEVs. More attention has been paid to the long-term and healthy development of the NEV industry.

Table 4
The topic prevalences for Beijing city's new energy vehicle policies in 2014.

Policy	The topic probability distribution of each policy			The sum of topics
	Topic 1	Topic 2	Topic 3	
Policy 1	0.014194	0.186069	0.799737	1
Policy 2	0.000547	0.559109	0.440345	1
Policy 3	0.244580	0.675244	0.080176	1
Policy 4	0.042561	0.137672	0.819767	1
Policy 5	0.000549	0.000549	0.998902	1
The sum of policies	0.30243	1.558643	3.138927	5

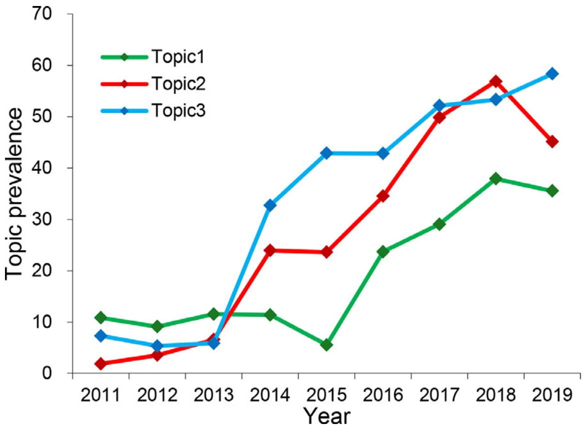

Fig. 6. The prevalence change of three types of topics.

Table 5
The impact of total topic prevalences on new energy vehicle sales.

	Model 1	Model 2	Model 3
Const	11.57 (0.53)	12.77(0.59)	−6.54(−0.30)
Pol_t	0.12*** (3.63)		
Pol_{t-1}		0.03 (1.03)	
Pol_{t-2}			0.01 (0.43)
Year	4.21*** (3.08)	3.89*** (3.68)	——
$\ln Tp$	0.33** (2.29)	0.30* (1.81)	0.28 (1.66)
$\ln Pop$	0.22 (0.13)	0.83 (0.49)	1.69 (0.95)
$\ln Di$	−1.15 (−0.68)	−1.66 (−1.10)	−0.26 (−0.19)
$\ln Cha$	0.29*** (3.31)	0.38*** (4.35)	0.39*** (4.10)
Adjusted R^2	0.87	0.87	0.84

Note:The number in parentheses are t statistics.
*, **, and *** denote the significance levels of 10%, 5%, and 1%, respectively.

It is worth noting that before 2013, the prevalence of production support topic is the highest, followed by the prevalence of promotion subsidy topic, and the prevalence of charging infrastructure operation topic is the lowest. After 2013, the prevalence of promotion subsidy topic increased first, followed by the prevalence of charging infrastructure operation topic, and the prevalence of production support topic rank last, which suggests that 2013 is a turning point in the pilot cities' policy preferences.

4.2. The result of the econometric model

4.2.1. The impact of total topic prevalences on NEV sales

According to the results of Section 4.1, the order of prevalence of three types of topics has changed significantly after 2013. Therefore, we introduce a dummy variable *Year*. Before 2013, *Year*= 0; after 2013, *Year*= 1. We further explore the reasons for the change of policy preference of pilot cities in 2013.

To evaluate the potential threat of multicollinearity, this paper estimates the variance inflation factor(VIF)of each variable. The results show that the maximum VIF value is lower than the recommended threshold of 5, which indicates that multicollinearity is not a problem in this paper. Considering that there may be a time-lag effect for policy, we comprehensively examine the current and lagging impact of total topic prevalences on NEV sales. We mainly consider the time-lag two order by maintaining an appropriate time to ensure that the policy's effectiveness is fully exerted and prevented obsolescence. The regression results are shown in Table 5, where Pol_t,Pol_{t-1} and Pol_{t-2} are the number of NEV policies issued by the municipal government in the year t,t-1 and t-2, respectively. We find that the total topic prevalences in the current significantly promote NEV sales whilePol_{t-1}andPol_{t-2}failing to pass the significance test, which indicates that the NEV market will quickly respond to the policies. But the impact of the lag period of the topic prevalences is not significant.

Since only the current total topic prevalences significantly promote NEV sales, we only focus on Model 1. It can be found that the dummy variable *Year* can significantly boost NEV sales. Through policy review, it may be that the "Air Pollution Prevention and Control Action Plan" issued by the State Council in September 2013 has had a profound impact on the NEVs industry. A series of policies on traffic restrictions, purchase restrictions, and subsidies are subsequently introduced, accelerating energy conservation and reduction. The pilot cities quickly followed up, release local air pollution prevention and control plans, increase financial support and subsidies for the purchase of NEVs, and boost the development of the NEVs industry. This means that the policy topic preference changes in the pilot cities lead to the prevalence change of three types of topics after 2013, making the prevalence of promotion subsidy topic jump to the first and the prevalence of charging infrastructure operation topic that complements NEVs rise to the second.

Based on the above analysis, when other influencing factors remain unchanged, the NEV sales increase by 12% when the total topic prevalences of NEV policies increases by 1. In addition to the topic prevalences factors, the number of charging piles and technological progress have a significant positive impact on NEV sales. NEV sales increased by 0.29% when the number of charging piles increases by 1%. The result is consistent with existing scholars' research (Liu et al., 2020b; Wang et al., 2017). When technological progress increases by 1%, NEV sales increase by 0.33% on average. This shows that cities with the higher technological progress of NEVs are more likely to promote NEV. The result is also proved by Dong and Liu's research (2020).

4.2.2. The impact of the prevalence of different types of topics on new energy vehicle sales

According to the previous analysis, NEV policies are categorized into three types, but the impact mechanism of different types of policies on NEV sales is still unclear. We assume that the prevalence of different types of topics will promote NEV sales. Nevertheless, long-term subsidies may contribute to NEV manufacturers' dependence, leading to slack R&D, expansion of low standards, and increasing overcapacity risks across the automotive industry (Jiang et al., 2018). We further explore whether the prevalence of

Table 6
The impact of prevalence of different types of topics on new energy vehicle sales.

	Model 1	Model 2
Const	10.71 (0.49)	11.56 (0.56)
*Topic*1	0.18** (2.66)	0.19*** (2.75)
*Topic*2	0.01 (0.08)	0.04 (0.47)
*Topic*3	0.16** (2.24)	0.62*** (4.00)
$Topic3^2$		−0.12*** (−3.74)
Year	4.16*** (3.11)	3.87*** (3.36)
$\ln Tp$	0.33** (2.36)	0.30** (2.31)
$\ln Pop$	0.13 (0.08)	0.01 (0.01)
$\ln Di$	−1.01 (−0.60)	−1.02 (−0.71)
$\ln Cha$	0.28*** (3.29)	0.30*** (3.52)
Adjusted R^2	0.87	0.87

Note:The number in parentheses are t statistics.
*, **, and *** denote the significance levels of 10%, 5%, and 1%, respectively.

promotion subsidy topic has an inverted U-shaped effect on NEV sales. According to the previous section results, only the total topic prevalences significantly promoted NEV sales in the current period. Therefore, we further explore the impact of different types of topics on NEV sales in the current period.

The regression results are shown in Model l of Table 6. The prevalence of promotion subsidy topic can significantly promote NEV sales in the current period. When the prevalence of promotion subsidy topic increases by 1, the NEV sales will increase by 16%. This is because the promotion subsidy topic includes reducing consumer purchase costs, government procurement, and mandatory regulations on the proportion of NEVs in public transportation, which can immediately increase NEV sales. The results of Model 2 show that the prevalence of promotion subsidy topic has an inverted U-shaped effect on the NEV sales. The excessively high subsidy will restrain the promotion of NEVs. This may be that the overly high prevalence of the promotion subsidy topic can easily lead to the short-sightedness of the interests and induce manufacturers to expand production capacity for more subsidies instead of improving the quality of NEVs.

The prevalence of production support topic increases by 1, and the NEV sales will increase by 19%. Production support policies mainly include financial support for cutting-edge technology research and development, investment attraction, innovation subsidies, discount interest on project loans, incentives for vital leading enterprises, land preferences, and subsidies for talent introduction, etc. The production support policy provides manufacturers with support and financial guarantees to increase the cruising range of NEVs, thereby increasing the manufacturers' enthusiasm and confidence. The more prevalent the production support topic is, the higher the NEV technology level will be. The technological progress will significantly reduce the cost of batteries and improve the cruising range and driving safety. Through a questionnaire survey of the first 13 demonstration and promotion cities of NEVs in China, Zhang et al. (2013) demonstrate that the performance attributes of NEVs, rather than economic benefits, are the most important indicators that affect consumers' acceptance of NEVs. Through a questionnaire survey of urban families in China, Dong et al. (2020) find that consumers pay more attention to the cruising range of NEVs than the price. From the perspectives of technology, industry, and market, the "2018 Global Electric Vehicle Development Index Research Report" mainly assesses the development level of NEVs in seven countries, including China, the United States, Japan, South Korea, Germany, Italy and France. China ranks first among the seven countries in terms of industry and market, but the technology that truly reflects the strength of the NEVs industry ranks second from the bottom, only superior to Italy. Therefore, China's NEV technology is still in the stage of "big but not strong". At present, the prevalence of production support topic is the lowest among the three types of topics. Local government should pay more attention to them.

The prevalence of charging infrastructure operation topic has no significant impact on NEV sales. This may be that China's policies to encourage the construction of charging infrastructure are relatively lagging. In November 2014, the central government officially issued the first policy to promote charging infrastructure construction (Hemmati et al., 2017). The local government followed up and proposed special charging infrastructure construction and operation policies. According to the "Notice on Adjusting and Improving the Fiscal Subsidy Policy for the Promotion and Application of New Energy Vehicles" issued by the Ministry of Finance and the Ministry of Industry and Information Technology, the local purchase subsidy funds for NEVs will be gradually transferred to support the construction and operation of charging infrastructure and the use and operation of NEVs from 2018. As a complementary product of NEVs, charging operation policy support is crucial. Cities should continue to increase infrastructure construction and improve the use environment of NEVs.

5. Discussion

5.1. Analysis of the change of topic prevalences under the context of COVID-19

To promote the steady and healthy development of the economy, local governments have issued policies to stimulate automobile demand and consumption under the context of COVID-19. However, most of the pilot cities' policies generally mention promoting automobile consumption in the package of stimulus measures, and few of them have targeted policies to stimulate the NEVs' purchase. For example, the "Several Opinions on Promoting Industrial Capacity Production, Capacity Expansion and Stable Growth" issued by the Ningbo municipal government mentioned that to promote passenger automobile consumption and upgrade the local brand. Local passenger automobile manufacturers are encouraged to make concessionary sales to consumers. From March 25, 2020, to September 30, 2020, consumers who purchase a locally produced and sold passenger automobile will be granted a one-time concession of 5000 CNY. The "Subsidy Measures on Guiding Automobile Consumption Upgrading" issued by Nanchang city pointed out that the 1000 CNY subsidy for purchasing a new automobile between February 26, 2020, and April 30, 2020. The "Notice on Encouraging Automobile Renewal and Consumption" issued by the Chongqing government emphasize that 2000 CNY of municipal financial fund subsidy will be given to consumers who want to buy new automobiles between May 1, 2020 and June 30, 2020. The payment will be made in the form of electronic consumption coupons.

It can be seen that these policies are valid before the end of 2020. They are not only based on short-term incentives but are limited to the subsidies purchase, and the stimulation is weak. There is almost no attention to NEVs. Under the background of COVID-19, reduced consumer income has led to a decline in willingness to purchase vehicles. In the current situation that has not solved the charging problem of NEVs and battery life anxiety, these measures against generalized automobile consumption will convert most of the indicators into fuel vehicles. At the same time, the "non-green" policies that focus on revitalizing the economy to stimulate the consumption of fuel vehicles may cause a rebound in energy and emissions, which will affect the economy and energy infrastructure for future decades, and even determine whether long-term energy and climate goals can be achieved.

Twelve pilot cities have issued particular policies to stimulate NEVs consumption. The prevalence of promotion subsidy topic in seven cities accounted for the highest proportion of the total topic

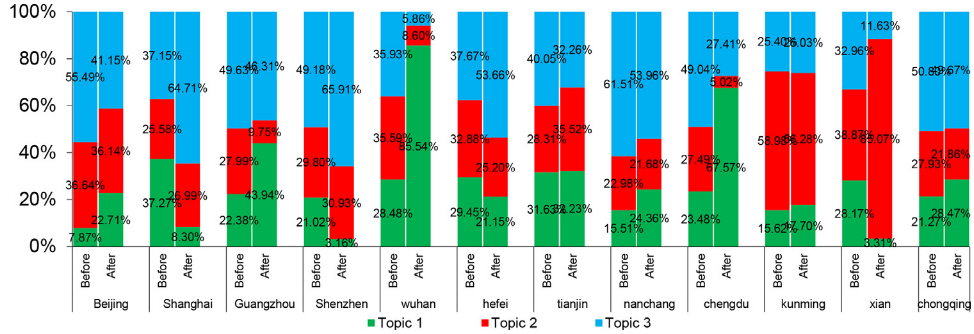

Fig. 7. The change of topic prevalences of the new energy vehicle stimulation policy under the context of COVID-19.

prevalence. Three cities have the highest proportion of charging operation prevalence, and only two cities have the highest proportion of production support prevalence. It can be found that, in general, after the COVID-19 outbreak, the local government still focuses on the promotion subsidies, aiming for direct support. From the change of topic prevalences of the new energy vehicle stimulation policy under the context of COVID-19 (see Fig. 7), compared with before the COVID-19 outbreak, the proportion of charging operation prevalence in the three types of topics of Shanghai, Shenzhen, Tianjin, and Xi'an increased by 1.41%, 1.13%, 7.2%, and 46.2% respectively. The proportion of promotion subsidy prevalence in the three types of topics of Shanghai, Shenzhen, Hefei, and Kunming increased by 27.56%, 16.72%, 15.99%, and 0.63%, respectively. The proportion of production support prevalence in Beijing, Guangzhou, Wuhan, Tianjin, Nanchang, Chengdu, Kunming, and Chongqing increased by 14.84%, 21.56%, 57.06%, 0.6%, 8.85%, 44.09%, 2.07%, and 7.21%, respectively. No matter the coverage or the growth rate, the performance of the production support policy is the most prominent. It can be seen that although the promotion subsidy policy is still dominant, the production support policy is paid more attention after the COVID-19.

5.2. New energy vehicle industry after COVID-19 epidemic

As the COVID-19 epidemic continues to spread around the world, China, as the first country to respond to the epidemic, successfully brought the epidemic under control and became the first world-class economy in the world to resume growth. As the economy recovers, several essential shifts in China's economic landscape that the COVID-19 crisis has accelerated have become apparent (Leung et al., 2020). The first notable shift is digitization. Digital tools have become increasingly popular. The digital economy leads to technological change and industrial upgrading. The second significant shift is declining global exposure. Some countries have called on companies in critical industries to move back home and announced financial support programs to facilitate the process. The characteristics of localization, neighborhood, and regionalization are further enhanced (Chen et al., 2020). The third notable shift is that the features of innovation leading become more prominent (Chen et al., 2020).

After the outbreak of the COVID-19 pandemic, new economic features accelerate the transformation of the NEV industry. Digital technology in vehicles accounts for at least 50% of the total vehicle value (Llopis-Albert et al., 2021). Digitalization will significantly improve the automotive industry's value chain by improving efficiency, reducing costs, and generating greater collaboration and innovation (Llopis-Albert et al., 2021). Companies that lead in developing new services and products related to the digital process will have a significant advantage in the competition in the automotive industry. After the epidemic outbreak, the prevalence of global protectionism will lead to more stringent restrictions on the flow of goods, services, capital, labor, technology, data, and information (Chen et al., 2020). The United States and other western countries will strengthen the blockade of high-tech and key components. China's NEV industry must rely more on independent research and development to break the bottleneck constraints of core technology and key components. In addition, consumers are looking for better quality and healthier options after the epidemic, which means that NEV companies need to respond to the changing needs of consumers with innovative products and new business models.

The government should actively implement the policy of digital technology application, support the vehicle to vehicle, vehicle to infrastructure and unmanned commercial operation, inject strong power into the electrification and intellectualization transformation, and help the digital transformation of NEVs industry. The government needs to drive the domestic cycle with "New Infrastructure" and release the vast domestic demand by promoting "New Infrastructure" such as 5 G base stations and NEV charging piles. The government should help automobile enterprises to reconstruct the value chain and supply chain quickly, increase investment in R&D to make up for technical shortcomings, and give favorable fiscal and tax policies to high-quality enterprises that possess independent innovation ability. In April 2021, Sinopec and Weilai cooperated in the innovative power-changing mode, a significant innovation in the global green intelligent transportation field, and provides better power on experience for intelligent electric vehicle users. The government can actively implement this kind of innovation mode to improve the supply capacity of automobile enterprises.

5.3. Robustness test

5.3.1. Replacing variables

To determine the impact of topic prevalences on NEV sales, we conduct robustness tests. In the previous panel model (see Table 5), we tested the effect of total topic prevalences on NEV sales by taking the annual number of NEV policies issued by each city as a proxy variable. Here, we use a dummy variable to proxy total topic prevalence. The dummy variable $Pol_t = 1$ indicates that the city has issued NEV policy in year t, and$Pol_t = 0$ suggests that it has not issued NEV policy. The robustness test results are shown in Table 8. In addition, we further test the robustness of the model by using the sales volume of NEVs per thousand people as the explained variable.

In Table 8, the total topic prevalences are represented in Model 1 by the total number of released NEV policies and Model 2 by the dummy variable. In Model 3, the dependent variable is NEV sales per thousand people instead of NEV sales of the studied city in Model 1. Although the coefficients in these three models inevitably have some changes, the overall significance of variables is consistent. This test not only verified the robustness of the total topic

Table 8
The robustness analysis of total topic prevalences.

	Model 1	Model 2	Model 3
Const	11.57 (0.53)	10.29 (0.48)	8.92 (0.40)
Pol_t	0.12*** (3.63)	0.60*** (2.81)	0.11*** (3.55)
Year	4.21*** (3.08)	4.72*** (3.80)	4.06*** (2.98)
$\ln Tp$	0.33** (2.29)	0.26 (1.68)	0.32** (2.24)
$\ln Pop$	0.22 (0.13)	1.08 (0.63)	−0.24 (−0.14)
$\ln Di$	−1.15 (−0.68)	−1.59 (−1.04)	−1.01 (−0.60)
$\ln Cha$	0.29*** (3.31)	0.28*** (3.26)	0.29*** (3.32)
Adjusted R^2	0.87	0.87	0.87

Note:The number in parentheses are t statistics.
*, **, and *** denote the significance levels of 10%, 5%, and 1%, respectively.

Table 9
The results of IV regression.

	IV method
Const	1.57 (0.46)
Pol_t	0.07** (2.16)
Year	1.51*** (4.15)
$\ln Tp$	0.06 (0.73)
$\ln Pop$	−0.14 (−1.39)
$\ln Di$	−0.05 (−0.14)
$\ln Cha$	0.80*** (11.50)
Adjusted R^2	0.77

Note:The number in parentheses are z statistics.
*, **, and *** denote the significance levels of 10%, 5%, and 1%, respectively.

prevalences but also confirmed that the policies of various cities do have a positive impact on NEV sales.

5.3.2. Instrumental variable method

Instrumental variable (IV) is a common method to solve the endogenous problems caused by unobserved variables, measurement errors, or bidirectional causality, which is widely used to improve the robustness of the model (Wang et al., 2021). In this study, because the increase of charging piles will promote the NEVs sales, and the increase in the NEVs sales will also drive the development of charging piles, there may be a two-way causal relationship. Therefore, we chose the number of charging piles lagging for one period as the IV. On the one hand, the number of charging piles is related to its lag variable. On the other hand, the number of charging piles in the current period can not affect the number of charging piles in the past, so the lag value of the number of charging piles is exogenous and meets the requirements of instrumental variables.

Table 9 presents the results of IV regression. After considering the possible endogenous issues, the coefficient of the total topic prevalences is still positive, indicating that the total topic prevalences can significantly promote the NEVs sales, which is consistent with the previous results.

6. Conclusions and policy implications

The smooth promotion of NEVs is of great strategic significance to reduce the pressure of energy and environment and improve the transformation and upgrading of China's automobile industry. Under the influence of COVID-19 and economic downward, the NEV sales have been severely frustrated. How to formulate effective policies to promote the healthy development of the NEV industry is crucial. Considering quantitative and text data, this paper uses the LDA topic model and econometric regression method to explore the latent topics of numerous policy texts and the roles in promoting NEVs from the city level. We draw the following main conclusions. (1) According to the topic prevalence changes, the prevalence of promotion subsidy topic is the strongest among production support topic, charging infrastructure operation topic, and promotion subsidy topic. (2) Total topic prevalences significantly promote NEV sales. There are differences in the impact of the prevalences of three types of topics on NEV promotion. The prevalence of promotion subsidy topic has an inverted U-shaped effect on NEV sales, and production support has a significant positive impact. The 2013 year is a turning point of topic prevalences in pilot cities. (3) After the COVID-19, there are different priorities on stimulating NEVs consumption among cities, and production support policy is paid more attention. (4) After the outbreak of the COVID-19 epidemic, the new characteristics of economic development require the transformation of the NEV industry towards digitalization, expanding domestic demand, and independent innovation.

Based on the research conclusions, we propose the following policy recommendations. (1) Given that the total topic prevalences significantly promote the NEVs industry, the government should continue to provide policy support. (2) Policymakers should consider the heterogeneity of the effects of different types of policies, gradually phase out purchase subsidies, and increase investment in production support policies. (3) The government should increase support for the digitalization and charging infrastructure of the NEV industry and continue to improve the industrial chain.

The analysis framework of this paper has reference significance for boosting NEV sales in other countries. Limited by article length and data availability, the sample cities in this paper are 36 cities to promote and demonstrate NEVs. After obtaining more detailed data in the future, we will further compare and analyze the latent topics in promotion demonstration cities and non-promotion demonstration cities and the differences of the impact on the NEV sales.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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