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Research article

Environmental policy uncertainty and green innovation: A TVP-VAR-SV model approach

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Abstract: This paper aims to measure the impacts of environmental policy uncertainty on green innovation and explore the transmission channel that is less understood in past scientific works. In this paper, we use a newspaper-based sentiment mining approach to establish an index of environmental policy uncertainty in China and implement web crawlers and text analysis techniques to construct a network public opinion index of the Chinese financial market. Then, we explore the relationships between environmental policy uncertainty, network public opinion, and green innovation through the time-varying parameter structural vector autoregressive with stochastic volatility (TVP-VAR-SV) model. The transmission channels of environmental policy uncertainty to green innovation are depicted by selecting different timing of policy release. Our empirical study results show that the fluctuations of environmental policy uncertainty, network public opinion, and green innovation have time-varying characteristics. Furthermore, the findings reveal interactions among the three variables: 1) The environmental policy uncertainty can influence green innovation through network public opinion. 2) The environmental policy uncertainty has both inhibited and promoted effects on network public opinion and green innovation. 3) There are differences in the direction and the degree of impulse responses among the above three variables in the context of uncertainty shocks. Besides, managerial relevance and policy implications are also provided for decision-makers facing sustainable development challenges.

Keywords: environmental policy uncertainty; green innovation; TVP-VAR-SV model; sentiment mining; network public opinion

JEL Codes: C32, D81, Q55, Q58

1. Introduction

A well-established ecological environment system is significant to China's sustainable economic growth in a new era of high-quality development. In 2021, the Guiding Opinions of The State Council on Accelerating the Establishment and Improvement of Green, Low-carbon, and Circular Development Economic System pointed out that "establishing and improving the green, low-carbon, and circular development economic system and promoting the overall green transformation of economic and social development are the basic measures to solve China's resources, environment, and ecological problems". As a combination of green and innovation-driven development, green innovation plays a vital role in breaking through resource and environmental problems and promoting sustainable transformation (Albio et al., 2009; Li et al., 2019). At the same time, as China's economy shifts from high-speed growth to high-quality development, especially since the five development concepts were put forward in 2015, China introduced a series of significant environmental policies to cope with the complex environmental situation.

Despite the ample evidence in the literature that uncertainty influences firms' investment decisions and equity valuation, relatively less known is about the influence uncertainty has on environmental innovation. Therefore, it is unclear whether policy uncertainty affects environmental innovation and, if so, what mechanism is operating. Faced with challenges in high-quality economic growth, there is an imperative need to explore the relationship between green innovation and the uncertainties of high-quality development-oriented policies, i.e., environmental policies. Moreover, led by the United Nations Sustainable Development Goals, understanding the effects policy uncertainty has on firms' environmental innovation will contribute to the pathway of sustainable development around the globe.

Traditional quantitative analysis methods such as vector autoregression (VAR) are widely accepted to study fixed relationships between variables. However, it may miss the information beneath time-varying characteristics. To cope with this shortage, we use crawlers and text analysis methods to construct a network public opinion index of the Chinese financial market. The sentiment-based index provides a continuous and quantifiable tracking policy uncertainty as time goes by. This allows the impact of policy uncertainty to be investigated in a time-series manner instead of short-window event research, which could raise problems as the event of interest may not completely resolve the uncertainties from policy changes. Then, the TVP-VAR-SV model explores the relationships and potential mechanisms among environmental policy uncertainty, network public opinion, and green innovation. The transmission channels of environmental policy uncertainty to green innovation are depicted by selecting different policy release points.

The main contributions of this paper are listed as follows. Firstly, in terms of research perspective, most existing studies are on the impact of economic policy uncertainty on corporate green behavior; this paper focuses on the impact of environmental policy uncertainty on corporate green innovation to provide a reference for the study of corporate behavior under uncertainty. Secondly, in terms of environmental policy uncertainty index construction, data are crawled through specified news media reports, environmental policy keywords are compiled, and keyword searches are conducted so as to construct an index that can comprehensively measure environmental policy uncertainty in China and the measurement index constructed in this paper is more targeted than the indirect index replacement. Thirdly, the TVP-VAR-SV model is established from time-varying and dynamic perspectives to study the impact of environmental policy uncertainty on corporate green innovation, which solves the defects of traditional econometric models with constant parameters and static analysis.

With respect to managerial relevance, the time-varying relationship exploration provides a valuable reference to the company's decision-making behavior under environmental policy uncertainty. Companies need to switch their business foci and innovative strategy in response to the dynamic industrial environment and legislative restraints under environmental policies. We strongly suggest companies exposed to the dynamic environmental policy may need to grow and monitor their managerial skills in the dynamic environment and thus design suitable R & D strategies, fill the governance voids, buoy operation performance, and circumvent undesirable investments when policy uncertainty increases.

Moreover, this study remains valuable policy implications. Since the expression of network public opinion is rooted in real-life society and its social and cultural background, how policymakers perceive the channel of uncertainty-sentiment-innovation is especially important to policy design, demonstration, and implementation. Hence, to policymakers and governments around the globe, this study underlines the importance of mitigating policy uncertainty to encourage green innovation. Besides, policymakers should consider the technology status quo in the industry that policies apply. Ensuring a scheduled policy pathway and government support in R&D would be essential for companies to invest in technology and comply with upgraded pro-green policies. A predictable regime where governmental policies are released is likely to facilitate optimal innovation for environmental protection or mitigation of hazards in the ecosystem. It is important to note that if policymakers were to introduce a change in policy parameters, they should consider the signal effect and release it predictably, for example, periodic adjustments with proper announcements to smooth the impact on environmental innovation. Besides, since companies and market participants learn the political signals over time, firms may learn to react negatively in the future after the witness of unpredictable policy-making.

The remainder of this study is organized as follows. Section 2 reviews the relevant literature. Section 3 reviews the construction of the TVP-VAR-SV model and the measurement of environmental policy uncertainty, network public opinion, and green innovation indicators. Section 4 uses the Markov chain Monte Carlo method to estimate the TVP-VAR-SV model and analyzes the impulse response results. Section 5 concludes.

2. Literature review

In this section, we briefly review the theoretical and empirical research on environmental policy uncertainty, network public opinion, and green innovation and their interrelated relationships.

2.1. Environmental policy uncertainty and green innovation

The transformation and application of innovations need a fertile policy-supporting environment that directly fosters the integration degree of innovation and economic development (Sirmon et al., 2007). Recent literature reveals that stimulus instruments can drive innovation growth in the early stage, but the positive effect may have ceilings. In vast policy measures, voluntary policies have a relatively persistent positive impact (Zhu et al., 2021; Li et al., 2021). The empirical results show that market-incentivized environmental regulation instruments have an inverted U-shaped relationship with innovation output, while voluntary environmental regulation produces a significant positive impact. Second, the U-shaped relationship between market-based environmental regulation and innovation output becomes more pronounced when economic policy uncertainty is high. Uncertainty in economic policies can impede firms' willingness to long-term planning and commitment while withdrawing investment decisions and scheduled R&D (Kyaw, 2022). When the environmental policy changes and the external business environment fluctuates remarkably, high uncertainty affects enterprises' investment decision-making and financial conditions (Song et al., 2018).

In other words, policy uncertainty can negatively impact firms' innovation processing. Although the promulgation of environmental policies promotes the industry structure to transform towards eco-friendliness, they also increase the uncertainty of environmental policies (Marcus,1981; Simmons et al., 2018). Environmental policy uncertainty is an integral part of uncertainty, which changes the external business environment of companies and redirects their decision-making and business model (Li et al., 2021). Kyaw (2022) also finds that uncertainty in policies and regulations debilitates the efforts in combating climate change and promoting environmental sustainability. Environmental policy is designed to drive the industry structure to transform towards eco-friendliness and sustainability, but uncertainties may dent intended economic performance. Specifically, environmental policy uncertainty may lead to short-sighted behaviors and speculation because it may raise practitioners' attention on short-term investments for the imperative requirements rather than long-term strategic planning for fostering green capacities, thereby waning the policy efficiency and flexibility (Teeter and Sandberg, 2017).

The conventional wisdom argues that environmental regulation will increase the burden on practitioners at the corporate level (Ambec and Lanoie, 2008). However, more stringent, well-designed environmental regulations can trigger innovation, partially or wholly offset the complying costs (Porter and Van der Linde, 1995). Different policy methods may result in efficiency divergence for pro-innovation; flexible regulatory policies, for example, are preferable to prescriptive regulation since companies are encouraged to explore indigenous innovation and technological advancement in this situation. Moreover, market-based instruments, such as carbon taxes, cap-and-trade emissions credits, and industrial standardization, are conducive to innovation growth because those allow companies to explore the most cost-effective business strategy and technological solution (Barrett, 1991; Porter, 1996; Calel, 2020).

2.2. Environmental policy uncertainty and network public opinion

Network public opinion can be evaluated to predict the price trend and simulate the development in certain research areas. Investors' emotions change depending on their portfolio attitude and current investment results, and the investment decision can be derived from their emotions. In predicting stock prices, the activity of online investment boards could be closely related to stock trading volume, price volatility, and abnormal return, even if they are used for successful attempts of insider trading and price manipulation (Luo et al., 2016). Given the development of virtual interactive activities and discussions in an online forum, there is an increasing demand for comprehensive data analysis to extract such valuable data for decision-making. In recent literature, scholars increasingly use sentiment mining techniques to assess network public opinion.

Sentiment mining is a natural language technique for analyzing grammatical structures, individual emotions, and opinions in text format. Through computational linguistics, sentiment mining can be applied to many academic fields, such as analyzing social network content and public opinion and determining the lexicon with specific emotional polarity (Vinodhini and Chandrasekaran, 2012; Chen M and Chen T, 2019). With machine automation and manual correction support, sentiment analysis can monitor, capture, refine, analyze, and integrate online flashpoints from various channels based on network public opinion and investor sentiment. Sentiment mining can discover and extract embedded emotions and potential semantic attitudes behind online social interactions. The sentiment is based on personal feelings and contextualized attitudes from various sources such as posted news, comments in investment forums, and investment recommendations (Chen M and Chen T, 2019; Bahrini and Filfilan, 2020).

Baker et al. (2016) use a weighted average of the newspaper reference frequency, tax regulation expiration rates, and disagreement about inflation and government spending to develop the economic policy uncertainty index (Baker et al., 2016). By comparing it to various alternative measures, this index is a suitable proxy for actual economic policy uncertainty because its swings correspond to important political and social events. The sentiment-based index provides a continuous and quantifiable tracking of policy uncertainty over time. This allows the effects of policy uncertainty to be studied in a time series rather than event studies with short time windows, which may pose problems because the event of interest may not fully resolve uncertainty due to policy changes (Brogaard and Detzel, 2015). Another application of news-based sentiment examines the impact of investor sentiment on stock prices using the daily volume of Internet searches related to household economic concerns. This sentiment measure is useful for predicting short-term return reversals and volatility increases. Mutual fund flows (Da et al., 2015).

2.3. Theoretical foundation for uncertainty-sentiment-innovation channel

Based on the above literature, we gain an understanding of the pair relationships between policy uncertainty and innovation, i.e., political uncertainty and network public opinion on the web (i.e., sentiment), and an additional understanding of the interaction between sentiment and innovation will rationalize the theoretical basis of the uncertainty-sentiment-innovation channel.

Using time-varying measures of sentiment, researchers have discovered a spillover channel of sentiment in which market sentiment affects R&D investment by influencing management sentiment, i.e., management's perception of the return on R&D investment and willingness to launch innovative projects. (Dang and Xu, 2018). The core of technological R&D is the human being's innovative activities in science and technology. R&D investments represent investments for innovation, while capital expenditure is an investment in fixed assets. However, both types of investment are associated with a lag in returns. Moreover, capital expenditures result in a productive operation, while R&D investments may or may not result in a positive outcome. Thus, R&D investments are associated with potential positive performance results in the distant future, while capital expenditures produce tangible outcomes in a relatively short time horizon. Moreover, high market sentiment stimulates the productivity of R&D activities in creating patent portfolios.

When investors are uncertainty averse, the choice of innovation intensity depends on the degree of investor sentiment. High-level market-wide investment sentiment has a positive relationship with companies' innovation activity, regardless of the high uncertainty and intangible nature of innovation outcomes (Brown et al., 2013; Dang and Xu, 2018). Investors with uncertainty aversion have strategic complementarities and hedging behaviors against uncertainty, and these generate endogenous beliefs and investment sentiments, leading to waves of innovation waves (Dicks and Fulghieri, 2021). The emergence of more innovative companies boosts investor confidence and thus enhances equity valuations. Similarly, the convergence of technologies endogenously leads to improved market sentiment and, thus, higher valuations. For example, a positive technological shock to LinkedIn may boost Uber's performance, although there is no clear correlation between the two. Competition diminishes the benefits of innovation waves making overall waves less attractive. However, the sentiment effect is mitigated by the negative impact of competition on the ultimate benefits of innovation, which negatively affects valuations. (Dicks and Fulghieri, 2021).

Aramonte and Carl (2018) document a positive effect of investor sentiment on innovation. Some empirical data suggest that uncertainty positively impacts R&D expenditures (Stein and Stone, 2013). R&D investment is crucial for environmental innovation but extremely susceptible to uncertainty due to the long time horizon and associated investment risks. In addition, environmental innovations are subject to some policy uncertainty. For example, new evidence catches on as scientists and researchers draw attention to certain environmental damages that were previously ignored. In response, regulations change when the benefits of regulatory interventions outweigh the costs of nonintervention, so policies change as policymakers gain new information and motivations (Kalamova et al., 2012). Investment in R&D, and consequently environmental innovation, is highly influenced by uncertainty. Firms may postpone investment decisions when uncertainty looms, which can halt and reverse firms' investments in innovative activities. The delay effect suggests that firms' environmental innovations exhibit certain patterns when uncertainty is imminent.

3. Model and data

3.1. TVP-VAR-SV model

The potential time-variability effects of EPU on GI and EPU itself have placed stringent requirements on the analytical framework. Traditional quantitative analysis methods such as VAR and SVAR are suitable for studies where the relationship between variables remains constant. However, in the case of EPU, which comes with time-varying characteristics, the traditional methods are likely to miss the critical time-varying information. Given this, the TVP-VAR-SV model is chosen in this paper to study the time-varying characteristics of the effect of EPU on GI.

The time-varying parameter structural vector autoregressive with stochastic volatility (TVP-VAR-SV) model is derived from the vector autoregressive (VAR) model, which can estimate the dynamic evolution of the endogenous joint variables without any prior constraints (Feng et al., 2021). But VAR models can only portray linear relationships among variables, and the estimated parameters are constant. Scholars expand it to a nonlinear and time-varying parameter model, which can accurately characterize the time-varying characteristics and non-linear relationships among variables. To evaluate the impact of green innovation on high-quality development, this paper embeds time-varying features in the traditional VAR model. It investigates the time-varying relationships between environmental policy uncertainty, network public opinion, and green innovation through the TVP-VAR-SV model.

First, we consider a simple structural vector autoregressive (SVAR) model:

$$Ay_t = F_1 y_{t-1} + \cdots + F_p y_{t-p} + \varepsilon_t \tag{1}$$

where y_t is a k dimensional column vector composed of endogenous variables, A is a $k \times k$ lower triangular matrix in the following special form:

$$A = \begin{bmatrix} 1 & 0 & \cdots & 0 \\ a_{21} & 1 & \cdots & \vdots \\ \vdots & \cdots & \ddots & 0 \\ a_{k1} & \cdots & \cdots & 1 \end{bmatrix} \tag{2}$$

F_i represents the dimensional matrix with the size $k \times k$ composed of the lag term coefficients, u_t is a k dimensional random perturbation term, and $\varepsilon_t \sim N(0, \Sigma)$, where

$$\Sigma = \begin{bmatrix} \sigma_1 & 0 & \cdots & 0 \\ 0 & \sigma_2 & \cdots & \vdots \\ \vdots & \cdots & \ddots & 0 \\ 0 & \cdots & \cdots & \sigma_k \end{bmatrix} \tag{3}$$

The above model can be further simplified as follows:

$$y_t = B_1 y_{t-1} + \cdots + B_p y_{t-p} + A^{-1}\Sigma e_t \tag{4}$$

where $B_i = A^{-1}F_i, i = 1, \cdots, p$, $e_t \sim N(0, I_k)$ is a random perturbed variable vector, and each element of B_i are stacked in columns to form a dimension vector called β. The model can be further simplified as follows:

$$y_t = X_t\beta + A^{-1}\Sigma e_t, X_t = I_t \otimes (y_{t-1}, \cdots, y_{t-p}) \tag{5}$$

where $\otimes$ represents the Kronecker product, the relevant parameters are fixed values without time variability. Primiceri (2005) proposed a time-varying parameter vector autoregressive model, assuming that the parameters can vary to identify possible time-varying structures between economic variables. The above model is further transformed into:

$$y_t = X_t\beta_t + A_t^{-1}\Sigma_t e_t, t = p+1, \cdots, n \tag{6}$$

This model is TVP-VAR-SV, a time-varying structure vector autoregression model with random volatility. Following Primiceri (2005), let

$$a_t = (a_{21}, a_{31}, a_{32}, a_{41} \ldots, a_{k,k-1})'$$

denote the entries of A below the main diagonal.

Assume that the parameters in Equation (3) obey the following first-order random walk:

$$\beta_{t+1} = \beta_t + u_{\beta_t}, a_{t+1} = a_t + u_{a_t}, h_{t+1} = h_t + u_{h_t} \tag{7}$$

where $h_t = (h_{1t}, \ldots, h_{kt})'$, $h_{jt} = \log \sigma_{jt}^2$, $j = 1, \ldots, k, t = p+1, \ldots, n$,with

$$\begin{bmatrix} \varepsilon_t \\ u_{\beta_t} \\ u_{a_t} \\ u_{h_t} \end{bmatrix} \sim N\left[0, \begin{bmatrix} I & 0 & 0 & 0 \\ 0 & \Sigma_\beta & 0 & 0 \\ 0 & 0 & \Sigma_a & 0 \\ 0 & 0 & 0 & \Sigma_h \end{bmatrix}\right] \tag{8}$$

However, since the above TVP-VAR model with stochastic volatility contains many parameters, and its likelihood function is complicated, following Nakajima (2011), we let $\Sigma_\beta, \Sigma_a, \Sigma_h$ be diagonal matrices in the form of Equation (3) and assume that $(\Sigma_\beta)_i^{-2} \sim \Gamma(40, 0.02)$, $(\Sigma_a)_i^{-2} \sim \Gamma(4, 0.02)$ and $(\Sigma_h)_i^{-2} \sim \Gamma(4, 0.02)$, where $(\Sigma_\beta)_i$ is the i^{th} entry on the main diagonal of Σ_β, and similarly for $(\Sigma_a)_i$ and $(\Sigma_h)_i$. We use the Markov chain Monte Carlo (MCMC) method to estimate the model parameters. Readers are referred to Nakajima (2011) for more details.

Table 1. Keywords of chinese environmental Policy Uncertainty Index.

Standard	Keywords
Environmental	Environment / Conservation / Environmental Protection
	Environmental / Regulation / Pollution Prevention
Uncertainty	Uncertainty / Unclear Volatile / Oscillating / Turbulent
	Unstable/Unspecified/Uncertain/Unclear/Unclear
Policy	Policy / System/Institution/Strategy / Measures / Regulation
	Politics / Governance / Prevention / Regulation / Government
	Political Committee / State Council / People's Congress / Central Government
	State President / General Secretary / National Leader / Premier
	Environmental Tax / Environmental Protection Tax
	Ministry of Ecology and Environmental / Environmental Protection Department / Environmental Protection Bureau

3.2. *Data*

3.2.1. Environmental Policy Uncertainty

Most current studies on policy uncertainty indices use the Economic Policy Uncertainty Index, but only a few studies of environmental policy uncertainty involve China's facts (Baker et al., 2016; Huang et al., 2020). This study establishes the environmental policy uncertainty index similar to Huang et al. (2020) and Wang et al. (2021). The core component of the environmental policy uncertainty index is the news index, which is compiled by keyword searches of specified news media reports. It reflects the proportion of articles with the terms - "environment", "uncertainty" and "policy" in the monthly articles published in People's Daily, Beijing Youth Daily, Guangzhou Daily, etc. The three terms are shown in Table 1, and the index is subdivided according to the relevant policy categories, which can better reflect the impact of different environmental policies. Let EPU_i denote the monthly environmental policy uncertainty index in the i^{th} month,

$$EPU_i = \frac{AVE|C_{Eij} - \frac{\mu}{\sigma}|}{AVE|C_{Eij} \cap C_{Uij} \cap C_{Pij} - \frac{\mu}{\sigma}|} \tag{9}$$

where AVE in the above is the mean value taking over the j^{th} newspaper category, C_{Eij}, C_{Uij}, and C_{Pij} are the frequency of "Environment", "Uncertainty", "Policy" in the i^{th} month of the j^{th} newspaper category, respectively; $C_{Eij} \cap C_{Uij} \cap C_{Pij}$ indicates the frequency of articles in which the three keywords appear together; μ and σ denote the mean and standard deviation of all data, respectively.

3.2.2. Network public opinion

In this paper, the network public opinion index is constructed through comment data, which is sourced from Dongfang Fortune, the most influential stock network forum in the Chinese stock market with the most significant number of visits, and the company's post comments are used as a proxy variable for network public opinion. The comment data are collected through web crawler technology, including post titles, clicks, replies, usernames, posting times, and content. We now describe the process of text ming in more detail.

Firstly, We cleaned the comment data, mainly by removing ad posts, duplicate posts, and duplicate words and sentences. That is, the comments with "recommendation", "unveiling," "stock recommendation," and other content in the posted titles will be eliminated. The comments with the posted username comments with content such as "Focus on Shanghai-Shenzhen-Hong Kong" and "Financial Commentary" will be removed because the above posts are all advertising posts. Otherwise, the measurement efficiency of network public opinion will decrease. Then, the same sentences and words for posts with duplicate titles and contents of the same user on the same day are deleted.

Secondly, We perform text splitting on the data-cleansed comment data. Since the fundamental constituents of Chinese utterances are Chinese characters rather than words, jieba splitting is used to split each comment into a collection of phrases. For words contained in the jieba lexicon, the combination is cut based on word frequency size. And for the words not in the lexicon, the Viterbi algorithm calculates the maximum probability path of their subscripts.

Finally, we construct online opinion indicators based on the sentiment lexicon. Since the word-sorting effect is closely related to the merits of the lexicon, we add the jieba lexicon, the Sogou financial lexicon, stock market terms, and common stock bar terms based on the financial dictionary and positive and negative sentiment word classification constructed by Wang and Wu (2015) and You et al. (2018). To correctly cut the stock market terms, we increase the word frequency of the added words. According to the positive and negative sentiment word classification for matching processing and corrected according to the word frequency of the article's word classification results, the financial sentiment thesaurus was finally compiled (including 11577 negative words and 10404 positive words). Deactivated words appear frequently but have no practical significance for text analysis, such as "de", "le", "bi ru", "bing qie ", etc. The method used to deactivate words in this paper is to build a deactivation word list and remove them by matching.

Network public opinion can be divided into three categories: positive, neutral, and negative public statements, and the numbers of positive, neutral, and negative words are counted for each comment after word separation. Then the weights of positive, negative, and neutral sentiment words are set to 1, -1, and 0, respectively, as in Antweiler and Frank 2004; Wang et al., 2015. If a negative word exists before the sentiment word, the sentiment tendency is changed, and the sentiment weight of the comment is set to -1. When there are degree adverbs such as "too" and "incomparable," the weight of the intense degree word is set to 2. When there are weak words such as "just" and "somewhat," the weight is set to 0.5.

The network public opinion index metric is defined as follows:

$$B_t = M_t^{pos} + M_t^{neu} + M_t^{neg}, \tag{10}$$

where

$$M_t^c = \sum_{i \in D(t)} w_i x_i \tag{11}$$

is the sum of weighted quantities of comments belonging to $\{pos, neu, neg\}$ in month t, $D(t)$ represents the entire time set, x_i represents positive, neutral and negative terms for each comment, w_i is the weight of each comment, *pos*, *neu*, and *neg* refer to positive, neutral, and negative sentiment words, respectively.

3.2.3. Green Innovation

This paper uses the number of green patent output per 10,000 R&D personnel to measure green innovation. Many scholars choose the green total factor productivity index to measure green innovation, which mainly measures the comprehensive impact of technological advancement. Still, the level of regional innovation is hard to illustrate. Because the connotation of a patent is closely related to innovation and its authorization criteria are objective and relatively stable, the number of patents granted could be a better measure of innovation output. This study chooses the number of green patents granted to measure green innovation. The data are obtained from the invention patents published by the State Intellectual Property Office. More specifically, according to the World Intellectual Property Organization (WIPO), the type of green patent and the corresponding classification number are classified into seven categories: transportation, waste management, energy conservation, etc. The green patents are screened against the data published by the State Intellectual Property Office according to the classification codes and division types to obtain green patent data (including green invention patents as well as green utility model patents), and the total green patent data is used to represent the degree of green innovation in the market. Based on the selection instructions for the above variables, this paper uses the data of listed companies in China between January 2010 and December 2019 as an institutional sample to study the time-varying relationship between environmental policy uncertainty, network public opinion, and green innovation.

4. Empirical results and discussion

4.1. Stationarity test

Referring to the estimation method of Nakajima (2011), the lag order is set to 1 according to the Bayes information criteria (BIC) of the VAR model, the sampling number of MCMC is set to 10,000, and the burn-in sampling is 1000. To avoid pseudo-regression, the Augmented Dickey-Fuller (ADF) test is employed to examine the stationarity of each variable, and the test results are shown in Table 2.

The test results listed in Table 2 show that the ADF test statistics for Environmental Policy Uncertainty Index (EPU), Network Public Opinion (NPO), and Green Innovation (GI) are all less than the critical value at the 1% significance level, indicating that the original hypothesis of the existence of unit root is rejected. Thus, each variable is stationary and can be used in the TVP-VAR-SV model.

Table 2. Unit root test of variables.

Variables	ADF test value	1% threshold	5% threshold	10% threshold	Stationarity
EPU	−5.9041	−3.4861	−2.8859	−2.5799	Stationary
NPO	−5.6064	−3.4861	−2.8859	−2.5799	Stationary
GI	−9.6143	−3.4861	−2.8859	−2.5799	Stationary

4.2. Parameter estimation

The MCMC method is used to estimate the parameters of the TVP-VAR-SV model, and the results are listed in Table 3.

From Table 3, it can be found that: the mean values of the posterior distributions of the parameter estimates are all within the 95% confidence interval, and the Geweke values are all less than the 5% critical value (1.96), indicating that the convergence of the parameter estimates to the posterior distribution cannot be rejected. The values of invalidation factors (IF's) (listed in the last column in Table 3) are all less than 100, so the TVP-VAR-SV model with a lag of order one can produce valid samples.

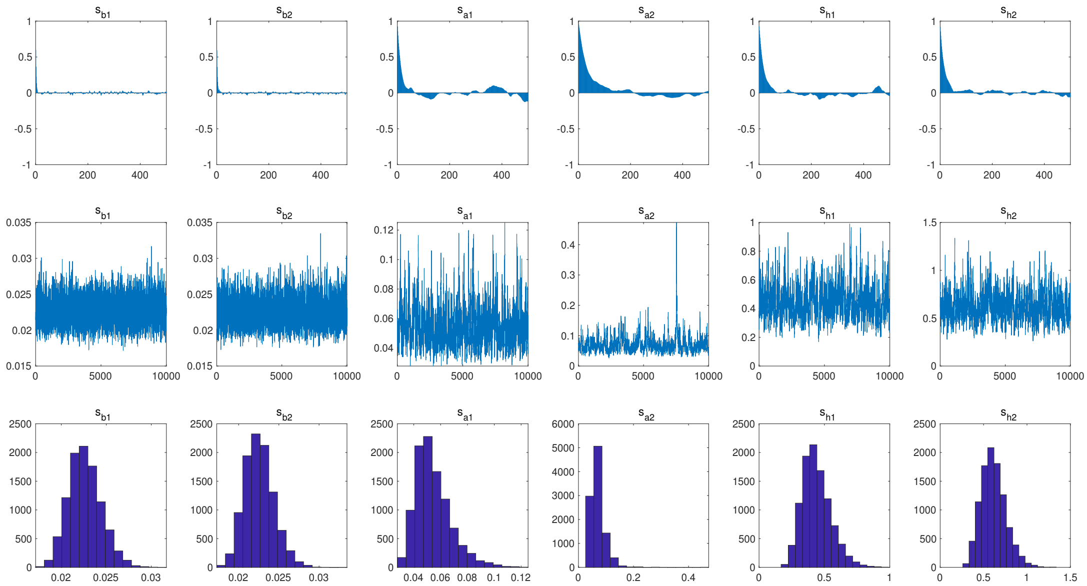

Figure 1. Sampling results of TVP-VAR-SV model.

Figure 1 exhibits the pairwise relationships among the sample correlation coefficient, the fetching path, and the posterior distribution density function from top to bottom, respectively. From Figure 1, one can observe the following facts: (1) the sample correlation coefficient is the maximum value at the beginning, and then starts to drop sharply and finally converges around 0, which indicates that the MCMC method can eliminate the correlation generated by the samples in the estimation process; (2) the fetching path fluctuates up and down around a specific value, which indicates that the fetching path is more stable; (3) the posterior density distribution functions all obey normal distribution, which is more concentrated; that is, it indicates that the MCMC method can effectively generate uncorrelated samples. Combining Table 3 and Figure 1, we find that the MCMC method is robust and can be used in the TVP-VAR-SV model for empirical analysis.

Table 3. Parameter estimation results

Parameters	Mean	S.D.	95% Confidence interval	Geweke value	value of IF
$sb1$	0.0224	0.0009	[0.0208,0.0243]	0.839	1.99
$sb2$	0.0224	0.0009	[0.0208,0.0242]	0.090	1.48
$sa1$	0.0567	0.0141	[0.0355,0.0912]	0.397	28.87
$sa2$	0.0716	0.0240	[0.0398,0.1326]	0.004	52.17
$sh1$	0.4393	0.1064	[0.2672,0.6849]	0.025	27.87
$sh2$	0.6075	0.1415	[0.3783,0.9314]	0.407	27.76

4.3. Impulse response analysis

Compared with the pulse response graph of the traditional VAR model, the pulse response graph of the TVP-VAR-SV model can analyze not only the dynamic evolution relationships among variables but also the pulse response analysis of different lead times and specific points in time by exploring the dynamic evolution relationship among variables at different angles. Considering the time-sensitive characteristics of green innovation, this paper selects the lags of 2, 5, and 8 issues. The pulse response of environmental policy uncertainty to network public opinion and green innovation and network public opinion to green innovation is time-varying. The pulse response graph trend of different lead times is similar. Still, other advanced period shocks' positive and negative directions will differ.

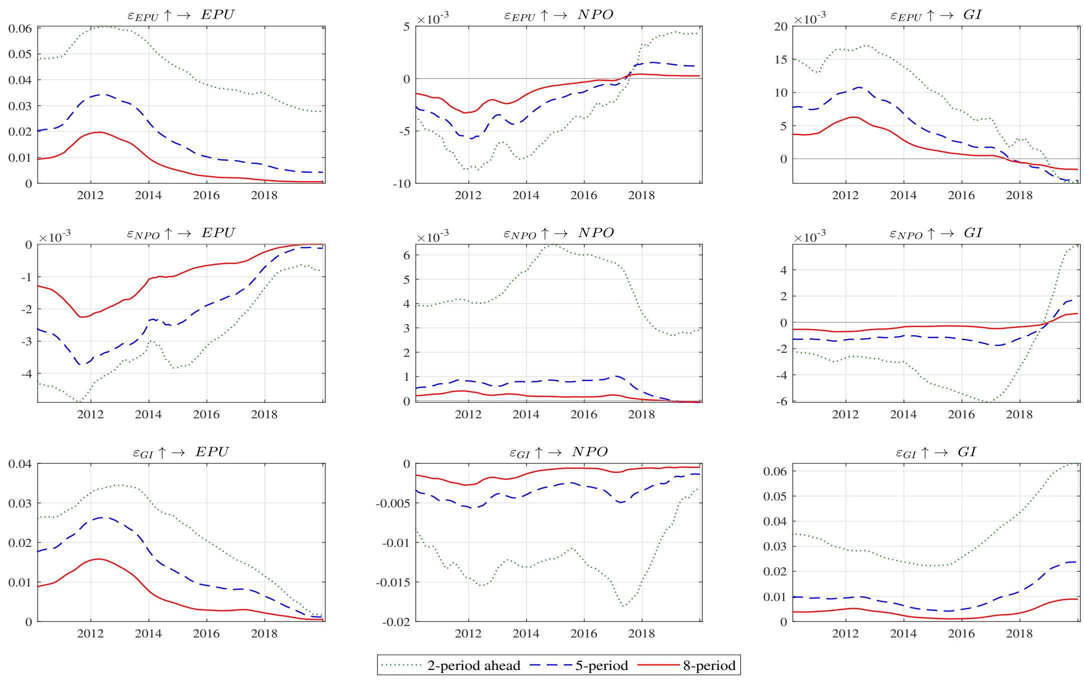

Figure 2. Equal-interval impulse response results among EPU, NPO, and GI.

From Figure 2, the green dotted line shows the impact of one variable, one standard deviation positive shock, on another variable two months later. The blue segment line and the solid red line indicate one variable's one standard deviation positive shock effect on another variable after five months and eight weeks, respectively. It can be found that the impulse responses of EPU to NPO and GI, as well as NPO to GI, are time-varying, and the impulse response plots follow roughly similar trends for different lead times. The specific performance is as follows.

The impulse response value of EPU to NPO ($\epsilon_{EPU\uparrow} \rightarrow NPO$) starts to be negative at the beginning and then gradually decreases, and the shock effect varies for different lags. Among them, the negative impacts of EPU on NPO is the largest at lag 2. It indicates that environmental policies negatively impact NPO and cause a rise in public opinion in the short term. However, the impact effect decreases as the advance period of the shock becomes larger, indicating that online public opinion has short-term memory for policy shocks.

There is some variation in the effect of EPU on GI($\epsilon_{EPU\uparrow} \rightarrow GI$), and the degree of impulse response varies across advance periods. The impulse responses for advance periods 2, 5, and 8 are all positive at the beginning, indicating that changes in EPU at this time may promote positive fluctuations in corporate green innovation and may cause concern about policy uncertainty, thus encouraging green innovation. After 2012, the impulse response values of GI showed a sharp decline, which may be explained by the fact that two years after the introduction of environmental policies, on the one hand, firms have already catered to the relevant environmental policies introduced by the state through sufficient green innovations. On the other hand, the uncertainty of the environmental policy is diminishing over time, leading to a gradual decrease in the efficiency of green innovation of enterprises. Besides, from Figure 2, we can also find that the impact of EPU on GI is more obvious two periods in advance, and the direction and degree of its impact are similar as time goes on.

From the impulse response plot of NPO to GI ($\epsilon_{NPO\uparrow} \rightarrow GI$), we can find that the impact of online public opinion will have a negative impact on corporate green innovation and its degree of impact is consistently negative, i.e., online public opinion will increase the degree of corporate green innovation, reflecting the current degree of importance of corporate development to the online public opinion. Notably, the degree of impact is greater for 2 periods in advance compared to 5 and 8 periods in advance, indicating that enterprises will be more able to promote green innovation when they pay more attention to immediate online public opinion. The results also provide evidence of the relationship between online public opinion and enterprise behavior.

4.4. Impulse response analysis at different times

Figure 3 depicts the pulse response formed by impact at different points in the TVP-VAR-SV model, compared to January 2012, July 2016, and December 2018, which were randomly selected.

In terms of environmental protection legislation construction, the Environmental Protection Law, known as the toughest in history, was amended and passed at the eighth meeting of the Standing Committee of the 12th National People's Congress in 2014 and came into effect on January 1, 2015. The newly revised Environmental Protection Law further strengthens the responsibility of the government and enterprises for environmental governance, and the punishment for environmental violations has been greatly enhanced, highlighting China's determination to solve the current severe environmental pollution problems. Therefore, this paper takes the two acts as the background and selects the Environmental Protection Law before its introduction (2012.1), after its introduction (2016.7), and two years after its introduction (2018.12) as three impulse response time points to obtain the impulse response results.

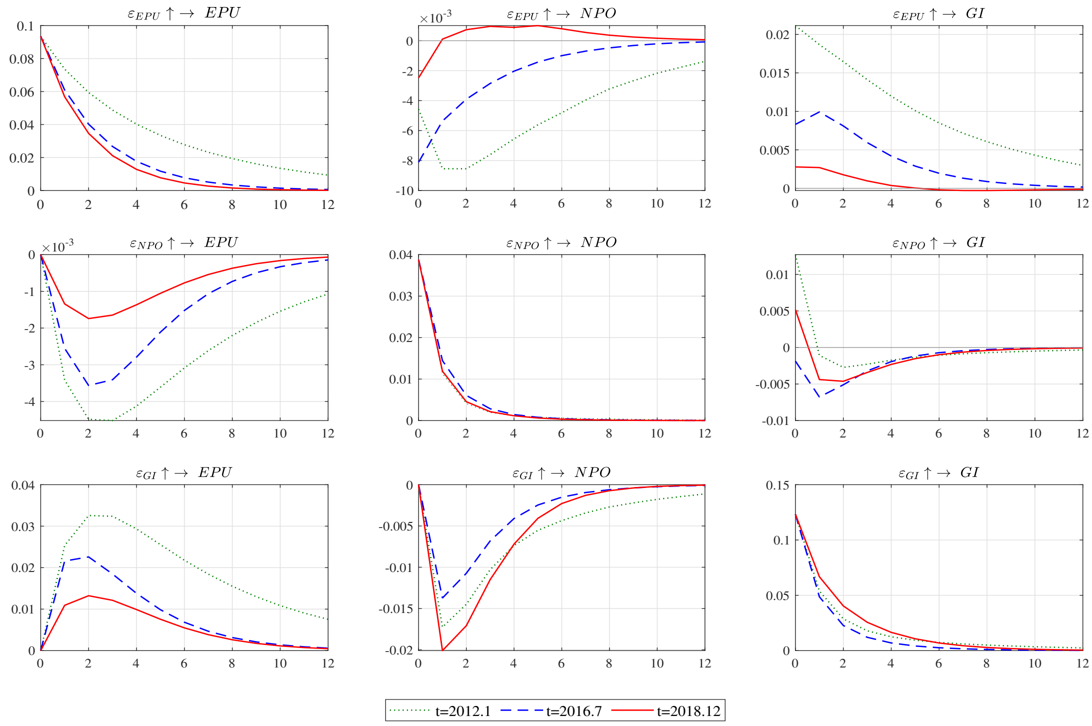

Figure 3. Time-point impulse response results between the EPU, NPO, and GI.

In the impulse response plot of EPU on NPO ($\epsilon_{EPU\uparrow} \rightarrow NPO$), there are differences in the shocks, and their impulse response changes at different time points. It can be found that before the EPU was introduced, and the EPU did not have a large negative impact on NPO. Still, with the introduction of the policy, its negative shock becomes larger over time and the impulse response value of the EPU on NPO peaks in period 2. Since EPU will be gradually released by market sentiment, its impulse response will gradually become smaller. After the introduction of EPU, there is a significant negative impact of EPU on NPO, indicating that network sentiment will be disturbed by environmental policies, and this negative impact will gradually decrease as constantly digested by the market, shrinking to 0 by period 12. In December 2018, the impulse response impact of EPU on NPO starts as negative, then gradually becomes positive, and then gradually converges to 0. from the three-time points, it can be seen that there is a negative shock of EPU to NPO. Still, this shock gradually converges over time, reflecting the process of gradual acceptance of environmental policy by market sentiment.

In the impulse response plot of EPU on GI ($\epsilon_{EPU\uparrow} \rightarrow GI$), there are some differences in the shocks, and their impulse response changes at different time points. A significant positive impact of EPU on GI before the introduction of the Environmental Protection Law can be found, i.e., the change in environmental policy will promote greater green innovation by firms. After the introduction of the Environmental Protection Law in July 2016, the magnitude of this positive impact became smaller compared to the pre-introduction, probably because enterprises have a clearer perception after the law's introduction. They will be more aware of how to make green innovations to respond to the

Environmental Protection Law instead of blindly innovating before the introduction, so the magnitude of this impact becomes lower. In 2018 The magnitude of this shock became lower but more pronounced in December 2018 as companies fully absorbed the challenges of environmental policy uncertainty. Hence, they only need to continue innovating green to steadily adapt to the current policy.

In the impulse response plot of NPO on GI ($\epsilon_{NPO\uparrow} \to GI$), there are small differences in the shocks, and their impulse response changes at different time points. It can be seen that there was a significant positive impact of NPO on GI before the introduction of the Environmental Protection Law, i.e., it is the rise of NPO that will lead companies to make green innovations and thus cater to the impact of public opinion. This impact will become negative after the first period, indicating that the impact of public opinion is only transient. Companies circumvent the impact caused by public opinion by making temporary innovations. After the introduction of Environmental Protection, NPO has had a negative impact on GI. This impact reaches its maximum in period 1, probably because enterprises have already started to generate green innovations after implementing the policy. The impact of online public opinion on green innovation is diluted by this effect, resulting in its impact effect in a negative direction. And after December 2018, with the radiation effect of the policy implementation gradually weakening, enterprises' green innovation response to online public opinion gradually returned to the level before the policy implementation.

5. Conclusions

This paper uses text mining to establish an environmental policy uncertainty index and a network public opinion index. We consider the time-varying characteristics of environmental policy uncertainty, network public opinion, and green innovation. The TVP-VAR-SV model with random fluctuations was used to analyze the dynamic evolution relationships among the above three factors. It is found that the pairwise relationships among the environmental policy uncertainty, the network public opinion, and the green innovation are not unique, and it shows different performance under different conditions, i.e., the linkage relationships among the three change over time. In contrast to conventional wisdom, the interactions between environmental policy uncertainty, the network public opinion, and green innovation are time-varying and complex, and the following findings are drawn. First, the fluctuations of environmental policy uncertainty, network public opinion, and green innovation have prominent time-varying characteristics. These three variables interact with each other, and their influence relationships are also time-varying. Second, there are direct and indirect channels for the impact of environmental policy uncertainty on green innovation; that is, environmental policy uncertainty can affect green innovation by influencing network public opinion. Third, the impulse response plots for different lead times at equal intervals indicate that both suppressive and facilitative effects exist on the environmental policy uncertainty to network public opinion and network public opinion to green innovation. Fourth, the impulse response plots at different time points show that the direction and the degree of impulse responses among variables differ in the context of environmental policy shocks at different time points. Based on empirical results, we suggest companies develop managerial skills in monitoring and evaluating the policy dynamics and designing suitable R&D strategies. Likewise, policymakers should alleviate the policy uncertainty level, release proper announcements, and release changes more predictably to encourage green innovation.

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Conflict of interest

All authors declare no conflicts of interest in this paper.

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