Environmental Research Communications

PAPER

Prediction of Post-COVID-19 economic and environmental policy and recovery based on recurrent neural network and long short-term memory network

Hui Hu1,2,7,*, Shuaizhou Xiong1, Yi Chen2,7, Lin Ye3,*, Shuliang Zhao4,*, Kun Qian5 and Michael C De Domenici6

1 Economic Development Research Centre, Wuhan University, People’s Republic of China
2 School of Economics and Management, Wuhan University, People’s Republic of China
3 Center for Cultural Industry Research, Central China Normal University, People’s Republic of China
4 University of Science and Technology of China, People’s Republic of China
5 School of Mathematics and Physics, China University of Geosciences(Wuhan), People’s Republic of China
6 Greenwich Business School, University of Greenwich, United Kingdom
7 These authors contributed equally.

* Authors to whom any correspondence should be addressed.
E-mail: hui.hu@whu.edu.cn, yelinlin@ccnu.edu.cn and shulz@ustc.edu.cn

Keywords: recurrent neural network, long short-term memory, time series prediction, post-COVID-19, global economic-and-environmental policy uncertainty, recovery, economic-and-environmental policy

Abstract

COVID-19 has brought significant impacts on the global economy and environment. The Global Economic-and-environmental Policy Uncertainty (GEPU) index is a critical indicator to measure the uncertainty of global economic policies. Its prediction provides evidence for the good prospect of global economic and environmental policy and recovery. This is the first study using the monthly data of GEPU from January 1997 to January 2022 to predict the GEPU index after the COVID-19 pandemic. Both Recurrent Neural Network (RNN) and Long Short-Term Memory (LSTM) models have been adopted to predict the GEPU. In general, the RNN outperforms the LSTM networks, and most results suggest that the GEPU index will remain stable or decline in the coming year. A few results point to the possibility of a short-term increase in GEPU, but still far from its two peaks during the first year of the COVID-19 pandemic. This forecast confirms that the impact of the epidemic on global economic and environmental policy will continue to wane. Lower economic and environmental policy uncertainty facilitates global economic and environmental recovery. Economic recovery brings more opportunities and a stable macroeconomic environment, which is a positive sign for both investors and businesses. Meanwhile, for the ecological environment, the declining GEPU index marks a gradual reduction in the direct impact of policy uncertainty on sustainable development, but the indirect environmental impact of uncertainty may remain in the long run. Our prediction also provides a reference for subsequent policy formulation and related research.

List of abbreviations

Economic-and-environmental Policy Uncertainty (EPU)
Global Economic-and-environmental Policy Uncertainty (GEPU)
Recurrent Neural Network (RNN)
Long Short-Term Memory (LSTM)

1. Introduction

Uncertainty in economic policies affects the macroeconomic environment, social economy, and the production and operation of enterprises. Especially since the outbreak of COVID-19, repeated outbreaks around the world
have been overlaid with economic downward pressure. Under such circumstances, economic-and-environmental policy formulation in various regions has faced more uncertainties and new challenges. Uncertainty in economic policies not only affects the speed and quality of global economic development but also poses a challenge to the stable operation of the global economic system. Meanwhile, the instability of economic policies not only affects economic development but also hurts the environment - both ecological and social - which cannot be ignored.

For the ecological environment, uncertainty in economic policies may induce ecological damage (Zahra and Badeeb 2022), increase energy consumption (Danish et al 2020), hinder decarbonization (Zakari et al 2021), and discourage sustainable ecological development (Adams et al 2020). In turn, environmental degradation harms socioeconomic development, especially during the COVID-19 pandemic, which caused more deaths (Magazzino et al 2020, Mele and Magazzino 2021). This brings more uncertainty to the development of economic policies. At present, the COVID-19 pandemic continues to rage globally and may affect the stimulating effect of economic incentives on economic recovery (Xu et al 2022). The pandemic, economic-and-environmental policy uncertainty, and environmental degradation co-exist and interact. Quantification and prediction of economic-and-environmental policy uncertainty can help governments, firms, and stakeholders prepare for the arrival of uncertainty in advance. For the social environment, economic-and-environmental policy instability may lead to lower consumption and investment dynamics and an imbalance in socio-economic development (Guedhami et al 2022).

To sum up, it is important for social-economic development, ecological sustainability, and policy planning to find methods to accurately measure and predict global economic-and-environmental policy uncertainty. The projections in this paper aim to reduce the impact of economic-and-environmental policy uncertainty on the social and ecological environment. And it also helps prevent the economy and environment from interacting in a vicious cycle. The purpose of this paper is to learn the changing patterns of global economic-and-environmental policy uncertainty in the past 25 years and predict the future trend of uncertainty through RNN and LSTM models. Economic-and-environmental policy uncertainty is influenced by multiple factors and is highly nonlinear. With this in mind, we innovatively use neural network techniques to solve the problem of predicting policy uncertainty. Our results can verify the unique advantages of neural networks for dealing with such nonlinear prediction problems. By predicting future uncertainty, we can provide development references and recommendations to governments, firms, investors, and other stakeholders, while providing feedback on the status of past economic-and-environmental policy implementation.

We refer to the economic-and-environmental policy uncertainty (EPU) index series, with data spanning from January 1997 to January 2021. By constructing LSTM and RNN models with different combinations of parameters, we learn and predict subsequent changes for this series. The economic-and-environmental policy uncertainty index is proposed by Baker et al (2016) and quantified mainly by the frequency of various keywords appearing in mainstream media and government platforms. The keywords used to quantify uncertainty are derived from the general level of society and the segmented economic areas. They extract articles containing at least one term from the following three categories: economic, policy and uncertainty. Among them, the economic segments cover various sections such as defense, taxation, and environmental regulation. In the environmental economy section, the EPU index is constructed with reference to energy policy, energy tax, carbon tax, cap and trade, cap and tax, drilling restrictions, offshore drilling, pollution controls, environmental restrictions, clean air act, clean water act, environmental protection agency, and other keywords related to the environmental field. Thus, while policy uncertainty affects the social and ecological environment, the EPU index itself partly reflects the stability of environmental economic policies.

Baker et al (2016) standardized the monthly EPU index of 20 countries including Australia, Brazil, Canada, Chile, China, France, Germany, Greece, India, Ireland, Italy, Japan, Mexico, Netherlands, Russia, South Korea, Spain, Sweden, United Kingdom, and the United States. After this, by weighting the EPU indices of each country or region by GDP, a composite indicator of global economic-and-environmental policy uncertainty, the GEPU indicator, can be obtained. The GEPU indicator used in this paper is calculated using the value of GDP adjusted for purchasing power parity. Since the EPU index was constructed, most of the related research has focused on the application of the EPU index. Through methods such as econometrics or machine learning, past studies have analyzed and discussed the economic, environmental and social impacts of such uncertainties. These studies have explained how economic-and-environmental policy uncertainty affects various aspects such as financial markets (Ashraf and Shen 2019), social production (Nilavongseng et al 2020), ecology (Ali et al 2022), and corporate responsibility (Ongsakul et al 2021). These studies often use the EPU index as the independent variable of the model, but few studies have focused on the changes in the EPU itself. The implementation of economic policies and the uncertainty therein are affected by complex macro-environmental factors and are highly nonlinear in nature. Therefore, it is difficult to predict them using traditional statistical methods. In this paper, we apply neural networks to forecast the EPU index series and complement the analysis of predicting the changes in EPU itself.
The present study makes three significant contributions. The first contribution is the focus of the GEPU index, which reflects the changes and development in global economic- and-environmental policy uncertainty over a certain period. It is significant for analyzing the stability of global economic development. However, due to the strong stochasticity of the GEPU, traditional time series forecasting methods (e.g., autoregressive integrated moving average model) face some challenges while predicting future index changes. There is little time-series forecast analysis of the GEPU related to COVID-19. Therefore, it leads to our second contribution that RNN and LSTM networks are adopted to forecast the development of the GEPU index, which fills the gap in time series forecasting of the GEPU index (Araujo 2020). This study makes the third contribution that we investigate and predict uncertainty of the policy related to social and ecological environment changes in the post-COVID-19 era. Most of the results predict that economic- and-environmental policy uncertainty will remain stable or decrease in the coming year, indicating a positive trend for future economic recovery. The fourth contribution is the inspiration for environmental governance. Economic- and-environmental policy uncertainty has implications for the ecological and social environment. Our study predicts the movement of the GEPU index in the post-epidemic era. It also reflects the magnitude of the direct impact of uncertainty on the environment. Also, we analyze the long-term ecological impacts of uncertainty caused by COVID-19 and make policy recommendations. Meanwhile, neural networks including LSTM and RNN are black-box models, which means it is difficult to figure out a specific path which affects the change of economic- and-environmental policy uncertainty in this paper. This is the major limitation of this paper, and should be continuously improved in subsequent studies by combining econometric models and other machine learning models.

The remainder of this paper proceeds as follows. Section 2 reviews the previous studies on the relationship between the GEPU index and other economic and environmental factors. Section 3 describes data and models. Section 4 presents the analysis results. Section 5 discusses the significance of the results. Section 6 concludes the study.

2. Literature review

2.1. EPU index and the application
In 2016, Baker et al (2016) constructed the GEPU index and the EPU index of major countries in the world. They conducted sentiment analysis on articles published in 10 major newspapers in the United States, and extracted articles containing at least one term from the following three categories: economic, policy and uncertainty. Monthly counts of standard media articles were scaled and normalized so that the EPU index could be quantified, and the relationship between the EPU index and the firm-level and overall investment and employment levels of the US economy was investigated. Besides, the policies related the EPU index involve economic, social, ecological and other environmental aspects.

Following the works of Baker et al (2016), many scholars have studied the impact of economic- and-environmental policy uncertainty on financial markets (Phan et al 2021). Research shows that EPU has a positive and significant impact on the fluctuation of crude oil output, but this impact is short-lived, with a decay cycle of about one year (Ma et al 2019). In terms of the exchange rate, Mei et al (2018) found that EPU plays a key role in explaining short-term and long-term exchange rates and can act as an indicator to improve the forecasting ability of macroeconomic models for the exchange rate. Chen et al (2020) proposed that the impact of EPU on China’s exchange rate showed asymmetry and heterogeneity in different markets. As for the interest rate, Ashraf and Shen (2019) proved that the uncertainty of the government’s economic- and-environmental policy is significantly positively related to the total interest rate of bank loans. Specifically, an increase of one standard deviation of EPU leads to an increase of 21.84 basis points in the average interest rate of total bank loans. They also speculate that the uncertainty of economic- and-environmental policy increases the loan price of banks by increasing the default risk of borrowers. Moreover, Yao and Sun (2018) used the Copula model to study the static tail dependency structure between the EPU and some financial markets. Due to the negative tail dependence area between the EPU and the Negotiable Certificate of Deposit markets, they suggest that higher economic- and-environmental policy uncertainty may reduce the actual risk premium.

When it comes to digital currency, the research of Wang et al (2019) shows that in most cases, the risk spillover effect of EPU on Bitcoin is negligible, and Bitcoin can act as a haven or a tool for diversified investment under the impact of EPU. On the contrary, Wu et al (2019) applied eneralized autoregressive conditional heteroskedasticity and dummy variable quantile regression and concluded that in most cases, neither gold nor Bitcoin acts as a strong hedge for EPU. At the same time, they found that Bitcoin is more responsive to EPU shocks, while gold remains stable with a smaller coefficient of hedging.

The EPU index has also been applied to various macro-econometric applications due to its technical flexibility. Nilavongse et al (2020) leveraged a structural vector autoregression to find a negative relationship between an EPU shock and industrial production in the USA. Besides, Yu et al (2017) estimated the long-term
beta coefficient of 10 industries driven by EPU in the United States based on the DCC-MIDAS framework and proved that EPU significantly promotes the industry beta coefficients. Bai et al. (2019) have used EPU data to study the economic risk contagion among the world’s major economies. The results show that the top six economies have strong correlations in economic risks. Besides, this paper insists that the United States is the main contributor and recipient of risk spillover effects among these major economies. Balli et al. (2017) proposed that bilateral factors such as trade and common language play an important role in explaining the size of the EPU spillover effect. In the research on the impact of EPU on decision-making, Chatjuthamard et al. (2020) affirmed that EPU can bring more sufficient and stronger risk-taking motivation for managers.

However, there are few studies on the prediction of the EPU index. Gupta and Sun (2020) have used high-dimensional vector autoregression parameters and data compression methods to predict and analyze the EPU index of 18 countries. Nevertheless, rather little literature predicts EPU or GEPU index using neural network methods. Therefore, this study attempts to use RNN and LSTM networks to predict the GEPU index respectively. In the context of COVID-19, the forecast results provide evidence for the economic recovery in the post-COVID-19 era.

2.2. Environmental impact of EPU
Uncertainty in economic-and-environmental policy can harm the ecology. The first and foremost is the growth of carbon emissions and energy consumption. Researchers confirm that EPU has a significant positive impact on CO2 emissions in China (Amin and Dogan 2021). The study by Adams et al. (2020) on 10 resource-consuming countries such as Brazil and India similarly finds that EPU increases carbon emissions and is detrimental to environmental sustainability. A study by Zakari et al. (2021) on OECD countries also supports this finding. The analysis of BRICS countries points out that EPU not only inhibits green energy development and economic growth, but also significantly increases carbon emissions in both the long and short term (Ali et al. 2022). Pirgaip and Dincergok (2020) further add that EPU significantly increases carbon emissions and energy consumption in G7 member countries. Also for G7 member countries, Chu and Le (2022) argue that EPU amplifies the contribution of energy intensity to environmental degradation. Such a ‘magnifying glass effect’ is also manifested in the effect on carbon emissions. EPU not only increases the ecological footprint, but also exacerbates the stimulating effect of increased energy intensity on carbon emissions (Danish et al. 2020, Zahra and Badeeb 2022). As for the whole ecosystem, EPU accelerates total environmental damage and compromises ecosystem vitality, especially in some developing regions (Su et al. 2022). In the face of the COVID-19 epidemic, the environmental degradation brought about by increased EPU may also increase mortality in the pandemic, creating more uncertainty and triggering more secondary crises (Magazzino et al. 2020, Mele and Magazzino 2021, Mele et al. 2021). Meanwhile, there are opposing views that the increase in carbon emissions due to EPU is insignificant for some given countries (Abbasi and Adedoyin 2021).

Many factors contribute to the ecological damage caused by EPU. First, the most direct cause stems from the policy itself. To promote a healthy environment, governments may employ a range of economic incentives. A study by Sagi et al. (2021) demonstrates that economic-and-environmental policy uncertainty may directly affect carbon emissions and ecological sustainability through policies related to environmental protection. Specifically, EPU can affect ecology through the parts of environmental economic policies that involve basic ecological elements such as land, forests, water, and air. Economic-and-environmental policy turbulence may limit the effectiveness of environmental policies as they should be, thus causing environmental degradation (Xue et al. 2022).

Second, EPU brings greater operational risk to trading markets, including but not limited to green technology markets and carbon trading markets (Wang et al. 2022). In addition, EPU can also affect energy markets (Qin et al. 2020, Zhu et al. 2021) and carbon trading markets (Adekoya et al. 2021, Dai et al. 2022), by exacerbating market volatility and increasing the risk. Volatility in such markets may in turn increase EPU, creating a vicious cycle (Su et al. 2021).

Third, EPU may change the attitudes and actual actions of people and firms on environmental protection issues. The level of policy uncertainty affects whether firms take the initiative to adopt green behaviors and assume corporate environmental responsibility (Wang et al. 2022). While facing higher EPU, firms tend to use cheaper fossil fuels with lower quality for production (Yu et al. 2021). At the same time, facing increased risks, firms are less willing to innovate, which inhibits green innovation activities (Xu 2020, Yu et al. 2021). There is also a different view that in times of economic-and-environmental policy instability, corporate managers are willing to engage in more environmental, social, and governance practices or activities that reflect corporate social responsibility to hedge against risks (Vural-Yavas 2021, Yuan et al. 2022).

Fourth, EPU reduces investment and technology use related to environmental sustainability. Darsono et al. (2022) find that EPU reduces sustainable stock market returns in the long run and discourages investment activity. Further, EPU reduces investment in environmental technologies in industrial production, increasing...
the ecological footprint in the long run (Hussain et al. 2022). At the same time, renewable energy use and R&D decrease as EPU increases (Amin and Dogan 2021, Shafullah et al. 2021). Uncertainty in investment costs and energy prices caused by market volatility slows the deployment of advanced energy technologies to the ground (Zetterholm et al. 2022). Therefore, stable, long-term economic-and-environmental policy support can facilitate the deployment of advanced green technologies and promote environmental sustainability.

EPU can also have an impact on the social environment. The most direct impact is on the three pillars of socioeconomic development - consumption, investment, and exports. Wu and Zhao (2022) suggest that higher EPU causes households to consume less. And Zhao (2022), using manufacturing as an example, confirms that value-added trade flows decrease with higher EPU in both importing and exporting countries. Investment is also dampened because EPU increases the difficulty of market forecasting (Beckmann and Czudaj 2017). Economic-and-environmental policy fluctuations, whether domestic or foreign, may reduce foreign direct investment (Hsieh et al. 2019, Zhang and Colak 2022). The negative impact of this uncertainty on investment is also evident in sustainable development areas such as energy (Ilyas et al. 2021) and ecology (Song et al. 2021). Further, EPU reduces the allocative efficiency of the market economy (Guedhami et al. 2022).

In addition to the negative effects on consumption, investment and exports, uncertainty increases the level of socioeconomic risk. Higher EPU shocks commodity markets and brings price volatility, especially in the energy and metals sectors (Xiao et al. 2022). In terms of social livelihoods, EPU may increase food price volatility (Xiao et al. 2019). In financial markets, EPU increases the likelihood of stock price crashes, especially for small and young companies (Luo and Zhang 2020). Further, it may also trigger systemic risk in the financial markets (Tsai 2017). At the firm level, EPU may stimulate firms to hold more cash for risk protection and reduce inventories, thus triggering a decline in supply (Zeng et al. 2019). It also increases the capital cost and inhibits firm innovation (Xu 2020). However, in the meantime, EPU can induce firms to take more social responsibility and disclose it to address environmental risks (Chen et al. 2021, Ongsakul et al. 2021).

2.3. COVID-19 and policy response

The COVID-19 pandemic has caused a huge impact on various aspects of socio-economic, environmental governance, and production operations, resulting in great uncertainty. Since the outbreak, many studies have analyzed the impact of COVID-19 on various aspects of society and made corresponding policy recommendations. Altig et al. (2020) quantified the impact of the COVID-19 epidemic on economic-and-environmental policy uncertainty and proposed a corresponding policy analysis. Mei (2020), on the other hand, discussed it from the perspective of policy consistency and policy style. Bashir and Haque (2021) propose implementation recommendations for health public policy in response to COVID-19 through two-stage least squares regression. Liu et al. (2021) focus on China’s vaccination policy in response to COVID-19. Chen et al. (2021) track the implementation and trends of COVID-19 research policy through cluster analysis. Rashid et al. (2021) analyzed the impact of the COVID-19 on the environment, macro economy, and industry segments through statistical data, and made corresponding policy recommendations. Sarkodie and Owusu (2021) combined qualitative analysis and empirical modeling to study the impact of COVID-19 pandemic on global socio-economic and environmental conditions. Magazzino et al. (2021) and Magazzino et al. (2022) quantified the relationship between air pollutants and COVID-19 pandemic deaths based on neural network and decision tree models and made recommendations for environmental and economic policies.

2.4. Prediction based on RNN and LSTM models

LSTM and RNN neural network models are widely used in the prediction and application of data series, thanks to their powerful ability to learn nonlinear relationships and their robustness to data noise. Dai and Zhou (2022) predicted financial market stability based on neural networks and intelligent optimization algorithms. Poulos and Zeng (2021), on the other hand, used RNN models to predict the effects of homestead policy. Kennedy et al. (2016) used neural networks to predict consumer choice of low-carbon technologies. In addition, neural network models have been used in time series forecasting problems such as weather forecasting (Karevan and Suykens 2020), stock market index (Wang et al. 2011), and carbon emission trends (Chai et al. 2022).

LSTM and RNN networks have performed well in sequence prediction in studies targeting the changes and impacts of the COVID-19 epidemic. Arora et al. (2020) used LSTM and RNN networks to predict the development of the COVID-19 epidemic in India. Luo et al. (2021) used LSTM networks and the XGBoost algorithm to predict the increase in confirmed cases during the COVID-19 pandemic in the U.S. Wang et al. (2020) and Safari et al. (2020) used similar methods to predict the spread of the COVID-19 epidemic in other regions. Alorini et al. (2021) applied RNN and LSTM networks to predict the outbreak of the COVID-19 along with changes in the mood of the population during the outbreak. Arunkumar et al. (2022) suggested through a comparative study that deep-learning-based LSTM models were more accurate than multivariate-statistics-based ARIMA models in predicting the COVID-19 cases in most areas. Borjes and Nascimento (2022) used a
two-stage Prophet-LSTM approach to predict the demand for ICU rooms during the COVID-19 epidemic. Eom and Byeon (2022) used RNN and LSTM networks to predict how COVID-19 led to an increase in obesity rates. Other scholars used LSTM or RNN neural networks to predict the stock price performance in the United States (Lopes et al 2021), China (Ye et al 2021) and Indonesia (Budiharto 2021) after the COVID-19 pandemic outbreak.

3. Data and method

3.1. Data

The GEPU index data sample comes from the Economic-and-environmental policy Uncertainty website (http://www.policyuncertainty.com/). It provides monthly EPU index data for 24 countries and regions and monthly GEPU data since 1997 in the form of time series. GEPU data are updated every month. The value of the GEPU is equal to the sum of the EPU indices of the 21 major economies weighted by their national GDP, where the GDP of each country is adjusted based on purchasing power parity. Economies related to the GEPU index include the United States, Canada, Italy, France, Germany, Ireland, Greece, the United Kingdom, Sweden, Spain, the Netherlands, Russia, China, Japan, Korea, India, Australia, Mexico, Brazil, Colombia, and Chile. The period of the GEPU time series sample in this paper is from January 1997 to January 2022, including 301 months. Data descriptive statistics are presented in Table 1, which shows statistical information on the GEPU index and the EPU index of the 21 countries making up the GEPU index in our time span of data (Baker et al 2016).

Table 1. Descriptive Statistics.

| Variable        | Obs | Mean  | Std. Dev. | Min  | Max  |
|-----------------|-----|-------|-----------|------|------|
| GEPU            | 301 | 131.62| 70.80     | 51.62| 437.17|
| United States   | 301 | 124.53| 53.77     | 52.05| 427.21|
| Canada          | 301 | 168.65| 113.88    | 30.10| 678.82|
| Italy           | 301 | 112.08| 41.11     | 31.70| 279.39|
| France          | 301 | 173.38| 105.12    | 11.29| 574.63|
| Germany         | 301 | 146.92| 86.60     | 28.43| 597.94|
| Ireland         | 301 | 125.15| 69.94     | 19.99| 415.00|
| Greece          | 289 | 122.03| 59.99     | 13.43| 344.23|
| United Kingdom  | 289 | 124.97| 68.75     | 23.32| 407.42|
| Sweden          | 301 | 94.13 | 19.74     | 53.73| 183.18|
| Spain           | 253 | 116.72| 56.75     | 22.69| 306.32|
| Netherlands     | 214 | 96.13 | 51.88     | 22.69| 238.33|
| Russia          | 301 | 150.92| 121.88    | 12.40| 793.63|
| China           | 301 | 180.23| 199.48    | 11.90| 1192.51|
| Japan           | 301 | 110.22| 35.99     | 47.60| 238.33|
| South Korea     | 301 | 132.41| 69.36     | 22.43| 538.18|
| India           | 229 | 91.32 | 49.47     | 23.35| 283.69|
| Australia       | 289 | 104.08| 58.41     | 25.66| 337.04|
| Mexico          | 301 | 94.45 | 66.21     | 8.51 | 428.73|
| Brazil          | 301 | 148.58| 91.14     | 22.30| 676.96|
| Colombia        | 240 | 103.96| 59.07     | 0.00 | 324.66|
| Chile           | 301 | 124.4 | 68.37     | 31.60| 454.58|

Figure 1 depicts that in the past 25 years, the uncertainty of global economic policies has been in a state of fluctuation and shown an overall upward trend. It is worth noting that the early days of the epidemic saw a sudden surge in uncertainty. As the epidemic has gradually stabilized, the uncertainty has returned to its regular level. In addition, due to the unpredictable nature of economic policies and economic events, the change curve of GEPU does not show obvious periodicity.

3.2. Methodology

In order to predict the future trend of the GEPU index, we need to choose a suitable model. The neural network model has the advantage of fitting complex nonlinear relationships, which is suitable for our data background. And among the neural network models, RNN models and LSTM models have excellent sequence learning and prediction performance due to their network structure characteristics. Therefore, they are chosen to be used. We preprocess the global GEPU data and set the model parameters at the same time. Considering the training set size, we did not set too many intermediate layers for the neural network. In addition, we did not consider data smoothing for two main reasons: first, because the data sequences available for learning are not long enough, and
smoothing may lead to non-negligible loss of data information; second, because policy uncertainty data are subject to unexpected events and have the possibility of sudden changes, and smoothing may lead to the loss of such features. In this paper, we use RNN and LSTM models to train the GEPU sequences of sample data and predict its future changes. This can provide some clues for the future recovery of the economy. The specific modeling framework is as follows. First, considering the complexity of the problem and the computing time, we set different numbers for the hidden layers. Second, we adjust the number of months used for forecasting, choosing a quarter or half year depending on practical factors. Then, with different combinations of hidden layers and backtracking times, we predicted the trend of GEPU index using RNN and LSTM networks, respectively. After that, we compare the respective errors of the training and test sets with different combinations of network parameters, and do both diagnostic tests and robustness tests. In the following two paragraphs, we give a detailed description of the applied RNN and LSTM models.

3.2.1. RNN
A recurrent neural network (RNN) (Mikolov and Karafiát 2009) is an improved multilayer perceptron network. It includes the input layer, hidden layer, and output layer. The connections between neurons can form a loop, which is widely used to process sequence data. The RNN performs the same task for each element of a sequence, with the output depending on the previous computations. For traditional fully connected neural networks (such as the feedforward neural network structure involved in the backpropagation algorithm), the accuracy of the prediction greatly depends on the accuracy of the data labels in the training set. The RNN improves prediction accuracy by building a mapping from previous inputs to each output that exploits the before-and-after correlation information within the sequence data. In theory, RNN can exploit information from arbitrarily long sequences. However, due to the risk of gradient disappearance and explosion, the RNN usually only utilizes data from a limited number of steps in the past. This feature can improve the memory of RNN.

Figure 2 gives what a typical RNN looks like (Zhu et al 2019). It has one input unit, one output unit, and one recurrent hidden unit unfolded into a full network. \( x \) is the input vector. \( o \) is the output vector. \( s \) is the hidden state vector, and all these form the ‘memory’ of the network. \( W, U, V \) are weight matrices in different network layers. Unlike a traditional deep neural network, which uses different parameters at each layer, an RNN shares the same parameters \( (U, V, W) \) across all steps. This greatly reduces the total number of parameters we need to learn. \( s_t \) is the output of the hidden layer at the time of \( t \). \( o_t \) is the output of the output layer at the time of \( t \) (Liu and Zhang 2016). The RNN remembers the information at each moment. The hidden layer at each moment is determined not only by the input layer at that moment, but also by the hidden layer at the previous moment. Therefore, the RNN is expected to solve the sequence problem. The calculation process is:

\[
\begin{align*}
o_t &= g(Vs_t) \\
s_t &= f(Us_t + Ws_{t-1})
\end{align*}
\]

3.2.2. LSTM
LSTM was first proposed by Hochreiter and Schmidhuber (1997) motivated by an analysis process in existing RNNs (Kremer and Kolen 2001). They found that the long time lags can’t be achieved using the existing architectures. Recall the principle of the RNN handling sequential data: each moment stores the value of the
hidden layer and uses it in the next moment, thus ensuring that each moment contains the information of the previous moment. The LSTM network, on the other hand, adds a gating system to the RNN for selectively storing important information. This compensates for the inability of the RNN to pick key information. This improvement greatly solves the problem of gradient disappearance. At the same time, the LSTM network presents significant advantages over the RNN in processing long sequences. The LSTM network adds three internal cell gates to the memory cell of the RNN to form new storage cells: namely the input gate, memory gate, and forget gate (Gers et al 2000). The input gate determines whether the information coming from the input layer at each moment can be delivered to the memory cell. The forget gate decides whether some information in the memory cell that is no longer important for the current moment should be deleted. The output gate tells whether the information is output from the memory cell (Hochreiter and Schmidhuber 1997). The LSTM network redesigns the computational nodes according to the structure of the RNN. A typical structure of the LSTM network cell is shown in figure 3 (Lazaris and Prasanna 2021). Memory blocks in LSTM are similar to the differential storage systems of a digital system. Gates in LSTM offer help in processing the information with the help of the activation function and the output is between 0 and 1. The reason behind using the sigmoid activation function is that we need to pass only positive values to the next gates to get a clear output.

4. Empirical results

4.1. RNN fitting and predicting results
In order to predict the future GEPU index, we use look_back to denote the number of months before the current month which will be used to forecast the current month’s GEPU index. For example, if look_back takes 5, we use the data from the past 5 months to predict the current month’s data. This paper changes the value of look_back and hidden_layer (the number of hidden layers) to predict the GEPU index in the post-epidemic era. Epoch_num represents the number of times the model was fully trained using the data with the same parameters. They are arranged as follows:

- look_back = 3, hidden_layer = 3, Epoch_num = 5000
- look_back = 3, hidden_layer = 6, Epoch_num = 5000
- look_back = 6, hidden_layer = 3, Epoch_num = 5000

Meanwhile, to test the fitting effect, we split the data into two parts. 70% of the data set is used as the training set, and the remaining 30% is the test set. We run our code on Python 3.8, and the obtained fitting and prediction results as well as loss function curves are shown in figures 4–6 below. The vertical bar in the figure of prediction and fitting results separates the training set and the test set.
Figure 4 shows that the RNN model performs best when $\text{look\_back} = 3$, $\text{hidden\_layer} = 3$, which means neither overfitting nor underfitting occurs. In this case, the results indicate that the GEPU will have a slight increase and then be flat. This indicates that two years after the outbreak, the impact of the COVID-19 pandemic on global economic-and-environmental policy has gradually leveled off, which is conducive to economic recovery. It should be noted that, from the loss function curve, the loss function still has a downward trend rather than convergence. This is due to the limited computing power and time of the computer. It can be speculated that if the Epoch continues to be increased reasonably, we can expect better learning outcomes.

Figures 5 and 6 depict that when $\text{look\_back} = 3$, $\text{hidden\_layer} = 6$, or when $\text{look\_back} = 6$, $\text{hidden\_layer} = 3$, the model performs worse on the test set. In these two cases, there are obvious oscillations in the test set. The predicted result of the GEPU trend in figure 5 is the same as that in figures 4. In figure 6, GEPU shows a significant downward trend. Overall, the results of figures 4–6 present that there will not be a significant increase in global economic-and-environmental policy uncertainty.

4.2. LSTM fitting and predicting results
LSTM networks are used to predict data as well. Like RNN, we divide the training set and test set with a ratio of 7 to 3, and analyze them with three sets of parameters:
The results are shown in figures 7–9 below.

Figure 7 shows that like the RNN model, the LSTM model also performs best when `look_back = 3` and `hidden_layer = 6`. At the same time, compared with the RNN model, the LSTM model shows huge fluctuations in the first half of the test set, but the fitting results in the second half are closer to the real data. In terms of the forecasting part, unlike RNN models in figures 4 and 5 which predict an increasing trend first and then tend to be stable, the LSTM model believes that the GEPU index will first drop sharply and then remain flat.

Figures 8 and 9 indicate that when `look_back = 3`, `hidden_layer = 6`, or when `look_back = 6`, `hidden_layer = 3`, the performance of the LSTM network on the test set is not as good as the performance of the RNN under the same conditions. With the increase of the number of hidden layers, when `hidden_layer = 6`, the LSTM network shows obvious over-fitting, which means that its fitting curve on the training set obviously fits the real data while the fitting data is quite different from the real data on the test set.

4.3. Diagnostic tests and robustness

To validate the accuracy of the models, Mean Square Error (MSE), Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) were selected to characterize the prediction errors of each of the LSTM and RNN models under different parameter sets, respectively. All errors are computed on both the test set and the training set. The errors on the test set are given in tables 2–4 with different network parameters. And the errors on the training set are shown in tables 5–7. By solving for the above errors, we summarize the results of the diagnostic tests of the models. From the results of the test set, it can be seen that in most cases, RNN models exhibit smaller errors compared to LSTM models. However, in general, the difference between the two error metrics is not significant. The difference between the MSE corresponding to the RNN and LSTM models is kept within 1% for all the parameter sets in this paper. To reflect the accuracy of the models more accurately, the mean errors of RNN and LSTM models after ten experiments are solved by averaging the experiments’ results. When the value of

- `look_back = 3, hidden_layer = 3, Epoch_num = 5000`
- `look_back = 3, hidden_layer = 6, Epoch_num = 5000`
- `look_back = 6, hidden_layer = 3, Epoch_num = 5000`

![Fitting Prediction Curve](image1)

![Loss Function Curve](image2)

**Figure 5. RNN Results (look_back = 3, hidden_layer = 6).**

![Fitting Prediction Curve](image3)

![Loss Function Curve](image4)

**Figure 6. RNN Results (look_back = 6, hidden_layer = 3).**
look_back and hidden_layers are both 3, the accuracy of LSTM and RNN models are basically the same, and the difference of MSE metrics is around 0.01%. The values of MSE, RMSE and MAE corresponding to the RNN model are smaller than those of the LSTM model. And the error difference between the two models is between 0.13% and 0.21% with the other two parameter sets. For the training set, LSTM exhibits higher accuracy than RNN for all network parameters and error metrics. For MSE, the difference between LSTM and RNN is between 0.03% and 0.06%. For RMSE, the gap is between 0.33% and 0.80%. For MAE, the gap is between 0.24% and 0.60%.

We also examined the robustness of the LSTM and RNN models. Higher robustness signifies a more stable operation of the model. Our repeated experiments show that the accuracy of both models varies slightly in each run. To quantify the stability of the results more precisely, we calculated the variance of the respective error metrics of the LSTM and RNN models after ten replicate experiments. Results are also shown in tables 2–7. The first column represents each run of our replicate experiments as well as statistical indicators. The model variance
is located at a very low level compared to the order of magnitude of the model error, indicating that both models have gratifying robustness. On the test set, the RNN model shows stronger robustness in prediction performance compared to the LSTM model in terms of the variance of MSE, RMSE, and MAE. For the MSE metric, the difference in robustness between the two models is the largest, where the variance of the LSTM model is 9.30 to 23.02 times higher than that of the RNN model. For the RMSE metric, the variance of the LSTM model is 3.27 to 4.60 times the variance of the RNN model. For the MAE metric, the difference in robustness between the two models was the smallest, where the variance of the LSTM model was 1.34 to 1.71 times higher than that of the RNN model. On the training set, the LSTM exhibits a larger variance overall compared to the RNN.

---

### Table 2. Error on the test set (look_back = 3, hidden_layer = 3).

| Items | RNN MSE (10^{-5}) | RMSE (10^{-5}) | MAE (10^{-5}) | LSTM MSE (10^{-5}) | RMSE (10^{-5}) | MAE (10^{-5}) |
|-------|-------------------|----------------|--------------|-------------------|----------------|--------------|
| 1     | 12.3173           | 35.0960        | 30.9161      | 12.1301           | 34.8282        | 30.5918      |
| 2     | 12.4029           | 35.2178        | 30.9543      | 12.4940           | 35.3468        | 31.1542      |
| 3     | 12.3281           | 35.1114        | 30.9663      | 12.4679           | 35.3100        | 31.0640      |
| 4     | 12.3383           | 35.1259        | 30.9980      | 12.4550           | 35.2916        | 31.0378      |
| 5     | 12.3273           | 35.1102        | 30.9520      | 11.6676           | 34.1578        | 29.5004      |
| 6     | 12.3744           | 35.1772        | 30.9408      | 12.3511           | 35.1442        | 30.9720      |
| 7     | 12.3578           | 35.1537        | 30.9476      | 12.3900           | 35.0842        | 30.7717      |
| 8     | 12.3065           | 35.0806        | 30.9076      | 12.4831           | 35.3314        | 30.9509      |
| 9     | 12.6124           | 35.5140        | 31.1669      | 12.4388           | 35.2687        | 31.1540      |
| 10    | 12.5325           | 35.4013        | 31.2348      | 12.8885           | 35.9005        | 31.4467      |

Mean (10^{-7}) 12.3897 35.1988 30.9984 12.3685 35.1663 30.8643
Variance (10^{-7}) 9.3923 18.8523 11.0304 87.3538 178.4267 253.9337

### Table 3. Error on the test set (look_back = 6, hidden_layer = 3).

| Items | RNN MSE (10^{-5}) | RMSE (10^{-5}) | MAE (10^{-5}) | LSTM MSE (10^{-5}) | RMSE (10^{-5}) | MAE (10^{-5}) |
|-------|-------------------|----------------|--------------|-------------------|----------------|--------------|
| 1     | 12.5951           | 35.4895        | 31.3962      | 12.5317           | 35.4002        | 31.3137      |
| 2     | 12.7807           | 35.7501        | 31.4931      | 12.5880           | 35.4796        | 31.5457      |
| 3     | 12.4813           | 35.3289        | 31.2558      | 12.9671           | 36.0099        | 31.7569      |
| 4     | 12.6299           | 35.5386        | 31.5111      | 12.7842           | 35.7530        | 31.6507      |
| 5     | 12.5071           | 35.3653        | 31.2931      | 12.5580           | 35.4373        | 31.3767      |
| 6     | 12.5303           | 35.3984        | 31.1992      | 12.5283           | 35.3953        | 31.2753      |
| 7     | 12.4563           | 35.2935        | 31.2431      | 12.5167           | 35.3789        | 31.2750      |
| 8     | 12.5053           | 35.3628        | 31.2850      | 12.9119           | 35.9331        | 31.8450      |
| 9     | 12.5105           | 35.3701        | 31.3009      | 12.6802           | 35.6902        | 31.3953      |
| 10    | 12.4774           | 35.3233        | 31.2583      | 12.8900           | 35.9027        | 31.8300      |

Mean (10^{-7}) 12.5474 35.4221 31.3236 12.6956 35.6301 31.5264
Variance (10^{-7}) 8.6126 17.0677 10.2951 28.3775 55.7333 47.3777

### Table 4. Error on the test set (look_back = 3, hidden_layer = 6).

| Items | RNN MSE (10^{-5}) | RMSE (10^{-5}) | MAE (10^{-5}) | LSTM MSE (10^{-5}) | RMSE (10^{-5}) | MAE (10^{-5}) |
|-------|-------------------|----------------|--------------|-------------------|----------------|--------------|
| 1     | 12.5456           | 35.4197        | 31.1218      | 12.1621           | 34.8742        | 30.8337      |
| 2     | 12.3060           | 35.0800        | 30.8387      | 12.6539           | 35.5723        | 31.1841      |
| 3     | 12.6047           | 35.5032        | 31.2472      | 12.7704           | 35.7357        | 31.3630      |
| 4     | 12.5514           | 35.4280        | 31.0324      | 12.7232           | 35.6696        | 31.2268      |
| 5     | 12.6520           | 35.5697        | 31.1522      | 12.7455           | 35.7008        | 31.3935      |
| 6     | 12.4562           | 35.2934        | 31.0235      | 12.7269           | 35.6747        | 31.3019      |
| 7     | 12.7326           | 35.6828        | 31.3410      | 12.6920           | 35.6258        | 31.3785      |
| 8     | 12.4091           | 35.2265        | 30.9637      | 12.6177           | 35.5214        | 30.8161      |
| 9     | 12.3545           | 35.1360        | 30.9673      | 12.7348           | 35.6859        | 31.2965      |
| 10    | 12.5544           | 35.4321        | 31.1146      | 12.6475           | 35.5633        | 31.1691      |

Mean (10^{-7}) 12.5158 35.3771 31.0803 12.6474 35.5624 31.2229
Variance (10^{-7}) 16.5083 32.9931 19.4108 28.2875 56.7954 26.0449
5. Discussion

The motivation for predicting the GEPU index through the RNN and LSTM networks is to learn nonlinear factors which are hard to be fully covered by traditional models. The variation of the global policy uncertainty has a certain temporal continuity in the form of time series. This indicates that forecasts of the GEPU index need to incorporate its past data characteristics. Therefore, RNN helps us to capture the influences of previous global policy uncertainty data on its current level and the future trend. LSTM networks, on the other hand, further

---

Table 5. Error on the training set (LSTM look_back = 3, hidden_layer = 3).

| Items | RNN MSE (10⁻²) | RMSE (10⁻²) | MAE (10⁻²) | LSTM MSE (10⁻²) | RMSE (10⁻²) | MAE (10⁻²) |
|-------|----------------|-------------|------------|----------------|-------------|------------|
| 1     | 0.2090         | 4.5715      | 3.2810     | 0.0870         | 2.9490      | 2.2682     |
| 2     | 0.1966         | 4.4335      | 3.2819     | 0.1798         | 4.2407      | 3.1305     |
| 3     | 0.2007         | 4.4804      | 3.2002     | 0.1765         | 4.2006      | 3.0766     |
| 4     | 0.2131         | 4.6165      | 3.3186     | 0.1403         | 3.7461      | 2.8707     |
| 5     | 0.2139         | 4.6245      | 3.3066     | 0.1958         | 4.4251      | 3.2463     |
| 6     | 0.2112         | 4.5955      | 3.2979     | 0.1569         | 3.9615      | 2.9430     |
| 7     | 0.1402         | 3.7438      | 2.9038     | 0.1418         | 3.7658      | 2.8214     |
| 8     | 0.2147         | 4.6333      | 3.3092     | 0.1782         | 4.2209      | 3.1384     |
| 9     | 0.1954         | 4.4209      | 3.2772     | 0.1853         | 4.3043      | 3.1535     |
| 10    | 0.2876         | 5.3625      | 3.8278     | 0.0849         | 2.9137      | 2.1041     |

Mean (10⁻²) 1.1389 4.5482 3.3005 0.1526 3.8728 2.8753

Variance (10⁻⁷) 1.1389 136.4584 44.8071 1.4076 266.3904 136.0766

Table 6. Error on the training set (LSTM look_back = 6, hidden_layer = 3).

| Items | RNN MSE (10⁻²) | RMSE (10⁻²) | MAE (10⁻²) | LSTM MSE (10⁻²) | RMSE (10⁻²) | MAE (10⁻²) |
|-------|----------------|-------------|------------|----------------|-------------|------------|
| 1     | 0.1885         | 4.3421      | 3.1212     | 0.1746         | 4.1782      | 3.0625     |
| 2     | 0.1712         | 4.1376      | 3.0711     | 0.1060         | 3.2563      | 2.5196     |
| 3     | 0.1283         | 3.5821      | 2.7381     | 0.1912         | 4.3729      | 3.1421     |
| 4     | 0.1944         | 4.4093      | 3.1833     | 0.1634         | 4.0422      | 2.9803     |
| 5     | 0.1401         | 3.7435      | 2.9533     | 0.1703         | 4.1271      | 2.9741     |
| 6     | 0.2106         | 4.5887      | 3.3041     | 0.1103         | 3.3215      | 2.5954     |
| 7     | 0.2013         | 4.4871      | 3.2642     | 0.1078         | 3.2837      | 2.5204     |
| 8     | 0.1572         | 3.9652      | 2.9983     | 0.1824         | 4.2710      | 3.1181     |
| 9     | 0.2119         | 4.6037      | 3.3206     | 0.1824         | 4.2712      | 3.1140     |
| 10    | 0.1929         | 4.3916      | 3.2474     | 0.1467         | 3.8302      | 2.8153     |

Mean (10⁻²) 0.1797 3.5688 2.6824 0.0828 2.7735 2.0794

Variance (10⁻⁷) 0.7711 114.0157 30.5991 1.0171 178.1762 57.6533

Table 7. Error on the training set (LSTM look_back = 3, hidden_layer = 6).

| Items | RNN MSE (10⁻²) | RMSE (10⁻²) | MAE (10⁻²) | LSTM MSE (10⁻²) | RMSE (10⁻²) | MAE (10⁻²) |
|-------|----------------|-------------|------------|----------------|-------------|------------|
| 1     | 0.1139         | 3.3744      | 2.6067     | 0.1424         | 3.7731      | 2.8781     |
| 2     | 0.1253         | 3.5401      | 2.7166     | 0.1049         | 3.2392      | 2.4730     |
| 3     | 0.1898         | 4.3570      | 3.1513     | 0.0880         | 2.9671      | 2.2230     |
| 4     | 0.0930         | 3.0501      | 2.2747     | 0.0241         | 1.5514      | 1.0750     |
| 5     | 0.0747         | 2.7337      | 2.1055     | 0.0652         | 2.5540      | 1.8592     |
| 6     | 0.1932         | 4.3958      | 3.2636     | 0.0671         | 2.5909      | 1.9652     |
| 7     | 0.1291         | 3.5924      | 2.7787     | 0.0773         | 2.7798      | 2.0997     |
| 8     | 0.1762         | 4.1970      | 3.0387     | 0.1748         | 4.1814      | 3.0892     |
| 9     | 0.0914         | 3.0235      | 2.3135     | 0.0404         | 2.0104      | 1.5529     |
| 10    | 0.1172         | 3.4237      | 2.5742     | 0.0436         | 2.0879      | 1.5784     |

Mean (10⁻²) 0.1304 3.5688 2.6824 0.0828 2.7735 2.0794

Variance (10⁻⁷) 1.6063 302.3900 134.7682 1.9904 586.3223 343.2271
improve the prediction performance on time series based on the RNN. LSTM networks can better capture the key features of time series through the unique structure consisting of output gates, input gates, and forgetting gates. Also, the structure of LSTM networks solves the problems of short-term data dependence and gradient explosion of RNN. From the overall effect, the prediction results of the RNN networks on the test set match the real data more closely than that of the LSTM networks.

We argue that the short-term correlation of GEPU data leads to a better prediction by the RNN than LSTM networks (Tao and Liu 2018, Sherstinsky 2020). Economic-and-environmental policy uncertainty is vulnerable to short-term shocks. However, in the long run, it is difficult to find an independent event that can keep global economic-and-environmental policy at a constant uncertainty level. Therefore, the current level of GEPU may be more relevant than that of a month or two ago, but the correlation with its level a decade ago is weak. In this regard, the short-term memorability of the RNN is more suitable. This is because the RNN focuses more on learning the features of recent data. However, the LSTM network affects the accuracy of predicting GEPU data instead because it remembers some of the features of the events that occurred a long time ago.

Such techniques as RNN and LSTM have also been used to predict the COVID-19 cases and exchange rates during the pandemic with reliable prediction results (Abedin et al 2021, Zandavi et al 2021). These works provide support for our choice of LSTM to predict GEPU index variation in the post-COVID-19 era. The data we used has covered the period of the COVID-19 pandemic outbreak and its ongoing spread. This helps us to detect the impact of the outbreak and the persistence of the epidemic on global uncertainty (Marlier et al 2020). In addition, we also used data from over two decades of non-COVID-19 pandemic time as part of the training set. By learning from this portion of the data, we incorporate the non-epidemic impact in our forecasts and thus more accurately identify the influences of the epidemic on global policy uncertainty.

Our prediction results are consistent with the previous quantification of economic-and-environmental policy uncertainty before and after the COVID-19 epidemic (Altig et al 2020). Those results show that economic-and-environmental policy uncertainty increases abruptly and then decreases gradually with the arrival of the COVID-19 shock. The starting point of the projections in this paper is January 2022, the exact time when the Omicron variant of COVID-19 becomes the dominant strain globally. 3.5 million people were diagnosed with COVID-19 globally on a single day on January 15, 2022, breaking the previous two-year record for the number of new cases on a single day. As a new round of epidemic shocks approaches, our projections also suggest a sudden increase and then a flattening or reduction in global economic-and-environmental policy uncertainty. The gradual decrease of EPU after a period of COVID-19 outbreak also verifies the weakening effect on uncertainty of information gain (Feldman Hall and Shenhav 2019). Overall, past studies of trends in economic-and-environmental policy uncertainty have all shown a gradual increase. Huang and Luk (2020) measure economic-and-environmental policy uncertainty in China based on information from several local newspapers, which has generally increased slowly since the turn of the century. They also find that economic-and-environmental policy uncertainty depresses production and employment. Ellington et al (2022) verify the changes in economic-and-environmental policy uncertainty in the UK after the outbreak of COVID-19 and suggest that economic-and-environmental policy uncertainty leads to a decline in GDP growth. Manski (2020) further adds that the development of diversified and differentiated policies to cope with the importance of developing diversified and differentiated policies to cope with the uncertainty caused by COVID-19. Zhou et al (2022) suggest that the increase in economic-and-environmental policy uncertainty caused by COVID-19 has significant national and regional spillovers.

By focusing on the GEPU index during the epidemic period, we gain some valuable insights into the future economic-and-environmental policy trend. We can predict that a stable economic-and-environmental policy will contribute to the fast recovery of the economy after having been devastated by COVID-19. This judgment is of great significance as it reinforces the confidence of firms and investors all around the world. In detail, most of the results of RNN and LSTM predictions show that the GEPU index will remain unchanged at the current level or decrease after January 2022. This result is not surprising. It reflects the transition in policy style and the continued improvement of medical technology. Over time, the government and market have prompted a more robust response to the spread of the pandemic. Such a result builds on a previous spike in the GEPU index, which soared after the COVID-19 outbreak. In April 2020, the GEPU index reached an unprecedented level of 437, the highest value of its record. This corresponds to the first wave of the pandemic, and the pessimistic market expectations created by skyrocketing patients as well as global inflation (Shehzad et al 2020, Zhang et al 2020, Yousaf 2021). At the same time, the panic caused by the epidemic spreads across international markets, thus amplifying its impact (Banerjee 2021). Such influences can be checked in figure 8. Within the interval of the test set (which covers the time of the outbreak and spreading of the COVID-19 pandemic), the trend of the forecast curve deviates from the actual situation with ups and downs. The predicted curve oscillates and slowly goes down, while the actual curve goes up rapidly. This contrast shows that the global pandemic of COVID-19 rapidly increases the uncertainty of national policies.
As populations gradually adapt to living with COVID-19 and build herd immunity, the extent of the epidemic’s impact on the GEPU index gradually decreases. Specifically, in October 2020, the GEPU index quickly shot up again after the pullback in April with global resurgences of the COVID-19 pandemic. This wave of the epidemic spread more rapidly and affected more people. However, the GEPU peaked at 379, lower than that of its peak in April (Nonetheless, it is still the second-highest on record). Afterward, the policy uncertainty associated with COVID-19 continues to weaken as countries further work on mass vaccination, medical efficacy, and policies in response to the outbreak. From October 2020 to May 2021, the GEPU fell by 50.7% at a rapid speed. This shows that the impact of COVID-19 on policy uncertainty continues to weaken as time passes by. In the absence of other major global emergencies, the GEPU index will remain flat or continue to decline from its current state. Even if there is an increase in the GEPU index as projected in figures 4 and 5, it is unlikely to go beyond the levels seen in April and October 2020. This finding also makes it clear that the countries must steadily set policies with both economic recovery and epidemic prevention and control taken into account. In turn, a lower GEPU index could better facilitate the recovery of global productivity and consumption, and improve the consistency of economic and social development policies (Goodell 2020).

The trend of the GEPU index after COVID-19 also has important implications for environmental governance and sustainable development. Although the GEPU index generally tends to decline slowly over time after the COVID-19 shock-induced surge, it may have long-term impacts on the environment. As summarized in the literature review section, the pathways through which uncertainty damages the ecosystem include the direct effects of unstable environmental economic policies and indirect factors such as market risks, firm choices, and technology investments. As the COVID-19 pandemic stabilized, countries began to gradually implement policies to recover their economies. Compared to the previous period, the direction of economic policies in each country is gradually stabilizing. In this regard, the direct impact of uncertainty on the ecological environment is expected to diminish. However, the problem of indirect effects remains acute. The COVID-19 pandemic has lasted for more than two years now, and its negative impact has been felt in all socio-economic aspects. Despite the stabilization of economic policies, the market panic, reduced supply capacity, weakened consumer demand, and shortage of funds caused by the epidemic have not been fully resolved. This has created indirect instability. That may result in a long-term negative impact of economic uncertainty on the environment without the necessary conditions to support it. Therefore, how to build a healthy environmental economic- and environmental policy for long-term ecological sustainability remains an important and urgent issue.

The impact of ‘black swan’ events on the accuracy of GEPU short-term forecasts is equally worth considering (Ricci and Sheng 2017). The occurrence of ‘black swan’ events may severely challenge the accuracy of big data prediction techniques (Batrouni et al 2018). This problem is at the forefront of current deep learning research. The ‘black swan’ event with the greatest impact on our GEPU index forecasting in the post-COVID-19 era may be the Russo-Ukrainian war in 2022. On February 7, 2022, the Ukrainian parliament enshrined the accession to the European Union and North Atlantic Treaty Organization (NATO) membership as a basic state policy in the constitution. This move was strongly opposed by the Russian government, triggering a new round of the Russo-Ukrainian conflict since 2014. In February 2022, the situation between Russia and Ukraine deteriorated rapidly. On February 24, Russia decided to launch a special military operation in the Donbas region. On the same day, Ukraine and Russia broke diplomatic relations, and the Russo-Ukrainian war broke out. Our data is available until January 2022, which means that the outbreak of this war is a factor hardly to be considered in the forecast of GEPU. Undoubtedly, it will have an appreciable effect on the global political situation for the next month or even a year. Worryingly, the spike in fossil energy and global commodity prices triggered by the Russo-Ukrainian war could further hamper the global economic recovery after the COVID-19 pandemic. In turn, fluctuation of the GEPU index may backfire on global energy markets, creating a vicious cycle (Ma et al 2019, Wu et al 2021). The outbreak of the Russo-Ukrainian war is expected to skew our estimates. The world may face policy uncertainty that is more volatile and severe than the predicted outcome. Nevertheless, this paper predicts the course of global economic- and environmental policy uncertainty in the absence of the Russo-Ukrainian war. This provides a comparison with the actual situation to see the impact of the Russo-Ukrainian war on economic- and environmental policy making.

6. Conclusions, policy implications and limitations

In recent years, the GEPU index has shown the characteristics of an overall increase and intensified volatility. The COVID-19 global pandemic outbreak has further increased economic- and environmental policy uncertainty (Sharif et al 2020). This is the first study to examine the predictability of the RNN and LSTM networks for the GEPU index in the post-COVID-19 era, using GEPU data from January 1997 to January 2022. We simulate and forecast the changes of GEPU index series by LSTM and RNN models and achieve good simulation results. Most results illustrate that the GEPU index will be flat or decrease in the short term. A few
results present the possibility of an increase in the GEPU index, but not beyond the levels of April and October 2020. Meanwhile, we compare the error and the stability of the results of LSTM and RNN for predicting GEPU indices with different parameter combinations. We found that the prediction accuracies of RNN and LSTM are basically the same on both the test and training sets, and the differences are small. On the test set, the error of RNN is slightly smaller than that of LSTM, and the opposite result is obtained on the training set. Also, the variance of the multiple experimental errors of RNN is significantly smaller than that of LSTM on both the training and test sets. It shows the stronger robustness of RNN in this prediction problem. Our work further confirms that the impact of the COVID-19 pandemic on GEPU is weakening over time. This provides optimistic expectations for future global economic recovery. Our finding is not negligible because global economic-and-environmental policy uncertainty can significantly affect future economic recovery and social development.

Our predictions are instructive for governments and other stakeholders to face the socio-economic uncertainty caused by the COVID-19 pandemic and develop appropriate policy responses. First, our simulation model predicts and quantifies the impact of the COVID-19 pandemic on global economic-and-environmental policy uncertainty, which informs policy formulation and the conduct of economic activities. Our results help government agencies and managers to better assess the implementation of their existing socio-economic policies and to prepare more carefully for the risk of global uncertainty. At the micro-level, it may suppress firm innovation and new investment (Gulen and Ion 2016, Wang et al 2016, Xu 2021). Therefore, for governments, our results can help review existing economic policies and minimize the risk of policy implementation in the future. For companies, quantifying and anticipating changes in global economic-and-environmental policy uncertainty can also help them adjust their economic production activities promptly and minimize the negative impact of COVID-19 on production. Second, our study helps investors and stakeholders to assess the impact of economic-and-environmental policy uncertainty on decisions and investment risks in the follow-up phase of the COVID-19 pandemic. As Kang and Ratti (2013) point out, economic-and-environmental policy uncertainty can shock financial markets. Higher economic-and-environmental policy uncertainty can significantly increase the market. Third, this study provides a reference for governments and stakeholders to anticipate future responses to sudden crises or global catastrophes, and helps them to plan ahead and make more prepared plans. This paper learns the changing patterns of global economic-and-environmental policy uncertainty for forecasting through neural network models, which enhances the understanding of governments and stakeholders on the overall behavior of global responses to sudden crises and disasters.

Our conclusions also contain implications for environmental governance. While the economic-and-environmental policy uncertainty created by COVID-19 slowly decreases over time, the direction of economic-and-environmental policy in each country tends to stabilize toward economic recovery. This can reduce some of the direct ecological impacts caused by the instability of environmental economic policies themselves. However, it is worth noting that the long-term effects of COVID-19 on supply, demand, risk response, and technology investment still warrant our vigilance. These factors indirectly influence ecological sustainability through corporate green behavior, green technology development, and green innovation investment. This makes the indirect impact of economic-and-environmental policy uncertainty on the ecological environment will be long-term. As Knights et al (2014) emphasize, regulators should adopt a gradual, systematic response to reduce the environmental harm caused by uncertainty. Encouraging the use of clean energy and investing in research and development of green technologies remain favorable solutions to reduce the environmental hazards of long-term uncertainty (Zetterholm et al 2022). At the same time, countries should take stock of their environmental and economic response experiences during COVID-19. After that, they are recommended to develop targeted environmental and economic measures in conjunction with economic recovery plans for the post-epidemic era.

There are still some limitations in this paper. First, since LSTM and RNN are black-box models, the specific influence paths of the factors affecting global economic-and-environmental policy uncertainty cannot be given. This can be supplemented with statistical models such as autoregressive or analytic equations in further studies. Second, since the GEPU index is updated monthly since 1997, the amount of data available for LSTM and RNN model learning in this paper is about three hundred. Considering the dependence of neural network methods on the amount of data used for machine learning, this amount of data limits the performance of model prediction to a certain extent. Finally, the studied target of this paper is the overall performance of global economic policies. It is possible to build differentiated prediction models for simulation in further studies on specific regions or countries, as well as on industry segments.

Based on the findings and limitations of this paper, we suggest that further research should be conducted in the following directions. First, follow-up research can further strengthen the study of economic-and-environmental policy uncertainty in specific countries or regions, as well as in specific industries. Macroscopic studies can help governments and stakeholders understand the general direction of economic-and-environmental policy changes. At the same time, research on specific geographic regions and industries can better help them formulate targeted policy responses. Second, neural networks and multivariate statistical models can be combined to further disentangle the influence factors. Future research could focus on how
COVID-19 affects economic-and-environmental policy and influences economic-and-environmental policy uncertainty. For example, trade relations between countries or geopolitical relations may exacerbate the global economic-and-environmental policy uncertainty. It is interesting to examine the role that these factors play in the post-epidemic era. Third, the impact of unexpected crisis events on economic-and-environmental policy uncertainty deserves more in-depth discussion and analysis. Future research can integrate government actions, industrial policies, economic and financial market laws, and other environmental influences. Fourth, policy uncertainty affects both the social and ecological environment. The relationship between policy uncertainty, environment, and public emergencies can be further empirically analyzed.

Acknowledgments

We thank the Major Program of the National Social Science Foundation (21&ZD071, 20&ZD072 and 19ZDA083) and the National Natural Science Foundation of China (71974151) for the financial support.

Data availability statement

The data that support the findings of this study are available upon reasonable request from the authors.

Disclosure of competing interest

The authors declare that they have no conflict of interest.

ORCID iDs

Hui Hu https://orcid.org/0000-0002-3614-8678

References

Abbasi K R and Adedoyin F F 2021 Do energy use and economic policy uncertainty affect CO2 emissions in China? Empirical evidence from the dynamic ARDL simulation approach Environmental Science and Pollution Research 28 23923–35

Abedin M Z et al 2021 Deep learning-based exchange rate prediction during the COVID-19 pandemic Ann. Oper. Res. 1–52

Adama S et al 2020 Energy consumption, economic policy uncertainty and carbon emissions; causality evidence from resource rich economies Economic Analysis and Policy 68 179–90

Adekoya O B, Oliyide J A and Noman A 2021 The volatility connectedness of the EU carbon market with commodity and financial markets in time- and frequency-domain: the role of the US economic policy uncertainty Resour. Policy 74 102252

Ali S et al 2022 A path towards carbon mitigation amidst economic policy uncertainty in BRICS: an advanced panel analysis Environmental Science and Pollution Research 29 62579–91

Alorini G, Rawat D and Alorini D 2021 LSTM-RNN based sentiment analysis to monitor COVID-19 opinions using social media data ICC 2021 - IEEE Int. Conf. on Communications (https://doi.org/10.1109/ICC42927.2021.9500897)

Altig D et al 2020 Economic uncertainty before and during the COVID-19 pandemic Journal of Public Economics 191 104274

Amin A and Dogan E 2021 The role of economic policy uncertainty in the energy-environment nexus for China: evidence from the novel dynamic simulations method J. Environ. Manage. 292 112865

Araujo J 2020 Performance comparison of solar radiation forecasting between WRF and LSTM in Gifu, Japan Environmental Research Communications 2 045002

Arora P, Kumar H and Panigrahi B 2020 Prediction and analysis of COVID-19 positive cases using deep learning models: a descriptive case study of India Chaos Solitions and Fractals 139 110017

Arunkumar K E et al 2022 Comparative analysis of Gated Recurrent Units (GRU), long-term short-memory (LSTM) cells, autoregressive integrated moving average (ARIMA), seasonal autoregressive Integrated moving average (SARIMA) for forecasting COVID-19 trends Alexandria Engineering Journal 61 7585–603

Ashraf BN and Shen Y 2019 Economic policy uncertainty and banks’ loan pricing Journal of Financial Stability 44 100695

Bai L, Zhang X, Liu Y and Wang Q 2019 Economic risk contagion among major economies: new evidence from EPU spillover analysis in time and frequency domains Physica A 535 122431

Baker S R, Bloom N and Davis S J 2016 Measuring economic policy uncertainty The Quarterly Journal of Economics 131 1593–636

Baker S R, Bloom N and Davis S J 2016 Measuring economic policy uncertainty Q. J. Econ. 131 1593–636

Bali F, Uddin G S, Madurar H and Yoon S 2017 Cross-country determinants of economic policy uncertainty spillovers Economics Letters 156 179–83

Banerjee A K 2021 Futures market and the contagion effect of COVID-19 syndrome Finance Research Letters 43 102018

Basher S A and Haque A K 2021 Public policy lessons from the Covid-19 outbreak: how to deal with it in the post-pandemic world? Journal of Social and Economic Development 23 234–47

Batrouni M, Bertaux A and Nicolle C 2018 Scenario analysis, from BigData to black swan Computer Science Review 28 131–9

Beckmann J and Czudaj R 2017 The impact of uncertainty on professional exchange rate forecasts Journal of International Money and Finance 73 296–316

Borges D and Nascimento M 2022 COVID-19 ICU demand forecasting; a two-stage Prophet-LSTM approach Appl. Soft Comput. 125 109181
Nilavongse R, Rubaszek M and Uddin GS 2020 Economic policy uncertainty shocks, economic activity, and exchange rate adjustments *Economics Letters* 186 108765

Ongsakul V, Jiraporn P and Treepongkaruna S 2021 Does managerial ownership influence corporate social responsibility (CSR)? The role of economic policy uncertainty *Accounting and Finance* 61 763–79

Phan D, Lyke B, Sharma SS and Affandi Y 2021 Economic policy uncertainty and financial stability—Is there a relation? *Economic Modelling* 94 1018–29

Piriga B and Dincergok B 2020 Economic policy uncertainty, energy consumption and carbon emissions in G7 countries: evidence from a panel Granger causality analysis *Environmental Science and Pollution Research* 27 90050–66

Poulos J and Zeng S 2021 RNN-based counterfactual prediction, with an application to homeland policy and public schooling *Journal of the Royal Statistical Society Series C—Applied Statistics* 70 1124–39

Qin M et al 2020 The stability of US economic policy: does it really matter for oil price? *Energy* 198 117315

Rasheed R et al 2021 Socio-economic and environmental impacts of COVID-19 pandemic in Pakistan—an integrated analysis *Environmental Science and Pollution Research* 28 19926–43

Ricci PF and Sheng H 2017 Assessing catastrophes—dragon-kings, black, and gray Swans—for science-policy *Global Challenges* 1 170021

Safari A, Hosseini R and Mazinani M 2020 A novel deep interval type-2 fuzzy LSTM model applied to COVID-19 pandemic time-series prediction *Journal of Biomedical Informatics* 123 103920

Sagi N, Zaguri M and Havlena D 2021 Soil CO2 influx in drylands: a conceptual framework and empirical examination *Soil Biology & Biochemistry* 156 108209

Sarkodie S and Owusu PA 2021 Global assessment of environment, health and economic impact of the novel coronavirus (COVID-19) *Environment, Development and Sustainability* 23 5005–15

Shafiullah M et al 2021 Does economic policy uncertainty affect renewable energy consumption? *Renewable Energy* 179 1500–21

Sharif A, Alou C and Yaroyava I 2020 COVID-19 pandemic, oil prices, stock market, geopolitical risk and policy uncertainty nexus in the US economy: fresh evidence from the wavelet-based approach *International Review of Financial Analysis* 70 101496

Shetabid K, Liu X and Kauzou H 2020 COVID-19’s disasters are perilsous than Global Financial Crisis: a rumor or fact? *Finance Research Letters* 36 101669

Sherstinsky A 2020 Fundamentals of recurrent neural network (RNN) and long short-term memory (LSTM) network *Physica D—Nonlinear Phenomena* 404 132306

Song Y et al 2021 Economic policy uncertainty, outward foreign direct investments, and green total factor productivity: evidence from firm-level data in China *Sustainability*. 13 2339

Su C, Huang S, Qin M et al 2021 Does crude oil price stimulate economic policy uncertainty in BRICS? *Pacific–Basin Finance Journal*. 66 101519

Su H et al 2022 Economic policy uncertainty, social development, political regimes and environmental quality *International Journal of Environmental Research and Public Health* 19 2450

Tao F and Liu G 2018 Advanced LSTM: a study about better time dependency modelling in emotion recognition 2018 IEEE Int. Conf. on Acoustics, Speech and Signal (ICASSP) 2906–10

Tsai I 2017 The source of global stock market risk: a viewpoint of economic policy uncertainty *Economic Modelling* 60 122–31

Vural-Yavas C 2021 Economic policy uncertainty, stakeholder engagement, and environmental, social, and governance practices: the moderating effect of competition *Corporate Social Responsibility and Environmental Management* 28 82–102

Wang G, Xie C, Wen D and Zhao L 2019 When Bitcoin meets economic policy uncertainty (EPU): measuring risk spillover effect from EPU to Bitcoin *Finance Research Letters* 31 489–97

Wang J, Wang J and Zhang Z 2011 Forecasting stock indices with back propagation neural network *Expert Syst. Appl.* 38 14346–55

Wang P et al 2020 Time series prediction for the epidemic trends of COVID-19 using the improved LSTM deep learning method: case studies in Russia, Peru and Iran *Chaos, Solitons Fractals* 140 110214

Wang X et al 2022 Exploring the bidirectional causality between green markets and economic policy: evidence from the time-varying Granger test *Environmental Science and Pollution Research* 1–16 Early Access

Wang Y, Chen C and Huang Y 2016 Economic policy uncertainty and corporate investment: evidence from China *Pacific–Basin Finance Journal* 26 227–43

Wu S, Tong M, Yang Z and Derbali A 2019 Does gold or Bitcoin hedge economic policy uncertainty *Finance Research Letters* 31 177–8

Wu W and Zhao J 2022 Economic policy uncertainty and household consumption: Evidence from Chinese households *Journal of Asian Economics* 79 101436

Wu X, Cui H and Wang L 2021 Forecasting oil futures price volatility with economic policy uncertainty: a CARR-MIDAS model *Applied Economics Letters* 1–6

Xiao D, Su J and Ayub B 2022 Economic policy uncertainty and commodity market volatility: implications for economic recovery *Energy Science and Pollution Research* 29 60662–73

Xiao X et al 2019 Economic policy uncertainty and grain futures price volatility: evidence from China *China Agricultural Economic Review* 11 642–54

Xu H et al 2022 The mediating role of public health between environmental policy tools and economic development *Energies*. 15 635

Xu Z 2020 Economic policy uncertainty, cost of capital, and corporate innovation *Journal of Banking & Finance* 111 105698

Xue C et al 2022 Clean energy consumption, economic growth, and environmental sustainability: what is the role of economic policy uncertainty? *Renewable Energy* 184 899–907

Yao C and Sun B 2018 The study on the tail dependence structure between the economic policy uncertainty and several financial markets *The North American Journal of Economics and Finance* 45 245–65

Ye R et al 2021 An empirical study on the equity performance of China’s health insurance companies during the COVID-19 pandemic-based on cases of dominant listed companies *Frontier in Public Health* 9 663189

Yousaf I 2021 Risk transmission from the COVID-19 to metals and energy markets *Resources*. Policy 73 102156

Yu H, Fang L, Du D and Yan P 2017 How EPU drives long-term industry beta *Finance Research Letters* 22 249–58

Yu J et al 2021 Economic policy uncertainty (EPU) and firm carbon emissions: evidence using a China provincial EPU index *Energy Econ.* 94 105071

Yuan T et al 2022 Being nice to stakeholders: the effect of economic policy uncertainty on corporate social responsibility *Economic Modelling* 18 105737

Zahra S and Badeeb RA 2022 The impact of fiscal decentralization, green energy, and economic policy uncertainty on sustainable environment: a new perspective from ecological footprint in five OECD countries *Environmental Science and Pollution Research* 29 54698–717
Zakari A, Adedoyin F F and Bekun F V 2021 The effect of energy consumption on the environment in the OECD countries: economic policy uncertainty perspectives Environmental Science and Pollution Research 28 52295–305
Zandavi S, Rashidi T and Vafaee F 2021 Dynamic hybrid model to forecast the spread of COVID-19 using LSTM and behavioral models under uncertainty IEEE Transactions on Cybernetics 92 2168–267
Zeng J, Zhong T and He F 2019 Economic policy uncertainty and corporate inventory holdings: evidence from China Accounting and Finance 60 1727–57
Zetterholm J et al 2022 We need stable, long-term policy support! - evaluating the economic rationale behind the prevalent investor lament for forest-based biofuel production Appl. Energy 318 119044
Zhang D, Hu M and Ji Q 2020 Financial markets under the global pandemic of COVID-19 Finance Research Letters 36 101528
Zhang L and Colak G 2022 Foreign direct investment and economic policy uncertainty in China Economic and Political Studies—EPS 10 279–89
Zhao T 2022 Economic policy uncertainty and manufacturing value-added exports Inżynieria Ekonomika—Engineering Economics 33 103–14
Zhou Y, Liu Z and Wu S 2022 The global economic policy uncertainty spillover analysis: In the background of COVID-19 pandemic Research in International Business and Finance 61 101666
Zhu H et al 2021 Time-frequency connectedness of crude oil, economic policy uncertainty and Chinese commodity markets: evidence from rolling window analysis North American Journal of Economics and Finance 57 101447
Zhu J et al 2019 Electric vehicle charging load forecasting: a comparative study of deep learning approaches Energies. 12 2692