An Options Pricing Method Based on the Atmospheric Environmental Health Index

Laijun Zhao

University of Shanghai for Science and Technology

Chenchen Wang (✉ wangchenchen_sust@163.com)

Shaanxi University of Science and Technology <https://orcid.org/0000-0003-0408-9041>

Yong Yang

Shaanxi University of Science and Technology

Jian Xue

Shaanxi University of Science and Technology

Deqiang Li

Shaanxi University of Science and Technology

Research

Keywords: Atmospheric environmental health index, Improved Ornstein-Uhlenbeck model, Options pricing, Esscher transform

Posted Date: August 12th, 2020

DOI: <https://doi.org/10.21203/rs.3.rs-55516/v1>

License: © ⓘ This work is licensed under a Creative Commons Attribution 4.0 International License.

[Read Full License](#)

An options pricing method based on the atmospheric environmental health index

Laijun Zhao¹, Chenchen Wang^{2,*}, Yong Yang^{2,3}, Jian Xue¹, Deqiang Li¹

¹Business School, University of Shanghai for Science and Technology, 516 Jungong Rd., Shanghai 200093, China

²School of Economics and Management, Shaanxi University of Science and Technology, University Park of Weiyang District, Xi'an 710021, China

³School of Arts and Sciences, Shaanxi University of Science & Technology, University Park of Weiyang District, Xi'an 710021, China.

*Corresponding author: Chenchen Wang, E-mail: wangchenchen_sust@163.com

Other authors: Laijun Zhao, E-mail: ljzhao@usst.edu.cn

Yong Yang, E-mail: yangyong@sust.edu.cn

Jian Xue, E-mail: xuejian2004@163.com

Deqiang Li, E-mail: ldqhb@126.com

Abstract

Background: Environmental finance has gradually become an important tool for solving atmospheric pollution problems. The creation of options based on an atmospheric environmental health index (AEHI) is designed to support a rational pricing of financial products related to the health of the atmospheric environment.

Method: First, the improved Ornstein-Uhlenbeck model is established to predict the change in air pollutant concentrations, and then the AEHI is constructed using exposure-response Poisson regression model. Then, an options pricing method for AEHI is proposed based on Esscher transform theory. Finally, the investment strategy for enterprises is formulated to hedge operational risk by using the AEHI option.

Results: AEHI options prices were determined for two diseases in each of three age groups using Beijing, China, as a case study, and AEHI option is applied to recompense for human health losses and hedge operating risk for an insurance enterprise.

Conclusion: The AEHI options should therefore be used to compensate for the damage to human health caused by air pollution, and to hedge against the operational risks of related industries such as insurance.

Keywords: Atmospheric environmental health index; Improved Ornstein-Uhlenbeck model; Options pricing; Esscher transform

Background

In recent years, atmospheric pollution has become increasingly serious. It not only damages public health and impedes the normal production activities and lives of urban residents, and has therefore also gradually become an important issue for the government [1, 2]. Harsh atmospheric pollution directly threatens human health [3-5], and also increases economic risks when it interferes with the operations of enterprises. For example, air pollution decreases the number of tourists and delays flights in affected regions, which has a significant negative impact on tourism, transportation, and other industries [6]. Environmental finance has gradually become an important tool for solving atmospheric pollution problems [7].

Insurance companies have developed health insurance products to account for the health damage caused by air pollution. However, the products were not implemented because of problems with their design mechanism. For instance, the

People's Property Insurance Company of China (PPICC) launched haze insurance in March 2014. As a result, these products like the PPICC product were cancelled by the China Insurance Regulatory Commission after only one week, based on the argument that the insurance does not conform to the two principles of insurance design: having the best interests of the policy-holder in mind, and the law of large numbers. The haze insurance resembled gambling more than it resembled a legitimate insurance product [8].

Although air pollution health insurance has been withdrawn from the Chinese market, the concept retains some merit if the abovementioned problems can be solved. In addition, it's necessary to develop a more rational method for developing such financial tools and determining effective pricing. If these problems cannot be solved, environmental health financial products cannot be popularized and applied to mitigating the health burden of urban residents [9]. Therefore, we designed an atmospheric environmental health index (AEHI) option to help enterprises hedge against the operational risk caused by air pollution.

The basis of the options pricing lies in the establishment of an accurate prediction model for subject matter. The characteristics of air pollutants are similar to those of weather factors, because air pollution and weather have obvious seasonal and periodic fluctuations. However, the prediction of atmospheric pollutant levels is more complicated. The variation of these concentrations is not only influenced by natural factors such as the season, weather, topography, and physical and chemical reactions, but also by human factors. It is therefore difficult to predict air pollutant levels

accurately [10]. Forecasting using numerical simulation models based on weather factors is often used to predict the changes of atmospheric pollutants. The improved Ornstein-Uhlenbeck (O-U) model has been widely used to simulate exponential time series [11, 12]. However, the periodic variation of air pollutants is still generally described by using the original AR model in O-U model. This approach did not distinguish which of various improved AR models was most suitable for describing these variations. This is an important omission, since the accuracy of the periodic fitting directly affects the accuracy of the predicted concentrations.

An effective index of options must be able to reflect changing trends in financial markets, and must directly influence the efficiency of index-based options pricing [13]. Methods of constructing the underlying index about the atmospheric environment are usually constructed based on AQI or the concentrations of specific air pollutants such as fine particulate matter ($PM_{2.5}$ and PM_{10}). For example, [14] designed an air pollution options based on air quality index. [15] constructed an average deviation index based on AQI to describe a city's air quality during a given period. Although atmospheric environmental indexes have been reported in the literature, the relationship between air pollution and human health has not been accounted for in research on financial derivatives related to these indexes.

The essence of options is to hedge against business risks. Options pricing methods can be divided into three categories. The first is traditional options pricing, such as the classical binary-tree pricing method and the Black-Scholes options pricing model [16, 17]. However, this category relies on too many idealized assumptions,

which reduces the applicability of the models and their ability to reflect the real market. The second is the option pricing method with a stochastic time transform [18-20]. Although this category can account for the jumping property of the subject index by using stochastic temporal transformations, this method has limited application in practice due to its heavy dependence on transaction time.

The third method is actuarial pricing [21]. The Esscher transform is the most common classical actuarial method. The Esscher transform was first proposed by [22], who determined the equivalent-martingale measure of options; that is, it is based on a sequence of random variables in which the conditional expectation of the next value in the sequence at a given time, predicted based on all prior values, is equal to the present value. In theory, the Esscher transform accounts for the basic hypothesis of options, which is the possibility of risk-free arbitrage. This method can be used to simulate a variety of statistical distributions, which makes options pricing more widely applicable [23].

In summary, there are three problems with current research on options pricing in the context of atmospheric pollution and health damage. (i) The accuracy of atmospheric pollutant predictions must be improved. (ii) A suitable AEHI has not yet been constructed. (iii) It is unclear how actuarial methods can be used to improve the efficiency of the AEHI option pricing. To solve these problems, we develop an approach that provides three contributions to the literature. (i) The improved O-U model is used to predict more accurately the variation of regional atmospheric pollutant concentration. (ii) Accounting for the damage to human health caused by

atmospheric pollution, we construct the AEHI for different diseases and age groups.

(iii) An option pricing method based on the AEHI is proposed by using Esscher transform, and developed investment strategy for an enterprise to hedge against its operational risk.

Methods

The AEHI options pricing method includes four parts. (i) It uses an improved O-U model to predict changes in the concentrations of atmospheric pollutants. (ii) It constructs the AEHI based on the predicted pollutant concentrations by using an exposure–response model. (iii) It proposes an AEHI options pricing method using an Esscher transform. (iv) It provides an investment strategy that hedges against operational risk. Fig. 1 shows the procedure of AEHI option pricing.

Fig. 1 The procedure used in the AEHI options pricing approach.

Prediction of atmospheric pollutants based on an improved O-U model

According to Lévy motion, an O-U model with reversion to the mean can be selected to predict the stochastic variation of atmospheric pollutant concentrations [24]. A standard Brownian motion process $E(t)$ has a corresponding original

stochastic differential equation:

$$d\rho(t) = ds(t) + \eta(\rho(t) - s(t))dt + \sigma(t)dE(t) \quad (1)$$

Where $\rho(t)$ denotes the concentration of atmospheric pollutants in an area on day t , and $s(t)$ is a continuously differentiable and bounded deterministic function that describes the long-term linear trend and seasonal variation characteristics of the atmospheric pollutant concentration's time series. According to the trend for the atmospheric pollutants, it partly reflects the actual control by the regional atmospheric environment. $(\rho(t) - s(t))$ represents the time series after removing the effects of long-term trends and seasonal variation. η measures the rate of reversion to the mean for the atmospheric pollutant concentration at time t . $\sigma(t)$ is also a continuously differentiable and bounded deterministic function, and represents the random disturbance of the atmospheric pollutant concentration (i.e. the daily fluctuation on day t).

By dispersing the daily data (i.e., by making it discrete), equation (1) can be converted into equation (2):

$$\Delta\rho(t) = \Delta s(t) + \eta(\rho(t-1) - s(t-1))\Delta t + \sigma(t)\Delta E(t) \quad (2)$$

In equation (2), if $\Delta t = 1$, $\Delta E(t) : N(0,1)$, therefore, equation (3) can be obtained:

$$\rho(t) - s(t) = (1 + \eta)(\rho(t-1) - s(t-1)) + \sigma(t)\varepsilon(t) \quad (3)$$

if $c(t) = (1 + \eta)(\rho(t-1) - s(t-1))$, thus, the time series model (4) can be obtained:

$$\rho(t) = s(t) + c(t) + \sigma(t)\varepsilon(t) \quad (4)$$

Although (4) is a general time series formula, it is still also suitable predict the stochastic variation of atmospheric pollutant concentrations due to the nature of pollutants. $\rho(t)$ indicates the concentration of atmospheric pollutants on day t , and $s(t)$ describes the long-term linear trend and seasonal variation characteristics of the atmospheric pollutant concentration's time series. $c(t)$ represents the periodic variation characteristic of the atmospheric pollutant concentration's time series. $\sigma(t)$ denotes random disturbance of the atmospheric pollutant concentration, and satisfies the condition $\varepsilon(t) : N(0,1)$.

According to this time series model, the long-term trend, the seasonal, periodic and random perturbation terms can be fitted successively by using a Fourier transform approximation function [25].

Trend and seasonality $s(t)$

Using the Fourier series to expand $s(t)$:

$$s(t) = (a + bt) + a_0 + \sum_{m=1}^{I_1} a_m \sin(m\omega t) + \sum_{n=1}^{J_1} b_n \cos(n\omega t) \quad (5)$$

In (5), $(a + bt)$ represents the long-term trend of the atmospheric pollutant concentration's time series. ω is the frequency of the seasonal, which is actually a contraction of the standard Fourier series about the time axis.

Periodicity $c(t)$

To fit the periodicity $c(t)$ to the observed data, it's necessary to obtain the solution of the linear non-homogeneous differential equation (1) using the Ito formula for an integral.

$$\rho(t) = s(t) + (\rho(t) - s(t))e^{-\eta t} + \int_0^t \sigma(u)e^{-\eta(t-u)}dE(u) \quad (6)$$

Because air pollutant concentration data is collected on a daily basis (i.e. $\Delta X(t) := X(t+1) - X(t)$), the discrete form of the difference in equation (6) is obtained:

$$\Delta \rho(t) = \Delta s(t) - (1 - e^{-\eta})(\rho(t) - s(t)) + e^{-\eta} \int_t^{t+1} \sigma(u)e^{-\eta(t-u)}dE(u) \quad (7)$$

The integral of the random perturbation terms can then be discretized and approximated.

$$\Delta \rho(t) \approx \Delta s(t) - (1 - e^{-\eta})(\rho(t) - s(t)) + e^{-\eta} \sigma(t) \Delta E(t) \quad (8)$$

As $\beta(t) := \rho(t) - s(t)$, $\beta(t)$ represents the time series of new atmospheric pollutant concentrations after removing the effects of any long-term linear trend and seasonality from the original time series. Equation (9) is equivalent to equation (8):

$$\beta(t+1) = e^{-\eta}[\beta(t) + \sigma(t)\varepsilon(t)] \quad (9)$$

Equation (9) is usually solved by using an AR model [26]. The AR models include the original AR model, the moving average (MA) model, and the autoregressive moving average (ARMA) model. In the specific calculation process, it is necessary to select the most appropriate model based on the characteristics of the data's autocorrelation coefficient and partial autocorrelation coefficient. Table 1 presents the criteria for choosing the optimal AR model.

Table. 1 Selection of the models.

AR model	Characteristic of the autocorrelation coefficient	Characteristics of the partial correlation coefficient
original AR(n1)	Trailing	Lag=n1 Censored
MA(n2)	Lag=n2 Censored	Trailing
ARMA(n1,n2)	Trailing	Trailing

Stochastic disturbance $\sigma(t)$

For convenience of data analysis and time series modeling, $\sigma^2(t)$ is usually used instead of $\sigma(t)$ for Fourier expansion.

$$\sigma^2(t) = c + \sum_{m=1}^{I_2} d_m \sin(m\omega t) + \sum_{n=1}^{J_2} q_n \cos(n\omega t) \quad (10)$$

Construction of the AEHI

Exposure-response models have often been used to assess the health damage and economic losses caused by air pollution in the field of atmospheric environmental epidemiology [27]. However, few specific indexes have been designed to describe the damage of atmospheric pollution to human health.

The long-term health impairment caused by atmospheric pollution is far greater than the short-term health impairment. The most significant health impairment outcome is death [28, 29]. We chose the number of premature deaths from q kinds of diseases caused by pollution as the health effect to measure long-term health damage when the AEHI is constructed. At the same time, we used $k \in \{1, 2, \dots, q\}$ to represent disease k in age group j . To measure the health impairment caused by disease k in age group j as a result of by air pollution, AEHI is constructed using an exposure-response Poisson regression model [30], as shown in equation (11):

$$L_{jkt} = P_j h_{jk} \beta_{jk} (C_t - C_{t-1}) \quad (11)$$

In (11), P_j is the population in age group j (persons). h_{jk} indicates the mortality rate for disease k in age group j (%). The dose response coefficient β_{jk} represents the change in mortality of disease k in age group j caused per unit change in the pollution concentration (%). C_t denotes the concentration of atmospheric pollutants on day t ($\mu\text{g}/\text{m}^3$).

AEHI Options pricing method using the Esscher transform

If $L(t)$ is the AEHI at time t and $X(t)$ is the growth rate of the underlying exponential change:

$$L(t) = L(0)e^{X(t)}, \quad t \geq 0 \quad (12)$$

The contract period for the AEHI options is divided into a loss period and an extended period. The loss period indicates that when the concentration of atmospheric pollutants is high, it will directly cause great damage to human health. The subsequent stage is defined as the extended period. Although the concentration of pollutants decreases during the extended period, it is still high enough to be harmful to human health. Depending on the cumulative and delayed effects of certain diseases caused by air pollution, the extended period includes not only the health damage caused by the current pollutants, but also the delayed human diseases caused by pollution during the loss period [31].

If t is the pricing time, $[0, T_1]$ is the loss period, and $[T_1, T_2]$ is the extended period, Equation (12) shows obvious differences in the change processes for the AEHI during different periods. That is, the change index should follow different incremental processes. If we assume that $A(t)$ is the stationary incremental process of the subject index during the loss period, $B(t)$ is the stationary incremental process of the subject index during the extended period, and the incremental processes during the two periods are relatively independent, then the growth rate of the change is expressed as:

$$X(t) = \begin{cases} A(t), & t \in [0, T_1] \\ A(T_1) + B(t - T_1), & t \in [T_1, T_2] \end{cases} \quad (13)$$

Thus, the growth of AEHI options at maturity can be expressed as follows:

$$X(T_2) = \begin{cases} X(t) + A(T_1 - t) + B(T_2 - T_1), & t \in [0, T_1] \\ X(t) + B(T_2 - t), & t \in [T_1, T_2] \end{cases} \quad (14)$$

From equation (12), the AEHI options at maturity are as follows:

$$L(T_2) = \begin{cases} L(t)e^{A(T_1-t)+B(T_2-T_1)}, & t \in [0, T_1] \\ L(t)e^{B(T_2-t)}, & t \in [T_1, T_2] \end{cases} \quad (15)$$

Because the options products of the subject index belong to the class of double-cap financial derivatives, we can set a maximum delivery price of H and an options execution price of K . The maturity income is then as follows for a call option:

$$V_{\text{call}}(T_2) = \begin{cases} 0, & L(T_2) \in (0, K] \\ L(T_2) - K, & L(T_2) \in [K, H] \\ H - K, & L(T_2) \in [H, +\infty) \end{cases} \quad (16)$$

The economic implication of equation (16) is that the payment amount is $(H-K)$ when the $L(t)$ value for the AEHI exceeds the H value. The Esscher transform has been proven to be a unique equivalent martingale measure [22]. Under the equivalent martingale measure, the price of a financial asset is equivalent to the discounted value of future earnings (with a risk-free discounting rate r).

Based on the Esscher transform's principle, AEHI at time t can be expressed as:

$$L(t) = \begin{cases} e^{-r(T_2-t)} E_t^*[L(t)e^{A(T_1-t)+B(T_2-T_1)}], & t \in [0, T_1] \\ e^{-r(T_2-t)} E_t^*[L(t)e^{B(T_2-t)}], & t \in [T_1, T_2] \end{cases} \quad (17)$$

The $*$ means that after the Esscher transform, the AEHI option price is obtained by directly discounting the earnings expectation (based on the risk-free discounting rate r) when the option contract expires. After simplification, equation (17) can be transformed into:

$$e^{r(T_2-t)} = \begin{cases} E_t^*[e^{A(T_1-t)+B(T_2-T_1)}], & t \in [0, T_1] \\ E_t^*[e^{B(T_2-t)}], & t \in [T_1, T_2] \end{cases} \quad (18)$$

The incremental process is processed by the Esscher transform, $A(T_1-t)$ and $B(T_2-T_1)$ with parameter h_1^* , and the moment-generating function for the incremental process is obtained as $M_A[z, T_1-t; h_1^*]$ and $M_B[z, T_2-T_1; h_1^*]$, respectively. Similarly, for the incremental process $B(T_2-t)$ with parameter h_2^* , the moment-generating function for the incremental process is obtained as $M_B[z, T_2-t; h_2^*]$. The increments $A(T_1-t)$ and $B(T_2-t)$ are independent of each other. When $z = 1$:

$$e^{r(T_2-t)} = \begin{cases} M_A[1, T_1-t; h_1^*] M_B[1, T_2-T_1; h_1^*], & t \in [0, T_1] \\ M_B[1, T_2-t; h_2^*], & t \in [T_1, T_2] \end{cases} \quad (19)$$

Because the option product involves different stages, the option pricing models during the loss and extended periods can be determined (see **Appendix A** for details of the calculations). Based on this analysis, we conclude that the AEHI option price OP_t at time t is as follows:

$$OP_t = \begin{cases} L(t)[F_X(m, T_2-t; h_1^*+1) - F_X(n, T_2-t; h_1^*+1)] \\ -Ke^{-r(T_2-t)}[F_X(m, T_2-t; h_1^*) - F_X(n, T_2-t; h_1^*)] \\ +(H-K)e^{-r(T_2-t)}[1 - F_X(m, T_2-t; h_1^*)], & t \in [0, T_1] \\ L(t)[F_B(m, v; h_2^*+1) - F_B(n, v; h_2^*+1)] \\ -Ke^{-r(T_2-t)}[F_B(m, v; h_2^*) - F_B(n, v; h_2^*)] \\ +(H-K)e^{-r(T_2-t)}[1 - F_B(m, v; h_2^*)], & t \in [T_1, T_2] \end{cases} \quad (20)$$

The economic implications are as follows with the AEHI option price during the loss period as an example.

(i) $[F_X(m, T_2-t; h_1^*+1) - F_X(n, T_2-t; h_1^*+1)]$ denotes the corresponding probability under the new probability measure (after the Esscher transform with parameter (h_1^*+1)) when the AEHI exceeds the execution price K and is less than the maximum delivery price H .

(ii) $[F_X(m, T_2-t; h_1^*) - F_X(n, T_2-t; h_1^*)]$ describes the probability that the AEHI

exceeds the execution price K and is less than the maximum delivery price H under the Esscher transform with parameter h_1^* .

(iii) To prevent default, the maximum delivery price H directly affects the maturity income of the AEHI option (where the maturity income only includes the part between the maximum delivery price H and the execution price K), and the excess part must be calculated with a quota. Therefore, the third item $(H - K)e^{-r(T_2 - t)}[1 - F_X(m, T_2 - t; h_1^*)]$ is generated. $(H - K)$ is a fixed value when the profit exceeds the limit, and the corresponding risk neutral probability is $[1 - F_X(m, T_2 - t; h_1^*)]$.

Although the equation (20) defines the AEHI option prices for call options, it is necessary to distinguish the distribution of incremental processes $A(t)$ and $B(t)$ to obtain a more specific AEHI options pricing model.

Enterprise investment strategy for hedging against operating risk

Reasonable option pricing provides a basis for enterprises to hedge against the operational risks caused by air pollution. How to hedge against these risks effectively, determine the break-even point, and formulate the corresponding investment strategy can directly affect the enterprise's operation.

The AEHI options belong to the class of double-cap financial derivatives. The profit and loss (PAL) functions for the buyer of call options are as follows:

$$PAL_{\text{call}} L(T_2) = \begin{cases} -N gOP_t, & L(T_2) \in (0, K] \\ PN L(T_2) - K - N gOP_t, & L(T_2) \in [K, H) \\ PN H - K - N gOP_t, & L(T_2) \in [H, +\infty) \end{cases} \quad (21)$$

In (21), N is the number of options to be purchased. P is the minimum variable

price (the unit price of index $L(T_2)$), and the break-even point is $L(T_2) = K + \frac{OP_t}{P}$.

Similarly, the profit and loss function of the putting option buyer is:

$$PAL_{\text{put}} L(T_2) = \begin{cases} PN[K - H] - NgOP_t, & L(T_2) \in (0, H] \\ PN[K - L(T_2)] - NgOP_t, & L(T_2) \in [H, K) \\ -NgOP_t, & L(T_2) \in [K, +\infty) \end{cases} \quad (22)$$

The break-even point is $L(T_2) = K - \frac{OP_t}{P}$.

AEHI Option Pricing

Beijing city is selected as a case, and the AEHI option prices for different types of diseases are determined in different age groups. On this basis, we provide an enterprise investment strategy to hedge against operational risk by using AEHI options.

Sample selection and data sources

The data we analyzed were the average SO₂ concentration in Beijing from January 1, 2013 to December 31, 2018 (Urban Air Quality Daily of the Ministry of Ecology and Environment of the People's Republic of China, <http://www.mee.gov.cn/hjzl/>). The sample set for predicting levels of this atmospheric environmental pollutant was from 2013 to 2017, and the verification set was from 2018. Beijing is not only the capital of China, but also the key monitoring area in the National Atmospheric Environment Program conducted by the Ministry of the Ecological Environment of the People's Republic of China (<http://www.mee.gov.cn/>).

We chose SO₂ as the target pollutant because it greatly harms human health. It can not only stimulate the human respiratory mucosa, but also cause rhinitis, aggravate asthma and chronic bronchitis, and even induce pulmonary edema and lung cancer. SO₂ therefore has a strong toxic effect on the human respiratory system. At the

same time, SO_2 can also easily stimulate the eye mucosa, penetrate the human body through the skin, and combine with water to produce harmful sulfites or sulfuric acid.

Prediction of SO_2

Trends and seasonality

According to the equation (5), the SO_2 concentration data of Beijing from 2013 to 2017 were fitted by using SPSS 21.0 (<https://www.ibm.com/analytics/us/en/technology/spss/>) and MATLAB 2012a (<https://www.mathworks.com/>). The result of the estimated parameters is that $a = 25.102$, $b = -0.055$, $a_0 = 15.128$, $a_1 = -0.262$, $b_1 = -0.87$, $\omega = -1.295$. Fig. 2 shows the Fourier series fitting diagram for $s(t)$.

Fig. 2 The Fourier series fitting diagram for $s(t)$.

Figure 2 shows obvious trends and seasonality in Beijing from 2013 to 2017 with a stable decrease in the SO_2 concentration. To fit the periodicity of the data, the trend and seasonality terms need to be eliminated to obtain a time series for the square of the residuals term.

Before fitting the periodicity, unit root test (the Dickey-Fuller test) is needed for confirming the rationality of selecting AR model. The test's t statistic was -13.7305, versus a critical value of -3.9683 for significance at $P < 0.01$. Therefore, the sequence is stationary, and the AR model can be used to describe periodicity.

Periodicity

The parameters in Table 1 support our use of the AR model to describe the periodic characteristics of the data. Fig. 3 shows the autocorrelation coefficients and partial autocorrelation coefficients for the residual terms.

Fig. 3(a) The autocorrelation coefficients for each lag.

Fig. 3(b) The partial autocorrelation coefficients for each lag.

Based on the results in Fig. 3, we used an AR model with a second-order lag to fit the periodicity. The general form of the model is as follows:

$$c(t) = \sum_{p=1}^P \beta_p (T_{t-p} - S_{t-p}) = \sum_{p=1}^P \beta_p X_{t-p} \quad (23)$$

The model was solved by Matlab to provide the following equation:

$$c(t) = 1 - 0.5895X_{t-1} - 0.3805X_{t-2} + \sigma_t \varepsilon_t \quad (24)$$

Stochastic disturbance

We used the data from 2013 to 2017 as inputs for equation (10), and used $I_2 = J_2 = 5$ from 2013 to 2017. The estimated values of each parameter are shown in Table 2.

Table. 2 The estimated values of each parameter.

Parameter	Estimated value	Parameter	Estimated value	Parameter	Estimated value
c	512.429	d_1	-39.197	d_2	3.364
d_3	-1.126	d_4	-4.516	d_5	-17.545
q_1	-16.517	q_2	-12.944	q_3	-11.939
q_4	-6.756	q_5	27.214	ω	1.003

Furthermore, the SO_2 concentration in 2018 can be predicted by accounting for these factors, and the actual SO_2 concentration can be compared with the predicted values. Fig. 4 shows the results of this comparison. The prediction the mean error is 13.4%.

Fig. 4 Comparison of real and predicted SO_2 concentration in 2018.

AEHI Options pricing

Construction of the AEHI

Beijing's AEHI can be obtained by using equation (11), and the specific values of the parameters are shown in Table 3.

Table. 3 The specific values of the parameters.

Age group	Population (persons)	Mortality rate (‰)	β_1 (%)	β_2 (%)
0-14 years	2264000	5.3	0.059734	0.048372
15-64 years	16067000	5.3	0.047104	0.048372
>64 years	2376000	5.3	0.044253	0.034668

Notes: Population and mortality data were obtained from the Beijing Municipal Bureau of Statistics (<http://www.bjstats.gov.cn/>). β_1 represents the dose response coefficient for cardiovascular disease [32]. β_2 represents the dose response coefficient for respiratory diseases [33].

Pricing results for AEHI options

AEHI can be calculated using the parameters in Table 3. It is necessary to distinguish the distribution of incremental processes $A(t)$ and $B(t)$ for determining the specific pricing form before pricing the options. After judging, we found that the growth rate of Beijing's AEHI followed the Wiener distribution. On this basis, the specific AEHI option pricing formula is obtained (Appendix B).

The loss period and extended period are defined according to the variation of the SO_2 concentration. SO_2 pollution is more serious from December of the current year to May of the following year [34], so we tentatively set the loss period as 6 months, from December to May, and set the extended period as the remaining 6 months, from June to November. The time span used for these two periods does not affect the calculation principle. The calculation process remains completely consistent if we change the dates, but the specific calculation results will differ.

The risk-free interest rate r is obtained based on the interest rate of 1-year

Chinese treasury bonds (Ministry of Finance of the People's Republic of China, http://gks.mof.gov.cn/guozaiguanli/gzfxgzdt/201812/t20181229_3111187.html).

Because the Wiener distribution is symmetrical, the mean values of incremental processes $A(u)$ and $B(v)$ are 0; that is, $\mu_A = \mu_B = 0$. The variances of the two incremental processes are based on the variance of the corresponding loss period and extended period, respectively, from 2013 to 2017.

The options contract types are influenced by the age of the affected individuals (younger than 14 years, 15 to 64 years, and older than 64 years), the diseases (cardiovascular versus respiratory), and the pricing time (loss period versus extended period). Therefore, the results for the AEHI options must be discussed separately for the different combinations of these situations. Due to space limitations, we have presented the AEHI options pricing for respiratory disease in Appendix C. Here, we will focus on the pricing results for cardiovascular disease.

Fig. 5(a) shows the effects of the pricing stages and execution price K on the AEHI (cardiovascular) options prices for individuals younger than 14 years old.

iii) extended period

Notes: graphs (ii) and (iii) show the same data from different perspectives.

Fig. 5(a) The pricing results of the AEHI (cardiovascular) options (younger than 14 years).

Fig 5(b) shows the effects of the pricing stages and execution price K on AEHI (cardiovascular) options prices for individuals 15 to 64 years old.

i) loss period

ii) extended period

iii) extended period

Notes: graphs (ii) and (iii) show the same data from different perspectives.

Fig. 5(b) The pricing results of the AEHI (cardiovascular) options (15 to 64 years old).

Fig. 5(c) shows the effects of the pricing stages and execution price K on AEHI (cardiovascular) options prices for individuals older than 64 years.

Notes: graphs (ii) and (iii) show the same data from different perspectives.

Fig. 5(c). The pricing results of the AEHI (cardiovascular) options (older than 64 years).

Analysis of the AEHI options pricing results

(i) Table 4 compares the AEHI options prices for the two kinds of disease based on the maximum options price for the two pricing periods, three age groups, and two diseases.

Table. 4 Comparison of the maximum options price.

Pricing time	Age group	Maximum options price (RMB)	
		Cardiovascular disease	Respiratory disease
Loss period	0-14 years	828	714
	15-64 years	1597	1759
	>64 years	658	518
Extended period	0-14 years	129	84
	15-64 years	817	861
	>64 years	125	77

Notes: all numbers keep integers.

Table 4 shows that during the same period (the loss or extended period), the AEHI options price is higher for cardiovascular disease than for respiratory disease, except in the age group from 15 to 64 years. In this middle age group, the highest

AEHI options price for respiratory disease was slightly higher than that for cardiovascular disease. This is due to the relationship between age and the dose-response coefficients for the two kinds of diseases.

(ii) Based on the comprehensive influence of the maturity time (T_2-t) and the execution price K on the option price, it is clear that the option price increases with increasing maturity time, increases with increasing execution price, and converges with final option price when the pricing time t occurs during the loss period. In addition, the option price gradually increases with increasing maturity time, but with increasing execution price, it reaches its maximum value first, then decreases, and then immediately converges with the final option price. The initial change range is large during the extended period. The change trend for options prices differs greatly between the two pricing periods, and the options prices during the extended period are far lower than those during the loss period.

(iii) For the same kind of disease AEHI (cardiovascular or respiratory), the options price was highest for individuals 15 to 64 years old, followed by individuals younger than 14 years old; the options price was lowest for the group older than 64 years. Therefore, individuals from 15 to 64 years old should be prioritized when designing or promoting the AEHI options.

Investment strategy by using AEHI options

The reasonable pricing of the AEHI options provides a basis for enterprises to hedge against their operational risks caused by air pollution. Based on the simulation pricing results earlier in section 3.3.3, the hedging mechanism based on the AEHI

options is examined with a hypothetical Beijing insurance company in 2018 as a case study.

Assuming that the insurance company has introduced insurance for cardiovascular diseases caused by atmospheric pollution for people aged younger than 14 years, with an average monthly sales volume of 100 individuals and an average income per individual of 10000 RMB. In this context, the insurance company would buy 100 of the AEHI (cardiovascular) call options on 1 December 2018 (the loss period) to avoid declining sales due to good weather. Based on the AEHI cardiovascular options prices for this age group, the option price is 828 RMB per share, for a total options cost of 82800 RMB for the 100 individuals. Because of improving pollution control by Beijing's Municipal Government and the improved air quality during the period covered by the options contracts, the sales of insurance policies would be 10% lower than before 2018, resulting in losses of about 100,000 RMB. However, if the AEHI rose by 100 points (at 20 RMB/point), the company could execute all of its call options and receive payment of 2,000 RMB/individual, for a total of 200,000 RMB. If we subtract the options fee, the net income would be 117,200 RMB, which would compensate for the loss of 10,000 RMB and result in a profit of 17,200 RMB.

Conclusion

Severe air pollution has increasingly become a focus of governments and the public, as it affects both human health and the stability and sustainable development of regional and national economies through its effects on the normal operation of

enterprises. To support efforts to combat such problems, an improved O-U model is used to predict the variation of atmospheric pollutants over time. The AEHI is developed by using an exposure-response model. Finally, an AEHI option pricing method is proposed based on Esscher transform theory, and the investment strategy is formulated for hedging against operational risk by an enterprise. Using Beijing as a case study, we determine the AEHI options prices for three age groups. The AEHI options prices for the two diseases changed in the same direction as the dose-response coefficients for the diseases. The change trends for the options prices during the two pricing periods (loss and extended) differed, with the options prices during the extended period far lower than those during the loss period. For the same kind of AEHI option, the options prices were highest for individuals 15 to 64 years old, followed by the group 14 years old or younger, and the lowest options price was for the group older than 64 years. Therefore, the middle group should be considered the priority. And then we illustrated an investment strategy to hedge against operational risk and used a hypothetical insurance company as an example of this strategy. The AEHI options should therefore be used to compensate for the damage to human health caused by air pollution, and to hedge against the operational risks of related industries such as insurance. In future research, we plan to consider other types of time series models to improve the prediction accuracy for air pollutant levels. The AEHI dose-response coefficients should also be improved by accounting for the characteristics of populations in different regions.

Supplementary information

Appendices

Appendix A. The option pricing model details

When $t \in [0, T_1]$, assuming that $T_1 - t = u$, $u \in [0, T_1]$ for convenience of calculation. In a random process, $F(x, t; h)$ and $f(x, t; h)$ are the cumulative probability-distribution function and probability density function respectively, after the Esscher transform of parameter h . At this point, the call option execution price is:

$$\begin{aligned} OP_t &= e^{-r(T_2-t)} E_t^*[V_{call}(T_2)] \\ &= e^{-r(T_2-T_1+u)} \left\{ \int_K^H (L(T_2) - K) f_X(x, T_2 - t; h_1^*) dx + \int_H^{+\infty} (H - K) f_X(x, T_2 - t; h_1^*) dx \right\} \end{aligned} \quad (A.1)$$

To simplify equation (A.1), supposing that $m = \ln[H / L(t)]$ and $n = \ln[K / L(t)]$. Therefore:

$$\begin{aligned} OP_t &= e^{-r(T_2-T_1+u)} \int_n^m [(L(T_2) - K) f_X(x, T_2 - t; h_1^*)] dx + \\ &\quad e^{-r(T_2-T_1+u)} \int_m^{+\infty} [(H - K) f_X(x, T_2 - t; h_1^*)] dx \\ &= e^{-r(T_2-T_1+u)} \left\{ \int_n^m [(L(t) e^{a(u)+b(T_2-T_1)} - K) f_X(x, T_2 - t; h_1^*)] dx \right. \\ &\quad \left. + e^{-r(T_2-T_1+u)} \int_m^{+\infty} [(H - K) f_X(x, T_2 - t; h_1^*)] dx \right\} \\ &= e^{-r(T_2-T_1+u)} L(t) \int_n^m e^{a(u)+b(T_2-T_1)} f_A(a, u; h_1^*) f_B(b, T_2 - T_1; h_1^*) dx - \\ &\quad K e^{-r(T_2-T_1+u)} \int_n^m f_A(a, u; h_1^*) f_B(b, T_2 - T_1; h_1^*) dx \\ &\quad + (H - K) e^{-r(T_2-T_1+u)} \int_m^{+\infty} f_A(a, u; h_1^*) f_B(b, T_2 - T_1; h_1^*) dx \\ &= e^{-r(T_2-T_1+u)} L(t) \int_n^m e^{a(u)} f_A(a, u; h_1^*) e^{b(T_2-T_1)} f_B(b, T_2 - T_1; h_1^*) dx - \\ &\quad e^{-r(T_2-T_1+u)} \left\{ K [F_A(x, u; h_1^*) F_B(x, T_2 - T_1; h_1^*)] \Big|_n^m \right. \\ &\quad \left. + (H - K) [F_A(x, u; h_1^*) F_B(x, T_2 - T_1; h_1^*)] \Big|_m^{+\infty} \right\} \\ &= L(t) \int_n^m \frac{e^{a(u)} f_A(a, u; h_1^*)}{e^{ru}} \frac{e^{b(T_2-T_1)} f_B(b, T_2 - T_1; h_1^*)}{e^{r(T_2-T_1)}} dx - \\ &\quad K e^{-r(T_2-t)} [F_A(m, u; h_1^*) F_B(m, T_2 - T_1; h_1^*) - F_A(n, u; h_1^*) F_B(n, T_2 - T_1; h_1^*)] \\ &\quad (H - K) e^{-r(T_2-t)} [1 - F_A(m, u; h_1^*) F_B(m, T_2 - T_1; h_1^*)] \end{aligned} \quad (A.2)$$

The joint distribution of the AEHI is $F_X = F_A F_B$. Equation (A.2) can be abbreviated as follows:

$$\begin{aligned} OP_t = & L(t)[F_X(m, T_2 - t; h_1^* + 1) - F_X(m, T_2 - t; h_1^*)] - \\ & Ke^{-r(T_2 - t)}[F_X(m, T_2 - t; h_1^*) - F_X(n, T_2 - t; h_1^*)] + \\ & (H - K)e^{-r(T_2 - t)}[1 - F_X(m, T_2 - t; h_1^*)] \end{aligned} \quad (A.3)$$

When $t \in [T_1, T_2]$, assuming that $T_2 - t = v$, $v \in [0, T_2 - T_1]$ for convenience of calculation. The call option execution price is then obtained:

$$\begin{aligned} OP_t = & e^{-r(T_2 - t)} E_t^*[V_{\text{call}}(T_2)] \\ = & e^{-rv} \left\{ \int_K^H (L(T_2) - K) f_X[x, T_2 - t; h_2^*] dx + \int_H^{+\infty} (H - K) f_X[x, T_2 - t; h_2^*] dx \right\} \\ = & e^{-rv} \left\{ \int_n^m (L(t)e^{b(v)} - K) f_X(x, T_2 - t; h_2^*) dx + \int_m^{+\infty} (H - K) f_X(x, T_2 - t; h_2^*) dx \right\} \\ = & e^{-rv} L(t) \int_n^m e^{b(v)} f_B(b, T_2 - t; h_2^*) dx - Ke^{-rv} \int_n^m f_B(b, T_2 - t; h_2^*) dx + \\ & (H - K) e^{-rv} \int_m^{+\infty} f_B(b, T_2 - t; h_2^*) dx \\ = & L(t)[F_B(m, v; h_2^* + 1) - F_B(n, v; h_2^* + 1)] - Ke^{-r(T_2 - t)}[F_B(m, v; h_2^*) - F_B(n, v; h_2^*)] \\ & + (H - K)e^{-r(T_2 - t)}[1 - F_B(m, v; h_2^*)] \end{aligned} \quad (A.4)$$

Appendix B. The specific AEHI option pricing formula under the Wiener distribution

Incremental processes $A(u)$ and $B(v)$ obey the laws for Brownian motion. Assuming that the incremental process $A(u)$ follows the Wiener distribution with mean $\mu_A u$ and variance $\sigma_A^2 u$, the incremental process $B(v)$ follows the Wiener distribution with mean $\mu_B v$ and variance $\sigma_B^2 v$, then after the Esscher transform of parameter h , their moment generating functions are obtained:

$$M_A[z, u; h] = \exp\{[(\mu_A + h\sigma_A^2)z + \sigma_A^2 z^2 / 2]u\} \quad (B.1)$$

$$M_B[z, v; h] = \exp\{[(\mu_B + h\sigma_B^2)z + \sigma_B^2 z^2 / 2]v\} \quad (B.2)$$

Equation (20) suggests that the price of AEHI options during the loss period under the Wiener distribution is as follows:

$$OP_t = L(t)[N(m; (\mu_1^* + \sigma_1^{*2})(T_2 - t), \sigma_1^{*2}(T_2 - t)) - N(n; (\mu_1^* + \sigma_1^{*2})(T_2 - t), \sigma_1^{*2}(T_2 - t))] + e^{-r(T_2 - t)}[H - K - HN(m; \mu_1^*(T_2 - t), \sigma_1^{*2}(T_2 - t)) + KN(n; \mu_1^*(T_2 - t), \sigma_1^{*2}(T_2 - t))] \quad (B.3)$$

In (B.3),

$$\mu_1^* = \frac{\mu_A u + \mu_B(T_2 - T_1) + h_1^* \sigma_A^2 u + h_1^* \sigma_B^2(T_2 - T_1)}{T_2 - t} = r - \frac{\sigma_1^{*2}}{2}, \quad \sigma_1^{*2} = \frac{\sigma_A^2 u + \sigma_B^2(T_2 - T_1)}{T_2 - t}$$

Similarly, when the pricing time is in the extended period, the AEHI options formula

is:

$$OP_t = L(t)[N(m; (\mu_2^* + \sigma_B^2)v, \sigma_B^2 v) - N(n; (\mu_2^* + \sigma_B^2)v, \sigma_B^2 v)] + e^{-r(T_2 - t)}[H - K - HN(m; \mu_2^* v, \sigma_B^2 v) + KN(n; \mu_2^* v, \sigma_B^2 v)] \quad (B.4)$$

Where $\mu_2^* = \mu_B + h_2^* \sigma_B^2 = r - \frac{\sigma_B^2}{2}$.

Appendix C. The AEHI options pricing for respiratory disease

Fig. C.1 shows the effects of the pricing stages and execution price K on AEHI (respiratory) options prices for individuals 14 years old or younger.

Notes: graphs (ii) and (iii) show the same data from different perspectives.

Fig. C.1 The pricing results for the AEHI (respiratory) options (14 years old or younger).

Fig. C.2 shows the effects of the pricing stages and execution price K on AEHI (respiratory) options prices for individuals 15 to 64 years old.

Notes: graphs (ii) and (iii) show the same data from different perspectives.

Fig. C.2 The pricing results of the AEHI (respiratory) the options (15 to 64 year old).

Fig. C.3 shows the effects of the pricing stages and execution price K on AEHI (respiratory) options prices for individuals older than 64 years.

iii) extended period

Notes: graphs (ii) and (iii) show the same data from different perspectives.

Fig. C.3 The pricing results of the AEHI (respiratory) the options (old than 64 years).

Acknowledgements

The authors are grateful to the National Natural Science Foundation of China and National Social Science Foundation of China for financial supports.

Authors' contributions

ZL conceived and designed the entire research, coordinated the overall project implementation and financial support. CW contributed to collection of research data, methodology, and writing the original draft. Visualization was analysed by YY. XJ participated in the research design and coordinated funding support. DL contributed to data curation and operation of software. All authors read and approved the final manuscript.

Funding

This work was supported by grants from the National Social Science Foundation of China (Projects No. 16BGL146, 18AZD005) and the National Natural Science Foundation of China (Projects No. 71874108).

Availability of data and materials

All data generated during this study are included in this published article and its additional files.

Ethics approval and consent to participate

This work do not include animal experiment.

Consent for publication

We have obtained consents to publish this paper from all the participants of this study.

Competing interests

The authors declare no conflict of interests.

References

1. Song C, Wu L, Xie Y, Mao HG. Air pollution in China: status and spatiotemporal variations. *Environ Pollut.* 2017;227:334-347.
2. da Silva I, de Almeida DS, Hashimoto EM, Martins LD. Risk assessment of temperature and air pollutants on hospitalizations for mental and behavioral disorders in Curitiba, Brazil. *Environ Health-glob.* 2020;19(1):79.
3. Cox LAT. Socioeconomic and air pollution correlates of adult asthma, heart attack, and stroke risks in the United States, 2010-2013. *Environ Res.* 2017;155:92-107.
4. Jans J, Johansson P, Nilsson JP. Economic status, Air quality, and child health: evidence from inversion episodes. *J Health Econ.* 2018;578:148-157.
5. Mueller W, Loh M, Vardoulakis S, Johnston HJ, Steinle S, Precha N, Kilengchuay W, Tantrakarnapa K, Cherrie JW. Ambient particulate matter and biomass burning: an ecological time series study of respiratory and cardiovascular hospital visits in northern Thailand. *Environ Health-glob.* 2020;19(1):77.

6. Deng TT, Li X, Ma ML. Evaluating impact of air pollution on China's inbound tourism industry: A spatial econometric approach. *Pac J Tour Res.* 2017;22(7):771-780.
7. Linnenluecke MK, Smith T, Mcknight B. Environmental finance: A research agenda for interdisciplinary finance research. *Econ Model.* 2016;59:124-130.
8. Hsiao YL, Chen YS. Pricing the haze option with the PM_{2.5} index. *Asia Pac Manage Rev.* 2019;24(1):27-36.
9. Wu J, Tal A. From pollution charge to environmental protection tax: A comparative analysis of the potential and limitations of China's new environmental policy initiative. *J Comp Policy Anal.* 2018;20(2):223-236.
10. Moisan S, Herrera R, Clements A. A dynamic multiple equation approach for forecasting pm2.5 pollution in Santiago, Chile. *Int J Forecasting.* 2018;34(4):566-581.
11. Sengupta I, Issaka A. Analysis of variance-based instruments for Ornstein-Uhlenbeck type models: swap and price index. *Ann Financ.* 2017;13(4):401-434.
12. James LF, Muller G, Zhang ZY. Stochastic volatility models based on OU-Gamma time change: theory and estimation. *J Bus Econ Stat.* 2018;36(1):75-87.
13. Li WX, French JJ., Chen CS. Informed trading in S&P index options? Evidence from the 2008 financial crisis. *J Empir Financ.* 2017;42:40-65.
14. Xue J, Xu Y, Zhao L J, Wang CC, Rasool Z, Ni MM. Wang Q, Li DQ. Air

- pollution option pricing model based on AQI. *Atmos Pollut Res.* 2019;10(3):665-674.
15. Liu ZX, Zhao LJ, Wang CC, Yang Y, Xue J, Bo X, Li DQ, Liu DG. An actuarial pricing method for air quality index options. *Int J Environ Res Public Health.* 2019;16(24):1660-4601.
 16. Bailey W, Stulz R. The price of stock index option in a general equilibrium model. *J Financ Quant Anal.* 1989;24(1):1-12.
 17. Hull J, White A. Numerical procedures for implementing term structure model I: Single-factor model. *J Deriv.* 1994;2(1):7-16.
 18. Friz P, Gerhold S, Pinter A. Option pricing in the moderate deviation's regime. *Math Financ.* 2018;28(3):962-988.
 19. Bao JY, Zhao YX. Option pricing in Markov-modulated exponential Lévy models with stochastic interest rates. *J Comput Appl Math.* 2019;357:146-160.
 20. Horrace WC, Wright IA. Stationary points for parametric stochastic frontier models. *J Bus Econ Stat.* 2020;38(3):516-526.
 21. Garnier J, Solna K. Option pricing under fast-varying long-memory stochastic volatility. *Math Financ.* 2017;2:39-83.
 22. Buhlmann H. An economic premium principle. *Astin Bull.* 1980;11(1): 52-60.
 23. Gambaro AM, Casalini R, Fusai G, Ghilarducci A. Quantitative assessment of common practice procedures in the fair evaluation of embedded options in insurance contracts. *Insur Math Econ.* 2018;81:117-129.
 24. Mariani MC, Al Masum Bhuiyan M, Tweneboah OK. Estimation of stochastic

- volatility by using Ornstein-Uhlenbeck type models. *Physica A*. 2018;491:167-176.
25. Rajačić MM, Todorovic DJ, Krneta Nikolic JD, Jankovic MM, Djurdjevic VS. The Fourier analysis applied to the relationship between ^7Be activity in the Serbian atmosphere and meteorological parameters. *Environ Pollut*. 2016;216:919-923.
 26. Cubadda G, Guardabascio G. Representation, estimation and forecasting of the multivariate index-augmented autoregressive model. *Int J Forecasting*. 2019;35(1):67-79.
 27. Tang SY, Yan QL, Shi W, Xiao UN. Measuring the impact of air pollution on respiratory infection risk in China. *Environ Pollut*. 2018;232:477-486.
 28. Lu ZN, Chen HY, Hao Y, Wang JY, Song XJ, Mok TM. The dynamic relationship between environmental pollution, economic development and public health: Evidence from China. *J Clean Prod*. 2017;166:134-147.
 29. Tapia V, Steenland K, Vu B, Liu Y, Vasquez V, Gonzales GF. PM_{2.5} exposure on daily cardio-respiratory mortality in Lima, Peru, from 2010 to 2016. *Environ Health-glob*. 2020;19(1):63.
 30. Li J, Guttikunda SK, Carmichael GR, Streets DG, Chang YS, Fung V. Quantifying the human health benefits of curbing air pollution in Shanghai. *J Environ Manage*. 2004;70(1):49-62.
 31. White RR. Catastrophe options: An experiment in the management of catastrophic risk in the United States. *J Environ Manage*. 2001;62(3):323-326.

32. Wang HW, Pan XD, Lin G. Effects of sulfur dioxide pollution in the air on mortality of cardiovascular diseases in Shenyang. J Environ Health. 2002;(01):50-52. (In Chinese)
33. Wang HW, Pan XD. Effects of sulfur dioxide pollution on mortality of respiratory diseases in Shenyang. J Environ Health. 2007;10:762-765. (In Chinese)
34. Zhao S, Liu SL, Hou XY, Cheng FY, Wu X, Dong SK., Beazley R. Temporal dynamics of SO₂, and NO_x pollution and contributions of driving forces in urban areas in China. Environ Pollut. 2018;242:239-248.

Figures

Figure 1

The procedure used in the AEHI options pricing approach.

Figure 2

The Fourier series fitting diagram for $s(t)$.

Figure 3

(a) The autocorrelation coefficients for each lag.

Figure 4

(b) The partial autocorrelation coefficients for each lag.

Figure 5

Comparison of real and predicted SO2 concentration in 2018.

i) loss period

ii) extended period

iii) extended period

Notes: graphs (ii) and (iii) show the same data from different perspectives.

Figure 6

(a) The pricing results of the AEHI (cardiovascular) options (younger than 14 years).

i) loss period

ii) extended period

iii) extended period

Notes: graphs (ii) and (iii) show the same data from different perspectives.

Figure 7

(b) The pricing results of the AEHI (cardiovascular) options (15 to 64 years old).

i) loss period

ii) extended period

iii) extended period

Notes: graphs (ii) and (iii) show the same data from different perspectives.

Figure 8

(c). The pricing results of the AEHI (cardiovascular) options (older than 64 years).