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Research article

Monetary policy document analysis for prediction of monetary policy board decision

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ABSTRACT

In terms of market capitalization, the bond market is larger than the stock market, and the bond market is affected by macroeconomic indicators. Despite this, there has been relatively little research, making it a good candidate for the use of data mining techniques. In this paper, a novel approach designed to predict the vote results of the Korean Monetary Policy Committee regarding the base interest rate was proposed. To predict sentence sentiment, prior monetary policy decision text was used as input for classification models. The sentence sentiment prediction model showed 83.7% performance when using a support vector machine. In addition, it was observed that the bigrams extracted from documents provided important descriptions of the Korean economy at the time. Finally, the document sentiment of monetary policy decision was calculated using aggregating sentence sentiment, and the vote results were predicted using this sentiment. As a result, when using the support vector machine to predict the Monetary Policy Committee vote results, the performance improved by 29.5% over the baseline model. Statistical tests confirmed whether there is a difference in document sentiments between unanimous and non-unanimous, and the null hypothesis was rejected at a significance level of 5%.

1. Introduction

The bond market is similar to the stock market in size, provides liquidity to the economy and serves as an indicator of the country's economic situation based on government-issued bond rates [22]. For example, in certain countries, high government bond rates can indicate a variety of meanings, such as, high economic growth rates, high inflation rates, or a situation where financing is difficult due to the deteriorating fiscal health of the country [30]. Therefore, various indicators of the bond market are important in terms of corporate and national decision-making because they can predict market conditions from various aspects; thus, research to predict the direction of the base rate, which is the basis of various bond rates, should be conducted. In general, base rate is closely related to bond prices. For example, the coupon rates of bonds are fixed when bonds are issued; consequently, if the base rate is raised, the demand for bonds decreases and their prices decline. Therefore, because bond prices are directly related to profits, bond transactions generate additional profits if the base rate is predicted or information about future base rates can be obtained.

The Korean base rate was determined monthly until 2016, however since 2017, it has been commonly determined eight times a year by the Monetary Policy Committee (MPC), the foremost decision-making body of the Bank of Korea (BOK). The MPC applies a look-at-everything approach and determines the base rate by considering inflation trends, domestic and international economic and

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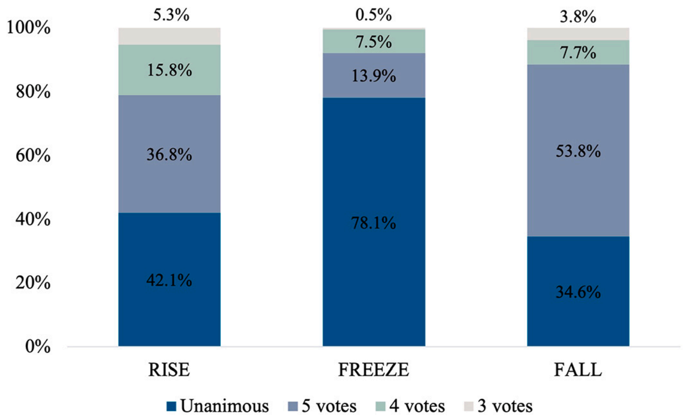

Fig. 1. Distribution of the vote results, May 1999 to December 2020.

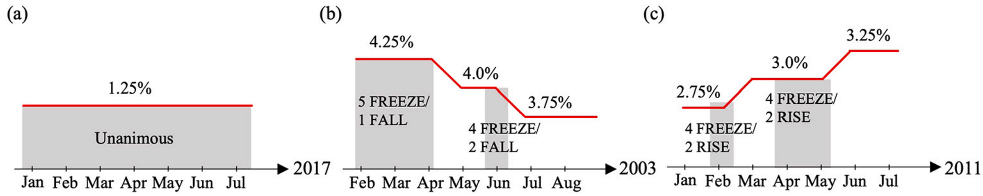

Fig. 2. The vote result and future base rate trends.

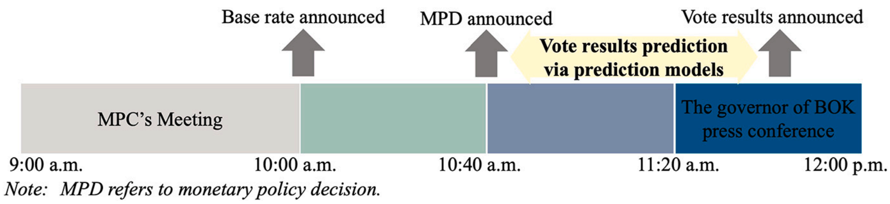

Fig. 3. Schedule of the MPC's meeting for monetary policy decision-making.

financial market conditions, etc. The MPC consists of seven people: six MPC members and the governor of the BOK. The MPC decides the base rate by a majority vote. In the event of a tie, the governor of BOK has a casting vote. The base rate decisions are categorized as follows: rate hike (RISE), frozen rate (FREEZE), and rate cut (FALL). Each base rate decision is taken by a unanimous vote, five votes, four votes, or three votes in accordance with the majority rule. The distribution of votes for each base rate decision from May 1999 to December 2020 is shown in Fig. 1. Fig. 1 shows that the distribution of the majority of the results varies for each interest rate decision. When the base rate decision is RISE, there is a relatively large (57.9%) proportion of one or more members opposed to the decision. In addition, when the base rate decision is FALL, there is 65.4% proportion of one or more members opposed to the decision. Therefore, a situation in which the results of a vote were one or more members opposed the decision occurs frequently. Moreover, future base rates change direction based on the results of prior votes. For example, even if the final decision about the base rate is FREEZE, future base rate trends differ between unanimous decisions and one or more FALL or RISE votes (see Fig. 2). Fig. 2(a) shows that from January to July 2017, the base rate does not fluctuate after FREEZE receives a unanimous vote. However, Fig. 2(b) shows that despite the base rate decision is FREEZE from February to April 2003, one member of the MPC continues to insist on a base rate cut. Subsequently, a 25-basis point (bp) rate cut occurred at the next MPC meeting in May 2003. In the same figure, the base rate decision for June is FREEZE; however, two members of the MPC insist on a base rate cut. Following this, an additional interest rate cut occurs in the next month. In Fig. 2(c), two members insisted on a rate hike in February 2011; however, the base rate decision is FREEZE; thereafter, a 25 bp rate hike occurred in March 2011. Then, a 4:2 vote in favor of FREEZE from April to May 2011 results in a 25 bp rate hike the following month. Most market participants believe there is a strong correlation between the MPC vote results and future base rate trends [18]. This confidence results in real transactions that directly affect the market, such as bond price fluctuations. Therefore, the results of the MPC's vote can be used as an important indicator.

The MPC's vote result is announced in the middle of a press conference held by the governor of BOK after the MPC meeting. The schedule of an MPC meeting for monetary policy decision-making is shown in Fig. 3. The meeting usually starts at 9 a.m. The base rate is announced at approximately 10 a.m. Then, the Monetary Policy Decision (MPD) text, which includes the statement written during the meeting, is disclosed approximately 10:40 a.m. on BOK's website. From 11:20 a.m., the governor of BOK held a press conference on monetary policy. During the conference, the governor outlines the detailed background of the committee's base

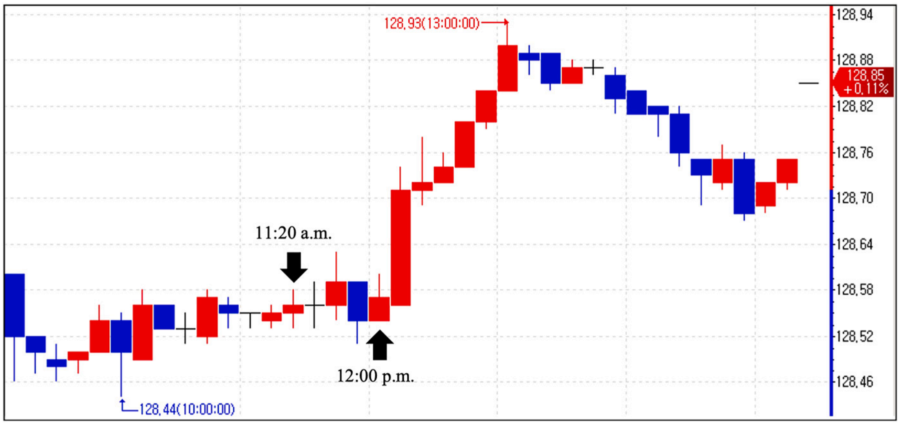

Fig. 4. 10-year treasury bond futures' prices (April 19, 2016).

(a) 4월중 소비자물가 상승률은 석유류 제외 공업제품가격의 상승폭이 확대되었으나 서비스요금의 오름세가 둔화됨에 따라 전월과 같은 1.0%를 나타내었다. 농산물 및 석유류 제외 근원인플레이션율은 전월의 1.7%에서 1.8%로 소폭 상승하였다. 앞으로 소비자물가 상승률은 저유가의 영향 등으로 낮은 수준을 이어갈 것으로 보인다. 주택매매가격은 전월 수준을 유지하였으며 전세가격은 낮은 오름세를 나타내었다.

(b) 3월중 소비자물가 상승률은 석유류 가격 하락폭 확대 등으로 전월의 1.3%에서 1.0%로 낮아졌다. 농산물 및 석유류 제외 근원인플레이션율도 전월의 1.8%에서 1.7%로 소폭 하락하였다. 소비자물가 상승률은 저유가의 영향 등으로 당분간 물가안정목표 2%를 상당폭 하회할 것으로 전망된다. 주택매매가격은 전월 수준을 유지하였으며 전세가격의 오름세는 둔화되었다.

(In translation)

(a) "Despite increases in the extents of upsurges in the prices of industrial products other than petroleum, consumer price inflation was 1.0% in April, the same as in March, owing primarily to a slowdown in the rate of service fee increase. Core inflation excluding agricultural and petroleum product prices increased slightly to 1.8% in April, up from 1.7% in March. Looking ahead, the Board forecasts that consumer price inflation will continue at a low level, owing to factors such as low oil prices. In the housing market, sales prices remained stable from the previous month, while leasehold deposit prices showed low rates of increase."

(b) "Consumer price inflation fell from 1.3% in the past month to 1.0% in March, owing primarily to increases in the extents of decline in petroleum product prices. Core inflation excluding agricultural and petroleum product prices also decreased slightly to 1.7%, from 1.8% in February. Looking ahead, the Board forecasts that consumer price inflation will fall considerably short of the 2% inflation target for the time being, owing primarily to the low oil prices. In the housing market, sales prices maintained their level since the previous month, while the uptrend in leasehold deposit prices slowed."

Fig. 5. (a) MPD with a vote of 6:0 in favor of FREEZE in May 2016; (b) MPD with a vote of 5:1 in favor of FREEZE in April 2016.

rate decision, provides any new comments on monetary policy, and announces a vote result that shows high interest among market participants. The significance of the MBC's vote results can be confirmed through the graph of the price change of 10-year treasury bond futures on the day the base rate is determined. Fig. 4 shows an example of the increase in market volatility of 10-year bond treasury futures prices following the announcement of a base rate decision. As shown in Fig. 4, the volatility of the 10-year treasury bond futures' prices is not high at around 10 a.m. when the base rate decision results are announced. Rather, market volatility increases as the governor of BOK announces the results of the vote and mentions the economic outlook at a press conference. The MPD, the only informative document released between 10 am when the base rate decision is announced and 11:20 am when the press conference of the BOK governor begins, contains the opinion of each MPC member. Therefore, the main purpose of this study is to analyze the MPD provided in the form shown in Fig. 5 to determine whether the vote result is predictable before the press conference. Fig. 5(a) and (b) are part of the MPD for the base rate FREEZE. In Fig. 5(a), opinions about the Korean economy are relatively neutral based on the comments that consumer price inflation is similar to the previous month and core inflation, excluding agricultural and petroleum product prices, rose from 1.7% to 1.8% in the previous month. There is no evidence to argue for a base rate cut or hike; hence, it can be seen that the base rate in May 2016 was unanimously frozen. However, there is a sentence in Fig. 5(b) regarding the decline in consumer price inflation and core inflation, excluding agricultural and petroleum product prices, and an overall opinion that consumer price inflation is expected to fall considerably below the 2% inflation target for the time being; hence, there is a slightly negative view of the Korean economy. These views are reflected by one member of the committee who proposes a rate cut based on the negative economic outlook. In fact, before the press conference, traders infer unanimous information by detecting changes in adjectives and nuances, considering the MPD texts of the last three to five months together with the MPD text released on the day. Then, ahead of the press conference of the BOK governor, they take a long or short position on financial instruments, such as various bond futures contracts and generate additional profits.

In this study, a prediction model is proposed that uses MPD text as the input and the vote result as the output. The bag-of-words (BoW) based on the unigram and bigram models is used to represent the MPD texts, then six prediction models are used to forecast the sentiment of each sentence in the MPD text, and the sentiment of each MPD text is calculated by aggregating this sentence sentiment. Finally, document sentiment was used to predict the vote result. If the MPC's vote result can be predicted before its announcement using the MPD text, traders will be able not only to generate additional profits through one-day volatility but also create competitive, long-term portfolio management based on future base rate direction.

The remainder of this paper is organized as follows. In Section 2, a brief review of previous studies regarding the interest rate is provided and the machine learning approaches used in this study are described in Section 3. Subsequently, in Section 4, the data and proposed methods used in this study are introduced, and the experimental results are presented in Section 5. Finally, our conclusions and future work are discussed in Section 6.

2. Related work

Because monetary policy affects several economic factors, various studies have examined the effect of monetary policy on stock prices, energy prices, exchange rates, and interest rates in financial markets [24,19]. In the era of digital transformation, monetary policy in financial markets has undergone significant shift, particularly affecting stock prices, energy prices, exchange rates, and interest rates [1,2]. In general, most of the research in the field of monetary policy and finance has mainly been used in traditional economic analysis, such as time series analysis, dynamic stochastic general equilibrium model, and generalized method of moments [4,15]. In addition, monetary policy is being used as a way to overcome the crisis, even during the global economic crisis, such as the financial crisis. For example, during the 2008 financial crisis, research on monetary policies conducted by central banks in each country is also being conducted [14,10,29]. In other words, the central bank of each country implemented quantitative easing policies, whereby the bank purchased government or corporate bonds in advance to stimulate the economy, resulting in almost zero interest rates in developed countries. In fact, an analysis of asset price movements on the day of a Federal Open Market Committee (FOMC) announcement confirmed that monetary policy has a significant impact on long-term treasury yields [21]. In particular, research has been conducted to find relevant insights by statistically analyzing the effects of monetary policy on interest rates [26,16,13]. Kuttner [25] analyzed monetary policy data published by federal funds and tried to classify the anticipated and unanticipated effect elements. As a result, the author statistically confirmed that the movement of the federal funds' interest rate had a minor effect on the anticipated element and a major effect on the unanticipated element. Moreover, a sudden change in the target rate did not affect the actions of the Federal Reserve System, however the author confirmed that such a change mainly provided explanatory power for short-term curves.

These studies mainly focused on analyzing monetary policy and interest rates using traditional economic analysis methods, however recently, data mining techniques have been used to analyze monetary policy and predict interest rates [32,38]. Kim and Noh [23] used a neural network (NN) to predict the interest rates of both Korea and the United States (US) and to establish whether they have a significant impact on a country's economic network and financial markets. A total of 36 input variables were used to predict US interest rates, with lag 0 to lag 5 applied to treasury bills with one-year maturity, the money stock, the consumer price index, the industrial production index, housing starts, and Standard & Poor's 500. To predict Korea's interest rates, the author used 36 input variables, with lag 0 to lag 5 applied to corporate bond yields with three-year maturity, the money stock, the consumer price index, the industrial production index, permits for building construction, and the Korean stock price index. The results showed that applying the integrated NN to the Korean interest rate was not significantly different from applying the random walk model; however, Kim and Noh [23] identified that applying the integrated NN to US interest rates surpassed the random walk model. Bernanke et al. [3] used factor-augmented vector autoregression (FAVAR) to determine the impact of the monetary policy process on the economy. By applying FAVAR to diverse variables, the authors identified the impact of monetary policy through two steps: finding the major components of diverse variables and accelerating the calculation using Bayesian methods based on Gibbs sampling. This model found variables in which monetary policy has a significant impact on the macroeconomy. For example, when a contractionary monetary policy shock occurred, responses, such as a decrease in the real activity measure, a decrease in monetary aggregates, and an increase in the dollar price were confirmed. This study provides a comprehensive picture of the impact of monetary policy. Moreover, diverse variables that responded to monetary policy were used in the macroeconomic model; thus, they provided empirical plausibility. In particular, text mining methods are also used to analyze monetary policy documents. Lee et al. [28] quantify the Monetary Policy Board (MPB) minutes of the BOK using text mining. They analyzed the BOK monetary policy board minutes using a field-specific Korean dictionary and n-grams. They applied standard vector autoregression systems or the dynamic stochastic general equilibrium model to interpret the relationship between the base rate and monetary policy sentiment. This study can be applied to measure uncertainty and sentiment regarding future monetary policy stances. Additionally, there have been studies analyzing the tone of news article around the date of the MPC meeting to explain long-term and short-term rates [27]. Also, Bholat et al. [5] provided intuitive results in the form of graphs, word clouds, and tree visualizations.

Prior studies have mainly used various economic indicators to analyze the impact of monetary policy on market interest rates. On the other hand, they have focused on studies in developed countries, such as the US and the United Kingdom. However, there are few studies on the monetary policy and interest rates of emerging countries, and research on these markets is limited, such as analyzing the impact of US monetary policy on the bond markets of emerging countries [8,33]. In emerging markets, the interest of many investors has recently increased, and the financial market has been stably established [36,22]. Therefore, it is necessary to study interest rates using various indicators and monetary policies based on the characteristics of a specific country.

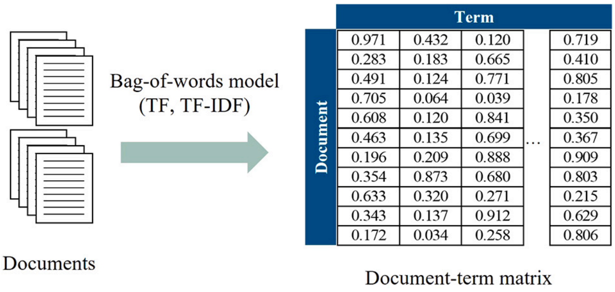

Fig. 6. Bag-of-words model.

3. Machine learning approaches

3.1. Text representation

In the process of text mining, it is importance to effectively represent text data as numerical data. To apply text data to various machine learning algorithms, they are expressed as vectors, and in this study, BoW was used as previously mentioned. BoW was used because the effect of each word on the model performance can be easily grasped. The BoW model is a method of mapping a document to a feature vector using the term information shown in the document, and a brief overview is shown in Fig. 6 [17]. As shown in Fig. 6, the term-weight methods of representing documents are required; if $a_{(t,d)}$ is a cell that corresponds to the term t in document d, $a_{(t,d)}$ can be defined with various weights. The current study described the term frequency (TF) and term frequency inverse document frequency (TF-IDF). TF categorizes documents by weighting them, assuming that documents containing many of the same words are similar documents. Each row represents the number of words in a document [35]. This study used the number of times that term t occurs in document $d(f_{(t,d)})$. The equation is expressed as follows:

$$TF(t,d) = f_{(t,d)} \tag{1}$$

TF-IDF is a method that includes not only TF information but also the importance of a term to a document in a corpus [20]. The value that reflects the commonness of a term in the entire document set is expressed as follows:

$$IDF(t,D) = \log \frac{\|D\|}{1 + \|d \in D : t \in d\|} \tag{2}$$

where D denotes the total number of documents, and $\|d \in D : t \in d\|$ is the number of documents containing the term t. One was added to the denominator so that it is not zero, and then Eq. (1) and Eq. (2) were combined to obtain the TF-IDF as follows:

$$\begin{aligned} TF - IDF(t,d,D) &= TF(t,d) \times IDF(d,D) \\ &= f_{(t,d)} \times \log \frac{\|D\|}{1 + \|d \in D : t \in d\|} \end{aligned} \tag{3}$$

A high weight in Eq. (3) is obtained through a high TF in a particular document and a low document frequency of the term in the entire document set. If a term appears in almost the entire document, the value inside the logarithm approaches 1; thus, the logarithmic value becomes 0. As a result, it is possible to filter out common words in every document. This study uses the BoW model using the TF-IDF weight to map MPD text and the minutes of MPC meetings to sentence-level feature vectors.

3.2. Prediction models

The text data converted into a term-document matrix is used as the input variable for the predictive modeling process in text mining. In this study, six representative simple and fast classification models: logistic regression (LR), support vector machine (SVM), multilayer perceptron (MLP), random forest(RF), adaptive boosting (AdaBoost), and gradient boosting (GB) were used. Descriptions of the prediction models are as follows:

LR is widely used when the output variable is categorical. The probability of response can be estimated using a logistic function [9, 37]. The logarithm of the odds ratio, y_i, which is the ratio of the probability of $Y = 0$ and $Y = 1$ at $X = x$, is predicted by a linear regression as follows:

$$y_i = \log(\frac{p_i}{1 - p_i}) = \beta_0 + \beta_1 x_1 + ... + \beta_n x_n + \epsilon_i, \epsilon_i \overset{\text{iid}}{\sim} N(0, \sigma^2) \tag{4}$$

where p_i is the probability that the response variable equals a case i, β_0 is the intercept from the linear regression equation, and $\beta_1, \ldots, \beta_n$ are the regression coefficients. The Eq. (4) can be expressed as an equation for p_i, defined as a logistic function, as follows:

$$\hat{p} = \hat{T}(Y = 1\|x) = \frac{exp(\hat{\beta}_0 + \hat{\beta}_1 x_1 + \hat{\beta}_2 x_2 + \ldots + \hat{\beta}_n x_n)}{1 + exp(\hat{\beta}_0 + \hat{\beta}_1 x_1 + \hat{\beta}_2 x_2 + \ldots + \hat{\beta}_n x_n)} \tag{5}$$

The resulting probability $\hat{p}$ shown in Eq. (5) ranged between 0 and 1. If $\hat{p}$ is greater than the predetermined criteria, x is classified as 1; otherwise, it is classified as 0. LR is easy to implement and provides an intuitive interpretation of the relationship between response variables and predictor variables. However, LR is often less accurate because of overfitting.

LP is one of the feed-forward artificial neural networks and consists of three or more layers: an input layer, one or more hidden layers, and an output layer [34]. Each node of hidden and output layers is expressed as a linear combination of nonlinear activation functions, as shown in Eq. (6).

$$\mathrm{y}(\mathbf{x}) = f_K\left(\boldsymbol{W}_K^T f_{K-1}\left(\dots \boldsymbol{W}_2^T f_1\left(\boldsymbol{W}_1^T \boldsymbol{x} + \boldsymbol{b}_1\right) + \boldsymbol{b}_2\right) \dots + \boldsymbol{b}_K\right) \tag{6}$$

where $\boldsymbol{b}_k$, $\boldsymbol{W}_k^T$, and $f_{k(x)}$ are the biases, weights, and activation functions of the k-th layer, respectively. In the classification problem, nodes in the intermediate layer can use various types of activation functions, such as hyperbolic tangent, sigmoids, and rectifier linear unit (ReLU); in the nodes of the output layer, the softmax function is generally used as the activation function, and the input is assigned the class corresponding to the node with the largest value among the nodes of the output layer, as shown in Eq. (7).

$$\mathrm{E} = \frac{1}{2}\sum_{\mathrm{k}=1}^{K} \| \| f(x_k) - y_k \| \|^2 \tag{7}$$

MLP is in the learning phase with the aim of reducing this error, and the back-propagation algorithm is typically used. During the back-propagation algorithm, the biases and weights of all hidden and output layers are updated, as shown in Eq. (8).

$$\theta_{ij}^{(k)} \leftarrow \theta_{ij}^{(k)} - \alpha \frac{\partial E}{\partial \theta_{ij}^{(k)}} \tag{8}$$

where θ is the parameter that needs to be updated; that is, biases and weights; k is the k-th layer; i is the i-th node of the $(k-1)$-th hidden layer, j is the j-th node of the k-th hidden layer, and α is the learning rate. To update all parameters, the change in the error function value based on the parameter change can be calculated and updated. Back-propagation algorithms iteratively update the parameters to minimize the error function until convergence. The MLP finds nonlinear relationships between the target and predictors, however the training time for MLP models is considerable owing to the model complexity and the number of hidden layers and nodes.

SVM is an algorithm used for classification and regression analysis and is generally a well-performing algorithm. The principle of SVM maximizes the margin, which is the distance between the decision hyperplane that separates the vector space and the nearest data point from each class to the hyperplane [31]. At this time, even if some data are not accurately separated, a decision hyperplane that can maximize the soft margin can be identified using the slack variable ξ as shown in Eq. (9).

$$\begin{aligned} &\min_{w,b,\xi_i} \tfrac{1}{2}\|w\|^2 + C\textstyle\sum_{i=1}^{N}\xi_i \\ &\text{s.t. } \mathbf{y}(\boldsymbol{W}^T\boldsymbol{x} + \boldsymbol{b}) \geq 1 - \boldsymbol{\xi} \\ &\qquad \xi \geq 0 \end{aligned} \tag{9}$$

where C represents a hyperparameter that adjusts tolerance outside the acceptable error rate. In other words, the value of the slack variable can be adjusted using parameter C. In addition, SVM can be used for nonlinear classification as well as linearly separated forms using kernel tricks [6]. Using the kernel trick, a feature space can be transformed from a low-dimensional to a high-dimensional feature, and a linear hyperplane that can classify data in a high-dimensional feature space can be identified. Therefore, the nonlinear classifier can be applied to a variety of problems in a manner similar to linear classification algorithms; however, it requires more time to converge than the other prediction models mentioned above.

RF, which is an ensemble learning method for classification, is a combination of a number of decision trees [7]. RF is a bootstrap aggregate-based method that extracts the same number of samples by allowing replacement to generate training data. For each training data set, n decision trees were generated. A feature that splits the decision tree is randomly selected, which prevents each decision tree of the RF from being similarly generated, thus reducing the correlation of the decision tree. After learning each decision tree, unseen samples were predicted by accepting a majority vote among the trees for classification from all trees on unseen samples. RF is one of the most accurate and widely known learning algorithms. For many datasets, it not only makes a highly accurate classifier, but also provides estimates of the variables that are important in the classification. However, RFs have been observed to overfit some datasets with noisy classifications or regression tasks.

AdaBoost is a boosting method that is short for adaptive boosting [11]. The boosting method is similar to the bootstrap aggregation method where it uses multiple training data to generate multiple decision trees, however it differs as it trains multiple data sets sequentially without generating decision trees at the same time. The boosting method assigns a high sampling weight to misclassified data from the previous decision tree, constructing the training data that will be used when training the next decision tree. This means that when constructing the next training dataset, a sample of misclassified data can be included more than once in the same training dataset. As such, it is said to be adaptive because the process of improving the performance of the model through the continuous learning model process is repeated and supplemented. Each decision tree that makes up AdaBoost is referred to as stump and consists of two leaves per node. Each stump is assumed to be a weak learner, because it cannot be accurately classified as it is divided only by one feature. After each stump is sequentially trained, the stumps have different weights according to their accuracy; therefore, in the case of a high-accuracy stump, it has a greater influence on the final decision. The result of a two-class problem is expressed by Eq. (10):

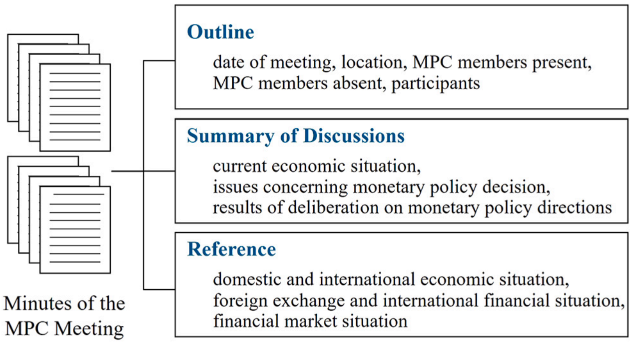

Fig. 7. Composition of the minutes of an MPC meeting.

$$\hat{h}\left(\boldsymbol{x}_i\right) = \mathrm{sign}\left(\sum_{j=1}^{M} w_j \hat{h}_j\left(\boldsymbol{x}_i\right)\right) \tag{10}$$

where M is the number of stumps, w_j is the weight of the j-th stump, and $\hat{h}_j(x_i)$ is the prediction value of the i-th data point of the j-th stump. Cross-validation techniques should be used to determine the appropriate M because AdaBoost has an overfitting problem when the number of tree stumps is very large.

Similar to AdaBoost, GB is a boosting algorithm that improves the model performance by fitting residuals. First, the training data are predicted through one decision tree, and the residuals are calculated using the true and predicted values. Then, the next decision model is iteratively trained to reduce the residuals [12]. This is called GB because negative gradients have the same residuals when the squared error is used as a loss function; here, the negative gradient indicates the direction of learning to reduce the loss function. GB uses the learning rate to adjust the degree to which the residual fitting model is updated; the higher the learning rate, the faster the model converges, however very small values are commonly used to obtain a fine classifier. It has the disadvantage of being sensitive to outliers, such as AdaBoost, because it attempts to compensate for the weakness of the characteristics of the GB model.

4. Materials and methods

4.1. Data

We collected 245 MPD documents, together with minutes of MPC meetings, from May 1999 to December 2020 from BOK's website. The MPD text is composed of five to seven paragraphs. It includes references to the global economic growth of the US, China, and emerging countries, as well as to the Korean economy. These references include exports, employment-to-population, the number of persons employed, consumer price inflation, the trend of housing sales and leasehold deposit prices, market interest rates, stock prices, and foreign exchanges. The minutes of an MPC meeting are released on BOK's website two weeks after the meeting. The minutes are usually composed of 10 to 40 pages with three major components, as shown in Fig. 7. The "Summary of Discussions" component contains the individual opinions of each member regarding monetary policy together with the result of the majority vote. In the past, opinions from government ministers, such as the Deputy Minister of the Ministry of Strategy and Finance, have been considered. These opinions represent the government's view on the current economic situation, inflation trends, policy direction, etc. However, recently, the individual opinions of each MPC member regarding issues, such as domestic and international economic situations have been recorded. The number of sentences in the MPD document was 2,215, and the number of sentences in the minutes of MPC meetings was 36,456. Preprocessing included the removal of specific morphemes and words that directly indicated interest rate direction, such as upward, downward, maintain, present level, and base rate. In addition, common sentences that were duplicated in different MPDs or minutes of the MPC meeting were removed. For example, sentences that appear repeatedly at the end of a document, such as "The monetary policy committee will continue to operate a monetary policy in consideration of financial stability so that growth will continue to recover and inflation will stabilize at the target level in the medium-term perspective" sentence, have been removed. As a result, 1,522 sentences and 34,764 sentences were extracted from MPD and the minutes of the MPC meeting, respectively. The minutes of the MPC meetings were used as training data to improve performance. Some of the MPD text and the minutes of the MPC meetings were employed as a training set, and the rest of the MPD text was used as a test set. In our study, we perform five-fold cross validation, using a training set consisting of 35,982 sentences (34,764 from the minutes of the MPC meetings and 1,218 from the MPD). The test set comprises 304 sentences from the MPD. Moreover, when using BoW to extract terms from documents, two datasets were constructed in the form of text representation: only the unigram model and the unigram and bigram models together.

4.2. Prediction models of sentence sentiment

Each MPD sentence has a different perspective on the direction of interest rate decision, therefore sentence units are used as input data for the model, and interest rate decisions FALL and RISE are used as output data. Here, the output data are defined as sentence

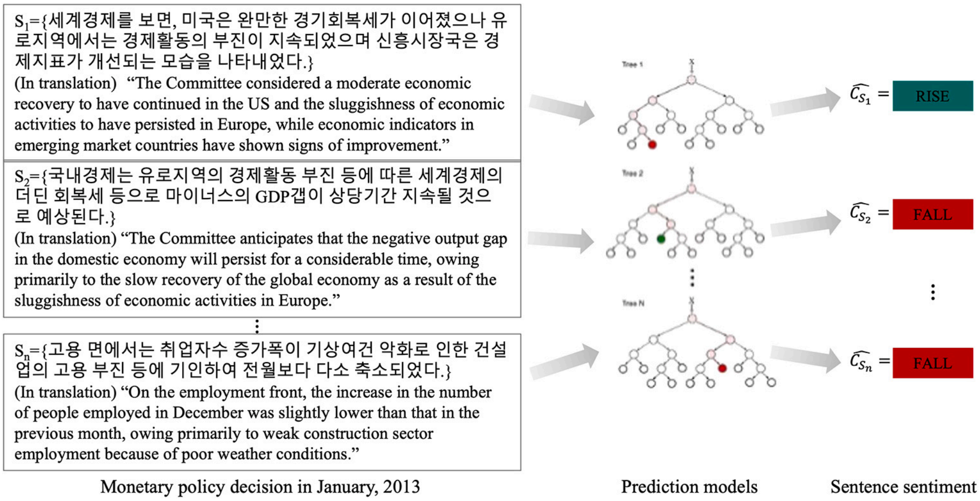

Fig. 8. Framework of the prediction models for sentence sentiment.

sentiments. Fig. 8 shows the framework for predicting sentence sentiment using each sentence of the MPD text in January 2013 as the input. As shown in Fig. 8, even a single document represents a different direction of interest rate decision for each sentence. In this case, although the final interest rate decision is RISE, FREEZE, or FALL, it can be regarded as a situation where the opinions of several members are divided, or the global and domestic market conditions show a different gap than before. In other words, this suggests that the final interest rate decision may not be unanimous. Therefore, each sentence sentiment was predicted before predicting the MPC's majority voting result of MPD, and the pseudocode of the prediction models for sentence sentiment (PMSS) is shown in Algorithm 1.

Algorithm 1 Prediction model for sentence sentiment (PMSS).

Input: dataset $\mathcal{D} = \mathcal{D}^R \cup \mathcal{D}^F = \{s_{i,j}, c_i\}$, for $\forall i = 1, \dots, N_d$, $j = 1, \dots, N_{S_i}$, $c_i \in \{1, \dots, C\}$, $\mathcal{D}^R = \{s^R_{i,j}, c_i\}$, $\mathcal{D}^F = \{s^F_{i,j}, c_i\}$, candidate classification algorithm $\mathcal{A}_1, \dots, \mathcal{A}_L$
Output: set of sentence classifier $\mathbb{C}$

```
procedure PMSS
    ℂ ← φ
    D^{R,U} ← sampling documents of RISE with unanimity from D^F
    D^{F,U} ← sampling documents of FALL with unanimity from D^R
    D^U ← D^{R,U} ∪ D^{F,U}
    c_{s_{i,j},A_k} ← candidate classifier trained from D^U using A_k, for ∀k = 1, ..., L
    A_best ← argmin_{A_k} Σ_{(s_{i,j},c_i)∈D^U} 1_{c_{s_{i,j},A_k} ≠ c_i}
    ℂ ← ℂ ∪ {c_{s_{i,j},A_best}}
end procedure
```

The notation is defined as follows: Monetary policy documents $\mathcal{D} = \{D_1, D_2, \dots, D_{N_d}\}$, where N_d represents the number of documents and the base rate decision $c_i \in \{1, \dots, C\}$ for $\forall i = 1, \dots, N_d$, where c_i represents a class of the i-th document. The final data set $\mathcal{D} = \{s_{i,j}, c_i\}$, for $\forall i = 1, \dots, N_d$, $j = 1, \dots, N_{S_i}$, where $s_{i,j}$ denotes the j-th sentence of the i-th document and N_{s_i} denotes the number of sentences in the i-th document, is composed by labeling the base rate decision for every sentence in each document collectively.

Next, we check the following sentences in the minutes of the MPB meeting, at which the base rate decision was FREEZE.

- *"It is also necessary to refine the monetary policy measures such as flexible liquidity control in case the liquidity in the market is not sufficient for a limited time because of the surge in overseas interest rates and large-scale capital outflows."*
- *"Looking at the domestic economy, the domestic economy is expected to recover weakly as exports continue to decline. However, as economic sentiment has gradually improved, domestic demand is showing signals of improvement."*

In these sentences, some passages indicate the need for the base rate to rise or fall, although the document overall advocates a base rate freeze. Thus, the two-class classification problem was solved except in the case of FREEZE, which has a sentence where it is difficult to assess the interest rate decision. Suppose that a data set $\mathcal{D} = \mathcal{D}^R \cup \mathcal{D}^F = \{s_{i,j}, c_i\}$ for $\forall i = 1, \dots, N_d$, $j = 1, \dots, N_{s_i}$ is given, where $\mathcal{D}^R$ represents the data set of documents with RISE decisions and $\mathcal{D}^F$ represents the data set of documents with FALL decisions. In addition, the minutes of the associated MPB meetings contain personal comments, however, if the interest rate decisions are not unanimous, there may be content that proposes different interest rate directions in one document. Thus, in the learning phase, only unanimously determined documents, $\mathcal{D}^{R,U}$ and $\mathcal{D}^{F,U}$ were used, where $\mathcal{D}^{R,U}$ and $\mathcal{D}^{F,U}$ are documents where the RISE and FALL decisions were unanimously determined, respectively.

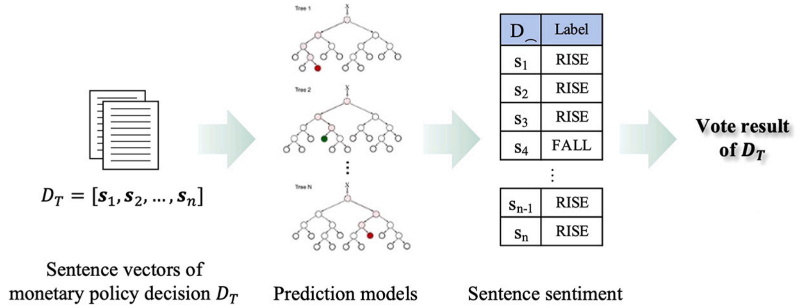

Fig. 9. Aggregation of sentence sentiment.

Table 1
The accuracy of sentence sentiment prediction.

Models	Unigram	Unigram+Bi-gram
Baseline	0.519	0.519
LR	0.761	0.811
RF	0.710	0.732
MLP	0.726	0.807
SVM	0.773	0.837
AdaBoost	0.731	0.802
GB	0.748	0.815

4.3. Prediction framework of vote result

Sentence sentiment can be predicted using the sentence feature vector of the MPD text released on a particular day as the input for the prediction model. Then, the MPB vote results can be calculated using sentence sentiment. A diagram of sentence sentiment aggregation is shown in Fig. 9. The MPD text consisted of 5–17 sentences. The feature vector of each sentence was used as the input data for the prediction model and was classified into two classes (RISE or FALL). The document sentiment of each MPD is calculated as shown in Eq. (11).

$$\text{document sentiment} = \begin{cases} \frac{n(RISE)}{N_s}, & \text{if } C_{D_T} = RISE, \\ \frac{n(FALL)}{N_s}, & \text{if } C_{D_T} = FALL, \end{cases} \tag{11}$$

where $n(RISE)$ denotes the number of sentences with a RISE decision, $n(FALL)$ denotes the number of sentences with a FALL decision, N_s denotes the number of sentences in each MPD text (D_T), and C_{D_T} is the class of D_T. The foregoing document sentiment has values from 0 to 1. When all sentences have the same label, the document sentiment is 1. Thus, it can be said that the base rate decision is unanimous because all sentences in the MPD text propose the same direction for the base rate. On the contrary, if the document sentiment is approximately 0.5, there may be members who propose a different direction for the base rate because some of the sentences include suggestions regarding the direction of the rate that differs from the current base rate decision. In addition, document sentiments for the MPD text with a FREEZE decision are calculated as follows:

$$\text{document sentiment} = \begin{cases} 1, & \text{if } \| \frac{n(RISE)-n(FALL)}{N_s} \| < \theta_{STAY}, \\ 0, & \text{otherwise} \end{cases} \tag{12}$$

where θ_{STAY} denotes the criterion indicating the proportion of sentences that correspond to interest rate hikes and cuts. When the interest rate decision is RISE or FALL, the document sentiment is calculated as a value between 0 and 1, whereas in the case of STAY, the document sentiment was designed to have a value of 0 or 1. When the interest rate decision is STAY and unanimous, document sentiment is assigned to 1 using the θ_{STAY} criteria because the difference in the number of sentences implying interest rate hikes and cuts is not considerable. On the contrary, if the interest rate decision in multiple sentences is directed to one side, it can be expected that there will be a few opinions claiming RISE or FALL, therefore the document sentiment is assigned to 0.

5. Results

5.1. Sentence sentiment prediction of a monetary policy decision

Before predicting an MPB's vote result, we can predict the sentence sentiment using the MPD text and the minutes of the MPB meeting. Thus, the proposed method is applied to monetary policy documents. The results are shown in Table 1. The general methods used to judge the performance of a classification problem are accuracy, precision, recall, and F1 measure [39]. Among these, using accuracy is sufficient when evaluating the performance of a typically balanced dataset. Additionally, the purpose of this study is

Table 2
Significant words.

Unigram	health, gap, stringency, restructuring, get lower, real estate, slump, upturn, be on the upturn, growth, control, shrinking, inflation, employment, recession, being in good condition, recovery, surplus, agricultural products, be normalized, stock, coronavirus disease, deficit
Unigram+Bigram	price rise, financial stability, inflation, credit crunch, lower oil price, be daunted, falling exchange rate, farm prices, coronavirus disease situation, price stabilization, unstable financial market, be rising

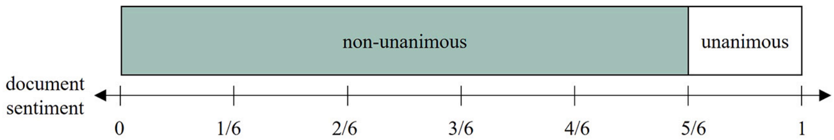

Fig. 10. Assignment of document sentiment with two classes.

Table 3
Confusion matrix of unanimous classification.

		Actual	
		unanimous	not unanimous
Predicted	unanimous	0.328	0.179
	not unanimous	0.164	0.328

to reduce the misclassification rate and clearly separate the two classes; thus, the accuracy measure was used (see Table 1). The values are the average of the test prediction accuracy over 10 repetitions. We suppose that the baseline model is the accuracy obtained when classifying all the test data into one class. Of the six prediction models, the SVM performed best at 0.837, and the SVM improvement compared with the baseline amount was 61%. In addition, it can be confirmed that performance is better when features are extracted using the bigram method together rather than using only the unigram method for all prediction models. This result is illustrated in Table 2. Table 2 lists some of the words selected as critical variables. As shown in Table 2, most words illustrate not only the economic situation but also the positive or negative meanings. However, when the input variables extracted from the unigram features are used, it is difficult to judge whether the words have positive or negative meanings because there is no object. With regard to bigram features, the selected critical variables clearly indicate the context in which economic conditions have changed. These important words will also serve as significant features when aggregating document sentiment. Moreover, by providing important features that significantly influence the model's performance along with quantitative performance metrics, the decision-making process can benefit from increased confidence in modeling results.

5.2. Vote result prediction

The document sentiment for each MPD was calculated in Section 4.3 using the respective MPD text as input for the prediction model. Of the prediction models explained in Section 5.1, SVM using both unigram and bigram showed the best performance; therefore, document sentiment was calculated using the SVM model. When the interest rate decision is RISE or FALL, the document sentiments are assigned to two classes, as shown in Fig. 10, to design a two-class classification model that predicts MPCs unanimous or non-unanimous. The reason for classification, as shown in Fig. 10, is that even if one of the six MPC members presented a negative opinion on the current interest rate decision, the interest rate decision would not have been unanimously determined. Therefore, if the document sentiment is less than or equal to 5/6, it is classified as the non-unanimous class. When the interest rate decision is STAY, document sentiment is assigned to two classes using the criteria introduced in Section 4.3. In this study, the criterion of 0.75, was used, and only 12% of MPDs with STAY decisions were extracted to alleviate the data imbalance problem. Table 3 shows the experimental results of the classification problem set up in this manner as a confusion matrix. The confusion matrix represents the decision made by the classifier in a structure. The confusion matrix consists of four categories: true positive (TP), which are correctly predicted as unanimous. False positive (FP) refer to unanimous examples incorrectly labeled as unanimous. True negative (TN) correspond to not unanimously labeled as not unanimous. Finally, false negative (FN) refer to unanimous examples incorrectly labeled as not unanimous. Accuracy is calculated from $(TP + TN)/(TP + FP + TN + FN)$ of the confusion matrix; thus, the accuracy of the SVM was 0.657. The accuracy of the baseline model, which was obtained when classifying all the test data into one class, was 0.507. The SVM improvement compared with the baseline amount was 29.5%. When an MPD is announced, these results imply that the model, based on historical data, can help assess the unanimity level. In addition, when the interest rate decision is RISE or

Table 4
Results of t-test.

Group	Mean	Standard deviation	Number of observation	T-statistic	$t_{(0.024;41)}$	T-test
A	0.894	0.234	19	7.504	2.020	**Reject** H_0
B	0.739	0.282	24			

FALL, because the greater the value of the document sentiment obtained in this experiment, the higher the probability of unanimous, a statistical test was conducted to determine whether there was a statistical difference in the means of the document sentiments between the actual unanimous (Group A) and the actual non-unanimous (Group B). First, a t-test was performed to analyze the significance of the difference in the document sentiment mean between the two groups, and the null hypothesis and the alternative hypothesis were set as shown in Eq. (13).

$$\begin{aligned} H_0 &: \mu_A = \mu_B \\ H_1 &: \mu_A \neq \mu_B \end{aligned} \tag{13}$$

In this case, the variance of the two groups is unknown, however, because the variance of the MPD's document sentiment is assumed to be the same, the test statistics are as shown in Eq. (14).

$$\mathrm{T} = \frac{\left(\overline{X_1} - \overline{X_2}\right)}{s_p\sqrt{\frac{1}{n_1} + \frac{1}{n_2}}} \tag{14}$$

where $s_p^2 = \frac{(n_1-1)s_1^2+(n_2-1)s_2^2}{n_1+n_2-2}$. In Eq. (12), if $T < t_{(\alpha;n_1+n_2-2)}$, the null hypothesis is rejected. That is, by rejecting the null hypothesis, it is possible to reject the hypothesis that there is no difference between the means of the two groups at the significance level α. Assuming a significance level of 5%, the results of the t-test for the two groups are shown in Table 4. The results in Table 4 imply that the null hypothesis is rejected because the means of the two groups are the same at a significance level of 5%. In other words, there is a significant difference in document sentiment calculated by the prediction models between the two groups.

6. Conclusion

We proposed a methodology for predicting MPC vote results using MPD text. The sentence feature vector of the MPD text was applied to a prediction model to predict sentence sentiment. Sentence sentiment is then aggregated to predict the vote result through document sentiment. First, sentence sentiment was predicted using MPD text and the minutes of the corresponding MPB meeting. Consequently, it was observed that the SVM performance compared with the baseline improved by 61%. In addition, it was confirmed that the extracted words are important variables when using the bigram model and can clearly judge the economic situation. It was also observed that when using the TF-IDF method, words that appear only in a small number of documents were extracted as important variables. Finally, document sentiment was aggregated using sentence sentiment. Document sentiment was used to classify unanimity; as a result, a classification performance of 65.7% was obtained with the SVM. In addition, a t-test was performed to verify the statistically significant difference in document sentiment between an actual unanimous decision and an actual non-unanimous decision. As a result, there is a significant difference in document sentiment between the actual unanimous decision and the actual non-unanimous decision at a significance level of 5%.

By extracting meaningful information, such as document sentiment from monetary policy documents through prediction modeling, it is possible to provide various insights to practitioners who interpret documents empirically. In particular, when an MPD is released, the vote result can be quickly established based on the prediction model. This insight facilitates the provision of a data-driven decision-making process for practitioners who use their business experience to assess minority opinions. Furthermore, document sentiment can be utilized as macro-level time series data, which can assist in predicting the long-term direction of the base rate. This approach enables practitioners to build a competitive position through fast and accurate bond trading. Because the base rate is the benchmark for various government bonds, traders can forecast the movement of bond rates and gain additional profits if they can predict the long-term direction of the base rate. Thus, it may be possible not only to generate additional profits through competitive transactions, but also to provide portfolio management tools based on future base rate information. The findings of this study can be utilized to extend the modeling research for applications in bond interest rate-related news or reports, rather than being limited to context documents similar to the minutes of the MPC and the MPD. This expansion would lead to studies with greater generality.

However, the data used in this study, which consists of the minutes of the MPC and the MPD, has a relatively limited amount, leading to limitations in improving performance solely with the used prediction models. To overcome these limitations, incorporating pre-trained language models, which have the potential to enhance sentence representation performance even with a small amount of data, could be a promising solution. Recently, pre-trained Bidirectional Encoder Representations from Transformers (BERT) have been used to extract embedding vectors from text data. The pre-trained BERT is trained using not only finance, but also various corpora, which can improve the quality of the embedding vector of each text data when there is a limit on the amount of data. BERT is a word embedding method that provides contextual word embedding in which the vector of each word is not fixed and the vector of words is different for each sentence. To utilize BERT in this study, fine-tuning is required by collecting text data related to monetary policy or financial markets. The study of applying BERT to MPD documents is another subject of research, therefore it is left as a future study. In addition, a variety of interesting studies can be conducted on monetary policy. First, each document's sentiment score could be obtained using the dictionary, following which the score could be compared with the base rate trend and visualized to identify whether it is a leading, coincident, or lagging indicator. It is expected that various studies will be undertaken to interpret the Korean financial market. These studies could include assessments of changes in the wording of monetary policy documents after the appointment of a new governor of BOK.

Additional information

No additional information is available for this paper.

CRediT authorship contribution statement

Misuk Kim: Writing – review & editing, Writing – original draft, Visualization, Methodology, Investigation, Funding acquisition, Data curation, Conceptualization. **Sungzoon Cho:** Supervision, Project administration, Funding acquisition.

Declaration of competing interest

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

Data availability statement

Data will be made available on request.

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