Measuring Monetary Policy Surprises Using Text Mining: The Case of South Korea*

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Abstract

We propose a novel approach to measure monetary policy shocks using sentiment analysis, which is free from specification errors compared to VAR-identified shocks and allows time for a wider circle of market participants to digest information compared to shocks identified through intraday Fed funds futures data. We quantify the tones of news articles around 152 dates of Monetary Policy Board (MPB) meetings of the Bank of Korea (BOK) from 2005 to 2017 and then measure monetary policy surprises using the changes of those tones following monetary policy announcements. We estimate its impact on asset prices and find that it better explains changes in long-term rates, while changes in the Bank of Korea's base rate and VAR-identified monetary shocks are more closely associated with changes in short-term rates. Our result strongly suggests that a text mining approach to measure monetary policy surprises can be a useful complement to extract market expectations on future monetary policy.

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1. Introduction

Does monetary policy matter to the economy? If so, how and by how much? To answer these important questions, it is essential to find exogenous changes in monetary policy (MP) stance or identify monetary policy shocks that are by nature unanticipated. Earlier studies include the narrative approach of Friedman and Schwartz (1963) and Romer and Romer (1989), which attempt to identify exogenous policy shifts. A more common and popular approach is to use the vector autoregression (VAR). In this framework, changes in the monetary policy instrument that are orthogonal to the variables included in the model are interpreted as monetary policy "shocks."[1] As Evans and Kuttner (1998) correctly point out, there have been debates on the validity of VAR approach. VAR models typically include a relatively small number of variables, while the central bank is presumed to "look at everything" in conducting monetary policy. Linearity and constant coefficients over time can be another problem.[2] Another strand of research that includes Kuttner (2001) and Gurkaynak, Sack, and Swanson (2005) uses the data of Fed funds futures to identify monetary policy. Since Fed funds futures rates necessarily reflect market opinions on where the daily official federal funds rate will be at the time of the contract expiry, any changes to the futures rate caused by monetary policy announcements can be a measure of monetary policy shocks or surprises.

Unlike the case of US, as there is no futures contract for the Bank of Korea's policy rate by which the Bank of Korea (BOK) conducts its monetary policy, the VAR approach has been the only option to identify monetary policy shocks in South Korea. To overcome this situation and provide an alternative measure of monetary policy shocks, we adopt the methodology of natural language processing (NLP), so called text mining. While high-frequency data of policy rate futures such as Fed funds futures would be better suited to address endogeneity, given the absence of such products in South Korea and most countries, we believe that our measure of MP surprises still has its own virtues and can be a valuable complement. First, our measure is constructed from different sources and may measure MP surprises in different dimensions. For example, Fed funds futures are used mostly by bank and portfolio managers for hedging fluctuations in short-term interest rates and traders for speculative purposes. Since our measure is constructed from daily news articles, it may contain more information from a broader set of the public. Second, as Cook and Hahn (1989) show, it takes time to digest information related to monetary policy announcements. Thus, our measure may include the delayed market responses that are not captured by measures based on high-frequency data. Third, our method can be used in countries in which futures of the

[1]See Christiano, Eichenbaum, and Evans (1999) for a survey and related literature of this line of research.
[2]Factor-augmented VARs and Markov-switching VARs are developed to partially address these problems.

central bank policy rates are not available. Since text mining is designed to extract valuable information from unstructured data such as text, it would complement the existing methods of identifying monetary shocks even in the countries that lack sophisticated macroeconomic and financial data.

We start from collecting 231,699 documents: 206,223 news articles that include the word 'interest rates,' 25,325 bond analyst reports, and 151 Monetary Policy Board (MPB) minutes for the period of March 2005–November 2017. To better capture the tone or sentiment, we make several refinements to the existing methodologies of text mining in the field of economics. Since it is not easy to determine the tone or sentiment of a single word (a unigram) or a bigram phrase that combines positive and negative words like "sluggish recovery," we use n-grams (from unigram to 5-gram) and ngram2vec to measure the polarity (hawkish, neutral, and dovish). We also use our own NLP tool called eKoNLPy (Korean Python Library for Economic Analysis) to address the difficulties associated with the Korean language and to consider the terminologies typically used in the field of economics and finance. Then we use 231,699 documents to train ngram2vec and quantify the tones of 24,079 news articles related to the monetary policy surrounding 152 times of Monetary Policy Board (MPB) meetings. Then we define 'MP surprises' as the differences of tones reflected in news articles before and after the meetings.[3]

With this alternative text-based measure of monetary policy surprises, we obtain several interesting results. First, our measure differs from policy rate changes, since changes in policy rate necessarily include both the anticipated and unanticipated components. We find that our measure takes a wide range of values on the dates of no policy rate changes. By collating our measure with the contents of news articles, we also confirm that, when a monetary policy decision is regarded as unexpected, our measure tends to exhibit a large value. Second, our measure, which quantifies the tones, is different from a simple quantity index of news such as the length or number of articles. Third, as the most important result, our measure of MP surprises better explains the changes in long-term interest rates, compared to changes in the policy rate and VAR-identified monetary policy shocks. It suggests that our measure is similar to the "path factor" in Gurkaynak et al. (2005) and can deliver information on forward guidance and the market's expectation on future monetary policy stances.

Our finding opens several future research avenues. For example, one can add our measure in standard VAR or DSGE models to gauge the impact of monetary policy on other macroeconomic variables. One can also compare our measure with shocks identified through VARs or high-frequency data and examine those shocks have differential impacts depending on time horizons and industry sectors. Another usage of our measure would be to evaluate

[3]We explain our methodology in more detail in Section 3.

the effectiveness of central bank communication. Lee, Kim, and Park (forthcoming) take the same approach and build the text-based indicators that describe how hawkish or dovish the sentiments of the MPB minutes themselves are. By comparing the tones of MPB minutes with those of news articles around MPB meeting dates, one can evaluate how and how much the public and market participants respond to the intention of the central bank.

The rest of the paper is structured as follows. Section 2 reviews the related literature. Section 3 explains our data and steps we take to measure the sentiment of news around monetary policy announcements. Section 4 examines the validity of our measure and estimates the impact of our measure on asset prices such as interest rates of various maturities, exchange rates, and stock market variables. Section 5 summarizes our findings and briefly discusses avenues for future research.

2. Literature Review

Monetary policy has trended toward openness and transparency, which in turn increased the capabilities of markets to anticipate policy actions (Poole, Rasche, and Thornton, 2002). Nevertheless, the anticipation and actual outcome always can be different. This discrepancy, which is often denoted by a shock or a surprise, can come from the policy action itself or the central banks' communication. Subsequent changes in the expectation then will affect the economy overall.

There are several studies to measure how much the market expectations are revised by the surprises. Kuttner (2001) presents a seminal study, in which the surprises by FOMC decisions are measured by intraday Fed funds futures price changes, showing that the 30 minute window of the price movements well captures market surprises after the FOMC announcements concerning the monetary policy. Gurkaynak et al. (2005) compare a daily base approach with an intraday event-study of Kuttner (2001), finding that surprise components of monetary policy announcement are suitably identified even in daily frequencies. Gertler and Karadi (2015) evaluate the monetary policy transmission by analyzing the joint responses of both macroeconomic and financial variables in VAR. They identify pure monetary shocks including the influences of the central banks' communication from 1-year government bond yields with instrument variables obtained from monetary policy surprises extracted from Fed funds and Eurodollar futures price changes within 30-minute windows. Pericoli and Veronese (2018) employ a two-factor approach in line with Gurkaynak et al. (2005) and identify monetary policy surprises in a single-dimensional factor (interest rate changes), which affect the long-end of yield curve. In line with Kuttner (2001) and Gurkaynak et al. (2005), Pescatori (2018) constructs MP surprises by comparing the median of survey forecasts of the policy rates and actual policy rate decision outcomes and shows that the predictability of policy decisions, as an inverse of MP surprise, has been relatively high for the case of the Central Bank of Chile.

However, when there is no policy rate future delivering market expectations on the future monetary policies as in the US, alternative approaches are employed such as an event study with short- and long-term market interest rates. Kearns and Manners (2006) quantify the impact of MP surprises, measured with daily bank bill interest rates within 70-minute event windows, on the exchange rate fluctuations. They demonstrate unanticipated monetary policy changes (surprises) have impacts on the exchange rates, which are stronger than the ones caused by the anticipated changes. Winkelmann, Bibinger, and Linzert (2014) use intraday tick-data of short and long-term German government bond futures to construct MP surprises and argue that the majority of the market reaction to surprises takes place during the ECB communication at the press conferences following the policy decisions. Fausch and Sigonius (2018) examine the impact of ECB monetary policy surprises on the German stock market. They measure MP surprises using 3-month Euribor futures as a close substitute to policy rate futures and also is strongly influenced by the market expectations on future monetary policy.

A recent strand in monetary policy analysis is the employment of natural language processing (NLP), which is often called text mining. Hendry and Madeley (2010) extract topics in the Bank of Canada's communication through LSA (Latent Semantic Analysis) and show that they affect not only short- and long-term interest rates but also their volatilities. Meinusch and Tillmann (2017) show how social networks such as Twitter messages can be used to measure public expectations on the timing of the exit strategy ("tapering") by the Federal Reserve. Picault and Renault (2017) classify sentences in the introductory statements at ECB press conferences and build a field-specific dictionary. Oshima and Matsubayashi (2018) use LDA to examine effective topics in the Bank of Japan's communications in a similar vein to Hendry and Madeley (2010). Lee et al. (forthcoming) show that text-based indicators abstracted from MPB minutes can provide better explanations for policy rate movements compared to other macroeconomic variables that are included in the feedback rules of central banks.

There are also some important attempts to combine text analysis and conventional VAR approach to inspect the implication of MP surprises to asset prices and economic activity. Lucca and Trebbi (2011) quantify tones from the text of FOMC statements to find that hawkish surprises measured by their semantic scores are more important for long-dated Treasury yields than immediate policy actions. Hansen and McMahon (2016) cluster sentences in FOMC communication with LDA (Latent Dirichlet Allocation) and, within a factor-augmented vector autoregression (FAVAR) framework, find that FOMC communication on forward guidance has a stronger impact on the financial market.

We contribute to this important strand of literature by measuring MP surprises using the technique of NLP. To the best of our knowledge, this study is the first attempt to directly estimate MP surprises by utilizing sentiment lexicons constructed via machine learning approach.

3. Data and Methodology

According to Liu (2009), sentiment analysis is a series of methods, techniques, and tools for detecting and extracting subjective information, such as opinion and attitudes, from language.[4] We use sentiment analysis to measure the tones of news articles. We then define MP surprises as the differences in the tones of news articles before and after the MPB meetings. Our measure is intended to capture the changes in both public assessments and expectations about future monetary policy stances after hearing the decision of the MPB meeting.

Sentiment analysis generally follows the following process: (i) preparing the corpus of interests, (ii) pre-processing texts, (iii) selecting features, (iv) classifying the polarity or sentiments of features and (v) measuring the sentiments of sentences and documents. We briefly explain what we do in each step.[5] Table 1 provides a summary of our work in each step.

3.1. Preparing Texts

We collect 231,699 documents, which include 206,223 news articles, 25,325 bond analyst reports and 151 minutes of MPB meetings, for the period of May 2005-December 2017. While our target texts are news articles surrounding the dates of 152 MPB meetings, we use a large amount of documents to build field-specific lexicons.[6]

News Articles We collect news articles that include the word "interest rates (금리)" from Naver and Infomax from January 2005 to December 2017.[7] These articles contain information

[4]The text mining approach has been introduced to the field of economics rather recently. See Gentzkow, Kelly, and Taddy (2017) for a summary of the application of text mining in the various fields of economics, and see Bholat, Hansen, Santos, and Schonhardt-Bailey (2015) for its application related to central banking.

[5]We borrow expositions from Lee et al. (forthcoming), mainly because we use the same n-gram polarity list used in Lee et al. (forthcoming).

[6]We have 152 MPB meetings and 151 meeting minutes because there were no minutes for an emergency meeting held during the Global Financial Crisis.

[7]https://news.naver.com, http://news.einfomax.co.kr

on the general economy, monetary policy, financial markets, and public perception about the BOK's future monetary policy stance. We use only the articles from the top three news agencies (in terms of number of articles produced) for there are many duplicate articles originating from them. The number of news articles for our final use is 206,223. Among them, 42% (86,538) are from Yonhap Infomax, 33% (68,728) from EDAILY, and 25% (50,957) from Yonhab News.

Bond Analyst Reports We also use bond analyst reports, for two reasons. One is that bond analyst reports reflect the views of experts on the monetary policy and the bond market. The other is to incorporate the informal styles of writing to our lexicons. Generally, bond analysts write more informally than journalists do. We obtain the reports from WIEfn, a financial information service provider in Korea.[8]

MPB Minutes The MPB minutes, recording discussions during MPB meetings, have been released at 4 p.m. on the first Tuesday two weeks after each meeting since September 2012.[9] We download the MPB minutes from May 2005 to December 2017 (151 minutes) from the BOK website.[10]

3.2. Pre-processing Texts

Pre-processing texts includes tokenization and normalization. Tokenization involves splitting longer strings of text into smaller pieces, or tokens, which are generally words. It can incorporate part-of-speech (POS) tagging, which assign word parts such as nouns, verbs, and adjectives. Normalization is the process of transforming a text into a single canonical form. It includes the following: removing punctuation, removing stop words, converting numbers to their word equivalents, stemming, lemmatization, and case folding.[11]

When we are dealing with Korean text, we run into unique issues, which stem from the specific characteristics of the Korean language.[12] The first issue is related to spacing. Unlike

[8] https://www.wisereport.co.kr

[9] Because of this convention of disclosing the minutes after two weeks after the market closes, it is difficult to perform event studies that attempt to gauge the market impact of monetary policy. They were released six weeks after each meeting during April 2005 to September 2012.

[10] http://www.bok.or.kr/portal/singl/crncyPolicyDrcMtg/listYear.do?mtgSe=A&menuNo=200755

[11] Stop words removal refers to dropping stop words such as "it," "the," "etc," and others. Stemming means to count only stems (for example, using "bank" for "banking" and "banks"). Lemmatization refers to grouping the inflected forms of words so that they can be analyzed as a single item. POS tagging often helps lemmatization. For example, "saw" can be the past tense of the verb "see" or a noun.

[12] One may wonder what if we translate Korean texts into English ones and apply the popular techniques for English. In a study to measure the sentiment of the MPB's minutes using sentiment analysis, Lee et al. (forthcoming) show that it is better to stick to the original texts in explaining the current and future base

English, postpositions are not space-delimited and spacing rules are not strictly observed. Second, there are many foreign words that do not follow the foreign language notation standards, and many of them are field-specific. Third, there are various notations for the same-meaning words (e.g., inflation for "인플레이션," "인플레," and "물가"). This issue can be important when n-grams are used. Various notations of synonyms increase the number of word combinations and dilutes the frequency of n-grams. Fourth, many verbs and adjectives conjugate irregularly. Irregular conjugation also aggravates the explosion of dimension in n-gram models, which hinders polarity classification. Currently available Korean morpheme analyzers do not handle these issues well. Therefore, we use eKoNLPy by Lee (2018), developed by one of this paper's authors. eKoNLPy is equipped with pre-supplied 4,202 field-specific terms that are acquired from readily available economic term dictionaries on the internet, and it has the functionality to easily add custom terms and foreign words to the dictionary for POS tagging. To deal with various notations of synonyms, eKoNLPy pre-defines 1,325 pairs of synonyms in the dictionary and supports the function of replacing synonyms. To deal with conjugation of adjectives and verbs, eKoNLPy supports lemmatization of 1,291 adjectives and verbs, which are frequently used in the domains of finance and economics.

3.3. Feature Selection

We use n-grams as features for measuring sentiments to address concerns associated with using single words.[13] A unigram or single word often loses the context. For example, while the word "recovery" in isolation appears to carry a positive message, the phrase "sluggish recovery" does not. Bi-grams are sometimes not enough. When positive and negative words are combined, like in "lower unemployment," the sentiment is not easy to measure. However, increasing the length of n-grams has a trade-off. With longer n-grams, the analysis becomes more text-specific (problem of over-fitting) and the computational burden is increased (curse of dimensionality).

Considering this trade-off and the fundamental structure of sentences that requires subjects, verbs, and objects along with adjectivies or adverbs, we use 5-grams as our feature. Note that our 5-gram feature includes unigrams to 5-grams. In order to improve the accuracy of the classification and to avoid double-counting, we consider only the highest n-gram when multiple overlapping n-grams are present in one sentence. If a sentence has a bigram "sluggish recovery," then unigram the "recovery" is ignored. If a sentence has only one unigram

rates. They also recommend to use a field-specific dictionary.

[13]Including Hutto and Gilbert (2014), many studies show that n-gram approach improves the performance of sentiment analysis. In general, they use bi-grams to 5-grams.

"recovery," then "recovery" is used to measure the sentiment of the sentence. By letting a higher n-gram always precede a lower n-gram that is included in the higher n-gram, we can significantly lower the chances that unigrams lose the context.[14]

To avoid the explosion of dimensions, we only use the words with POS, tags of nouns (NNG), adjectives (VA, VAX), adverbs (MAG), and verbs (VA), and negations.[15] We also drop n-grams that occur fewer than 15 times throughout the corpus. The final word set is composed of 2,712 words and the number of n-grams is 73,428. The next step is to classify the polarity of these n-grams to use them for measuring sentiments of sentences and documents.

3.4. Polarity Classification

3.4.1. Corpus-Based Polarity Classification

When classifying sentiments of English texts, one usually uses the well-known polarity-word lists like Harvard-IV or LM dictionary.[16] However, these dictionaries are for unigrams, not for n-grams. To address this, we use ngram2vec of Zhao, Liu, Li, Li, and Du (2017) instead of word embedding. Just like the motivation of word embedding, the rationale for using ngram2vec can be found in the famous insight of Firth (1957): "You shall know a word by the company it keeps." That is, if two words (n-grams in our case) appear together frequently in the same context, they are likely to have the same polarity. Thus the polarity of a word can be determined by calculating the relative frequency of co-occurrence with another word. This could be done with the concept of pointwise mutual information (PMI), using Semantic Orientation from PMI (SO-PMI) proposed by Turney (2002) for polarity classification.[17] We place the seed set of n-grams and our n-grams in a vector space (lexical graph) and measure the proximity of our n-grams to this seed. The polarity of an n-gram is

[14] We also perform the sensitivity analysis and find that any n-gram model outperforms the unigram model, and the performances are not that sensitive to the choice of n (=2, 3, 4, and 5) in our case.

[15] Appendix A shows the POS tagging list of the eKoNLPy.

[16] For unigrams (single words), the oldest is the General Inquirer (Stone, Dunphy, and Smith, 1966) also known as Harvard IV-4, which has many categories of word lists, including 1,915 words of positive outlook and 2,291 words of negative outlook. In a financial context, negative words are mainly used for sentiment analysis (Tetlock, 2007). A widely used word list in finance literature is that of Loughran and McDonald (2011), which has lists of single words by category (Negative, Positive, Uncertainty, Litigious, Modal, Constraining). Their research indicates that the LM dictionary has a better correlation with financial metrics. The LM dictionary is available at the following link: https://sraf.nd.edu/textual-analysis/resources/

[17] PMI is a technique for quantifying the similarity between two random variables based on probability theory. Using PMI, the similarity between two lexicons is measured as:

$$PMI(w_1, w_2) = \log \frac{P(w_1, w_2)}{P(w_1)P(w_2)},$$

where w_1 and w_2 are the two lexicons under consideration.

proportional to the probability of a random walk from the seed set hitting that n-gram. Each feature will have two probabilities: one for hawkish, the other for dovish. A final polarity score is the relative ratio of the two as in equation (1):

$$polarity\ score = \frac{p^{hawkish}(feature)}{p^{dovish}(feature)} \tag{1}$$

Roughly speaking, an n-gram will be labeled hawkish if it presents more often in hawkish documents than in dovish ones.

We train ngram2vec using our entire 231,699-document corpus. The parameters we use for training are 5-gram for center words, 5-gram for context words, window size of 5, negative sampling size of 5, and 300 dimension for vector representation. Our corpus has 344,293 unique n-grams with a minimum frequency limit of 25, which yield 410,902,512 pairs of n-grams (21.7 GB in size). With this resulting n-gram vector, we bootstrap by running our propagation 50 times over 10 random equally sized subsets of the hawkish and dovish seed sets. Table 2 shows seed sets.

We classify the polarity of our lexicon as hawkish (dovish) if the polarity score of (1) is greater (less) than 1, excluding lexicons in the grey area using intensity of 1.1 as a threshold. The final numbers are 11,710 hawkish lexicons and 12,246 dovish ones. A sample of polarity lexicon is provided in table 3.

While this approach is quite intuitive, there are two problems. First, it sometimes fails to recognize antonyms because it judges the polarity based on co-occurrence. Second, the outcome is affected by choices of seed words. As to the first question, this is another reason why we use ngram2vec by Zhao et al. (2017) instead of word embedding. They show that n-gram embedding is effective in finding antonyms. For the second problem, we adopt the SentProp framework of Hamilton, Clark, Leskovec, and Jurafsky (2016), a relatively new and effective domain-specific sentiment induction algorithm. The SentProp framework addresses this issue by bootstrapping seed words to reduce problems associated with their arbitrariness.

3.4.2. Evaluation

In this section we evaluate the accuracy of our lexicon classification in several ways. In principle, the criteria of judging the accuracy is how well the classification of sentiment agrees with human judgments. In addition, we use the typical set of metrics to measure the performance: accuracy, recall, precision, and F1 score.[18]

First, we compare the performance of our indicators using introductory statements from the BOK Governor's news conferences about monetary policy decisions, which were not used in building our lexicons. With documents from May 2009 to January 2018, we manually label 2,341 sentences as hawkish, neutral, and dovish. To check the consistency of our classification, we train a Naïve Bayes classifier with a random selection of 60% of hawkish and dovish sentences and test with the remaining sentences. After 30 iterations, the average accuracy of classifiers is about 86%, which we think is above par.[19]

Second, we check the accuracy of our lexicons using labeled sentences that are completely out of sample. The accuracy is 67% (positive precision: 69%; positive recall: 71%; positive F1: 70%; negative precision: 65%; negative recall: 62%; and negative F1: 63%). In order to put the above numbers in context, we compare the performance of our lexicons with Korean Sentiment Analysis Corpus (KOSAC).[20] Note that KOSAC is a general-purpose Korean sentiment dictionary, while we use a field-specific dictionary.[21] In comparison, KOSAC performs relatively poorly: the accuracy is only 53% (positive precision: 71%; positive recall:

[18] Accuracy is the most intuitive performance measure, which is simply a ratio of correctly predicted observation to the total observations:

$$\text{Accuracy} = \frac{\text{True Positives} + \text{True Negatives}}{\text{True Positives} + \text{False Positives} + \text{True Negatives} + \text{False Negatives}}$$

where the predicted "positive" and "negative" refer to a model's prediction (positive and negative corresponds to hawkish and dovish in our case), and the terms "true" and "false" refer to whether the prediction corresponds to the actual value. Precision is the ratio of correctly predicted positive observations to the total predicted positive observations. It is an informative measure when the cost related to false positive is high:

$$\text{Precision} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Positives}}$$

Recall is the ratio of correctly predicted positive observations to all observations of actual positives:

$$\text{Recall} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Negatives}}$$

F1 score is the weighted average of precision and recall. Therefore, this score takes both false positives and false negatives into account.

$$\text{F1 score} = 2 \times \frac{\text{Recall} \times \text{Precision}}{\text{Recall} + \text{Precision}}$$

While F1 does not seem intuitively straightforward, it is more useful than accuracy in case of an uneven class distribution.

[19] According to research by Amazon's Mechanical Turk, human raters typically agree only about 79% of the time (https://mashable.com/2010/04/19/sentiment-analysis/#skdJb2rbx5qg). In this regard, it would be good to refer to this 79% as a benchmark when evaluating the raw accuracy of sentiment analysis.

[20] http://word.snu.ac.kr/kosac

[21] Given the lack of research conducted in the Korean language in this field, this is the only dictionary available for comparison. In the case of English, Ribeiro, Araújo, Gonçalves, Gonçalves, and Benevenuto (2016) provide an extensive comparison among various sentiment analysis methods.

57%; positive F1: 63%; negative precision: 29%; negative recall: 43%; and negative F1: 35%), which is lower than the 67% accuracy of our lexicons.

3.5. Measuring MP Surprises

From the news articles we collected, we select news articles that include the word '금융통화위원회 (Monetary Policy Board)' or '금통위 (MPB)' one day before and after the 152 MPB meetings from March 2005 to November 2017.[22] We exclude news articles released between 9 a.m. and 10 a.m. (between 9:30 a.m. and 10:30 a.m. before 2009), which is the time when MPB meetings are being held. The total number of news articles is 18,157.[23] Table 4 reports the number of news articles by providers and relative shares.

We count the number of articles and characters of each article before/between/after the MPB dates to see some characteristics of our target texts. Table 5 shows some patterns. It is unsurprising to see that both the number and length of articles increase after each MPB meeting. And there is an asymmetry: there are more news articles following the BOK's base rate cuts. In terms of length, there is more media coverage when the BOK raises its rate. This suggests that media coverage depends on the direction of the monetary policy decision. However, with a mere counting of news articles, we cannot differentiate expected responses and surprises, and discern the direction of surprises about monetary policy decisions. Therefore, we measure MP surprises with the more sophisticated text mining methodology. We compare ours with this quantity index in section 4.1.

Measuring the tones of news articles is done by a two-step approach. First, we calculate the tone of a sentence based on the number of hawkish and dovish features it contains. Specifically, the tone of a sentence s is defined by the following formula:

$$tone_s = \frac{No.\ of\ hawkish\ features - No.\ of\ dovish\ features}{No.\ of\ hawkish\ features + No.\ of\ dovish\ features} \tag{2}$$

[22] There is a possible concern that the news articles might include other topics other than monetary policy, because we use all the texts from news articles that include the keyword '금융통화위원회 (Monetary Policy Board)' or '금통위 (MPB)'. To alleviate this concern, we also do our analysis only with the sentences that are directly related to the monetary policy topic among all topics extracted using latent Dirichlet allocation (LDA) method, a topic modeling method. We find that the result is not qualitatively different.

[23] News providers can be categorized into three groups. The first group is economic newspapers (9,754 articles): EDAILY, Korea Economic Daily, Maeil Economic. The second group is regular newspapers (1,351): Donga Ilbo, Hankyoreh, and Kyunghyang. The last group is news agencies (12,974): Yonhap Infomax and Yonhap News. To avoid duplication, we use articles from Yonhap Infomax, Yonhap News, and EDAILY. We confirm that our main result does not change much when we include news articles from economic and regular newspapers.

Then, we calculate the tone of a group of articles i by the following formula:

$$tone_i = \frac{No.\ of\ hawkish\ tone_{s,i} - No.\ of\ dovish\ tone_{s,i}}{No.\ of\ hawkish\ tone_{s,i} + No.\ of\ dovish\ tone_{s,i}} \tag{3}$$

This creates a continuous variable $tone_i$ for each group, which is bounded between -1 (dovish) and $+1$ (hawkish).

We divide news articles into two groups. One is news articles published before the MPB meetings and the other is those published after meetings. We measure the tone of the former group and denote it by $tone^{before}$. With the latter, we measure the tone after the MPB decisions are released and denote it by $tone^{after}$. With these two tones, we define MP surprises by the following formula:

$$\Delta tone^{news} = tone^{after} - tone^{before} \tag{4}$$

Panels (a)–(d) in figure 1 show the time series of the MP sentiments of newspaper articles before and after the MPB meetings ($tone^{before}$ and $tone^{after}$), with the sentiments of MPB minutes ($tone^{minutes}$), our measure of MP surprises ($\Delta tone^{news}$) and changes in the BOK base rate (Δbase rate). The two tones of newspapers and the MPB minutes move closely with each other. Panel (e) in figure 1 reports that the correlation coefficient between the tones of articles before and after MPB meeting is 0.82. The correlation coefficients between the tones of the BOK MPB's minutes and those of articles before and after the MPB meeting are 0.75 and 0.80, respectively. On the other hand, the correlation coefficient between MP surprises and changes in the BOK base rate is relatively low at 0.33.

Figure 2 displays an interesting relationship between the base rate changes and our measure of MP surprises ($\Delta tone^{news}$). Note that there are many variations in $\Delta tone^{news}$ on the dates when the base rate is kept unchanged. For example, there is a large positive surprise on 10 December 2009, on which the tone of news articles becomes hawkish. This can occur when the public expects a rate cut but the central bank freezes the rate. Meanwhile, with the same unchanged base rate, there is a large negative surprise on 13 November 2014, suggesting the public might have expected a rate hike before the meeting. In the following section, we examine the MPB's decisions on the dates of the 6 largest positive and negative surprises to check if our text-based surprise measure is valid for monetary policy shocks.

4. Empirical Analysis

4.1. Validation of Our Measure as MP Surprises

We examine if our measure of MP surprises ($\Delta tone^{news}$) well captures the surprises right after monetary policy announcements. First, we select the dates of the largest MP surprises and examine the narratives of news coverage on those dates. By doing so, we find out if those MPB decision announcements are regarded as news that would surprise investors or unexpectedly affect the public expectation on future monetary policy directions, regardless of whether the MPB cuts or raises its base rate. Second, we compare our measure with the amount of news coverage. Bang and Ha (2013) define the amount of news coverage as the number of characters in news articles after MP announcements. They show that the amount increases on the days of base rate changes compared to the days of no change. They also report that unanticipated rate hikes receive less attention than anticipated ones, while unanticipated rate cuts receive more attention than anticipated ones.[24] Their interpretation is that unexpected rate hikes are less effective in transmitting the BOK's signal to general public than expected ones. One may wonder if the changes in the amount of news coverage can be used as a measure of MP surprises. Given that our measure quantifies changes in sentiment while Bang and Ha (2013) measure changes in the amount of news stories, it would be problematic if these two measures provide the similar information. As the NLP methodology is far more complicated, it would then be meaningless to apply the text-mining approach to quantify the surprises. We examine whether our measure delivers a similar amount of information compared to the amount of news coverage.

First, we examine the tones of news coverage on several dates when large MP surprises occurred. Table 6 shows the dates of the eight largest positive (hawkish) and negative (dovish) MP surprises with the base rate changes and newspaper headlines on the corresponding dates. As shown in figure 2, note that large MP surprises do not necessarily correspond to large changes in the base rate. Among the eight dates with the largest surprises, there were no changes in the base rate on the four of the dates and 0.25%p changes in the other four dates. To see if our MP surprise measure really captures unexpected market responses, we review the contents of news coverage on the dates of the six largest positive and negative surprises. The following dates are those with the largest positive (hawkish) surprises:[25]

- December 10, 2009: This is the date of the largest hawkish surprise. $tone^{news}$ jumps from -0.37 to 0.14, even though the BOK has frozen its policy rate. The then-governor

[24] They define unanticipated rate changes as MP decisions when the majority opinion in the Yonhap Infomax Poll is different from the actual MP decision.

[25] Table 7 also provides the website addresses of the news articles.

Seong-Tae Lee suggested an exit strategy by saying, "We have to mull the timing of a rate hike by closely monitoring economic performance and inflation every month amid signs of an economic rebound." Thus, even with base rate unchanged, our measure seems to capture the high probability of a rate hike in the future.

- July 9, 2010: $tone^{news}$ increases from 0.02 to 0.52 following a 0.25% increase to the base rate. The then-governor Choong-soo Kim said, "We didn't change it for 16 months, because we thought the economy was still caught in the global crisis . . . I'm not saying that we have completely overcome the crisis, and the rate hike of 0.25 percentage points merely reflects a change of direction, not a change from an expansionary policy." Even though the governor emphasized that the 0.25%p increase would not imply the end of expansionary policy, the first rate hike in 16 months took place and he mentioned "a change of direction."
- July 12, 2007: The BOK raised its policy rate for the first time in 11 months. According to the Korea Times, "Economists were split in their forecasts of the central bank's move in a survey last week by Yonhap Infomax, the financial news arm of Yonhap News Agency, when half of the 26 experts predicted a rate hike and the other half forecast a freeze." Given this disagreement among economists, the rate increase was not well anticipated.

The following dates are those with the largest dovish surprises:

- November 13, 2014: This is the date of the largest dovish surprise. An economist quoted in the news article said, "Today's rate freeze has toned down the market's expectations for a further rate cut," and a report from Nomura Securities said, "The BOK will likely cut the rate in December or the first quarter of next year." The rate freeze seemed to extinguish hawkish expectations and strongly suggested a rate cut in the near future, resulting in the largest dovish surprise.
- October 13, 2010: According to the BBC, "The decision came as a surprise as most economists had expected an interest rate rise to 2.5%."[26] In addition, an article cited in table 7 says "beating market expectations, Bank of Korea (BOK) Gov. Kim Choong-soo and his fellow policymakers froze the benchmark seven-day repo rate, dubbed the base rate, at 2.25 percent." These two articles confirm that the decision came as a surprise.
- June 9, 2016: Only 4 of 23 economists polled by Thomson Reuters were expecting a policy easing at this meeting. In addition, note that an article cited in table 7 uses the term of "stun," saying that "South Korea's central bank, the Bank of Korea (BOK),

[26] https://www.bbc.com/news/business-11539559

stunned financial markets on Thursday by cutting interest rates to a record-low level of 1.25%. It's the first time the BoK has eased policy since June 2015."

Considering the narratives in news articles on the dates of the largest surprises, it seems that our measure of MP surprises, $\Delta tone^{news}$, well captures the changes in public expectation about future monetary policy stances.

Next, for comparison with the amount of news coverage used in Bang and Ha (2013), we run the following regression equations:

$$y_t = \alpha + \beta_1 I(\Delta\text{base rate} > 0) + \beta_2 I(\Delta\text{base rate} < 0) + \varepsilon_t, \tag{5}$$

and

$$y_t = \alpha + \beta_1 I(\text{upper 10\% hawkish surprise}) + \beta_2 I(\text{upper 10\% dovish surprise}) + \varepsilon_t, \tag{6}$$

where y_t is the number or length of news articles, $I(\Delta\text{base rate} > 0)$ is a dummy variable that takes a value of one on the days of rate hike, and $I(\text{upper 10\% hawkish surprise})$ is a dummy on the days of the upper 10% hawkish surprises. Among 152 MPB dates during the sample period, there are 14 rate hikes and 14 rate cuts (each accounting for 9.2% of meetings). Thus we choose the 10 percentile for MP surprises.[27]

Column (1) and (2) in table 7 show the estimation results of equation (5). Column (1) tells us that the average number of articles in economic newspapers is 81.1, and increases by 54.4 and 93.2 articles on the days of rate increases and cuts, respectively. In terms of the average length of articles, column (2) reports the same pattern. The news articles are lengthier on the days of rate changes and more so on the days of rate cuts. This result is consistent with Bang and Ha (2013). Columns (3) and (4) based on equation (6) show a different result. Only the coefficient β_2 is statistically significant when the dependent variable is the number of news articles and R^2's are very low, compared to the ones in columns (1) and (2). This result suggests that our measure of MP surprises, measured by changes in tones of news coverage around MP announcements, is very different from a simple quantity index of news coverage.

[27]Using 25th percentile or $\Delta tone^{news}$ itself instead of 10th percentile does not change the result much.

4.2. MP Surprises and Financial Market Reactions

4.2.1. Explanatory Power of MP Surprises over Maturities

In this section, we further investigate the property of our MP surprises by estimating its impact on asset prices such as bond yields of various maturities. For this purpose, we use the popular regression specification used in Cook and Hahn (1989):

$$\Delta y_t = \alpha + \beta_1 \Delta \text{base rate} + \beta_2 \Delta tone^{news} + \varepsilon_t, \tag{7}$$

where Δy_t is the change in asset price or return.[28]

First, we estimate the responses of interest rates of various maturity. Table 8 shows the result. Model 1 refers to the equation only with Δbase rate and Model 2 refers the one with both Δbase rate and $\Delta tone^{news}$. The result from Model 1 and Model 2 shows that changes in the base rate (Δbase rate) can explain changes in interest rates up to a maturity of one year. The magnitude and statistical significance of $\hat{\beta}_1$ becomes smaller and lower as the maturity becomes longer. For example, a 1%p increase in base rate is associated with 0.52%p increase in 3-month KORIBOR and 0.44%p increase in 1-year KORIBOR.[29] The estimated coefficients get smaller and insignificant as we move to longer durations past one year. Model 2 shows that our measure of MP surprises ($\Delta tone^{news}$) is very different from Δbase rate in that it better explains changes in long-term rates. While changes in base rate explain changes in interest rates up to one year, our MP surprise measure starts to be statistically significant from one-year interest rates. In terms of R^2, adding the MP surprise measure ($\Delta tone^{news}$) does not raise the value of R^2 much for short-term rates. In comparison, adding it helps raise the value of R^2 for long-term rates.

The scatter plots in figure 3 confirm these results. Panel (a) shows the relation between changes in the base rate and 3-month KORIBOR. It clearly shows that most observations are located in the northeast and southwest quadrant, suggesting that changes in 3-month KORIBOR and change in the base rate tend to move in the same direction. By contrast, Panel (b) shows that changes in 3-month KORIBOR bear little relation to MP surprises.[30] Panel (c) shows that, for the case of 5-year KTB yield, the positive relation observed in Panel (a) vanishes. That is, changes in the base rate are not closely associated with changes in long-term yields. Meanwhile, Panel (d) shows a positive relationship, which is not shown

[28] All the changes in asset prices and returns are measured by the differences between MPB day and the day before.

[29] KORIBOR (Korean Inter-Bank Offered Rates) is the offered interest rates among the commercial banks in South Korea, which is similar to LIBOR (London Inter-Bank Offered Rates).

[30] An observation deep in the southwest quadrant corresponds to December 11, 2008, when the BOK decided to cut its base rate by 1.00%p.

in Panel (b). In fact, the slope is 0.158 with t-value of 4.60. Figure 3 graphically supports the result in table 8.

4.2.2. Text-Based Shocks vs. VAR-Identified MP Shocks

We compare our text-based MP shocks with VAR-identified shocks in terms of explaining the interest rates of various maturities. We add VAR-identified shocks, denoted by ΔMP^{VAR}, to equation (7).

In order to get ΔMP^{VAR}, we use the standard VAR procedure of Christiano et al. (1999), in which a VAR system consists of six variables. Let ip_t, cpi_t, IE_t, BR_t, tr_t, and m_t denote the time t values of the log of real industrial production, the log of consumer price index, the inflation expectation, the BOK base rate, the log of total reserves, and the log of M2, respectively. The structural representation is as follows:

$$Ay_t = \alpha + \sum_{i=1}^{k} A_i y_{t-1} + \varepsilon_t, \tag{8}$$

where $y_t = (ip_t, cpi_t, IE_t, BR_t, tr_t, m_t)$ and where ε_t denotes the vector of serially and mutually uncorrelated structural innovations. For monthly frequency, we replace GDP and PCE with industrial production and inflation. And we replace the index of sensitive commodity prices with expected inflation because of its availability.[31] We assume that A^{-1} has a recursive structure such that the reduced form errors e_t can be expressed as $e_t = A^{-1}\varepsilon_t$.

$$e_t = \begin{pmatrix} e_t^{ip} \\ e_t^{cpi} \\ e_t^{IE} \\ e_t^{BR} \\ e_t^{tr} \\ e_t^{m} \end{pmatrix} = \begin{bmatrix} a_{11} & 0 & 0 & 0 & 0 & 0 \\ a_{21} & a_{22} & 0 & 0 & 0 & 0 \\ a_{31} & a_{32} & a_{33} & 0 & 0 & 0 \\ a_{41} & a_{42} & a_{43} & a_{44} & 0 & 0 \\ a_{51} & a_{52} & a_{53} & a_{54} & a_{55} & 0 \\ a_{61} & a_{62} & a_{63} & a_{64} & a_{65} & a_{66} \end{bmatrix} \begin{pmatrix} \varepsilon_t^{1} \\ \varepsilon_t^{2} \\ \varepsilon_t^{3} \\ \varepsilon_t^{4} \\ \varepsilon_t^{5} \\ \varepsilon_t^{6} \end{pmatrix}$$

We can recover the orthogonalized shocks with $\varepsilon_t = Ae_t$ where $A = chol(\Sigma)$, which is the Choleski decomposition of the covariance matrix of residuals.

Table 9 shows the estimation results when we consider the orthogonalized monetary shocks through the VAR. Model 1 considers the variable of ΔMP^{VAR} only and shows that it explains the changes in interest rates whose maturity is up to 2-year. However, when we include it with our text-based surprises $\Delta tone^{news}$ in Model 2, its explanatory power becomes

[31] One notable difference with Christiano et al. (1999) is that we do not include the variable of non-borrowed reserves because the Bank of Korea does not publish the data in a compliance with the IMF manual.

lower. And, in Model 3, its explanatory power is subsumed by Δbase rate. Also note that the explanatory power of $\Delta tone^{news}$ still survives, especially for the interest rates whose maturity is at least 1-year. This result strongly suggests that our measure of monetary policy surprises obtained through text mining delivers important information for long-term interest and its information is distinct from the one we obtain from the VAR approach.

4.2.3. MP Surprises and Other Financial Market Variables

Next, we examine the responses of exchange rates and stock market variables. Table 10 shows the results when exchange rates of the major currencies and stock market variables are used as dependent variables. Both Δbase rate and $\Delta tone^{news}$ are not statistically associated with changes in exchange rates, which is consistent with the finding of Ahn (2012). Ahn (2012) shows that the USD/KRW exchange rate responds to monetary policy news only within a 30-minute window, and this surprise effect is not found in 60-minute, open-close, and daily intervals. For the stock market, the coefficients on $\Delta tone^{news}$ are statistically significant for some variables such as KOSPI, KOSDAQ, and trading value. Interestingly, the signs of the estimates associated with $\Delta tone^{news}$ turn out to be positive, while those with Δbase rate are negative.[32] Considering that our measure of MP surprises comprises policy action and communication of the BOK, a hawkish surprise might have been regarded as a positive news in the stock market, in which the market participants take the central bank outlook as more positive than expected. In this regard, our measure may contain the information close to "information shock" of Jarocinski and Karadi (2018), who decompose central bank announcements into information about monetary policy and the central bank's assessment of the economic outlook.

We also examine the responses of the credit spread and term premium. We define the credit spread as the difference between the yields of 3-year BBB- and AA- corporate bonds. The term premium is defined as the difference between the yields of 10-year and 1-year KTBs. We also calculate break-even inflation using the differences between the yields of 10-year KTBs and 10-year inflation-linked KTBs. Table 11 shows the results. While the estimated coefficient of MP surprises ($\Delta tone^{news}$) on credit spread is not statistically different from zero, this is because $\Delta tone^{news}$ affects the yields of both AA- and BBB- corporate bonds with similar magnitudes. The estimates for AA- and BBB- bonds are 0.134 and 0130, respectively, and both are statistically significant. The same pattern happens with the term premium. Meanwhile, since changes in the base rate (Δbase rate) do not affect a yield whose

[32] Sohn, Sung, and Kwon (2005) manually collect 138 news articles that are related to monetary policy during the period of May 1999–December 2004 and categorize them into tight/normal/accommodating. Their index is positively associated with stock market volatility, not with the stock market index.

maturity is longer than one year, the estimated coefficients on 3-year corporate bonds, 10-year KTBs, and 10-year inflation-linked KTBs are not statistically different from zero. As a result, the estimate on the term premium is statistically significant. In case of the credit spread, even though Δbase rate does not affect both AA- and BBB- yields, it affects their difference.

5. Concluding Remarks

Our study is motivated mainly by two observations. First, while using the change in the federal funds futures rate following FOMC meetings is an effective way to address the endogeneity issues in measuring monetary policy shocks, such a financial product is not readily available in other countries, including South Korea. Second, it would be advantageous and instrumental to utilize the unstructured data in the realm of central banking.[33] Given the increased importance of central bank communication after the Global Financial Crisis, it is important to extract the information from its under-utilized source of communication.

We use text mining approach to measure monetary policy surprises. We quantify the tones of news articles before and after MPB meetings and define MP surprises as the changes in tone following the meetings. Our approach is relatively free from model specification error of the VAR approach. Unlike the approach based on federal funds futures, our approach considers a broader audience and a greater length of time to digest new information. As the most important result, our text-based measure of MP surprises better explains the changes in long-term interest rates, compared to changes in the base rate and VAR-identified shocks. It suggests that our measure may extract different dimensions of information and can deliver the information on forward guidance and the market's expectation about the future monetary policy stance.

We believe that text mining approach can provide many promising research avenue, which would not have been possible before without this methodology. Shapiro and Wilson (2019) can be one example. They find that the FOMC had an implicit inflation target of approximately 1.5 percent on average over their baseline 2000 - 2013 sample period, without assuming any knowledge of the underlying macroeconomic structure nor observation of central bank actions. This approach will also complement the existing research. For example, one can incorporate a measure based on our methodology into VAR framework or DSGE models to see how differently a set of MP shocks affects macroeconomic and financial variables.

[33] Reportedly, 80% of world's data is unstructured. https://www.ibm.com/blogs/watson/2016/05/biggest-data-challenges-might-not-even-know/

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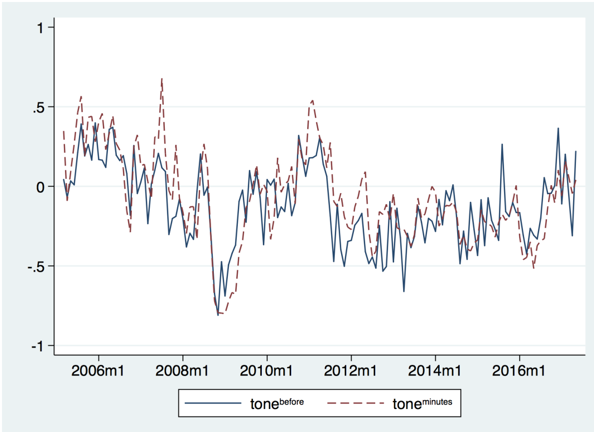
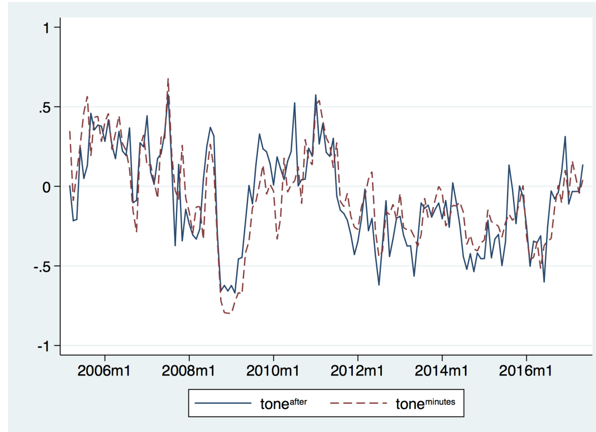
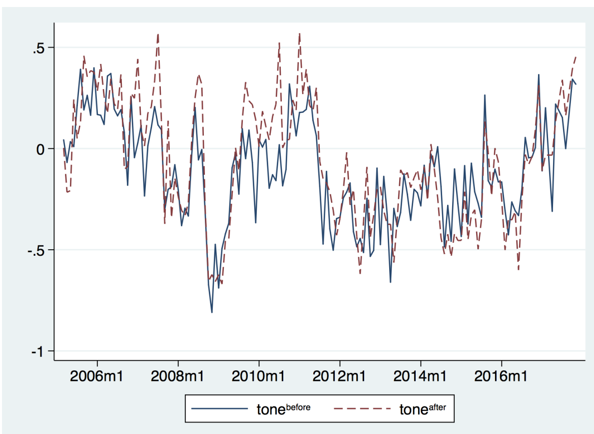


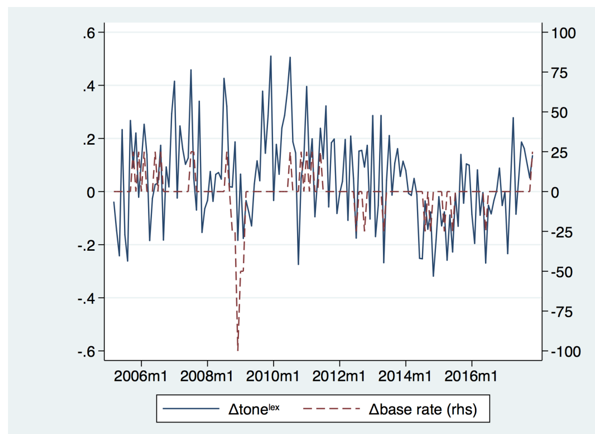
(a) $tone^{before}$ and $tone^{minutes}$



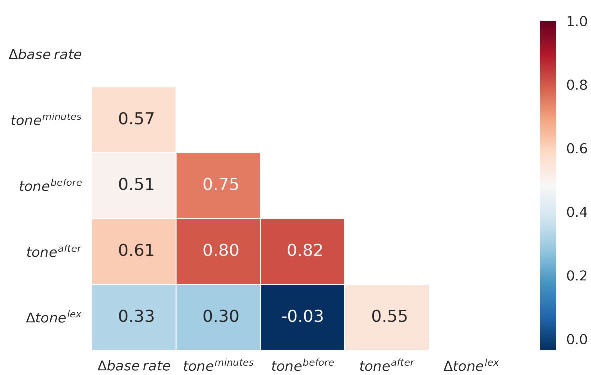
(b) $tone^{after}$ and $tone^{minutes}$



(c) $tone^{before}$ and $tone^{after}$



(d) $\Delta tone^{news}$ and Δbase rate



(e) Correlation coefficients

Fig. 1. Time-series of key variables and their correlation coefficients
Panels (a)–(d) show the time series of the MP sentiments of newspapers before and after MPB meetings, $tone^{before}$ and $tone^{after}$; the sentiments of MPB minutes, $tone^{minutes}$; our measure of MP surprise, $\Delta tone^{news}$; and changes in the BOK base rate, Δbase rate. Panel (e) shows the correlation coefficients.

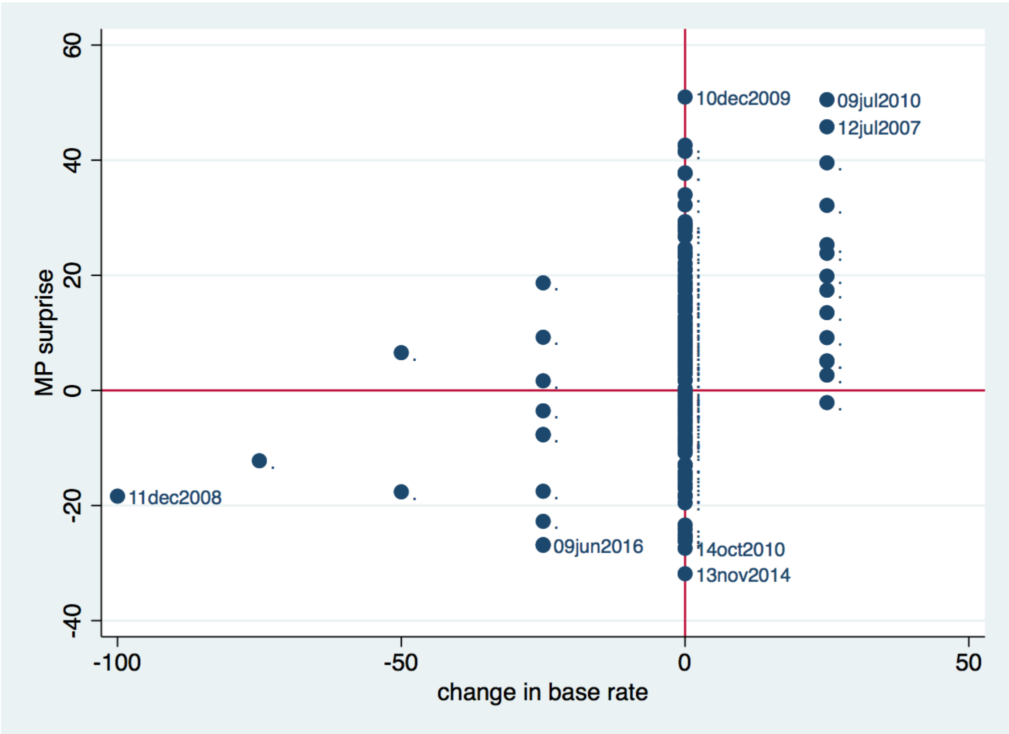
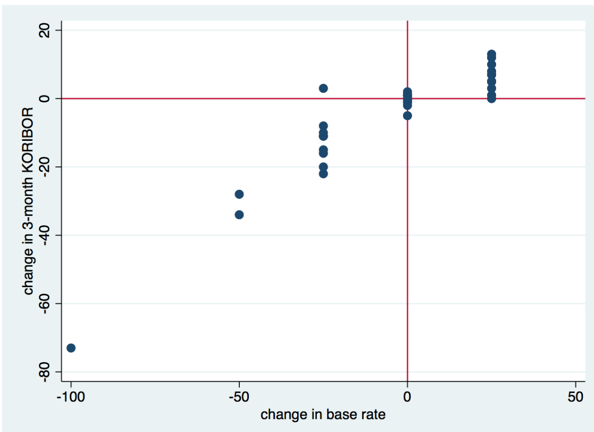
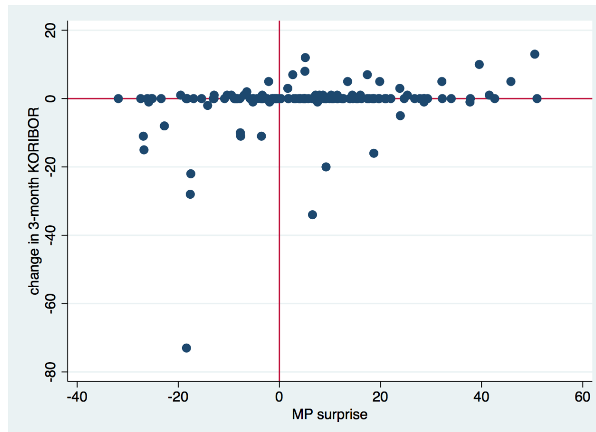


Fig. 2. Changes in base rate and MP surprise

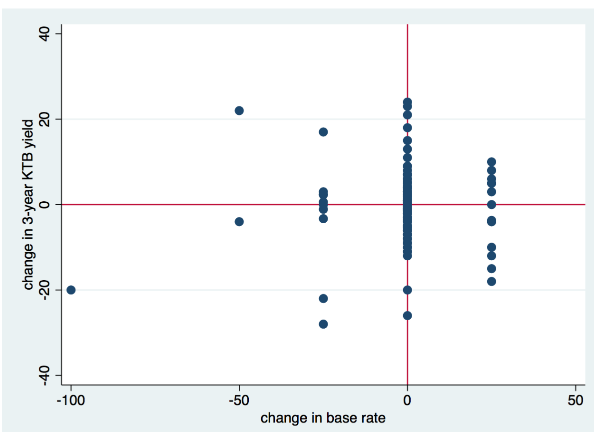
This figure shows the relationship between base rate changes and monetary policy surprises ($\Delta tone^{news}$).



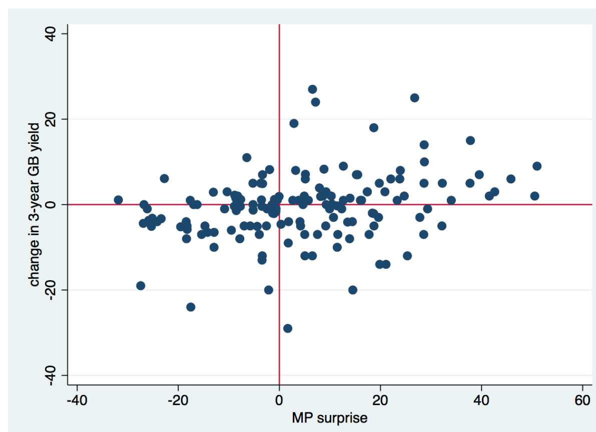
(a) 3-month KORIBOR and base rate



(b) 3-month KORIBOR and and MP surprise



(c) 5-year KTB yield and base rate



(d) 5-year KTB yield and MP surprise

Fig. 3. Changes in base rate, MP surprise ($tone^{news}$), 3-month and 5-year interest rates

Table 1: Process of sentiment analysis

This table summarizes what we do in each step of the sentimental analysis. See section 3 for more details.

1. Preparing the corpus	• 231,699 documents – 151 MPB minutes – 206,223 news articles related to interest rates – 25,325 bond analyst reports
2. Pre-processing texts	• Tokenization • Normalization – removing stop words – stemming and lemmatization • Morphological analysis of the Korean language → eKoNLPy – spacing – field-specific and foreign words
3. Feature selection	• N-grams as a feature – 73,428 n-grams
4. Polarity classification	• Corpus-based approach – ngram2vec – SentProp of Hamilton et al. (2016) • Evaluation – 2,341 manually classified sentences – out-of-sample test – comparison with KOSAC
5. Sentiment measurement	• Measuring tones of sentences from the features of n-grams • Measuring tones of documents from tones of sentences

Table 2: Seed words for polarity induction

	Hawkish		Dovish
높/high	팽창/expand	낮/low	축소/reduce
인상/hike	매파/hawkish	인하/cut	비둘기/dovish
성장/growth	투기/speculate;억제/suppress	둔화/slow	악화/worse
상승/rise	인플레이션/inflation;압력/pressure	하락/fall	회복/revocer;못하/not
증가/increase	위험/risk;선호/prefer	감소/decrease	위험/risk;회피/averse
상회/exceed	물가/inflation;상승/increase	하회/lower	물가/inflation;하락/decrease
과열/overheat	금리/rate;상승/increase	위축/shrink	금리/rate;하락/decrease
확장/expand	상방/upward;압력/pressure	침체/recession	하방/downward;압력/pressure
긴축/tighten	변동성/volatility;감소/decrease	완화/ease	변동성/volatility;확대/increase
흑자/surplus	채권/bond;가격/price;하락/drop	적자/deficit	채권/bond;가격/price;상승/rise
견조/solid	요금/price;인상/hike	부진/weak	요금/price;인하/cut
낙관/optimistic	부동산/real estate;가격/price;상승/rise	비관/pessimistic	부동산/real estate;가격/price;하락/drop
상향/upward	(Total 25 seeds)	하향/downward	(Total 25 seeds)

Table 3: A sample of polarity lexicons

Hawkish	Dovish
인상/hike	인하/cut
확장/expand	하향/downward
상향/upward	부진/weak
투기/speculate;억제/supress	회복/recover;못하/not
금리/rate;상승/increase	금리/rate;하락/decrease
상회/exceed	악화/worse
채권/bond;가격/price;하락/drop	침체/recession
인플레이션/inflation;압력/pressure	하락/fall
과열/overheat	변동성/volatility;확대/increase
견조/solid	위축/shrink
팽창/expand	하회/lower
물가/inflation;상승/increase	둔화/slow
부동산/real estate;가격/price;상승/rise	완화/ease
성장/growth	채권/bond;가격/price;상승/rise
긴축/tighten	물가/inflation;하락/decrease
흑자/surplus	위험/risk;회피/averse
요금/price;인상/hike	하방/downward;압력/pressure
상방/upward;압력/pressure	부동산/real estate;가격/price;하락/decrease
낙관/optimistic	비관/pessimistic
변동성/volatility;감소/decrease	요금/price;인하/cut
위험/risk;선호/prefer	적자/deficit
매파/hawkish	비둘기/dovish
부동산/real estate;과열/overheat;억제/suppress	둔화/slow;경기/economy;침체/recession
부동산/real estate;과열/overheat	경기/economy;침체/recession;빠지/fall
과열/overheat;우려/concern	악화/worsen;경기/economy;침체/recession
과열/overheat;억제/suppress	경기/economy;침체/recession
과열/overheat;막/prevent	침체/recession;빠지/fall
경기/economy;과열/overheat	침체/recession;가능성/possibility;높/high
부동산/real estate;과열/overheat;우려/concern	경기/economy;침체국면/recession;빠지/fall
경기/economy;과열/overheat;우려/concern	침체/recession;경기/economy;침체/recession
가격/price;억제/suppress	둔화/slow;침체/recession
투자/invest;과열/overheat	경기/economy;침체/recession;빠지/fall;않/not
부동산/real estate;가격/price;억제/suppress	이미/already;침체/recession
경기/economy;과열/overheat;억제/suppress	길/long;침체/recession
과열/overheat;조짐/sign	침체/recession;빠지/fall;우려/concern
인플레이션/inflation;긴축/tighten	침체국면/recession;빠지/fall
경기/economy;과열/overheat;막/prevent	이미/already;경기/economy;침체/recession
경제/economy;과열/overheat	침체/recession;최악/worst
긴축/tighten;압력/pressure	경제/economy;침체/recession;빠지/fall
과열/overheat;방지/prevent	침체/recession;늪/swamp

Table 4: Number of news articles on MP decisions by source
This table shows the number of news articles produced surrounding MPB dates from March 2005 to November 2017 during which 152 MPB meetings were held.

Provider group	Newspaper	Number of articles	Proportion
News agency	Yonhap News	4,340	18.0
	Yonhap Infomax	8,634	35.9
	Subtotal	12,974	53.9
Economic	EDAILY	5,183	21.5
	Maeil Economic	2,598	10.8
	Korea Economic Daily	1,973	8.2
	Subtotal	9,754	40.5
Regular	Donga Ilbo	393	1.6
	Hankyoreh	317	1.3
	Kyunghyang	641	2.7
	Subtotal	1,351	5.6
Top 3		18,157	75.4
Total		24,079	100.0

Table 5: Summary of the news articles on MP decisions

This table summarizes the number of articles and characters by two dimensions: direction of the monetary decision (cut, hike or freeze) and release timing of news articles (before release of the MPB decision or after release of the MPB decision). Between is for the news articles released between 9 a.m. and 10 a.m. (between 9:30 a.m. and 10:30 a.m. before 2009), which is the time when MPB meetings are held.

		Number of articles				Number of characters			
	Direction	Cut	Hike	Freeze	Total	Cut	Hike	Freeze	Total
Timing	Provider								
Before	News agency	37.7	33.9	20.9	23.7	67,693	45,426	28,074	33,322
	Economic	23.5	24.4	11.8	14.0	29,120	33,017	13,862	17,032
	Regular	3.3	1.6	1.8	1.9	4,541	2,360	2,484	2,757
	Subtotal	63.8	59.8	33.4	38.7	100,381	80,634	42,998	51,750
	Top 3	48.9	48.8	28.5	32.3	81,161	66,699	37,191	43,959
After	News agency	117.9	78.6	46.3	55.8	126,983	104,489	59,888	70,176
	Economic	76.7	69.6	37.5	44.0	87,710	87,004	48,153	55,375
	Regular	16.1	10.9	6.3	7.6	19,706	14,930	7,101	8,983
	Subtotal	210.6	159.1	90.0	107.5	234,399	206,424	115,142	134,534
	Top 3	148.1	116.4	64.2	76.7	164,111	152,801	86,129	99,453
Between	News agency	8.5	9.8	5.5	6.2	6,490	6,929	4,307	4,759
	Economic	10.3	6.6	6.5	6.9	6,658	6,392	4,047	4,492
	Regular	2.0	1.0	1.6	1.6	864	1,391	835	875
	Subtotal	18.6	14.6	11.3	12.3	12,870	11,693	7,855	8,671
	Top 3	14.5	13.0	9.7	10.5	10,187	9,810	6,890	7,463
All	News agency	163.4	122.4	72.4	85.4	200,703	156,844	92,026	108,006
	Economic	110.5	98.6	55.0	64.2	123,488	124,586	65,638	76,396
	Regular	19.1	12.5	7.3	8.9	23,459	17,320	8,331	10,553
	Subtotal	293.0	233.5	134.7	158.4	347,650	298,751	165,996	194,955
	Top 3	211.4	178.1	102.4	119.5	255,459	229,310	130,211	150,874

Table 6: Dates of the largest surprises

This table shows the dates of the eight largest positive and negative surprises, which are measured by $\Delta tone^{news}$. The url of the news articles in the table are:

- http://www.koreatimes.co.kr/www/tech/2009/12/129_57067.html
- http://www.koreatimes.co.kr/www/tech/2007/07/129_6363.html
- http://www.koreatimes.co.kr/www/tech/2007/07/129_6363.html
- http://www.koreatimes.co.kr/www/tech/2008/07/129_27382.html
- http://www.koreatimes.co.kr/www/biz/2014/11/602_168088.html
- http://www.koreatimes.co.kr/www/tech/2010/10/129_74528.html
- https://www.businessinsider.com.au/the-bank-of-korea-stuns-markets-by-cutting-rates-2016-6
- https://www.koreatimes.co.kr/www/biz/2018/07/488_135433.html

dates	Δbase rate	$\Delta tone^{news}$	headlines or main theme
December 10, 2009	0%p	51.0	Central Bank Hints at Possible Rate Hike
July 9, 2010	0.25%p	50.5	BOK preempts markets with rate hike
July 12, 2007	0.25%p	45.8	Call Rate Up by 0.25% pt to 4.75%
July 10, 2008	0%p	42.6	Central Bank Hints at Rate Hike
November 13, 2014	0%p	-31.9	BOK freezes key rate at 2%
October 14, 2010	0%p	-27.4	Key rate frozen for 3rd month
June 9, 2016	-0.25%p	-26.9	The Bank of Korea stuns markets by cutting rates
May 9, 2013	-0.25%p	-26.8	BOK's rate cut takes markets by surprise

Table 7: Number and length of news articles

This table shows the estimation results of equations (5) and (6). Standard errors are in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

	(1) Number	(2) Length	(3) Number	(4) Length
$I(\Delta\text{base rate} > 0)$	54.40***	72342.1***		
	(7.661)	(8841.9)		
$I(\Delta\text{base rate} < 0)$	93.18***	82654.8***		
	(15.69)	(12478.0)		
$I(\text{upper 10\% hawkish surprise})$			8.403	22183.3
			(10.12)	(11764.6)
$I(\text{upper 10\% dovish surprise})$			32.47*	23676.3
			(15.97)	(14067.9)
Constant	81.10***	97350.0***	90.66***	107100.4***
	(2.283)	(2666.1)	(3.535)	(3763.6)
N	152	152	152	152
R^2	0.500	0.480	0.053	0.044

Table 8: Responses of interest rates of various maturity

This table shows the responses of interest rates of various maturity to base rate changes and monetary policy surprises, based on regression equation (7). KORIBOR, MSB, and KTB stand for Korean Inter-Bank Offered Rate, Monetary Stabilization Bond, and Korea Treasury Bond, respectively. Standard errors are in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

	Model 1		Model 2			
one day change in	Δbase rate	R^2	Δbase rate	$\Delta tone^{news}$	R^2	N
call (1-day)	0.736***	0.71	0.728***	0.0186	0.71	149
	(0.108)		(0.112)	(0.0244)		
KORIBOR (3-month)	0.516***	0.82	0.527***	-0.0257	0.82	144
	(0.0754)		(0.0777)	(0.0152)		
KORIBOR (6-month)	0.468***	0.81	0.480***	-0.0288	0.81	138
	(0.0779)		(0.0805)	(0.0164)		
KORIBOR (1-year)	0.436***	0.76	0.450***	-0.0322*	0.77	149
	(0.0837)		(0.0857)	(0.0151)		
MSB (1-year)	0.197*	0.18	0.163	0.0828**	0.22	149
	(0.0796)		(0.0877)	(0.0295)		
KTB (1-year)	0.147*	0.11	0.113	0.0855**	0.16	149
	(0.0592)		(0.0656)	(0.0271)		
MSB (2-year)	0.111	0.04	0.0602	0.124**	0.10	149
	(0.108)		(0.120)	(0.0405)		
KTB (3-year)	0.0341	0.004	-0.0234	0.142***	0.09	149
	(0.0796)		(0.0885)	(0.0368)		
KTB (5-year)	-0.0325	0.003	-0.0966	0.158***	0.11	149
	(0.0716)		(0.0781)	(0.0343)		
KTB (10-year)	0.0303	0.003	-0.0145	0.110***	0.07	149
	(0.0871)		(0.0960)	(0.0325)		

Table 9: Text-Based Monetary Surprises vs. VAR-identified Monetary Shocks
This table shows the responses of interest rates of various maturity to base rate changes, monetary policy surprises, and VAR-identified shocks. KORIBOR, MSB, and KTB stand for Korean Inter-Bank Offered Rate, Monetary Stabilization Bond, and Korea Treasury Bond, respectively. Standard errors are in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

	Model 1		Model 2			Model 3			
one day change in	ΔMP^{VAR}	R^2	$\Delta tone^{news}$	ΔMP^{VAR}	R^2	Δbase rate	$\Delta tone^{news}$	ΔMP^{VAR}	R^2
call (1-day)	5.405***	0.43	0.110**	5.097***	0.45	0.651***	0.0235	0.582	0.69
	(0.974)		(0.0350)	(0.950)		(0.145)	(0.0258)	(1.147)	
KORIBOR (3-month)	2.704*	0.25	0.0662**	2.516*	0.27	0.638***	-0.0223	-1.908*	0.82
	(1.178)		(0.0233)	(1.144)		(0.0927)	(0.0159)	(0.743)	
KORIBOR (6-month)	2.481*	0.25	0.0574**	2.303*	0.27	0.571***	-0.0232	-1.618*	0.81
	(1.114)		(0.0205)	(1.087)		(0.0980)	(0.0171)	(0.681)	
KORIBOR (1-year)	2.302*	0.24	0.0425*	2.183*	0.25	0.546***	-0.0300	-1.603**	0.77
	(1.030)		(0.0189)	(1.001)		(0.103)	(0.0153)	(0.600)	
MSB (1-year)	1.681**	0.14	0.101***	1.398*	0.21	0.137	0.0829**	0.451	0.25
	(0.629)		(0.0288)	(0.629)		(0.114)	(0.0297)	(0.691)	
KTB (1-year)	1.474**	0.12	0.0939***	1.211*	0.19	0.0638	0.0854**	0.769	0.20
	(0.511)		(0.0273)	(0.525)		(0.0863)	(0.0276)	(0.639)	
MSB (2-year)	1.441*	0.07	0.121**	1.101	0.13	-0.0223	0.124**	1.256	0.13
	(0.685)		(0.0377)	(0.704)		(0.167)	(0.0410)	(1.014)	
KTB (3-year)	1.126	0.04	0.124***	0.780	0.11	-0.132	0.141***	1.696	0.14
	(0.633)		(0.0350)	(0.680)		(0.122)	(0.0375)	(0.960)	
KTB (5-year)	0.732	0.02	0.129***	0.371	0.10	-0.211	0.157***	1.833	0.15
	(0.689)		(0.0327)	(0.746)		(0.108)	(0.0350)	(1.029)	
KTB (10-year)	0.893	0.03	0.0976**	0.620	0.08	-0.0910	0.110**	1.251	0.10
	(0.638)		(0.0302)	(0.669)		(0.130)	(0.0330)	(0.918)	

Table 10: Responses of foreign exchange rates and stock market

This table shows the responses of exchange rates and stock market variables. KOSPI index is set at 100 on January 4, 1980. The unit of trading volume is 10,000. The unit of trading value and foreign net purchase is 100 million won. Standard errors are in parentheses. + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$.

	Δbase rate	$\Delta tone^{news}$	N	R^2
exchange rates				
USD	-0.0686	0.0412	149	0.011
	(0.142)	(0.0520)		
JPY	-0.160	0.0359	149	0.028
	(0.219)	(0.0656)		
EUR	-0.114	0.0584	149	0.013
	(0.156)	(0.0693)		
CNY	-0.00437	0.00713	21	0.011
	(0.0312)	(0.0139)		
stock market				
KOSPI	-0.133	0.199*	149	0.032
	(0.112)	(0.0905)		
KOSPI (trading volume)	-22.12	33.02	149	0.008
	(27.66)	(32.04)		
KOSPI (trading value)	-28.73	76.20+	149	0.023
	(48.47)	(45.87)		
KOSPI (foreign net purchase)	8.461	26.11	149	0.022
	(19.42)	(17.63)		
KOSDAQ	-0.0482+	0.0508*	149	0.031
	(0.0246)	(0.0255)		
KOSDAQ (trading volume)	-32.99	28.99	149	0.005
	(45.39)	(45.54)		
KOSDAQ (trading value)	-3.871	24.70+	149	0.026
	(10.93)	(13.27)		
KOSDAQ (foreign net purchase)	-2.979*	2.639+	149	0.026
	(1.300)	(1.414)		

Table 11: Responses of credit spread, term premium and break-even inflation
This table shows credit spread is the difference between the yields of corporate bond (3-year, BBB-) and corporate bond (3-year, AA-). Term premium is the difference between the yields of KTB (10-year) and KTB (1-year). Break-even inflation is defined as the difference between the yields of KTB (10-year) and inflation-linked KTB (10-year). Standard errors are in parentheses. + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$.

	Δbase rate	$\Delta tone^{news}$	N	R^2
corporate bond (3-year, AA-)	0.00574	0.134**	149	0.103
	(0.0859)	(0.0343)		
corporate bond (3-year, BBB-)	-0.0266	0.130**	149	0.090
	(0.0837)	(0.0329)		
credit spread	0.0324**	0.00421	149	0.252
	(0.00666)	(0.00380)		
KTB (1-year)	0.113+	0.0855**	149	0.162
	(0.0656)	(0.0271)		
KTB (10-year)	-0.0145	0.110**	149	0.065
	(0.0960)	(0.0325)		
term premium	-0.127**	0.0250	149	0.177
	(0.0365)	(0.0174)		
inflation-linked KTB (10-year)	0.0487	-0.0642*	93	0.070
	(0.0329)	(0.0253)		
break-even inflation	0.0222	-0.0255	93	0.016
	(0.0294)	(0.0159)		

Appendices

A. *eKoNLPy Tagset for POS Tagging*

Table A1: Tagset used in Mecab tagger of eKoNLPy

Tag	Name	Tag	Name
NNG	General Noun	JKQ	Case Postposition (Quotation)
NNP	Proper Noun	JC	Conjunctive Postposition
NNB	General Dependent Noun	JX	Auxiliary Postposition
NNBC	Unit Word	EP	Prefinal Ending
NR	Number Word	EF	Final Ending
NP	Pronoun	EC	Conjunctive Ending
VV	Verb	ETN	Nominal Ending
VA	Adjetive	ETM	Adnominal Ending
VAX	Derived Adjetive	XPN	Noun Prefix
VX	Auxiliary Predicate	XSN	Noun Suffix
VCP	Positive Copula	XSV	Verbalization Suffix
VCN	Negative Copula	XSA	Adjectivization Suffix
MM	Determiner	XR	Root Word
MAG	Adverb	SF	Sentence Ending Marker
MAJ	Conjunctive Adverb	SE	Ellipsis Symbol
IC	Exclamaation	SSO	Left Quotation Mark
JKS	Case Postposition (Nominative)	SSC	Right Quotation Mark
JKC	Case Postposition (Complementive)	SC	Separator Symbol
JKG	Case Postposition (Determinative)	SY	Symbol
JKO	Case Postposition (Objective)	SH	Chinese Charachter
JKB	Adverbial Postposition	SL	Foreign Word
JKV	Case Postposition (Vocative)	SN	Number