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C O L U M B I A U N I V E R S I T Y I N T H E C I T Y O F N E W Y O R K

Quantifying the Sentiments for the Japanese Economy as Predictors of Stock Prices[†]

Hiroshi Ishijima^{*}

Abstract

This paper quantifies market sentiment as four indexes and examines whether they can help predict stock prices in Japanese markets. Sentiment analysis is gaining increasing interest in both academia and business. Previously, Ishijima et al. (2014) created a sentiment index that quantifies the positive or negative emotions that might appear in the *Nikkei*, which is the most popular business newspaper in Japan. They concluded that the sentiment index significantly predicts stock prices three days in advance. We re-examine their recent 5-year-worth results by extending in two dimensions; that is, we extend the coverage of the *Nikkei* to 29 years and create variations of their original sentiment index.

On the basis of 29-year-worth daily sentiment indexes, we thoroughly examine the predictability of Japanese stock prices. The findings of our year-by-year analysis are two-fold: (1) sentiment indexes created from all of *Nikkei's* articles persistently predict the Nikkei 225 stock prices, in both in-sample and out-of-sample bases, and (2) these periods can be interpreted using business cycles defined by Japan's Cabinet Office.

Keywords: Sentiment, Nikkei, Stock Market, Predictability, Text Mining, Big Data

JEL Classification: C88, E37, G17

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1 Introduction

Sentiment analysis is gaining increasing interest in both academia and business. As sentiment invisibly reflects the atmosphere of economic activities and the psychology of economic agents, analyzing sentiment helps us understand the economy and security markets in a more sophisticated manner.

As a background to market sentiment analysis, we briefly outline the literature. Recent attention to market sentiment stems from a question cast upon market rationality. According to the theory of efficient markets, information spreads quite efficiently throughout global markets; thus, no one can obtain excess return on investment above that rationally expected from its relevant risk (Fama, 1965, 1991). Although many empirical studies have supported this hypothesis, a growing number of studies attempt to demonstrate the opposite. In fact, such studies seek evidence of the opportunity for excess returns and reveal the predictability of stock prices.

Some theories attempt to support econometric analysis for evidence of market anomalies. In particular, behavioral economics, pioneered by Kahneman and Tversky (1979), developed the foundation for economic agent behavior by focusing on its psychological aspect. Ritter (2003) offered a brief but very clear summary of the behavioral finance literature regarding cognitive psychology and its limits to arbitrage. A typical analysis is that market participants do not always trade rationally. Instead, they trade irrationally and in accordance with their prevailing psychological state, which presents an opportunity to gain excess returns. Other theories proposed that economic agents are sometimes influenced by information that is irrelevant to economic circumstances, including social atmosphere, public opinion, and social trends. "Sentiment" is a word that reflects these perceptions of information; however, it has been considered insubstantial.

Sentiment analysis is a recent movement that attempts to make sentiment definable and measurable. Recent advances in text mining technology make this goal feasible by building useful indices that precisely reflect sentiment. Having been supported by contests against the rationality assumption and by the theory of behavioral economics, sentiment analysis is gaining attention in the fields of social and economic analysis.

Among the growing literature on sentiment analysis, the following studies are worth mentioning because they refer to stock prices. Tetlock (2007) investigated the interaction between the media and the stock market; in a subsequent work, Tetlock et al. (2008) examined whether a quantitative measure of language can help predict individual firms' accounting earnings and stock returns. Bollen et al. (2011) suggested several types of sentiment indexes (SIs) based on Twitter, and Boudoukh et al. (2012) examined how news sentiment drives stock price movements.

Interesting examples of sentiment analysis in a general context, not necessarily related to stock markets, include the following. Gruhl et al. (2005) studied the relationship between online chat and book sales. Mishne and Glance (2006) investigated the sales of film distributors as influenced by

critics' blogs, whereas Asur and Huberman (2010) studied similar effects based on Twitter. Liu et al. (2007) developed the "probabilistic latent semantic analysis" (PLSA) model to extract SIs from blogs and suggested its use for sales prediction. Choi and Varian (2009) studied the role of Google searches in investigating relationships between several consumer-related indices and the rate of disease infection. Schumaker and Chen (2009) found direct causality between spot financial news announcements and stock price responses. Asur and Huberman (2010) did a similar study, focusing on Twitter.

With this background, Ishijima et al. (2014) analyzed the sentiment for the Japanese economy that appears in daily news articles. In fact, they created a word frequency index that accounts for words that affirmatively or negatively describe the current economic situation. News articles were taken from the *Nikkei*, a popular business newspaper in Japan. They then performed a statistical analysis to examine the interaction between the SI and the Nikkei 225 stock prices. Interestingly, they concluded that the index significantly predicts stock prices three days in advance.

The purpose of this paper is to re-examine the analysis of Ishijima et al. (2014) and provide a more comprehensive analysis of Japanese economic sentiment as it appears in the *Nikkei*. To this end, we extend their analysis in two dimensions: one is to extend the coverage of the *Nikkei* to 29 years and the other is to create variations of the original SI.

(1) Data that covers a 29-year-horizon:

Ishijima et al. (2014) covered only the recent five year period, from January 2007 to September 2012. In contrast, we work on a much longer sample period of 29 years that spreads from March 1984 to September 2012. For each year, we examine the predictability of stock prices by our SIs.

(2) Variations of SI:

We reconsider the methodology of creating an index and propose four new indexes:

Scoring process

We quantify the market sentiment along a one-dimensional semantic axis, from negative to positive feelings. For every single word that appears in the *Nikkei*, we match it to the prescribed semantic dictionary developed by Takamura (2007). For every match, we record a score paired with the word that represents its extent of association with the negative feeling of the Japanese people. In this scoring process, there are two criteria of measurement: how to score each matched word and to what extent we cover the *Nikkei* pages (just headlines or entire articles). We will elaborate on each of these aspects.

Scoring method

The semantic dictionary (Takamura, 2007) provides a list of words that are scored from -1 to 1 . The closer the score comes to -1 , the more negative the feelings that people associate with that word, and vice versa. We then exploit the score in one of two ways: using the raw score or rounding to the nearest integer score that is either 1 or -1 . We call the former scoring “real-valued” and the latter “integer-valued.” In the latter case, we round to -1 if the raw score ranges between -1 and 0 , and otherwise 1 .

Coverage of source in the Nikkei

We then sum these scores over the following two sources: headlines only or the entire article text. We call the former coverage “Headlines Only” and the latter “Entire Article.” As the position of the word in the *Nikkei* might affect the reader’s sentiment, these two coverage profiles in scoring help us understand the importance of the sentiment exhibited either in headlines alone or in the entire set of article texts for predicting stock prices.

Using the above methodology, we obtain two types of scoring methods for the two *Nikkei* coverage profiles. This results in four ways to create the SIs. In contrast, Ishijima et al. (2014) only created and examined one of four SIs, which is the integer-valued SI created from the entire article text in our study.

The rest of this paper is organized as follows. Section 2 elaborates on how to create market SIs. Section 3 develops the analytical models. Section 4 implements an empirical analysis of the Japanese stock market. Section 5 concludes the paper.

2 Creating sentiment indexes

2.1. Procedures

(1) Prerequisite text processing steps

The *Nikkei* is published in Japanese; due to a unique feature of the Japanese language, text-processing steps are a prerequisite before applying the normal text mining technique. As words are not separated with spaces in Japanese texts, we first inserted spaces to separate words. This step has become feasible only with recent advances in Japanese text mining technologies. We used MeCab 0.996,¹ an application equipped with the ability to select nouns, adjectives, and verbs and to remove punctuation marks and other unnecessary characters and elements.

¹ MeCab 0.996 is an application for conducting morphological analysis developed by the Graduate School of Informatics, Kyoto University and NTT Communication Science Laboratories in 2013. For details, see <http://mecab.googlecode.com/svn/trunk/mecab/doc/index.html> (accessed 30 August 2014).

(2) Source: selection based on word position

Every page in the newspaper comprises pairs of headlines and articles. The position of the word (either in the headline or article text) might affect the impact on a reader's positive or negative invoked sentiment around that word. In this aspect, we strictly distinguish the words in articles from the words in headlines and clarify this by introducing specific notations.

In the newspaper delivered at day t , we have n_t headlines and articles. Each headline and article are denoted by $H_{i,t}$ and $A_{i,t}$ ($i = 1, \dots, n_t$). Each headline and article have $n_{i,t}^{(H)}$ and $n_{i,t}^{(A)}$ words, respectively. The words in headline $H_{i,t}$ and article $A_{i,t}$ are denoted by $W_{ij,t}^{(H)}$ ($j = 1, \dots, n_{i,t}^{(H)}$) and $W_{im,t}^{(A)}$ ($m = 1, \dots, n_{i,t}^{(A)}$), respectively.

At this point, we introduce aggregate notation to represent whether the word selected is headline or article text. This enables later discussion on how to quantify the sentiment. The choice of word position is limited to either headlines or articles, and is denoted by $\mathcal{G} := \{H, A\}$. We simply call \mathcal{G} the "source." We then let $G \in \mathcal{G}$ to show either headline H or article A . Then, in the newspaper delivered at day t , $W_{ij,t}^{(G)}$ denotes the j th word ($j = 1, \dots, n_{i,t}^{(G)}$) that comprises the i th source $G_{i,t}$ ($i = 1, \dots, n_t$).

(3) Semantic dictionary

The semantic dictionary used in our analysis, the *Tango Kanjyo Kyokusei Taiou Hyou (Semantic Orientations Dictionary)* was developed by Takamura (2007). The dictionary is denoted by $\mathcal{D} := \{(D_k, S(D_k)) | k = 1 \dots K\}$. The dictionary comprises pairs of word D_k and their semantic scores $S(D_k)$, which range from -1 to $+1$. Regarding the semantic score, the closer to -1 (or $+1$) the score becomes, the more negative (or positive) feeling the word invokes for the Japanese people. As a reference, the number of words that invoke positive feelings, i.e., those with positive scores $S(D_k) > 0$, is 5,122. Conversely, the number of words that induce negative feelings (scores) is 49,983. As these negative words number some ten times that of positive words, we might say that the Japanese language is rich in expressing negative feelings. This is, however, not unique to Japanese; for example, the English semantic dictionary, developed by Loughran and McDonald (2011), and optimally tuned for both finance and accounting fields, has 2,337 negative words and 353 positive words. Hence, we should treat this bias carefully in the analysis.

(4) Semantic index: two methods to quantify positive or negative feelings

We define an indicator function to identify a word match with the dictionary:

$$I_{ij,t}^{(G)}(k) := \begin{cases} 1 & \text{(if } W_{ij,t}^{(G)} \text{ matches } D_k) \\ 0 & \text{(otherwise)} \end{cases}. \quad (1)$$

To score the positive or negative feelings, we introduce two methods for deriving SIs.

(a) Real-valued SI

The first method uses the semantic score $S_k = S(D_k)$ assigned to the listed word D_k . We define an index created in this first way as the “*real-valued SI*.”

$$x_t^{(G,R)} := \sum_{i=1}^{n_t} \sum_{j=1}^{n_{i,t}^{(G)}} \sum_{k=1}^K I_{ij,t}^{(G)}(k) \cdot S_k. \quad (2)$$

For source $G = H$, the coverage is limited to headline words and the real-valued SI is given by $x_t^{(G,R)} = x_t^{(H,R)}$. Similarly, for the source of $G = A$ (articles), the real-valued SI is given by $x_t^{(G,R)} = x_t^{(A,R)}$.

(b) Integer-valued SI

The second method rounds the semantic score S_k to the nearest binary integer: either -1 or $+1$. Introducing the integer variable for each semantic score, we obtain

$$J_k := \begin{cases} +1 & \text{(if } 0 < S_k \leq 1) \\ -1 & \text{(if } -1 \leq S_k \leq 0) \end{cases}. \quad (3)$$

We then define an index created in the second manner as an “*integer-valued SI*.”

$$x_t^{(G,I)} := \sum_{i=1}^{n_t} \sum_{j=1}^{n_{i,t}^{(G)}} \sum_{k=1}^K I_{ij,t}^{(G)}(k) \cdot J_k. \quad (4)$$

Recalling that each of the two SIs has an option in picking the source, either headlines ($G = H$) or entire set of articles ($G = A$), we have four types of SI in the analysis.

As a summary, we use the following notation to represent these four SIs:

$$x^{(G,\#)} := \begin{cases} x^{(H,I)} & \text{(integer – valued headline s. i.)} \\ x^{(H,R)} & \text{(real – valued headline s. i.)} \\ x^{(A,I)} & \text{(integer – valued article s. i.)} \\ x^{(A,R)} & \text{(real – valued article s. i.)} \end{cases}, \quad (5)$$

where G denotes one of the sources (H or A) and $\#$ denotes the scoring method (integer-valued “ I ” scoring or real-valued “ R ” scoring).

Following the procedures described above, we created a 29-year daily time-series of four SIs, based on headlines and articles from the *Nikkei*. We remark that these SIs are normalized so that they have zero means and unit standard deviations.

2.2. Data description and summary statistics of the SI

In creating these SIs, we used 7,188 daily issues of the *Nikkei* published during 343 months from March 1984 to September 2012 (archives supplied by Nikkei Digital Media, Inc.). For Japanese stock prices, we used the daily closing prices of the Nikkei 225 converted into log-returns. The

Nikkei is published daily and delivered with a few no-issue days, but the Japanese stock market is closed every weekend. To handle this incongruence in the daily data set, which creates an inconsistency in frequency, we follow the approach of Bollen et al. (2011), by eliminating every Saturday and Sunday from the complete data set prior to implementing the analysis. Hence we obtain data for about 21 days per month, on average.

Basic data about the *Nikkei* is summarized in Table 1 and Table 2. The total number of headlines—or, equivalently, that of articles—is 4,747,942. Among headlines and entire articles, the numbers of words matched to the semantic dictionary are 11,919,412 and 134,337,485, respectively. Using these matched words in the *Nikkei*, we created four types of daily SIs on the basis of the procedures already described. Table 1 and Table 2 show the summary statistics of headline and article SIs, respectively.

2.3. Preliminary insights

In this study, we are interested in exploring whether our SIs can help predict stock prices. Before implementing a rigorous analysis, we describe Figure 1 through Figure 4, which exhibit time-series of the stock log-returns and real-valued article SI around historical events that might affect the Japanese economy. These include the Plaza Accord in 1985 (Figure 1), highest peak of the Nikkei 225 in 1989 (Figure 2), climax of the Internet Bubble in 2000 (Figure 3), and the Great East Japan Earthquake in 2011 (Figure 4).

From these figures, stock prices and SIs seem to co-vary in the same direction around these historical events. Here we remark that the SIs are plotted five or six days in advance. Hence, these snapshots show a possibility that market sentiment leads stock prices in the Japanese stock market. We then proceed to model these insights and conduct a plausible empirical analysis, which is presented in the following sections.

3 Model

To explore whether our SIs can predict stock prices, we employ the vector auto-regression (VAR) model, which is conventionally used in econometrics literature. In our VAR modeling, stock log-returns are denoted by $y = \{y_t: t = 1, \dots, T\}$ and the four types of SI are denoted by $x^{(G,\#)} = \{x_t^{(G,\#)}: t = 1, \dots, T\}$, where G denotes one of the sources, either H (headlines) or A (entire articles), and $\#$ denotes the scoring method, which is either integer-valued “ I ” scoring or real-valued “ R ” scoring.

For each of the two scoring methods, we estimate three VAR(p) models comprising independent variables of (H) headline SI, (A) article SI, or both (H&A) headline and article SIs, respectively. Thus, each of the three VAR(p) models is specified as follows:

$$\text{Model (H)} \quad y_t = \sum_{i=1}^p \alpha_i y_{t-i} + \beta_i x_{t-i}^{(H,R \text{ or } I)} + \varepsilon_t, \quad (6)$$

$$\text{Model (A)} \quad y_t = \sum_{i=1}^p \alpha_i y_{t-i} + \gamma_i x_{t-i}^{(A,R \text{ or } I)} + \varepsilon_t, \quad (7)$$

$$\text{Model (H\&A)} \quad y_t = \sum_{i=1}^p \alpha_i y_{t-i} + \beta_i x_{t-i}^{(H,R \text{ or } I)} + \gamma_i x_{t-i}^{(A,R \text{ or } I)} + \varepsilon_t, \quad (8)$$

where p denotes the number of lags.

Within these VAR(p) model specifications, the *Granger causality* can be stated as follows: if the SIs ($x^{(G,\#)}$) *Granger-cause* (*G-cause*) stock log-returns (y), then the past SIs should help predict stock log-returns, beyond the prediction by past stock log-returns alone. Using these three VAR(p) models, we implement three Granger causality tests (G-tests) as follows:

(1) “*G-test for Model (H)*” tests whether the headline SI G-causes stock log-returns by exploiting Equation (6). The null hypothesis is $\beta_i = 0$ ($i = 1 \dots p$).

(2) “*G-test for Model (A)*” tests whether the entire article SI G-causes stock log-returns by exploiting Equation (7). The null hypothesis is $\gamma_i = 0$ ($i = 1 \dots p$).

(3-1) “*G-test 1 for Model (H\&A)*” tests whether the headline SI G-causes stock log-returns by exploiting Equation (8). The null hypothesis is $\beta_i = 0$ ($i = 1 \dots p$).

(3-2) “*G-test 2 for Model (H\&A)*” tests whether the entire article SI G-causes stock log-returns by exploiting Equation (8). The null hypothesis is $\gamma_i = 0$ ($i = 1 \dots p$).

4 Empirical Analysis in the Japanese Stock Market

In terms of Granger causality tests, we explore whether the four SIs can predict Japanese stock prices for each year from 1984 to 2012. More specifically, our interests lie in finding (i) the SIs for which the VAR model provides the best goodness-of-fit in terms of AICs, and (ii) whether the best-fitted VAR model persistently predicts Japanese stock prices over 29 years.

(1) *Unit root tests*

Before estimating the VAR models Eqs. (6)–(8), we implemented augmented Dickey–Fuller tests. These results are shown in Table 3. For each year, we verified that all the time-series of stock log-returns, headline, and article SIs do not have a unit root with 1% significance.

We then proceed to estimate VAR models and implement Granger tests. As seen in Table 1 and Table 2, our SIs are rather negatively skewed and might contain sample biases. Hence, we employ robust covariance-matrix estimators in conducting the Granger causality tests to consider heteroskedasticity due to such possible sample biases.

Table 4 and Table 5 show the results of Granger causality tests with real- and integer-valued SIs, respectively. For each year, Models (H), (A), and (H\&A) or relevant Eqs. (6), (7), and (8), are estimated and tested. For each estimation, we search the lag p from 1 to 7 to identify the best p in terms of AICs; for those models with the best p , the relevant test statistics (“Granger”-labeled columns) and AIC values are reported in the tables.

(2) *Goodness-of-fit*

For both the real- and integer-valued cases shown in Table 4 and Table 5, Model (H&A) fits best in terms of AICs throughout the 29 years. When comparing the real- and integer-valued cases, the former performs better in the aspects of AICs. Hence, in the following discussion, we will mainly focus on the results for estimating Model (H&A) on the basis of real-valued SI.

(3) *Predictability of stock prices*

From the right-most panel in Table 4, Model (H&A) of Eq. (8) persistently shows the predictability of stock prices on the basis of a real-valued SI. More specifically, the article index persistently and significantly Granger-causes stock log-returns in conjunction with the headline index (“Granger A” column in that right-most panel). In addition, the headline index Granger-causes stock log-returns in conjunction with the article index (“Granger H” column in the same panel). Conversely, Models (H) and (A) of Eqs. (6) and (7) do not seem to provide persistent Granger causalities. These results imply that it is important for our VAR modeling to incorporate both headline and article SIs to predict stock prices and that it is insufficient to separately introduce either headline or article SIs.

It should be noted that the Granger causality seems to be weakened during some periods. During the period from 2001 to 2004 that was right after the burst of the Internet Bubble, and in 1987 that brought Black Monday, the Japanese economy had experienced a downturn. In those periods, the article index seems to have stronger Granger causality than the headline index.

(4) *Significant lagged variables*

Table 6 exhibits the year-by-year estimates of Model (H&A), represented by Eq. (8), on the basis of a real-valued SI. Interestingly enough, we found nine cyclical patterns in our estimation results.

(i) *Cycle 1 was significant*

Cycle 1 is defined as the period from 1984 to 1985. Cycle 1 was uphill two years toward the peak of Japan’s 10th business cycle, as defined by Japan’s Cabinet Office. In this Cycle, two SIs with shorter lags of 1 and 2 and a long lag of 6 serve as significant variables.

(ii) *Cycle 2 was not significant*

Cycle 2 is defined as the period from 1986 to 1987, around the bottom that defined the beginning of the 11th business cycle. In this Cycle, we could not find any significant lagged variables on either headline or article indexes.

(iii) Cycle 3 was significant

Cycle 3 is defined as the period from 1988 to 1992, around the peak of the 11th business cycle. In this Cycle, two SIs with short lag 1, middle lag 3, and long lag 5 serve as significant variables.

(iv) Cycle 4 was not significant

Cycle 4 is defined as a longer six year period from 1993 to 1998, which corresponds to the 12th business cycle. Cycle 4 also covers the first half of the “Lost Ten Years” in which Japan experienced long-term economic stagnation. In Cycle 4, we could not find any significant lagged variables in the SIs.

(v) Cycle 5 was significant

Cycle 5 is defined as the period from 1999 to 2000, which was uphill two years toward the peak of the 13th business cycle and which is often referred to as the “Internet Bubble.” In this Cycle, two SIs with short lag 1 and middle lags 3 and 4 were significant.

(vi) Cycle 6 was not significant

Cycle 6 is defined as the period from 2001 to 2005, around the bottom that defines the end of the 13th business cycle and the beginning of the 14th business cycle. Cycle 6 follows the “Japanese Big Bang,” which refers to the financial system reforms conducted from 1996 to 2001. The Bank of Japan also adopted a zero-interest rate policy during this cycle. Although real GDP growth marked about 2% per year on average, Japan was still suffering from the “Lost Twenty Years” since the early 1990s. In this Cycle, we could not find any significant lagged variables on SIs.

(vii) Cycle 7 was significant

Cycle 7 is defined as the period from 2006 to 2007 that brought the 2008 financial crisis and was uphill two years toward the peak of the 14th business cycle. In this Cycle, two SIs, with short lag 1 and middle lags of 3 and 4, were significant variables.

(viii) Cycle 8 was not significant

Cycle 8 is defined as three years from 2008 to 2010. Cycle 8 includes and follows the 2008 financial crisis. It is spread around the end of the 14th business cycle and beginning of the 15th business cycle. In this Cycle, we could not find any significant lagged variables on SIs.

(ix) Cycle 9 was significant

Cycle 9 is defined as the period from 2011 to 2012. Although Japan suffered from the earthquake on March 11, 2011, it had been uphill two years toward the peak of the 15th business cycle. In this Cycle,

two SIs with shorter lags 1 and 2 serve as significant variables.

(5) *Comparisons with other relevant work*

Ishijima et al. (2014) reported that following the 2008 financial crisis, the integer-valued article SI significantly predicts stock prices three days in advance. This can be found in Table 5 (middle panel, titled ‘‘Article Eq. (7)’’). Indeed, we can see significant Granger causalities around 2008. Unfortunately, this finding does not seem to be persistent when we review this from 29-year-horizontal results that we have shown in this paper.

(6) *Out-of-sample predictability*

On an in-sample basis, the Granger causality tests provided evidence that our SIs can help predict Japanese stock prices. Furthermore, we will address the question of out-of-sample predictability of stock prices using these indexes by elaborating on the empirical analysis design.

We divide each year in half, from 1984 to 2012. For each half year, tracking periods are set, followed by estimation periods. More specifically, we set appropriate periods for tracking the out-of-sample predictability performance of Model (H&A), as represented by Eq. (8). This tracking period is denoted \mathcal{U} , and M is the number of days in \mathcal{U} . At time $u \in \mathcal{U}$, we estimate Model (H&A) using the *expanding window* over two time-series for log-returns of the Nikkei 225 and market SIs, which are denoted by datasets $\{y_t; y_{t-i}, x_{t-i} \ (i = 1, \dots, p; t = p + 1, \dots, u)\}$. We then evaluate the out-of-sample predictability performance via the following three steps:

Step 1: Estimate models

At time $u \in \mathcal{U}$, we estimate Model (H&A) over the expanding window to obtain the estimated parameters: $\{\hat{\alpha}_i, \hat{\beta}_i, \hat{\gamma}_i \ (i = 1, \dots, p)\}$.

Step 2: Predict out-of-sample rate of return

We then predict the out-of-sample log-return of the Nikkei 225 on the next day $u + 1$.

Using estimated parameters, the predicted log-return is given by

$$\hat{y}_{u+1} = \sum_{i=1}^p \hat{\alpha}_i y_{u+1-i} + \hat{\beta}_i x_{u+1-i}^{(H,R)} + \hat{\gamma}_i x_{u+1-i}^{(A,R)}. \quad (9)$$

Step 3: Measure out-of-sample performance

We evaluate the out-of-sample performance by two measures. The first measure is the prediction error. By defining $\varepsilon_{u+1} := y_{u+1} - \hat{y}_{u+1}$, we measure the prediction error as its standard deviation through tracking period \mathcal{U} . This is given by $\sqrt{\sum_{u \in \mathcal{U}} (\varepsilon_{u+1} - \bar{\varepsilon})^2 / M}$.

As the second measure, if the sign of the realized rate of return y_{u+1} is the same as that of its prediction \hat{y}_{u+1} , then we state that the model at least predicts the direction of stock price movement. We refer to this prediction measure as the *winner*. We introduce an indicator function to count the number of winners: $\iota_{u+1} = 1$ (if $y_{u+1} \cdot \hat{y}_{u+1} > 0$) and $\iota_{u+1} = 0$ (otherwise). Then, the total number of winners is given as $\iota := \sum_{u \in \mathcal{U}} \iota_{u+1} / M$.

By varying the tracking periods, we report the out-of-sample predictability for each year in Table 7 on a prediction error basis and in Table 8 on a winner basis.

As shown in Table 7, in terms of average prediction errors for every five years, the shortest 10-day tracking period provides the best predictability in every first half of the year: except in the 2000s, the average prediction error is below 30%. In the second half of the year, 10-day or 20-day tracking periods provide the best predictability, but with an error rate above 30%. Hence, on an out-of-sample basis, the market SI might be able to predict Japanese stock prices better in every first half of the year using the shortest tracking periods. Predictability also deteriorates as the tracking period becomes longer; possibly, because as the tracking period is extended, the Japanese stock market tends to change its structure, as implied by VAR estimation from the past data set.

As shown in Table 8, in the aspects of winners for every five years, the 10-day tracking period again provides the best predictability in every first half of the year. Moreover, the average winner marks between 57% and 70%, except during the 2000s, whereas in the second half of the year, the average winner deteriorates as opposed to the first half of the year, except the first five years of the 1990s.

As a summary of out-of-sample predictability, we conclude that the market SI can help predict Japanese stock prices in every first half of the year, using the 10-day tracking period.

5 Conclusion

We created a 29-year daily time-series of four SIs that reflect the positive or negative feelings represented in articles in the *Nikkei*. The analysis is based on Ishijima et al. (2014), using a sophisticated version of their analysis. We showed that (1) SIs created from the *Nikkei*'s entire articles persistently predict the Nikkei 225 stock prices on both in-sample and out-of-sample bases, and (2) these periods can be interpreted using the business cycles defined by Japan's Cabinet Office.

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7 Tables and Figures

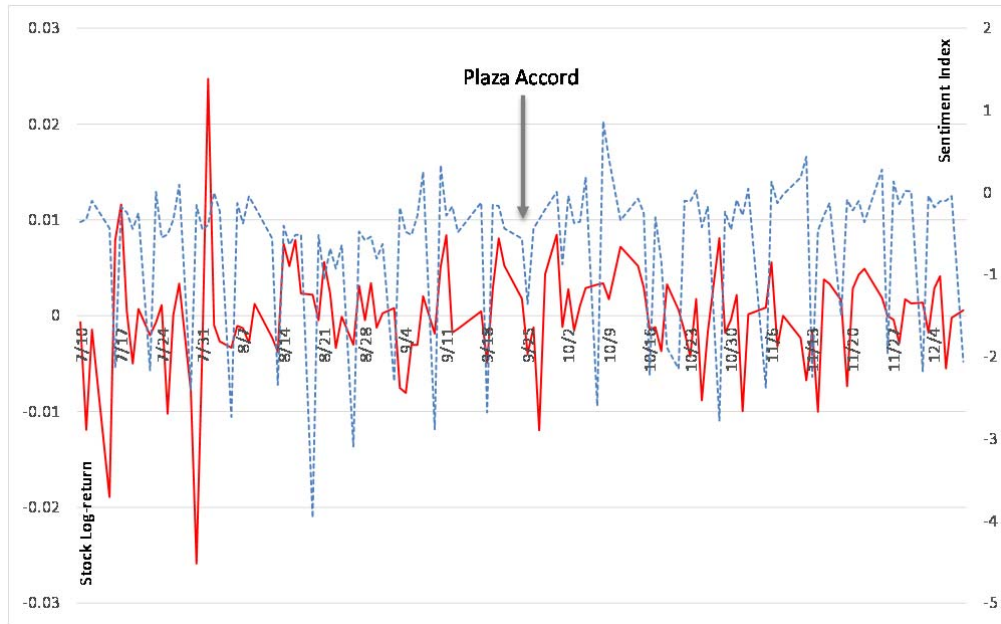


Figure 1: Stock log-returns and sentiment index around the Plaza Accord (September 22, 1985), shown by red solid and blue dashed lines, respectively. The latter is plotted six days in advance.

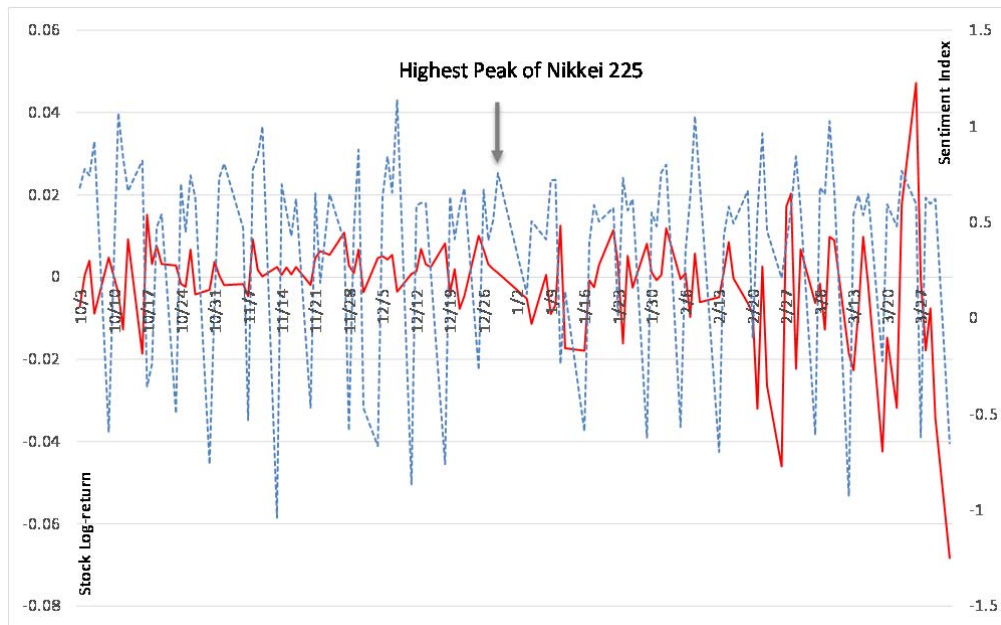


Figure 2: Stock log-returns and sentiment index around the highest peak of Nikkei 225 (December 29, 1989), shown by red solid and blue dashed lines, respectively. The latter is plotted five days in advance.

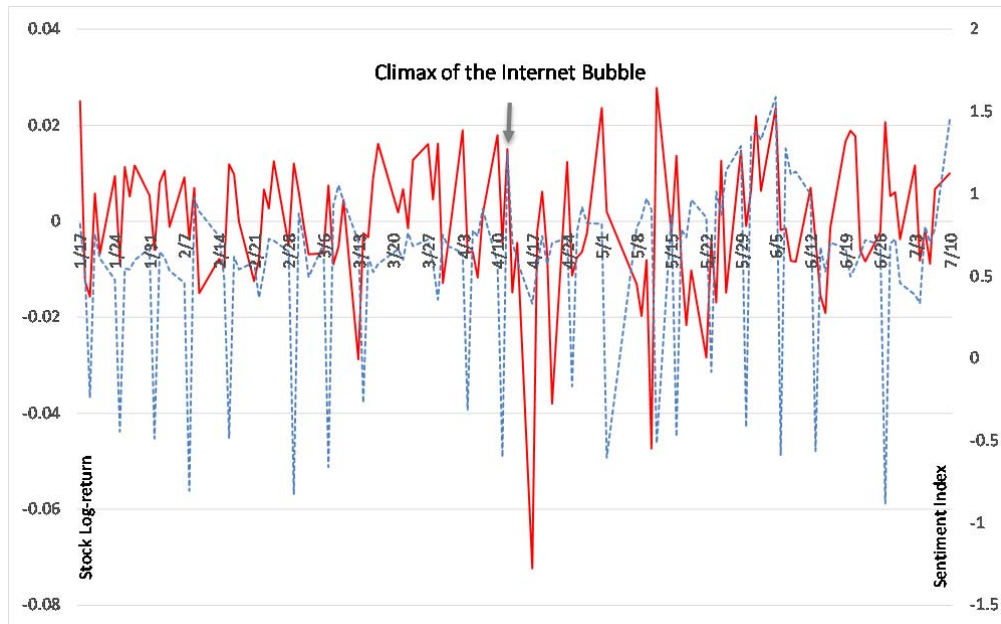


Figure 3: Stock log-returns and sentiment index around the climax of the Internet Bubble (April 12, 2000) shown by red solid and blue dashed lines, respectively. The latter is plotted six days in advance.

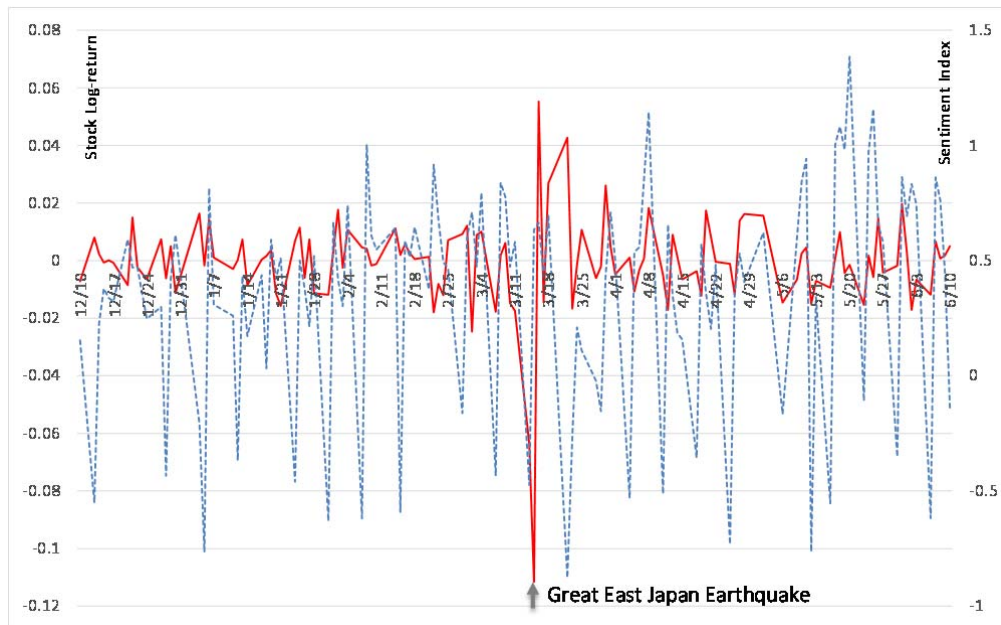


Figure 4: Stock log-returns and sentiment index around the Great East Japan Earthquake (March 11, 2011), shown by red solid and blue dashed lines, respectively. The latter is plotted five days in advance.

Table 1: Summary statistics of headlines of the *Nikkei*, and integer- and real-valued headline sentiment indexes.

Year	# Days	Headlines									
		Nikkei Basic Data		Integer-valued Headline S.I.				Real-valued Headline S.I.			
		# Headlines	# Words	Mean	Stdev	Max	Min	Mean	Stdev	Max	Min
1984	230	65,726	183,769	0.0876	0.0148	0.1711	0.0500	-234	73	-26	-354
1985	285	88,177	240,997	0.0832	0.0135	0.1353	0.0145	-257	79	-24	-400
1986	279	111,341	281,921	0.0830	0.0124	0.1332	0.0528	-300	87	-24	-449
1987	274	144,420	348,966	0.0869	0.0123	0.1772	0.0550	-364	85	-56	-518
1988	273	147,246	357,073	0.0918	0.0118	0.1617	0.0629	-366	85	-58	-500
1989	249	160,890	381,651	0.0912	0.0136	0.1667	0.0563	-395	91	-77	-546
1990	246	169,788	406,462	0.0918	0.0144	0.1790	0.0630	-419	93	-73	-578
1991	246	176,807	427,366	0.0901	0.0130	0.1595	0.0548	-442	102	-69	-639
1992	247	172,317	429,971	0.0867	0.0115	0.1419	0.0637	-451	109	-80	-606
1993	246	170,922	422,787	0.0863	0.0128	0.1814	0.0641	-447	112	-86	-594
1994	247	170,194	423,289	0.0858	0.0105	0.1311	0.0600	-458	111	-97	-638
1995	249	176,302	437,018	0.0864	0.0111	0.1494	0.0552	-476	115	-99	-724
1996	247	181,199	443,118	0.0882	0.0133	0.2196	0.0625	-475	117	-91	-685
1997	245	180,477	449,381	0.0859	0.0106	0.1204	0.0589	-485	121	-99	-686
1998	247	182,539	458,607	0.0876	0.0113	0.1574	0.0627	-494	121	-97	-665
1999	245	177,713	458,276	0.0895	0.0101	0.1344	0.0680	-482	120	-96	-642
2000	248	179,270	457,163	0.0894	0.0141	0.2304	0.0545	-490	122	-102	-642
2001	246	172,078	449,533	0.0861	0.0117	0.1972	0.0643	-497	123	-99	-703
2002	246	169,966	426,710	0.0837	0.0101	0.1302	0.0498	-467	111	-110	-612
2003	245	172,756	433,157	0.0880	0.0123	0.1564	0.0543	-466	110	-102	-616
2004	246	178,129	444,992	0.0902	0.0112	0.1757	0.0615	-470	117	-123	-629
2005	245	184,827	463,459	0.0913	0.0126	0.1462	0.0464	-489	122	-116	-648
2006	248	188,322	472,318	0.0897	0.0106	0.1163	0.0426	-503	119	-127	-664
2007	245	186,054	470,880	0.0942	0.0125	0.1861	0.0557	-497	124	-120	-665
2008	245	187,137	476,570	0.0896	0.0101	0.1191	0.0601	-510	134	-131	-680
2009	243	180,747	467,410	0.0945	0.0122	0.1419	0.0631	-492	130	-106	-669
2010	245	173,716	446,999	0.0965	0.0122	0.1364	0.0560	-466	118	-99	-630
2011	245	168,901	436,051	0.0926	0.0120	0.1481	0.0553	-454	116	-101	-639
2012	186	129,981	323,518	0.0943	0.0107	0.1220	0.0605	-450	105	-99	-611
Total	7,188	4,747,942	11,919,412								

Table 2: Summary statistics of entire articles of the *Nikkei*, and integer- and real-valued article sentiment indexes.

Year	# Days	Articles									
		Nikkei Basic Data		Integer-valued Article S.I.				Real-valued Article S.I.			
		# Articles	# Words	Mean	Stdev	Max	Min	Mean	Stdev	Max	Min
1984	230	65,726	2,323,610	0.1152	0.0086	0.1528	0.0947	-4,915	1,211	-603	-6,653
1985	285	88,177	2,905,806	0.1122	0.0078	0.1364	0.0945	-5,017	1,253	-619	-6,678
1986	279	111,341	3,305,971	0.1093	0.0087	0.1601	0.0927	-5,457	1,273	-531	-7,765
1987	274	144,420	4,100,562	0.1096	0.0071	0.1440	0.0885	-6,546	1,225	-1,202	-9,545
1988	273	147,246	4,163,680	0.1123	0.0065	0.1352	0.0955	-6,614	1,250	-1,328	-9,064
1989	249	160,890	4,541,870	0.1126	0.0073	0.1498	0.0908	-7,160	1,308	-1,455	-9,646
1990	246	169,788	4,834,260	0.1117	0.0074	0.1401	0.0974	-7,623	1,385	-1,758	-10,430
1991	246	176,807	5,017,746	0.1100	0.0074	0.1433	0.0947	-7,938	1,562	-1,677	-10,670
1992	247	172,317	4,753,806	0.1071	0.0078	0.1465	0.0902	-7,632	1,570	-1,670	-10,240
1993	246	170,922	4,683,689	0.1071	0.0075	0.1328	0.0919	-7,677	1,669	-1,517	-12,190
1994	247	170,194	4,748,646	0.1073	0.0066	0.1294	0.0925	-7,953	1,629	-1,905	-12,670
1995	249	176,302	5,057,085	0.1076	0.0061	0.1290	0.0920	-8,453	1,781	-1,685	-14,310
1996	247	181,199	4,776,664	0.1062	0.0073	0.1454	0.0909	-7,705	1,699	-1,625	-12,310
1997	245	180,477	4,860,673	0.1055	0.0068	0.1335	0.0901	-7,835	1,738	-1,612	-11,510
1998	247	182,539	4,962,891	0.1066	0.0067	0.1364	0.0933	-7,944	1,776	-1,669	-11,890
1999	245	177,713	4,962,023	0.1086	0.0062	0.1311	0.0938	-7,953	1,750	-1,774	-13,070
2000	248	179,270	4,956,864	0.1081	0.0067	0.1318	0.0923	-8,137	1,852	-1,748	-12,670
2001	246	172,078	4,962,740	0.1056	0.0070	0.1404	0.0892	-8,291	1,960	-1,735	-12,930
2002	246	169,966	4,714,323	0.1053	0.0061	0.1260	0.0919	-7,797	1,773	-1,682	-12,330
2003	245	172,756	4,758,561	0.1096	0.0083	0.1685	0.0949	-7,782	1,766	-1,653	-11,500
2004	246	178,129	4,927,544	0.1103	0.0062	0.1513	0.0977	-7,990	1,897	-1,969	-12,030
2005	245	184,827	5,211,410	0.1128	0.0087	0.1824	0.0942	-8,473	2,013	-1,906	-11,880
2006	248	188,322	5,322,696	0.1110	0.0058	0.1306	0.0937	-8,735	1,897	-2,294	-12,340
2007	245	186,054	5,315,917	0.1148	0.0076	0.1620	0.0961	-8,675	1,978	-2,080	-12,010
2008	245	187,137	5,295,990	0.1112	0.0065	0.1387	0.1005	-8,717	2,067	-2,311	-12,210
2009	243	180,747	5,182,147	0.1158	0.0096	0.1862	0.0987	-8,491	2,048	-1,859	-12,250
2010	245	173,716	5,026,066	0.1155	0.0069	0.1544	0.1021	-8,255	1,965	-1,903	-11,440
2011	245	168,901	4,897,555	0.1109	0.0072	0.1424	0.0886	-8,175	1,842	-1,968	-10,600
2012	186	129,981	3,766,690	0.1141	0.0061	0.1325	0.0972	-8,312	1,798	-2,072	-10,900
Total	7,188	4,747,942	134,337,485								

Table 3: Augmented Dickey–Fuller tests for stock log-returns, integer- and real-valued headline sentiment indexes, and integer- and real-valued article sentiment indexes. *, **, and * mark the test statistics that are 10%, 5%, and 1% significant, respectively.**

Year	Stock Log-Returns	Headlines		Articles	
		Integer-valued	Real-valued	Integer-valued	Real-valued
1984	-5.4880***	-5.0318***	-3.7591**	-4.0380***	-3.297*
1985	-7.1004***	-5.2897***	-5.7496***	-5.2504***	-4.6607***
1986	-7.2527***	-5.1843***	-5.2708***	-4.9970***	-5.1246***
1987	-6.5413***	-5.9684***	-5.3246***	-5.5712***	-5.4409***
1988	-6.4063***	-5.9290***	-5.4239***	-6.1967***	-4.8352***
1989	-6.9547***	-5.0145***	-5.8790***	-4.5831***	-5.2179***
1990	-6.9928***	-5.4893***	-5.6240***	-5.3558***	-5.7184***
1991	-5.1598***	-5.7939***	-4.8037***	-6.3355***	-4.1888***
1992	-5.4792***	-6.3532***	-5.1348***	-4.6200***	-4.5096***
1993	-6.4808***	-6.9314***	-5.0504***	-5.1176***	-4.2791***
1994	-6.9909***	-6.1131***	-5.1849***	-5.2693***	-4.8160***
1995	-6.9673***	-6.1640***	-5.3160***	-5.2780***	-4.6730***
1996	-5.6239***	-6.5991***	-5.6797***	-5.6666***	-4.3760***
1997	-6.6696***	-5.2706***	-4.7062***	-5.4686***	-4.7215***
1998	-6.8693***	-6.0819***	-5.9142***	-4.6294***	-4.3624***
1999	-6.3387***	-6.2330***	-4.9845***	-5.3332***	-4.0785***
2000	-5.9670***	-5.2204***	-5.4203***	-4.5614***	-4.3051***
2001	-6.0622***	-5.0882***	-5.0572***	-4.5301***	-5.4627***
2002	-5.5326***	-5.5353***	-4.7518***	-4.9812***	-3.7554**
2003	-6.3994***	-5.1537***	-5.4731***	-5.1329***	-5.1982***
2004	-5.6038***	-5.9536***	-4.8208***	-4.7719***	-5.3203***
2005	-5.8754***	-4.2963***	-5.1393***	-4.7266***	-5.5057***
2006	-5.7207***	-6.5611***	-5.4300***	-4.9215***	-5.4060***
2007	-6.6422***	-4.8775***	-4.6821***	-4.6387***	-5.1797***
2008	-6.3624***	-5.2850***	-4.6569***	-4.0132***	-4.1611***
2009	-5.5606***	-3.9091**	-5.7807***	-4.6055***	-5.7466***
2010	-6.4374***	-4.3466***	-5.1214***	-4.2901***	-5.4635***
2011	-6.4182***	-5.5632***	-5.4443***	-6.7019***	-5.2036***
2012	-4.7733***	-5.4585***	-4.0999***	-5.0250***	-4.5472***

Table 4: Predictability of “real-valued sentiment index” in terms of Granger tests and AICs. Test statistics for Granger causality are given in the columns titled “Granger.” *, **, and * mark the test statistics that are 10%, 5%, and 1% significant, respectively.**

Year	Healine Eq. (6)			Article Eq. (7)			Headline & Article Eq. (8)			
	Lag (p)	Granger	AIC	Lag (p)	Granger	AIC	Lag (p)	Granger H	Granger A	AIC
1984	3	1.29	-10.17	6	1.44	-10.10	6	4.74***	3.94***	-11.19
1985	7	1.61	-10.46	6	1.91*	-10.65	6	5.07***	3.49***	-11.45
1986	2	2.14	-10.18	6	1.40	-10.44	6	2.12**	2.25***	-11.60
1987	2	0.02	-9.21	6	0.62	-9.77	6	1.12	0.78	-11.17
1988	2	1.04	-11.07	6	0.61	-11.38	6	4.65***	2.21**	-12.88
1989	2	2.60*	-11.53	5	1.11	-12.01	5	4.59***	2.10**	-13.70
1990	2	0.16	-8.73	7	1.55	-9.63	5	4.11***	4.04***	-11.21
1991	2	0.26	-9.37	5	0.44	-10.35	5	2.91***	5.28***	-11.72
1992	5	1.50	-8.69	5	1.02	-9.48	5	2.76***	2.18**	-10.79
1993	1	1.68	-9.18	5	0.17	-10.03	5	2.67***	3.77***	-11.29
1994	1	0.48	-9.46	5	0.42	-10.27	5	1.15	5.99***	-11.52
1995	5	0.59	-9.19	5	0.34	-9.98	5	9.07***	8.92***	-11.48
1996	5	1.37	-10.05	5	0.75	-11.08	5	2.99***	3.94***	-12.61
1997	2	0.09	-8.78	5	1.22	-9.72	5	2.56***	4.93***	-11.21
1998	5	3.25***	-8.80	5	1.86	-9.94	5	4.06***	5.65***	-11.28
1999	1	0.66	-9.29	5	0.36	-9.99	5	1.15	3.17***	-11.22
2000	1	4.24**	-8.99	5	1.41	-10.04	6	2.22***	7.01***	-11.36
2001	2	0.30	-8.59	1	0.39	-9.72	1	2.12	1.55	-11.17
2002	2	2.37*	-8.90	5	1.31	-10.10	5	1.13	1.61*	-11.74
2003	1	0.12	-8.89	5	0.25	-10.30	1	0.53	2.22	-11.99
2004	1	0.13	-9.50	5	1.05	-10.70	1	0.13	5.55***	-12.26
2005	5	0.28	-10.10	5	0.39	-11.24	1	5.10***	17.16***	-12.81
2006	5	0.94	-9.37	5	1.81	-10.53	5	1.40	5.50***	-12.27
2007	6	0.39	-9.59	6	0.22	-10.70	5	2.80***	4.96***	-12.32
2008	6	0.49	-7.68	5	0.67	-8.59	5	2.70***	6.65***	-10.15
2009	6	0.63	-8.87	6	0.67	-9.88	6	3.71***	2.55***	-11.36
2010	5	1.95*	-9.24	5	2.18*	-10.36	5	1.88**	5.71***	-12.02
2011	1	0.08	-9.18	5	0.80	-10.00	5	1.39	2.12**	-11.44
2012	2	3.30**	-9.71	5	0.99	-10.91	5	2.56***	2.41***	-12.32

Table 5: Predictability of “integer-valued sentiment index” in terms of Granger tests and AICs. Test statistics for Granger causality are given in the columns titled “Granger.” *, **, and * mark the test statistics that are 10%, 5%, and 1% significant, respectively.**

Year	Healine Eq. (6)			Article Eq. (7)			Headline & Article Eq. (8)			
	Lag (p)	Granger	AIC	Lag (p)	Granger	AIC	Lag (p)	Granger H	Granger A	AIC
1984	1	0.24	-9.76	1	0.96	-10.04	1	2.99*	4.55**	-10.19
1985	2	2.97*	-10.39	3	4.04***	-10.72	1	1.02	1.04	-10.83
1986	1	2.63	-9.62	1	2.91*	-9.49	1	6.56***	1.06	-9.79
1987	1	0.22	-8.40	6	1.64	-8.70	1	0.20	6.18***	-9.08
1988	2	0.74	-10.37	5	1.64	-10.77	1	0.24	2.54*	-11.15
1989	6	1.14	-10.42	1	2.17	-10.86	1	0.40	0.96	-11.11
1990	2	0.09	-7.65	2	1.37	-8.16	2	0.59	1.48	-8.28
1991	1	0.38	-8.69	1	1.05	-9.03	2	2.97**	2.38*	-9.39
1992	1	2.38	-8.28	5	0.98	-8.29	1	3.16**	0.62	-8.80
1993	4	4.37***	-8.81	1	0.02	-9.06	1	0.50	0.04	-9.34
1994	5	1.66	-9.55	1	0.02	-9.59	1	0.09	0.61	-10.31
1995	1	0.07	-8.86	1	0.09	-9.28	1	0.19	1.32	-9.74
1996	1	4.47**	-9.33	1	0.10	-9.73	1	2.40*	0.51	-9.91
1997	2	1.04	-8.67	2	0.39	-8.82	2	1.33	0.67	-9.48
1998	2	1.16	-8.49	5	1.88*	-8.78	1	2.82*	1.10	-9.40
1999	1	0.12	-9.35	1	0.05	-9.57	1	0.18	4.94***	-10.39
2000	1	0.14	-8.41	1	0.70	-9.11	1	0.26	1.07	-9.23
2001	1	1.75	-8.28	1	0.02	-8.48	1	1.82	1.47	-9.13
2002	1	0.12	-8.82	1	1.31	-9.01	1	0.03	1.51	-9.78
2003	5	2.50**	-8.70	4	1.80	-8.63	1	5.55***	2.36*	-9.10
2004	1	0.01	-9.38	1	0.00	-9.69	1	3.74**	0.34	-10.38
2005	1	0.58	-9.74	5	0.34	-9.67	5	1.55	1.60	-10.13
2006	1	0.21	-9.24	2	0.15	-9.70	2	2.35*	2.79**	-10.30
2007	1	1.64	-9.06	6	1.91*	-9.27	1	2.18	1.89	-9.66
2008	1	0.37	-7.62	3	0.62	-7.68	1	2.26	3.93**	-8.31
2009	3	2.01	-8.38	6	2.18**	-8.02	1	5.06***	0.84	-8.60
2010	3	1.13	-8.89	5	2.71**	-9.22	3	4.69***	1.44	-9.56
2011	1	0.05	-8.61	4	1.89	-8.95	1	1.56	2.62*	-9.21
2012	1	0.96	-9.56	3	0.85	-9.86	1	1.98	0.15	-10.36

Table 7: Out-of-sample predictability performance in terms of “prediction errors (%)”

Year	1st Half				2nd Half			
	10 Days	20 Days	30 Days	40 Days	10 Days	20 Days	30 Days	40 Days
1984	11.2%	15.3%	20.1%	31.4%	42.6%	46.9%	46.5%	45.5%
1985	25.6%	40.7%	58.9%	53.3%	34.1%	30.8%	36.1%	36.3%
1986	39.1%	36.5%	41.0%	46.0%	16.7%	19.5%	19.6%	18.6%
1987	19.5%	40.5%	36.6%	46.9%	22.6%	24.4%	31.7%	45.6%
1988	8.2%	9.1%	9.9%	14.9%	13.5%	13.5%	14.1%	13.9%
1989	51.4%	54.2%	51.8%	56.1%	74.9%	61.2%	53.5%	52.5%
1990	64.6%	69.0%	71.0%	78.7%	59.5%	45.1%	48.9%	48.9%
1991	5.7%	9.7%	10.4%	16.3%	42.2%	37.6%	36.9%	36.3%
1992	14.9%	14.4%	33.1%	47.2%	26.5%	29.3%	31.7%	32.8%
1993	6.1%	22.4%	28.4%	25.7%	26.9%	34.7%	34.0%	31.2%
1994	32.4%	27.1%	40.3%	49.0%	25.8%	27.3%	28.7%	29.5%
1995	38.6%	33.4%	28.0%	28.2%	18.4%	27.5%	30.9%	30.7%
1996	9.4%	9.1%	8.9%	10.2%	46.2%	41.0%	35.5%	35.6%
1997	7.1%	34.7%	35.2%	45.3%	30.9%	32.0%	73.0%	68.3%
1998	13.6%	17.7%	16.4%	17.5%	19.1%	19.7%	18.5%	20.7%
1999	15.7%	17.1%	16.1%	20.1%	49.9%	46.0%	44.7%	44.8%
2000	53.3%	52.9%	57.0%	63.6%	32.0%	36.9%	38.1%	36.1%
2001	26.3%	50.5%	50.6%	84.1%	26.4%	38.9%	38.3%	40.4%
2002	19.8%	28.1%	30.5%	53.7%	15.1%	16.6%	21.6%	23.9%
2003	23.5%	43.2%	40.6%	60.8%	23.0%	24.2%	45.0%	40.3%
2004	41.3%	40.9%	35.7%	34.5%	27.3%	32.8%	34.0%	32.4%
2005	45.2%	130.4%	126.6%	124.5%	47.6%	38.3%	32.8%	31.8%
2006	51.2%	41.5%	42.7%	42.5%	36.9%	34.3%	30.5%	30.1%
2007	45.8%	42.6%	54.2%	57.4%	54.7%	46.1%	48.3%	46.8%
2008	38.8%	52.3%	76.2%	87.8%	29.0%	30.2%	29.0%	39.5%
2009	55.5%	50.9%	57.7%	70.3%	23.9%	30.0%	27.9%	31.3%
2010	23.5%	23.3%	32.8%	45.0%	24.1%	21.9%	26.3%	25.8%
2011	39.6%	36.3%	31.1%	86.0%	27.5%	23.5%	24.7%	30.3%
2012	26.7%	62.4%	65.7%	65.7%	51.4%	56.4%	51.5%	48.4%
Ave. Overall	29.4%	38.1%	41.6%	50.4%	33.4%	33.3%	35.6%	36.1%
Ave. 84-89	25.8%	32.7%	36.4%	41.4%	34.1%	32.7%	33.6%	35.4%
Ave. 90-94	24.7%	28.5%	36.6%	43.4%	36.2%	34.8%	36.1%	35.7%
Ave. 95-99	16.9%	22.4%	20.9%	24.3%	32.9%	33.2%	40.5%	40.0%
Ave. 00-04	32.9%	43.1%	42.9%	59.3%	24.8%	29.9%	35.4%	34.6%
Ave. 05-09	47.3%	63.5%	71.5%	76.5%	38.4%	35.8%	33.7%	35.9%
Ave. 10-12	29.9%	40.7%	43.2%	65.6%	34.3%	33.9%	34.2%	34.8%

Table 8: Out-of-sample predictability performance in terms of “winners (%)”

Year	1st Half				2nd Half			
	10 Days	20 Days	30 Days	40 Days	10 Days	20 Days	30 Days	40 Days
1984	70.0%	60.0%	50.0%	50.0%	70.0%	60.0%	63.3%	55.0%
1985	60.0%	50.0%	43.3%	42.5%	40.0%	30.0%	43.3%	45.0%
1986	70.0%	65.0%	66.7%	67.5%	30.0%	30.0%	43.3%	47.5%
1987	60.0%	65.0%	60.0%	55.0%	50.0%	40.0%	36.7%	37.5%
1988	70.0%	50.0%	46.7%	42.5%	40.0%	45.0%	50.0%	50.0%
1989	60.0%	45.0%	53.3%	50.0%	70.0%	65.0%	63.3%	65.0%
1990	90.0%	70.0%	66.7%	70.0%	70.0%	65.0%	66.7%	67.5%
1991	50.0%	40.0%	46.7%	50.0%	80.0%	75.0%	63.3%	55.0%
1992	60.0%	45.0%	40.0%	47.5%	70.0%	65.0%	66.7%	70.0%
1993	50.0%	50.0%	50.0%	55.0%	70.0%	55.0%	50.0%	47.5%
1994	50.0%	70.0%	66.7%	67.5%	50.0%	60.0%	53.3%	52.5%
1995	60.0%	60.0%	50.0%	55.0%	50.0%	40.0%	46.7%	50.0%
1996	40.0%	45.0%	50.0%	45.0%	60.0%	55.0%	46.7%	52.5%
1997	70.0%	60.0%	46.7%	52.5%	60.0%	50.0%	46.7%	47.5%
1998	60.0%	50.0%	53.3%	52.5%	40.0%	55.0%	53.3%	55.0%
1999	60.0%	60.0%	50.0%	52.5%	60.0%	65.0%	60.0%	57.5%
2000	50.0%	50.0%	43.3%	42.5%	70.0%	60.0%	53.3%	55.0%
2001	40.0%	30.0%	33.3%	40.0%	50.0%	55.0%	46.7%	40.0%
2002	70.0%	60.0%	53.3%	52.5%	30.0%	35.0%	36.7%	30.0%
2003	20.0%	40.0%	50.0%	42.5%	20.0%	30.0%	36.7%	37.5%
2004	20.0%	35.0%	26.7%	37.5%	30.0%	35.0%	40.0%	40.0%
2005	70.0%	50.0%	46.7%	57.5%	40.0%	45.0%	53.3%	50.0%
2006	40.0%	45.0%	56.7%	55.0%	70.0%	65.0%	60.0%	60.0%
2007	40.0%	45.0%	40.0%	42.5%	50.0%	50.0%	50.0%	50.0%
2008	50.0%	55.0%	56.7%	57.5%	40.0%	45.0%	46.7%	47.5%
2009	60.0%	65.0%	63.3%	55.0%	40.0%	45.0%	50.0%	55.0%
2010	60.0%	70.0%	60.0%	57.5%	30.0%	40.0%	43.3%	42.5%
2011	80.0%	60.0%	60.0%	55.0%	60.0%	50.0%	40.0%	37.5%
2012	70.0%	45.0%	53.3%	50.0%	50.0%	45.0%	50.0%	52.5%
Ave. Overall	56.9%	52.9%	51.1%	51.7%	51.4%	50.2%	50.3%	50.1%
Ave. 84-89	65.0%	55.8%	53.3%	51.3%	50.0%	45.0%	50.0%	50.0%
Ave. 90-94	60.0%	55.0%	54.0%	58.0%	68.0%	64.0%	60.0%	58.5%
Ave. 95-99	58.0%	55.0%	50.0%	51.5%	54.0%	53.0%	50.7%	52.5%
Ave. 00-04	40.0%	43.0%	41.3%	43.0%	40.0%	43.0%	42.7%	40.5%
Ave. 05-09	52.0%	52.0%	52.7%	53.5%	48.0%	50.0%	52.0%	52.5%
Ave. 10-12	70.0%	58.3%	57.8%	54.2%	46.7%	45.0%	44.4%	44.2%