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Interest Rate Model with Investor Attitude and Text Mining ¹

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• **ABSTRACT** This paper develops and estimates an interest rate model with investor attitude factors, which are extracted by a text mining method. First, we consider two contrastive attitudes (optimistic versus conservative) towards uncertainties about Brownian motions driving economy, develop an interest rate model, and obtain an empirical framework of the economy consisting of permanent and transitory factors. Second, we apply the framework to a bond market under extremely low interest rate environment in recent years, and show that our three-factor model with level, steepening and flattening factors based on different investor attitudes is capable of explaining the yield curve in the Japanese government bond (JGB) markets. Third, text mining of a large text base of daily financial news reports enables us to distinguish between steepening and flattening factors, and from these textual data we can identify events and economic conditions that are associated with the steepening and flattening factors. We then estimate the yield curve and three factors with frequencies of relevant word groups chosen from textual data in addition to observed interest rates. Finally, we show that the estimated three factors, extracted only from the bond market data, are able to explain the movement in stock markets, in particular Nikkei 225 index.

• **INDEX TERMS** Interest rate model, text mining, filtering.

I. INTRODUCTION

When some changes occur in the bond market, the whole yield curve changes its location and/or shape. Typically, the change can be characterized in three categories: parallel shift (level shift), steepening, and flattening, and the actual change of the yield curve is the combination of these three components. The shape (steepening and flattening) of the yield curve is no less important than the location (level) of the curve. The change in the shape introduces various trading opportunities and provides us with important information about the factors that drive the bond market as a whole.

The first purpose of this study is to develop an empirical framework of a three-factor model of the yield curve, which explicitly takes account of the above-mentioned three components of the yield curve change

separately. Specifically, we consider a three-factor model in which the actual short rate is determined by (1) a level factor representing the fundamentals-determined short rate, and two transitory factors, which are (2) a bull-steepening factor which, after the initial shock lowering the interest rate, eventually increases the rate to the fundamentals-determined rate, and (3) a bear-flattening factor which, after the initial shock raising the interest rate, eventually decreases the rate to the fundamentals-determined rate. The second purpose is to apply this framework to an extremely low interest rate environment of recent years in Japan and to show our three-factor model with level, steepening and flattening factors based on different investor attitudes are capable of explaining the yield curve in the government bond markets with the

maturity of more than two years.² To do this, we examine Japanese Government Bond (JGB) markets. Japan is a spearhead of globally declining interest rates, where overnight rates have been close to zero for decades and long-end rates lower than any other countries. As for an estimation method, we take a state space Bayesian filtering approach and apply the Monte Carlo filter as a particle filtering method.³ Moreover, a text mining of a large text base consisting of daily financial news reports enables us to identify events and economic conditions that are associated with the steepening and flattening factors.

We examine daily JGB markets of six calendar years from January 2012 to December 2017. The starting date, January 2012 is chosen partly because the severe effects of two crises (the Global Financial Crisis of 2008 and the Great East Japan Earthquake and Fukushima Nuclear Power Plant Accident of 2011) were settled down and the real economy was back to “new normal” conditions, though they were not back to the before-crisis conditions. Also, at the beginning of 2012, most of the unconventional monetary policy tools were already in place, except for negative interest rates and yield curve controls of 2016. As financial news data, we utilize publicly available Reuters Japan’s news reports of the same period.

The third purpose of this study is to examine whether estimated level, steepening and flattening factors extracted only from bond market data are capable of explaining the movement in stock markets. It is often argued that the change in the yield curve may represent the change in market sentiment, especially a risk-on or risk-off state of the financial market, which affects stock prices. We take the Nikkei 225 index, and explore whether level, steepening & flattening factors explain the movement of this index.

For prediction of US Treasury yields based on Nelson and Siegel [11], Diebold and Li [10] develop and estimate an interest rate model with three factors, namely level, slope and curvature factors. Since in the principal component analysis (PCA) of Japanese government bond yields, it is well-known that level and slope factors provide the first and second largest contributions, which explain at least about 90% of interest rates variations, and a curvature factor is more difficult to interpret in terms of macroeconomic fundamentals, the current paper

focuses on level and slope factors, while an analysis with a curvature factor is one of our future topics. In fact, our model is a short rate based one with three factors which represent a level, a steepening, and a flattening effect. The model is originally derived from the sup-inf/inf-sup stochastic control problem on market sentiments, in which an equilibrium interest rate under optimistic and pessimistic sentiments is obtained and this model is new, to the best of our knowledge. By specifying dynamics of the variables in the sup-inf/inf-sup problem, we obtain the three-factor short rate model as a special case of the equilibrium interest rate, which is a linear combination of existing short rate models. Particularly, the three factors consist of two quadratic Gaussian factors of opposite sign and one Gaussian level factor. Specifically, the quadratic Gaussian short rate model originates from Leippold and Wu [12]. The two Gaussian processes underlying the quadratic factors are transitory stochastic processes with zero mean-reverting levels. In detail, the first quadratic Gaussian factor has a negative coefficient, thus, it has a lowering effect on the short rate initially, but the effect lessens as time passes. Thus, it works as a steepening factor for the yield curve. Similarly, the second quadratic Gaussian factor with a positive coefficient has a flattening effect on the yield curve. Also, the Gaussian part in the short rate model originates from Vasicek, Hull-White, and Ho-Lee model ([13], [14], [15]). The third Gaussian factor controls the level of the short rate. Since it can take negative values, this and the first quadratic factors help express low interest rate environments including negative interest rates. Thus, this model particularly explains the low interest situation observed in the recent Japanese bond markets, in which the interest rates are controlled by the central bank. A relevant study <https://www.bis.org/publ/work715.pdf> also models and estimates interest rates using macroeconomic data in a low interest rate environment.

For other related studies on empirical analysis of yield curve models, Wang and Zhou [16] investigate Chinese government bond prices based on a two-factor affine yield curve model. Zhou et al. [17] develop an algorithm for parameter estimation of a yield curve model by a particle swarm optimization method. Liu et al. [18] estimate a three-factor affine yield curve model by Kalman filter method. For other literature on estimation of yield curve models, Ren et al. [19], Qing and Huahua [20], Liu et al. [21], and Maciel et al. [22] deal with estimation of yield curve models for government bonds. In addition, Maciel et al. [23] and Rong-xi et al. [24] utilize yield curve models for forecasting of interest rates.

Moreover, there have been various studies on text mining applications to financial markets due to considerable influence of text news on the markets. Wang et al. [25] propose a hybrid time-series predicted neural network

²In the extremely low interest environment, the government bonds yields of short maturities are in fact forced down close to the overnight interbank rate that the central bank controls and thus the yield curve is essentially flat in the short-end bond markets.

³The Monte Carlo filter method is proposed by Kitagawa [1]. See Takahashi and Sato [2] and Nishimura et al. [3] for its application to estimation of an interest rate model. See also Fukui et al. [4] and Nakano et al. [5], [6], [7], [8], [9] for its application in other fields of finance.

for forecasting stock volatility. Crone and Koeppel [26] explore efficacy of using sentiment indicators as a predictor for foreign exchange rates. (For applications of text mining to stock returns, see Siering [27], Day and Lee [28], Growth and Muntermann [29], Ming et al. [30], Li et al. [31] and references therein.) Although there are a large number of works on predictions of stock markets using financial news, there has not been literature on text mining applications to interest rate markets, particularly a study explaining factors in an interest rate model by texts in financial news, to the best of our knowledge. In our work, by estimating the three factors by using the data on frequencies of words in financial news in addition to yield curve data, we observe improvement in the model fitting, which factor affected changes in the yield curve, and what words were behind the changes. Moreover, by using the three-factor model, our work shows for the first time that the steepening and flattening factors correspond to pessimistic and optimistic market sentiments, respectively, and those factors with the level factor (x_3) are capable of explaining movement of the Nikkei 225 stock market index.

The organization of the paper is as follows: After the next section introduces our theoretical framework, Section III describes method and procedure of our empirical analysis. Section IV shows the result for simultaneous estimation of a three-factor model together with word groups frequencies extracted by text mining. It also discusses a regression analysis, where the price index of Nikkei 225 is regressed on the estimated factors in the three-factor model with dummy variables for policy/political events. Section V gives concluding remarks. Appendix provides additional comments on the regression analysis in Section IV.

II. FUNDAMENTAL UNCERTAINTY AND INVESTOR ATTITUDES

This section briefly explains a theoretical foundation for an interest rate model used for an empirical analysis in the subsequent sections. The model incorporates (i) fundamental uncertainty, about which investors do not know the true stochastic process and only know it is in a set of likely stochastic processes (essentially, Brownian motions in this paper), and (ii) investors' different attitudes toward such fundamental uncertainty: namely, (ii-a) a conservative attitude in which investors prepare for the worst-case scenario among this set of likely stochastic processes, and (ii-b) an optimistic attitude in which they count on the best-case scenario.

A. MODEL WITH INVESTOR ATTITUDES

Let $(\Omega, \mathcal{F}, \{\mathcal{F}_t\}_{0 \leq t \leq T}, P)$ be a filtered probability space satisfying the usual conditions. We consider a pure exchange economy with a representative investor and an

exogenously specified endowment to the investor at each time t . Then, under an equilibrium condition that the investor consumes all the given endowment at each time t , the investor's optimal consumption must be equal to the endowment process. Hence, let us suppose a non-negative endowment process c whose expected return and volatility depend on a \mathcal{R}^l -valued state vector x as an $\{\mathcal{F}_t\}$ -adapted progressively measurable process satisfying the following stochastic differential equations (SDEs):

$$\begin{cases} \frac{dc_t}{c_t} = \mu_c(x_t, t)dt + \sigma_c(x_t, t) \cdot dB_t, \\ dx_t = \mu_x(x_t, t)dt + \sigma_x(x_t, t)dB_t, \end{cases} \quad (1)$$

with R^d -dimensional Brownian motion B , $\mu_c(x_t, t) \in \mathcal{R}$, $\mu_x(x_t, t) \in \mathcal{R}^l$, $\sigma_c(x_t, t) \in \mathcal{R}^d$, $\sigma_x(x_t, t) \in \mathcal{R}^{l \times d}$.

Here, while the economy is driven by specific Brownian motions representing fundamental risk sources, the investor is *not* certain about *all* Brownian motions. The investor thinks there is fundamental uncertainty about *some* of these fundamental risks, Brownian motions. We formulate that under the fundamental uncertainty the investor does not face a single probability measure, but a set of probability measures. In particular, in the diffusion process framework, we postulate that the investor's fundamental uncertainty is represented by a *set of different Brownian motions*, i.e. a set of d -dimensional Brownian motions B^{λ_1, λ_2} defined by the equation (4) with a particular set of stochastic processes, (5) below. Moreover, the investor may be "conservative" about the fundamental uncertainty for some Brownian motions (in the sense that the investor considers their worst possible case), while at the same time the investor may be "optimistic" about the fundamental uncertainty about some other Brownian motions (in the sense that the investor considers the best possible case).

To explicitly model the above concept, let us introduce a probability measure P^{λ_1, λ_2} by

$$P^{\lambda_1, \lambda_2}(A) := E[\mathcal{Z}_T(\lambda)1_A]; A \in \mathcal{F}_T, \quad (2)$$

for a \mathcal{R}^2 -valued $\{\mathcal{F}_t\}$ -progressively measurable processes $\lambda = (\lambda_1, \lambda_2)$, where $\mathcal{Z}_t(\lambda)$ defined by

$$\mathcal{Z}_t(\lambda) := \exp \left\{ \sum_{j=1}^2 \int_0^t \lambda_{j,s} dB_{j,s} - \sum_{j=1}^2 \frac{1}{2} \int_0^t \lambda_{j,s}^2 ds \right\} \quad (3)$$

is assumed to be a martingale. Then, by Girsanov's theorem, we can define a d -dimensional Brownian motion under P^{λ_1, λ_2} as $B^{\lambda_1, \lambda_2} = (B_1^{\lambda_1, \lambda_2}, \dots, B_d^{\lambda_1, \lambda_2})$, by

$$\begin{aligned} B_{1,t}^{\lambda_1, \lambda_2} &= B_{1,t} - \int_0^t \lambda_{1,s} ds, & B_{2,t}^{\lambda_1, \lambda_2} &= B_{2,t} - \int_0^t \lambda_{2,s} ds, \\ B_{j,t}^{\lambda_1, \lambda_2} &= B_{j,t} \quad (3 \leq j \leq d). \end{aligned} \quad (4)$$

We also define a set Λ as

$$\Lambda = \{(\lambda_1, \lambda_2); \mathcal{Z}(\lambda) \text{ is a martingale and } |\lambda_{j,t}| \leq |\bar{\lambda}_j(x_t)|, 0 \leq t \leq T, j = 1, 2\}, \quad (5)$$

where each $\bar{\lambda}_j(x_t)$ is a function of x_t in (1), which is exogenously specified so that $\mathcal{Z}(\bar{\lambda})$ is a martingale under P .

We remark that λ_j ($j = 1, 2$) represent fundamental uncertainty about the j -th risk. Namely, we only know the true j -th risk is one of $\{B_j^\lambda; \lambda_j \in \Lambda\}$ with $B_{j,t}^{\lambda_1, \lambda_2} := B_{j,t} - \int_0^t \lambda_{j,s} ds$, and we cannot tell which is the true one. Also, there are upper and lower limits characterized by $|\bar{\lambda}_j(x_t)|$ ($j = 1, 2$) in the set Λ . On the contrary, there is no fundamental uncertainty about the j -th risk, B_j with $j = 3, \dots, d$.

Next, we introduce an investor's utility process V^{λ_1, λ_2} as follows: with a function $u : \mathcal{R} \rightarrow \mathcal{R}$, $\xi \in \mathcal{F}_T$ and a constant discount factor $\beta > 0$,

$$V_t^{\lambda_1, \lambda_2} = E^{P^{\lambda_1, \lambda_2}} \left[\xi + \int_t^T e^{-\beta(s-t)} u(c_s) ds \middle| \mathcal{F}_t \right], \quad (6)$$

Under this setup we consider a situation where the investor takes his/her own views for uncertainties (risks) associated with Brownian motions into account. Specifically, the investor who has a conservative (optimistic) view on Brownian motion B_1 (B_2) assumes the worst (best) case. Thus, he/she implements optimization with respect to λ_j ($j = 1, 2$), that is, minimize (maximize) the expected utility with respect to λ_1 (λ_2). In contrast, for the risk B_j ($j = 3, \dots, d$), the investor has perfect confidence with $\lambda_j \equiv 0$.

Precisely, setting the time-0 utility as a functional of λ_1 and λ_2 , $J(\lambda_1, \lambda_2)$ as

$$J(\lambda_1, \lambda_2) = V_0^{\lambda_1, \lambda_2}, (\lambda_1, \lambda_2) \in \Lambda, \quad (7)$$

we consider the following sup-inf (max-min) problem for the utility $J(\lambda_1, \lambda_2)$ with respect to λ_1 and λ_2 : sup-inf (max-min) problem:

$$\begin{aligned} & \sup_{\lambda_2 \in \Lambda_2} \inf_{\lambda_1 \in \Lambda_1} J(\lambda_1, \lambda_2) \\ &= \sup_{\lambda_2 \in \Lambda_2} \inf_{\lambda_1 \in \Lambda_1} E^{P^{\lambda_1, \lambda_2}} \left[\xi + \int_0^T e^{-\beta s} u(c_s) ds \right], \quad (8) \end{aligned}$$

where we define as

$$\Lambda_j = \{\lambda_j; |\lambda_{j,t}| \leq |\bar{\lambda}_j(x_t)|, 0 \leq t \leq T\}, \quad j = 1, 2, \quad (9)$$

The associated inf-sup (min-max) problem is defined in the similar way.⁴ Here, *conservatism and optimism* are expressed by \inf_{λ_1} and \sup_{λ_2} , respectively.

⁴While the solutions of sup-inf and inf-sup problems are different in general, they become the same in our case. See the proof of Theorem 1 in Saito-Takahashi [33] for the details.

(Remark) When a weak version of Novikov's condition (e.g. Corollary 3.5.14 in Karatzas and Shreve [32]) is satisfied for $\bar{\lambda}_j(x_t)$, $j = 1, 2$, for all $\lambda = (\lambda_1, \lambda_2)$ with $|\lambda_{j,t}| \leq |\bar{\lambda}_j(x_t)|$ ($0 \leq t \leq T$, $j = 1, 2$), $\{\mathcal{Z}_t(\lambda)\}_{0 \leq t \leq T}$ is a martingale. Moreover, for Λ defined by (5), we have $\Lambda = \Lambda_1 \times \Lambda_2$. See Theorem 1 in Saito-Takahashi [33] for the details.

To solve the sup-inf/inf-sup problem, we take a backward stochastic differential equation (BSDE) approach, and with certain conditions, show the optimal measure characterized by $\lambda_{j,t}^*$ ($j = 1, 2$) which are given as follows:

$$\lambda_{j,t}^* = (-1)^j |\bar{\lambda}_{j,t}(x_t)| \text{sgn}(\sigma_{V^{\lambda_1^*, \lambda_2^*}}), \quad j = 1, 2, \quad (10)$$

where $\lambda_{1,t}^* < 0$ and $\lambda_{2,t}^* > 0$ represent the investor's conservative attitude towards a risk source, Brownian motion B_1 and optimistic attitude towards B_2 , respectively.⁵

Then, under the optimal probability measure $P^{\lambda_1^*, \lambda_2^*}$, we have

$$\begin{cases} \frac{dc_t}{c_t} = \mu_c^* dt + \sigma_c(x, t) \cdot dB_t^{\lambda_1^*, \lambda_2^*}, \\ dx_t = \mu_x^* dt + \sigma_x(x, t) dB_t^{\lambda_1^*, \lambda_2^*}, \end{cases} \quad (11)$$

where

$$\begin{cases} \mu_c^* = \mu_c(x, t) + \lambda_t^* \cdot \sigma_c(x, t), \\ \mu_x^* = \mu_x(x, t) + \sigma_x(x, t) \lambda_t^*. \end{cases} \quad (12)$$

Next, let π be a state-price density process under $P^{\lambda_1^*, \lambda_2^*}$. Then, the economy is in equilibrium, if it holds that

$$\frac{d\pi_t}{\pi_t} = -r_t dt - \theta_t \cdot dB_t^{\lambda_1^*, \lambda_2^*}, \quad \pi_0 = 1, \quad (13)$$

and at the same time that $\pi_t = e^{-\beta t} u'(c_t)$ with a utility function u . Here, r is a risk-free interest rate and θ is a market price of risk. (For instance, see the equations (3.5) and (3.6) in Nakamura et al. [35].) Hence, by applying Ito's formula to $\pi_t = e^{-\beta t} u'(c_t)$ and compare its drift and diffusion terms with those in (13), we obtain r and θ :

$$\begin{aligned} r_t &= \beta + RRA(c_t) \left[\mu_c^* - \frac{1}{2} P(c_t) |\sigma_c(x, t)|^2 \right], \\ \theta_t &= RRA(c_t) \sigma_c(x, t), \\ RRA(x) &:= -x u''(x) / u'(x), \\ P(x) &:= -x u'''(x) / u''(x). \end{aligned} \quad (14)$$

Then, the zero-coupon bond price at time- t with maturity T denoted by $\bar{P}(t, T)$ is expressed by

$$\bar{P}(t, T) = E^{Q^{\lambda^*}} \left[e^{-\int_t^T r_s ds} \middle| \mathcal{F}_t \right], \quad (15)$$

⁵Under the setting in Section II-B used for our empirical analysis, see Section 1-2 in the online appendix of this paper, CARF-F-470 [34]. Under a general setting, see Theorem 1 in Saito and Takahashi [33].

where Q^{λ^*} is given as

$$Q^{\lambda^*}(A) = E^{\lambda_1^*, \lambda_2^*}[\mathcal{Z}_T^{Q^{\lambda^*}} 1_A]; A \in \mathcal{F}_T, \\ \mathcal{Z}_T^{Q^{\lambda^*}} = \exp\left(-\frac{1}{2} \int_0^T |\theta_s|^2 ds - \int_0^T \theta_s \cdot dB_s^{\lambda_1^*, \lambda_2^*}\right), \quad (16)$$

and $B^{Q^{\lambda^*}}$ defined by $B_t^{Q^{\lambda^*}} = B_t^{\lambda_1^*, \lambda_2^*} + \int_0^t \theta_s ds$ is a Brownian motion under Q^{λ^*} .

B. THREE-FACTOR GAUSSIAN QUADRATIC-GAUSSIAN INTEREST RATE MODEL

This subsection describes a three-factor yield curve model, so called a Gaussian quadratic-Gaussian model, as a special case in the previous subsection.

In (6), we set the utility function as

$$u(c_t) = \log c_t \text{ with } \xi = \log c_T,$$

and specify (1) as follows: with $\sigma_{c,1} > 0, \sigma_{c,2} > 0; \sigma_{c,3}, \sigma_{x,j} \in R (j = 1, 2, 3)$,

$$\begin{cases} \frac{dc_t}{c_t} = (\mu_0 + x_3)dt + \sum_{j=1}^2 \sigma_{c,j} x_{j,t} dB_{j,t} + \sigma_{c,3} dB_{3,t}, \\ dx_{j,t} = -b_j x_{j,t} dt + \sigma_{x,j} dB_{j,t}; b_j > 0, (j = 1, 2), \\ dx_{3,t} = \sigma_{x,3} dB_{3,t}. \end{cases}$$

Moreover, setting $\bar{\lambda}_{j,t}(x_t) = \bar{\lambda}_{j,t} x_{j,t} (j = 1, 2)$, we have the optimal $\lambda_j^* (j = 1, 2)$ in (10) as

$$\begin{aligned} \lambda_{1,t}^* &= \bar{\lambda}_{1,t} x_{1,t}, (\bar{\lambda}_{1,t} < 0); \\ \lambda_{2,t}^* &= \bar{\lambda}_{2,t} x_{2,t}, (\bar{\lambda}_{2,t} > 0). \end{aligned} \quad (17)$$

Then, under $P \equiv P^{\lambda_1^*, \lambda_2^*}$, (11) becomes

$$\begin{cases} \frac{dc_t}{c_t} = \mu_c^{\lambda^*} dt + \sum_{j=1}^3 \sigma_c^j(x, t) dB_{j,t}^{\lambda_1^*, \lambda_2^*}, \\ dx_{j,t} = -\kappa_j^P x_{j,t} dt + \sigma_{x,j} dB_{j,t}^{\lambda_1^*, \lambda_2^*}, (j = 1, 2), \\ dx_{3,t} = \sigma_{x,3} dB_{3,t}^{\lambda_1^*, \lambda_2^*}, \end{cases} \quad (18)$$

where

$$\begin{cases} \mu_c^{\lambda^*} := \mu_0 + \bar{\lambda}_1 \sigma_{c,1} x_1^2 + \bar{\lambda}_2 \sigma_{c,2} x_2^2 + x_3, \\ \sigma_c^j(x, t) = \sigma_{c,j} x_j, (j = 1, 2); \sigma_c^3(x, t) = \sigma_{c,3}, \\ \kappa_j^P := b_j - \bar{\lambda}_j \sigma_{x,j} > 0. \end{cases}$$

Since $RRA(c_t) = 1$ and $P(c_t) = 2$ when $u(c_t) = \log c_t$, the interest rate r and the market price of risk θ in (14) become

$$\begin{aligned} r_t &= \beta + \mu_c^{\lambda^*} - |\sigma_c(x, t)|^2, \\ \theta_t &= \sigma_c(x, t) = (\sigma_{c,1} x_1, \sigma_{c,2} x_2, \sigma_{c,3}). \end{aligned} \quad (19)$$

In particular, the interest rate is expressed as

$$r_t = c_0 + c_1 x_{1,t}^2 + c_2 x_{2,t}^2 + x_{3,t}, \quad (20)$$

where $c_0 \equiv (\beta + \mu_0 - \sigma_{c,3}^2)$, which we assume to be 0, and $c_j \equiv \bar{\lambda}_j \sigma_{c,j} - \sigma_{c,j}^2 (j = 1, 2)$. We note $c_1 < 0$ and $c_2 > 0$ with $\bar{\lambda}_2 > \sigma_{c,2}$ ⁶, that represent the investor's

⁶ $\bar{\lambda}_2 > \sigma_{c,2}$ implies that the extent of the optimism $\bar{\lambda}_2 > 0$ is larger than the risk from the second risk-source (i.e. volatility of the second Brownian motion).

conservative and optimistic attitudes, respectively. As a result, $c_1 x_{1,t}^2 < 0$ and $c_2 x_{2,t}^2 > 0$ have negative and positive impact on the interest rate r , respectively. These initial impacts fade away, so that $x_{1,t}^2$ eventually increases (steepening) and $x_{2,t}^2$ eventually decreases (flattening).

Under the specification in this section, the interest rate model becomes to consist of (1) x_1^2 , a transitory, bull-steepening-shock factor based on conservative attitude assuming the worst-case, (2) x_2^2 , a transitory, bear-flattening-shock factor based on optimistic attitude assuming the best case, and (3) x_3 , the level factor representing the permanent changes in fundamentals.

We also note that under $Q \equiv Q^{\lambda^*}$, the state variable $x_{j,t} (j = 1, 2, 3)$ are the solutions to the SDEs:

$$\begin{cases} dx_{j,t} = -\kappa_j^Q x_{j,t} dt + \sigma_{x,j} dB_{j,t}^{Q^{\lambda^*}}, (j = 1, 2), \\ dx_{3,t} = \lambda_3^Q dt + \sigma_{x,3} dB_{3,t}^{Q^{\lambda^*}}, \end{cases}$$

where $\kappa_j^Q := \kappa_j^P + \sigma_{x,j} \sigma_{c,j} > 0 (j = 1, 2)$ and $\lambda_3^Q := -\sigma_{x,3} \sigma_{c,3}$.

Then, based on (15), we obtain time- t zero coupon bond price and zero yield with maturity τ , denoted respectively by $P_t(\tau)$ and $Y_t(\tau)$ as follows⁷:

$$\begin{aligned} P_t(\tau) &= E_t^Q \left[e^{-\int_t^{t+\tau} r_u du} \right] \\ &= \exp[-\tau \{X_{1,t}(\tau) + X_{2,t}(\tau) + X_{3,t}(\tau)\}], \end{aligned} \quad (21)$$

$$Y_t(\tau) = X_{1,t}(\tau) + X_{2,t}(\tau) + X_{3,t}(\tau), \quad (22)$$

where

$$X_{j,t}(\tau) = \frac{-1}{\tau} [A_j(\tau) + C_j(\tau) x_{j,t}^2], (j = 1, 2) \quad (23)$$

$$X_{3,t}(\tau) = x_{3,t} + \frac{\lambda}{2} \tau - \frac{\sigma_3^2}{6} \tau^2, (\sigma_3 \equiv \sigma_{x,3}). \quad (24)$$

Here, with $c_1 \in [-(\kappa_1^Q)^2 / \sigma_1^2, 0)$, $c_2 > 0$ and $\sigma_j \equiv \sqrt{2} \sigma_{x,j} (j = 1, 2)$, the functions $C_j(\tau) (j = 1, 2)$ are defined as

$$\begin{aligned} C_j(\tau) &= C_{0j} + \frac{1}{z_j(\tau)}, \\ C_{0j} &= \frac{\kappa_j^Q + \sqrt{(\kappa_j^Q)^2 + c_j \sigma_j^2}}{\sigma_j^2}, \\ z_j(\tau) &= \frac{\sigma_j^2}{\alpha_j} - e^{\alpha_j \tau} \left(\frac{1}{C_{0j}} + \frac{\sigma_j^2}{\alpha_j} \right), \\ \alpha_j &= 2(\kappa_j^Q - \sigma_j^2 C_{0j}), \end{aligned}$$

and $A_j(\tau), j = 1, 2$ as

$$\begin{aligned} A_j(\tau) &= \frac{\sigma_j^2}{2} \int_0^\tau C_j(s) ds \\ &= \frac{1}{2} \left\{ \left(\kappa_j^Q + \frac{\alpha_j}{2} \right) \tau + \ln \frac{(1 + C_{2j})}{(1 + C_{2j} e^{\alpha_j \tau})} \right\} \end{aligned}$$

with $C_{2j} = \frac{\alpha_j}{\sigma_j^2} z_j(0) - 1$ and $z_j(0) = \frac{-1}{C_{0j}}$. We also remark that a condition $c_1 \geq -(\kappa_1^Q / \sigma_1)^2 (\sigma_1 \equiv \sqrt{2} \sigma_{x,1})$

⁷See Appendix B.2 in Nishimura et al. [3] and Appendix in Nakano et al. [8] for outlines of the derivation of (23) and (24), respectively.

is necessary for a zero coupon bond price to be well-defined.

C. STEEPENING AND FLATTENING FACTORS AND NEWS WORDS CORRELATED TO THE FACTORS

Given the three-factor model, our aim is to obtain word groups meaningful in terms of economics and finance, which are able to stand for steepening and flattening factors embedded in our interest rate model, in order to delineate what kind of events or changes of economic conditions drive these factors. Incorporating these textual data in the estimation, we can not only improve the fit of the estimation results, but also explain the change in the steepening and flattening factors in the plain language of economic news. To attain such an objective, we construct and estimate a state space model with state equations for the factors $x_j (j = 1, 2, 3)$ and observation equations for zero yields $Y_t(\tau)$ and word groups' frequencies relevant with steepening factor (x_1^2) and flattening factor (x_2^2), of which details will be given in the subsequent sections.

Before implementing this simultaneous estimation of the three factors and relevant word groups, we adopt a preliminary analysis that takes the following steps of which details will be shown in the subsequent sections:

- 1) Estimate factors in the interest rate model with observation equations only for the zero yields in our state space model (without "text mining".)
- 2) Find meaningful word groups based on a text mining and a regression analysis, whose frequencies have strong correlations with the estimated factors in Step 1).

We remark that in Step 1 above, we are unable to use our three-factor model, because the estimation of the three-factor model without text mining turns out to be unstable, mainly due to a strongly negative correlation between the estimated steepening and flattening factors. Thus, instead of the three-factor, we consider two-factor models with steepening & level factors (x_1^2 and x_3) and flattening & level factors (x_2^2 and x_3) for a preliminary analysis. More concretely, setting $c_1 \in -(\kappa_1^Q/\sigma_1)^2, 0]$ & $c_2 = 0$, or $c_1 = 0$ & $c_2 > 0$ in (20) provide two-factor models with (i) $r_t = c_1 x_{1,t}^2 + x_{3,t}$ or (ii) $r_t = c_2 x_{2,t}^2 + x_{3,t}$, respectively.

Hereafter, let us call the model with instantaneous short rate (i) as "two-factor steepening" that stands for steepening and level factors in the term structure of interest rates, and the model with (ii) as "two-factor flattening" that represents flattening and level factors. The corresponding zero yield with term τ is given by

$$Y_t(\tau) = X_{1,t}(\tau) + X_{3,t}(\tau) \quad (25)$$

for "two-factor steepening", and

$$Y_t(\tau) = X_{2,t}(\tau) + X_{3,t}(\tau) \quad (26)$$

for "two-factor flattening", where $X_{j,t}(\tau) (j = 1, 2)$ and $X_{3,t}(\tau)$ are defined as the equations (23) and (24).

III. PROCEDURE OF EMPIRICAL ANALYSIS

A. OVERVIEW

First, Figure 1 shows the overview of our procedure.

This empirical study has three major parts as follows.

- 1) **Preliminary two-factor models (level and steepening/level and flattening)**: We estimate factors with Monte Carlo filter to obtain preliminary steepening/flattening factor time series, respectively.
- 2) **Text mining**: From big text data, we extract key word groups whose frequencies are strongly correlated with the preliminary steepening and flattening factors obtained in 1).
- 3) **Three-factor model (level, steepening, and flattening)**: With Monte Carlo filter⁸, we estimate three factors that simultaneously explain time series of the yield curve and key word groups' frequencies obtained in 2).

B. STATE SPACE MODELS

The two-factor and a three-factor models are estimated in a state space framework shown below, where system equations describe a discretization of state variables $x_j (j = 1, 2, 3)$ in (18).

[Two factor steepening model]

In the case of the two-factor steepening model, state variables are the steepening factor and the level factor. In observation equations, we monitor 10-2y spread, 20-10y spread, 20y rate and 30y rate.

(System equation)

$$x_{1,t} = e^{-\kappa_1^P \Delta t} x_{1,t-\Delta t} + \frac{\sigma_1}{\sqrt{2}} \sqrt{\frac{1-e^{-2\kappa_1^P \Delta t}}{2\kappa_1^P}} \epsilon_{1,t} \quad (27)$$

$$x_{3,t} = x_{3,t-\Delta t} + \sigma_3 \sqrt{\Delta t} \epsilon_{3,t} \quad (28)$$

where $\epsilon_{i,t} \sim i.i.d.N(0, 1), i = 1, 3$ and we set Δt as $1/250$.

(Observation equation)

$$Y_t(10) - Y_t(2) = \sum_{l=1}^3 \{X_{l,t}(10) - X_{l,t}(2)\} + e_{t,10-2y}$$

$$Y_t(20) - Y_t(10) = \sum_{l=1}^3 \{X_{l,t}(20) - X_{l,t}(10)\} + e_{t,20-10y}$$

$$Y_t(20) = \sum_{l=1}^3 X_{l,t}(20) + e_{t,20y}; Y_t(30) = \sum_{l=1}^3 X_{l,t}(30) + e_{t,30y} \quad (29)$$

$X_{1,t}(\tau), X_{2,t}(\tau)$ and $X_{3,t}(\tau)$ are defined on (23) and (24). In two-factor steepening model, $X_{2,t}(\tau) \equiv 0$. Here, we assume $e_{t,j} \sim i.i.d.N(0, \gamma_j^2), (j = 10 - 2y, 20 - 10y, 20y, 30y)$.

⁸For an algorithm of Monte Carlo filter, see Section 3 in the Online appendix, CARF-F-470 [34]

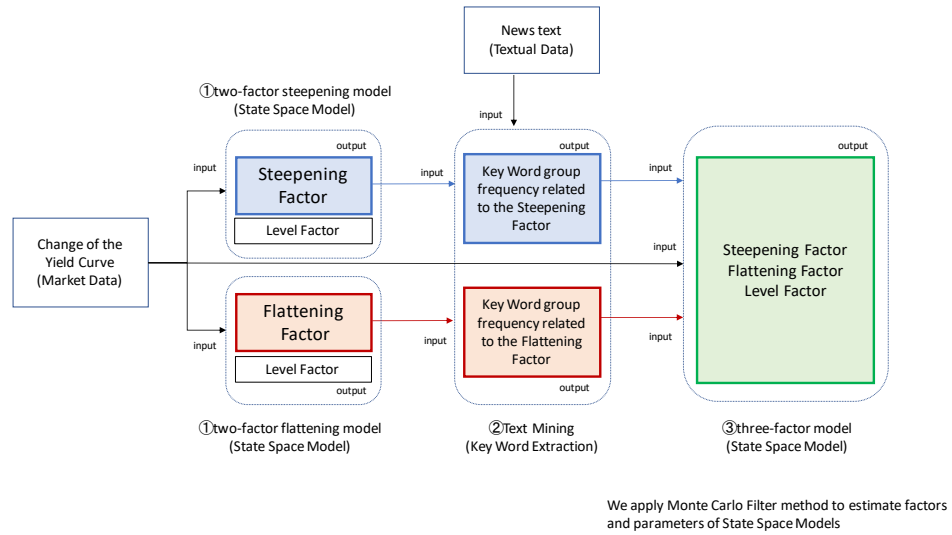


FIGURE 1. Overview of the proposed empirical study procedure.

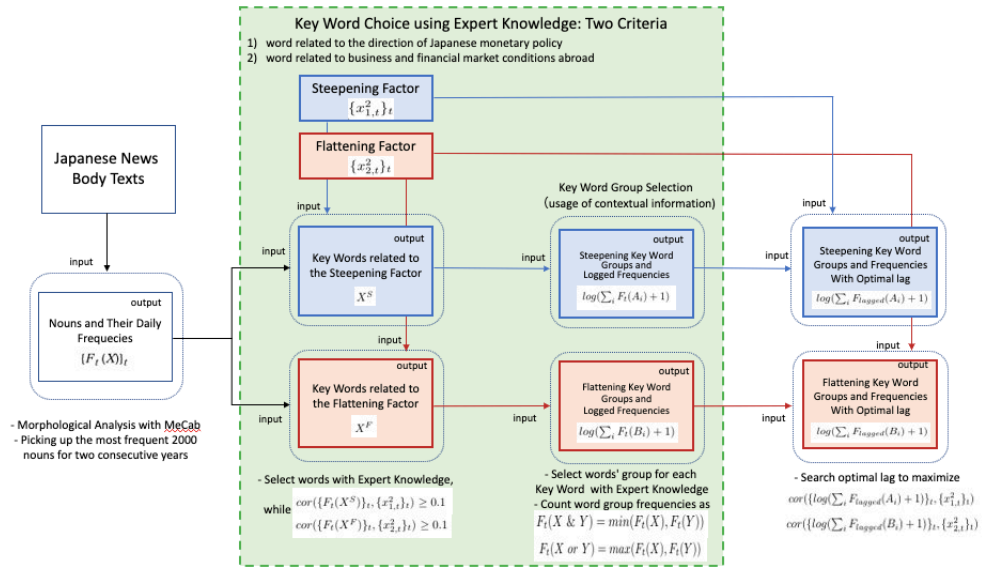


FIGURE 2. Overview of the text mining procedure.

[Two factor flattening model]

In the two-factor flattening model below, state variables are the flattening factor instead of the steepening factor, and level factor.
 (System equation) The equation (28) for $x_{3,t}$, and (27) is replaced by

$$x_{2,t} = e^{-\kappa_2^P \Delta t} x_{2,t-\Delta t} + \frac{\sigma_2}{\sqrt{2}} \sqrt{\frac{1 - e^{-2\kappa_2^P \Delta t}}{2\kappa_2^P}} \epsilon_{2,t} \quad (30)$$

(Observation equation)
 (29) with $X_{1,t}(\tau) \equiv 0$.

[Three-factor model]

In the three-factor model, state variables are the steepening factor, the flattening factor and the level factor. In observation equations, in addition to rates and spreads, we observe the log frequencies of key word groups with the optimal lag obtained by text mining.

(System equation) The equations (27), (30) and (28) for $x_{1,t}$, $x_{2,t}$ and $x_{3,t}$, respectively.

(Observation equation)

In addition to (29), we define additional observation equations of lagged-word frequencies with optimal lag:

with notations in Step 9) of Section III-C below,

$$\log\left(\sum_i \text{Flagged}(A_i) + 1\right) = \xi_{1,c} + \xi_1 x_{1,t}^2 + e_{t,w1}, \quad (31)$$

$$\log\left(\sum_i \text{Flagged}(B_i) + 1\right) = \xi_{2,c} + \xi_2 x_{2,t}^2 + e_{t,w2}. \quad (32)$$

We remark that the procedure described in Figure 1 is explained more in detail as follows. Firstly, we find groups of words correlated to the steepening/flattening factor by using the two factor steepening/flattening model (27)-(30). Then, we use the groups of words together with the yield curve data as variables in observation equations of the three-factor model (27)-(32). In the model, x_1 (x_2) is a transitory Gaussian factor with a zero mean-reversion level, and x_1^2 (x_2^2) affects the short rate negatively (positively), while x_3 is a Gaussian level factor representing economic fundamentals. Particularly, since x_1^2 has a negative coefficient and x_3 is a Gaussian random variable, this short rate can take negative values and represent negative interest rates. As a result, we will observe that incorporation of the frequencies for relevant word groups chosen from textual data into the observation equations enhances the model fitting (See Table 5 in Section IV-C and an explanation below the table). Moreover, we can identify which factors affected movements in particular parts of the yield curve (e.g. the 20-10 and the 10-2 year yield spread) and what words were behind the changes (Tables 6 and 7 in Section IV-C). Finally, in Section IV-D, by using a regression analysis on a stock market index, we will confirm that the steepening (x_1^2) and the flattening (x_2^2) factor correspond to pessimistic and optimistic market sentiments, respectively, and those factors with the level factor (x_3) are capable of explaining movement of the stock market index.

C. TEXT MINING

This subsection explains how news words and word groups are selected to be used in observation equations. Figure 2 shows an overview of our text mining procedure. We take financial and economic news in Japanese from publicly available data at the Reuters Japan site. We use news data from January 1st 2012 to December 31st 2017.⁹ We show the procedure of our text mining method below:

- 1). In each year, we apply a morphological analysis to all the news sentences and decompose each news into words by using MeCab software to select only nouns, though they include the ones with adjectival usage. Then, we remove symbols, only-one-character words and numbers.
- 2). In each year, we count the word frequencies for all the words and pick up those included in the top 2,000 list for two consecutive years or more (for example, for both of 2013 and 2014) in terms of their frequency of appearance.
- 3). We count the daily (day- t) appearance frequency of each picked-up word to get its time series, denoted by $\{F_t(X)\}_t$ for word X , where day- t is determined based on Japan Standard Time (JST).
- 4). In each period of Jan 2012 - Dec 2015 and Jan 2016 - Dec 2017, we calculate the correlation between time series of daily appearance frequencies of each picked-up word and each factor estimated by the two-factor models of the preliminary analysis. Then, we make the list of words for each factor each period, whose correlations with the factor are equal to or greater than 0.1.
- 5). Next step is to choose key words for each factor each period. For the words showing correlation stronger than 0.1 with the steepening/flattening factor, we arrange them in descending order and carefully choose the most meaningful words, which affected the JGB yield curve, from the words particularly showing stronger correlations. We examine which news word in the lists is important in that events regarding the word have significant impacts on the changes in the future interest rates. We note that it is difficult to determine it automatically through some rules, (partly) because a strong correlation does not necessarily mean the importance of the word. However, we, one former Central Banker and three former market participants have expert knowledge based on our own past experiences and market participants' remarks collected from portfolio managers of hedge funds and others who are actively participating in Japanese government bond markets. We know events strongly affecting steepening/flattening of Japanese interest rates are those of the following two kinds:
 - Events indicating directions of the Japanese monetary policy.
 - Events indicating business & financial market conditions abroad.
- 6). Firstly, following criteria of 5), we select two to three words associated with major events triggering changes in the yield curve for each factor each period. Secondly, we examine contextual information about the selected word to make it sure that our word choices are appropriate. In the paragraphs including the selected word, we search for additional word(s) which, in combination with the selected word, explain the importance of the event more clearly. Then, for each originally selected noun indexed by i ($i = 1, 2, \dots$), we obtain sets of word

⁹we do not have the news data for the year 2018 because the historical news page in Reuters Japan has been closed.

groups $\{A_i\}_i$ for a steepening factor and $\{B_i\}_i$ for a flattening factor.

- 7). Then, we define and count the daily appearance frequency of each word group $\{A_i\}_i$ ($\{B_i\}_i$) that consists of an originally selected noun and the relevant word groups chosen through the procedure explained above to get its time series $\{F_t(A_i)\}_t$ ($\{F_t(B_i)\}_t$) for a steepening factor (for a flattening factor). Let us explain it more precisely by using an example: When an originally selected noun is "crisis", we pick up meaningful idioms including "crisis" in each news that contains noun "crisis" at day- t . For instance, we choose "financial crisis" and "debt crisis" as those idioms. Then, we search country names relevant with "financial crisis" and "debt crisis", which turns out to be "Greece" and "Spain", for example. Hence, we have A_i as $A_i = \{\text{"crisis"}, \text{"Greece"}, \text{"Spain"}, \text{"financial"}, \text{"debt"}\}$. Next, we calculate appearance frequencies, $F_t(\text{"crisis"})$, $F_t(\text{"Greece"})$, $F_t(\text{"Spain"})$, $F_t(\text{"financial"})$ and $F_t(\text{"debt"})$.

Then, let

$$F_t(\text{"Greece or Spain"}) = \max\{F_t(\text{"Greece"}), F_t(\text{"Spain"})\},$$

and

$$F_t(\text{"financial or debt"}) = \max\{F_t(\text{"financial"}), F_t(\text{"debt"})\}.$$

Finally, we define $F_t(A_i)$ as

$$F_t(A_i) = \min\{F_t(\text{"crisis"}), F_t(\text{"Greece or Spain"}), F_t(\text{"financial or debt"})\}.$$

- 8). Then, as long as the correlation of time series between $\log(\sum_i F_t(A_i) + 1)$ and a steepening factor becomes stronger than the one between $\log(\sum_i F_t(A_i) + 1)$ without $F_t(A_j)$ and the steepening factor, we adopt a word group A_j , otherwise we do not adopt it to obtain time series $\{\log(\sum_i F_t(A_i) + 1)\}_t$.

Similarly, we get time series $\{\log(\sum_i F_t(B_i) + 1)\}_t$ for a flattening factor.

- 9). We search the optimal lag for each word group frequency maximizing the correlation between $\{\log(\sum_i F_t(A_i) + 1)\}_t$ and the steepening factor $x_{1,t}^2$ and the correlation between $\{\log(\sum_i F_t(B_i) + 1)\}_t$ and the flattening factor $x_{2,t}^2$. More concretely, for each word group, the n -days lagged word frequency $F_{n-lagged}(A_i)$ or $F_{n-lagged}(B_i)$ is defined as:

$$\begin{aligned} F_{n-lagged}(A_i) &= F_{t-n}(A_i), \\ F_{n-lagged}(B_i) &= F_{t-n}(B_i), \end{aligned}$$

$n = 10, 20, \dots, 100$. Then, we choose the combination of the lags maximizing the correlation between $\{\log(\sum_i F_t(A_i) + 1)\}_t$ and $x_{1,t}^2$ ($\{\log(\sum_i F_t(B_i) + 1)\}_t$ and $x_{2,t}^2$), and define the optimal $F_{n-lagged}(A_i)$ ($F_{n-lagged}(B_i)$) as

$$F_{lagged}(A_i) \text{ (} F_{lagged}(B_i)\text{)}.$$
¹⁰

- 10). We use time series $\{\log(\sum_i F_{lagged}(A_i) + 1)\}_t$ and $\{\log(\sum_i F_{lagged}(B_i) + 1)\}_t$ in an observation equation for a steepening factor and a flattening factor, respectively.

Remark 1. *On the text mining technique, our main purpose of this study is to explain the steepening and the flattening factor in our three factor interest rate model by word groups within financial news in Japanese, which are proxy for market sentiments. As in Section 2.2 in Li et al. [36], due to complexity of languages, judging the meaning of words by a syntax analysis in the context of financial news, is a difficult problem. This seems especially the case in the Japanese language. Thus, we focused on incorporating markets sentiments in an interest rate model by appropriately choosing words from financial news in Japanese, which affected the yield curve movements, rather than exploring automated extraction methods of sentimental and influential words in financial news. Owing to the carefully chosen words having strong correlations with the steepening or the flattening factor, transitions of the word frequencies vividly exhibit relationships with the factor and specific parts of the yield curve, such as the 20-10 and the 10-2 year yield spread as in Section IV-C. Developing an elaborate text mining method in the selection of meaningful words that affect movements of yield curves is one of our future research topics.*

Remark 2. *For the multi-variate analysis using global market data, it can happen that the JGB yield curve is affected by foreign market events. In our model, in addition to the JGB yield curve data, which are the primary information used to estimate our model, we utilize frequencies of words on not only domestic but also foreign market events to take such effects into account. In detail, while the third Gaussian factor on the level, which is explained mainly by JGB yield curve data, reflects economic fundamentals, the first two factors represent market sentiments estimated by frequencies of words appropriately chosen from financial news in Japanese including events on foreign markets. Building a model that incorporates the foreign market data as additional information is also one of our future research topics.*

IV. EMPIRICAL ANALYSIS RESULT

¹⁰News reports are often about anticipation of possible events in the future. Thus, it sometimes happens that appearance of particular news words of, say, a month ago is strongly correlated with today's events. We take account of this nature of news reports using search for the optimal lag.

A. ESTIMATION RESULT FOR TWO-FACTOR MODEL

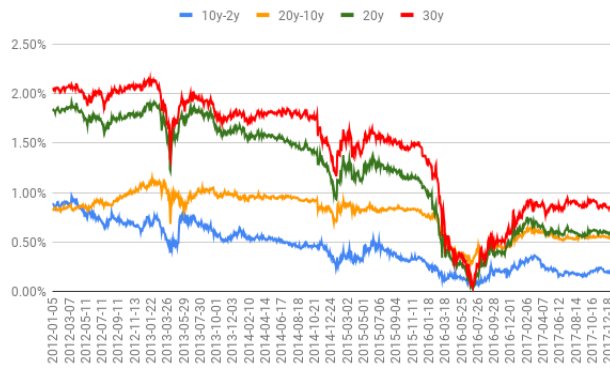


FIGURE 3. Plot of 20y zero rate, 30y zero rate, 10-2y spread and 20-10y spread during the period Jan 2012 - Dec 2017

First, Figure 3 shows the historical changes in zero yields and spreads, namely, 20 and 30 year zero yields, 10-2 and 20-10 year spreads in the whole estimation period. Here, we use the daily zero yields of Japanese Government Bond (JGB) from January 4th 2012 to December 30th 2017. The zero yields are estimated from par rate data available on the website of Ministry of Finance (MOF) Japan, with a cubic spline and a bootstrap method.¹¹ The time series plot indicates that the Japanese interest rate environment has drastically changed since Jan 2016.

	10y-2y	20y-10y	20y	30y	average
Jan 2012- Dec 2017	5.6	12.4	6.4	6.4	8.2
Jan 2012- Dec 2015	5.5	6.8	5.1	4.9	5.6
Jan 2016- Dec 2017	1.4	8.3	5.6	6.9	6.1

TABLE 1. Square-root of mean squared errors (RMSEs) of estimated yields and spreads by two-factor flattening model for the whole period, the former sub-period and the latter sub-period (basis points (bps))

Table 1 shows the estimation errors (RMSEs) of estimated yields and spreads in estimation by two-factor steepening model. As expected, we find that the estimation precision improves by dividing the whole period into two sub-periods. We obtain a similar result for our 2-factor flattening model.

B. TEXT MINING RESULT

Tables 2 and 3 show the events represented by word groups selected based on the text mining in Section III-C.

We remark that for the selected word groups, the following analyses indicate that their word frequencies move together with the relevant yield spread.

Firstly, Tables 2 and 3 also provide qualitative explanations on relations between the word groups and interest rate movements. In detail, the tables explain that an increase in the frequency of A_i (B_i) indicates an increase (a decrease) in the interest rate. Particularly, for some word groups ("Substantial monetary easing" (B_1 in Table 2), "Crude oil decline/crash" (B_2 in Table 2), "Criticism of monetary easing" (A_1 in Table 3), "Tax reduction in U.S." (A_3 in Table 3), and "Negative interest rate in Japan" (B_1 in Table 3)), Table 4, showing excerpts from JGB annual market reports published by MOF ([37]- [42]), explain cause-and-effect relationships between events on these word groups and the yield curve movements. Then, for these word groups, combined with Table 4, Tables 2 and 3 qualitatively explain the steepening (flattening) effects on the yield curve by the events on the word groups A_i (B_i).

Moreover, Figures 4-7 display decomposition of the frequencies by word groups. Since the frequency of each word group accounts for a part of the factor movement, the resulting total frequencies of the word groups explain the entire factor movement, which leads to the strong correlations with the steepening or flattening factor in the two-factor model, as indicated in the captions of Figures 4-7.

Furthermore, Figures 8-11 in Section IV-C show that the frequencies of the word groups move together with the relevant yield spread as well as the estimated steepening or flattening key word frequency (equivalently, the estimated steepening or flattening factor) in the three-factor model in Section III-B.

¹¹See, for example, Nakano et al. [8] for the details.

Key Word Group	Optimal Lag	Description
A ₁ : European debt (financial) crisis	90 days	News about "European debt (financial) crisis" indicated that interest rates in debt-ridden European countries would rise up. This might put upward pressure on interest rates of the most debt-ridden country (Japan) through the global financial linkage, though with some time-lag.
A ₂ : overcoming deflation	0 days	News concerning "overcoming deflation" might suggest Japanese interest rates would rise up eventually, since after overcoming deflation the ultra-easy monetary policy would be normalized to raise interest rates from extraordinary low levels.
B ₁ : substantial monetary easing	70 days	News related to "substantial monetary easing" might imply that the current strong monetary easing would continue or further stronger monetary policy would be introduced in the near future. This would put downward pressure on Japanese interest rate. In fact, Abe's Cabinet had been sending strong messages on this issue more than two months before Kuroda became the governor of the Bank of Japan. Thus, market participants were likely to expect the substantial monetary easing well before actual implementation.
B ₂ : crude oil & (decline or crash)	0 days	Global news about "crude oil (price) decline or crash" implied world-wide deflationary pressure. The central bank had to introduce further monetary easing to counter this global slow growth and deflation. This would put direct downward pressure on Japanese interest rate.

TABLE 2. Text mining result for Jan 2012 - Dec 2015.

Key Word Group	Optimal Lag	Description
A ₁ : criticism of monetary easing	10 days	News about "criticism of monetary easing" indicated that the side effects of the extraordinary monetary easing were pointed out, implying the prospect of no more cutting rates was increased. This might suggest future rate increases.
A ₂ : reduction of crude oil production	0 days	Global news about "reduction of crude oil production" implied a turn-around of the global economy and easing deflationary pressure worldwide. Then, the central bank might weaken its strong monetary easing bias because of easing deflationary pressure, which implies upward pressure on Japanese interest rates in the near future.
A ₃ : tax reduction in U.S.	20 days	News about "tax reduction in U.S." indicated that US budget deficits would rise in coming years, which put upward pressure on US rates in the future. Prospects of rising US rates would put upward pressure on Japanese interest rates through the financial market interaction. This indirect effect could occur with some time-lag.
B ₁ : negative interest rate policy in Japan	70 days	News about "negative interest rate in Japan" were those of the Bank of Japan's introduction of the negative interest rate to break the zero floor of the policy rate. This implied the Bank had room for more rate cuts in the future, putting strong downward pressure on Japanese interest rates. However, market participants might need some time to confirm the feasibility of further cuts and their sustainability.
B ₂ : (Consumption) tax increase in Japan	90 days	(Consumption) tax increases had brought negative effects on the economy in the past in Japan. Thus, news about (consumption) tax increase would enhance the expectations of further monetary easing to counter the negative effects. This information would put downward pressure on Japanese interest rates. The political debate took place well in advance of actual implementation of taxes, so that there was time-lag between news and actual implementation.

TABLE 3. Text mining result for Jan 2016 - Dec 2017.

Key Word Group	Description
<p><i>B₁</i>: substantial monetary easing (Jan 2012- Dec 2015)</p>	<p>JGB yields fell with the trend of the yen's appreciation and stock price falls under such global financial market and economic trends. <i>Under this situation, the BOJ introduced "Supplementary Measures for Quantitative and Qualitative Monetary Easing" in December to facilitate the "Quantitative and Qualitative Monetary Easing" policy.</i> While maintaining its policy of "purchasing JGBs so that their amount outstanding will increase at an annual pace of about 80 trillion yen," the BOJ implemented these supplementary measures in preparation for an increase in the gross amount of its JGB purchases that was expected to come in 2016 due to an expansion in the redemption of JGBs at maturity. <i>In response to the supplementary measures, JGB market participants increasingly expected the BOJ to purchase longer-term JGBs, leading to drops in super long-term JGB yields including the 20-year JGB yield that slipped below 1.0 %.</i> (FY2015, 1. Trends of JGB Market in FY2015 (1) Yields continued a downtrend)</p>
<p><i>B₂</i>: crude oil & (decline or crash) (Jan 2012- Dec 2015)</p>	<p>As well as the BOJ's massive JGB purchases, the crude oil price plunge has been cited as one of the factors behind the JGB yield decline in the second half. The benchmark crude oil price, which had stood above \$100 per barrel, started to plunge in the summer of 2014 and hit a low of around \$45 in January 2015. <i>Long-term bond yields dropped not only in Japan</i> but also in other countries. <i>Some people attributed the long-term bond yield decline to a flow of funds for crude oil investment into government bond markets.</i> Later, the benchmark crude oil price stopped its downslide and stood at around \$55 at the end of FY2014. (FY2014, (1) Trends of JGB Market, C. Long-term JGB yield remains volatile after hitting a new low)</p>
<p><i>A₁</i>: criticism of monetary easing (Jan 2016- Dec 2017)</p>	<p>While the interest rate hike in Japan was limited to a relatively low level under the BOJ's yield curve control, the JGB market was influenced by the BOJ's first ever fixed-rate JGB-purchase operation (November 17) and changes to its JGB purchases in the super long-term zone (December 14 and 28) under growing upward pressure on interest rates. <i>The BOJ's failure to implement a market-expected JGB-purchase operation in the medium-term zone in late January and weak results of a 10-year JGB auction in February led the 10-year JGB yield to rise to a one-year high of 0.150%</i> briefly on February 3. (FY2016, 1. Trends of JGB market in FY 2016, (1) Review)</p>
<p><i>A₂</i>: tax reduction in U.S. (Jan 2016- Dec 2017)</p>	<p>From the second half of December, U.S. and other stock indexes rose to record highs, with European and U.S. bond yields rising, as <i>the enactment of the U.S. Tax Cuts and Jobs Act</i> was expected to trigger an economic pickup. <i>In the JGB market, yields mainly in the super long-term zone increased</i> as speculations about Japan's monetary policy normalization grew mainly among foreign investors on the BOJ's cut in JGB purchase operations for the zone in early January. <i>As the 10-year JGB yield rose to 0.095%</i> following foreign bond yields hike, the BOJ conducted a fixed-rate JGB-purchase operation for the long-term zone (with no bids made) on February, global bond yield hikes paused as Japanese and other stock markets plunged with volatility increasing. (FY2017, 1. Trends of JGB Market in FY2017, (1) Review)</p>
<p><i>B₁</i>: negative interest rate policy in Japan (Jan 2016- Dec 2017)</p>	<p>As JGB yields decreased sharply on the 10-year JGB yield's first-ever entry into the negative zone due to the BOJ's introduction of "Quantitative and Qualitative Monetary Easing with a Negative interest Rate" in January 2016, <i>the yield curve flattened amid investors' purchases of longer-term JGBs</i> in pursuit of positive yields. (FY2016, 1. Trends of JGB market in FY 2016, (1) Review)</p>

TABLE 4. Relations between word groups and the JGB yield curve. Excerpts from JGB annual market report (MOF [37]- [42])

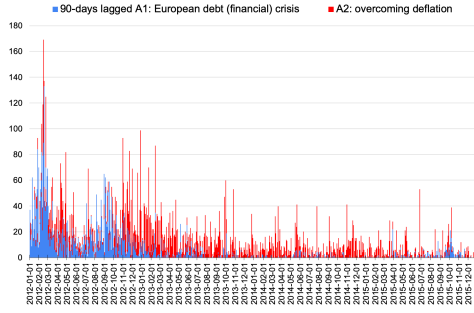


FIGURE 4. Lagged frequencies of relevant words of the steepening factor($\{F_{lagged}(A_i)\}_t$) in Jan 2012 - Dec 2015 (Corr.0.57)

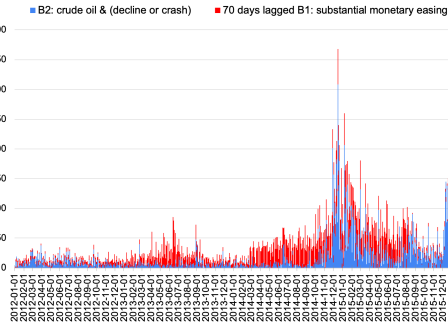


FIGURE 5. Lagged frequencies of relevant words of the flattening factor($\{F_{lagged}(B_i)\}_t$) in Jan 2012 - Dec 2015 (Corr.0.63)

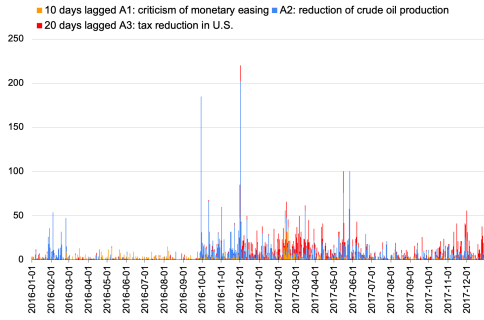


FIGURE 6. Lagged frequencies of relevant words of the steepening factor($\{F_{lagged}(A_i)\}_t$) in Jan 2016 - Dec 2017 (Corr.0.53)

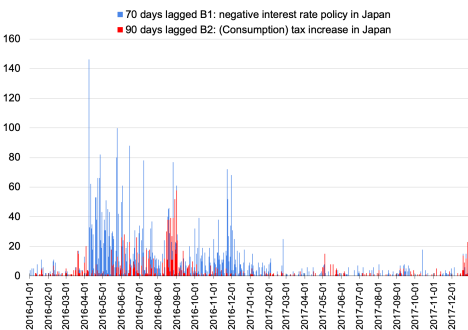


FIGURE 7. Lagged frequencies of relevant words of the flattening factor($\{F_{lagged}(B_i)\}_t$) in Jan 2016 - Dec 2017 (Corr.0.55)

C. ESTIMATION RESULTS FOR THREE-FACTOR MODEL

This subsection summarizes the estimation result for our three-factor interest rate model with word group frequencies.¹² Particularly, changes in the correlations between spreads and factors are important, since they indicate changing investor influences between periods. In addition, if some keywords are shown to be "leading" the factors, then such information may be used to predict the change in the corresponding factor.

	10y-2y	20y-10y	20y	30y	average
(i) Jan 2012- Dec 2015	5.9	6.4	5.0	4.6	5.5
(ii) Jan 2016- Dec 2017	4.2	5.3	5.7	6.6	5.5

TABLE 5. Square root of mean squared errors (RMSEs) of estimated yields and spreads by three-factor model (basis points (bps))

Table 5 shows estimation errors (RMSEs) of the estimated yields and spreads. Although two observation equations regarding log-frequencies of the selected word groups are added in this case, they are almost equivalent to or slightly better than those for the two-factor models. (Two-factor models' average errors are (i) 5.6 bps & (ii) 6.1 bps for the steepening model (Table 1), and (i) 5.5 bps & (ii) 5.7 bps for the flattening model, respectively.)

	x_1^2	x_2^2	x_3
10y-2y	0.66	-0.69	0.92
20y-10y	0.81	0.13	0.63
20y	0.84	-0.52	0.99
30y	0.82	-0.5	0.98
$\log(\sum_i F_{lagged}(A_i) + 1)$	0.47	-0.35	0.57
$\log(\sum_i F_{lagged}(B_i) + 1)$	-0.34	0.67	-0.64

TABLE 6. Correlations between factors and rates, spreads & log-frequencies of word groups in Jan 2012- Dec 2015

	x_1^2	x_2^2	x_3
10y-2y	0.47	-0.35	0.70
20y-10y	-0.09	-0.80	0.96
20y	0.00	-0.72	0.96
30y	-0.14	-0.79	0.97
$\log(\sum_i F_{lagged}(A_i) + 1)$	0.56	-0.02	0.35
$\log(\sum_i F_{lagged}(B_i) + 1)$	0.23	0.61	-0.61

TABLE 7. Correlations between factors and rates, spreads & log-frequencies of word groups in Jan 2016- Dec 2017

Table 6 shows that the steepening factor x_1^2 has strongly positive correlations with 20 & 30 year yields and the 20-10 year spread, the flattening factor x_2^2 has a strongly negative correlation with the 10-2 year spread, and the level factor x_3 is strongly correlated with the 20 & 30 year yields. Table 7 shows that the steepening factor x_1^2 has a relatively strong correlation with the 10-2 year spread, the flattening factor x_2^2 has a strongly negative correlation with the 20-10 year spread, and the level factor x_3 are strongly correlated with the 30 & 20

¹²See Section 4 in the online appendix CARF-F-470 [34] for the details of parameter estimates.

year yields as well as with the 20-10 year spread.

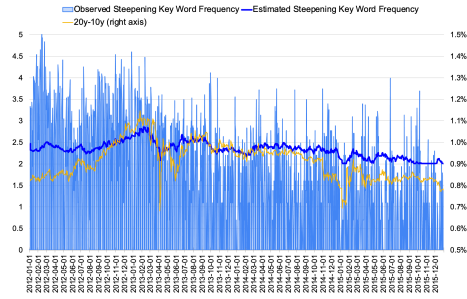


FIGURE 8. Observation and estimation of steepening key word group frequencies and 20-10y yield spread for Jan 2012- Dec 2015

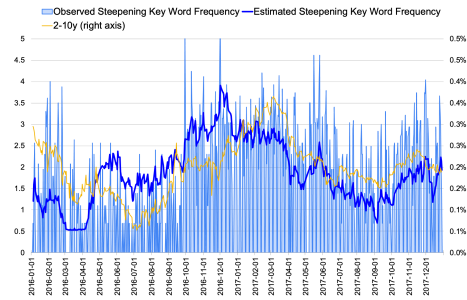


FIGURE 9. Observation and estimation of steepening key word group frequencies and 10-2y yield spread for Jan 2016- Dec 2017

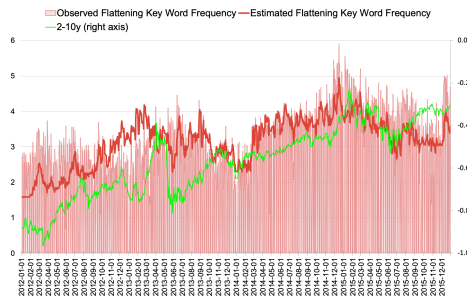


FIGURE 10. Observation and estimation of flattening key word group frequencies and 2-10y yield spread for Jan 2012- Dec 2015

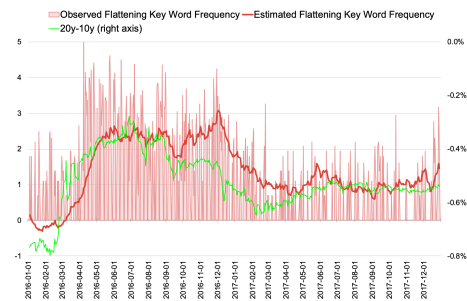


FIGURE 11. Observation and estimation of flattening key word group frequencies and 10-20y yield spread for Jan 2016- Dec 2017

Figures 8 and 9 show the time series plots of observed log-frequency, its estimate based on the steepening factor (x_1^2) and most relevant spreads 20-10y and 10-2y, respectively, while Figures 10 and 11 show the time series

plot of observed log-frequency, its estimate based on the flattening factor (x_2^2) and its most relevant spreads 2-10y and 10-20y, respectively.

In sum, we have two major findings.

- 1) Whereas the flattening factor (anticipating eventual decline of the interest rate) has a strongly negative correlation with 10-2 year spread in 2012-2015, it has a strongly negative correlation with 20-10 year spread in 2016-2017.

This suggests that investors who are concerned mostly with 10-2 year spread (that is, those who are concerned with interest rate changes in a business cycle) in 2012-2015 are more concerned with 20-10 year spread in 2016-2017, since the yield curve becomes very flat up to 10 year.

- 2) Whereas the steepening factor (anticipating eventual rise of the interest rate) has a strongly positive correlation with 20-10 year spread in 2012-2015, it is almost uncorrelated in 2016-2017. This may imply that the investors who are concerned mostly with 20-10 year spread (that is, those who are concerned with ultra-long rates) in 2012-2015 lose their importance in 2016-2017, and is overwhelmed by the investors mentioned in 1).

D. REGRESSION ANALYSIS

We have already shown that the model is capable of explaining the yield curve of the Japanese Government Bond (JGB) markets in an extraordinary period of extremely low interest rates under unconventional monetary policy. Then, a natural question arises: Are the factors we extract from the bond market also capable of explaining the stock market, where investor attitudes are supposedly most important elements?

To answer this question, we take the stock market price index of Nikkei 225 to test our model. This is because the index is considered to be the most barometric stock price index in the Japanese stock market, so that it is likely to reflect investors' sentiment in the most conspicuous way. In the remaining of this subsection, we proceed in a heuristic and empirical way. Specifically, we suppose a simple linear relationship between the stock price and factors:

$$S_t = a + bx_{3,t} + d_1x_{1,t}^2 + d_2x_{2,t}^2, \quad (33)$$

where we expect the coefficients' signs as follows: negative for the conservative factor $x_{1,t}^2$, positive for the optimistic factor $x_{2,t}^2$ and positive for the interest rate's level factor $x_{3,t}$, namely, $b > 0$, $d_1 < 0$, and $d_2 > 0$. Then, our base empirical model is given for period k as

$$S_{k,t} = a_k + b_kx_{3,t} + d_{1,k}x_{1,t}^2 + d_{2,k}x_{2,t}^2 + \varepsilon_{k,t}.$$

However, the stock market specific factor may change occasionally by some events in stock markets (outside

of bond markets). To incorporate this possibility, we replace a_k with $a_{k,0} + \sum Dummy_{k,i}$, so that

$$S_{k,t} = a_{k,0} + \sum f_{k,i} Dummy_{k,i} + b_k x_{3,t} + d_{1,k} x_{1,t}^2 + d_{2,k} x_{2,t}^2 + \varepsilon_{k,t}. \quad (34)$$

One dummy variable represents one event which triggers the change in the stock price index. A positive dummy is a rise in the stock price index, while a negative dummy shows a fall in the stock price index. There are several events (i.e., stock market specific factors), which are likely to trigger the change in the stock price index for given factors. We use the following dummy variables for each period.

- 2012-2015: (1) Abenomics dummy (drastic expansionary policy with substantial monetary easing) takes the value 0 before Jan 4th 2013 and 1 after that date. (2) QQE2 dummy (further expansionary policy with strengthened easing) takes the value 0 before Oct 31st 2014 and 1 after that date.
- 2016-2017: (1) Negative Interest Rate Dummy (further expansionary policy with breaking the zero bound of policy rates) takes the value 0 before Jan 29th 2016 and 1 after that date. (2) Direct Cap1 Dummy (clear demonstration of expansionary policy stance by not allowing 5-year-less rates to rise to a positive range) takes the value 0 before Nov 16th 2016 and 1 after that date. (3) Direct Cap2 Dummy (further demonstration of expansionary policy stance by not allowing 10-year rates to rise over zero) takes the value 0 before February 17th 2017 and 1 after that date.

Then, the above linear multiple regression model (34) is estimated for each period separately by an ordinary least squares method. We summarize the result as follows¹³:

- First, with regarding to the steepening factor $x_{1,t}^2$, the flattening factor $x_{2,t}^2$ and the level factor $x_{3,t}$, we obtain the results that $b_k > 0$, $d_{1,k} < 0$, and $d_{2,k} > 0$ for both periods, as expected. These p -values are less than 0.01.
- Second, with regarding to dummy variables, we obtain the positive coefficient signs that we expect a priori. These p -values are also less than 0.01 except for "Negative Interest Rate Dummy" whose p -value is less than 0.05.
- Thus, all the explanatory variables are statistically significant and their coefficient signs are the ones we expect a priori.
- Finally, we report adjusted R^2 as 93.0% and 80.2% for the periods 2012-2015 and 2016-2017, respectively, where the p -values for F -Statistics are less than 0.01 for all the periods.

¹³See Section 5 in the online appendix CARF-F-470 [34] for the details.

We remark that we incorporate the dummy variables in the regression analysis so that the steepening and flattening factors explain the movements of the stock index well. The reduction in heteroskedasticity when we incorporate the dummy variables into the regression also strengthens the effectiveness of the steepening and flattening factors as explanatory variables. Figures 12-15, which will be provided in Appendix, are scatter diagrams in which differences between the squares of the residual terms of the samples in the regression and those means are plotted. These figures show that the variance of the residual terms reduces if we incorporate the dummy variables in the regression, though the samples are not necessarily homoskedastic (see Appendix for details).

V. CONCLUDING REMARKS

The contributions of this work are summarized as follows: First, our theoretical framework is able to explain the daily changes of the yield curve very well for years, even under sometimes drastically-changing unconventional policies of the Bank of Japan with direct and massive intervention in some cases.

Second, our analysis with a text mining method has revealed that transitory steepening and flattening factors, which are influenced by investors' attitudes toward fundamental uncertainty about transitory changes in the economy, are important determinants of the daily changes of the yield curve, as well as the level factor, which represents permanent changes.

Third, we have shown that the estimated level, steepening, and flattening factors, which are extracted only from the Japanese government bond (JGB) market, are able to explain the stock market movement (market price index of Nikkei 225), where investors' risk-on, risk-off status is most vividly represented.

APPENDIX. BREUSCH-PAGAN TEST

In this appendix, we conduct the Breusch-Pagan (BP) test for heteroskedasticity of our regression results in Section IV-D for the period 2012-2015 ($n = 981$) and 2016-2017 ($n = 492$). For this test, we use the `bptest` function within the `lmtest` library in R.

Tables 8-9 show the test results. We observe that the p -value are below $2.2e-16$ for the both period with or without Dummy variables. Although the null hypothesis that the samples are homoskedastic is rejected, the test statistic in the case of with the dummy variables is lower than the case without them. This indicates that the heteroskedasticity of the samples reduces if we incorporate the dummy variables into the regression.

	Test Statistic	p.value
without Dummy	129.32	<2.2e-16
with Dummy	84.646	<2.2e-16

TABLE 8. BP Test Result for 2012-2015

	Test Statistic	p.value
without Dummy	164.59	<2.2e-16
with Dummy	88.661	<2.2e-16

TABLE 9. BP Test Result for 2016-2017

Moreover, Figures 12-15 show the scatter plot for estimation of the Japanese stock market price index (horizontal) versus the regression residuals (vertical). We observe less heteroskedasticity in the case of the regression with dummy variables.

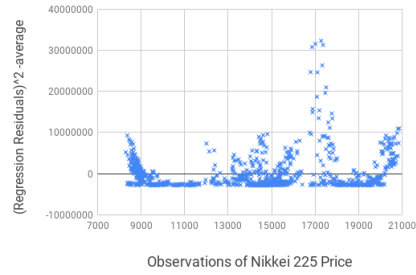


FIGURE 12. Scatter plot of observations and squared residuals without Dummy variables for Jan 2012- Dec 2015

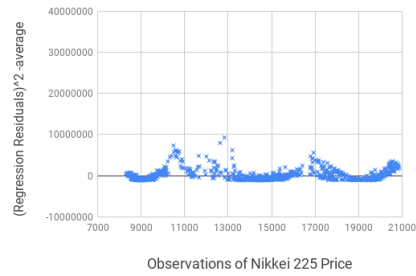


FIGURE 13. Scatter plot of observations and squared residuals with Dummy variables for Jan 2012- Dec 2015

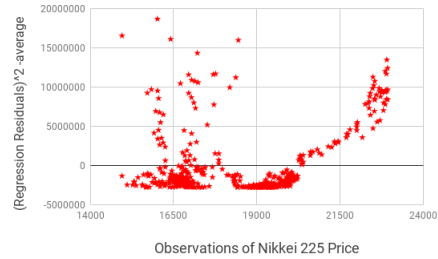


FIGURE 14. Scatter plot of observations and squared residuals without Dummy variables for Jan 2016- Dec 2017

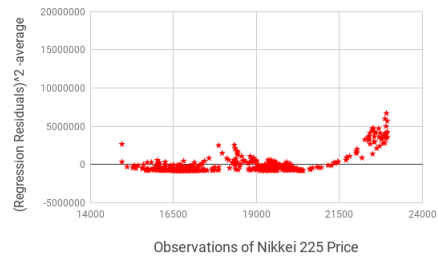


FIGURE 15. Scatter plot of observations and squared residuals with Dummy variables for Jan 2016- Dec 2017

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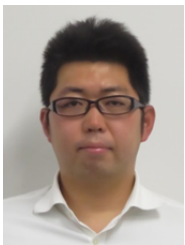
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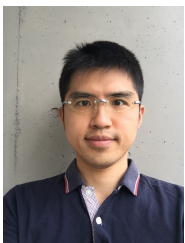
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