

Effects of Central Bank Communication on Financial Markets: A Factor-Augmented Vector Autoregressive Approach

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ABSTRACT

The study empirically explores the effects of central bank communication shocks in a high-dimensional data setting. The techniques in computational linguistics are employed to quantify the central bank communication from the 69 press releases from 2010–2018. Central bank communication variables are proxied by the net tone and the semantic similarity of the Bank of Thailand's press releases. Effects of central bank communication shocks on financial markets are analyzed through the impulse response functions in a factor-augmented vector autoregressive (FAVAR) model.

Findings indicate that central bank communication shocks matter for financial markets. That is, the stock market returns and the yields of the government debt securities with the maturity 3-month to 16-year, increase in response to the net tone shock while only 3-month to 4-year government bond yields increase in response to the semantic similarity shock. In addition, the money supply (M1) decreases in response to both net tone and the semantic similarity shocks.

Keywords: Textual Analysis, Central Bank Communication, Financial Markets

ผลของการสื่อสารของธนาคารกลางต่อตลาดการเงิน ด้วยกรอบการวิเคราะห์ Factor-Augmented Vector Autoregression

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อาจารย์ประจำภาควิชาการเงิน

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บทคัดย่อ

วแปรโทนของค่าและตัวแปรความคล้อยคลึงเชิงภาษาถูกสร้างขึ้นจากแถลงการณ์นโยบายการเงิน 69 ฉบับของธนาคารแห่งประเทศไทยตั้งแต่ พ.ศ. 2553–2561 เพื่อใช้เป็นตัวแปรการสื่อสารของธนาคารกลางด้วยเครื่องมือทางภาษาศาสตร์คอมพิวเตอร์ เพื่อวิเคราะห์ถึงผลกระทบและลักษณะการส่งผ่านของช็อก (Shock) ไปยังอัตราผลตอบแทนจากตราสารทุนและตราสารหนี้โดยใช้ตัวแบบ Factor-Augmented Vector Autoregression (FAVAR)

ผลการศึกษาพบว่า ช็อกที่ส่งผ่านตัวแปรการสื่อสารของธนาคารกลางมีความสำคัญต่อตลาดการเงิน โดยที่ อัตราผลตอบแทนจากตลาดหลักทรัพย์ และ อัตราผลตอบแทนจากพันธบัตรรัฐบาลอายุ 3 เดือน ถึง 16 ปี ปรับตัวเพิ่มสูงขึ้นตอบสนองต่อช็อกจากตัวแปรโทนของแถลงการณ์นโยบายการเงิน ขณะที่เพียงอัตราผลตอบแทนจากพันธบัตรรัฐบาลอายุ 3 เดือน ถึง 4 ปี ที่ปรับตัวเพิ่มขึ้นตอบสนองต่อช็อกจากตัวแปรความคล้อยคลึงเชิงภาษา นอกจากนี้ ปริมาณเงิน (M1) ปรับตัวลดลงตอบสนองต่อช็อกจากตัวแปรโทนและความคล้อยคลึงเชิงภาษา

คำสำคัญ: การสื่อสารของธนาคารกลาง ตลาดการเงิน การทำเหมืองข้อความ

INTRODUCTION

During the period of the ultra-low interest rates, an exogenous shock to monetary policy may produce different impacts on the economy and it seems that what central banks around the globe have relied on after the Great Financial Crisis (GFC) is unconventional monetary policy. One aspect of the practice of monetary policy after the GFC is that central banks communicate to the general public. In this regard, minutes, press releases and even the voting records published by the central bank to the public make channels of central bank communication. Central bank communication has become common unlike the conventional wisdom of the central bank in the past (Blinder, Ehrmann, Fratzscher, De Haan & Jansen, 2008). That is, the central bank should remain secretive. The process of monetary policy deliberations involves a great amount of data, both structured and unstructured. Thus, the monetary policy is made under the rich information environment (Bernanke, Boivin & Elias, 2005; Bernanke & Boivin, 2003). That is, for example, the low-dimensional Vector Auto Regressive (VAR) model may omit some critical information that is used by the policy makers.

In this paper, the question: how do financial market variables respond to an exogenous shock to central bank communication under a data-rich framework? is asked. Two dimensions of the central bank communication are explored. The first dimension is the net tone of the content in the central bank press releases and the second dimension is the semantic similarity of the language used in the corpus of the press releases. I study the communication of the Bank of Thailand (BOT) and apply the techniques in the computational linguistics with the BOT's press releases to measure both dimensions of the BOT communication. The applications of the textual analysis to the central banking have been increasingly popular for a decade. For example, Acosta and Meade (2015) apply the cosine similarity to measure the semantic similarity of the FOMC's post-meeting statements. Hansen and McMahon (2016) use the Latent Dirichlet Allocation (LDA) and the dictionary method to analyze the content of the FOMC statements. In finance, Loughran and McDonald (2016) use the textual analysis to study various issues of finance. In this study, I measure the communication from 69 press releases from 2010–2018 by employing the dictionary technique and the cosine similarity. Figure 1 shows a sample of a press release.

The paper is partly related to Hansen and McMahon (2016) in which they study the effects of the shock to forward guidance on financial markets and macroeconomic variables. Unlike Hansen and McMahon (2016), this study investigates the effects of the shocks to the net tone and the semantic similarity of the BOT's press releases. A shock to the central bank communication is analyzed in the factor-augmented vector auto regressive (FAVAR) model. FAVAR allows researchers to deal with a large amount of information. At first glance, this study may be similar to Bernanke, Boivin and Elias (2005). However, to my knowledge, the analysis of the net tone and the semantic similarity of the BOT communication in FAVAR is new and the main objective of this study is to analyze the central bank communication rather than the key policy rate.

Surprisingly, the findings of the study resemble the tightening monetary policy shock in the pertinent literature. The short-term government debt securities significantly respond to the central bank communication shock while the effects of the shocks on the long-term government bond yields are ambiguous. For the equity markets, stock market returns increase in response to the net tone shock for 3–4 months and gradually decline after month 4. The money supply significantly declines in response to the central bank communication shocks.

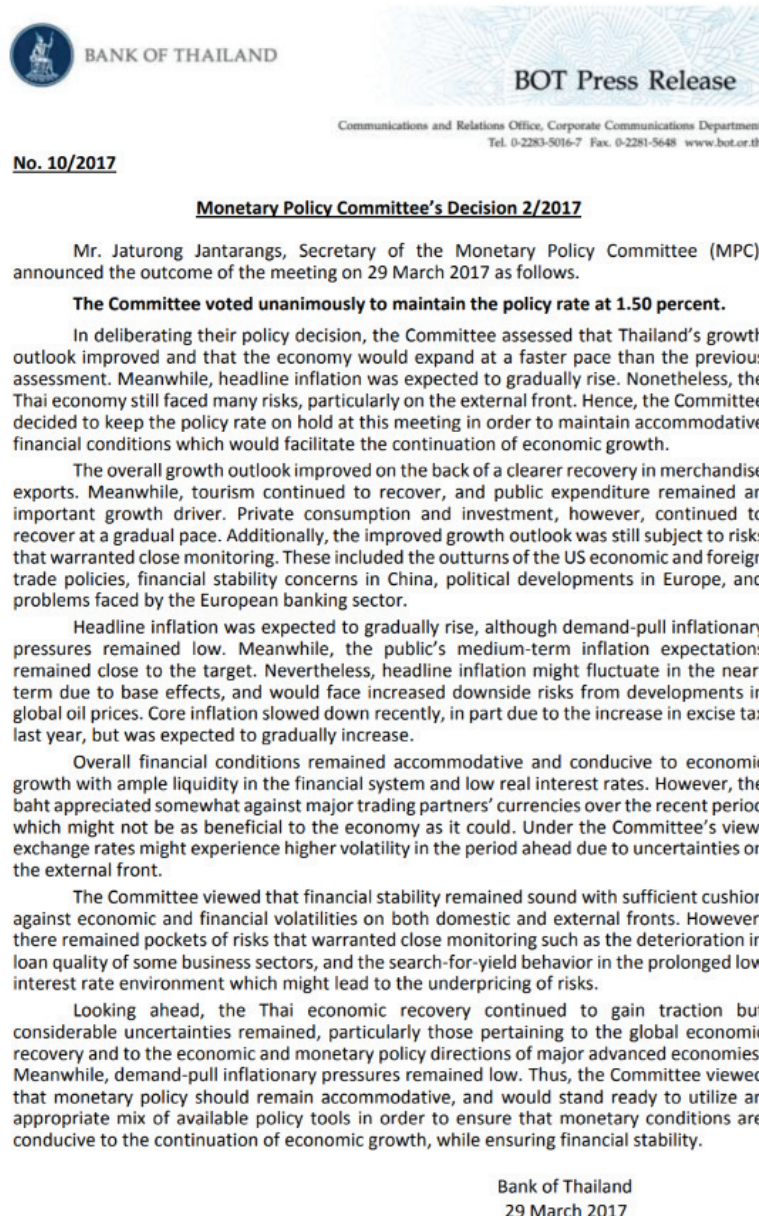


Figure 1: The Monetary Policy Committee's press release on 29 March 2017.

LITERATURE REVIEW

In the past, the practice of the central bank was mysterious. Central bankers did not communicate to the general public or if they were to do, they would not talk much and would keep the secret of monetary policy. It has been in recent decades that central banks increase the level of communication and use the communication as one of the monetary policy toolkits. As the monetary policy is about expectations management, central bank communication has become increasingly important to central banks around the globe. In their seminal paper, Gürkaynak, Sack and Swanson (2005) study effects of the U.S. monetary policy on asset prices. Using high frequency data from 1990–2004, Gürkaynak et al. (2005) use the high frequency event analysis approach to analyzing factors that affect asset price movements during announcement dates. Findings suggest that two factors, which can be interpreted as ‘current fed funds rate target’ and ‘the future path of monetary policy’, affect bond yields, especially the movements of 5-year and 10-year bonds. The future policy path is the factor associated with FOMC statements and, as being highlighted in Gürkaynak et al. (2005), the FOMC statement is not an independent policy tool, but it, in fact, influences the movements of financial markets through expectations of the future policy path.

The topic of monetary policy shocks and the effects on macroeconomic and financial market variables is comprehensively studied in Christiano, Eichenbaum and Evans (1999). They address the question that is related to the monetary policy shocks and explore the consequences of the exogenous monetary policy shocks through various identification schemes. One thing that is worth noting is, in Christiano et al. (1999), the economic interpretation of monetary policy shocks. The paper presents three interpretations. The first interpretation is that the monetary policy shock is the shock to the preferences of the monetary policy authority. The second is the strategic considerations and the last one is the technical factors. After the global financial crisis (GFC), many studies also examine the monetary policy shocks. Recently, Bu, Rogers and Wu (2021), they construct a series of monetary policy shocks in the U.S. from the full maturity of various interest rates and apply a partial least squares approach to the study. They find that their constructed shocks exert a considerable influence on the middle of the term structure. Both output and inflation fall in response to the monetary policy shock and these are consistent with the conventional characteristics of the impulse responses. Various identification strategies of monetary policy shocks are also studied. For example, Cheng and Yang (2020) impose a combination of sign restrictions and narrative sign restrictions in the SVAR. In addition to the papers that employ the SVAR and VAR models, the issue of the information in the system has also become one of the concerns. The issue of over parameterization may arise in the VAR system and this affects the degree of freedom. To cope with this issue, the Bayesian method is used in estimation. Auer (2019) employs a large Bayesian VAR to examine the transmission mechanism of monetary policy in the U.S. and Canada. The impacts of the monetary policy shock in the Bayesian VAR system on foreign investment income, exchange rate, trade flows and domestic aggregates are studied. The findings are that gross and net investment income flows significantly respond to the tightening monetary policy shock. Effects of monetary policy on foreign

investment income flows are different across asset classes and the approach used in the study helps eliminate price and exchange rate puzzles.

However, the policy makers make their monetary policy decisions based on a large amount of macroeconomic, financial market and other relevant variables. Failing to incorporate this information may lead to the issue of omitted variables. Thus, the factor-augmented vector autoregression (FAVAR) proposed by Bernanke, Boivin and Elias (2005) may be appropriate to the study of the effects of monetary policy shocks because the approach does not leave the large set of information behind. The study of the exogenous shocks to central bank communication has been studied in many respects. For example, Hansen and McMahon (2016) employ the FAVAR to analyze the effects of forward guidance on key macroeconomic and financial market variables.

Unlike the pertinent literature, the paper examines the effects of exogenous shocks to the tone and the semantic similarity of the content of the BOT's press releases. The study of the shock to the semantic similarity is new. This study is most related to Ehrmann and Talmi (2020). However, Ehrmann and Talmi (2020) study the effects of semantic similarity on financial market volatility in the case of Canada, the Euro zone, Japan and the U.S. while, in this study, I employ the FAVAR approach to measure the central bank communication shocks on financial market variables instead of financial market volatility.

RESEARCH METHODOLOGY

The study was conducted by using monthly data from January 2010 to December 2018. The sample period was selected based on the availability of the data during the period of the study. Thus, there are 108 monthly observations in total. The latent factors are extracted from the financial market data in table 1 by the Principal Components Analysis. For the central bank communication and macroeconomic data, which are observable variables, they are the tone and the semantic similarity of central bank press releases, the consumer price index and the manufacturing production index. In table 1, for the financial market section, data are the rates of the short-term and the long-term government debt securities, the stock market index and the money supply (M1). All stock market indices are collected from https://www.set.or.th/en/market/market_statistics.html and the data of M1, the rates of government debt instruments and macroeconomic data can be obtained from <https://tide.pier.or.th/>. For the variables of central bank communication, the tone is constructed from the dictionary technique and the semantic similarity is calculated from the cosine similarity. The dictionary technique and the cosine similarity are explained in the subsequent section. Data in table 1 are transformed by (1). r_t represents each variable in the table.

$$r_t = \ln \left(\frac{r_t}{r_{t-1}} \right) \times 100 \quad (1)$$

Table 2 summarizes the descriptive statistics for financial market data and table 3 shows that all data in this study pass the unit root test. Thus, this rules out the spurious relationships and the transformed data are stationary.

Table 1: Data Description

Financial Market Data

Variable	Data description
TB1	T-bill & Government bond yield: 1 month
TB3	T-bill & Government bond yield: 3 months
TB6	T-bill & Government bond yield: 6 months
GB1	T-bill & Government bond yield: 1 year
GB2	T-bill & Government bond yield: 2 years
GB3	T-bill & Government bond yield: 3 years
GB4	T-bill & Government bond yield: 4 years
GB5	T-bill & Government bond yield: 5 years
GB6	T-bill & Government bond yield: 6 years
GB7	T-bill & Government bond yield: 7 years
GB8	T-bill & Government bond yield: 8 years
GB9	T-bill & Government bond yield: 9 years
GB10	T-bill & Government bond yield: 10 years
GB11	T-bill & Government bond yield: 11 years
GB12	T-bill & Government bond yield: 12 years
GB13	T-bill & Government bond yield: 13 years
GB14	T-bill & Government bond yield: 14 years
GB15	T-bill & Government bond yield: 15 years
GB16	T-bill & Government bond yield: 16 years
SET	SET index
SET50	SET50 index
SET100	SET100 index
Money	Broad money: M1

Central Bank Communication and Macroeconomic Data

Variable	Data description
CPI	Consumer Price Index
MPI	Manufacturing Production Index
TONE	Net tone
SIM	Semantic similarity

Table 2: Descriptive Statistics

Financial Market Data

Variable	Mean	Median	Maximum	Minimum	Std. Dev.	Observations
TB1	0.19	0.00	16.43	-12.36	4.57	108
TB3	0.21	0.00	17.67	-12.36	4.54	108
TB6	0.18	-0.34	18.87	-13.02	4.50	108
GB1	0.13	0.00	15.69	-13.02	4.11	108
GB2	-0.16	-0.31	15.62	-10.22	4.46	108
GB3	-0.33	-0.56	14.80	-9.69	4.66	108
GB4	-0.39	-1.07	13.70	-10.60	4.88	108
GB5	-0.44	-0.88	12.44	-14.38	5.22	108
GB6	-0.45	-0.68	15.23	-18.05	5.53	108
GB7	-0.46	-1.08	15.32	-16.86	5.54	108
GB8	-0.47	-0.56	14.22	-15.62	5.49	108
GB9	-0.46	-0.61	14.14	-15.55	5.52	108
GB10	-0.48	-1.01	14.59	-16.28	5.50	108
GB11	-0.44	-0.61	14.69	-14.11	5.43	108
GB12	-0.44	-0.72	13.73	-14.31	5.17	108
GB13	-0.43	-0.77	14.59	-14.31	5.08	108
GB14	-0.42	-0.96	14.43	-13.82	4.94	108
GB15	-0.42	-0.82	14.55	-14.40	4.67	108
GB16	-0.42	-0.75	13.44	-14.56	4.48	108
SET	0.70	1.31	8.83	-15.52	4.27	108
SET50	0.64	1.32	9.50	-16.05	4.41	108
SET100	0.66	1.27	9.62	-16.37	4.51	108
MONEY	0.59	0.48	2.82	-1.42	0.69	108

Central Bank Communication and Macroeconomic Data

Variable	Mean	Median	Maximum	Minimum	Std. Dev.	Observations
CPI	0.13	0.15	1.37	-0.66	0.30	108
MPI	-0.05	0.05	20.67	-29.98	4.52	108
TONE	-0.01	0.00	0.07	-0.09	0.03	108
SIM	0.82	0.83	1.00	0.53	0.16	108

Table 3: Unit Root Test

Financial Market Data

Variable	t-statistic	p-value
TB1	-4.26	0.00
TB3	-6.41	0.00
TB6	-6.51	0.00
GB1	-6.42	0.00
GB2	-7.07	0.00
GB3	-7.75	0.00
GB4	-7.68	0.00
GB5	-7.91	0.00
GB6	-7.75	0.00
GB7	-7.93	0.00
GB8	-8.07	0.00
GB9	-8.32	0.00
GB10	-8.39	0.00
GB11	-8.01	0.00
GB12	-7.78	0.00
GB13	-7.82	0.00
GB14	-7.85	0.00
GB15	-7.62	0.00
GB16	-7.46	0.00
SET	-9.19	0.00
SET50	-9.79	0.00
SET100	-9.55	0.00
MONEY	-4.23	0.00

Central Bank Communication and Macroeconomic Data

Variable	t-statistic	p-value
CPI	-6.47	0.00
MPI	-7.93	0.00
TONE	-9.36	0.00
SIM	-10.81	0.00

Textual Analysis: Analytical Preprocessing

Central bank press releases make a channel of central bank communication. Nowadays, the information in the corpus is mostly recorded as digital text that the general public can access from the Bank of Thailand's website. Textual data are unstructured. That is, they are alphanumeric and they also contain non-alphanumeric characters. Text, thus, is different from other forms of data. Dealing with text as data begins with analytical pre-processing. The key concept of analytical pre processing is to remove the noises in the corpus before conducting further textual analysis. As a result, this process reduces the dimension of the term-document matrix. The output of the pre-processing is the bag-of-words model. In this study, I collect 69 BOT press releases from <https://www.bot.or.th/English/PressAndSpeeches/Press/layouts/application/BOTNews/News.aspx?catID=3>.

The following procedures are a series of critical steps in the analytical pre processing. First, I lower a string of characters and remove the white space. Second, the English stop words are eliminated from the corpus. Then, I stem the text with the Porter stemmer and, after that, I tokenize stemmed words and construct the bag-of-words model. The result of this is the term-document matrix. The row of the matrix is the number of the terms in the whole corpus while the column of the matrix is associated with the number of the BOT press releases. After weighting the matrix with the term-frequency inverse document frequency, the dimension of the matrix is 69×906 . The term-document matrix can be represented by the word cloud in figure 2. The techniques of the textual analysis have been well documented in Bholat, Hansen, Santos and Schonhardt-Bailey (2015).



Figure 2: Word Cloud of the corpus of the BOT's press releases from 2010–2018.

Dictionary Technique

The dictionary technique is a word counting method. I construct a word list of predetermined words and count the words that occur in each document in the whole corpus. In this study, I use a word list of directional words employed by Hansen and McMahon (2016) as the dictionary. The list consists of expansionary (positive) and contractionary (negative) words. I count positive and negative words and calculate the tone according to equation (2).

$$TONE_{i,t} = \frac{w_{i,t}^{up} - w_{i,t}^{down}}{w_{i,t}} \quad (2)$$

$w_{i,t}^{up}$ denotes the number of expansionary words in document i at time t . $w_{i,t}^{down}$ is the number of contractionary words in document i at time t . $w_{i,t}$ is the number of all words in document i . Table 4 shows some examples of contractionary and expansionary words. $TONE_{i,t}$ is the “tone” or the “net tone” variable.

Table 4: The Dictionary of Directional Words

Contraction		Expansion	
collaps	lowest	acceler	increas
contract	moder	boom	rise
cool	slow	expand	risen
deceler	slower	fast	strength
decreas	slowest	faster	strong
fall	soften	fastest	stronger
fell	subdu	foster	strongest
lose	weak	gain	expands
loss	weaken	high	
lost	weaker	higher	
low	weakest	highest	
lower		improv	

The net tone is plotted in in figure 3. The graph fluctuates around -0.0174 and it is quite volatile during document 1 to document 45. The negative/positive numbers represent the negative/positive net tone of the BOT press releases. 48 documents exhibit the negative tone while the rest is positive.

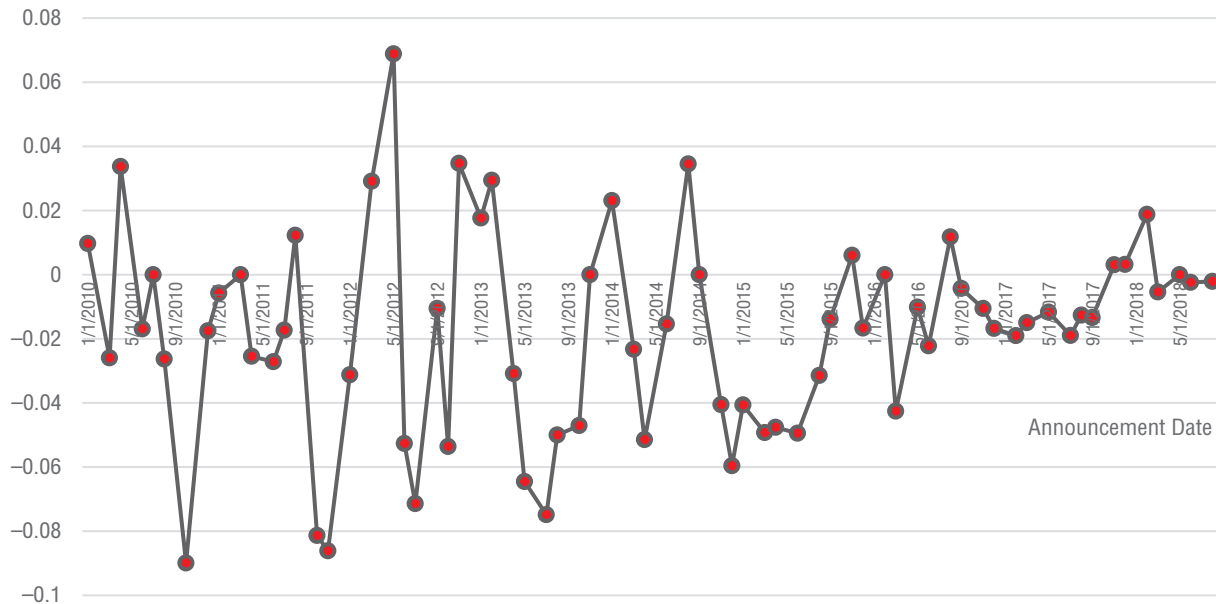


Figure 3: Tone of the BOT Press Releases.

Textual Semantic Similarity

In order to measure linguistic similarity of the two documents, cosine similarity, (3), is employed. The cosine similarity represents a value of an angle between two column vectors in a term-document matrix. The value of cosine similarity ranges between 0 and 1. 0 indicates that two documents are not relevant. In other words, two documents are orthogonal. 1 means that the two documents are the same.

$$SIM_i = \frac{\sum S_i S_{i-1}}{\sqrt{\sum S_i^2} \sqrt{\sum S_{i-1}^2}} \quad (3)$$

S_i is a vector of words in document i and S_{i-1} is a vector of words in document $i-1$. $SIM_i \in [0,1]$ is the semantic similarity. The graph of the semantic similarity is shown in figure 4.

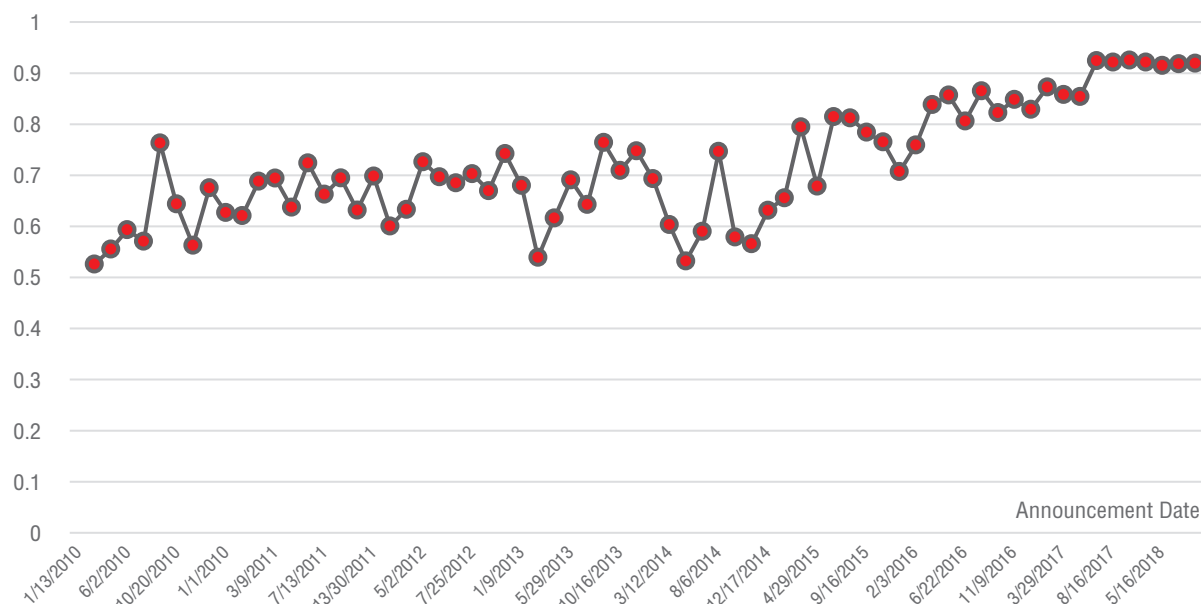


Figure 4: Semantic Similarity of the BOT Press Releases

The average value of the semantic similarity is 0.73. All in all, the content of the corpus of the BOT press releases is relatively similar. Figure 4 shows that the semantic similarity comes close to 1.

Factor-Augmented Vector Autoregression (FAVAR)

When it comes to monetary policy deliberations, the MPC committee and policy maker take into account a large amount of information that is related to macroeconomy. Using a standard VAR that incorporates only a handful of macroeconomic and financial market variables to analyze effects of monetary policy may not reflect the true nature of monetary policy decisions. In addition, increasing the number of variables in the VAR system results in over parameterization and this may lead to the issue of degree of freedom. Thus, the low-dimensional VAR system may neglect some key information. In order to incorporate a large amount of information to the VAR system, the study employs the Factor-Augmented Vector Auto Regression (FAVAR) to study the effect of central bank communications on the responses of financial market variables.

FAVAR is a special case of the Dynamic Factor Models (DFMs) (Stock and Watson, 2016). The key feature of the DFMs is that a large number of variables are dependent to latent factors, which are unobserved. The number of latent factors is far less than the number of time series variables that we use them to extract the latent factors. For example, for a single-factor DFM, a single factor is obtained from 50 time series data. DFMs help researchers deal with a large amount of information from a small number of variables. FAVAR is the case in which one or more factors in DFMs can be observed while the remaining factors remain unobserved. FAVAR, thus, requires some certain identification scheme for

DFMs help researchers deal with a large amount of information from a small number of variables. FAVAR is the case in which one or more factors in DFMs can be observed while the remaining factors remain unobserved. FAVAR, thus, requires some certain identification scheme for DFMs. I present FAVAR in the state-space representation and, without loss of generality, I do not include the vector of intercepts in (4) and (5). The following dynamic system shares the same spirit of Bernanke et al. (2005)'s.

The Measurement Equation

$$\begin{bmatrix} x_t \\ y_t \end{bmatrix} = \begin{bmatrix} \Lambda^f & \Gamma^y \\ 0 & I \end{bmatrix} \begin{bmatrix} f_t \\ y_t \end{bmatrix} + \varepsilon_t \quad (4)$$

The State Equation

$$\begin{bmatrix} f_t \\ y_t \end{bmatrix} = \Phi(L) \begin{bmatrix} f_{t-1} \\ y_{t-1} \end{bmatrix} + \tilde{\varepsilon}_t \quad (5)$$

x_t is a 23×1 vector of observable financial market variables. f_t is a 5×1 vector of unobserved factors. y_t is a 3×1 vector of observable variables, which are inflation, output and one of central bank communication variables that are either tone or semantic similarity. Λ^f is a 23×5 matrix of factor loadings and Γ^y is a 23×3 matrix of coefficients. I is a block of a 3×3 identity matrix. $\Phi(L)$ is a lag polynomial of order p . ε_t and $\tilde{\varepsilon}_t$ are vectors of error terms. Two distinct dynamic systems are fitted according to (3) and (4). The first system is for the study the tone effects and the second dynamic system is for the study of the semantic similarity effects on the variables of interest.

Shock Identification

In vector y_t , the central bank communication variable is the policy-related variable, which can be observed from the BOT's press releases. Other observable variables are grouped into two categories. The first category is the fast-moving category, which contains the variables that respond to the shock to the central bank communication variable within the period of the shock. The second category is the slow-moving category, which does not respond to the central bank communication shock contemporaneously. This identification follows Bernanke et al. (2005). Unlike the pertinent literature, in this paper, I assume that the slow-moving variables are bond yields with the maturity greater than 1 year, inflation and real economic activity.

FAVAR Estimation

I apply the Gibbs sampler, which is the Markov Chain Monte Carlo (MCMC), to estimate the FAVAR. The Gibbs sampling is an iterative procedure that is used to approximate joint distributions through the sampling from conditional distributions. It is widely used in the Bayesian estimation. The Gibbs sampler takes 30,000 iterations and the first 15,000 iterations are treated as the burn-in phase and they are

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discarded. The Gibbs sampling takes 233.50 seconds for the FAVAR with the central bank tone and 336.8233 seconds for the FAVAR with semantic similarity

The first step is that I extract the latent factors from the informational vector x_t by applying the Principal Components Analysis (PCA) to (3). The PCA is the nonparametric method and it is easy to implement. It is worth noting that the variables in y_t are not used in the PCA. In order to fix the idea, I rewrite (3) to (5), which is a univariate equation.

$$x_{i,t} = \lambda_i^f f_t + \gamma_i^y y_t + \varepsilon_{i,t}, i = 1, 2, \dots, M \quad (6)$$

I use the Normal-Gamma, which is the natural conjugate prior, to sample λ_i^f and σ_i . Thus,

$$\lambda_i \sim N(0, cI) \quad (7)$$

$$(\sigma_i^2)^{-1} \sim G(a, \beta) \quad (8)$$

The latent factors are solely extracted from the information in x_t . The output of this step is a series of factors and the factor loadings. The number of the factors is equal to 4, which is based on eigenvalues. Moreover, I also estimate the FAVAR with 2-factor, 3-factor and 5-factor. However, the qualitative results and interpretations are not that different from the 4-factor case. Figure 5 illustrates 4 factors that are used in FAVAR.

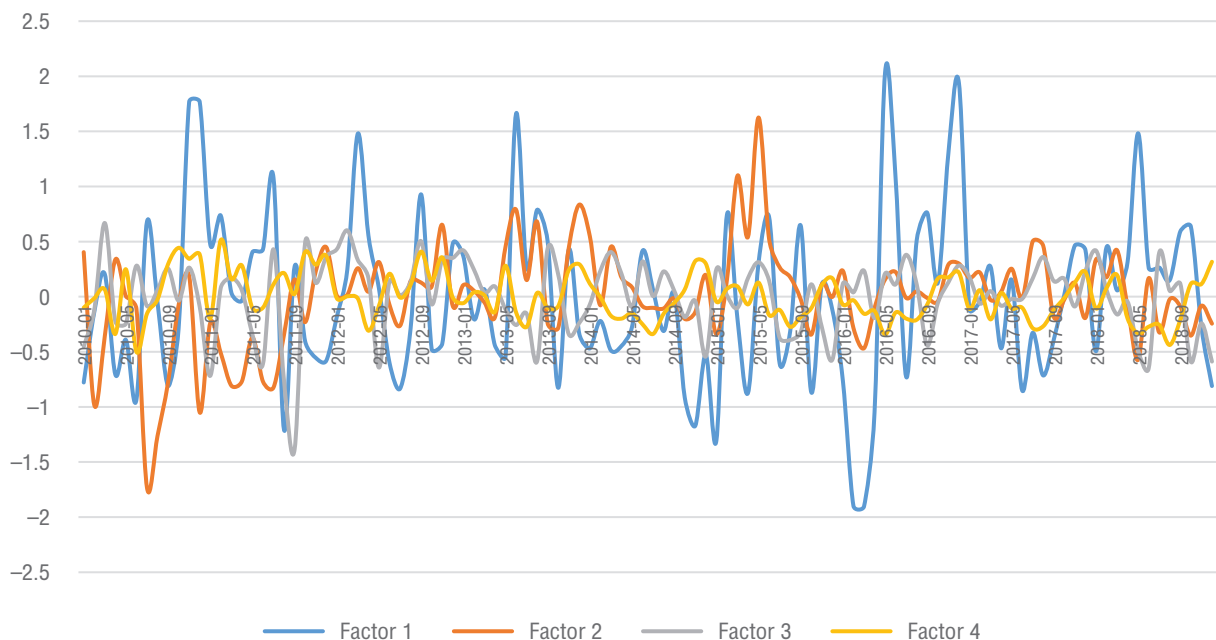


Figure 5: 4 Latent Factors.

The second step is to estimate (5). I use the normal inverted Wishart priors for Φ and $\tilde{\Sigma}$. This step follows the standard Bayesian VAR. The lag value of the FAVAR is 7 because it captures the dynamic of the system and is consistent with the previous study of the monetary policy transmission mechanism, such as Bernanke et al. (2005).

RESULTS

The effects of the exogenous shocks to the central bank communication variables are analyzed through the Impulse response functions in figure 6 and 7. The analysis allows us to picture the dynamic responses of financial market variables for each shock over time. The unit of the horizontal axis is on a monthly basis and they show the response 21 months ahead for each diagram. The magnitude of a shock is 1 SD.

Shocks to the Net Tone

Government securities are categorized into two groups of which are the short-term (the maturity less than or equal 1) and the long-term (the maturity greater than 1 year) government debt instruments. For the short-term bonds, the yield of 1-month treasury bill decreases at the same time when a 1-unit shock hits the net tone of the press releases. In other words, the net tone of the content of the BOT press releases is unexpectedly positive to the general public.

The 1-month yield gradually increases and reaches its peak in month 6. The responses of 3-month and 6-month yields share the same patterns but they are slightly different from the yield of 1-month. Both 3-month and 6-month yields gradually increase and reach the peak in month 6. This is not surprising because if we take a look at the raw data, the yields of the short-term securities resemble one another. For the 1-year treasury bill, the yield increases contemporaneously in response to the shock to the net tone and reaches its peak around month 5. Thus, for the FAVAR with 4 factors, the effects of the shocks to the net tone last for 5 to 6 months.

With regard to the impulse response diagrams of the long-term bonds, after the 1-unit of the net tone shock, the yield reaches its peak around month 7 to month 8. This feature of the impulse responses is significant across the long-term category.

The shock to the net tone also matters for the stock market returns calculated from SET, SET50 and SET100. All stock market returns go up when there is a positive shock and the effects of the shocks on the returns last for only 4 months. The patterns of the stock market returns share the same characteristics.

In addition to financial market variables, the money supply (M1), which is treated as the fast-moving variable in the FAVAR, decreases within the same period of the shock to the net tone.

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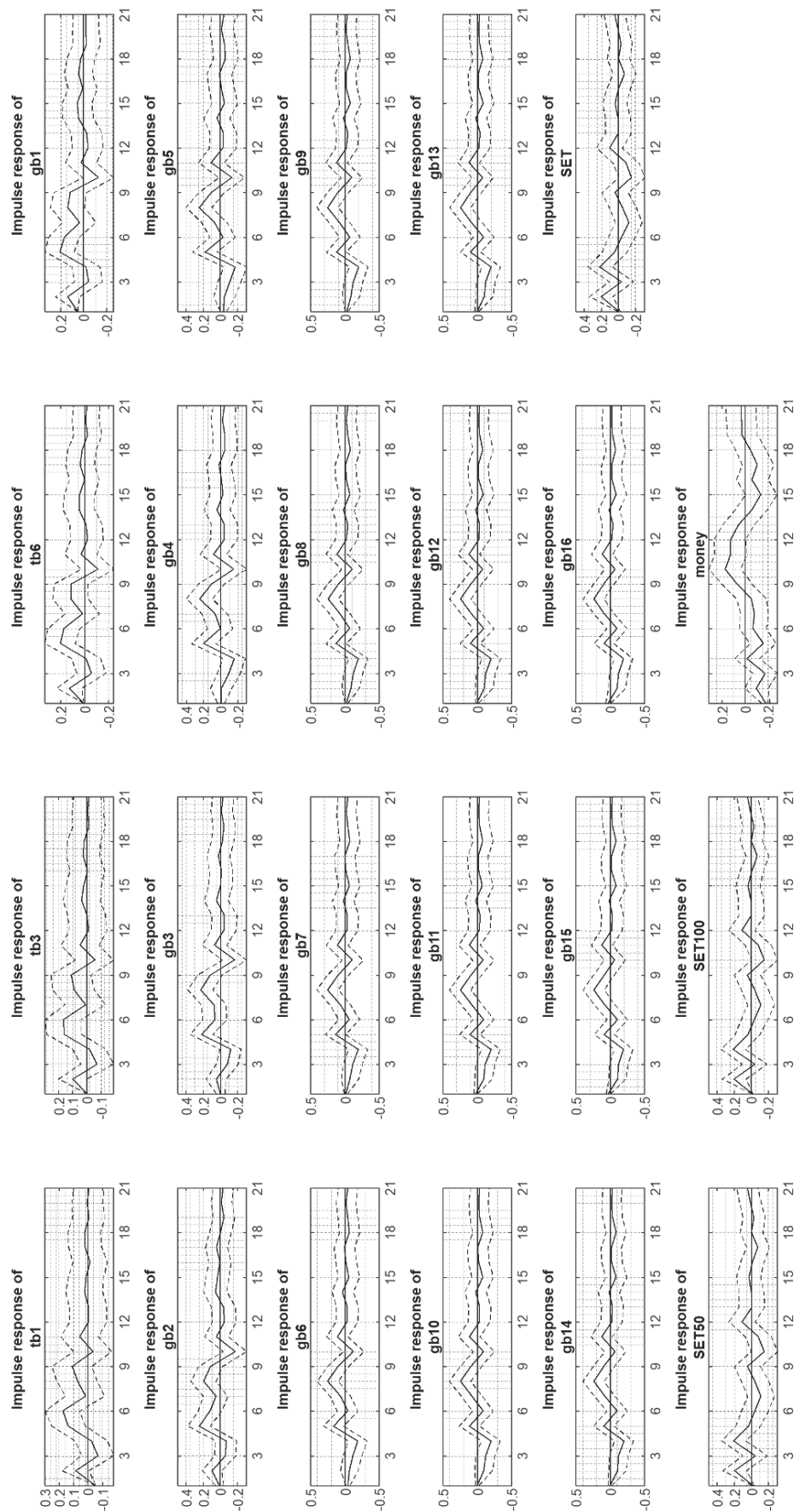


Figure 6: The Diagram illustrates the Impulse Responses of Bond Yields, Stock Market Returns and Money Supply to a 1-Unit Shock to the Central Bank Tone.

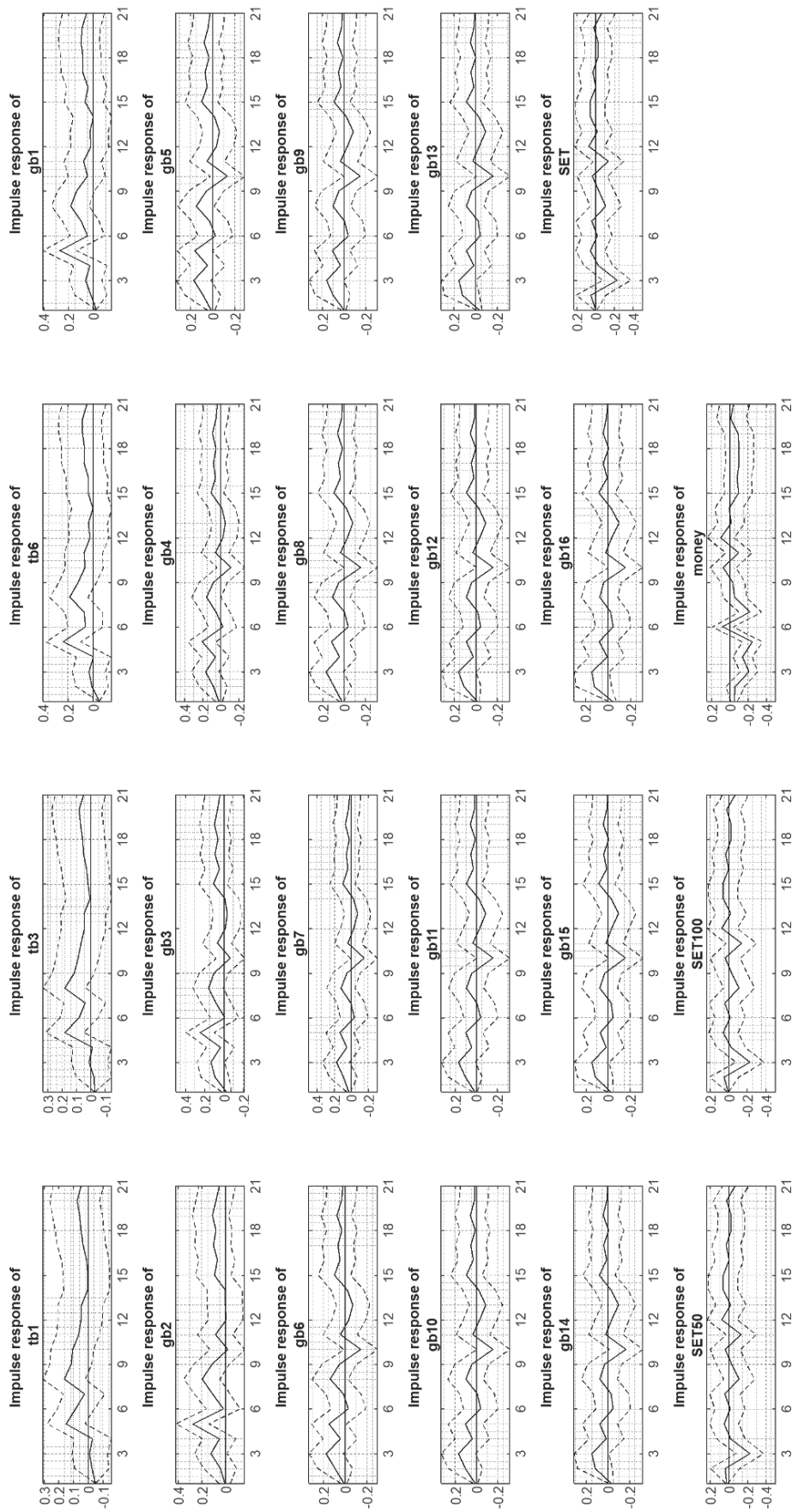


Figure 7: The diagram shows the impulse responses of bond yields, stock market returns and money supply to a 1-Unit Shock to the semantic similarity of the BOT's press releases.

Shocks to the Semantic Similarity

A shock to semantic similarity can be interpreted as the content of the two consecutive documents is unexpectedly similar in the view of the general public. When there is a shock to the similarity of the content, the yields of 1-month, 3-month, 6-month and 1-year government debt securities decline contemporaneously. The yields of all short-term government bonds reach the peak around month 5. The effect of the shock to semantic similarity is relatively pronounced in the 1-year bond yields.

Unlike the short-term bonds, the effects of the semantic similarity shocks have a less influence on the long-term bonds. That is, even though the yields of the 2-year to 4-year bonds reach its peak around month 5, the effects of the shocks tend to be less pronounced in the bonds with the maturity greater than 4-year. We can see from figure 7 that the impacts of the shock are insignificant.

For the equity market, the stock market returns decline in response to the semantic similarity shock of the BOT's press releases. The returns hit the bottom around month 3 and the effects of the shocks are insignificant afterwards.

Interestingly, the money supply decreases contemporaneously when there is a shock to the similarity of the content of the press releases.

DISCUSSION

Compared with the pertinent literature that studies the monetary policy transmission mechanism, when there is an exogenous shock to the key policy rate, the short-term interest rates increase in response to the policy rate (Alessi & Kerssenfischer, 2019). In this paper, the short-term and the long-term yields also increase in response to the shock to the net tone. Findings result in the same way as the conventional monetary policy shock. The impulse responses of the bond yields to the semantic similarity shock are somehow insignificant for the yields with the maturity greater than 4 years. It may be interpreted that the effects of the semantic similarity are influential to only the short-term government securities.

As for the response of stock market returns, the effects of the shock to the net tone are more pronounced than of the impulse responses of the language similarity. The stock market returns increase in response to the shock to the net tone and these findings are consistent with the findings in the literature, such as Christiano et al. (1999), Disyatat and Vongsinsirikul (2003), that studies the effects of the shock and the monetary policy transmission mechanism. The positive tone of the BOT press releases gives the financial market participants good economic outlooks and, thus, results in the confidence of the investors. These effects last for 3 to 4 months. After that, the stock market returns gradually decrease.

The last variable of the interest is the money supply, which is measured by the broad money or M1. The money supply reduces in response to the shock to the net tone and the semantic similarity of the BOT's press releases. As for the conventional monetary policy, the decrease in the money supply in response to the shock to the policy rate is consistent to the tightening monetary policy. The effects of the central bank communication on the money supply are quite significant.

CONCLUSION

Central bank communication has become increasingly important among the central banks since the conventional monetary policy was constrained by the ZLB. The study addresses the question that how do the central bank communication shocks affect financial market variables?

The techniques in the textual analysis are employed to measure the content of which the BOT aims to communicate to the general public through the BOT's press releases from 2010-2018. The net tone and the semantic similarity are two central proxies of the policy communication. By leveraging the data in financial markets and key macroeconomic data, the study measures the effects of the central bank communication with the factor-augmented vector autoregressive (FAVAR) approach. FAVAR represents the nature of monetary policy deliberations and helps incorporate relevant variables while the model is still parsimonious.

The yields of the short-term government debt instruments respond significantly to the shocks from the net tone and from the semantic similarity. Stock market returns respond more to the net tone shock while the responses of the stock returns to the semantic similarity shock are ambiguous. In addition, the money supply (M1) decreases in response to the shocks to the net tone and to the semantic similarity. The effects of central bank communication shocks on financial markets and macroeconomic variables are similar to the conventional monetary policy to some degree. I leave the study of the transmission mechanism of the central bank communication for future research.

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