



PUEY UNGPHAKORN INSTITUTE
FOR ECONOMIC RESEARCH

Central Bank Communication and Monetary Policy Effectiveness: Evidence from Thailand

by

Pongsak Luangaram and Yuthana Sethapramote

February 2016

Discussion Paper

No. 20

The opinions expressed in this discussion paper are those of the author(s) and should not be attributed to the Puey Ungphakorn Institute for Economic Research.

**Central Bank Communication and Monetary Policy Effectiveness:
Evidence from Thailand ¹**

Pongsak Luangaram²,

Faculty of Economics, Chulalongkorn University

and

Yuthana Sethapramote³,

School of Development Economics, National Institute of Development Administration

January 2016

Abstract:

This paper has two main objectives. First, we introduce a novel textual analysis technique for estimating latent policy position in the monetary policy committee (MPC) statement based on word frequencies (so-called ‘Wordfish’, developed by Slapin and Proksch, 2008). This method is applied to extract informational content embed in the MPC statements during the first decade of inflation targeting in Thailand. Second, we provide a comprehensive assessment of communication on monetary policy effectiveness in three main aspects, i.e. predictability of short-run policy interest rate, monetary transmission mechanism and the ability to anchoring long-run inflation expectations. Specifically, by augmenting our communication measure with various Taylor-type rule specifications, it is found that monetary policy statements help to improve short-run predictability of policy interest rate. Furthermore, using structural vector autoregression, we find that the impulse responses of policy rate shock on output and inflation are stronger when communication is included, indicating the improved efficacy of the transmission mechanism process. Our econometric results also indicate that the MPC statement exerts its influence over the yields with longer maturities. Finally, an increase in policy interest rate can anchor expected inflation only in the short run, while monetary policy communication provides additional effects to long-term inflation expectations.

Keywords: Monetary policy statement, Central bank communication, Taylor rule, Monetary policy transmission mechanism.

JEL Classifications: E43, E52, E58

¹ We would like to thank Kiatipong Ariyaprachya, Santitarn Sathirathai, Jon Wongswan for useful comments and suggestions. Financial support from the Thailand Research Fund (TRF), under project entitled ‘A Study of Monetary Policy Effectiveness through the Bank of Thailand Communication’, is gratefully acknowledged. In revising this paper, the first author was Visiting Research Fellow at Puey Ungphakorn Institute for Economic Research (PIER) and he thanks them for the hospitality. All remaining errors are ours.

² Author contact: Corresponding author: Pongsak Luangaram, Faculty of Economics, Chulalongkorn University, Phayathai Road, Bangkok 10330, Thailand, E-mail: pluangaram@gmail.com, Telephone +66 81 9288096. Fax +662 251-3967

³ Yuthana Sethapramote, School of Development Economics, National Institute of Development Administration, 118 Seri-Thai Road, Bangkapi, Bangkok, 10240, Thailand. E-mail: yuthanas@gmail.com, Telephone +66 83 0507962. Fax +662 3758842

1. Introduction

During the last decade, significant progress has been made on enhancing central bank communication, both from evolving real-world practice and from rapidly growing academic research. In their comprehensive literature survey, Blinder et al. (2008) conclude that communication can be an important toolkit for helping central bank to achieve its macroeconomic objectives. This is because it has ability to move financial markets and to improve the predictability of monetary policy.

The measurement of central bank communication is of crucial importance. Several papers in the literature often use either an indirect approach (i.e. by measuring financial market reactions during event window of policy announcement) or a subjective assessment from direct reading the policy statements and coding into numerical scales. [See Blinder et al. (2008) for more details of these methods.] As noted in Lucca and Trebbi (2011, p.2), “literature on central bank communication is still relatively infant stage owing in part to the challenge of measuring verbal information directly in ways that are transparent, objective applicable across researchers”. More recently, Bholat, et. al. (2015), based on developments in text mining that has been widely used in other fields, provide an excellent overview to demonstrate the value added central bank can gain from applying various text mining techniques.

To measure the content of the MPC statements without resorting to researcher’s subjective judgment, this paper contributes to the economics literature by introducing an alternative method (so-called Wordfish) -- proposed by Slapin and Proksch (2008) -- that has been used mainly in political science. Wordfish is basically a statistical technique for estimating policy position based on word frequencies and the underlying idea is that relative word usage within documents should reveal information of policy positions. Note that statistical analysis of political texts has been a subject of extensive research. One of the most-widely used algorithms is so-called Wordscores, proposed by Laver et al. (2003); and this method shares the same underlying concept as in Wordfish (i.e. by using word counts as data). Jansen and de Haan (2010) apply Wordscores methodology to evaluate the consistency of ECB communication. However, as noted by Lowe (2008), there are at least two main problems, i.e. scaling issues and the absence of an underlying statistical model. These problems are resolved in Wordfish; Slapin and Proksch argue that their methodology is more suitable for producing time-series estimates of political/policy positions.

Among the earlier work in monetary economics is a paper by Gorodnichenko and Shapiro (2007) that makes a simple use of word counts for reflecting policy objectives during Alan Greenspan and Ben Bernanke periods. In addition, Boukus and Rosenberg (2006), and Hendry and Madeley (2010) apply a more sophisticated statistical technique so-called Latent Semantic Analysis (which is similar to the extraction of factor loading using principal component analysis) to identify multiple themes in the FOMC minutes and the Bank of Canada monetary policy statements, respectively. Lucca and Trebbi (2011) interestingly proposes a new automated method based on computational linguistics literature for measuring central bank communication using the FOMC statements. Their measures of the FOMC statements are calculated from the number of search hits using Google search engine and Dow-Jones Factiva newswire search.

Methodologically, there is a practical trade-off between the statistical modeling (in our proposed method of Slapin and Proksch) and the language modeling (for example, in Lucca and Trebbi, 2011). The difference in these modeling choices is also a common problem in the analysis of political text. As discussed in Monroe and Schrodtt (2008), the statistical modeling deals with frequencies of words without concerning for syntax, so allowing inferential models to be built on assumptions of count or discrete choice processes; and this has advantage in applying to multiple languages. However, the language modeling requires more attention to syntax and has advantage in facilitating the interpretation more intuitively.

This paper aims to examine informational content of the monetary policy statements made by the Monetary Policy Committee (MPC) of the Bank of Thailand during the first decade of inflation targeting. Specifically, the paper provides a comprehensive evaluation of the MPC statements on monetary policy effectiveness in three main aspects.

Firstly, we analyze the short-run predictability of interest rate decisions through the ordered-probit Taylor-type rule using the Bank of Thailand economic forecasts that are publicly available in the inflation reports. This is because the MPC would focus its policy decision on own economic projection, see Luangaram and Sethapramote (2015). By augmenting the ‘qualitative’ communication from the policy statements with ‘hard data’ (i.e. growth/inflation forecasts) in the Taylor-type equations, this paper should give a complete investigation whether the MPC statement is merely a reflection of own economic forecasts or can, in fact, help improving the predictability of monetary policy.

Secondly, we examine the role of central bank communication channel in the context of monetary policy transmission mechanisms. Using structural vector autoregression, we

study the dynamic response of output growth and inflation to shocks in monetary policy variables, i.e. both policy interest rate and our communication measure. Thirdly, we assess how monetary policy statements could affect long-run inflation expectation. To the best of our knowledge, the association between the central bank communication and inflation expectation has not been investigated in the emerging markets. By extracting inflation expectation from the term structure of zero-coupon government bonds using the Soderlind and Svensson (1997)'s methodology, we analyze whether monetary policy actions (via change in policy interest rate and change in communication) could anchor inflation expectations.

This paper is organized as follows. In Section 2, we present the methodological description of Wordfish, and in Section 3 we describe the data used in the paper. Section 4 presents the results from measuring the MPC statements and we interpret our communication measure using cross-correlation with various macroeconomic indicators. In Section 5, we investigate the predictability of monetary policy via the order-probit Taylor rule with various specifications. In Section 6, we examine the communication channel of monetary transmission mechanism. Section 7 focuses on inflation expectations and central bank communication. Section 8 concludes.

2. Methodology⁴

2.1. Introduction to Wordfish

Wordfish is an automated content analysis for estimating policy positions based on word frequencies from the documents of interest. It is recently developed by Slapin and Proksch (2008) who apply their technique to the case of German political system. Thus far, it has been used mainly in the study of comparative politics where locating parties in a political space over time is a challenging task. Since party or policy positions cannot be observed directly, they are then treated it as a latent variable. Nevertheless, like other quantitative position estimation techniques (including Wordscores proposed by Laver et al., 2003), the underlying idea in Wordfish is that the relative word usage by political parties should convey information about their positions in a policy space.

⁴This section is based extensively on Slapin and Proksch (2008) and Proksch and Slapin (2009a and 2009b).

As noted in Slapin and Proksch (2008), and Proksch and Slapin (2009a), in the case of Wordscores methodology, researcher needs to make subjective judgment by assigning some texts, for example, to be left-wing and others to be right-wing. These ‘reference texts’ are then used to anchor the end of the political spectrum. However, Wordfish algorithm simply uses relative word frequencies as data to estimate the documents on a scale. It is up to the researcher to make own assessment about what constitutes ‘left’ and ‘right’ based on his/her knowledge of politics. Slapin and Proksch (2008) also note that there are three main advantages in their approach; first, its ability to produce time-series estimates; second, it does not require researcher to choose reference texts since Wordfish assumes an underlying statistical distribution of word frequencies; and third, the ability to use all words in every document and to estimate the importance of each words.

In Wordfish, word frequencies are assumed to be generated by a Poisson process. This assumption has a nice feature that there is only one parameter (mean equals its variance) to be estimated. While it is simple, such distribution is found to be robust relative to other complicated statistical distributions (see Slapin and Proksch, 2008). The functional form is as follows:

$$y_{ijt} \sim \text{Poisson}(\lambda_{ijt})$$

$$\lambda_{ijt} = \text{esp}(\alpha_{it} + \psi_j + \beta_j * \omega_{it})$$

where y_{ijt} is the count of word j in document i at time t ; α is a set of document fixed effects; ψ is a set of word fixed effects; β is the estimate of word weights capturing word j in distinguishing between policy positions; and ω is the estimate of policy position in document i 's in year t . The document fixed effects are used to control of the length of the document and the word fixed effects are included to capture some words that are more often and has no substantive meaning. The key parameters of interest are the policy position and the word discrimination parameters.

2.2. Estimation process in Wordfish

Once the documents have been collected, the first step before implementing the Wordfish is preprocessing the documents by removing all ‘stop words’. The remaining words are then stemmed by removing suffixes, so that words sharing common root are grouped into a single term or unique word. [Note that there are many available computer algorithms for doing these tasks, including Yoshikoder and jfreq.] The next step is creating the so-called term frequency matrix where multiple document are put together and each column represents

a document and each row represents a unique word, or term. And each cell in the matrix contains the number of times the unique word is mentioned in each document.

Because all four parameters on the right-hand side of the equation shown above need to be estimated, Wordfish employs an expectation maximization (EM) algorithm which is an iteration process for computing the maximum likelihood estimates for latent variables. Note that Wordfish algorithm, written in *R*, is downloadable from wordfish.org and the program manual can be found in Proksch and Slapin (2009b). Here, we summarize main steps for implementing Wordfish.

Step 1: Calculate starting values for all four parameters.

Word fixed effects (ψ) is calculated by taking logged mean count of each word in the row matrix. And the document fixed effects (α) can be found by taking logged ratio of the mean word count in each document (column matrix) relative to the first document. To obtain the starting value for word weights (β) and policy position (ω), the logged word frequencies in each cell will be subtracted from the word and document fixed effects. Then a singular value decomposition (SVD) of this matrix can then be calculated to obtain the left-singular vector and right-singular vector. Note that, in Wordfish, only the first eigenvalue has used for the starting values of β and ω . For further detailed method of SVD, see Boukus and Rosenberg (2006).

Step 2: Estimate document parameters (α , ω)

Document parameters are then estimated conditional on word parameters (ψ , β). During the first iteration, these word parameters that set to their starting values from Step 1 in order to maximize the following log-likelihood for each document *it*:

$$\sum_{j=1}^m (-\lambda_{ij} + \ln(\lambda_{ij}) * y_{ij}),$$

$$\lambda_{ij} = \exp(\alpha_{it} + \psi_j^{start} + \beta_j^{start} * \omega_{it}).$$

To identify the model, Slapin and Proksch set α_{it} to zero and the mean and standard deviation of all document positions to zero and one, respectively. ψ_j^{start} and β_j^{start} are used as starting value in the maximization stage.

Step 3: Estimate word parameters (ψ , β)

Now, word parameters are estimated conditional on expectation of document parameters, obtained from step 2. For each word *j*, the following log-likelihood is maximized:

$$\sum_{j=1}^m (-\lambda_{ij} + \ln(\lambda_{ij}) * y_{ij}),$$

$$\lambda_{ij} = \exp(\alpha_{it}^{step\ 2} + \psi_j + \beta_j * \omega_{it}^{step\ 2}).$$

Step 4: Calculate log-likelihood

The log-likelihood of the model is calculated by the sum of the individual word log-likelihood from step 3, which are conditional on the party log-likelihood in step 2:

$$\sum_{j=1}^m \sum_{it=1}^n (-\lambda_{ij} + \ln(\lambda_{ij}) * y_{ij}).$$

Step 5: Repeat steps 2-4 until convergence

3. Data

Data used in our analysis contain 90 monetary policy statements from the Monetary Policy Committee (MPC) meetings and 44 quarterly monetary policy reports, since the beginning of the inflation-targeting regime in 2000 until April 2011. Regarding the monetary policy reports, we specifically collect the official economic forecasts from the distribution tables both output growth and headline/core inflations from one to eight periods ahead.

4. Analyzing Thai monetary policy statements

In this section, we report the results from measuring the MPC statements using Wordfish algorithm and compare with ‘hand-coding’ score which is constructed from reading the monetary policy statements by a group of economics student at Chulalongkorn University (45 students in total). We then interpret our automated score via cross-correlation with various economic indicators including BOT own economic forecasts.

Before turning to the results, it would be useful to see the most frequent keywords (after removing stopped and stemmed words) in the MPC statements during the past 10 years. As can be seen from the Table 1, words related to inflation (i.e. inflation, price, pressure, core, oil, stability) have relatively been mentioned much more often than words related to growth (i.e. growth, recovery).

4.1. Measures of monetary policy statements: Objective vs Subjective approaches

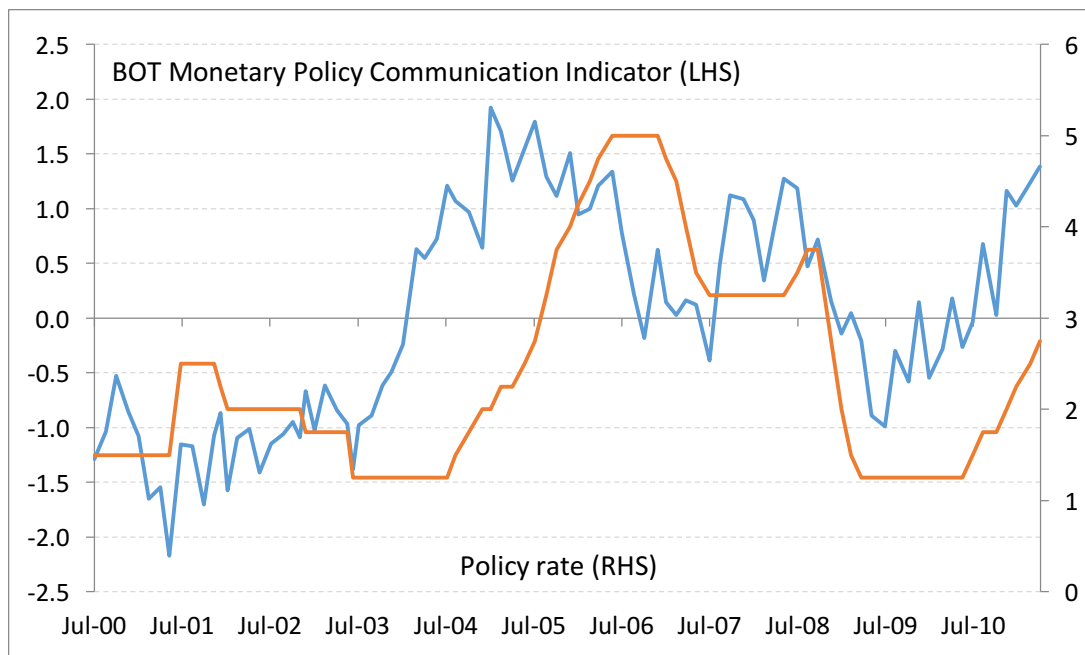
Figure 1 shows the result of monetary policy statements as measured by Wordfish algorithm (using only forward-looking sentences that appear in each statement). The higher the score, the higher inclination that the MPC would raise its policy rate, and vice versa. [Note that this score are normalized to have zero mean and the variance is set to 1.] How accurate is our measure of the MPC statements in capturing monetary policy stance? As shown in figure, the MPC statements generally lead the policy rate. During the first two years of inflation targeting, the communication indicator fluctuates considerably and does not seem to track movements in the policy rate. Starting from 2003, however, it is much clearer that the measure can pick up both the up and down cycles of the policy rate in advance. Interestingly, when the Thai economy was unexpectedly hit by the global financial crisis in late 2008 and the MPC had to cut its policy rate aggressively, the statements co-moved contemporaneously with the policy rate and later lagged behind its action.

Table 1 Top ten keyword counts

1. econom (303)	6. pressur (72)
2. inflat (191)	7. recoveri (67)
3. growth (127)	8. core (64)
4. risk (102)	9. oil (60)
5. price (88)	10. stabil (40)

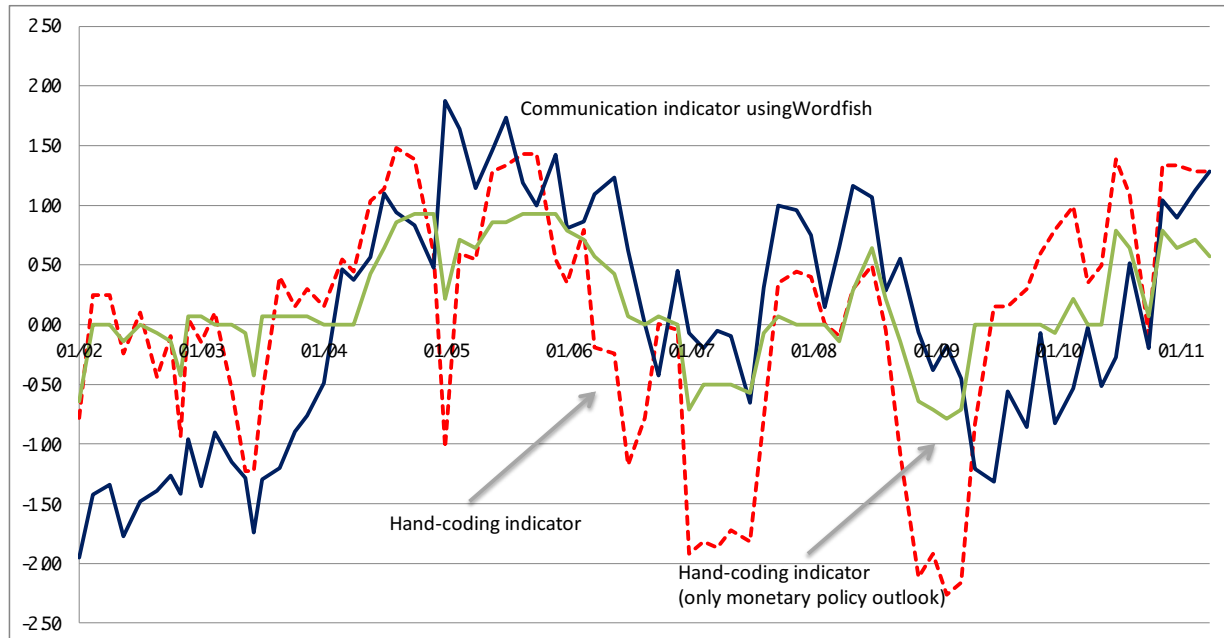
To supplement our measure, we asked 45 undergraduate students at the faculty of Economics, Chulalongkorn University to read every policy statements since 2002. In doing so, we extend the methodology used by Erhmann and Fratzscher (2007) and classify the forward-looking statements into three dimensions: (i) output growth outlook, (ii) inflation outlook, and (iii) monetary policy outlook. [Note that Ehrmann and Fratzscher (2007) look at two aspects i.e. economic outlook and monetary policy outlook.] The classification is as follows: if the statement indicates stronger growth/higher inflation outlook, we use +1; if the view is unchanged from the previous statement, we use 0; and if weaker growth/lower inflation outlook is indicated, we use -1. As for monetary policy outlook, we use +1 with tightening inclination; 0 without any inclination and -1 with easing inclination. We then take a simple average of these three values in each statement.

Figure 1: BOT monetary policy communication indicator vs Policy rate



Source: Communication indicators are calculated by authors using Wordfish. Policy interest rate is collected from Bank of Thailand.

Figure 2. Monetary policy communication: Subjective vs objective measures



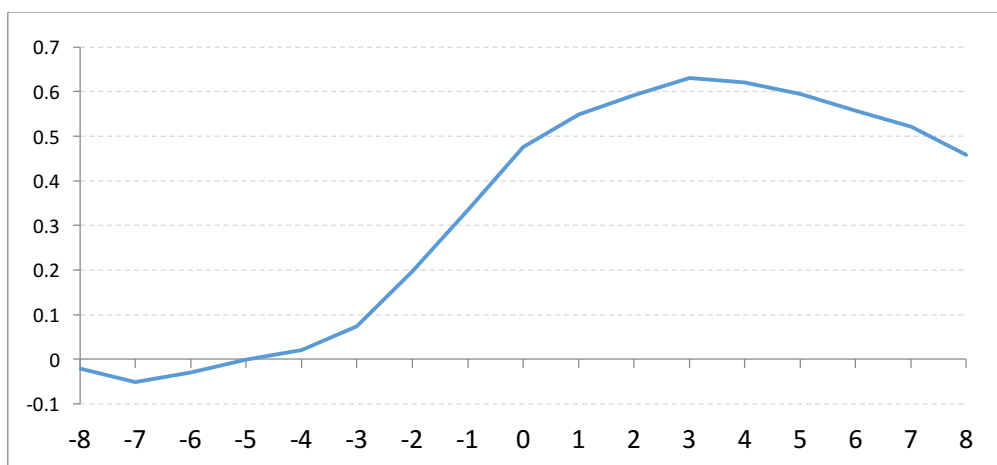
Source: Communication indicators are calculated by authors using Wordfish. Hand-coding indicators are computed based on students' reading of the statements using the Erhmann and Fratzscher (2007)'s methodology.

As shown in the Figure, the co-movements between our objective measure from Wordfish and the hand-coding score based on students' reading of the statements (simple average of three classifications as mentioned above) are not too far apart. The correlation is 0.40 during 2002-2011. However, when using the simple average score on monetary policy outlook, the correlation with our Wordfish measure is quite high i.e. 0.62. Note that this hand-coding indicator, by construction as stated above, measures the 'direction', not the magnitude, of economic outlook. Both measures have their own strengths and weaknesses. The strength from the hand-coding indicator is that it facilitates reading between lines but the problem is that it is subjective, depending on reader's judgment and can be time-consuming. As for our automated indicator, it is better in terms of no judgment involved and therefore reproducible and easy to implement; but order of words is lost because it is based only on word frequencies.

4.2. Interpreting the BOT monetary policy communication indicator

Figure 3 plots the cross-correlations between our communication indicator and the policy rate. When this indicator lags the policy interest rate, the cross-correlation is falling rapidly while it is rising when the communication indicator leads the policy rate. It can be observed that the cross-correlation is peak (0.63) when the indicator precedes the policy rate by three quarters. This would not be surprising given that our indicator contains only forward-looking information in the MPC statements.

Figure 3: Cross correlation between communication index (t) and policy rate (t+j), j=quarter

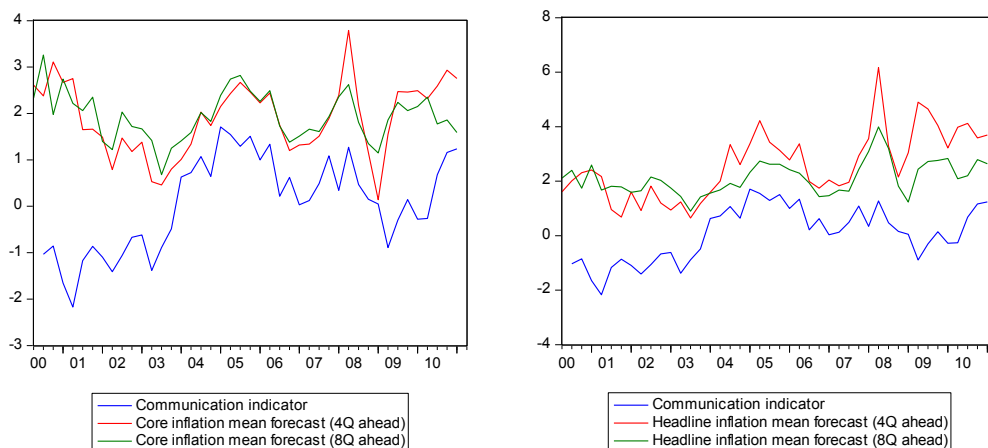


Source: Authors' calculation

To investigate further, we look at how the monetary policy statements as measured by Wordfish reflect the MPC own forecasts of inflation and growth outlook. Since the beginning of inflation-targeting regime, the MPC released its forecasts for future inflation and output growth in the quarterly Monetary Policy Report. The forecasts are presented in terms of both the fan charts and the tables of probability distribution, with the horizons ranging from one to eight quarters ahead. Based on the data in the probability distribution table, we can calculate the mean forecasts by multiplying mid-point in each range to its corresponding probability.

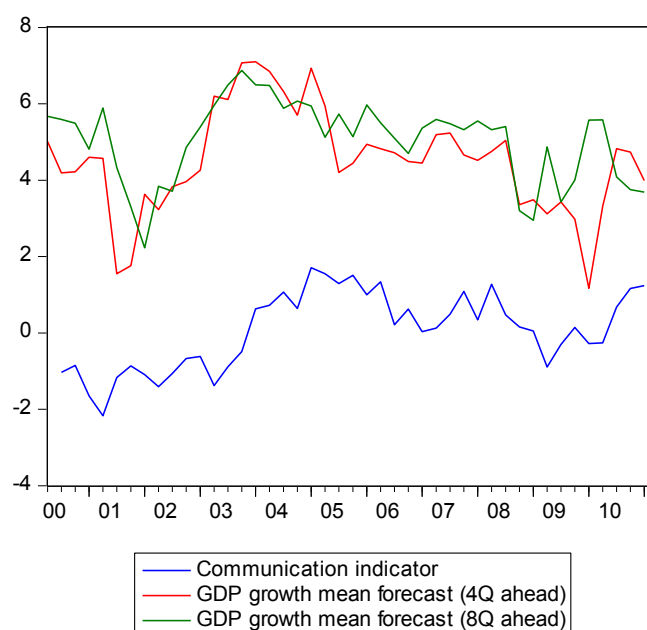
Figure 4 and 5 plot the MPC communication indicator against the mean forecasts of inflation and output growth four and eight quarters ahead. As can be seen from the figures, the MPC statements appear to be more consistent with both core and headline inflation outlook than output growth projection. In particular, when the supply-side pressure driven mainly by rising oil prices had been more prominent during 2004q1-2007q4, the correlations between communication indicator and two-year inflation forecasts of core inflation and headline inflation rise substantially to 0.87 and to 0.89 from 0.59 and 0.39 during 2003q1-2011q1, respectively.

Figure 4: Core and Headline Inflation Forecasts vs Communication Indicator



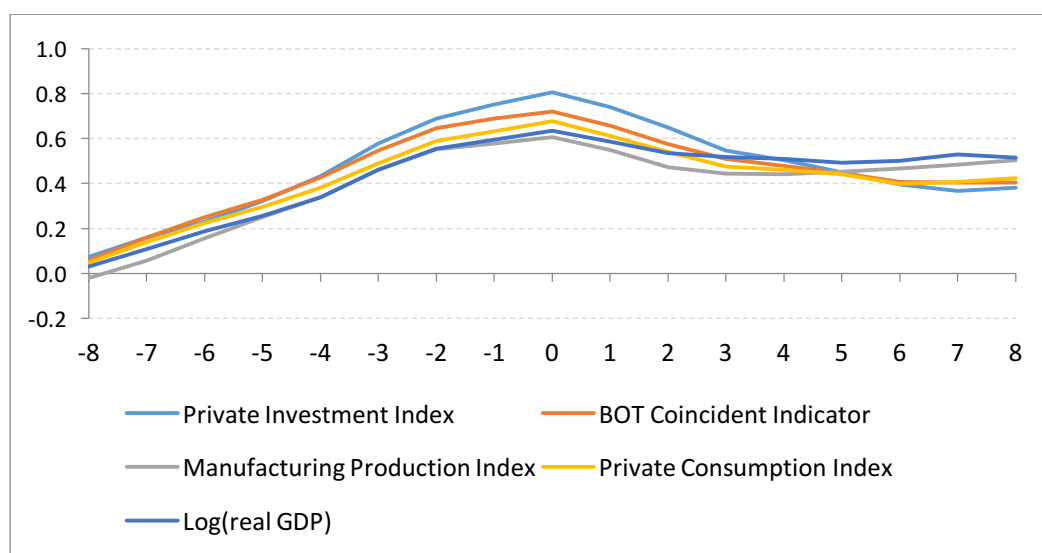
Source: Communication indicators are calculated by authors using Wordfish. Core and headline inflation forecasts are collected from the Inflation Reports.

Figure 5: GDP Growth Forecast vs Communication Indicator



Source: Communication indicators are calculated by authors using Wordfish. GDP growth forecasts are collected from the Inflation Reports.

Figure 6: Cross correlations between communication index (t) and various macroeconomic indicators (t+j), j=quarter



Source: Authors' calculation. The data of macroeconomic indicators are collected from Bank of Thailand.

As for the real economy, we look at the cross-correlations using various main macroeconomic indicators including private investment index, private consumption index, manufacturing production index as well as log of real GDP and BOT's coincident economic indicator. As shown in Figure 6, our measure of the MPC statements correlates contemporaneously with all key macro indicators, ranging from 0.60 for manufacturing production index to as high as 0.80 for private investment index. In terms of the lead-lag structure, while the cross-correlations are peak at $t=0$, they are all declining more rapidly when the communication index lags these macro indicators. This suggests that the statements seem to lead economic activities.

What conclusions can be drawn from the cross-correlation analysis? Overall, our measure of the MPC communication reasonably reflects future economic activity and generally leads the actual policy rate decision by a few quarters. In particular, it is clear that the MPC statements are more in line with its inflation projections than output growth forecasts. This should not be surprising, given that Thailand has adopted inflation targeting regime and so maintaining inflation within its targeting band is clearly a priority task in order to gain credibility from the public. In the next section, formal econometric investigation will be employed to see if the MPC communication helps to provide extra informational value on the predictability of monetary policy through the lens of the Taylor-type equations.

5. Predictability of the MPC Interest Rate Decisions

The role of central bank communication for forecasting the future central banks' decision on policy interest rate decision has been investigated in many recent studies. Heinemann and Ullrich (2007), Rosa and Verga (2007) and Sturm and De Haan (2011) suggest that communication efforts make market expectation of monetary policy decision more accurate. However, Jansen and De Haan (2009) suggest that information obtained from communication cannot improve predictability over models with macroeconomic data.

In this section we investigate whether our measure of communication provides clear signal about the future direction of monetary policy and can provide additional information to predict future policy interest rate decision over the Taylor-type predictive variables, i.e. output gap and inflation. For this purpose, the ordered probit model is applied to estimate the Taylor-type predictive regression. The choice of interest rate decision can be represented by ordered dummy variable that take value of -1 if policy rate decreases, 0 if policy rate is kept

unchanged and 1 if policy rate increases. And the probabilities of these three outcomes are written as:

$$\begin{aligned}\Pr[\Delta i(t) = -1|z(t)] &= \phi(\tau_1 - z(t)'\beta) \\ \Pr[\Delta i(t) = 0|z(t)] &= \phi(\tau_2 - z(t)'\beta) - \phi(\tau_1 - z(t)'\beta) \\ \Pr[\Delta i(t) = 1|z(t)] &= 1 - \phi(\tau_2 - z(t)'\beta)\end{aligned}$$

where τ_1 and τ_2 are unobserved threshold, and

ϕ denotes the cumulative standard normal distribution, and

$z(t)$ is a vector with explanatory variables.

According to the Taylor rule, monetary policy decision is reacted to deviation of inflation (π_t) and output growth (x_t) and from their targets. In this paper, we apply ‘forward-looking’ Taylor-type equation. Therefore, the standard benchmark model (i.e. ‘hard data only’) are written as follows.

Model 1

$$\Delta i_t = \beta_1(\pi_{t+h,t} - \pi^*) + \beta_2(x_{t+h,t} - x^*) + \varepsilon_t$$

where $x_{t+h,t}$ and $\pi_{t+h,t}$ are ex-ante forecasts made in period t of output growth and inflation at h period ahead. π^* is desired inflation target and x^* is potential GDP growth. Following Luangaram and Sethapramote (2015), we use core inflation target of 2% and potential output growth of 5.25% and time horizon target of eight quarters ahead for both inflation and output growth forecasts⁵.

Secondly, we include the past interest rate decision (Δi_{t-1}) and the level of past interest rate (i_{t-1}) in the benchmark model. The past interest rate decision is used to capture interest rate smoothing pattern (Kuttner, 2004). The level of past interest rate (i_{t-1}) is suggested by Goodhart and Lim (2011) as the predictor of the future policy interest rate. When interest rates remain at low level, the possibility that interest rate will be converse to the long-run average value should be increased, and vice versa. Therefore, the augmented forward-looking Taylor-type equation can be written as:

Model 2

$$\Delta i_t = \beta_1(\pi_{t+h,t} - \pi^*) + \beta_2(x_{t+h,t} - x^*) + \beta_3\Delta i_{t-1} + \beta_4i_{t-1} + \varepsilon_t$$

⁵ See Luangaram and Sethapramote (2015) for details of how to translate from ex post forecasts (i.e. those published after the MPC decision), and incorporating, the preceding interest rate decision into ex ante forecasts (i.e. those presented to the MPC before that decision). Moreover, Luangaram and Sethapramote (2015) also provide the the discussion on the advantage of the forward-looking Taylor-type equations in Thailand and the setting of the inflation and output growth targets in Thailand.

Next, the role of central bank communication is examined by including the communication index (CI) in Models 1 and 2. The predictive regressions are written as follows.

Model 3

$$\Delta i_t = \beta_1(\pi_{t+h,t} - \pi^*) + \beta_2(x_{t+h,t} - x^*) + \beta_3\Delta CI_{t-p} + \varepsilon_t$$

Model 4:

$$\Delta i_t = \beta_1(\pi_{t+h,t} - \pi^*) + \beta_2(x_{t+h,t} - x^*) + \beta_3\Delta i_{t-1} + \beta_4 i_{t-1} + \beta_5\Delta CI_{t-p} + \varepsilon_t$$

The lag order of communication index (p) is determined by statistical criteria, i.e. pseudo R^2 and the testing for significance of estimated coefficients. The estimation results of models 1 to 4 are displayed in Table 2.

Table 2 Estimation results for ordered probit models with **core inflation**

Variables	Model without CI		Model with CI	
	Model (1)	Model (2)	Model (3)	Model (4)
$\pi_{T+8}^f - 2.00$	1.359** (0.365)	1.488** (0.481)	2.124** (0.513)	1.769** (0.542)
$y_{T+8}^f - 5.25$	0.292* (0.171)	0.383** (0.188)	0.285 (0.183)	0.330* (0.193)
Δi_{t-1}^*		1.090** (0.375)		0.987** (0.395)
i_{t-1}		-0.343* (0.193)		-0.353* (0.205)
τ_1	-1.373** (0.295)	-2.557** (0.661)	-1.774** (0.374)	-2.694** (0.691)
τ_2	0.406* (0.225)	-0.135 (0.480)	0.142 (0.273)	-0.339 (0.532)
<u>Communication index</u>				
CI_{t-3}			0.933** (0.471)	0.735 (0.480)
Pseudo- R^2	0.228	0.409	0.368	0.465

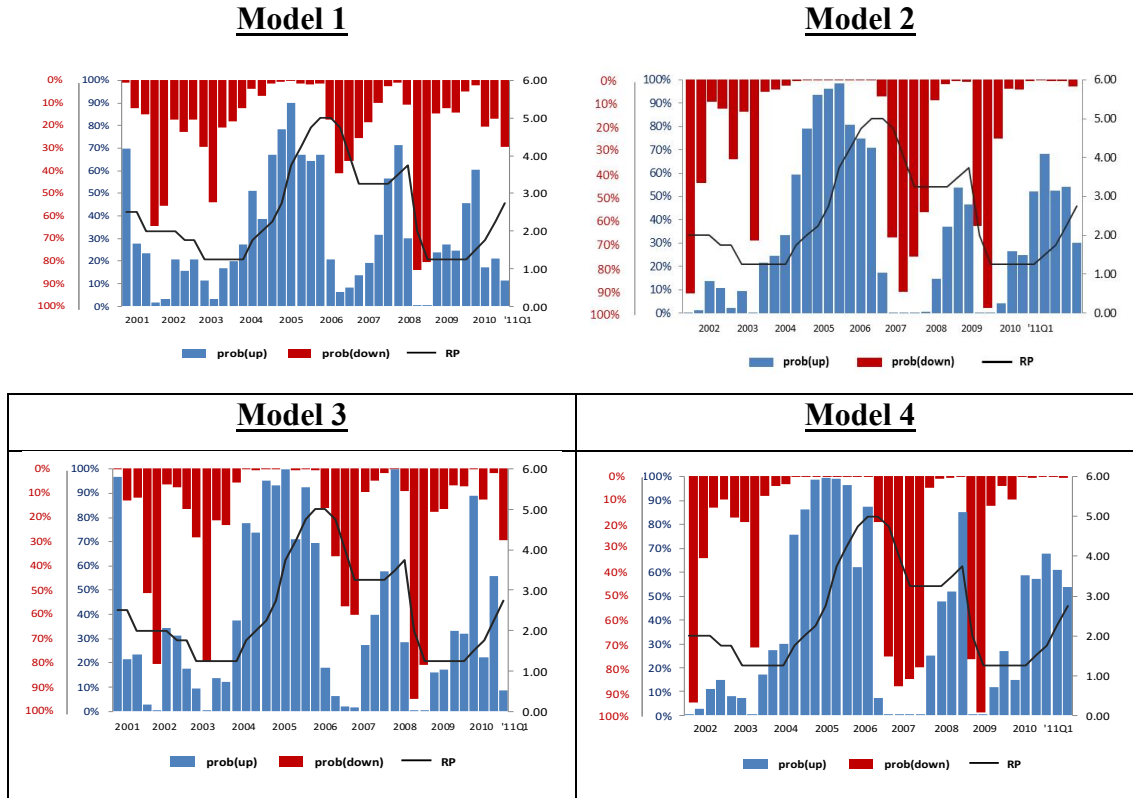
Notes: Sample period is 2002, quarter 3 to 2011, quarter 1. Figures in parentheses are standard errors of estimated coefficients.

* and ** denote significance at 10 and 5% level.

τ_1 and τ_2 denote the estimated thresholds separating three categories of dependent variable (interest rate decisions - down, status quos and up).

Communication index (CI_{t-3}) is the three period lagged of the first difference of communication index. The lagged order are selected by the statistical criteria, i.e. pseudo R^2 and the testing for significance of estimated coefficients.

Figure 7 Probability estimates of MPC decisions using the results from ordered probit predictive regression



Note: The probability estimates are calculated from the order-probit model based on models 1 to 4.

Table 2 shows econometric results for the models 1 to 4 using core inflation. Based on the goodness of fit criteria, the three-period lagged of communication index (CI_{t-3}) is used. We first consider the model without communication variable. As can be seen in the table, the estimated coefficients on the inflation and output growth are significant in both forward-looking Taylor-type regressions. Once considering the impact of communication, the results of models 3 and 4 show that the coefficient on CI_{t-3} is significant at 5% level for model 3 but is not significant for model 4. When we compare the results between model 1 and model 3, the value added from communication is confirmed since pseudo R^2 in model 3 is considerable higher than that of model 1⁶.

Next, the probability of three possible outcomes of MPC action (up, status quos, and down) are estimated from the ordered probit models to check the ability of the models (with and without communication indicator) in predicting future interest rate changes. The results from models 1 to 4 are presented in Figure 7.

⁶ For sensitivity check, we also estimate the augmented Taylor-rule like ordered probit regression using the forecasts of headline inflation as indicator for inflation pressure. The estimated results are available on requested

Probability estimates in Figure 7, show that probability estimates from models 3 to 4, provide information on the decisions of MPC. The upward and downward trends in interest rates are explained by increases in probability of the corresponding events. The figures show that including communication indicator helps improving probability predictions, especially when the MPC decides to change its policy interest rate.

Finally, we compute the percentage that probability estimates can provide corrected prediction of the actual outturn. From the figures above, we observe that the probability estimates cannot explain timing of a cut in policy interest rate correctly. Therefore, we compute percentage of correctly predicting MPC action in two sample periods. First, we consider data for whole sample (2001q2 to 2011q1). Second, the sub-sample between 2004q1 to 2011q1 is used. The results are displayed in Table 3.

Compare between models with same explanatory variable, adding communication indicator provide improvement in predictability; models 3 and 4 have higher percentage correction than their counterpart (models 1 and 2, respectively).

Table 3 Percentage of correction in prediction of MPC decision

Full Sample 2001q2 - 2011q1	Model (1)	Model (2)	Model (3)	Model (4)
$\Delta i^* = -1$	2 out 8 (25.00%)	5 out 8 (62.50%)	4 out 8 (50.00%)	5 out 8 (62.50%)
$\Delta i^* = 0$	13 out 17 (76.47%)	12 out 17 (70.59%)	13 out 17 (76.47%)	12 out 17 (70.59%)
$\Delta i^* = 1$	10 out 15 (66.67%)	13 out 15 (86.67%)	12 out 15 (80.00%)	15 out 15 (100.00%)
Total	25 out 40 (62.50%)	30 out 40 (75.00%)	29 out 40 (72.50%)	32 out 40 (80.00%)
Sub-sample 2004q1 - 2011q1	Model (1)	Model (2)	Model (3)	Model (4)
$\Delta i^* = -1$	2 out 5 (40.00%)	5 out 5 (100.00%)	4 out 5 (80.00%)	5 out 5 (100.00%)
$\Delta i^* = 0$	9 out 10 (90.00%)	8 out 10 (80.00%)	9 out 10 (90.00%)	8 out 10 (80.00%)
$\Delta i^* = 1$	9 out 14 (64.29%)	12 out 14 (85.71%)	11 out 14 (78.57%)	14 out 14 (100.00%)
Total	20 out 29 (68.97%)	25 out 29 (86.21%)	24 out 29 (82.76%)	27 out 29 (93.10%)

Note: The percentage of correction in prediction of MPC decision are calculated from the order-probit model based on models 1 to 4.

When comparing the results between whole sample and sub-sample, the improvement in predictability is found in all forward-looking Taylor rule equation after 2003. These results show that communication during the beginning of inflation targeting still provide confused signal about timing of interest rate change. Consider the results from sub-sample, the predictive power of model 3 (forward-looking Taylor-rule variables plus communication index) is quite high (82 percent) and the predictive power is highest in model 4 where the lagged of policy decision and level of interest rate are included (93 percent).

Therefore, the results from Table 3 strengthen our findings that interest rate change are consistent with communication presented in both quantitative (inflation and output growth forecast presented in Inflation Report) and qualitative communication (statements released after MPC meeting)

6. The role of central bank communication in the transmission of monetary policy

In this section, the role of central bank communication in the context of monetary policy transmission mechanisms is examined. We first consider the dynamic response of output growth and inflation to shocks in monetary policy variables, i.e. policy interest rate and communication indicator. The vector autoregressive model is applied for measuring monetary policy transmission mechanism. Neuenkirch (2013) use a VAR model and find that actual inflation and inflation expectations are strongly affected by shocks in communication. Moreover, he also suggests that central bank communication has the complement role to the policy interest rate in the monetary policy transmission mechanism.

Additionally, Lucca and Trebbi (2011) suggest that central communication has the important role in transmission mechanism because its influence in long-term interest rates. Previous empirical studies find evidence that yields with short maturities (3-months to 1 year) significantly react to shocks in monetary policy interest rate. However, yields with long maturities (10 years and more than 10 years) react with only the small proportion to monetary policy shocks⁷. Anderson et al. (2006) further investigate this issue by comparing the responses of financial market's yields to both policy interest rates and central bank

⁷ See Berument and Froyen (2009) for the summary of the empirical studies on the feedback of term structure of interest rates to the monetary policy shocks.

communications. They find that the long-term interest rates respond more to communication than to policy interest rate change.

Therefore, we examine on the role of communication channel in transmission mechanism of monetary policy to both macroeconomic variables and term structure of interest rates using the structural VAR (SVAR) model. The five macroeconomic variable, i.e. Inflation (natural logarithm of headline consumer price index: PCPIH), Real output (natural logarithm of real GDP: YR), monetary policy interest rate (1-day repurchase rate: RP1), central bank communication (communication index: CI), and term structure of interest rates (zero-coupon government bond yields: YIELD).

The standard SVAR set-up can be written as.

$$\mathbf{A}\mathbf{Y}' = \mathbf{a}(\mathbf{L})\mathbf{Y}' + \mathbf{B}\boldsymbol{\epsilon}_t^Y$$

where $\mathbf{A}$ and $\mathbf{B}$ matrices represent the restrictions in contemporaneous relationship in endogenous variables ($\mathbf{Y}$; $\mathbf{Y} = [\text{PCPIH}, \text{YR}, \text{RP1}, \text{CI}, \text{YIELD}]$) and in a matrix of the structural shocks ($\boldsymbol{\epsilon}_t^Y$), respectively, while an $\mathbf{a}(\mathbf{L})$ matrix defines a restriction on dynamic response of each endogenous variable in the model.

We follow Lucca and Trebbi (2011) to define the recursive assumptions in identification of shock in VAR based on restriction in an $\mathbf{A}$ matrix. First, the inflation does not contemporaneous react to the output growth shock. Second, the macroeconomic variables (PCPIH, YR) respond with lag time to a shock in monetary policy variables (RP1, CI). Third, we put the order of RP1 in the recursive structure before the CI, which imply that the RP1 will not respond to the change in CI in the same period. Finally, we set a restriction in a $\mathbf{a}(\mathbf{L})$ matrix assuming that the interest rates at any maturities do not affect other variables but can respond contemporaneously to a shock in other variables. Hence, the configuration of the variables in the SVAR model can be summarized as follow.

$$\mathbf{A} = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ A_{21} & 1 & 0 & 0 & 0 \\ A_{31} & A_{32} & 1 & 0 & 0 \\ A_{41} & A_{42} & A_{43} & 1 & 0 \\ A_{51} & A_{52} & A_{53} & A_{54} & 1 \end{bmatrix}, \mathbf{B} = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix}, \text{ and}$$

$$\mathbf{a}(\mathbf{L}) = \begin{bmatrix} a_{11}(\mathbf{L}) & a_{12}(\mathbf{L}) & a_{13}(\mathbf{L}) & a_{14}(\mathbf{L}) & 0 \\ a_{21}(\mathbf{L}) & a_{22}(\mathbf{L}) & a_{23}(\mathbf{L}) & a_{24}(\mathbf{L}) & 0 \\ a_{31}(\mathbf{L}) & a_{32}(\mathbf{L}) & a_{33}(\mathbf{L}) & a_{34}(\mathbf{L}) & 0 \\ a_{41}(\mathbf{L}) & a_{42}(\mathbf{L}) & a_{43}(\mathbf{L}) & a_{44}(\mathbf{L}) & 0 \\ a_{51}(\mathbf{L}) & a_{52}(\mathbf{L}) & a_{53}(\mathbf{L}) & a_{54}(\mathbf{L}) & a_{55}(\mathbf{L}) \end{bmatrix}.$$

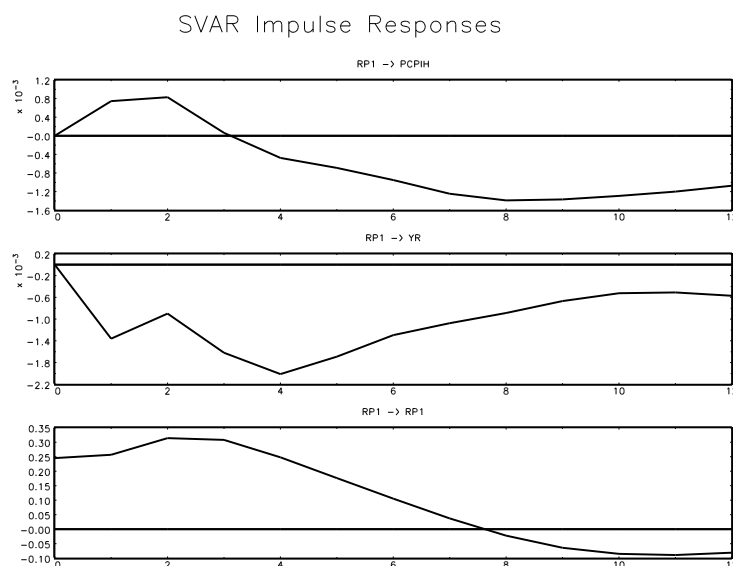
We measure the effect of monetary interest rate decision and communication to the yields in different maturities. Hence, we consider the term structure of interest rates that include the short-term and long-term yields. The yield maturities used in the SVAR model consist of 3-months, 6-months, 1-year, 2-years, 3-years, 4-years, 5-years, 7-years, 8-years, 9-years, 10-years and 15-years. We apply one maturity of government bond yield in each of the SVAR estimation. Therefore, we estimate twelve SVAR models that cover these twelve yield maturities. Our SVAR model are based on assumption that yield have no immediate and dynamic impact on other variables. Hence, estimation results for dynamic response of the remaining five variables in the SVAR model with different yields will be identical. The differences in the results from the SVAR models are the response of interest rates with different maturities.

We first estimate the SVAR models without central bank communication variables. Therefore, endogenous variables in the SVAR model ($\mathbf{Y}$) consists of four variables outlined as follow.

$$\mathbf{Y} = [\text{PCPIH}, \text{YR}, \text{RP1}, \text{YIELD}]$$

The impulse response functions of macroeconomic variables (PCPIH, YR) to a shock in monetary policy interest rate (RP1) are displayed in Figure 8.

Figure 8. Impulse response functions of macroeconomic variables to a shock in monetary policy interest rate in the SVAR model without the communication index

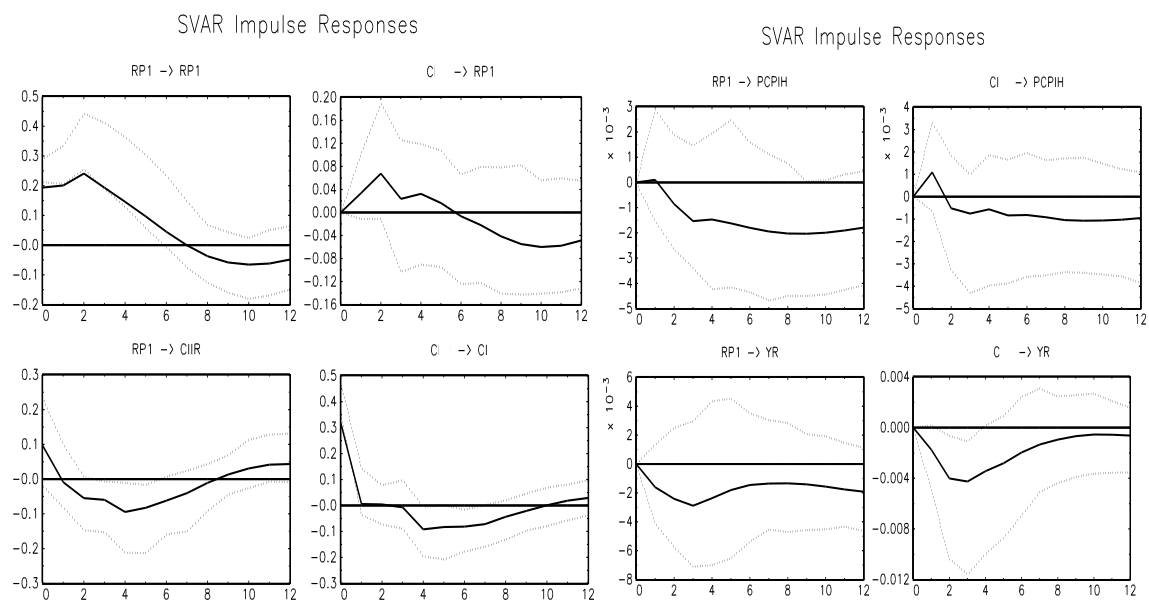


Source: Authors' calculation.

The results from Figure 8 show that inflation (PCPIH) takes a long time to response to monetary policy, the decrease in inflation are found after 1 year of an initial shock in RP1. Moreover, we also find the price puzzle pattern in which the inflation increases at the first two quarters after a shock in RP1. For the output variables, the responses to a monetary policy shock are quicker than those of the inflation. The maximum effect of monetary policy to output growth follows within a year after an initial shock. These results are consistent to those of the previous studies of a transmission of monetary policy in Thailand⁸.

Next, we estimate the SVAR model with all of five variables and compute the impulse response analysis to a shock in monetary policy interest rate (RP1) and communication index (CI). The results are shown in Figure 9.

Figure 9 Impulse response functions of macroeconomic and monetary policy variables in the SVAR model with the communication index



Source: Authors' calculation.

The important findings in Figure 9 are summarized as follow. We first consider the reaction between a shock in policy interest rate and communication index. One standard deviation of shock in RP1 has a size around 20 basis points, which close to the step of policy interest rate change (25 basis points). Next, a positive shock in communication index indicates that the MPC statement give a surprise hawkish view about monetary policy stance. Our empirical results show that the policy interest rate responses to a shock in

⁸ See Disyatat and Vongsinsirikul (2003) and Charoenseang and Manakit (2007) for the empirical result of transmission mechanism of shock in monetary policy interest rate in Thailand.

communication index with a time lagged around two to four quarters. This number of time lagged is similar to the finding in Section 5 where a change in degree of hawkish of policy statement can use to predict the future interest rates in the next three quarters.

Second, we examine the effect of a policy shock to the macroeconomic variables. The prize puzzle in which the inflation increases in response to a positive change in monetary policy interest rate is not observed. Inflation rate declines after two quarter of a shock. In case of a shock in communication index, we observe the prize puzzle. However, inflation declines after two quarters. The full effects of RP1 to inflation (output) take about ten (four) quarters after a shock

Comparing the impulse response functions from Figure 9 with those of Figure 8, we find that, with the communication index, the key macroeconomic variables response to a shock in RP1 are quicker than that of the model without CI by one quarter in case of inflation and two quarters in case of real output. Moreover, the sizes of response in the model with CI are also larger than those of the model without CI. For example, the inflation adjusted to a RP1 shock by 0.0015 without CI comparing to 0.002 in the model with CI.

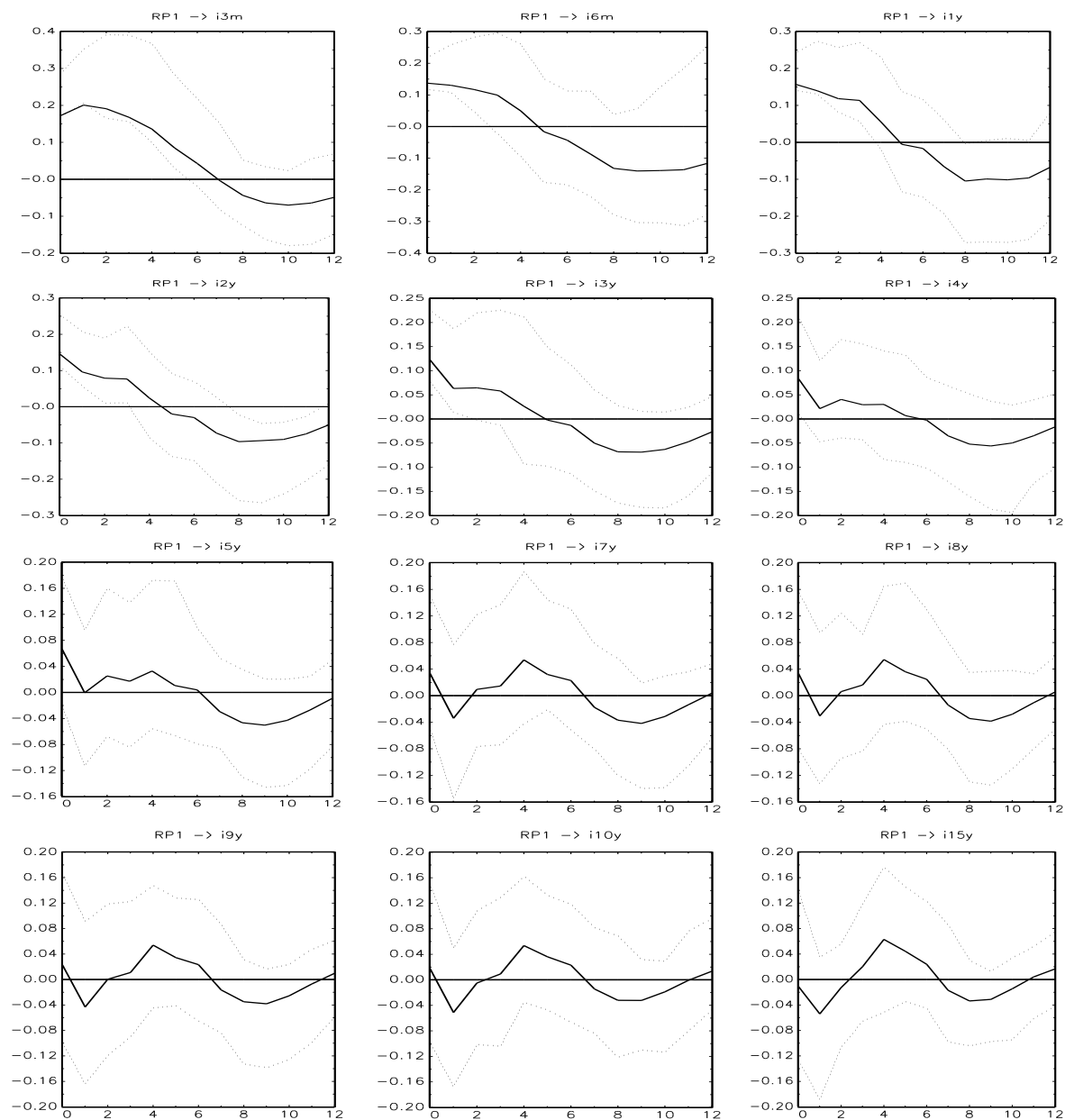
In summary, the results from the SVAR model show that communication index provide the direct and indirect effects to the key macroeconomic variables (inflation, output growth). Even though the sizes of a direct effect are relatively small compare to a shock in policy interest rate, an indirect effect via its impact on RP1 in the following period provide the important channel of transmission mechanism of monetary policy.

Subsequently, we investigate the financial market response to a monetary policy shock. The government bond yields with different maturities are used. We consider the SVAR models estimated with twelve maturities of yield ranging from short-term (3-months, 6-months), medium-term (1 year, 2 years, 3 years, 5 years, 7 years, 8 years, 9 years) and long-term government bond yields (10-years and 15-years). The results are shown in Figures 10 and 11 for the response of term structures of interest rates to monetary policy interest rate and communication index, respectively.

The results from Figure 10 show that the short-term interest rates react to a shock in policy interest rate. The contemporaneous response of short-term yields is high as 3- months yield increases around 89 percent of the size of shock in policy rate. In the medium term yields, the size of response to a policy rate shock decrease in the yield with long-term maturities, i.e. the sizes of contemporaneous response are equal to 81, 75 and 34 for the yields with 1-year, 2-years and 5-years maturities, respectively. In case of long-term yield, the sizes of response considerably decline as the 10-years yield increases by only 9 percent of

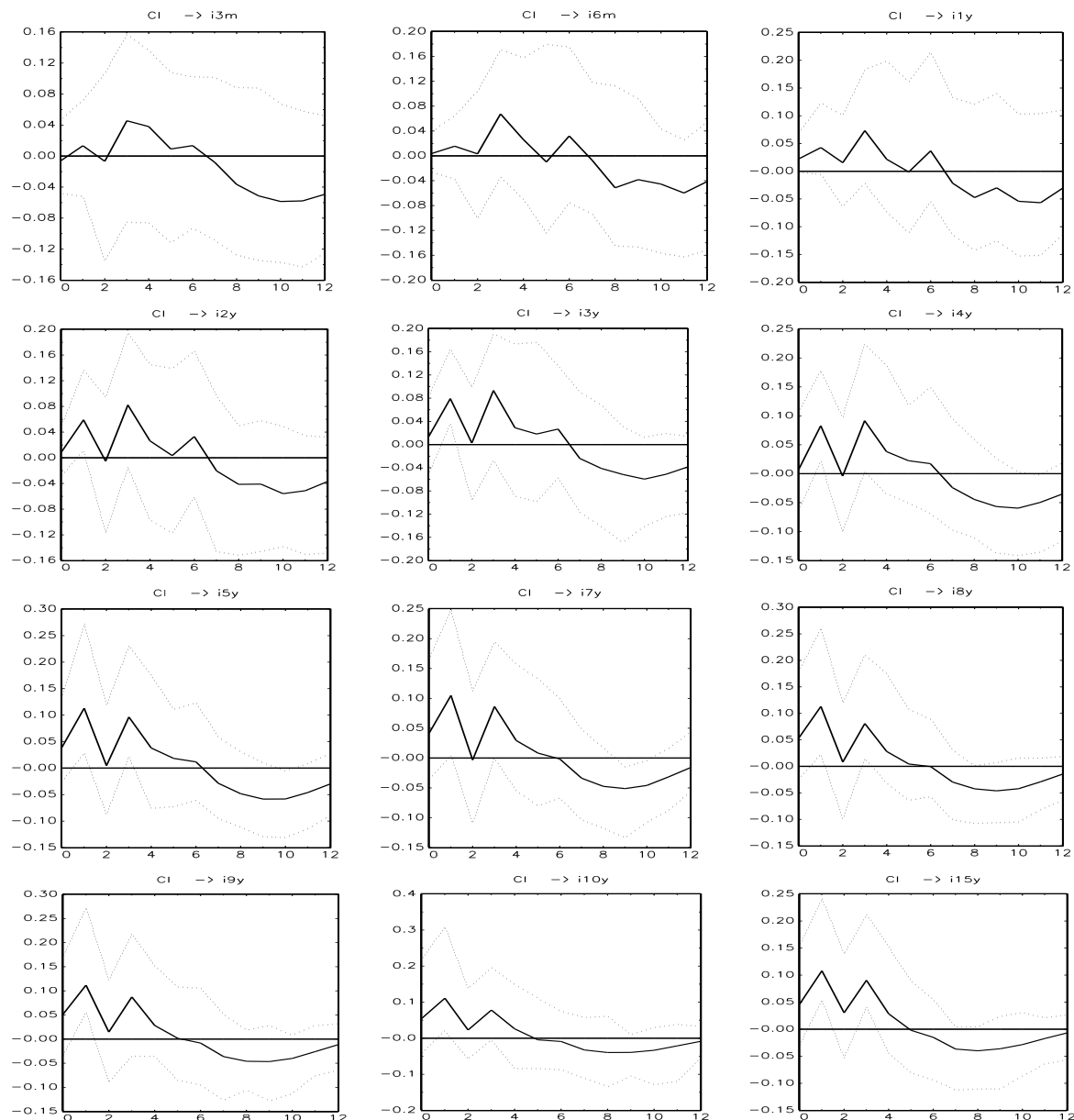
a shock in policy rate. These results provide evidence that the policy interest rate has limited effects on the long-term interest rate in financial market.

Figure 10. Impulse Response Functions in the response of term structure of interest rate to shock in policy interest rate (RP1)



Source: Authors' calculation.

Figure 11. Impulse response functions in the response of term structure of interest rate to shock in central bank communication (CI)



Source: Authors' calculation.

Furthermore, the results of the response from a shock in communication index (CI) are considered. From Figure 11, a one standard deviation shock in CI leads to increases in interest rates by 4.6, 7.3, 6.8, and 8.2 basis points for the government bond yields with 3-months, 6-months, 1-year and 2-years respectively. Interestingly, the sizes of reaction in the long-term interest rates are larger than those of interest rate with short- and medium- term maturities. The response of yields with 5-year, 10-years and 15 years increase around 11 basis points in the next quarter after a shock in CI. These results provide supportive evidence

that central bank communication via MPC statement improve the effectiveness of monetary policy by providing additive effects on the long-term bond yields where a change in policy interest rate can provide only the small effects.

7. Inflation expectations and central bank communication

The ability of central bank to control inflation expectation is one of the ultimate goals of inflation-targeting monetary policy. Previous studies, e.g. Kohn and Sack (2003) and Kliesen and Schmid (2004) show that the monetary policy signal from FOMC can decrease the variance of inflation expectation by providing additional information to public to anticipating the direction of future inflation rate. Recently, Neuenkirch (2013) finds that inflation expectations are strongly affected by shocks in communication in Euro zone. However, to the best of our knowledge, the association between the central bank communication and inflation expectation has not been investigated in the emerging markets. Therefore, in this section we analyses the effects of central bank communication on inflation expectation.

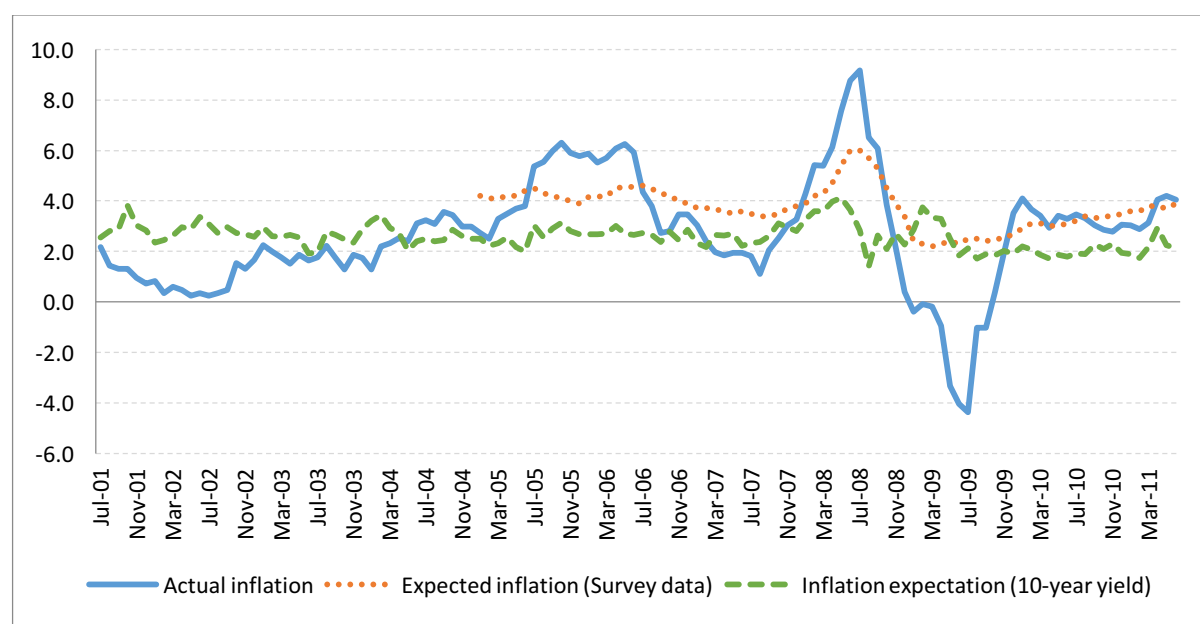
In empirical studies, inflation expectation data can be obtained from the survey-based and market-based measures. Currently, the continuous series of survey data on inflation expectation is still limited in Thailand. The survey data are obtained from the monthly business sentiment indicator (BSI) survey organizing by Bank of Thailand. This survey is based on data from business firms in manufacturing sector and has included questions about 1-year ahead inflation expectation since 2006. Henceforth, this dataset is still too short to analyze the effect monetary policy to inflation expectations. Moreover, the survey's sample consists of entrepreneurs from the manufacturing sectors who are not familiar with monetary policy data comparing to specialists in financial markets.

In this study, we extract inflation expectation from trading information of the term structure of zero-coupon government bonds using the Soderlind and Svensson (1997)'s methodology. This method starts from estimating the forward curves of both real and nominal interest rates. The break-even inflation is estimated by the difference between the nominal and real forward rates at the same maturity. Because of the limitations of explicit forward rates, the implied forward rates can be computed using the data from the existing yield curve. In this study, we estimate the forward rates by estimated by fitting the spot curves using the function forms of Nelson and Siegel (1987). Afterwards, inflation

expectations are computed as the difference between nominal and real forward rates at the same maturities.

The nominal yield curves are obtained from the zero-coupon bond yields at different maturities collected from the Bloomberg database. The real spot yield curves can be computed from the term structure of the inflation-linked bond yields. However, the inflation-linked bonds are introduced in July, 2011 and still have limit liquidity. Therefore, we cannot use the series of real forward rate from the market trading data. In this paper, we apply the real spot yield curve from Apaitan (2015) that published in the Thai bond market association database. We compute the market-based inflation expectations using the yield curves data. The 1-year, 2-years, 5-years and 10-years inflation expectations are show in Figure 12. Moreover, the data on actual inflation and one-year expected inflations from the monthly Business Sentiment Survey are also display in Figure 13.

Figure 12 Actual headline inflation, survey-based and market-based inflation expectations in Thailand

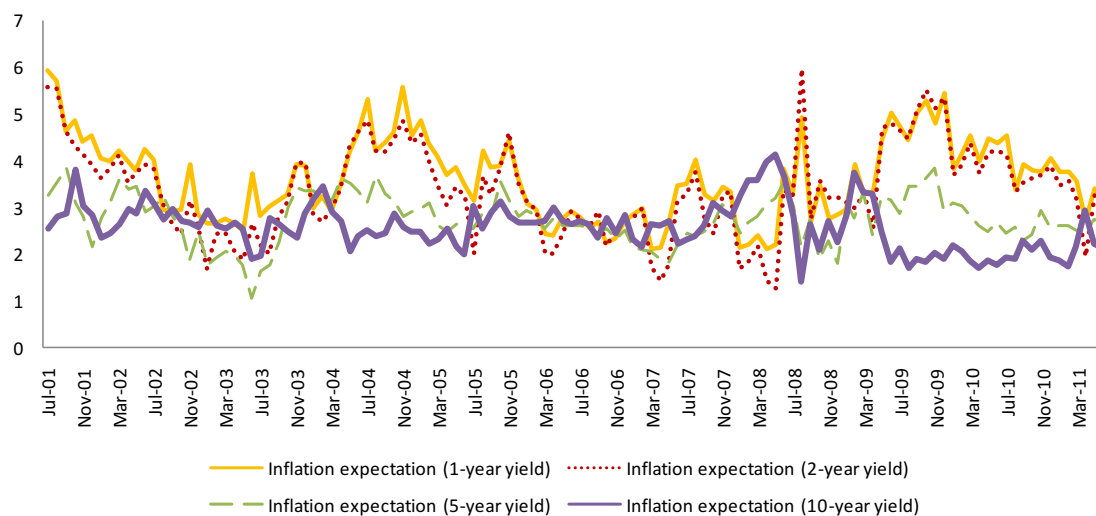


Source: Survey-based inflation expectation is collected from Bank of Thailand's monthly business sentiment survey reports. Market-based inflation expectation is calculated from 10-years yields using Soderlind and Svensson (1997)'s method. Actual inflation data are collected from CEIC database.

The data from Figure 12 illustrate that the market-based long-term expected inflations, the survey-based short-term inflation expectations and actual inflations are move together. The long-term inflation expectations usually lead actual inflation but short-term inflation expectations seem to concurrently move in line with actual inflations. Next, we

compare the data of market-based inflation expectations at different horizon. As can be seen from Figure 13, the long-term expected expectations are less fluctuated than the short-term counterparts. The 1-year and 2-years expected inflations appear to move together. In addition, there is similarity in variation of the 5-years and 10-years inflation expectations. Therefore, we consider the inflation expectation at 1-year, and 10-years to represent the short-term and long-term expectations, respectively.

Figure 13 1-year, 2-years, 5-years and 10-years inflation expectations



Source: Authors' calculation from yield curves using the Soderlind and Svensson (1997)'s method.

The SVAR models from Section 6 are applied to estimate the association between inflation expectations and monetary policy actions. The variables in the SVAR model consist of actual inflation (PCPIH), output growth (YR), monetary policy interest rate (RP1), communication index (CI), inflation expectations. We estimate the SVAR models for the short-term (1-year) inflation expectations (INFE1Y) and long-term (10-years) inflation expectations (INFE10Y), separately. The models are written as follow.

$$\mathbf{Y} = [\text{PCPIH}, \text{YR}, \text{RP1}, \text{CI}, \text{INFE1Y}]$$

$$\mathbf{Y} = [\text{PCPIH}, \text{YR}, \text{CI}, \text{INFE10Y}]$$

Next, we consider the effect of inflation forecast data release, which potentially affect inflation expectations. The central bank signals from inflation forecast could potentially increase inflation expectations. Therefore, we evaluate this issue using the SVAR models with the short-term (4-quarters ahead) and long-term (8-quarters ahead) inflation forecasts

data (INF_F4, INF_F8). The inflation forecasts data are obtained from Inflation Reports. The SVAR models are shown as follow.

$$Y = [PCPIH, YR, RP1, CI, INF_F4]$$

$$Y = [PCPIH, YR, RP1, CI, INF_F8]$$

Finally, we evaluate the effect of communication to inflation expectation by assessing central bank creditability. If central bank has creditability, financial market participants can expect that the monetary policy will be tighten to control the inflation. This creditability implies that inflation expectations should increase less than inflation forecasts. Therefore, this argument implies that an increase in degree of communication could decrease the gap between inflation forecasts and inflation expectations. We investigate this issue using the SVAR model with the long-term (short-term) expectation gaps calculated from the difference between 8-quarters (4-quarters) ahead inflation forecasts and the 10-years (1-year) inflation expectations.

The endogenous variables in the SVAR models are written as follow

$$Y = [PCPIH, YR, RP1, CI, INF_G10Y]$$

$$Y = [PCPIH, YR, RP1, CI, INF_G1Y]$$

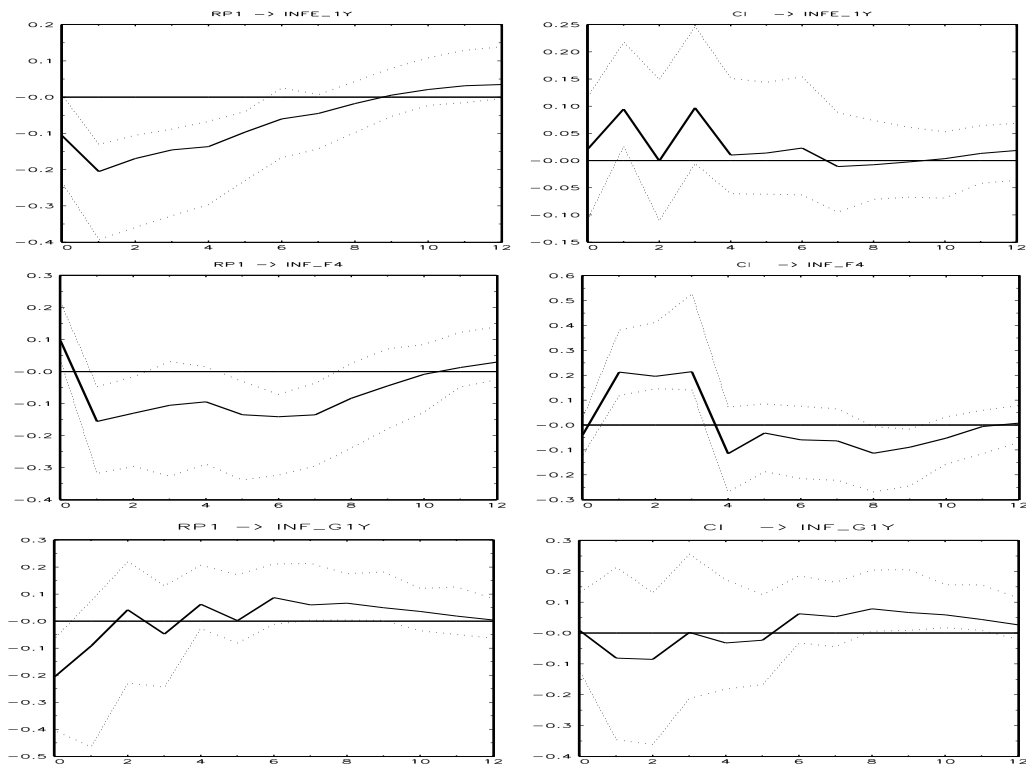
where INF_G10Y and INF_G1Y denote the long-term expectation gap and the short-term expectation gap, respectively.

We still impose the same restrictions as those of Section 6 in estimation of the SVAR model. We assume the inflation expectations, inflation forecasts and expectation gaps to have no contemporaneous and lagged effects to the other variables but can immediately response to a change in other variables in the systems. Consequently, the three lagged SVAR model are estimated⁹. The impulse response functions from shocks in policy interest rates (RP1) and communication (CI) to inflation expectations, inflation forecasts and expectation gaps are computed and displayed in Figures 14 and 15.

The results show that a shock in RP1 has negative effects on inflation expectations only in case of the 1-year expectations. The long-term inflation expectations increase after a shock in RP1. These results show the monetary policy action via interest rate decision can only control short-term inflation expectations but has no impact on the long-term expectation. In case of a communication shock, the inflation expectations react positively in both short-term and long-term expectations.

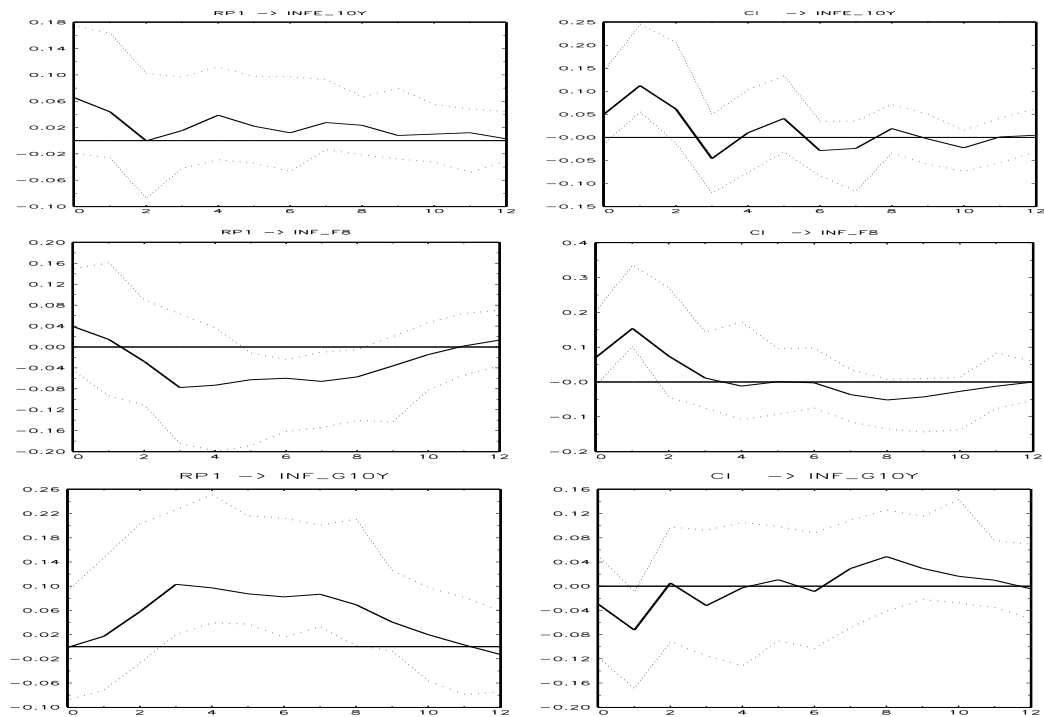
⁹ This number of lagged is corresponding to those of the SVAR model used in Section 6

Figure 14. Impulse response functions of short-term inflation expectations, inflation forecasts and expectation gap to macroeconomic variables to monetary policy shocks



Source: Authors' calculation.

Figure 15 Impulse response functions of long-term inflation expectations, inflation forecasts and expectation gap to macroeconomic variables to monetary policy shocks



Source: Authors' calculation.

Consider the response in inflation forecast, the results are similar to those of the inflation expectation in most of corresponding cases, e.g. both short-term the inflation forecasts react negatively to a shock in RP1 but react positively to a shock in CI. However, the sizes of response of inflation forecast to a communication shock are larger than those of the inflation expectation in short-term and long-term. Consequently, the expectation gaps decrease when there is a positive shock in CI.

In case of a policy interest rate, the reactions of expectation gaps are different. A shock in RP1 can control the expectation only in case of the short-term expectation gaps where expectation gaps decrease. However, the long-term expected inflations response in the opposite direction to those of the inflation forecasts. Therefore, the long-term expectation gaps are widening after a shock in RP1.

Therefore, our results show that monetary policy action via interest rate decision only negatively affects short-term expectations but it has no effect on the long-term expectations. In addition, the central bank communications cannot directly control the inflation expectations in both short-term and long-term expectations. However, the role of central bank communication in anchoring expected inflation can be obtained by the fact that the size of an increase in inflation expectations are smaller than an increase in inflation forecasts. Therefore, these results provide additional supporting evidence on effectiveness of monetary policy via central bank communication in case of Thailand.

8. Concluding remarks

This paper has employed a statistical technique which is free of researcher's subjective judgment to measure central bank communication by using Wordfish, developed by Slapin and Proksch (2008). While this method has not yet been used in economics literature, we find that it appears to provide a reasonable estimate of the MPC statements in Thailand. This can be judged by comparing it with subjective hand-coding indicator as well as the ability to capture both various key macroeconomic variables, and inflation and output growth forecasts released in the Inflation Report. Since this method is automated and objective, it might be interesting for future research to do a comparative study with other central bank communications such as in the Federal Reserve and the ECB, for example.

Regarding the issue of monetary policy effectiveness, our econometric evidence in Thailand indicates that the MPC statements provide not only additional improvement in predicting policy interest rate decisions beyond the standard Taylor-rule specification but also

improve the transmission mechanism of monetary policy. This implies that the residuals obtained from Taylor-rule model without communication should not be treated as completely unexpected shock on monetary policy. So our findings provide some support to the point made in Lucca and Trebbi (2011, p.25), who also emphasized the role of central bank communication and wrote that: “econometrician may omit significant information available to economic agents when identifying monetary policy shocks in standard monetary models.”

References:

- Anderson, M., Dillen, H., & Sellin, P. (2006, November). Monetary Policy Signaling and Movements in the Term Structure of Interest Rates. *Journal of Monetary Economics* , 1815 - 1855.
- Apaitan, T. (2015). Extracting Market Inflation Expectations: A Semi-structural Macro-finance Term Structure Model. PIER Discussion Paper No.2.
- Berument, H., and Froyen, R. (2009). Monetary Policy and U.S. Long-term Interest Rates: How Close Are The Linkages? *Journal of Economics and Business*, 61 (1), 34 - 50.
- Bholat, D., S. Hansen, P. Santos and C. Schonhardt-Bailey (2015). “Text Mining for Central Banks,” Centre for Central Banking Studies Handbook, No. 33.
- Blinder, A. S., Ehrmann, M., Fratzscher, M., De Haan, J., & Jansen, D. J. (2008). *Central bank communication and monetary policy: A survey of theory and evidence* (No. w13932). National Bureau of Economic Research.
- Boukus, E., & Rosenberg, J. V. (2006). The information content of FOMC minutes. Mimeo (July).
- Charoenseang, J., & Manakit, P. (2007). Thai monetary policy transmission in an inflation targeting era. *Journal of Asian Economics*, 18(1), 144-157.
- Disyatat, P., & Vongsinsirikul, P. (2003). Monetary policy and the transmission mechanism in Thailand. *Journal of Asian Economics*, 14(3), 389-418.
- Ehrmann, M., & Fratzscher, M. (2007). Communication by central bank committee members: Different strategies, same effectiveness?. *Journal of Money, Credit and Banking*, 39(2-3), 509-541.
- Goodhart, C. A. E., & Bin Lim, W. (2011). Interest rate forecasts: a pathology. *International Journal of Central Banking*, 7, 135-172.
- Gorodnichenko, Y., & Shapiro, M. D. (2007). Monetary policy when potential output is uncertain: Understanding the growth gamble of the 1990s. *Journal of Monetary Economics*, 54(4), 1132-1162.
- Heinemann, F., & Ullrich K. (2007). Does it Pay to Watch Central Bankers’ Lips? The Information Content of ECB Wording, *Swiss Journal of Economics*, 143(2), 155-185.
- Hendry, S., & Madeley A. (2010). Text mining and the information content of Bank of Canada communications. Bank of Canada Working Paper, November.

- Jansen, D. J., & De Haan, J. (2009). Has ECB communication been helpful in predicting interest rate decisions? An evaluation of the early years of the Economic and Monetary Union. *Applied Economics*, 41(16), 1995-2003.
- Jansen, D. J., & De Haan, J. (2010). An assessment of the consistency of ECB communication using Wordscores. DNB Working Paper, No. 259 (April).
- Kliesen, K. L., & Schmid, F. A. (2004). Monetray Policy Actions, Macroeconomic Data Release, and Inflation Expectations. *Federal Reserve Bank of St. Louis Review*, 86(3), 9 - 21.
- Kohn, D. L., & Sack, B. P. (2003). Central Bank Talk: Does It Matter and Why? Federal Reserve Board Finance and Economics Discussion Series No. 55. Washington DC: Board of Governors of the Federal Reserve System.
- Kuttner, K. N. (2004). The role of policy rules in inflation targeting. *REVIEW-FEDERAL RESERVE BANK OF SAINT LOUIS*, 86(4), 89-112.
- Laver, M., Benoit, K., & Garry, J. (2003). Extracting policy positions from political texts using words as data. *American Political Science Review*, 97(02), 311-331.
- Lowe, W. (2008). Understanding wordscores. *Political Analysis*, 16(4), 356-371.
- Luangaram, P. & Sethapramote, Y. (2015). Forecast-based Inflation Targeting: Evidence from Thailand. Mimeo.
- Lucca, D. O., & Trebbi, F. (2011). Measuring Central Bank Communication: An Automated Approach with Application to FOMC Statements. Technical Report 15367, 2009 version, NBER WP.
- Monroe, B. L., & Schrod, P. A. (2008). Introduction to the special issue: The statistical analysis of political text. *Political Analysis*, 16(4), 351-355.
- Nelson, C.R., Siegel, A.F. (1987). Parsimonious modeling of yield curves, *Journal of Business*, 60(4), 473-489.
- Neuenkirch, M. (2013). Monetary policy transmission in vector autoregressions: A new approach using central bank communication. *Journal of Banking & Finance*, 37(11), 4278-4285.
- Proksch, S. O., & Slapin, J. B. (2009a). How to avoid pitfalls in statistical analysis of political texts: The case of Germany. *German Politics*, 18(3), 323-344.
- Proksch, S. O., & Slapin, J. B. (2009b). Wordfish: Manual. Mimeo (January).
- Rosa, C., & Verga, G. (2007). On the consistency and effectiveness of central bank communication: Evidence from the ECB. *European Journal of Political Economy*, 23(1), 146-175.
- Slapin, J. B., & Proksch, S. O. (2008). A scaling model for estimating time-series party positions from texts. *American Journal of Political Science*, 52(3), 705-722.
- Soderlind, P., & Svensson, L. (1997). New Techniques to Extract Market Expectations from Financial Instruments. *Journal of Monetary Economics*, 40 (2), 383-429.
- Sturm, J. E., & De Haan, J. (2011). Does central bank communication really lead to better forecasts of policy decisions? New evidence based on a Taylor rule model for the ECB. *Review of World Economics*, 147(1), 41-58.