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Words Matter: Effects of Semantic Similarity of Monetary Policy Committee's Decision on Financial Market Volatility

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Words Matter: Effects of Semantic Similarity of Monetary Policy Committee's Decision on Financial Market Volatility

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Abstract

The objective of the paper is to study the effects of semantic similarity of the Bank of Thailand's press releases on volatility of financial markets in Thailand from 2010-2018. The Natural Language Processing (NLP) is employed to construct the semantic similarity from 72 press releases. The semantic similarity represents the public signal that the central bank delivers to the public in the framework of a Keynesian beauty contest game.

The semantic similarity of MPC press releases significantly reduce the volatility in 1-month, 3-month, 10-year and 15-year government debt securities. Findings imply that relatively similar language in the MPC press releases reduces the volatility in short-term and long-term bonds. Effects of semantic similarity matter most in the volatility of 10-year bond yield. However, effects of semantic similarity are insignificant in both equity and foreign exchange markets.

JEL classification: E52, E58

Keywords: Volatility, Financial markets, Monetary policy, Natural language processing

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Introduction

The Bank of Thailand (BOT) has published the statements of Monetary Policy Committee' s decision on the BOT' s website and has held the press conference after the Monetary Policy Committee (MPC) meeting since 2009. The BOT's press releases has been received the attention from the public, such as local and global media and financial market participants. The media closely track the changing in the statement and provide the analysis and the interpretation for each BOT' s monetary policy decision. The central bank statements explain the monetary policy decisions and are among the important source of financial market movers (Blinder et al.,2008, Ehrmann and Talmi, 2017).

> In deliberating their policy decision, the Committee assessed that the Thai economy continued to gain further traction ~~over the previous assessment,~~ and would achieve higher growth than previously assessed, driven by stronger momentum from both domestic and external demand. ~~driven by both growth in the external sector and gradual improvements in domestic demand.~~ Headline inflation ~~gradually rose in line with the previous assessment.~~ was projected to rise slightly more than the previous assessment, while core inflation was expected to rise slowly. Overall financial conditions remained accommodative and conducive to economic growth. Financial stability remained sound overall, but it was deemed necessary to monitor pockets of risks that might lead to the build-up of vulnerabilities in the financial system in the future especially given prolonged monetary accommodation. The Committee viewed that the current accommodative monetary policy stance remained conducive to the continuation of economic growth and should support the rise of headline inflation toward target in a sustainable manner. ~~although the process would take some time.~~ Thus, ~~the Committee~~ most members decided to keep the policy rate unchanged at this meeting. Nevertheless, one member viewed that the economic expansion was sufficiently robust and that prolonged monetary accommodation might induce households and businesses to underestimate potential changes in financial conditions, and thus voted to raise the policy rate at this meeting in order to start building policy space

Figure 1: Comparison between the third paragraph in MPC statements and the statement in June and May. Sentences in green are added and sentences in red are eliminated from the statement in June. Sentences in light blue are those that share the same message.

Drafting the statement often begins from the previous statement as a starting point as can be seen in figure 1. The central bank may compose the current statement by marginal updating the previous statement or even keeps the previous statement unchanged. This is beneficial to market participants in terms of tracking the new information in the current statement and the message in the statement may not cause much disagreement among participants. As for the central bank, although starting from the previous statement may be convenient for financial market participants and media in terms of interpretation, there might be the case in which the central bank may have to substantively rewrite the content of the statement. Thus, this approach of drafting the current statement may cause the central bank to adopt only the incremental change of the message from the previous one (Ehrmann and Talmi, 2017). To this end, the semantic similarity of the MPC's monetary policy decisions may influence the asset price in financial markets. Investors may find the relatively similar statement easy to interpret. This may result in less volatility of asset prices. Less semantic similarity, on the contrary, may lead to the disagreement among financial market participants and may result in high volatility.

The paper explores the impact of semantic similarity of the BOT's monetary policy statements from January 2010 to 20 June 2018 on the volatility of stock market returns and bond yields, which incorporate 1-year and 10-year government bonds and SET and SET50 returns. Of course, this study is not the first that analyzes the semantic similarity and the volatility in financial markets. In Canada, Ehrmann and Talmi (2017) studies the impact of similarity in the Bank of Canada' s press releases on the volatility in financial markets. Acosta (2015) analyzes the transparency of the monetary policy in the US and employs the Latent Semantic Analysis (LSA) to study the semantic similarity in the FOMC meeting press releases. LSA is used instead of the cosine similarity is to overcome the issue of polysemy. Acosta and Meade (2015) provide the application of Cosine similarity as a tool to measure the similarity. To the best of my knowledge, this paper is the first that offers the analysis of the impact of semantic similarity on stock market returns and bond yields in Thailand.

In this paper, the public signal is represented by the semantic similarity of the MPC press releases. When the information structure available to the market participant is a man-bites-dog signal. The agent largely responds to the signal. The more unusual the realization, the larger the agent's response. This finding from the theoretical side is consistent with the empirical findings in bond markets. That is, the relatively similar MPC press releases reduce the volatility of short-term and long-term bond yields. However, the effects of the similarity are insignificant in stock markets in Thailand.

Methodology

Theoretical framework: The information structure: Man-bites-dog signal

The Man-bite-dog signal is first introduced in Nimark (2012) and is used to explain characteristics of business cycle. In this paper, the concept of Man-bite-dog is applied to the information set of financial market participants. The man-bite-dog is an unusual event that is newsworthy to agents. In the context of the study, traders respond to unusual changes in the content of the current MPC press release from the content of the previous releases. Traders observe unusual changes in the contents of press releases and update their beliefs and trading strategies.

Empirical strategy

We employ Exponential GARCH (1,4) to analyze the impact of semantic similarity of MPC press releases on the volatility in financial markets, bond market, stock market and foreign exchange market. EGARCH(1,4) is estimated because it is sufficient to capture ARCH effects in financial market data.

All daily financial market data are from Thai BMA and the Stock Exchange of Thailand. Data range from 2010 to 2019. There are 2,201 observations available.

Data	Description
1-month bond yield	1-month Treasury bill
3-month bond yield	3-month Treasury bill
6-month bond yield	6-month Treasury bill
10-year bond yield	10-year government bond
15-year bond yield	15-year government note
SET	The Stock Exchange of Thailand index
MAI	Market for Alternative Investment index
Foreign exchange rate (THB/USD)	THB/USD exchange rate

Table 1: Financial market data

Bond yields enter into EGARCH(1,4) in the first difference. This measures changes in bond yields both short-term and long-term debt securities. Whereas, stock market data, SET and MAI, and the THB/USD exchange rate enter into EGARCH (1,4) as the log return, $RET = \ln\left(\frac{X_t}{X_{t-1}}\right) * 100$. All financial data pass the unit root tests. Table 3 shows the descriptive statistics for financial variables.

Data	Description
Net tone	1-year government bond yields
Semantic similarity	10-year government bond yields
Monetary policy surprise	Difference between Actual and Survey of BOT's policy rate
Foreign exchange rate (THB/USD)	THB/USD exchange rate

Table 2: Monetary policy variables

In order to obtain variables for net tone and semantic similarity, I apply Natural Language Processing (NLP) with MPC press releases, which are publicly available at www.bot.or.th. In the study, we use press releases from 2010-2018. This results in a corpus consisting of 72 central bank press releases.

Monetary policy surprise is collected from Bloomberg terminal with a Bloomberg key word "BTRR1DAY" from the Faculty of Economics Chulalongkorn University. Monetary policy surprise will be controlled in EGARCH (1,4) in order to purge the effect of monetary policy surprise from the effect of semantic similarity.

Financial market data	Obs.	Mean	Std. Dev.	Min	Max
1-month bond yield	2201	0.0002	0.0133	-0.2377	0.1220
3-month bond yield	2201	0.0002	0.0136	-0.2512	0.1440
6-month bond yield	2201	0.0002	0.0136	-0.2628	0.0953
10-year bond yield	2201	-0.0009	0.0372	-0.2389	0.2627
15-year bond yield	2201	-0.0009	0.0234	-0.2398	0.2137
SET	2201	0.0340	0.9794	-5.8119	5.7515
MAI	2201	0.0230	1.1629	-7.8858	8.0512
THB/USD	2201	-0.0011	0.2846	-2.0891	1.1904

Table 3: Descriptive statistics for financial variables

Textual Analysis: Analytical Preprocessing

Text is an unstructured data. They contain characters, such as alphanumeric, non-alphanumeric characters, punctuation. The analytical preprocessing is a critical step as well elaborated in Loughran and McDonald (2016) because poor quality inputs of textual preprocessing will return faulty outputs. The goal of preprocessing is to reduce noises from a corpus as much as possible. When it comes to the analytical preprocessing, the following procedures are employed.

- Extract only the financial market section in the press releases.
- Lowering the string of characters and Removing the white space
- Eliminating the English stop words
- Stemming text with Porter stemmer
  For example, “decreasing” and “decrease” are stemmed into “decreas”. At this step, the dimensionality of the term-document matrix will tremendously reduced.

- Tokenization.
  Tokenization is a word cut. A string of characters was tokenized into tokens, which is a stemmed word.

- A bag-of-word model
  The row of the term-document matrix corresponds to the number of terms in the corpus, and the column of the matric corresponds to the number of press releases, which is 72.

Figure 2-3 illustrate the Bag of Words in the word cloud. The thicker stemmed words are, the higher frequency of words in the corpus. In the corpus of financial conditions, the word ‘economi’ has the highest occurrence in documents.

Figure 2: The corpus before TF-IDF weighting

Figure 3: WordCould after TF-IDF weighting

The dimension of the term-document matrix after trimming by the TF-IDF is 72×906. This significantly reduces the dimensionality of the sparse matrix.

Semantic Similarity with Cosine Similarity

After the pre-processing, the term-document matrix is a 906-by-72 matrix. Each row is a unique term in the language of forward guidance and each column corresponds to each MPC press release. The element in each cell is the frequency of the term. I compute the cosine similarity of a vector-space model of each pair of documents. The cosine similarity measures how similar the content of statements has been over time.

Following Acosta and Meade (2015), Equation (3) shows how to calculate cosine similarity index.

$$Similarity = \frac{\sum_{i=1}^{n} \alpha_i \beta_i}{\left(\sqrt{\sum_{i=1}^{n} \alpha_i^2}\right)\left(\sqrt{\sum_{i=1}^{n} \beta_i^2}\right)} \tag{3}$$

$Similarity$ is the value of cosine similarity. Suppose "α" and "β" are two consecutive statements, "α_i" and "β_i" are the number of times that word "i" appears in statement "α" and "β". "n" is the total number of the unique term and "n" is 296. From (3), the cosine similarity will equal 0 if two documents are orthogonal. On the contrary, the value of cosine similarity will be close to 1 if two documents use the same words in nearly the same proportion. Therefore, the value of cosine similarity is bounded between 0 and 1.

Figure 4 shows the cosine similarity of the language of forward guidance from 2010 to 2018. The blue line is the cosine similarity after dropping some terms out of the document by means of TF-IDF. The language in BOT's MPC press releases exhibit high consistency over time. In Acosta and Meade (2015), the corpus of whole FOMC statements shows the average cosine similarity of 0.65. Whereas, Ehrmann and Talmi (2017) find that the similarity of the Bank of Canada's statements is just 0.44.

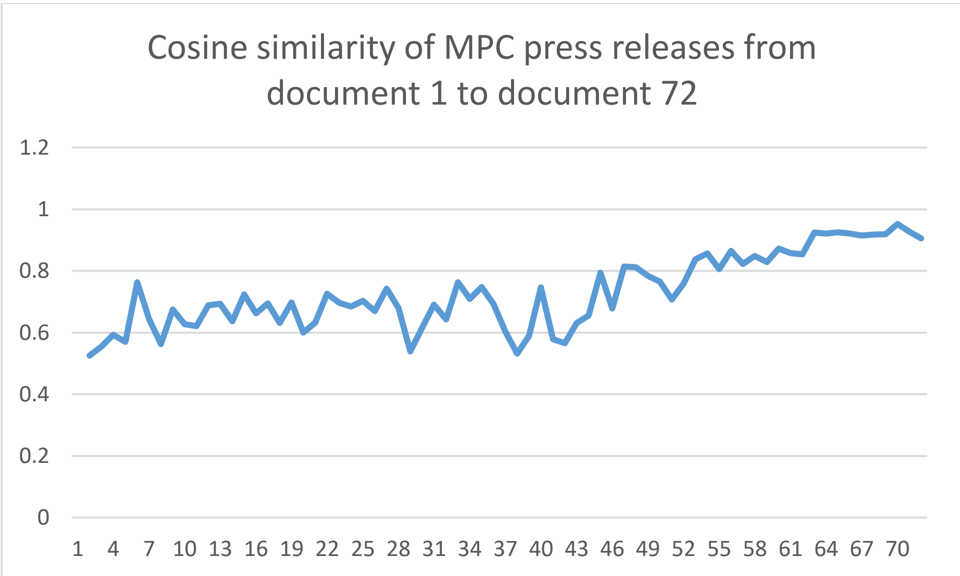

Figure 4: **shows the cosine similarity of MPC press releases**

Following Ehrmann and Talmi (2017), I set the value of semantic similarity equals 1 on days without the FOMC press release because there is no news on days. Therefore, the content of forward guidance in the earlier statement is still in place, which implies the perfect similarity.

Tone Analysis with Dictionary Method

The tone variable was constructed from the term-document matrix. In order to extract the tone from the corpus, a list of directional words in Hansen and McMahon (2016) was employed as a dictionary. Table 4 shows a list of directional words. Words that associated with expansion indicate the positive tone, and those with contraction indicate the negative tone. The dictionary method is a method of word counting. That is, the number of expansionary and contractionary words were counted in each statement and the tone was computed according to equation 4.

$$Tone_t = \frac{n_{d,t}^{up} - n_{d,t}^{down}}{n_{d,t}} \tag{4}$$

"t" is a date at which the press releases published. $Tone_t$ is the tone of the paragraph associated with financial markets. $n_{d,t}^{up}$ is the number of expansionary words in a document d at date "t". $n_{d,t}^{down}$ is the number of contractionary words in a document d at date "t". $n_{d,t}$ is the total number of words in the document.

Expansion		Contraction	
Acceler	increas	collaps	Lower
Boom	rise	contract	Lowest
Expand	risen	cool	Moder
Fast	strength	deceler	Slow
Faster	strong	decreas	Slower
Fastest	stronger	fall	Slowest
Foster	strongest	fell	Soften
Gain	expands	lose	Subdu
High		loss	Weak
Higher		lost	Weaken
Highest		low	Weaker
Improv			Weakest

Table 4: shows an example of the dictionary.

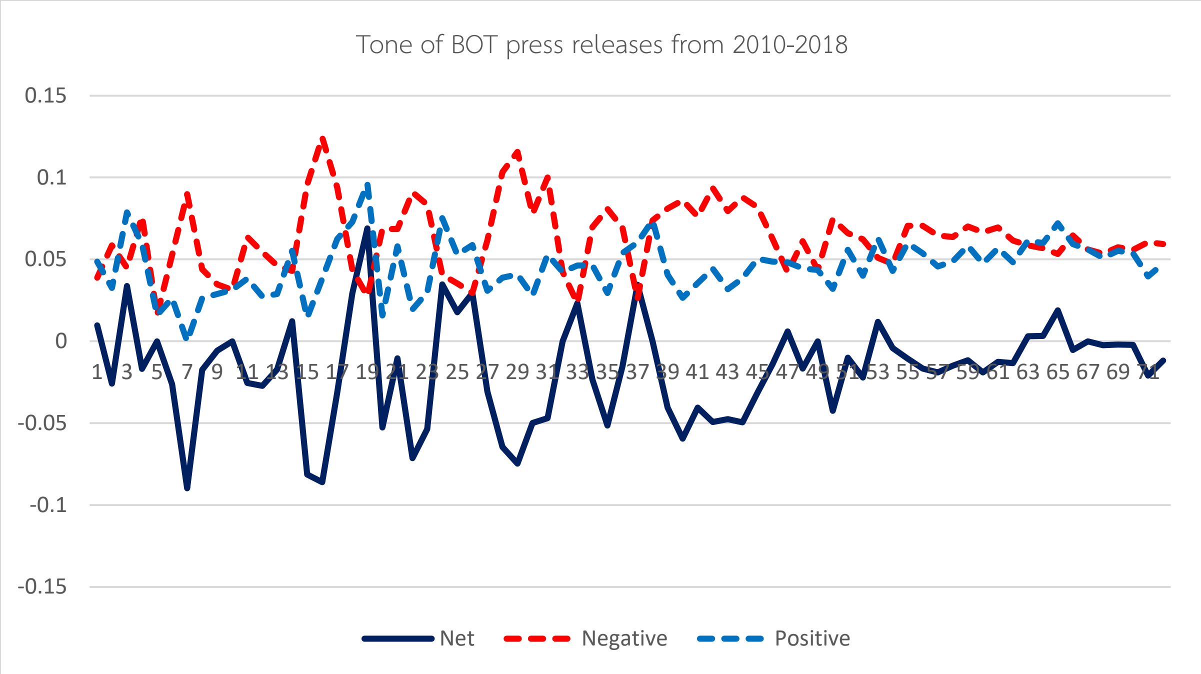

Figure 5:The net tone of MPC press releases

Figure 5 plots both negative and positive tone variable with the net tone that are extracted from the corpus of financial conditions in the BOT 's press releases. In the study, the change in the net tone will be used as the control variable in the mean equation.

Econometrics methodology

Exponential General Autoregressive Conditional Heteroscedastic (EGARCH)

Three major limitations can be found in GARCH model (Nelson, 1991). First, GARCH assumes that only the magnitude of unanticipated excess returns, not the positivity or negativity excess returns, influences the conditional variance. The assumption eliminates the evidence that the volatility rises in response to bad news and falls in response to good news. Second, the non-negativity constraints imposed on GARCH parameters to ensure the positive conditional variance. Third, it is difficult to interpret the persistence in the conditional variance. Thus, Nelson (1991) proposes Exponential GARCH model (EGARCH) as an alternative to GARCH.

EGARCH model has an advantage over GARCH because it ensures that the conditional variance is positive and allows for the asymmetric response of the volatility to good and bad news. EGARCH also incorporate the asymmetric leverage. This paper therefore employs Nelson's EGARCH as a tool to analyze effects of the semantic similarity of BOT's press releases on the volatility in financial markets, which are bond, equity and foreign exchange market.

EGARCH (1,4) specification

$$y_t = \beta_0 + \beta_{tone}\Delta Tone_t + \beta_{sur}Surprise_t + \omega_t \tag{5}$$
$$\omega_t \sim (0, h_t)$$

$$\log(h_t) = \alpha_0 + \alpha_1\left(\frac{\omega_{t-1}}{\sqrt{h_{t-1}}}\right) + \alpha_2\left(\left|\frac{\omega_{t-1}}{\sqrt{h_{t-1}}}\right| - \sqrt{\frac{2}{\pi}}\right) + \alpha_3\log(h_{t-1}) + \alpha_{sur}\,|Surprise_t| + \alpha_{tone}\,|\Delta Tone_t| + \alpha_{sim}\,Similarity_t \tag{6}$$

I follow Ehramann and Talmi (2017) 's specification and estimate EGARCH (1,1) because it is sufficient to capture the non-normality of the data in this paper. "t" is an index of time. y_t is the independent variable. ω_t is the disturbance term. h_t is the variance of ω_t. (5) is the mean equation. The change of the net tone ($\Delta Tone_t$) appears in the mean equation. (6) is the variance equation. The cosine similarity ($Similarity_t$) is in the variance equation. Maximum likelihood[2] is the estimation method for EGARCH. I fit the model with different assumptions of the distribution of residuals, namely, the student's t-distribution, the Gaussian distribution and the generalized error distribution (GED). Findings are not different in terms of statistical significance but EGARCH (1,4) is sufficient to capture ARCH effects in financial data. Thus, I report only EGARCH (1,4) with the Gaussian distribution of the error terms.

In order to analyze the effect of semantic similarity on the volatility in financial markets, the key hypothesis is that $\alpha_{sim} < 0$ and α_{sim} is the parameter of cosine similarity. Intuitively, as the cosine similarity increases, the language of forward guidance becomes more similar. Then, the financial market participants may find the language of forward guidance easy to interpret. Therefore, this may associate with lower volatility of financial markets. The expected sign of the estimated coefficient of similarity is negative.

Empirical findings

Effects of Semantic Similarity on Short-term and Long-term Government Debt Securities

From table 5, the estimated coefficients in variance equations of EGARCH (1,4) are considered as the effects of semantic similarity of BOT press releases on bond yields with different maturities.

For short-term government securities, the effects of semantic similarity are statistically significant at 1% significance level in 1-month and 3-month treasury bills with minus signs. That is , the semantic similarity or semantic difference of BOT's press releases influences volatility in 1-month and 3-month yields. As the content of BOT press releases has become more similar, the volatility of both 1-month and 3-month yields decreases.The effect of similarity on the volatility of 6-month yield is not statistically significant . However, the coefficient is negative. For long-term government securities, the estimated coefficients are negative and statistically significant at 1% level. Therefore, as a press releases exhibits more similar content compared to the previous release, this reduces the volatility in the long-term government securities. From table 5, we can observe that the semantic similarity mostly influences the volatility of the 10-year government bond.

[2] see Tsay (2013)

Effects of Semantic Similarity on equity markets and foreign exchange market

On the contrary, effects of semantic similarity of press releases on both equity markets, SET and MAI, are amorphous.Estimated coefficients of semantic similarity are not statistically significant in equity market even though similarity coefficients are negative. The volatility of stock market returns may not be influenced by the similarity or difference of the content of BOT press releases. The same pattern also emerges in foreign exchange market. The estimated coefficient of semantic similarity is not statistically significant in THB/USD , yet the coefficient sign is negative.

Semantic similarity significantly influences changes in market for government bond yields rather than returns in equity and foreign exchange markets. This findings seem to be consistent with Ehrmann and Talmi (2017), which study the effect of semantic similarity on financial markets in Canada, the U.S. and Japan.

	Bond Market						Stock Market		FX market
	Surprise component 1-month yields	Benchmark 1-month yields	3-month yield	6-month yield	10-year yield	15-year yield	SET return	MAI return	Exchange rate return (THB/USD)
Mean equation									
Change in Net Tone	-	0.0379*** (0.0069)	0.0077 (0.0294)	0.0133 (0.0236)	0.0001 (0.1016)	-0.0760 (0.0624)	3.6500 (3.1685)	-0.4855 (3.0289)	-0.7622 (0.5935)
Surprise	0.5687*** (0.0382)	0.5508*** (0.0352)	0.6012*** (0.0306)	0.6489*** (0.0403)	0.2460*** (0.0390)	0.1660*** (0.0304)	-1.2469 (1.3096)	-2.0243 (1.7012)	-0.1550 (0.7725)
Constant	0.0004*** (0.0001)	0.0003*** (0.0001)	0.0005*** (0.0294)	0.0007*** (0.0001)	-0.0012*** (0.0004)	-0.0012*** (0.0004)	0.0578*** (0.0155)	0.0552*** (0.0185)	-0.0086 (0.0055)
Variance equation									
Semantic Similarity	-	-1.8635*** (0.3427)	-1.4235*** (0.2314)	-0.1041 (0.2530)	-2.4068*** (0.3650)	-1.7739*** (0.1389)	-0.0191 (0.3182)	-0.4522 (0.1945)	-0.5030 (0.6591)
Absolute change in Tone	-	-1.6876 (0.5366)	4.9636*** (1.7294)	7.1960*** (2.1372)	-16.5337*** (3.0545)	-3.9017*** (1.3261)	-2.2602 (2.5715)	-8.5824*** (3.0724)	-10.6143** (4.9728)
Absolute surprise	16.1319** (0.7193)	14.1343*** (0.6787)	11.2888*** (0.6211)	13.9996*** (0.8590)	1.1880* (0.7174)	-0.4169 (0.5056)	-0.5240 (0.5407)	-0.0814 (1.0842)	1.1754 (1.4611)
Constant	-1.1131*** (0.0463)	0.8247** (0.3283)	0.6119*** (0.2244)	-0.7175*** (0.2513)	1.9551*** (0.3476)	1.4679*** (0.1389)	-0.1045 (0.3198)	0.2243 (0.3479)	0.0424 (0.6542)
Observations	2,201	2201	2201	2201	2201	2201	2201	2201	2201
Log likelihood	7871.2496	7894.6704	7693.5196	7761.6937	4391.3095	4877.1633	-2769.6319	-3132.4	-233.9469

Table 5: Effects of Semantic Similarity of BOT Press Releases on Financial Markets

Numbers in brackets are standard errors. ***/**/** denote statistical significance at the 1%/5%/10% level.

	Word count	Tone (Level)	ARCH-m (Standard Deviation)	GARCH	Log(GARCH)
Mean equation					
Change in Net Tone	0.0383*** (0.0099)	-	-0.0424*** (0.0066)	0.0377*** (0.0075)	0.0377*** (0.0072)
Surprise	0.5506*** (0.0351)	0.5711*** (0.0381)	0.6489*** (0.0403)	0.5477*** (0.0428)	0.5507*** (0.0351)
Constant	0.0003*** (0.0001)	0.0003*** (0.0001)	0.0004*** (0.0001)	0.0003*** (0.0001)	-0.0003 (0.0007)
Additional variables	0.0000 (0.0000)	0.0442*** (0.0067)	-0.0130 (0.0228)	0.0238 (0.8404)	-0.0001 (0.0001)
Variance equation					
Semantic Similarity	-1.8599*** (0.3410)	-2.0460*** (0.2454)	-2.0502*** (0.3756)	-0.5998** (0.2802)	-1.8355*** (0.3519)
Absolute change in tone	-1.8327 (2.7166)	-	-2.1338 (2.8149)	6.8618*** (2.6160)	-1.4479*** (2.8089)
Absolute surprise	14.1227** (0.6813)	13.6167*** (0.7668)	13.7365 (0.6707)	15.1284*** (0.8207)	14.0943*** (0.6757)
Constant	-1.1131*** (0.0463)	1.0307*** (0.2323)	1.0096*** (0.3636)	-0.6045** (0.2742)	1.4679*** (0.1389)
Additional variable	-	6.6137*** (1.9769)	-	-	-
Observations	2201	2201	2201	2201	2201
Log likelihood	7895.0151	7903.9900	7890.6470	7889.3750	7894.9282

Table 6: Robustness tests for 1-month bond yield

Numbers in brackets are standard errors. ***/**/** denote statistical significance at the 1%/5%/10% level

As the content of a current press release becomes more semantically similar to a previous press releases, it may facilitate market participants to interpret the new information from the document. As we can see from the finding, the more similar the press release is, the lower the volatility in financial markets, especially bond markets.

Robustness tests

In order to verify whether the effect of similarity on changes in the short-term government security exists in different setting, different versions of EGARCH (1,4) are estimated and table 6 shows estimated results.

From table 6, the estimated coefficients of semantic similarity are statistically and signs are negative. At least, this ensures that the content of press release statistically influences the volatility of 1-month treasury bill.

Conclusion

In this paper, I empirically study the effect of semantic similarity on the volatility of bond markets, equity markets and foreign exchange market from 2010 to 2018. In bond markets, the relatively similar language of MPC press releases significantly reduces the volatility 1-month, 3-month, 10-year and 15-year government bond yields. The semantic similarity tends to have more effect on 10-year bond. In equity and foreign exchange markets, effects of semantic similarity on the volatility of returns are insignificant.

On a theoretical side, market participants with the common knowledge largely react to the public signal if the signal is unusual as presented in Nimark (2012)'s the man-bites-dog. The action of market participants as a result of the public signal may generate the volatility in the underlying market. In this study, the semantic similarity of press releases over time is employed to show the unusual change of the public signal from the Bank of Thailand. Thus, the similarity of press releases could reduce the disagreement among financial market participants in terms of contents and their interpretation. The relatively similar content may be interpreted as the usual event and this may result in quick price adjustment in response to the new information quickly and less market volatility. Therefore, relatively similar press releases leads to less volatility in volume, returns and yields.

A number of extensions are warranted in future work. The first is to extend the analysis to countries with long history of forward guidance, such as Sweden, will give more comprehensive picture of forward guidance and its effects on the volatility of financial markets. Second, it is useful to study the effect of semantic similarity of central bank communication on the volatility in the foreign exchange market in emerging countries, such as Thailand. I leave these for future work.

Policy implications

Financial market participants largely respond to the public signal from the unusual event. The signal from rare events, such as the man-bites-dog signal, influence the decision making of market participants. The public signal in this study is contained in the Bank of Thailand 's MPC press releases that are publicly available to all market participants in the economy and is measured by the semantic similarity. From the empirical findings, as MPC press releases become more consistency (semantic similarity→ 1), this reduces the volatility in the bond markets. However, if the content within the MPC press releases is semantically different from the previous one, this may generate the volatility in the bond markets. Thus, the policy makers should be aware that the communication to the public may be the double-edged sword and have to draft the statements with great care, especially, when introducing the new information to the public. The practice of communication can be both an art and a science.

Further Research

Recently, there has been a development of "Bayesian Persuasion" (Kamenica and Gentzkow, 2011). The concept, which is the topic of information design rather than the mechanism design, deals with the problem of how one can design the information, chooses a set of information, sends such information to the receiver and even to persuade the behaviors of others. In the setting of central bank communication, there will be one sender and many receivers of the information. How the central bank influences the public may be another topic that is worth exploring through Bayesian persuasion.

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