IFC-Bank of Italy Workshop on "Data Science in Central Banking: Applications and tools"

14-17 February 2022

Measuring text-based sentiments from monetary policy statements – a Malaysian case study using natural language processing[1]

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[1] This contribution was prepared for the workshop. The views expressed are those of the authors and do not necessarily reflect the views of the Bank of Italy, the BIS, the IFC or the other central banks and institutions represented at the event.

Measuring Text-Based Sentiments from Monetary Policy Statements

A Malaysian Case Study using Natural Language Processing

Eilyn Chong and Sui-Jade Ho[1]

Abstract

Central banks publish monetary policy statements (MPS) to provide insights into economic development and outlook, as well as to communicate judgment on the balance of risks and expectations on the future course of monetary policy. Using automated content analysis to extract the sentiment from each MPS published between August 2004 to September 2020 by the Central Bank of Malaysia, we analyse the relationship between the sentiment measures from these statements and financial market movements. These sentiment measures are derived from three dictionaries, including one specially developed in this paper for monetary policy analysis. We find the sentiment measures move in line with changes in the policy rate, the Overnight Policy Rate (OPR). Furthermore, using a high-frequency event-study methodology, we find evidence of an asymmetric impact of the sentiments on sovereign (Malaysian Government Securities, MGS) yields at higher maturity and interest rate swap rates. In particular, negative or dovish words are stronger predictors of a decline in yields and swap rates beyond the actual change in the OPR. Conversely, the relationship between positive or hawkish words and financial market movements is less evident. Our findings provide some evidence that the wording in the Central Bank of Malaysia's MPS is informative for the financial markets, especially during stress periods.

Keywords: Central bank communication, text analysis, dictionary, sentiment

JEL classification: D83, E52, E58, G14

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1. Introduction

This paper documents our method of extracting the sentiments in the monetary policy statements (MPS) published by the Monetary Policy Committee (MPC) of the Central Bank of Malaysia and estimating the impact of these sentiments on financial markets. We employ an automated content analysis to extract sentiment measures from the published MPS texts. We then assess whether these measures influence the sovereign (Malaysian Government Securities, MGS) yields and interest rate swap (IRS) rates above and beyond the actual change in the policy rate, OPR. The relationship between policy statements and financial market reactions is important since it could have spillovers to real economic activity, thereby underscoring the need to pay attention to how the central bank conveys information.[2]

This study relates to the literature on the link between sentiments derived from text analytics and financial market responses. Nyman et al. (2021) show that sentiment derived from financial market text-based data is correlated with financial market activity during periods of stress. This is also corroborated by a study by García (2013) using financial news-derived sentiment. Related to this strand of the literature are studies that explore the information content specifically in central bank communications. These include Jegadeesh & Wu (2017), who quantify the tone in the Federal Reserve meeting minutes and find a significant relationship between the topic content and financial market volatility. The study by Bligh & Hess (2013) finds that speeches by the US Federal Reserve (Fed) Chairman (Alan Greenspan), testimonies and FOMC statements contribute to the prediction of financial market variables. Moniz & de Jong (2014) predict the impact of central bank communications on investors' interest rate expectations using Bank of England's Monetary Policy Committee Minutes as their corpus.

The paper is organised as follows: we first describe our methodology in Section 2. In this regard, we make several key contributions to the literature. First, we extract and analyse the sentiments from the MPS by the Central Bank of Malaysia, thus contributing to the small body of research for emerging market economies. Second, for the automated content analysis, we build upon existing dictionaries that are oriented towards finance or the financial stability context to develop a specially designed version for monetary policy context. We especially look at phrases that connote economic relationships that could convey a different sentiment than what the individual words suggest.

Using a high-frequency event-study methodology to demonstrate the ability of these sentiment measures in explaining financial market movements is our main contribution – especially as it is applicable in other contexts where MPS text is used as an input into modelling. Section 3 discusses the results. We find that MPS-derived sentiments exhibit relationships with financial market movements within the one-day window around the release of the MPS, and that sentiments contained within MPS can impact MGS yields at higher maturity and IRS rates. The sign of the marginal impact from the derived sentiment measures on MGS yields and IRS rates is generally consistent with the theoretical predictions. In addition, we found that negative word

[2] See Blinder et al. (2008), for example, for a survey of the literature on central bank communication with evidence suggesting the ability of central banks' communication to move financial markets, to enhance the predictability of monetary policy decisions, and potentially to help achieve central banks' macroeconomic objectives.

counts are stronger predictors of higher maturity MGS yields and IRS rates. Section 4 concludes the paper.

2. Methodology

A. Extracting sentiment measure from Monetary Policy Statements (MPS)

Our main text corpus used in this study are Monetary Policy Statements (MPS) from August 2004 to September 2020 that are published on the website of the Central Bank of Malaysia. These statements are retrieved via web-scraping — filtering out the subject headers and the paragraphs related to the schedule of the upcoming Monetary Policy Committee (MPC) meetings that are typically released every November. We further clean the text of each MPS by enforcing lowercase and removing punctuations, hyperlinks, HTML tags, and extra white spaces.

We then analyse the cleaned MPS text using automated content analysis, where a computer programme counts the frequency of certain words appearing in a text corpus based on a pre-specified wordlist or dictionary. Automated content analysis of texts offers some advantages over manual classification as it is less labour-intensive, less reliant on subjective judgment, and more likely to detect systematic patterns that would otherwise be missed. For this method, we use three dictionaries: Two are off-the-shelf dictionaries: one was developed by Loughran & McDonald (2011) (LM hereafter) tailored specifically to finance, and the other was developed by Correa et al. (2021) (Correa thereafter), which is a refinement of the LM dictionary catered to the financial stability context. Both dictionaries have a set of positive and negative words. Words that do not fall in either category are considered neutral. We then construct another dictionary that combines both LM and Correa dictionaries (Monetary Policy dictionary, MP thereafter) and refine it to better fit the monetary policy context.

Although the LM and Correa dictionaries are designed for financial-related context, many of their words could be used to describe the economy. These include words such as: *deterioration, recession, slowdown, improve* and *rebound*. For the MP dictionary, we reassign positive words from LM and Correa dictionaries as 'hawkish' words as a hawkish monetary policy stance is consistent with an overheating economy that can be described with positive words such as *strong* and *higher* in most cases. Similarly, we reassign negative words from LM and Correa dictionaries as 'dovish' words in the MP dictionary to describe a weak or weakening economy that could warrant a looser monetary policy.

Nevertheless, some cross-checking was undertaken and further refinements are included in the MP dictionary to incorporate nuances in the monetary policy context. The refinements consider:

1. Additional words such as *expansion* and *upside*.
2. Economic relationships that would render words or phrases to have different connotations than originally intended. Phrases such as *low unemployment* and *diminishing slack* would have been assigned a negative tone in the LM

and Correa dictionaries due to the presence of negative words *low* and *diminishing* but are reassigned as hawkish in our MP dictionary to account for the monetary policy context, along with other positive words such as *strong growth* and *high inflation*.

3. Dropping any words that describe OPR adjustments from the count of hawkish or dovish words, as we wish to assess the sentiment of the MPS independently of policy rate adjustments. For example, when *increase* is used to describe an OPR adjustment, we do not assign the word as a positive or hawkish tone.

Any positive or negative word used to describe changes in the stress, pressure or volatility in the financial market will be reassigned as neutral as it does not have a clear bearing on the monetary policy stance.[3] Finally, the polarity of a word is swapped when negation words such as *not, not expected to, unlikely to, no reason to* and *despite* are used to negate a positive/hawkish or negative/dovish word. Each MPS can then be represented in terms of the frequency of words of specific tone based on these dictionaries. In doing so, we measure the intensity of the positive/hawkish and negative/dovish word usage.[4] We then take a net count of words of opposing sentiments and normalise it by the total word count of each MPS to derive the sentiment measures.

$$sentiment_t = \frac{\sum positive\ or\ hawkish\ words\ _t - \sum negative\ or\ dovish\ words_t}{\sum word\ count_t} \quad \text{for each MPS } t$$

$$= sentiment_t^{(+)} - sentiment_t^{(-)} \quad \text{for each MPS } t$$

where $sentiment_t^{(+)} = \frac{\sum positive\ or\ hawkish\ words\ _t}{\sum word\ count_t}$, which refers to positive/hawkish word count (normalised by total word count)

and $sentiment_t^{(-)} = \frac{\sum negative\ or\ dovish\ words\ _t}{\sum word\ count_t}$, which refers to negative/dovish word count (normalised by total word count)

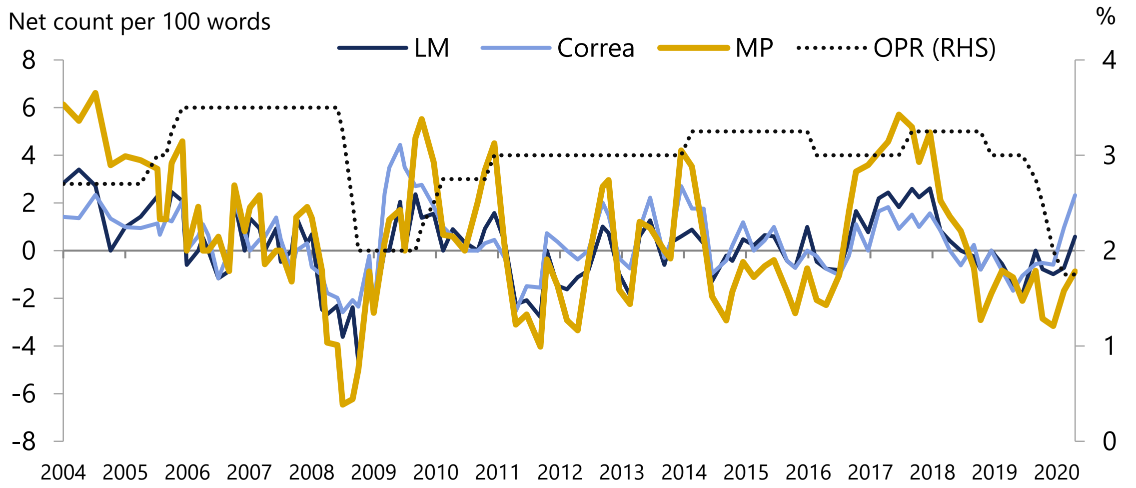
Figure 1 shows the sentiment measures produced using the three dictionaries. Of particular note is the sharp deterioration of sentiment leading up to the 2007-08 financial crisis and the recent COVID-19 pandemic, which reflect greater usage of dovish words. The decline in the derived sentiment measures moves in line with the imminent adjustments in the OPR in the sample period.

3 Instead of relying on word polarity, another approach is to train machine learning models on sentences from monetary policy statements mapped to sentiment ratings assigned by humans to better capture the specific contextual characteristics and nuances. However, this approach involves constructing a large, labelled training dataset which is resource intensive and requires familiarity with economic relationships and monetary policy jargon.

4 Note that our measure of intensity is derived purely from the frequency of hawkish or dovish words used in the MPS. We do not consider the intrinsic intensity of a given word, e.g. the different degree of dovishness between the words: *collapse* and *decline*.

Figure 1: Sentiment measures derived from MPS and OPR

(Positive net count indicates hawkish perceived sentiment, negative indicates dovish)



B. Relationship between sentiment measures and financial market

We employ a high-frequency event-study approach to analyse the relationship between the derived sentiment measures and the financial market. By estimating the impact of sentiments on financial market variables around a narrow window of one day around monetary policy announcement days, we measure the impact of the sentiment measures upon MPS release and limit other confounding factors that could influence asset prices.[5]

Specifically, we estimate the equation below:

$$\Delta y_t^m = \alpha + \beta_1\, sentiment_t + \beta_2\, \Delta\, opr_t + \varepsilon_t$$

where

Δy_t^m is the 24-hour window change in MGS yields of maturity with year, m ∈ {1,2,..,10} or IRS rates of maturity with year, m ∈ {1,3,5} around MPS announcement days;

$sentiment_t$ is the sentiment measure derived from MPS using LM, Correa or MP dictionaries. All sentiment measures are normalised by the total number of words in the MPS;

$\Delta\, opr_t$ is the change in OPR, with β_2 measuring the impact of OPR change on Δy_t^m

[5] This approach is popular in the literature of estimating the impact of monetary policy shocks e.g. Kuttner (2001). Our approach in this paper is closely related to the literature on monetary policy shocks but with one key difference, given that our control variable is the actual daily change in the OPR and not the surprise component of the policy change. Nevertheless, as part of our robustness checks (not shown), we repeated this analysis using the daily change of the 3-month Kuala Lumpur Interbank Offered Rate (KLIBOR), which could move prior to an actual OPR change reflecting market expectations, as our control variable. The general pattern of our results remains in line.

Our variable of interest is β_1. We assume that information available for market participants prior to the monetary policy meetings such as expectations on macroeconomic outlook have already been priced in asset valuations. According to the expectations hypothesis, the magnitude of the increase in MGS yields should be greater for MGS with longer maturity as changes in long-term rates are mainly determined by future monetary policy expectations, which would be inferred from the sentiments of the current period MPS.[6] Figure 2 which shows the magnitude of β_1 suggests that the sentiment measures from MPS have an influence on MGS yields at longer maturity. The sign of the marginal impact is also consistent with the theoretical predictions, where a more positive (negative) net sentiment measure is associated with an increase (a decrease) in MGS yields controlling for OPR changes.

3. Results and Discussion

Relationship between sentiment measures and policy rate change

Table 1

	Dependent variable: Δopr_t					
	Dictionary: LM		Correa		MP	
	(1)	(2)	(3)	(4)	(5)	(6)
sentiment $_t$	4.819***		4.119***		3.112***	
	(1.240)		(1.333)		(0.725)	
sentiment$^{(+)}_t$		3.368**		0.553		2.204***
		(1.334)		(1.194)		(0.776)
sentiment$^{(-)}_t$		-5.667***		-7.999***		-3.836***
		(1.531)		(2.376)		(1.067)
Observations	100	100	100	100	100	100
R-squared	0.236	0.245	0.155	0.243	0.331	0.340

[1] All regressions include a constant term. Robust standard errors in parentheses.
[2] Asterisks denote p-values; 1%: ***, 5%: **, 10%: *.
Sources: Authors' estimates

As a starting point, we assess the relationship between OPR adjustments and sentiment measures of the MPS derived from the three dictionaries. The positive coefficient for *sentiment*$_t$ confirms the observation from Figure 1, where the sentiment measures move in line with the changes in the OPR. Furthermore, when we regress the normalised count of positive words *sentiment*$^{(+)}_t$ and normalised count of negative words *sentiment*$^{(-)}_t$ separately (Columns 2, 4 and 6), *sentiment*$^{(-)}_t$ has a stronger association with OPR adjustments.

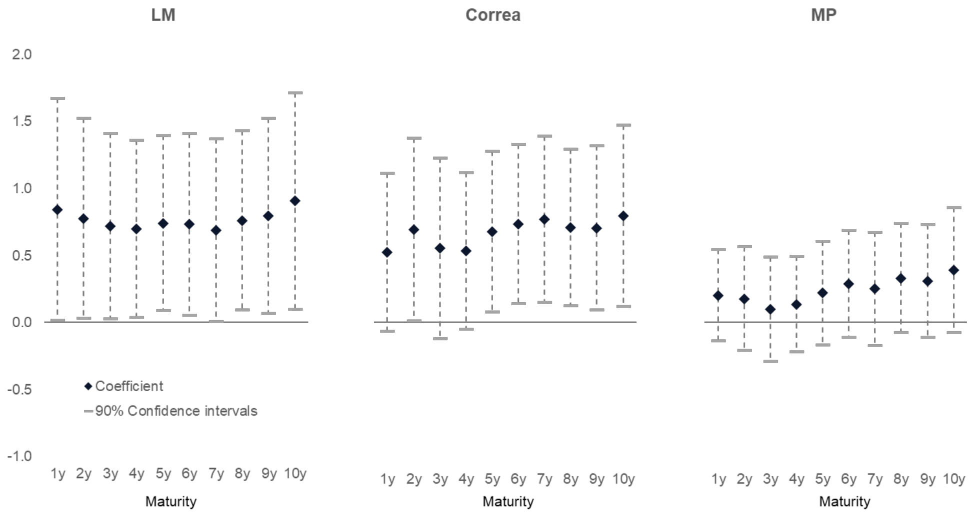
[6] Nevertheless, there could be instances where certain market participants interpret a hawkish stance, especially a strong one, to be indicative of a potential slowdown in long-term growth. This may result in a more muted increase in longer-maturity bond yields than anticipated under the expectations hypothesis.

Figures 2 and 3 visualise the extent of the relationship between the derived sentiment measures and MGS yields and IRS rates, respectively, within a day of the MPS release. Panel B and C in both figures suggest evidence of an asymmetric impact of the sentiments on yields at higher maturity, especially for IRS rates. In particular, negative or dovish words are stronger predictors of a decline in yields and swap rates. Conversely, the relationship between positive or hawkish words and yield movements is less evident. These findings provide some evidence that the wording in the MPS is informative for the financial markets, especially during stress periods when negative or dovish words are more likely to be used in the MPS.

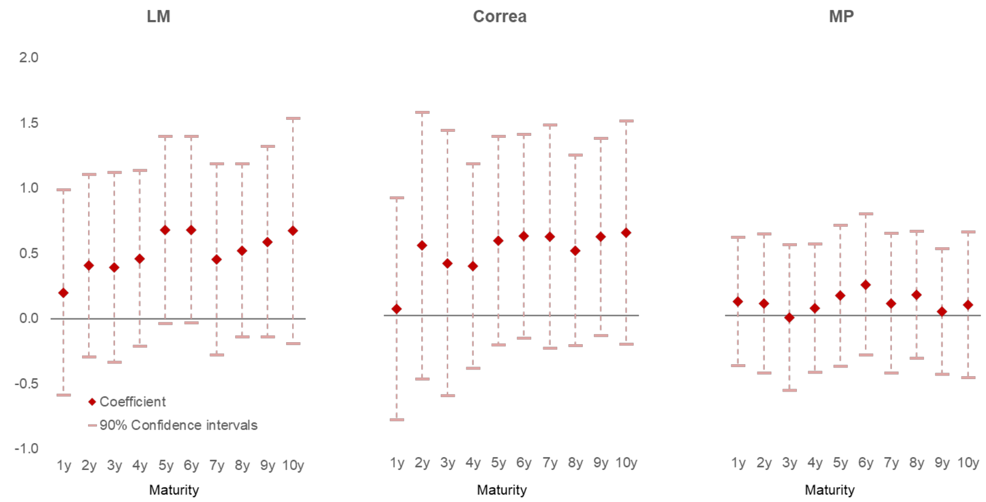
Notwithstanding these findings, one limitation of this study is that we cannot completely rule out the presence of other systematic confounding factors that could have influenced the financial markets especially during stress periods, given that our window of analysis is a 24-hour period, instead of minutes. In addition, our estimates rest on the precision of the sentiment indices themselves.

Figure 2: Estimated relationship between derived sentiment measures and bond yields, β_1, across bond maturity

A. Using net sentiment measure, $sentiment_t$



B. Using positive/hawkish word count (normalised by total word count), $sentiment_t^{(+)}$



C. Using negative/dovish word count (normalised by total word count), $sentiment_t^{(-)}$

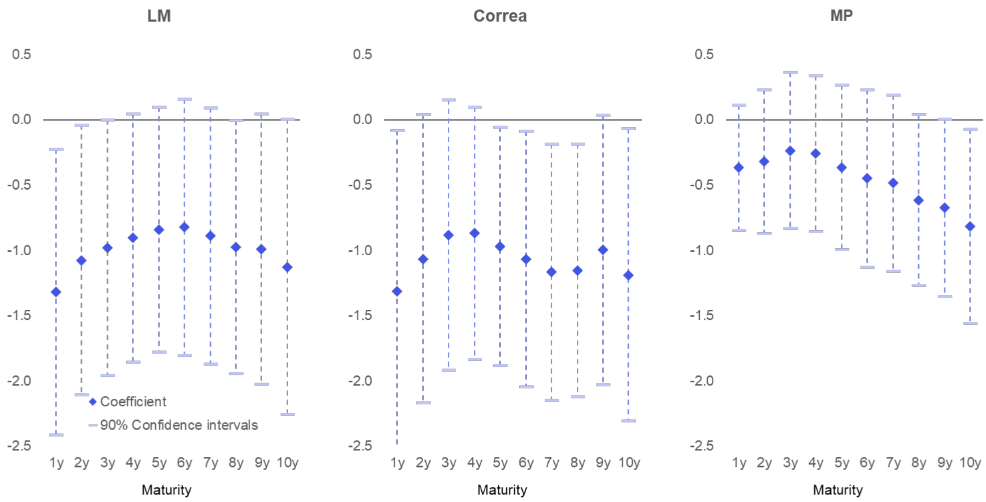
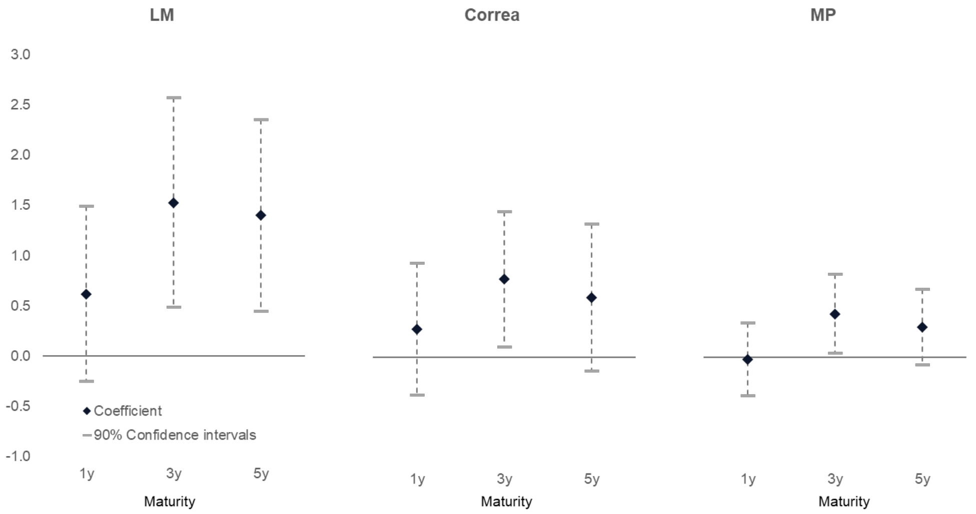
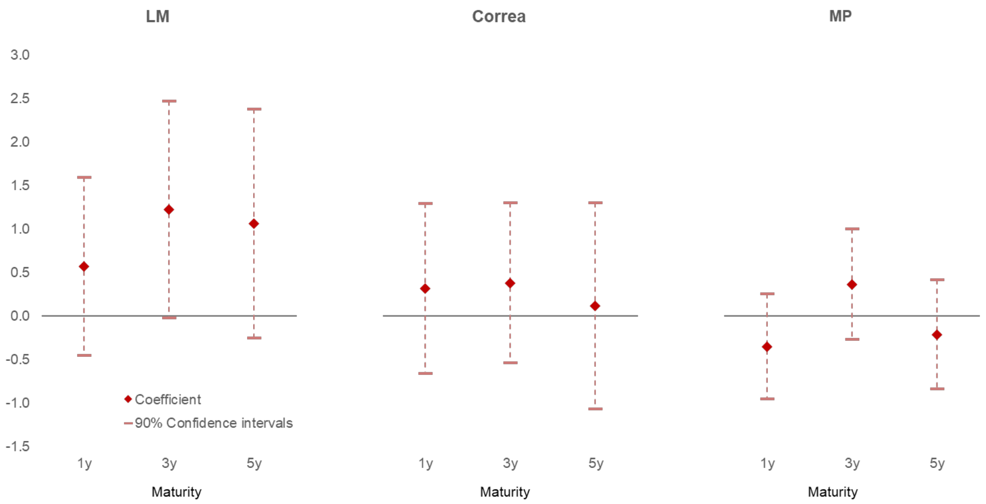


Figure 3: Estimated relationship between derived sentiment measures and IRS yields, β_1, across swap maturity

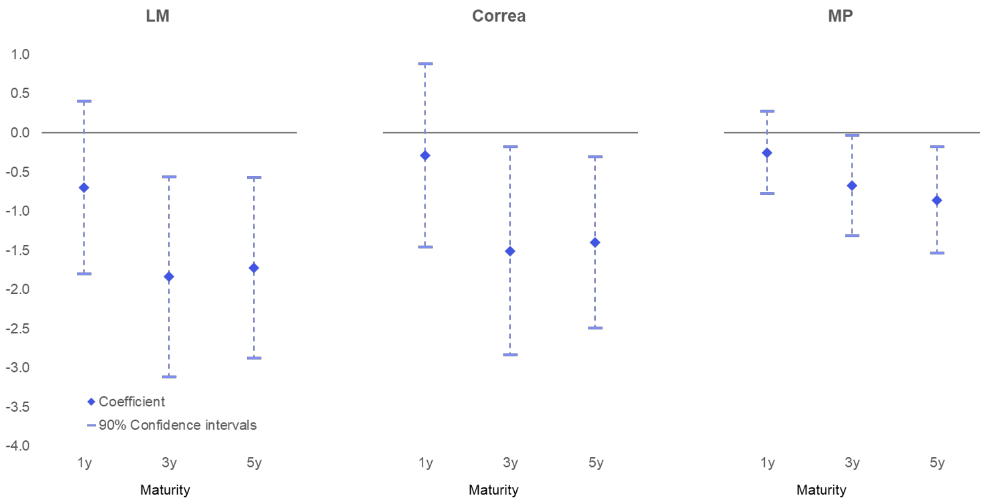
A. Using net sentiment measure, $sentiment_t$



B. Using positive/hawkish word count (normalised by total word count), $sentiment_t^{(+)}$



C. Using negative/dovish word count (normalised by total word count), $sentiment_t^{(-)}$



4. Conclusion

In this paper, we build on the existing literature on text-sentiment analysis, which has mainly been conducted in the advanced economies, and make two contributions. First, we extract and analyse the sentiments from the MPS by the Central Bank of Malaysia. Second, for the automated content analysis, we build upon existing dictionaries that are oriented towards finance or the financial stability context to develop one that is specially designed for monetary policy context. We find the sentiment measures move in line with changes in the policy rate, the OPR. In addition, there is also some evidence of an asymmetric impact of the sentiments on sovereign (MGS) yields and interest rate swap rates. Notwithstanding these findings, there remain some limitations to this study, such as the potential presence of other systematic confounding factors and the precision of the sentiment indices themselves. These issues could be further explored in future research.

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Measuring Text-based Sentiments from Monetary Policy Statements

A Malaysian Case Study using Natural Language Processing

Sui-Jade Ho and Eilyn Chong

Using automated content analysis, we derive sentiment measures to gauge how hawkish or dovish a monetary policy statement (MPS) is perceived to be

- Central banks publish MPS to provide insights into economic development and outlook, as well as to communicate judgment on the balance of risks and expectations on the future course of monetary policy.

- Using automated content analysis to extract the sentiment from each MPS published in 2004 – 2020 by the Central Bank of Malaysia, we derive a sentiment indicator to measure how often hawkish or dovish words are mentioned in each MPS.

$$sentiment_t = \frac{\sum positive\ or\ hawkish\ words\ _t - \sum negative\ or\ dovish\ words_t}{\sum word\ count_t} \text{ for each MPS } t$$

< 0	0	> 0
Net "dovish"	***Neutral***	***Net "hawkish"***
(More dovish terms > hawkish terms)	*(# dovish terms = # hawkish terms)*	*(More hawkish terms > dovish terms)*

- Then, we analyse the relationship between the sentiment measures from these statements and financial market movements.

The count of positive/hawkish or negative/dovish words in the MPS is based on 3 dictionaries, including one specially refined to incorporate nuances in the monetary policy context ("MP")

Loughran-McDonald ("LM")

- Tailored specifically to finance
- Word lists by examining word usage in at least 5% of 10-Ks (i.e. annual reports) since 1994

Correa et al. ("Correa")

- Calibrated to the language of financial stability reports to generate a financial stability sentiment index

Monetary Policy ("MP")

- Combines the lexicon from LM and Correa, and reassigns words to *hawkish* or *dovish* tone
- Accounts for the monetary policy context

1 Additional words	*For example:* ***Expansion/upside/robust*** *(positive/hawkish)*	
2 Economic relationship	***Low unemployment*** *(negative/dovish)*	***Low unemployment*** *(positive/hawkish)*
3 Tone to be independent of policy rate* adjustments	***OPR increase*** *(positive/hawkish)*	***OPR increase*** *(neutral)*
4 Fin. mkt. movements with no clear bearing on MP stance	***FM stress receding*** *(negative/dovish)*	***FM stress receding*** *(neutral)*

* The Overnight Policy Rate (OPR) is the indicator of the monetary policy stance.

Source: Correa, Ricardo, Keshav Garud, Juan-Miguel Londono-Yarce, and Nathan Mislang. 2017. "Constructing a Dictionary for Financial Stability." *IFDP Notes* 2017 (33).
Loughran, Tim, and Bill McDonald. 2011. "When Is a Liability Not a Liability? Textual Analysis, Dictionaries, and 10-Ks." *The Journal of Finance* 66 (1).

Impact of sentiment measures on financial markets through high-frequency event studies

Goal

- Investigate if the sentiment measures can explain movements in financial markets upon MPS release

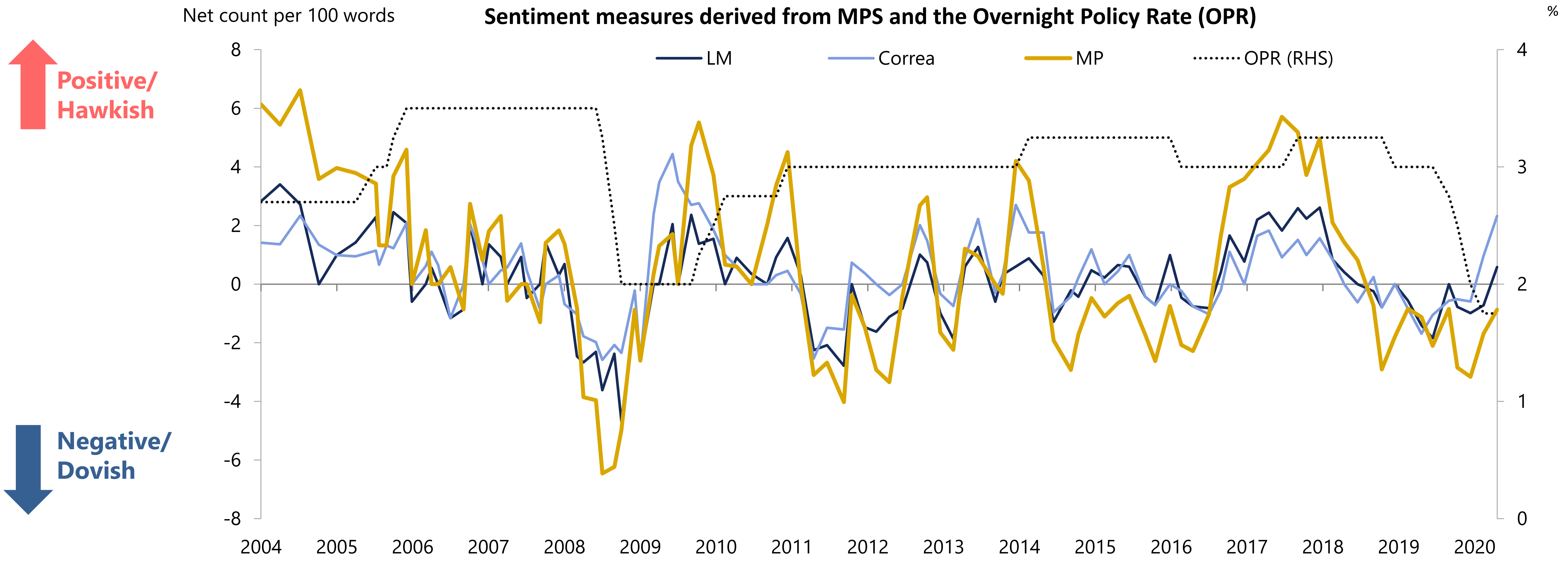
Hypothesis

- Controlling for OPR changes, a more positive (negative) net sentiment measure is associated with an increase (a decrease) in sovereign (Malaysian Government Securities, MGS) yields or interest rate swaps (IRS) rate

Empirical methodology

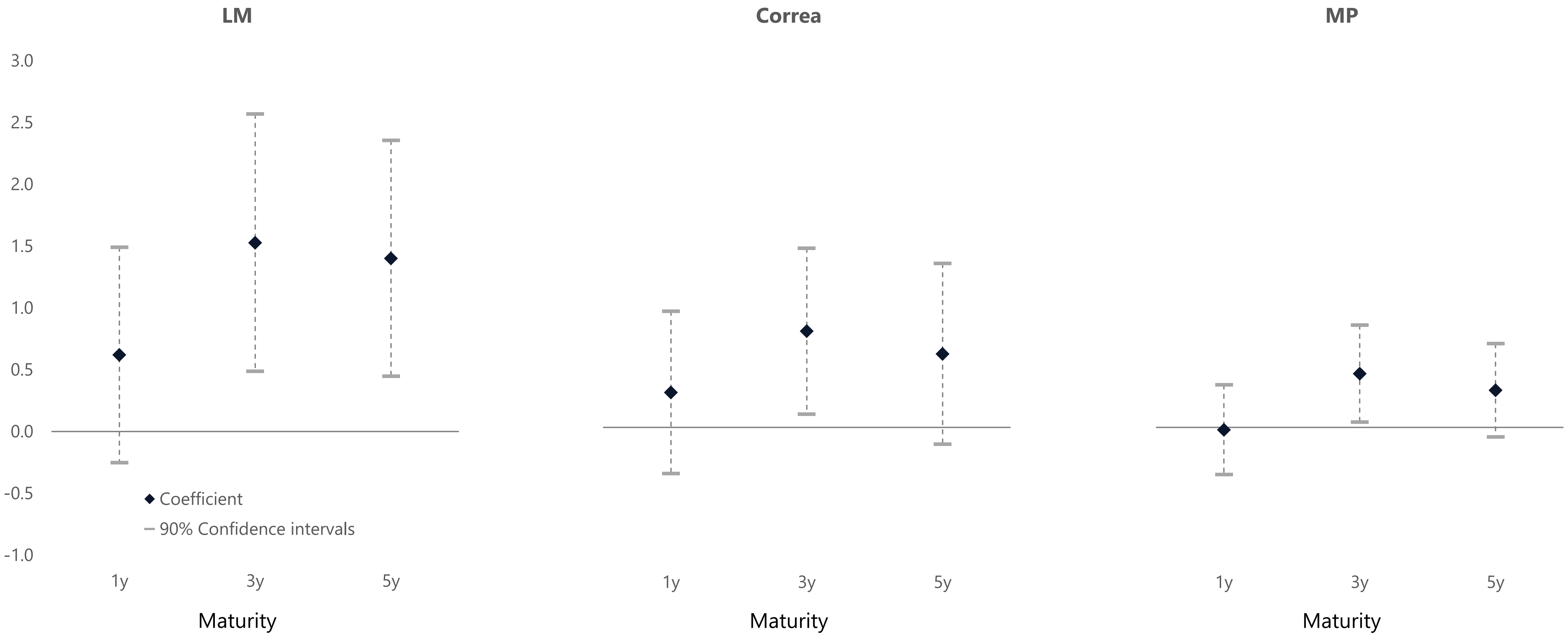
- Estimating equation : $\Delta y_t^m = \alpha + \beta_1 sentiment_t + \beta_2 \Delta opr_t + \varepsilon_\mathrm{t}$
  - Δy_t^m is the 24-hour window change in MGS yields of maturity with year, m ∈ {1,2,..,10} or IRS rates of maturity with year, m ∈ {1,3,5} around MPS announcement days
  - $sentiment$ ∈ *(LM, Correa, MP)*. All sentiment measures are normalised by total word count in the MPS
  - Δopr_t is the change in the Overnight Policy Rate (OPR). β_2 measures the impact of OPR change on Δy_t^m
  - Our coefficient of interest is β_1
  - Key identification assumption: Other factors affecting MGS yields and IRS rates within the short window are on average, orthogonal to MPS sentiment index

The sentiment measures generally move in line with changes in the policy rate



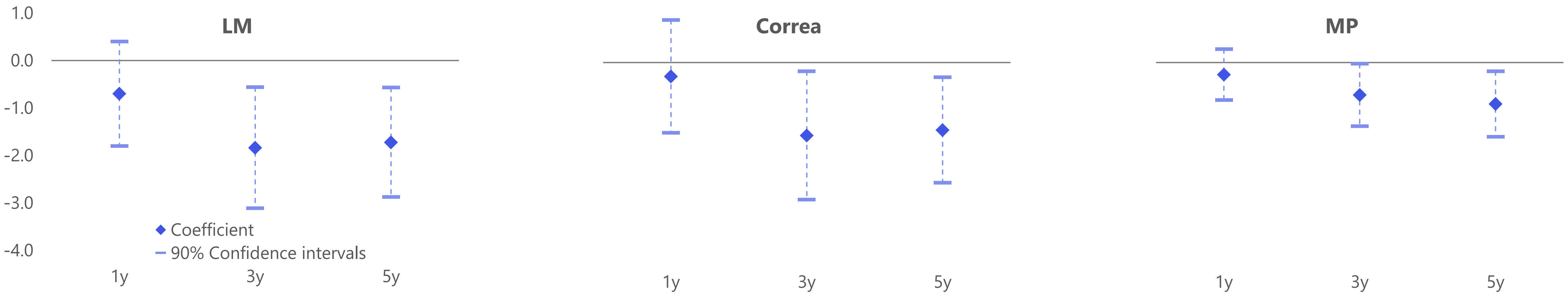
Some evidence that the sentiment measures can impact IRS rates

Estimated relationship between net sentiment measures and interest rate swap rates , β_1 across swap maturity

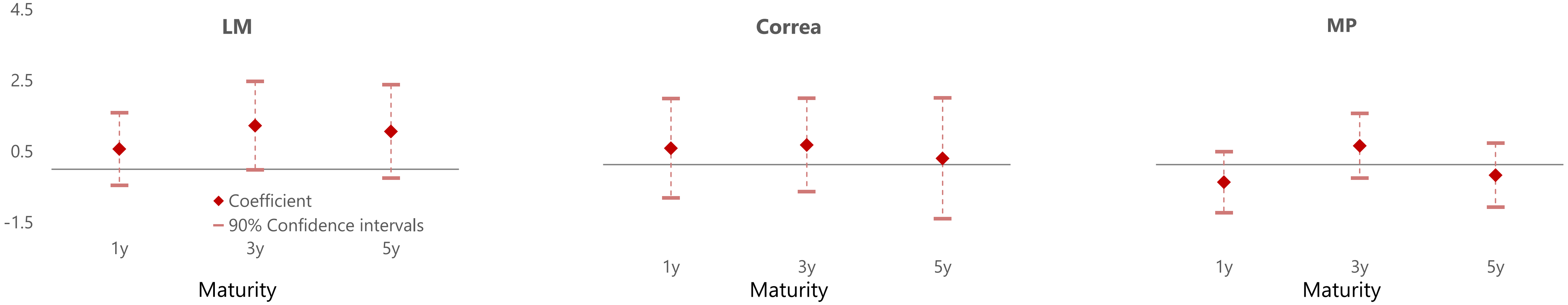


Dovish (negative) words appear to have stronger associations with a decline in swap rates

Estimated relationship between negative sentiment measures and interest rate swap rates , β_1 across swap maturity



Estimated relationship between positive sentiment measures and interest rate swap rates , β_1 across swap maturity



Conclusion

1. We derive sentiment measures from the monetary policy statements published by the Central Bank of Malaysia using three dictionaries, including one specially developed for monetary policy context.

2. We find the sentiment measures move in line with changes in the policy rate.

3. There is an asymmetric impact of the sentiment measures on sovereign yields and interest rate swaps rates. Our findings provide some evidence that the wording in the monetary policy statement is informative for the financial markets, especially during economic stress periods.