

Special Feature A

Text Analysis of MAS Monetary Policy Statements

This Special Feature presents a quantitative text analysis of the Monetary Policy Statements issued by the Monetary Authority of Singapore (MAS) over the past two decades. The study focuses on three key dimensions: sentiments, readability, and focus areas. Results may be used to assess the effectiveness of MAS' monetary policy communication and the public's comprehension of the statements.

1 Introduction

Effective communication is important to central banks. It facilitates public and financial market understanding of the rationale for monetary policy decisions and helps anchor views of the state of the economy. Like other central banks, MAS has enhanced and increased the frequency and channels of communication over time, including through media and industry engagements, and various publications.

Central bank communication should be easy to understand, objective, and its content should be relevant to the bank's mission. As detailed in a European Central Bank Strategy Review working paper (Assenmacher *et al.*, 2021), effective communication builds public trust, which in turn allows the shaping of expectations and subsequently the smooth conduct of monetary policy. Managing expectations well can be impactful to the extent that communication itself becomes a key intermediate instrument of policy. Central banks including the US Federal Reserve have utilised communication regarding both current and forward-looking actions as a key tool in their monetary policy toolkit (Kliesen *et al.*, 2018).

To evaluate MAS' monetary policy communication efforts, this paper examines the Monetary Policy Statements issued by MAS over the period 2001–23, by applying quantitative text analysis. The dimensions covered by this study are sentiments, readability, and focus areas. Correlation with economic data is also studied to buttress the insights of the analysis.

2 Data and Approach

Several major central banks have evaluated the effectiveness of their monetary policy communication. Notable examples include a study by the Reserve Bank of New Zealand (Cherry and Tong, 2023), which found high levels of objectivity in its Monetary Policy Statements, and a topic analysis by the European Central Bank (Fraccaroli and Giovannini, 2020) to discern the focus areas of its monetary policy parliamentary hearings over time.

The approach taken in this analysis follows Cherry and Tong (2023), who studied the three primary areas of sentiments, readability and topical areas using general Natural Language Processing (NLP) concepts including bag-of-words and cosine-similarity. These

approaches are readily implementable in Python frameworks such as those developed by Řehůřek and Sojka (2010), DeRobertis (2020) and Honnibal *et al.* (2020).

The analysis covers 53 MAS Monetary Policy Statements from February 2001 to October 2023.¹ The dataset is first pre-processed² before text analysis of the words is applied in four ways as elaborated below.

Gauge of Sentiments

The sentiments conveyed by the text in the Monetary Policy Statements are assessed using dictionaries that set out words associated with positive or negative sentiments. Two authoritative dictionaries in the NLP field are used, namely the Harvard-IV dictionary geared towards general language usage and the Loughran-McDonald dictionary intended for economic and financial analysis. The Harvard-IV dictionary comprises 1,188 known root words with positive connotations and 1,634 known root words with negative connotations. The Loughran-McDonald dictionary consists of 140 root words with positive connotations and 893 root words with negative connotations. Some examples of positive and negative words from the two dictionaries are given in **Table 1**.³

The number of words that are associated with positive or negative sentiments in each dictionary is derived and used to generate indicators for the direction and level of sentiments of the statements.

Table 1 Examples of root words applied in sentiment analysis

Dictionary	Sentiment	Examples
Harvard-IV	Positive	perfection, safe, improv, conqueror, opportun, counsel, cogent
Harvard-IV	Negative	defeat, dishearten, detach, fraudul, hypocrisi, counterfeit, worst
Loughran-McDonald	Positive	favorit, highest, vibrant, recept, resolv, greater, boom
Loughran-McDonald	Negative	dampen, writeoff, deprec, riskiest, anticompetit, shorttag, fallout

Determination of Readability

The ease of readability of the Monetary Policy Statements is assessed via the use of two indicators, the Flesch-Kincaid score and the Gunning-Fog score, which use proxies to capture the complexity of the statements and education attainment required to understand them.

¹ The Monetary Policy Statements analysed include the off-cycle monetary policy announcements, for example in 2001, 2015 and 2022.

² All words are first converted to lowercase letters, with punctuation and stop words that do not contribute meaningfully to the analysis such as "and" and "or" removed. Words are then converted to their original form (e.g., "car's" and "cars" to "car") in a process known as lemmatisation, which is the grouping together of words of different forms or inflections but of the same meaning.

³ The roots or stems of the words instead of the complete words are given in the dictionaries to capture different expressions of the words. For example, "improv" is included instead of "improve", so that "improving" would be captured.

Alignment with Industry Sentiments

The correlation between sentiments conveyed by the emotive words in the Monetary Policy Statements and by industry indicators are computed to compare the degree to which these sentiments vary together. The presence of a strong correlation between these sentiments is taken as evidence of effective communication between policymakers and the public. Business outlook indices, based on the Economic Development Board's (EDB) Survey of Business Expectations of the Manufacturing Sector and the Department of Statistics' (DOS) Business Expectations Survey for the services sector, are used as measures of industry sentiments in the computation of the correlation coefficients.

Topic Analysis

Finally, topic analysis is conducted based on the correspondence of terms used in the Monetary Policy Statements to bags-of-words that are associated with pre-defined topics. These bags-of-words are based on text analyses of parliamentary hearings of the European Central Bank, Bank of England and Federal Reserve and were verified by Cherry and Tong (2023).

3 Results and Discussion

Sentiments and Emotionality

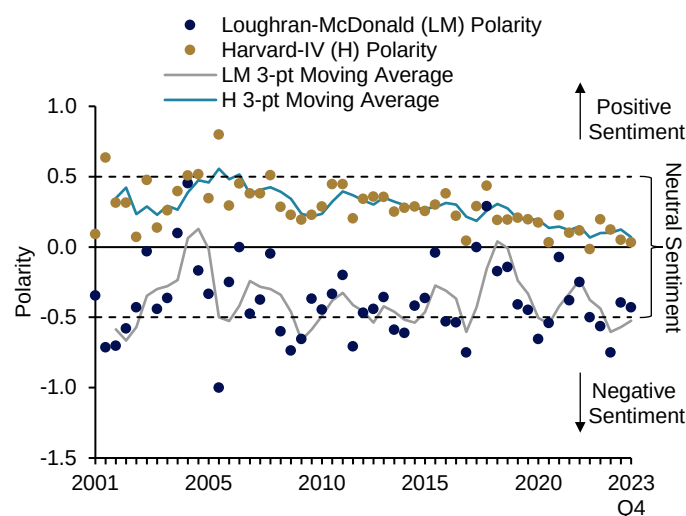
Polarity

The polarity of the Monetary Policy Statements is defined in Equation (1) below as the ratio of the "net" number of positive words to the sum of positive and negative words and the score ranges from -1 to 1.

$$Polarity = \frac{\#Positive - \#Negative}{\#Positive + \#Negative} \quad (1)$$

In NLP, polarity indicates the slant of emotive words, which are words with roots found in the related dictionaries. A polarity score of less than -0.5 is considered a negative or pessimistic slant, while a score greater than 0.5 is a positive or optimistic slant. There is no "right" or "wrong" slant, as it depends on the context and purpose of the texts.

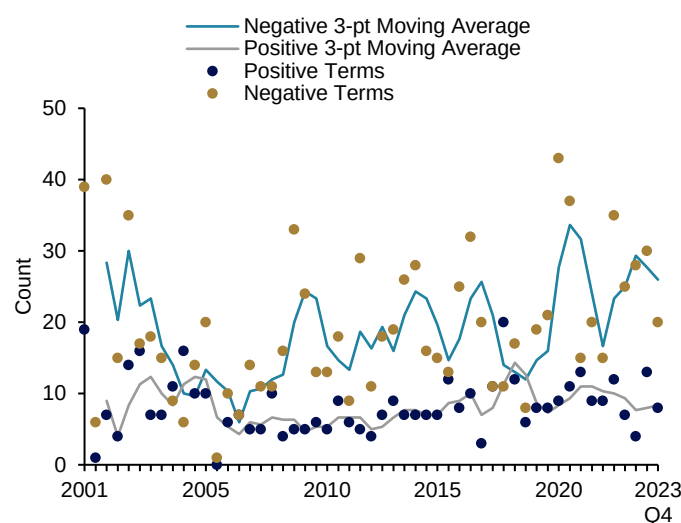
There appears to be a neutral-to-borderline negative slant to words in the statements that are associated with technical economic and financial terms in the Loughran-McDonald dictionary (**Chart 1**). In comparison, the slant of the general language in the statements according to the Harvard-IV dictionary is found to be relatively neutral.

Chart 1 Polarity of MAS Monetary Policy Statements

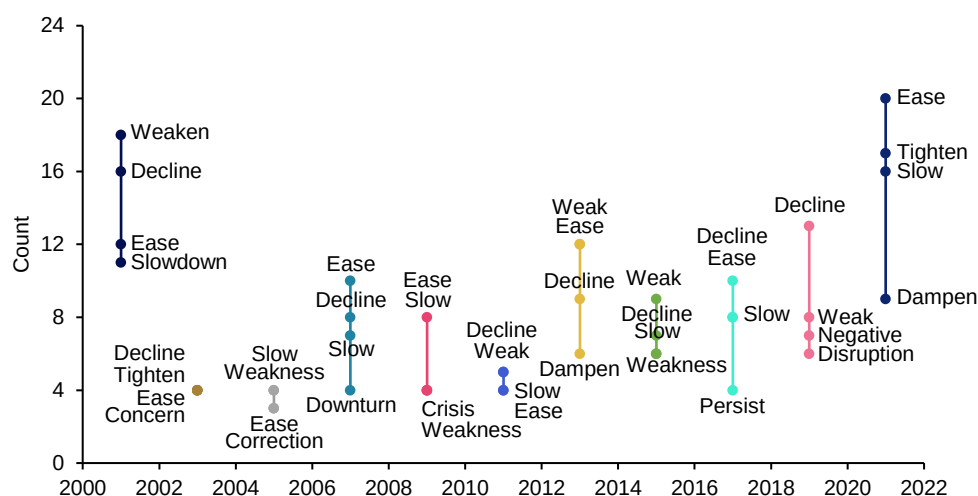
Source: EPG, MAS estimates

The results suggest that to readers who are attuned to economic and finance terminology, the emotive words in the statements evoke borderline negative (or cautious) sentiments. However, the negative polarity associated with sharp declines becomes more evident during periods characterised by economic shocks such as the Global Financial Crisis of 2008 and the COVID-19 pandemic in 2020. For the lay person with a general vocabulary, the statements come across as neutral on average.

Further word analysis is conducted to identify the cause of the sharp declines in the Loughran-McDonald polarity measure to negative territory during crises. The more significantly negative polarity is found to be due to the increased usage of negative terms while maintaining a relatively constant number of positive terms, as shown in **Chart 2**. The four most common negative terms (as classified by the Loughran-McDonald dictionary) in each biyearly compilation of Monetary Policy Statements are presented in **Chart 3**.

Chart 2 Usage of emotive words based on the Loughran-McDonald dictionary

Source: EPG, MAS estimates

Chart 3 Four most common negative words in MAS Monetary Policy Statements

Source: EPG, MAS estimates

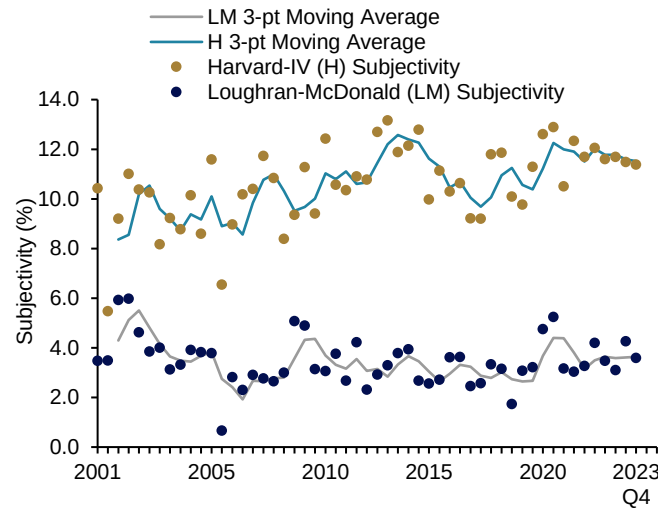
Note: Each line indicates the counts of the four most common negative words in the four Monetary Policy Statements issued that year and the year after. For example, the first dark blue line with four dots corresponds to the four Monetary Policy Statements issued in 2001 and 2002. Over that period, the words “Weaken”, “Decline”, “Ease” and “Slowdown” were the four most common negative words. The four most common negative words over 2003–04 are represented as a single dot as they appear the same number of times. The bag-of-words approach to sentiment analysis has the advantage of interpretability, but may not fully capture the possible contexts in which terms occur. For example, the term “Ease”, which could be intended to convey positive news in some contexts (e.g., easing wage or price pressures) and negative news in other contexts (e.g., easing of growth) is classified as a negative term by the dictionary. Aggregating positive and negative terms mitigates these issues somewhat, as mistaken classification of positive terms should be balanced out by mistaken classification of positive terms.

Subjectivity

The subjectivity of the statements is evaluated by the proportion of emotive words, both positive and negative ones, as given in Equation (2). A highly subjective piece implies that words are designed to elicit an emotive response, as opposed to an objective piece that emphasises facts.

$$\text{Subjectivity} = \frac{\#Positive + \#Negative}{\#Total\ Words} \times 100\% \quad (2)$$

MAS Monetary Policy Statements are found to have objectivity levels in line with other central banks’ texts, with approximately less than 4% of the words in each statement measured using the Loughran-McDonald dictionary being emotive on average (**Chart 4**). This is within the range of 1–4% in the statements of the Reserve Bank of New Zealand, reported by Cherry and Tong (2023), and the statements of Bank Negara Malaysia, estimated by Chong and Ho (2023) using the same dictionary.

Chart 4 Proportion of subjective words in MAS Monetary Policy Statements

Source: EPG, MAS estimates

Readability and Difficulty of Text

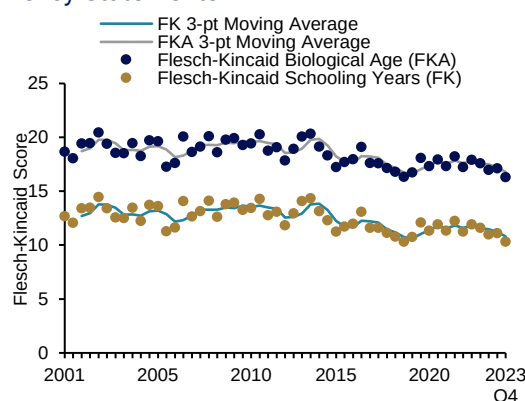
For effective public communication, Monetary Policy Statements should not be hard to comprehend for readers who do not have specialised training. The Flesch-Kincaid and the Gunning-Fog scores measure readability by counting the number of words per sentence, the number of syllables per word and the complexity of the vocabulary, as defined in Equations (3) and (4). Complex words are words with at least three syllables. These formulae were established from the studies by Kincaid *et al.* (1975) and Gunning (1952).

$$\text{Flesch} - \text{Kincaid} = 0.39 \left(\frac{\# \text{Words}}{\# \text{Sentences}} \right) + 11.8 \left(\frac{\# \text{Syllables}}{\# \text{Words}} \right) - 15.59 \quad (3)$$

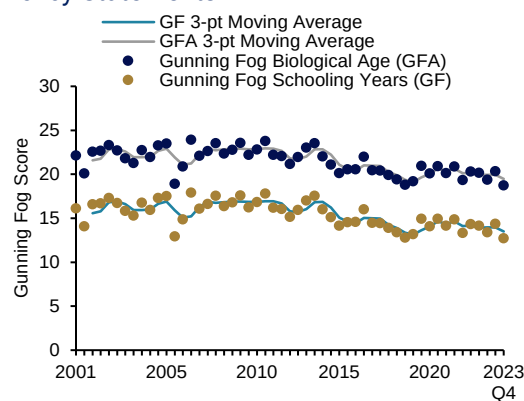
$$\text{Gunning} - \text{Fog} = 0.4 \left(\left(\frac{\# \text{Words}}{\# \text{Sentences}} \right) + 100 \left(\frac{\# \text{Complex Words}}{\# \text{Words}} \right) \right) \quad (4)$$

The Flesch-Kincaid and Gunning-Fog scores correspond to years of formal schooling required to understand the text. For ease of interpretation, the scores are converted to the corresponding biological age based on Singapore's education framework (e.g., Primary 1 is assigned age 7, Secondary 1 age 13, tertiary education age 17 onwards).

Both measures suggest an improvement in the readability of MAS Monetary Policy Statements over time. The Flesch-Kincaid scores in **Chart 5** show that the age required to read the statements fell from an average of 19.1 years before 2010, to 18.3 years over 2010–20 and to 17.4 years after 2020. Similarly, the Gunning-Fog scores in **Chart 6** indicate a drop in the age required from an average of 22.3 years before 2010 to 20 years after 2020. Based on the two measures, 18–20 years of age is required to understand the statements, which corresponds to individuals who likely have had some tertiary education (i.e., beyond education in Junior Colleges).

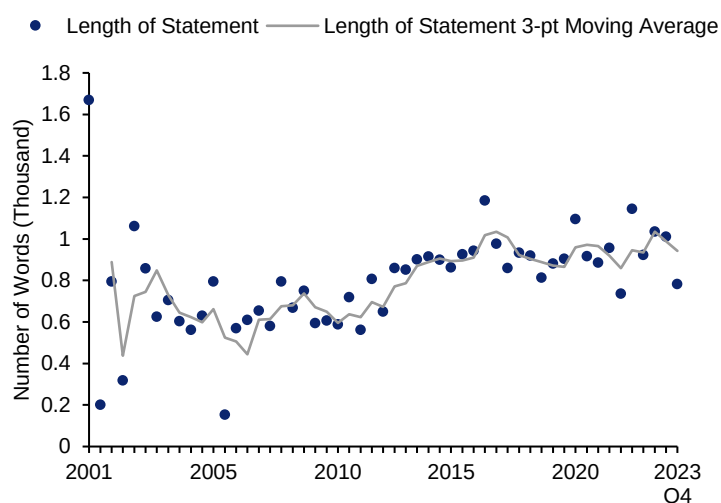
Chart 5 Flesch-Kincaid scores for MAS Monetary Policy Statements

Source: EPG, MAS estimates

Chart 6 Gunning-Fog scores for MAS Monetary Policy Statements

Source: EPG, MAS estimates

While the statements have improved in terms of readability, they have also become lengthier—the number of words used increased from an average of 673 before 2010, to an average of 855 in the 2010s and 949 in the 2020s as seen in **Chart 7**. The latest January 2024 and April 2024 Statements have, however, broken this trend and recorded lower word counts of 852 and 812 respectively.

Chart 7 Word count in MAS Monetary Policy Statements

Source: EPG, MAS estimates

Alignment with Industry Sentiments

At times, a lack of alignment between the sentiments conveyed in the statements and the private sector's views on the economic outlook may be indicative of ineffective monetary policy communication. A recent strand of research also suggests that disagreement between central banks and financial markets can reduce the effectiveness of monetary policy and have negative macroeconomic effects (Caballero and Simsek, 2022).⁴ It is therefore useful to

⁴ Caballero and Simsek (2022) find that if financial markets disagree with a monetary policy decision, they tend to act in ways that counteract monetary policy. For example, if markets assess monetary policy to be overly-expansionary, inflation expectations tend to surge, causing a larger than expected increase in actual inflation and necessitating a reversal of monetary policy in the next period.

ascertain the strength of the correlation between the sentiments conveyed in MAS' statements and those held by businesses.

First, a measure of the sentiments conveyed by the emotive words in the statements, the sentiment ratio, is computed using the formula in Equation (5) below. The sentiment ratio measures the polarity of sentiments expressed in the statement, controlling for its overall length.⁵ The ratio is derived from each of the two sources of emotive words—the Harvard-IV dictionary and the Loughran-McDonald dictionary, since reactions could differ between general readers and readers who are familiar with financial and economic terms.

$$\text{Sentiment Ratio} = \frac{\#Positive - \#Negative}{\#Total Words} \quad (5)$$

Next, a measure of optimism and pessimism in industry is created using EDB's and DOS' Business Expectations indices of manufacturing and services sectors, respectively, for the next six months following the publication of each Monetary Policy Statement. The computed correlation coefficients between the sentiment ratio and these sets of expectations data show a positive correlation (> 0.5) based on the financial terms used in the statements (**Table 2**). The correlation ratios for the financial terms are also found to be statistically significant (p-value < 0.05). In comparison, there is no evidence of correlation between the sentiments conveyed by the non-technical language in the statements and the industry indicators, which is consistent with the earlier finding of a neutral tone of the statements from the perspective of a lay person (**Chart 1**). To readers attuned to financial terms and industry practitioners looking for policy guidance, these estimates suggest that MAS' statements have been effective in communicating expectations about the economy.

Table 2 Correlation between business sentiments and sentiment ratio of MAS Monetary Policy Statements

	Sentiment Ratio	
	Based on Loughran-McDonald Dictionary (Financial Terms)	Based on Harvard-IV Dictionary (General Terms)
Business Expectations (Manufacturing)	0.52 (p = 0.00)	0.17 (p = 0.21)
Business Expectations (Services)	0.66 (p = 0.00)	0.26 (p = 0.059)

Source: EPG, MAS Estimates

Topic Analysis

There are groups of words that correspond to certain topics common to both economics and finance, as identified in Cherry and Tong (2023) and listed in **Table 3**.

⁵ Having the number of total words in the denominator captures the intensity of sentiments by inversely scaling the net number of emotive words by the length of each statement. Hence, for pieces that have higher emotive word count, the net "density" of emotive words would be low if they are also correspondingly lengthier.

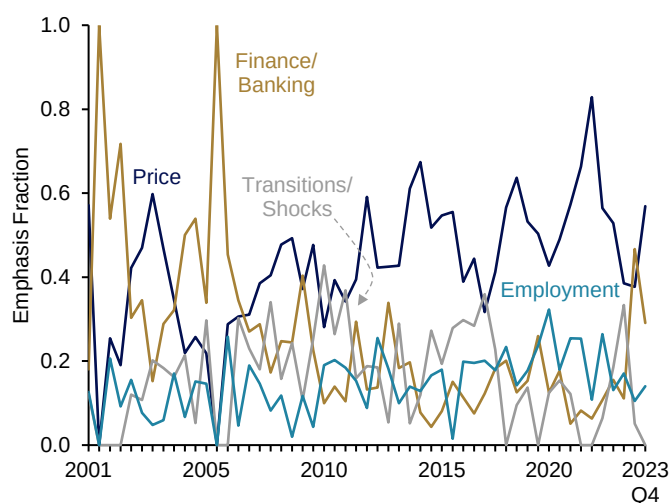
Table 3 Words associated with topics

Topic	Associated Words
Price	price, inflate, cpi, deflate, tradable, wage, salary, pay, anchor, medium term, embed, cost, capacity pressure, supply capacity, supply chain, midpoint, target, persist, scarce, slack, resource
Employment	participate, skill, matching, migrate, hour, overtime, employ, firing, fixed-term, full-time, part-time, inactive, job, labour, vacancy, worker, working age, working time
Finance/Banking	financial, banks, systemic risk, contagion, bubble, misalign, credit, insurer, hedge fund, investment fund, securities, lever, capital, derivative, off-balance, special purpose vehicle, payment system, settlement system, deposit, loan, currency
Transitory/Shocks	temporary, transitory, short-lived, one-off, look through

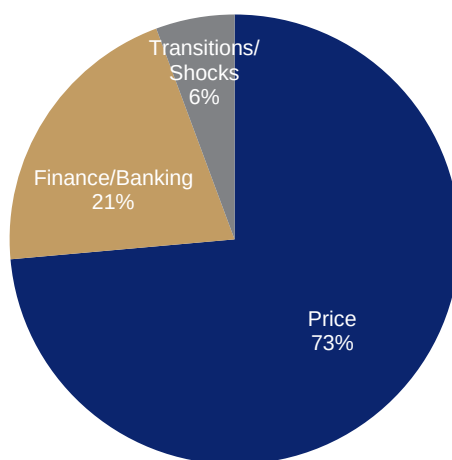
A classical text analysis is adopted based on the concept of correlation between the frequency of the terms (how often the terms occur), defined as $freq(term)$ in Equation (6), and their importance. The frequency of the terms on its own cannot establish importance because some words may occur very often and yet do not carry any distinctive emphasis. These would include words such as “a” and “and”. Hence, $freq(term)$ is adjusted by multiplying it with the logarithm of the inverse ratio of the number of documents (i.e., statements) containing the term out of the total number of documents included in the study. In the NLP literature, this adjusted frequency is referred to as the Term-Frequency-Inverse-Document-Frequency (TFIDF).

$$TIFDF = freq(term) \times \log\left(\frac{\#Documents}{\#Documents\ with\ term}\right) \quad (6)$$

Each document comprises many terms, and hence may be expressed as a vector of TFIDF scores. Each topic may also be described by the terms in **Table 3** and may be expressed as a vector of TFIDF scores as well. To capture the similarity between a document and a topic, the normalised vector dot product between the two sets of TFIDF scores is computed as the similarity score. The relative importance of a topic, represented by the emphasis fraction, is then derived by dividing the similarity score of the topic by the total scores of all topics such that the emphasis fractions of all topics sum to one. The resulting trend over time is shown in **Chart 8**. In addition, the number of occurrences of each topic representing the dominant topic of a statement is counted, with the results depicted in **Chart 9**.

Chart 8 Topic analysis of MAS Monetary Policy Statements

Source: EPG, MAS estimates

Chart 9 Proportions of dominant topics in MAS Monetary Policy Statements from April 2001 to October 2023

Source: EPG, MAS estimates

Overall, “Price” was the dominant issue in 73% of MAS Monetary Policy Statements in the past two decades, followed by “Finance/Banking” references at 21%. This suggests the predominance of price concerns for MAS in its monetary policy communication, with financial system stability possibly being an important subsidiary contextualisation. Both themes reflect MAS’ dedication to ensuring non-inflationary economic growth in the context of broader financial sector stability.

4 Summary and Conclusion

This paper has examined quantitative measures on the interpretation of Monetary Policy Statements issued by MAS in the past two decades.

The statements are found to be objective, with less than 4% of each statement containing emotive words on average. Where emotive words are present, a strong correlation is observed between sentiments expressed about Singapore's monetary policy and actual industry expectations. In terms of ease of understanding, the statements have improved in readability over the years such that it can be followed by young adults aged 18–20 years. This is despite the increase in word count in the statements in the last three decades. Based on the strong alignment with business sentiments, objectivity, and improved readability, the statements can be seen as effective in providing guidance and communicating expectations on the economy. In relation to focus areas, prices and inflation are the dominant themes.

While an attempt has been made to cover the relevant metrics involved in text analysis, there are limitations to this study. Notably, the scope and breadth of the vocabulary used in topic modelling could be expanded to capture a wider variety of expressions. In addition, the metrics considered are not exhaustive and there could be other higher-frequency indicators that correlate with the statements' sentiments. Nonetheless, a preliminary investigation conducted separately using Large Language Models for topic extraction strongly corroborated the results of this study.

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