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Hawkish-Dovish Signal Analysis in Bank Indonesia's Board of Governors Meeting Press Releases Using Large Language Model

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Abstract

Background: In signaling policy direction, central bank communication is crucial for aligning the expectations of financial market participants and the public with forthcoming monetary policy. This helps reduce economic uncertainty and enhance policy predictability.
Objective: This study examines the strategic role of Bank Indonesia's communication in shaping market expectations and influencing public perception through policy direction signals in Bank Indonesia Board of Governors Meeting press releases.
Methods: Observations of these signals were conducted semi-automatically using a large language model (LLM) to analyze sentence-level interpretations by classifying each sentence according to hawkish, neutral, and dovish criteria. Using an ordered probit model, the relationship between policy direction signals in the sentences and changes in policy rates in the subsequent period was investigated.
Results: The results show that policy direction signals in press release texts are significantly positive in predicting future policy interest rates.
Conclusion: The findings confirm that hawkish and dovish signals embedded in Bank Indonesia's monthly Board of Governors Meeting press releases significantly predict future policy interest rates, with 80% prediction accuracy. Central bank communication thus serves as a reliable monetary policy instrument that supports market expectation management, reduces financial market volatility, and enhances monetary policy credibility and effectiveness.

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INTRODUCTION

Quoting a sentence delivered in the press release of Bank Indonesia's Monthly Board of Governors Meeting (Rapat Dewan Gubernur, RDG), "Bank Indonesia views that the room for monetary policy easing is increasingly open with the maintenance of macroeconomic stability, especially inflation," reveals a signal of the policy direction that Bank Indonesia may take in the next period. This signal is very important in influencing the public, especially financial market participants, so that their perceptions are aligned with the policy direction to be taken by Bank Indonesia.

Communication is one of the strategic tools that can be used to convey the objectives, direction, and policy changes of a central bank (Farina, 2018; Shapoval, 2021). Communication can also affect the expectations of economic actors in the future (Candia et al., 2020). The role of central bank communication in providing signals to the public can influence asset prices and help predict future policy decisions (Gertler & Horvath, 2018; Lehtimäki & Palmu, 2019).

In an effort to carry out its role, the central bank needs a Monetary Policy Framework (MPF), which is a structure that can be used as a guide for the implementation of monetary policy. This includes the legal basis that establishes independence and accountability, as well as the design, implementation, and communication practices of monetary policy (Unsal et al., 2022). Communication is one of the pillars of the MPF that functions to increase the effectiveness of achieving policy objectives (Marie, 2025). Communication improves policy effectiveness, reduces economic and financial uncertainty, shapes and reinforces market expectations, and can serve as an additional policy driver (Bernanke, 2015; Blinder et al., 2008). Further emphasis is placed on the combined design of communication and policies, as well as operational strategies, given that such strategies are the cornerstones of communication, while communication enhances the understanding and credibility of those strategies (Unsal et al., 2022). Indonesia presents a unique institutional context as a large emerging economy with a diverse financial sector, high exchange rate sensitivity, and significant capital flow volatility, which makes Bank Indonesia's communication role particularly critical compared to that of central banks in developed economies (Ahokpossi et al., 2020).

Communication strategy plays an important role in assessing the performance of a central bank. There is a clear relationship between rules-based policy and communication. Three factors that can make communication strategies effective are ease of understanding, clear boundary corridors, and clear policy rules (Davig & Foerster, 2023). The article explains how the inflation target, tolerance band, and inflation forecast, which serve as the basis for issued policies, can be communicated clearly and easily understood. A proper communication strategy from the central bank can help economic actors understand the policies taken by the central bank, thereby increasing policy effectiveness.

Bank Indonesia's monetary policy framework, the Inflation Targeting Framework (ITF), which later developed into the Flexible ITF, is built on five main elements, one of which is strengthening policy communication strategies as part of the policy instruments. The implementation of the Flexible ITF is carried out through flexibility in integrating the monetary and financial system stability frameworks through the application of monetary, macroprudential, exchange rate, capital flow, and institutional strengthening instruments to optimize the role of policy coordination and communication. This policy sets an explicit inflation target and announces it transparently as a signal to the public and market participants regarding Bank Indonesia's commitment to maintaining price stability and strengthening public confidence.

To achieve the objective of maintaining and stabilizing the value of the rupiah, as reflected in a low and stable inflation rate, Bank Indonesia sets the benchmark interest rate as the policy rate to influence economic activity through financial markets and society. This benchmark interest rate represents a monetary policy stance announced to the public. Bank Indonesia's policy interest rate was called the BI Rate, which, on August 19, 2016, changed to the BI 7-Day Reverse Repo Rate (BI7DRR). However, starting December 21, 2023, Bank Indonesia again used the name BI Rate for its policy interest rate.

In the digital information era, policy communication has become increasingly complex and faces various challenges. The increased speed of information dissemination has the potential to generate speculation that is biased against actual conditions. This can increase volatility and uncertainty for the public.

The use of long sentences and complicated word structures reduces the clarity of the communication conveyed. The tone of the sentence conveyed by central bank officials can be interpreted as a policy signal by the public. A positive tone can be associated with unexpected changes in monetary policy conveyed by the central bank. Hubert (2021) state that the tone of communication from central banks can help predict future policy decisions. In addition, the information provided by the central bank can offer clues that allow financial markets to anticipate the policies imposed.

Central bank communication has an impact that goes beyond merely directing future interest rate expectations (Candia et al., 2020; Cœuré, 2017). Studying the tendency to interpret sentences conveyed by central banks as signals in the form of hawkish or dovish stances influences public decision-making, especially in financial markets, because this interpretation is related to the direction of central bank policy. Hawkish refers to the possibility that the central bank will raise interest rates or tighten monetary policy because certain conditions need to be addressed to maintain monetary stability. In contrast, dovish refers to the opposite of hawkish, namely the possibility that the central bank will delay raising interest rates or ease monetary policy by lowering interest rates.

There are various studies that discuss central bank policy signals. Most of this research has been conducted in developed countries, such as a study on the Federal Reserve that examined the FOMC decision-making process and the factors influencing it during periods of high inflation using Natural Language Processing (NLP), a study on the European Central Bank (ECB) on the relationship between communication intonation and the predictability of monetary policy decisions Baranowski (2021), and a study on the Bank of England (BoE), which states that assessments of BoE texts accurately reflect short-term economic conditions (Jones et al., 2020). However, research informing the role of central bank policy communication in developing countries remains relatively limited. Automated or semi-automated text-based linguistic approaches are often used to analyze tone and signals in policy texts to understand how they might be interpreted by the public and the market. Specifically, while existing studies primarily employ static keyword dictionaries or bag-of-words approaches that are sensitive to lexical ambiguity and fail to capture contextual nuance, this study addresses that limitation by adopting sentence-level LLM-based classification that accounts for semantic context and Indonesian central bank communication patterns.

The press release from the RDG decision conveys various forms of information; therefore, the information contained in the press release text is interesting to analyze further to understand current conditions, including signals for future policies. However, the extent to which policy signals in RDG press release texts affect the BI Rate in the future is not fully understood. Therefore, this study attempts to identify the policy signals contained in Bank Indonesia's Monthly RDG press release texts and analyze the extent to which those policy signals can predict the BI Rate in the next period.

To analyze the policy signals, a semi-automated text-based approach was applied to each complete sentence using a Large Language Model (LLM). This research involves artificial intelligence (AI), which helps analyze sentence interpretation by classifying each sentence based on hawkish, neutral, and dovish criteria. This approach differs from most previous studies that analyzed a single set of keywords indicating hawkish or dovish signals. In addition, other studies have used a combination of two keywords to corroborate the results of the analysis (Apel & Blix Grimaldi, 2012). By analyzing whole sentences, the risk of interpreting positive words that are commonly associated with hawkish signals but are used in dovish situations can be minimized. In the case of Bank Indonesia's Monthly RDG press release texts, the sentences delivered often use positive word choices to mitigate excessive negative impacts when informing the public about less conducive conditions. Thus, when tabulated, the positive keywords describing hawkishness remained more frequent than the negative keywords describing dovishness, despite the interest rate policy decided in that period being dovish. Unlike prior studies that assigned hawkish/dovish labels based solely on individual keywords, this study classifies entire sentences using contextual LLM inference, which substantially reduces misclassification risks arising from polysemous words commonly deployed in Indonesian central bank communication to soften negative signals (Apel & Blix Grimaldi, 2012; Benchimol et al., 2022).

Furthermore, this paper is structured as follows: a theoretical review that describes the theories underlying the research; a research method section that explains the analytical method used in this study; a results section presenting the information obtained from the equation tests conducted; a discussion of the research findings; and, finally, conclusions and suggestions.

Theoretical Review

Bank Indonesia, in the process of determining policy interest rates, does not disclose the voting results of each member of the Board of Governors (Anggota Dewan Gubernur [ADG]) who attends the Board of Governors Meeting (Rapat Dewan Gubernur [RDG]). Therefore, indications of individual preferences behind interest rate decisions cannot be known in the same way as in the Federal Reserve's benchmark interest rate decision-making process. Furthermore, the results of the BI Rate decision are immediately conveyed in writing through the text of the Monthly RDG press release and published on the Bank Indonesia website.

The structure of Bank Indonesia's press release begins with the results of the RDG decision on the BI Rate, the Deposit Facility rate—the interest rate given by Bank Indonesia to commercial banks that place excess liquidity at the end of the day—and the Lending Facility rate—the interest rate given by Bank Indonesia to commercial banks that require liquidity from Bank Indonesia at the end of the day. Furthermore, the press release presents current variables, issues, or conditions that affect BI Rate decisions, including expectations regarding future economic conditions.

In addition, the press release text presents policy responses to the latest economic conditions, measures that have been implemented, including coordination with other institutions, global and domestic economic conditions, and data on Indonesia's economic performance as reflected in Indonesia's Balance of Payments (BOP), exchange rate, inflation rate, banking liquidity conditions, lending rates, macroprudential indicators, and payment system policies. However, Bank Indonesia's press release paragraphs and sentences have become longer, indicating that the clarity of the message conveyed has weakened over time.

The overall information provided by Bank Indonesia aims to provide signals and projections regarding future economic conditions, thereby helping to reduce market uncertainty, improve monetary policy transmission, and ensure that policy rate decisions are clearly interpreted by market participants.

Changes in central bank policy interest rates are influenced by various factors. The monetary policy framework proposed by John B. Taylor, later known as the Taylor Rule, provides a reference for central banks in setting interest rates based on specific economic conditions, especially inflation and economic output. Changes in interest rates reflect responses to changes in inflation and economic output, in this case, Gross Domestic Product (GDP). The Taylor Rule states that nominal interest rates must be adjusted based on the difference between actual inflation and target inflation, as well as between actual output and potential output (Taylor, 1993). The basic formula of the Taylor Rule is as follows:

$$it = rt^{*} + \pi t + 0.5(\pi t - \pi^{*}) + 0.5(yt - y*) \quad (1)$$

where it is the nominal interest rate; r_{t*} is the neutral real interest rate; π_t is the current inflation rate; $\pi*$ is the inflation target; y_t is the current real output; $y*$ is the potential output. Economically, the Taylor Rule implies that when inflation exceeds its target, the central bank should raise the nominal interest rate by more than the increase in inflation, known as the Taylor principle, thereby increasing the real interest rate to cool inflationary pressures. Conversely, when actual output falls below potential output, indicating a negative output gap, the central bank should lower interest rates to stimulate economic activity. This rule-based framework provides a transparent and predictable basis for monetary policy, which is directly relevant to the analysis of central bank communication signals as leading indicators of interest rate changes.

Based on the Taylor Rule, policy signals can be analyzed from the observed Board of Governors Meeting press release texts. Changes in the benchmark interest rate are often accompanied by explanations of inflation dynamics and economic growth conditions. Using the Taylor Rule, it is possible to assess whether interest rate changes are consistent with movements in inflation and GDP.

Beyond the Taylor Rule, this study is also grounded in signaling theory and rational expectations theory. Signaling theory posits that central banks strategically use communication to convey credible information about future policy intentions, thereby reducing information asymmetry between policymakers and market participants (Blinder et al., 2008). Rational expectations theory suggests that economic agents form expectations based on all available information, including central bank communications, making the tone and direction of press releases key determinants of market behavior. Additionally, transparency and credibility frameworks in monetary policy underscore that consistent and interpretable communication reinforces the effectiveness of policy instruments beyond the direct effects of interest rate adjustments (Davig & Foerster, 2023). Together, these theoretical perspectives motivate the analysis of hawkish-dovish signals as predictors of future policy rate decisions.

METHOD

This study uses an ordered probit regression quantitative approach to analyze the relationship between the net signals contained in the Monthly RDG press release text and the determination of future policy interest rates (BI Rates).

The dependent variable in this equation is in ordinal form, namely the change in BI Rate $_{t+1}$ (which is a multiple of 25 bps sorted from -25 bps, 0 bps, 25 bps to 50 bps. The four categories refer to the entire sample of dependent variable data used. Here is a series of $\Delta_{r_{t1}}$) thresholds from BI Rate $_{t+1}$ which are denoted as Ordinal rt1: These four categories encompass the complete range of BI Rate changes observed during the 2014–2023 sample period. The selection of 25 bps increments reflects Bank Indonesia's standard policy adjustment convention, while the inclusion of the 50 bps category captures the exceptional tightening episodes observed during periods of heightened inflationary and exchange rate pressures (e.g., 2018 and 2022). The distribution of observations across categories—19 decreases, 88 unchanged, 10 increases of 25 bps, and 4 increases of 50 bps—demonstrates the predominance of the "Fixed" outcome, which justifies the use of the ordered probit model given its capacity to handle ordinal outcomes with unequal category frequencies.

$$\text{Ordinalrt1} = \begin{cases} 1 & \text{jika } \Delta_{r_{t1}} * \leq -25\text{bps} \\ 2 & \text{jika } -25\text{bps} < \Delta_{r_{t1}} * \leq 0 \text{ bps} \\ 3 & \text{jika } 0 \text{ bps} < \Delta_{r_{t1}} * \leq 25 \text{ bps} \\ 4 & \text{jika } 25 \text{ bps} < \Delta_{r_{t1}} * \leq 50 \text{ bps} \end{cases}$$

The Ordinal BI Rate $_{t+1}$ data is a continuous latent variable (y*) which is assumed to have a linear relationship with independent variables and term errors. The transformation from y* to y through the threshold value causes a non-linear relationship between the independent variable and the ordinal dependent variable.

Observations of policy signals in RDG press releases that affect BI Rate decisions were conducted semi-automatically using an LLM, a machine learning model trained on large amounts of textual data to understand and generate natural language. This research involved OpenAI's GPT-4, which assisted in analyzing sentence interpretation by classifying each sentence based on hawkish, neutral, and dovish criteria. The main empirical challenge in analyzing central bank communications is converting raw words into meaningful quantities so that they can be analyzed (Hansen & McMahon, 2016). The interpretation of sentences generated by the LLM may not be entirely accurate; therefore, it was manually validated by referring to the literature and findings from similar studies.

The results of the sentence interpretation analysis in each RDG manuscript were then tabulated using an application that facilitated the validation process. Specifically, this study employed GPT-4 (OpenAI) as the LLM. Each sentence was submitted individually using a structured zero-shot prompt that instructed the model to classify the sentence as hawkish, neutral, or dovish based on its monetary policy implications for Bank Indonesia. The prompt specified explicit criteria: hawkish sentences indicate tightening pressure, such as inflationary concerns, exchange rate depreciation, and financial instability; dovish sentences indicate easing conditions, such as declining inflation, a stable exchange rate, and economic slowdown; and neutral sentences convey factual or descriptive information without directional policy implications. All sentences from 121 monthly RDG press releases from January 2014 to December 2023 were processed sequentially.

The validation process was carried out by compiling a list of sentences containing information, conditions, or data that could encourage or influence monetary policy tightening, classified as hawkish, or, conversely, monetary policy easing, classified as dovish. Manual validation was conducted by two independent researchers with expertise in monetary economics and central bank communication. To assess inter-rater reliability, a random sample of 200 sentences, approximately 2.5% of the total corpus, was independently classified by both validators. Cohen's kappa coefficient was computed to measure agreement, yielding $\kappa = 0.78$, indicating substantial agreement and confirming classification reliability. Discrepancies were resolved through discussion and reference to policy-relevant literature. This validation process minimized subjective bias while acknowledging that residual interpretive subjectivity cannot be entirely eliminated.

Furthermore, to determine the net signal from the RDG press release manuscript, a calculation was conducted using a methodology based on positive, or hawkish, and negative, or dovish, news (Birz & Lott Jr, 2011):

$$Net\ Signal = \left[\left(\frac{\#\,hawkish}{\#hawkish+\#dovish}\right) - \left(\frac{\#\,dovish}{\#hawkish+\#dovish}\right)\right] + 1 \qquad (2)$$

Where Net Signal is the value generated from the equation for each monthly RDG press release script during the observation period, #hawkish is the number of hawkish sentences, and

#dovish is the number of dovish sentences. The addition of the number 1 (one) in equation (2) is used to produce an equation with a positive value within the range of 0.00–2.00. This treatment can be interpreted as the "net hawkishness" of each press release script (Apel & Blix Grimaldi, 2012).

To analyze the effect of the net signal on the BI Rate decision in the following period, an initial test was conducted using the following ordered probit regression:

$$\Delta BIRate_{t+1} = \alpha_1 \Delta BIRate_t + \alpha_2 NetSinyal_t + \epsilon_{t+1} \quad (3)$$

ΔBIRatet+1 is an ordinal dependent variable, with 4 categories of ordinal variables, namely -25 bps, 0 bps, 25 bps and 50 bps which are sequential variables. This variable is then denoted as Ordinalrt1. While the ΔBIRatet is a change in the BI Rate in period t expressed in multiples of 25 basis points, this variable is notated as rt0. $NetSignal_t$ is the calculation value of the net signal in equation (2) which is notated with NetSignal. Furthermore, α_1 and is the regression coefficient obtained from the results of $\alpha_2$the ordered probit regression. Both are α_1 and are expected to have a positive value. is $\alpha_2 \epsilon_{t+1}$an Error term, the residual variable generated at the time of this model does not fully represent the true relationship between the dependent variable and the independent variable.

Referring to Taylor's Rule, regression is carried out by including price variables that are reflected through inflation and exchange rates, as well as output variables notated by GDP as done by Apel (2012) in the research The Information Content of Central Bank Minutes, so that the following equations are obtained:

$$Ordinalrt1 = \alpha_1 rt0 + \alpha_2 NetSinyal + \alpha_3 \Delta\_Inflasi + \alpha_4 \ln\_Nilai\ Tukar + \alpha_5 PDB\_growth + \epsilon_{t+1} \quad (4)$$

The definitions of Ordinalrt1 and rt0 in this equation are the same as those in the previous equation. NetSignal is the net signal calculation value in Equation (2), and ΔInflation is the difference in monthly national inflation. Ln_Nilai Conversion represents the daily USD/IDR exchange rate, which is aggregated monthly. Meanwhile, the PDB_growth value represents the monthly interpolation of quarterly GDP growth (q-to-q) in the previous period (t-1), and the definition of the error term is the same as that explained in the previous equation. Equation (4) illustrates the relationship between the current BI Rate, net signal, inflation, exchange rate, and GDP growth in influencing the next BI Rate decision. The use of monthly interpolation of quarterly GDP growth follows the Chow-Lin interpolation procedure, which distributes quarterly values across monthly intervals while preserving the quarterly total. This approach is consistent with prior studies using mixed-frequency macroeconomic data in ordered probit frameworks (Apel & Blix Grimaldi, 2012). A key limitation of this procedure is that it assumes linear growth within each quarter, which may underrepresent within-quarter volatility; however, given the relatively smooth GDP series in Indonesia during the observation period, this limitation is considered acceptable.

Probability, *Marginal Effect at Mean* and *Split Sample*

Probability tests, marginal effects (ME) at the mean, and split samples in ordered probit equations serve purposes related to model evaluation, interpretation, and validation. By conducting these three tests, the equations used can be considered not only valid but also well interpreted and reliable for predicting the BI Rate in the next period.

Probability

The Ordinalrt1 variable has four categories and therefore has three thresholds. The probability is expressed as follows:

$$P(Ordinalrt1 = j) = P(\tau_{j-1} < y^* \leq \tau_j \quad (5)$$

with the probabilities for each category are as follows:

$$P(Ordinalrt1 = 1) = P(y^* \leq \tau_1) = \Phi(\tau_1 - X\beta) \quad (6)$$

$P(Ordinalrt1 = 2) = P(\tau_1 < y^* \leq \tau_2) = \Phi(\tau_2 - X\beta) - \Phi(\tau_1 - X\beta)$
$P(Ordinalrt1 = 3) = P(\tau_2 < y^* \leq \tau_3) = \Phi(\tau_3 - X\beta) - \Phi(\tau_2 - X\beta)$
$P(Ordinalrt1 = 4) = P(y^* > \tau_3) = 1 - \Phi(\tau_3 - X\beta)$

where P(Ordinalrt1 = j) is the probability value for each category of the Ordinalrt1 variable (categories 1–4), y* is a continuous latent variable that is not directly observed but determines the category of the ordinal dependent variable, τ is the cutoff point or threshold of Ordinalrt1, X is the vector of independent variables, β is the regression coefficient vector associated with the independent variables, and Φ is the cumulative distribution function (CDF) of the standard normal distribution, which gives the probability that a random value from the standard normal distribution is less than or equal to a given value.

The probability calculation for the Ordinalrt1 category was carried out to identify which independent variables have a significant relationship with the probability of a particular outcome. Therefore, it can help determine the main factors affecting the Ordinalrt1 variable, namely the BI Rate in the subsequent period, in this study.

Marginal Effect

The marginal effect (ME) in the ordered probit model provides information about changes in the probability of a category of the Ordinalrt1 variable associated with a one-unit change in an independent variable. The ME value calculated in this study is the marginal effect at the mean, which measures how much the probability of an Ordinalrt1 category changes when an independent variable increases by one unit, while the other independent variables remain constant at their mean values. Marginal effects calculated at the mean provide a more general and easier-to-understand interpretation of the impact of independent variables.

Mathematically, marginal effects are calculated based on the following equation:

$$\partial P\left(\frac{Ordinalrt1=j|X}{\partial X_k}\right) \tag{7}$$

For each category of Ordinalrt1 variable, *the marginal effect* is calculated as follows:

$$\partial P\left(\frac{Ordinalrt1 = 1}{\partial X_k}\right) = -\beta_k \phi(\tau_1 - X\beta)$$
$$\partial P\left(\frac{Ordinalrt1 = 2}{\partial X_k}\right) = \beta_k[\phi(\tau_1 - X\beta) - \phi(\tau_2 - X\beta)]$$
$$\partial P\left(\frac{Ordinalrt1 = 3}{\partial X_k}\right) = \beta_k[\phi(\tau_2 - X\beta) - \phi(\tau_3 - X\beta)]$$
$$\partial P\left(\frac{Ordinalrt1 = 4}{\partial X_k}\right) = \beta_k \phi(\tau_3 - X\beta) \tag{8}$$

where is the $\partial \mathrm{P}\left(\frac{\mathrm{Ordinalrt1=j|X}}{\partial \mathrm{X_k}}\right)$marginal effect at means value of each category of Ordinalrt1 variables (categories 1-4), which describes the change of each unit unit to the probability. is the τcut-off point or threshold of the Ordinalrt1 variable. is the regression coefficient for the independent variable β_kXk while Xβ is a linear combination of the independent variable with its regression coefficient. Meanwhile, it is a probability density function (ϕPDF) that describes the probability density (concentration) of a continuous random variable around a certain value.

Significant ME suggests that such independent variables have a significant influence on the probability of a particular outcome, which is important for policy analysis and an in-depth understanding of the relationships between the variables in this study. The ME at means test in this study used the Stata application.

Split Sample

To ensure that the model is reliable and has good generalization ability, testing was conducted by dividing the research object through a split-sample procedure into two subsets. Split sampling enables the evaluation of model consistency by dividing the dataset into two parts: one used to train the model (training set) and the other used to test the model (test set). The selection of observations assigned to the training and testing subsets was determined randomly and automatically using Stata software.

The steps for conducting these two tests began with the random division of the dataset by Stata into proportions of 70% and 30%. Next, equation model (4) was estimated using the training subset, followed by category prediction on the test subset. After the results were obtained, the model's performance was evaluated to calculate the accuracy and consistency of the equations used in this study. Based on the calculation results, conclusions can be drawn regarding the consistency of performance and reliability of the equations used.

RESULTS AND DISCUSSION

Results

Referring to the research results obtained, with a focus on hypothesis testing and data interpretation, this discussion aims to connect the empirical evidence with the Taylor Rule previously discussed, using the established research methodology. This discussion seeks to assess whether the research results support or reject the formulated hypothesis.

The observed population consisted of 121 monthly RDG manuscripts, covering the observation period from January 1, 2014, to December 31, 2023. During this period, the BI Rate decreased by 25 basis points (bps) 19 times, remained stable 88 times, increased by 25 bps 10 times, and increased by 50 bps 4 times.

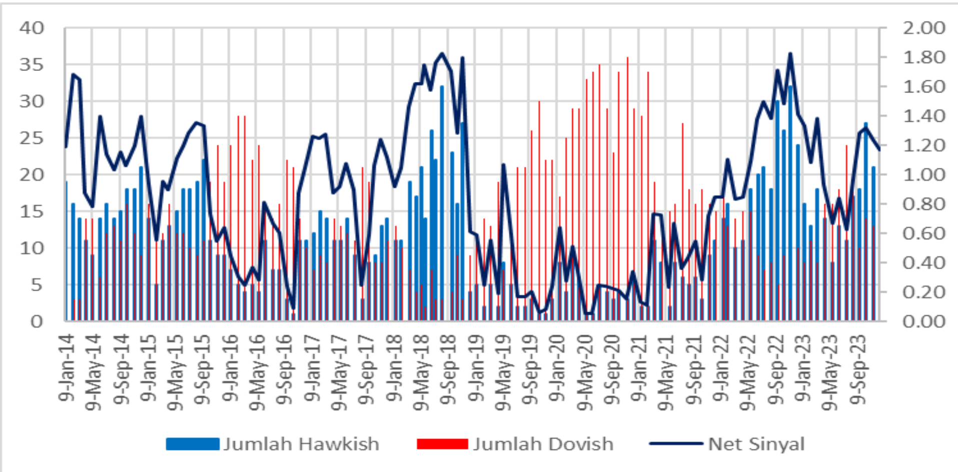

Figure 1. Number of *Hawkish*, *Dovish* and Net Signals

The calculation and interpretation of hawkish and dovish sentences use Equation (2), producing the net signal information presented in Figure 1. The figure shows that, among all observed monthly RDG press release manuscripts, the highest number of hawkish signals was 32 sentences, occurring during the RDG periods of August 15, 2018, and November 17, 2022. Meanwhile, the highest number of dovish signals occurred in the RDG period of November 19, 2020, with 36 sentences. The right vertical axis in Figure 1 shows the net signal value, while the left vertical axis shows the number of sentence interpretations based on the hawkish and dovish categories. Based on the observation results, there were 7,844 sentences across all monthly RDG press release manuscripts, with the detailed sentence interpretation results presented in Table 1 below:

Table 1. Number of Sentences Containing *Hawkish – Dovish Signals*

Observation Results	*Hawkish*	Neutral	*Dovish*
Number of sentences	1.405	4.575	1.864
Percentage	17,91%	58,33%	23,76%

From the results of the analysis of the sentence, it is known that more than half or 58.33% of the information conveyed was neutral, 23.76% contained *dovish* signals and the remaining 17.91% contained *hawkish* signals.

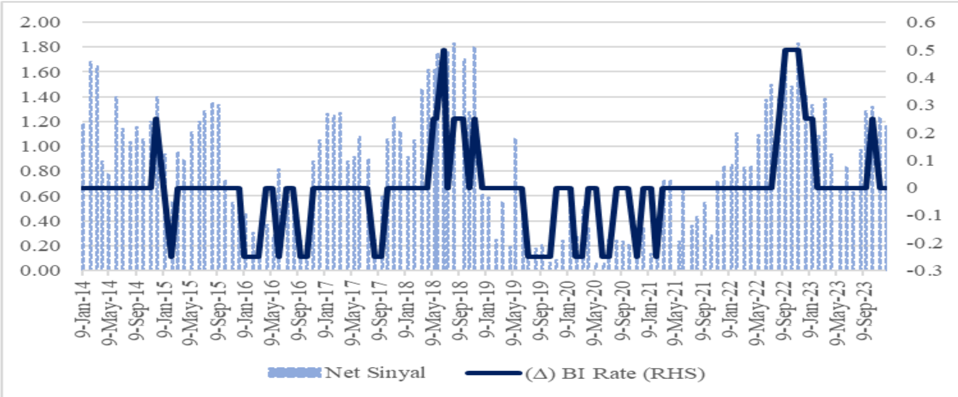

Figure 2. Net Signal Pattern with BI *Rate Change*

Figure 2 combines the net signal pattern with the BI Rate. The change in the BI Rate is expressed in basis points on the right axis, while the net signal is expressed numerically on the vertical axis on the left side of the figure. By comparing the net signal results with changes in the BI Rate, the net signal pattern in the preceding period is relatively aligned with subsequent interest rate changes. When the BI Rate increased in May 2018, the net signal moved upward, indicating a more hawkish stance than in the previous period.

Table 2. Descriptive Statistics Summary

Variable	Mean	Median	Standard deviation	Min.	Max.
Δ BI Rate $_{t+1}$	-0.0021	0	0.1524	-0.25	0.50
Δ BI Rate $_{t}$	-0.0021	0	0.1524	-0.25	0.50
Net signal	0.8637	0.8800	0.4919	0.06	1.83
Inflation (CPI)	-0.0492	-0.0400	0.5139	-2.17	2.13
Ln Exchange Rate	9.5394	9.5517	0.0728	9.34	9.67
GDP *growth*	1.0227	1.1400	2.0382	-4.19	5.05

Descriptive statistics provide an overview of the research variables collected. Table 2 presents the descriptive statistics for all observed data. This analysis was conducted to help understand the distribution, dispersion, and central tendency of the data before further analysis was performed.

Results of Net Signal Testing on BI Rate Decision for the Next Period

To analyze the effect of the net signal on the BI Rate decision, a test was conducted using Equation (3) as the starting point. In this equation, the Ordinalrt1 value is influenced by changes in the current interest rate (rt0) and the net signal. The results of this test are presented in Table 3, column (1), where the independent variable RT0 has a coefficient value of 2.305 with a significance level of 5%. Meanwhile, the net signal has a coefficient value of 1.889 with a significance level of 1%. The test results from Equation (3) indicate a positive and significant relationship between rt0, the net signal, and Ordinalrt1. Any increase in rt0 and the net signal increases the likelihood or probability that Ordinalrt1 will fall into a higher category.

Table 3. Test Results of the Influence of Net Signals and Other Variables on the Next BI Rate

Dependent Variable: Ordinalrt1								
	(1)	(2)	(3)	(4)	(5)	(6)[a]	(7)[b]	(8)[c]
VARIABLES	Ordinalrt1	Ordinalrt1	Ordinalrt1	Ordinalrt1	Ordinalrt1	Ordinalrt1	Ordinalrt1	Ordinalrt1
rt0	2.305**	2.366**	1.466	2.301**	1.527	1.527	1.528	1.528
	(1.016)	(1.024)	(1.096)	(1.018)	(1.101)	(1.062)	(1.101)	(1.059)
Net_Sinyal	1.889***	1.956***	2.194***	1.889***	2.309***	2.309***	2.309***	2.309***
	(0.444)	(0.467)	(0.486)	(0.444)	(0.520)	-0.425	(0.520)	(0.425)
Δ_Inflasi		0.409*			0.445*	0.445	0.445*	0.445
		(0.243)			(0.249)	(0.277)	(0.248)	(0.277)
ln_Nilaitukar			4.558**		4.801**	4.801**	4.801**	4.801**
			(2.052)		(2.100)	(1.896)	(2.100)	(1.896)
PDB_growth				0.00489	0.00115	0.00115		
				(0.0612)	(0.0635)	(0.0603)		
/cut1	0.043	0.00893	43.71**	0.0476	46.01**	46.01**	46.01**	46.01**

	(0.315)	(0.321)	(19.67)	(0.32)	(20.12)	(18.19)	(20.13)	(18.20)
/cut2	3.545***	3.671***	47.42**	3.551***	49.95**	49.95***	49.95**	49.95***
	(0.582)	(0.622)	(19.83)	(0.588)	(20.32)	(18.3)	(20.32)	(18.31)
/cut3	4.619***	4.758***	48.56**	4.626***	51.11**	51.11***	51.11**	51.11***
	(0.651)	(0.689)	(19.86)	(0.658)	(20.36)	(18.35)	(20.36)	(18.36)
Prob > Chi2	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Pseudo R2	0.3189	0.3330	0.3445	0.3189	0.3603	0.3603	0.3603	0.3603
Observations	121	121	121	121	121	121	121	121

Note: ***, **, *, represent statistical significance of 1%, 5%, and 10%, respectively. The number of observations was 121. The bound variable is Ordinalrt1. The equation is estimated using *ordered probit*. The inflation-free variable is the difference between this month's national CPI and the previous month. The Nilai_Tukar free variable is a *natural log* of the daily exchange rate that is flattened on a monthly basis. The free variable PDB_growth is the interpolation value of monthly GDP growth calculated from quarterly GDP growth.a test results with VCE Robust; b test results without GDP variables; c test results without PDB variables with *VCE Robust*

Thresholds denoted by (/cut1, /cut2, /cut3) indicate the points at which ordinal outcome variables transition between categories. For example, a /cut2 value of 3.545 in Test 1 is significant at the 1% level. This means that, after passing the /cut1 threshold (the category shift from -25 bps to 0 bps according to the ordinal variable criteria described earlier), an independent variable (predictor) value that reaches or exceeds 3.545 increases the probability of moving the dependent variable (Ordinalrt1) to the /cut2 category, namely from 0 bps to 25 bps. Significant cut values, marked with *, **, and *** according to their respective significance levels, indicate that the equation can effectively distinguish among the four ordered categories of BI Rate changes, as described earlier.

Thus, referring to Equation (2), the variables rt0 and Net Signal, as variables affecting changes in the BI Rate in the next period, indicate that any increase in the current BI Rate or in the net signal value will increase the probability of a BI Rate increase in the subsequent period. From a policy perspective, this finding implies that investors, financial institutions, and economic agents can meaningfully use the tone of Bank Indonesia's press releases as a forward-looking indicator when forming interest rate expectations. A press release with predominantly hawkish sentences signals the central bank's concern about inflationary or exchange rate pressures, thereby conveying a higher likelihood of rate tightening in the subsequent period. This is consistent with signaling theory, which posits that credible communication by a central bank reduces information asymmetry and aligns market expectations with policy intentions (Blinder et al., 2008).

Results of Net Signal Testing and Macroeconomic Variables on BI Rate Prediction for the Next Period

To obtain further empirical evidence regarding the role of the current BI Rate variable and the net signal in influencing the BI Rate in the next period, additional independent variables were included as control variables. This was done to improve the accuracy of the equation estimation. The variables serving as control variables refer to the Taylor Rule, namely inflation, exchange rate, and GDP growth, which represent key macroeconomic variables.

The results of separate tests for each macroeconomic variable in Table 3, test columns (2), (3), and (4), show that the inflation variable has a positive effect with a significance level of 10%, while the exchange rate variable, ln_nilai, also has a positive effect with a significance level of 5%. Meanwhile, the GDP growth variable has a positive but insignificant effect.

Furthermore, all independent variables were tested simultaneously using two approaches: without VCE (Variance-Covariance Estimator) Robust and with VCE Robust. VCE Robust was used to ensure that the standard error estimates and the resulting test statistics remain valid even when the assumption of homoscedasticity, or constant variance of residuals, is not satisfied. The results of these tests are presented in Table 3, with column (5) showing the results without VCE Robust and column (6) showing the results with VCE Robust.

To examine the validity of inflation, exchange rate, and GDP growth in influencing the outcome of Ordinalrt1, all these variables were included together in the estimation presented in Equation (4). In Table 3, the results of Test (6) show that the current interest rate variable (rt0), inflation, and GDP growth have positive but insignificant effects on the BI Rate in the next period. The change in the significance of the rt0 variable is influenced by the inclusion of control variables in the equation. The addition of control variables can change both the sign and the magnitude of the regression coefficient. Meanwhile, the exchange rate variable ln_nilai and the net signal variable show consistent positive and significant effects on the BI Rate in the next period. The significance level of the exchange rate variable ln_nilai is 95%, while that of the net signal variable is 99%. These results are broadly consistent with the Taylor Rule framework, insofar as inflation and exchange rate movements, which proxy for external price pressures, are found to be associated with future rate adjustments. The positive coefficient of the exchange rate variable ln_nilai is economically intuitive: exchange rate depreciation increases imported inflation and may require monetary tightening to defend the value of the Rupiah, consistent with Taylor Rule extensions for open economies. The divergence from theoretical predictions occurs in the GDP growth variable, which is discussed further below.

Test results (7) and (8) in Table 3 are presented to provide additional information. By excluding the GDP growth variable from the tested equation, the results remain relatively similar. This was done to confirm that the GDP growth variable is consistently insignificant in affecting the BI Rate in the next period. The consistent insignificance of the GDP growth variable across all model specifications may reflect several empirical and institutional factors specific to Indonesia's monetary policy framework. First, Bank Indonesia's primary mandate centers on price stability and exchange rate stabilization rather than short-term output stabilization, making it less reactive to quarterly GDP fluctuations. Second, the use of monthly interpolated GDP growth may introduce measurement noise that weakens the variable's statistical significance. Third, the lagged nature of GDP releases, which are available with a one-quarter delay, may limit their real-time relevance to monetary policy decisions. This finding is consistent with Ahokpossi (2020), who similarly report that Bank Indonesia's policy reactions are more strongly driven by inflation and exchange rate dynamics than by output gap considerations.

Furthermore, referring to Equation (3), the total latent score was calculated to determine the category of the ordinal dependent variable based on the values of the independent variables and the estimated regression coefficients. The calculation results are presented in Table 4, which shows that the total latent score is 48.47. This indicates that Ordinalrt1 is in the second category ("Fixed"), since the value of 48.47 lies between (/cut1) 46.01 and (/cut2) 49.95. This testing process was conducted to help predict the dependent variable based on the values of the independent variables. The actual BI Rate in April 2014 did not change compared with the previous month; therefore, the latent score calculation for the March 2014 period was valid for predicting the BI Rate in the April 2014 period, which showed a fixed BI Rate.

Table 4. Results of Calculation of Latent Scores for the Period of March 2014

VARIABLES	Coef. Regression (α)	Variable Values	α x Var Value. (Var. latent score)
rt0	1.53	0.00	0.00
Net_Sinyal	2.31	1.65	3.80
Δ_Inflasi	0.45	-0.43	-0.19
ln_Nilaitukar	4.80	9.34	44.86
PDB_growth	0.00	-2.18	0.00
Total latent score			48.47
Category ordinalrt1			2.00
Meaning for rt1			Fixed
/cut1	46.01		
/cut2	49.95		
/cut3	51.11		

Results of Probability, Marginal Effect at Mean and Split Sample

These three tests were conducted to provide confidence that the ordered probit model used is not only valid and interpretable but also reliable in predicting the BI Rate in the subsequent period.

Probability Test Results

The probability test in this study was conducted to provide a deeper explanation of how the independent variables affect the categories of the dependent variable. This test allows for a more intuitive interpretation through a better understanding of probability distributions, the evaluation of the influence of independent variables, category prediction, and the formulation of more effective policies. The margin values in Table 5 represent the average predicted probability for each outcome category. As explained earlier, the Ordinalrt1 variable in this study has four outcome categories: "down 25 bps," "fixed," "up 25 bps," and "up 50 bps." The results of the probability test indicate that the highest margin value, 73.05%, is found in category 2, "fixed (2)," which represents the prediction that the BI Rate in the subsequent period will remain fixed. The z-value and p-value for "fixed (2)" indicate a highly statistically significant probability at the 95% confidence interval, meaning that this prediction is very unlikely to occur by chance, with the actual probability ranging from 66.18% to 79.93%. Meanwhile, the lowest probability is found in category 4, "up 50 bps (4)," with a margin value of 3.22%, and this probability is also statistically significant.

Table 5. Probability Test Results

Outcome (x)		*Margin*	*Delta-Method Std. Err*	*z*	*P > / z /*	*[95% Conf. Interval]*	
down 25 bps (1)	_cons	0.156314	0.0280972	5.56	0.000	0.1012445	0.2113833
Fixed (2)	_cons	0.730543	0.0350742	20.83	0.000	0.6617988	0.7992872
Up 25bps (3)	_cons	0.080923	0.0203695	3.97	0.000	0.0409999	0.1208470
Up 50bps (4)	_cons	0.03222	0.0135461	2.38	0.017	0.0056698	0.5876960

Thus, referring to the results of the probability test presented in Table 5, it is known that the BI Rate decision with the highest probability for the next period is "Fixed," indicating that there will be no change in the BI Rate in the next period, with a probability value of 73.05%. In Table 6, the results of the probability test show that the calculated BI Rate is relatively similar to the actual BI Rate. This indicates that the regression model used performs very well in generating BI Rate predictions for the next period.

Table 6. Actual BI *Rate* vs. Probability Test Results

BI Rate	**Down 25 bps**	**Fixed**	**Up 25 bps**	**Up 50 bps**
Actual	15.70%	72.73%	8.26%	3.31%
Probability Test	15.63%	73.05%	8.09%	3.22%
Difference	**0.07%**	**-0.32%**	**0.17%**	**0.09%**

Marginal Effect at Mean *Test Results*

The results of the marginal effects at means (MEMs) test are very important for understanding the influence of independent variables on the probability of each outcome category of the dependent variable. This test is useful because it provides a more understandable and comprehensive interpretation of the effects of independent variables. Through this test, it can be determined which independent variable has the greatest influence on the BI Rate in the subsequent period.

This test helps explain how independent variables affect the category probabilities of an ordinal dependent variable in an ordered probit model. Table 7 presents a summary of the results of the marginal effects at means test for all independent variables, performed using Stata. The test results indicate that only the Net_Sinyal variable shows that a one-unit change significantly affects the BI Rate in the subsequent period. In summary, the significant results of the marginal effects at means test can be presented as follows: 1) Every one-unit increase in Net_Sinyal reduces the probability of Ordinalrt1 (the BI Rate in the subsequent period) being in the "down 25 bps" category by 19.63%. 2) Every one-unit increase in Net_Sinyal increases the probability of Ordinalrt1 being in the "up 25 bps" category by 8.21%. 3) Every one-unit increase in ln_Nilaitukar reduces the probability of Ordinalrt1 being in the "down 25 bps" category by 40.82%.

The results of the marginal effects at means test indicate that an increase in the net signal value reflects a higher degree of hawkishness. This can be interpreted as a lower probability of a BI Rate cut in the subsequent period and a higher probability of a BI Rate increase in the subsequent period. Furthermore, in line with the Taylor Rule, an increase in the exchange rate, which reflects a weakening of the rupiah against the U.S. dollar, has the potential to reduce the probability of a BI Rate decline in the subsequent period.

This is because exchange rate depreciation may increase the likelihood of a BI Rate hike in the subsequent period. To illustrate, during the tightening cycle of 2022, when Bank Indonesia raised the BI Rate by a cumulative 225 bps, the net signal in press releases consistently shifted toward hawkish territory in the preceding months, with net signal values exceeding 1.3 on a 0–2 scale. Conversely, during the easing cycle of 2020–2021, net signal values remained below 0.7, consistently preceding rate cuts. These empirical patterns corroborate the marginal effect findings and demonstrate that tracking communication tone provides actionable foresight for financial market participants.

Table 7. Marginal Effect at Mean *Test Results*

Variable	Average Score	Significance of ME and Mean			
		Down 25 bps	Fixed	Up 25 bps	Up 50 bps
rt0	-0.00207	X	X	X	X
Net_Sinyal	0.86367	√	X	√	X
Δ_Inflasi	-0.04917	X	X	X	X
ln_Nilaitukar	9.53938	√	X	X	X
PDB_growth	1.02273	X	X	X	X

Referring to these three significant results, only the net signal and exchange rate ln_nilai variables are significant macroeconomic variables affecting changes in the BI Rate in the subsequent period. A one-unit increase in the Net Signal variable significantly reduces the probability of a 25-bps decrease in the BI Rate at t+1 (category 1) and increases the probability of a 25-bps increase in the BI Rate at t+1 (category 3) by 8.21%. In addition, a significant increase in the exchange rate ln_nilai variable reduces the probability of a 25-bps decrease in the BI Rate at t+1 (category 1). This finding indicates that signals embedded in press release texts play a significant role in supporting BI Rate prediction, although this role is often overlooked (Apel & Blix Grimaldi, 2012).

These findings are broadly consistent with prior empirical evidence from other central banks. Apel (2012) similarly found that the net hawkish tone in Sveriges Riksbank minutes significantly predicted future policy rate decisions, confirming the cross-institutional validity of communication-based signal analysis. Baranowski (2021) reported analogous results for the European Central Bank, where communication tone improved the predictability of monetary policy decisions. In contrast to studies on the Federal Reserve, which benefit from formal voting records and dot plot projections, Bank Indonesia's press releases operate under greater informational opacity because they do not disclose individual voting records. This makes textual signals a relatively more important source of forward guidance. The 80% split-sample accuracy achieved in this study is comparable to, or exceeds, the out-of-sample performance reported in similar central bank text analysis studies.

Split Sample *Test Results*

Split-sample (SS) testing provides information on whether the model is overfitted to a particular dataset. In addition, SS testing can increase confidence that the research findings can be generalized beyond the sample used to build the model. The dataset partition was randomly selected using Stata, with a composition of 70% for training data and 30% for testing data. The Ordinalrt1 column in Table 8 shows the actual categories of the ordinal dependent variable (Ordinalrt1), namely "Down 25 bps," "Fixed," "Up 25 bps," and "Up 50 bps." Meanwhile, the yhat_test_category column indicates the model's predicted category. In yhat_test_category, no sample data were taken for the "Up 50 bps" BI Rate category; therefore, the categories presented include only categories 1, 2, and 3.

In addition, Table 8 shows that 35 samples were randomly selected to compare the observed results with the predictions generated using Stata. In the "Down 25 bps" category, three observations were correctly predicted as belonging to the "Down 25 bps" category. In addition, for Prediction 2, four observations were predicted to be in the "Fixed" category, and no observations were predicted to be in the "Up 25 bps" category. Thus, it can be concluded that the model correctly predicted 3 of the 7 observations in the "Down 25 bps" category.

Table 8. Split Sample *vs Actual* Test Results

Ordinal rt1	**yhat_test_category**			
	1	**2**	**3**	**Total**
Down 25bps	3	4	0	**7**
Fixed	2	23	0	**25**
Up 25bps	0	1	1	**2**
Up 50bps	0	0	1	**1**
Total	**5**	**28**	**2**	**35**

This calculation was continued for the categories "Fixed," "Increase by 25 bps," and "Increase by 50 bps." Further analysis of these tests yielded the following information. In the "Fixed" category, the model performed excellently, correctly predicting 23 out of 25 observations. In the "Increase by 25 bps" category, the model showed a slight prediction error, correctly predicting 1 out of 2 observations. In the "Increase by 50 bps" category, the model correctly predicted 1 out of 1 observation. A total of 35 observations were analyzed, with 28 correct predictions. Thus, the overall accuracy value was 80%. These results indicate that the equation using the ordered probit model in this study demonstrates good overall performance, particularly in predicting the "Fixed" category. However, some inaccuracies remain in predicting other categories, which may be caused by various factors, such as an imbalanced amount of data or independent variables that are not sufficiently strong in predicting certain categories.

To provide a more nuanced assessment of model performance in light of class imbalance, where the "Fixed" category accounts for 71% of observations, additional performance metrics are reported. For the "Fixed" category, the model achieves a sensitivity, or recall, of 92% (23/25) and a positive predictive value, or precision, of 82.1% (23/28). For the "Decrease by 25 bps" category, sensitivity is 42.9% (3/7). Therefore, the overall accuracy of 80% should be interpreted with caution. While the model is highly reliable in predicting the dominant "Fixed" outcome, its performance in predicting rate-change categories is more limited, reflecting the inherent challenge of predicting directional changes in infrequent policy adjustment events. This is a known limitation of ordered probit models applied to datasets with imbalanced outcome distributions.

Based on all these tests, the hypothesis that the net signal affects the BI Rate decision in the following period is accepted. This is because the results of various tests show that the Net Signal variable is consistently significant and has a positive effect on the BI Rate in the subsequent period.

The identification of policy signals, namely hawkish-dovish signals, contained in the text of Bank Indonesia's monthly Board of Governors Meeting press releases through observation and analysis using manually validated large language models (LLMs) showed a consistently significant positive relationship with the BI Rate in the following period. The results of the study indicate that the regression equation provides excellent predictability for the BI Rate in the subsequent period. Thus, through the analysis of signals conveyed in the Board of Governors Meeting press releases, the public and market participants can develop better investment strategies or financial decisions that are aligned with the signals provided by the central bank. This can reduce volatility in financial markets, thereby encouraging effective inflation control, achieving sustainable economic growth, and supporting financial system stability.

A potential endogeneity concern in this study relates to the possibility that press release language may already reflect anticipated macroeconomic conditions and forthcoming rate decisions, creating simultaneity bias between communication signals and BI Rate changes. Although this study does not formally address endogeneity through instrumental variable estimation, several design features mitigate this concern: (1) the ordered probit specification models future rate changes (t+1) as a function of current-period signals (t), thereby establishing temporal precedence; (2) the inclusion of macroeconomic control variables, namely inflation, exchange rate, and GDP growth, accounts for the underlying economic conditions that jointly drive both communication tone and rate decisions; and (3) the consistently significant predictive power of Net Signal across all specifications suggests that communication contains information beyond what is already captured by contemporaneous macroeconomic variables. Future research should consider employing instrumental variable approaches or structural vector autoregression (VAR) models to formally address this identification challenge.

CONCLUSION

The analysis of Bank Indonesia's Monthly Board of Governors Meeting press releases demonstrates that central bank communication serves as a statistically and practically significant predictor of future monetary policy decisions. Using an ordered probit framework with large language model (LLM)-based sentence classification, the net hawkish-dovish balance of press release language is strongly associated with subsequent BI Rate changes. Probability and marginal effect (ME) tests indicate that variations in the net signal significantly influence predictions of BI Rate shifts, while split-sample tests confirm an 80% prediction accuracy. These results validate the model's practical utility and suggest that press release signals can effectively guide market expectations.

Central bank communication functions as a critical policy instrument that enhances credibility, reduces pre-announcement volatility, and supports effective monetary policy transmission. The consistent significance of the Net Signal variable across models, even when controlling for inflation and GDP, indicates independent predictive power beyond underlying economic conditions. The policy implications include standardizing press release structures, clearly signaling directional bias, and monitoring aggregate hawkish-dovish tones as a real-time communication audit. Despite LLM limitations and potential manual validation bias, this study contributes to understanding communication as a de facto policy tool, with potential applicability for improving policy clarity during periods of heightened economic uncertainty.

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AUTHOR CONTRIBUTION STATEMENT

Reski Patrianie conceptualized the study, conducted data collection, and led the manuscript writing. Beta Yulianita Gitaharie performed the data analysis, validated the LLM results, and contributed to interpreting the findings. All authors jointly reviewed the manuscript, contributed to the discussion, and approved the final version for submission, ensuring accountability for all aspects of the work.

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