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| RESEARCH ARTICLE

Impact of Implicit Disagreement in MPC Meetings on Long-Run Government Bond Yields: A Panel Analysis

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| ABSTRACT

This study focuses on the impact of implicit disagreement among MPC members of UK, Australia, Japan and South Korea on long-term government bond yields. The implicit disagreement measures are constructed in the context of inflation using NLP techniques specifically trained on FOMC meetings' minutes. We see that disagreement(inflation) has a positive and significant impact on long-term government bond yields. Unlike postulates in the existing literature, the findings of this study establish the importance of disagreement in guiding movements in bond yields and thereby advocate incorporating it into important policy discussions that influence the economic health of nations.

| KEYWORDS

Monetary Policy Committee, Implicit measure of disagreement, NLP, BERT method, Panel Data

| JEL Classification

C23, E52, E58

| ARTICLE INFORMATION

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1. Introduction

Monetary policy communication has attracted attention in academic research and policy forums, especially after Blinder's seminal work in the wake of the 2008 financial crisis. The role of transparent policy communication in sending a clear signal to the market and thus improving the efficacy of monetary policy transmission has been extensively scrutinized in the economic literature.

One of the key aspects of policy communication is disagreement or dissent amongst the MPC (Monetary Policy Committee) members, which has been analyzed for a few advanced economies, mainly due to the availability of meeting minutes and the required data. While earlier works have argued that disagreement is mere noise and may be discarded since it does not provide any significant signal to the market **(Tillmann,2021)**, recent empirical evidence is weighing on a contrarian view. At the advent of advanced AI enabled NLP text analysis tools, central bank communication assumed an interesting turn. Recent studies are employing such tools on a vast corpus of minute of meetings of FOMC, ECB and other central banks as well as speeches and notes to assess the tone of communication of members of committees alongside their policy stance on interest rate. Such analyses help in unearthing nuanced and till then masked information. **Su et.al (2025),** for example, investigate the minutes of the meetings PBOC(People's Bank of China) from 2002Q3 to 2023 Q4 using NLP techniques like TF-IDF to quantify sentiment and assess their impact on forecasting monetary policy decisions.

In this context, some authors are arguing in favour of notions like implicit dissent, a subtle form of difference of opinion amongst members and its positive impact on economic decision making, like forecast accuracy of real variables like growth and inflation by market experts. **Sil et.al (2024)** and **Banerjee et.al (2024)** have argued that disagreement, even if implicit in nature, may contribute due to its rich information content which helps experts to frame a more accurate market outlook. Recent work by **Djourelova et al. (2025)** highlights how diverse opinions amongst FOMC members provide better insight about the changing dynamic of long-term fundamentals. This study aims to assess the effect of such disagreement on bond yield, an indicator that plays a significant role in assessing the health of the financial market and a critical barometer for real economy's health. Central bank's policy statements impact bond yield through the expectation channel (**Demiralp et al. ,2012)** and it has been observed that risk premia also play an influential role (**Leombroni et al.,2021**). Few studies highlighted the asset price channel which links the shift in yield and policy communication (**Romer and Romer (2000) and Nakamura and Steinsson (2018**)). This empirical work attempts to extract the potential effect of signals, shrouded in nuanced information content, of implicit dissent of members on bond yield for selected countries' central banks.

Owing to the availability of long and detailed data, this study focuses on four major advanced nations namely, Australia, South Korea, Japan and the UK. These four countries are G20 economies and are classified as developed economies. NLP tool BERT is trained over the minutes of the US FOMC. The US FOMC controls the world global reserve currency, the US dollar, so its language and pronouncements have spillover effects on other countries, a fact which is borne out by studies like **Degasperi et.al(2021)** which quantifies global US monetary policy spillovers using high-frequency identification and big data techniques across thirty economies.

Further, we construct an implicit disagreement variable from this BERT analysis. We see the impact of such disagreement on long run government bond yields for the aforementioned economies during January 2006 to May 2025. The choice of the time period for our study is pertinent because it covers the timespan of the onset of the 2008 Financial crisis and its onset and also the Covid-19 Pandemic at its peak which also caused severe economic disruptions. Owing to differing data availability for some countries and the number of time periods being much larger than the number of countries studied, the panel is highly unbalanced.

Following two sections include methods and findings which are followed by a concluding remark. These sections are however preceded by a brief note explaining the BERT model which is given just below.

A note on the BERT Model

The analysis for this paper has been done using NLP sentiment analysis techniques, specifically BERT sentiment modelling. We will briefly explain BERT modelling in this section.

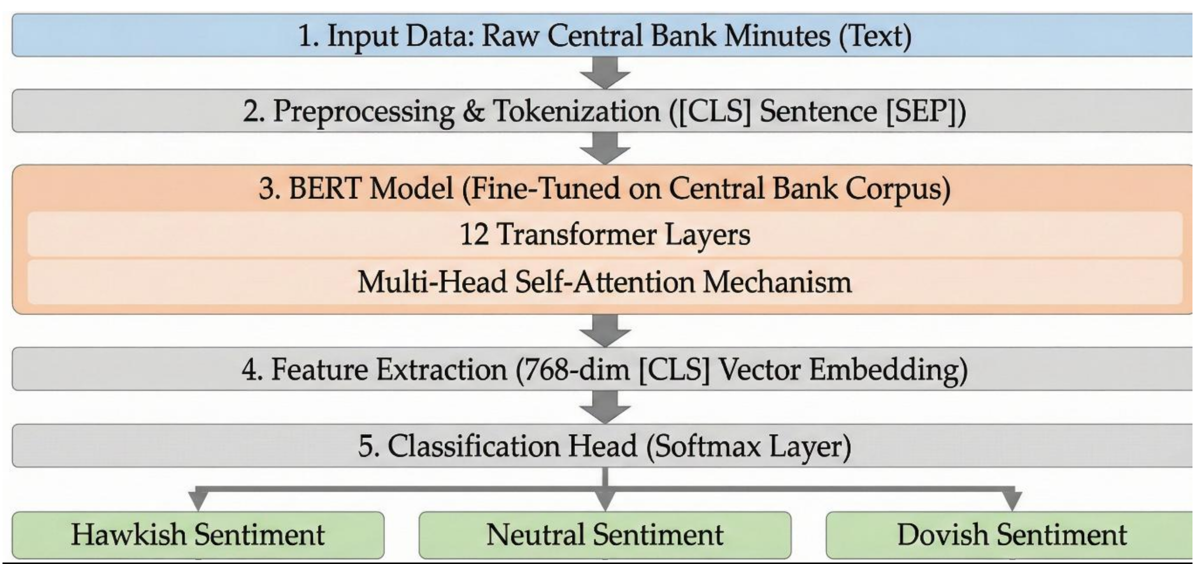

Fig 1: The BERT Process

BERT (Bidirectional Encoder Representations from Transformers) is a state-of-the-art model developed by Google for the purpose of sentiment analysis. Although it was originally developed to better understand the meaning of Google search, it has since generated state of-the-art results for tasks like sentence pair classification tasks, question answer tasks, etc.

The foundation of BERT is the idea of exploiting bidirectional context to acquire complex and insightful word and phrase interpretations. By simultaneously examining both sides of a word's context, BERT provides a more complete interpretation of the meaning than earlier models which only examined the left or right side of a word's context.

FinBERT is a specialized version of BERT which is used for sentiment analysis and other NLP tasks with regard to financial text. It is trained using deep learning on a corpus of financial text including financial reports, articles in newspapers and other financial documents.

BERT can also be adapted to different contexts by training the model on suitable corpuses of texts, for example central bank MPC meetings minutes for central bank communication sentiment analysis.

Figure 1 details the BERT modelling process, where the process of training the model and obtaining the output is described. The diagram illustrates the end-to-end process of transforming the unstructured text(central bank minutes) into a structured economic variable(the implicit disagreement variable)

Input Data: This is the raw text corpus of the entirety of the minutes of the MPC meetings of the four countries for the time period 2006-2025.

Preprocessing and Tokenisation: (CLS and SEP) BERT doesn't recognize or read words like humans do, it reads numeric tokens. We use a Word Piece tokenizer that breaks words into sub-words (e.g., "tightening" "tight", "##en", "##ing").

Domain-Specific BERT Model: Unlike pre-trained BERT models like FinBERT which are attuned to financial domain texts, we have trained our own BERT model for the sentiment analysis using the corpus of the minutes text of the MPC meetings of the four countries to better conform to the nature of the Monetary policy communication. The model utilizes twelve transformer layers with multi-head self-attention, but the weights of these layers have been adjusted to minimise loss specifically on the vocabulary and sentence structures used by central bankers.

Feature Extraction: After the model passes through the twelve layers, it produces a vector representation for every token. Only the vector corresponding to the [CLS] token was extracted. This is a 768-dimensional vector (a list of 768 numbers) that serves as the "mathematical summary" of the entire sentence's semantic meaning.

Classification Head (SoftMax Layer): The 768-dimensional vector is fed into a simple feed-forward neural network (the "Head") that projects it down to 3 dimensions (representing our 3 classes). The SoftMax function converts the raw numbers (logits) into probabilities that sum to 100%.

Sentiment Classification Output(Hawkish/Dovish/Neutral):The output is classified into one of three categories, hawkish , dovish or neutral. Sentences favouring higher interest rates or citing higher inflation risks are hawkish in nature, sentences favouring lower interest rates or citing lower inflation risks are dovish in nature, and status quo maintaining sentences or not sentences not mentioning interest rates or inflation are neutral in nature.

2.Methodology

For the purposes of our analysis. We have used BERT model trained on the Central Bank minutes of the countries studied, viz., Australia ,South Korea, Japan and the UK. We have annotated a few sentences from the minutes of each of the four countries, labelled them with hawkish ,dovish or neutral labels , built a corpus of training sentences for each country, and then trained the BERT model on the corpuses using Python. As a result, we have a model which maps the sentiments contained in the minutes based on a representative sample collected from the same minutes of the MPC meetings for all the four countries combined.

So, for every meeting, we get a hawkish, dovish and neutral score by analysing the full minutes for that meeting using our trained BERT model. Further, these are compared to decision with regard to policy rates for respective country's meeting. Finally, a distinct measure of disagreement is constructed, namely disagreement(inflation) based on whether there is a mismatch between the sentiments expressed and actual decision taken, considering the inflation management objective which is the primary objective of the central bank. The details of this process are given in the following paragraphs.

If minutes sentiment is dovish and the decision is rate hike, it is in complete opposition with respect to inflation because if sentiments with regards to inflation are dovish, i.e. it will decrease, then interest rate should be cut, not hiked. So, disagreement(inflation) will take value 2. Similarly, if minutes sentiment is hawkish and there is a rate hike, and disagreement inflation will be 0.

If there is a neutral sentiment or if the policy rate is unchanged, the disagreement variable takes value 1, as the neutral or no change point is the midpoint essentially. But if both neutral sentiment is present and there is no change in policy rate, then the disagreement variable takes value 0. The table for the disagreement variables construction is given below:

Table 1: Disagreement variable construction

Minutes Sentiment	Policy Decision	Disagreement(inflation)
Dovish	Hike	2
Dovish	Cut	0
Dovish	No change	1
Hawkish	Hike	0
Hawkish	Cut	2
Hawkish	No change	1
Neutral	Hike	1
Neutral	Cut	1
Neutral	No change	0

Source: Authors' construction

The data for each country and variable is taken from the FRED database (Federal Reserve Bank of St. Louis).

3.Findings and Discussion

In a panel framework, potential spillover may cause cross-sectional dependence (CD), which has been tested before conducting unit root tests. Table 2 shows evidence of cross-sectional dependence since all test statistics are statistically significant at either 1% or 5% level of significance.

Table 2: Cross-sectional dependence test results

Test	Statistic Value
Breusch-Pagan LM	22.94*
Pesaran scaled LM	4.89*
Pesaran CD	1.96**

*=1% level of significance

**=5% level of significance

Source: Authors' estimations

Order of integration for each variable is verified using cross sectional Augmented Im–Pesaran–Shin(CIPS) unit-root test. Choice of the test is also to accommodate a highly unbalanced (N=4,T=219) panel. The results show that the independent variables *sr* and *ie* are integrated of order I(1), while *di* and the dependent variable *gy* are stationary.

A mix of different integration orders is instrumental for the application of the panel ARDL method, which also helps in examining the long-run association among variables. The CCEMG (Common Correlated Effects Mean Group estimator) is employed to perform the Panel ARDL in the presence of cross-sectional dependence. Further, short-run coefficients are also estimated using CCEMG with the first differences of each variable.

The underlying long-run cointegrating relationship is estimated using the following equation for each country i at time t:

$$gy_{it} = \alpha_i + \beta_{1i} sr_{it} + \beta_{2i} ie_{it} + \beta_{3i} di_{it} + \varepsilon_{it}$$

Where:

- gy_{it} is the 10-year government bond yield.
- sr_{it} is the 90-day short-term interest rate.
- ie_{it} is inflation expectations.

- di_{it} is the disagreement(inflation) measure.
- α_i represents country-specific fixed effects.
- $\beta_{1i}, \beta_{2i}, \beta_{3i}$ are the country-specific long-run coefficients.
- ε_{it} is the error term.

The Short-Run CCEMG-ARDL Model

The long run coefficients are derived from the estimation of the following augmented Error Correction Model(ECM):

$\Delta gy_{it}=\alpha_i+\varphi_i ec_{i,t-1}+\sum_{j=1}^{p-1}\lambda_{ij}\Delta gy_{i,t-j}+\sum_{j=0}^{q-1}\delta_{1,ij}\Delta sr_{i,t-j}+\sum_{j=0}^{q-1}\delta_{2,ij}\Delta ie_{i,t-j}+\sum_{j=0}^{q-1}\delta_{3,ij}\Delta di_{i,t-j}+\omega_i\bar{\bar{Z}}_t+\mu_{it}$…(i)

Where:

- Δ is the first-difference operator (e.g., $\Delta gy_{it} = gy_{it} - gy_{i,t-1}$).
- p and q are the optimal lag lengths for the dependent and independent variables, respectively.
- λ_{ij} and δ_{ij} are the short-run dynamic coefficients.
- $ec_{i,t-1}$ is the lagged error correction term, representing the long-run equilibrium relationship:

  $ec_{i,t-1} = (gy_{i,t-1} - \beta_{1i}sr_{i,t-1} - \beta_{2i}ie_{i,t-1} - \beta_{3i}di_{i,t-1})$
- φ_i is the speed-of-adjustment coefficient, expected to be negative and significant for a stable long-run relationship. This is reported as *ec* in Table-2.
- $\bar{Z}_t$ is the vector of cross-sectional averages that constitutes the CCEMG augmentation.
- ω_i is the vector of coefficients for these cross-sectional averages, which captures the effect of unobserved common shocks.

Table-3 highlights the short run and long run coefficients of panel ARDL model.

Table 3: Short run and long run coefficients of (CCEMG)

Variable	**Short run Coefficient**	**Long Run coefficients**
sr	0.4574865** (0.1960382)	0.5451929* (0.1940597)
ie	0.0129599 (0.0190375)	0.2335807* (0.0884642)
di	0.0272128* (0.0089948)	0.1286789* (0.0265839)
ec	-0.1370643* (0.0335911)	--
Cons	0.0038362 (0.0020043)	0.3026722 (0.1664778)

*=1% level of significance

**=5% level of significance

Source: Authors' estimations

Empirical findings suggest the presence of a long-run stable equilibrium relationship among the chosen variables, since the error correction term (ec) is negative and statistically significant. It is evident from Table 3 that, both in the short- and long-run, the coefficients for the short-term rate and disagreement (inflation) are significant and positive. This is in consonance with standard economic theory. An increase in short-term interest rate causes bond prices to fall as investors don't find the existing bonds attractive at present returns and this induces a drop in demand. As bond prices fall, bond yields rise until they match those of a new bond issued.

On the other hand, higher disagreement regarding inflation causes bond yields to rise, as greater uncertainty leads investors to be more reluctant to purchase new bonds. Bond prices fall as demand declines, leading to a surge in bond yields. However, the disagreement coefficient being positive and significant contradicts the findings of Tilmann (2021), who found that the non-forecastable portion of the dissent actually weakens the response of long-term rates to policy surprises and thus disrupts the monetary policy transmission mechanism. The same paper also found that the yield response was significantly stronger when unanimity was present compared to when dissent was present. This is also contrary to our findings, which clearly show that disagreement doesn't weaken yield response. Rather, it strengthens it. In the long run, the inflation expectations(*ie*) coefficient is also significant and positive. This also aligns with standard economic logic. When investors expect rising inflation in the future, they demand higher bond yields to compensate for the fall in the purchasing power of fixed-income investments like Government bonds.

We also conduct some robustness checks, such as the robust outlier mean method, details of which are given below.

Robustness Checks

For robustness checks, we estimate the long-run coefficients using outlier-robust means, i.e., the median and truncated mean, rather than unweighted means. The results are as follows:

Table 4: Robustness checks-CCEMG with robust-outlier means

Variable	**Coefficient**
sr	0.4178055*** (0.2171794)
ie	0.2323289** (0.1040753)
di	0.1273619* (0.0319592)
cons	0.3038211 (0.1907367)

*=1% level of significance

**=5% level of significance

***=10% level of significance

Source: Authors' estimations

The results are similar; only the short-term interest rate coefficient is now significant at the 10% level instead of the 1% level. Rest of the results are similar in sign and significance. Thus, long run findings are robust to the choice of means (coefficient averages).

The outlier-robust means are used to eliminate the influence of extreme values in the dataset and thus make the results robust to extreme fluctuations. It confirms that the results are not dependent on a few data points and that no outlier significantly affects the results.

Checking for the MG estimator, we find that only the short-term interest rate coefficient is significant at the 5% level. It further highlights the importance of accounting for cross-sectional dependence in the data.

4.Conclusion

This paper proposes to assess the impact of disagreement amongst MPC members on government bond yields for selected economies. The long-term positive impact of disagreement among members is intuitively appealing. Disagreement is not mere white noise that has been discarded as insignificant in erstwhile literature. Instead, central banks cannot and should not ignore disagreement amongst MPC members even if it exists in its implicit form which can be exploited from the minutes of meetings. In other papers, such as Banerjee et al. (2024), it is found that disagreement among policy takers can improve the accuracy of forecasts of inflation and growth. This study examines the impact of implicit disagreement on another critical indicator of the market's economic health, namely long-run government bond yields. Central banks must consider the role of disagreement in their meetings and not merely dismiss it and deliberately try to force a consensus or present a united front. Even if the disagreement is implicit, it's still economically significant.

Data Disclosure Statement

The dataset will be made available on request.

Disclosure of Interest

This is to declare that the authors have no competing interests involved in the publication of this work.

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