Doomed in din or synced with signal: A study of dissent within Indian Monetary Policy Committee.

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Abstract

The paper investigates the effect of latent discord present amongst Indian Monetary Policy Committee members on the accuracy of inflation and growth forecasts. We use FinBERT, a deep learning model, to propose a refined measure of Implicit Dissent and use it to further investigate how such discord can affect the forecast accuracy. Our results show that lower levels of implicit dissent increase uncertainty and impair forecasters' ability to make accurate predictions. In contrast, higher levels of implicit dissent mitigate uncertainty and help anchor forecasts. Our study concludes that heterogeneity in signals by central bankers increases the mean decision quality of forecasters.

JEL Classification: E52, E58, C53

Keywords: Monetary policy; implicit dissent; FinBERT; forecasters; Structural equation model

1. Introduction

Among the many aspects of monetary policy communication, dissent has gradually emerged as a significant anchor of market expectations (Tillmann (2021)). (Ehrmann and Fratzscher (2013)) point out an important debate in this context: whether central bank communication should reflect the consensus view of the MPC committee or whether the public should be provided with information about the dispersion of opinions within the committee. In this debate, a majority of researchers ascertain that multiplicity of views on monetary policy lessens the predictability of decisions, thereby debilitating the ability of market participants to judge the due course of monetary policy. This perception has increasingly led to designating dissent as noise in the literature. However, in the context of the central bank of India, a contrarian view (Sil et al. (2023)) was found to be true regarding the communication of the Indian central bank. While this might be the case, it is important to realize the magnitude of dissent to discern its meaningful impact. As posited by (Rieder (2022)), if committee members do not express extreme views, this could lead to the rise of free-riding among members, where free-riders do not produce information but rely on the efforts exerted by others. Consequently, free-riding may lead to increased consensual decision-making on the surface, without providing a solid argumentative basis for consensus. To this end, this study attempts to understand the magnitude of dissent to examine its heterogeneous impact on augmenting market perception.

Accordingly, this study proposes two measures, Implicit Low Order Dissent and Implicit High Order Dissent, to measure the magnitude of dissent in augmenting market perception. Our results establish evidence in support of a non-linear relationship between dissent and accuracy of policy forecast; where higher levels of dissent have a differential impact upon forecast precision as compared to lower levels of dissent.

Contrary to studies that quantify information clarity in terms of the readability[1] of central bank documents (Bulíř et al. (2013)), we use Natural Language Processing technique (NLP) and Deep learning techniques (DL) to construct the proposed measure. The study utilizes the FinBERT model, which performs a context-based analysis of the text, providing a more accurate result than other dictionary-based approaches (Correa

[1]Bulier et al 2013 uses Flesch Kincaid (FK) Grade level which computes the number of years of education required to read by considering number of words per sentence and number of syllables per word.

et al. (2021)).

The paper is organized as follows: Section 2 would present the data and Methodology used, Section 3 would detail the main findings followed by concluding remarks in Section 4.

2. Data and Methodology

2.1. Data and Sources

The data on policy communication is obtained from the minutes of bi-monthly Monetary Policy Committee (MPC) meetings in India. In the meeting, six members vote on the Indian policy rate named repo rate. Three of these members are internal one like Governor, deputy Governor etc. of RBI and rest of the three are externally appointed. The written minutes of the meeting by members are used to formulate the Implicit Dissent (DI), Higher order Implicit Dissent (HDI) and Lower order Implicit Dissent (LDI) variables. The current study focuses on the MPC meetings from October 2016 till February[2] , 2024.

We also use economic policy uncertainty (EPU) index developed by (Baker et al. (2016)) as a proxy for media coverage frequency. The weighted average of EPU values for two months following a MPC meeting is considered. Higher weight is provided to the month closer to the date of forecaster deciding on the growth and inflation forecasts following a MPC meeting. This practice has been adopted since perception of the forecaster is likely impacted more by immediate than distant information (Poidevin 2000). For instance, if the meeting is in April 2017, the weighted average of EPU for April and May has been considered. The weights provided for April and May are 0.3 and 0.7 respectively. The forecast is published on the Reserve Bank of India website in June. The next MPC meeting happens in June and the same calculation follows here.

The data on median growth and inflation forecasts is taken from the Survey of Professional Forecasters (SPF) published by RBI on a bimonthly basis. The SPF consists of dozens of experts from private and public banks, financial institutions, stock exchanges

[2]Data for growth is available only till October 2023 and data for inflation is available only till February 2024 in RBI's Handbook of statistics.

and credit rating agencies etc. The bimonthly forecasts of these experts are projected into quarterly growth and inflation statistics to create quarterly forecast error series, further updated following the frequency of the MPC meetings held in each quarter. These projection error data capture the absolute disparity for both growth and inflation.

2.2. Variable Creation

For quantification of the policy communication text, we resort to NLP and DL techniques. FinBERT, a DL model is used to predict the sentiments expressed within financial textual data. (Huang et al. (2023))[3] introduced the FinBERT model pre-trained on a huge corpus including corporate filings and financial analyst reports. This involves two steps: pre-training the model on a large financial text corpus and fine-tuning the model for downstream tasks like sentiment analysis. The model predicts the probability with which a sentence falls into positive, negative and neutral classes. The sum of probabilities of each sentence in all three classes adds to 1.

2.2.1. Implicit Dissent (DI):

In line with the measure of implicit dissent proposed by (Sil et al. (2023)), the present study offers a more refined version of the measure using FinBERT method. Assume that the stance taken by a member is positive. If the sum of sentiments in the positive class is greater than sum of sentiments of other two classes individually, it implies that there is consistency[4] between the stance and the minutes given by the member. This implies there is no implicit dissent (DI) shown by the member.

The DI variable takes the whole number values between 0 and 6. DI takes the value 0 when no member in the MPC shows implicit dissent, takes the value 1 when only 1 member shows implicit dissent and so on[5] .

2.2.2. Implicit Higher order Dissent (HDI):

HDI measures the presence of high levels of dissent within the Monetary Policy Committee. HDI is implicit dissent under the condition of majority rule, ie, if more than half the number of members in the MPC (> 3 members) express DI.

[3]Refer Appendix 2 for a detailed explanation of the FinBERT model.

[4]We assign positive stance to contractionary policy while negative stance to expansionary policy. This is just the convention we use. For our purpose of deriving the dissent variable it is only necessary that the same convention is used in labelling the vote and the speech.

[5]Detailed explanation on the construction of the variables is given in appendix.

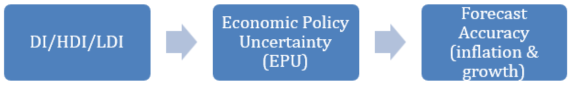

Figure 1: Schematic representation of the SEM

HDI = DI, when DI>3.
HDI =0, when DI $<$ 3.

2.2.3. Implicit Lower order Dissent (LDI):

LDI measures the presence of low levels of dissent within the Monetary Policy Committee. LDI is implicit dissent under the condition of minority rule, ie, if less than half the number of members in the MPC ($<$ 3 members) express DI.
LDI = DI, when DI<3.
LDI =0, when DI >3.

2.3. Structural Equation Model (SEM):

The impact of the implicit dissent on the forecaster is gauged by mapping the transmission mechanism of dissent. We hypothesize that implicit dissent should impact the overall economic climate first, which in turn would influence the accuracy of key policy forecasts. Accordingly, we construct a Structural Equation Model (SEM) which measures the impact of implicit dissent on policy uncertainty and its further impact on forecasters. We use the dissent measures at the policymaker level (Policymakers' dissent), EPU to measure policy uncertainty and absolute inflation and growth error indicating accuracy of the forecaster (Forecast accuracy (inflation growth).

According to the theoretical framework shown in the above figure, the equations for our empirical exercise are as follows:

Equation 1: DI
Inflation

$$EPU = \alpha_0 + \alpha_1(DI) \tag{1}$$

$$(Absoluteerror)_{infl} = \alpha_0 + \alpha_2(EPU) \tag{2}$$

Growth:

$$EPU = \alpha_0 + \alpha_1(DI)$$
$$(Absoluteerror)_{growth} = \alpha_0 + \alpha_2(EPU)$$

Equation 2: LDI
Inflation

$$EPU = \alpha_0 + \alpha_1(LDI) \tag{3}$$
$$(Absoluteerror)_{infl} = \alpha_0 + \alpha_2(EPU) \tag{4}$$

Growth:

$$EPU = \alpha_0 + \alpha_1(LDI)$$
$$(Absoluteerror)_{growth} = \alpha_0 + \alpha_2(EPU)$$

Equation 3: HDI
Inflation

$$EPU = \alpha_0 + \alpha_1(HDI) \tag{5}$$
$$(Absoluteerror)_{infl} = \alpha_0 + \alpha_2(EPU) \tag{6}$$

Growth:

$$EPU = \alpha_0 + \alpha_1(HDI)$$
$$(Absoluteerror)_{growth} = \alpha_0 + \alpha_2(EPU)$$

3. Results and Discussion

Tables 1, 2 and 3 illustrate the results of our empirical exercise for DI, LDI and HDI. In table 1, we observe that as the overall implicit dissent increases, uncertainty reduces.

This helps the forecaster make better forecasts (Sil et al. (2023)). In table 2, we observe that as the lower order implicit dissent increases, it induces higher uncertainty in the economy. This leads to increase in forecast errors. When dissent is low, forecaster may tend to dismiss that as noise or outlier. In table 3, we see that the higher order implicit dissent helps reduce the uncertainty and thereby minimize the inflation forecast errors. In contrast to LDI, when the forecasters see majority of the members dissenting in unison, they are incentivized to delve deeper and revise their estimates further.

Table 1: Structural Equation Model for Growth and Inflation (DI).

	Growth	Inflation
EPU <-		
	-4.51742*	-4.798457*
DI	(2.601722)	(2.706089)
Forecast Error <-	0.0474925**	0.005445**
EPU	(0.0223134)	(0.0027737)
N	43	45
Log-likelihood values	-392.72068	-321.40135
LR test of model vs. saturated: chi 2(1)	0.27	1.03
Prob > chi 2	0.6525	0.6055

Source: Author's estimation. Note: Standard errors in parentheses ***p<0.01, **p<0.05, *p<0.1. Forecast errors have been calculated for growth as well as inflation. It refers to the absolute deviation of the predicted rate vis-a-vis actual rates of the quarter.

Table 2: Structural Equation Model for Growth and Inflation (LDI).

	Growth	Inflation
EPU <-		
	8.735747*	8.137035*
LDI	(4.729292)	(4.95088)
Forecast Error <-	0.0474925**	0.005445**
EPU	(0.0223134)	(0.0027737)
N	43	45
Log-likelihood values	-366.65422	-294.63459
LR test of model vs. saturated: chi 2(1)	2.23	4.38
Prob > chi 2	0.1351	0.0363

Source: Author's estimation. Note: Standard errors in parentheses ***p<0.01, **p<0.05, *p<0.1. Forecast errors have been calculated for growth as well as inflation. It refers to the absolute deviation of the predicted rate vis-a-vis actual rates of the quarter.

Table 3: Structural Equation Model for Growth and Inflation (HDI).

	Growth	Inflation
EPU <-		
	-2.641779	-3.248063*
HDI	(1.693277)	(1.71758)
Forecast Error <-	0.0474925**	0.005445**
EPU	(0.0223134)	(0.0027737)
N	43	45
Log-likelihood values	-411.73562	-341.45594
LR test of model vs. saturated: chi 2(1)	0.17	1.28
Prob > chi 2	0.6846	0.2581

Source: Author's estimation. Note: Standard errors in parentheses ***p<0.01, **p<0.05, *p<0.1. Forecast errors have been calculated for growth as well as inflation. It refers to the absolute deviation of the predicted rate vis-a-vis actual rates of the quarter.

4. Conclusion

Our study is a maiden empirical attempt to gauge the magnitude of dissent and see the heterogeneous impact of dissent on policy forecast. Managing uncertainty is crucial to promoting an optimal investment climate. Our study underscores the need for heterogeneity in the communication of the central bank's MPC. This aligns with a key conclusion from (Rieder (2022)) and (Bhattacharjee and Holly (2015)), who argue that heterogeneity in signals not only increases the mean decision quality but also helps to "take personalities out of policy decisions." The presence of higher dissent would indeed help to realign the positions and views of members, thereby giving each member further ownership and authenticity in their opinions. This would better guide forecasters and market participants in picking up the right signals to have a better perception of the macroeconomic outcome.

Appendices

Table A1. Descriptive statistics.

Variable	Obs	Mean	Std.Dev.	Min	Max
Growth error	43	2.167	3.905	0.085	25.849
Inflation error	45	0.510	0.514	0.008	2.137
Weighted EPU	45	73.505	26.540	28.330	165.671
DI	45	3.044	1.413	0	6
HDI	45	1.533	2.217	0	6
LDI	45	0.444	0.776	0	2

Source: Author's Computation

Table A2. Variable sources.

Variable names	Description	Data Source
EPU	weighted average of Economic policy uncertainty Index for India (Baker et al. 2015) for 2 months.	Author's computation.
DI	inconsistency between speech and stance of the policy member, then the member shows implicit dissent. If one member shows implicit dissent, DI takes value 1. If two members show Implicit dissent, DI takes value 2 and so on.	Author's computation
HDI	if majority (n>3) number of policy members show implicit dissent, then DI=HDI, otherwise HDI=0.	Author's computation
LDI	if minority (n<3) number of policy members show implicit dissent, then DI=LDI, otherwise LDI=0.	Author's computation
Growth error Statistics forecasters	Absolute value of growth error (Actual-forecast)	Reserve Bank of India Handbook of and Survey of Professional
Inflation error Statistics	Absolute value of inflation error (Actual-forecast)	Reserve Bank of India Handbook of and Survey of Professional forecasters

A. Note of FinBERT

FinBERT is a large language model (LLM) customized for sentiment analysis of financial and economic text. Huang et al (2022) introduced the FinBERT model in an attempt to expand the original BERT (Bidirectional Encoder Representations for Transformers) (Devlin et al. (2018)) architecture for use in the financial domain. This involves two steps: pretraining the model on a large financial text corpus and fine tuning the model for downstream tasks like sentiment analysis.

Unlike BERT (Bidirectional Encoder Representations from Transformers) which is pre-trained on non-specific sentences from wikipedia and *BookCorpus, FinBERT is pre-trained on financial content from corporate filings and financial analyst reports. There are mainly two steps in pre-training: masked language modeling (MLM) and next sentence prediction (NSP). In MLM, a percentage of words in a sentence are masked and the BERT algorithm predict them using the unmasked words in the sentence, keeping the context of the sentence intact. In NSP, the algorithm is trained to predict if a sentence is followed by the succeeding sentence in a sentence pair. In the next step, the pretrained model undergoes fine tuning to prepare it for sentiment analysis. For the same, a random selection of 10000 sentences from financial analyst reports is manually annotated into positive, negative, and neutral classes. In the fine-tuning process, the model undergoes training, validation and testing which prepares the model to perform the downstream task, i.e., sentiment analysis effectively.

Research has shown that BERT models predict sentiments better than other Natural Language Processing (NLP) models such as naive Bayes and support vector machine (Huang et al. (2023)). Stop words are removed in bag of words models whereas the entire sentence is used as input data in BERT Language models preserving the context in which the words have been used. Further, the attention mechanism technique used in Transformers allows the model to assign a higher weightage to more relevant words in a sentence which improves the model performance in downstream tasks like sentiment classification involving sequential input data (Vaswani et al. (2017)).

B. Calculation of DI, LDI and HDI

B.1. DI:

The minutes of each member is divided into sentences. Each sentence is assigned three probability scores corresponding to the polarity (positive, negative and neutral sentiment classes) of a sentence.

For instance, consider the sentence: "The persistence of core inflation remains a concern." The FinBERT model can assign a probability of 0.9, 0.05 and 0.05 to the negative, positive and neutral sentiment classes respectively. This shows that the sentence signals a negative sentiment to the recipient.

Assume that the stance taken by a member is positive. If the sum of sentiments in the positive class is greater than sum of sentiments of other two classes individually, it implies that there is consistency[6] between the stance and the minutes given by the member. This implies there is no implicit dissent shown by the member. Otherwise, implicit dissent is shown by the member.

The MPC member shows no implicit dissent when:

Sum of probability scores of positive sentiment class > Sum of probability score of

[6] We assign positive stance to contractionary policy while negative stance to expansionary policy. This is just the convention we use. For our purpose of deriving the dissent variable it is only necessary that the same convention is used in labelling the vote and the speech.

negative sentiment class & Sum of probability scores of positive sentiment class > Sum of probability score of neutral sentiment class.
Otherwise the member express implicit dissent.
If no member shows implicit dissent, then the implicit dissent (DI) variable takes the value 0, if one member shows implicit dissent the DI variable takes value 1 and so on.

B.2. HDI

HDI is implicit dissent under the condition of majority rule, ie, if more than half the number (4) of members in the MPC express DI.

HDI = DI, when DI>3.
HDI =0, when DI<3.

This variable captures implicit dissent when more than three members in the MPC committee show inconsistency between their vote and minutes.

B.3. LDI

LDI is implicit dissent under the condition of minority rule, ie, if less than half the number (4) of members in the MPC express DI.
This variable captures implicit dissent when less than three members in the MPC committee show inconsistency between their vote and minutes.

LDI = DI, when DI <3.
LDI =0, when DI>3.

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