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Chorus in the Cacophony: Dissent and Policy Communication of India’s Monetary Policy Committee

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Abstract

Using minutes of consecutive Monetary Policy Committee (MPC) meetings of the Indian central bank, we have constructed two novel measures of implicit dissent at the individual level as well as across groups. We have used VADER sentiment analysis to arrive at the proposed measures and investigated their influence on anchoring Indian growth and inflation forecasts. Our empirical findings show discordance amongst members increases forecast accuracy. This implies promoting an environment that supports nuanced opinions could improve policy outcomes.

Keywords: Monetary policy, Dissent, NLP, Supply shock, Linear Regression

Model JEL Code: E52, E58, C22

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1 *Introduction*

In an increasingly interconnected world, the impact of monetary policymaking and economic stability are largely influenced by how policymakers use actual words or natural language in order to convey their vision for the future economy. Economists and political scientists have long examined the way the masses are influenced by anchors associated with the policy communications. Over the years research largely focussed on the way these anchors are shaped by the size, composition and ideological cohesion (Owens and Wedeking (2011)) of the committee members involved in the decision making process. Following the literature, researchers have used committee members' voting behaviour as important data to compute central bankers' policy preferences (Montes et al. (2016))

There are majorly two strands of literature which offer interesting insights; one strand has extensively discussed how *quantitative communications* of the Central Bank have significantly influenced the forecasts of key economic variables (Ehrmann et al. (2012); while on the *qualitative communications* front, Ullrich (2008) finds how the wording indicator of the European Central Bank influenced the inflation surprises.

The literature on *dissent* or *dissent voting* is quite rich and diverse. Since the theoretical model proposed by (Havrilesky and Schweitzer (1990)), predicted how career backgrounds of members would influence their predisposition towards *dissent voting*, several others have contributed to the literature either by econometrically verifying this conjecture (Adolph (2005)) or by positing interesting insights on how the media publicity (Gerlach-Kristen (2003)) or the members' personal experience would govern their inclination towards 'hawkish' or 'dovish' dissent (Malmendier et al. (2021)). Additionally, Spencer (2006) has shown how internal members would be susceptible to preference alignment as opposed to external members who would be more willing to dissent. Despite a large body of literature on the determinants of dissenting behaviour, there is a dearth of studies that investigate the impact of dissent on other macroeconomic variables. In an attempt to fill the vacuum, our paper makes two distinct contributions: First, we propose an interesting and, to our knowledge, a novel measure in the Indian context to capture dissent of the members of the

Monetary Policy committee (MPC). We term it as *implicit dissent*.[1] As opposed to studies that have attempted to empirically measure dissent ((Meade and Stasavage (2008)), we have resorted to Natural Language Processing technique (NLP) to arrive at our proposed measure. Second, using the consecutive MPC meetings of the Reserve Bank of India (RBI) we have constructed two measures of implicit dissent and investigated their influence on anchoring the growth and inflation forecasts of the country. Our findings highlight the importance of dissent in shaping policy outcomes.

2 *Data and Methodology*

2.1 *Data and Sources*

For the data on qualitative communication, we have used the minutes of bi-monthly MPC meetings. The MPC, comprising a mix of central bank officials and external members, fixes the benchmark policy repo rate in India. The meetings are held at least 6 times a year. Each member votes on the repo rate and explains the vote taken in written minutes. The current study focuses on the MPC meetings from April 2017 till May 2022.

Our study focuses on two major macroeconomic indicators, namely the bimonthly median forecasts of GDP and inflation respectively. These two variables are the primary mandates of monetary policy as envisioned in the Preamble to the RBI Act, 1934. The data on these indicators is taken from the Survey of Professional Forecasters (SPF) published by RBI on a bimonthly basis. Following Goyal and Parab (2021), international prices of Crude Oil (Indian Basket) and policy repo rate have been taken as control variables. While the former has been calculated on a month-on-month basis, corresponding to the time period of our

[1] Drawing motivation from the findings of a specific strand of literature which discuss how committee members tend to veil their actual stance (Ottaviani and Sørensen (2001)), we use the word implicit in order to highlight the presence of such tendencies among the MPC members as well.

analysis, the latter has been created as a dummy variable which takes the value 0 if the repo rate has remained the same from the previous MPC meeting and 1 if the rate has decreased.[2]

2.2 *Variable Creation*

For the purpose of the quantification of the qualitative text, we resort to Natural Language Processing (NLP) techniques. Sentiment analysis is a subfield of NLP that investigates people's opinion, sentiments, evaluation, attitude via computational treatment of subjectivity in text. A novel method named VADER[3] (Valence Aware Dictionary and sEntiment Reasoner) is applied, which is a lexicon and rule-based sentiment analysis tool that is specifically attuned to sentiments expressed in social media (Hutto and Gilbert (2014)).[4] This compound score (CS), computed from VADER, capturing the sentiment intensity could be seen as the sum of positive, negative or neutral scores for each word. It is calculated at the sentence level. The range for the scores is given as follows:-

1. $x1 = 0$ when $CS < 0.05$ (neutral tone)

2. $x1 = 1$ when $CS \geq 0.05$ (positive tone)

3. $x1 = 2$ when $CS \leq -0.05$ (negative tone)

The VADER scale ranges from -1 to 1 with the polarity score being calculated at sentence-level and the mean value is calculated for the whole text (speech). We used this technique in the creation of variables capturing the implicit dissent.

[2] A detailed description of the variable can be found in the appendix.

[3] Although VADER accounts for the subjectivity in the word context and compositionality, and is shown to be robust, it is still a heuristic rule-based scoring system. Natural language or communication tends to be more creative and nuanced; hence these NLP tools can only capture sentiments to an extent.

[4] See appendix for a detailed discussion on the methodology.

2.3 *Implicit Dissent*

Implicit dissent occurs when there is a discord between the written minutes and the voting of members of the MPC. In this section, we define dissent at an individual member level (henceforth termed as DI), and across groups (DG).

2.3.1 *Dissent at individual level*

From the previous section, we use the compound score to know whether the given member's minutes are positive, negative or neutral. Similarly, we look at the vote of these members with respect to repo rate tightening, loosening and status quo and assign it as positive, negative and neutral respectively. x_1 is defined as the variable capturing the sentiments obtained from the members' minutes. Then it follows that,

1. positive sentiment: $CS \geq 0.05$, $x_1 = 1$
2. neutral sentiment: $CS < 0.05$, $x_1 = 0$
3. negative sentiment: $CS \leq -0.05$, $x_1 = 2$

Similarly, x_2 captures the stance taken by the member during a particular meeting[5]. Then it follows that,

1. $x_2=0$ when member votes for repo rate status quo (Neutral vote)
2. $x_2=1$ when member votes for repo rate tightening (Positive vote)
3. $x_2=2$ when member votes for repo rate loosening (Negative vote)

[5] 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.

[4]See the appendix for the detailed groupings.

We then define DI that captures the concordance of his/her minutes and vote. There is dissent if voting differs from the sentiment score. Formally,

$$DI = \begin{cases} 0\, if x_1 = x_2 \\ 1\, otherwise \end{cases} \tag{1}$$

For each of the meetings, we then cumulate the values of DI in order to find out the total number of members having discordance between their vote and minutes.

2.3.2 *Dissent across groups*

The second measure is constructed for those meetings where there was a clear distinction in the stance taken by MPC members, named as group C1 and C2[4]. DG captures similar sentiment but disparate stance is constructed as follows:

DG = 1 *if at least one of the members' minutes, belonging to C1, is equal to at least one of the members' minutes, belonging to C2*
= 0 otherwise

. The variables DG and DI have been used in the regression framework as explanatory variables.

3 *Methodology*

In order to understand the impact of the discord of the MPC communication on professional forecasters' performance, we have taken the median GVA forecast and median CPI inflation forecast. The bimonthly forecasts are mapped into quarterly growth and inflation data to obtain quarterly forecast error series which are then adjusted in accordance with the frequency of the MPC meetings held in each quarter. Since the forecasts depend upon the preceding MPC meeting rather than the upcoming MPC meeting, we have adopted a one lag structure in our econometric framework. To the best of our knowledge, this paper has made the first attempt at estimating the equations of the following form:[6]

$$Growtherror_t = \alpha_1 + \beta_1 DI_{t-1} + \gamma_1 DG_{t-1} + \omega_1 \delta Oilshock_t + \phi_1 RepoRateDummy_t \qquad (2)$$

$$Inflationerror_t = \alpha_2 + \beta_2 DI_{t-1} + \gamma_2 DG_{t-1} + \omega_2 \delta Oilshock_t + \phi_2 RepoRateDummy_t \qquad (3)$$

The dependent variables in the above equations are absolute deviations of the forecaster's prediction of the growth and inflation rate pertaining to the period vis-a`-vis the actual growth and inflation rate of that period. The coefficients of the dissent variable will capture the impact of dissent on the forecast error. A significant positive coefficient will imply dissent worsens forecasts as the error rises, while a negative coefficient will imply dissent improves forecasts. We have also included two other variables in our framework to control for major factors affecting forecasts. The first captures a supply shock *namely* δ(*Oilshock*) and the second policy change *namely RepoRateDummy*.

4 *Results and Discussion*

From Table 1 it is evident that DG significantly reduces growth forecast error whereas DI brings the inflation forecast error down. The two dissent variables have negative and significant coefficients. The presence of dissent both at an individual and at group level captures heterogeneity of views expressed through the latent discomfort that the committee members have with their own official vote. Higher values of DG and DI signal higher levels

[6] The works by Meade (2005), Meade & Stasavage (2008) have used the word *Dissent* in their papers where they have proposed an empirical specification to investigate whether transparency affects the incentive to dissent. However, their works were based solely on the sources that recorded an explicit account of dissent by the committee members whereas we propose a novel measure of dissent utilizing the explicit accounts along with the latent discomforts shown by the committee members.

of discomfort of committee members; this may be encouraging forecasters to revise their forecast and thereby minimize the error in their estimation, as opposed to a scenario where they receive a unanimous decision from a committee with aligned preferences. Our work gives an empirical estimation of dissent which may be expressed implicitly, either due to institutional pressure or otherwise (Prat (2005)). Contrary to Blinder's (2009) finding our work provides empirical validation for the fact that signals become stronger if they arise from chaos.

Table 1: Results of Linear Regression

	(1)	(2)
	Growth Error	**Inflation error**
DG	-1.079***	-0.293
	(0.560)	(0.319)
δOilshock	0.00277	0.0444**
	(0.0268)	(0.0153)
DI	0.118	-0.207**
	(0.167)	(0.0953)
RepoRateDummy	-0.0853	0.625
	(0.593)	(0.338)
Constant	1.673	2.078**
	(0.863)	(0.491)
N	30	30

Source: Authors' estimations. Note: Standard errors in parentheses **p < 0.05, ***p< 0.1. Outcome variables: Growth error and inflation error refer to absolute deviations of predicted rates vis-a-vis actual rates of the quarter.

Additionally, we also see that supply shock (i.e. $\delta OilShock$) increases the inflation forecast error. This is to be expected if the oil shock is unexpected and volatile. That a change in oil price widens the gap between estimation and actual realization suggests the impact of an oil shock is varied. The government has policy tools to smooth shocks but they are not used uniformly. The insignificance of the RepoRate dummy suggests that forecasters' factor in changes in monetary policy so it does not affect forecast error.

5 *Conclusion*

Our work contributes to the existing body of literature on central bank communication by proposing a novel measure of implicit dissent both at an individual as well as group level and investigates its relationship with macroeconomic variables. We find evidence that discordance in the views of the members leads to better forecasts. This has a larger bearing for policy making, implying that the promotion of nuanced and diversified views amongst national decision-making bodies could improve outcomes.

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Data availability statement:

The data that support the findings of this study are openly available and can be accessed via the following:

https://www.rbi.org.in/scripts/Annualpolicy.aspx

Appendix

Table 2: Summary Statistics

Variable	**Obs**	**Mean**	**Std. Dev.**	**Min**	**Max**
Growth error	31	1.866	1.398	.085	6.314
Inflation Error	31	1.665	.963	.078	4.235
DI	30	.333	.479	0	1
DG	31	4.548	1.546	0	6
$\delta OilShock$	30	10.4	10.186	.35	40.43
RepoRateDummy	30	.267	.45	0	1

Table 3: Variable Sources

Variable Names	**Description**	**Data Source**
RepoRateDummy	Takes 1 if any change in repo and 0 otherwise	Reserve Bank of India Handbook of Statistics
DI	Sum of Individual conflicts across meetings	Author's computation
DG	Varibale capturing dissent (Dissent at Group Level)	Author's computation
Growth error	Absolute value of Growth error (Actual-Forecast)	Survey of Professional Forecasters (RBI) and Reserve Bank of India Handbook of Statistics
inflation error	Absolute value of inflation error (Actual-Forecast)	Survey of Professional Forecasters (RBI) and Reserve Bank of India Handbook of Statistics
$\delta OilShock$	Month on Month change in the prices of Indian basket of crude oil	Petroleum Planing Analysis Cell (Ministry of Petroleum Natural Gas, Government of India)

Table 4: Dissent at Individual level and across Group[7]

Meeting ID	Meeting Consensus	DG	DI
Meeting 6 2016	06:00	0	4
Meeting 1 2017	06:00	0	5
Meeting 2 2017	05:01	1	6
Meeting 3 2017	04:02	1	6
Meeting 4 2017	05:01	1	6
Meeting 5 2017	05:01	1	6
Meeting 6 2017	05:01	1	5
Meeting 1 2018	05:01	1	5
Meeting 2 2018	06:00	0	0
Meeting 3 2018	05:01	1	1
Meeting 4 2018	05:01	1	4
Meeting 5 2018	06:00	0	3
Meeting 6 2018	04:02	1	5
Meeting 1 2019	04:02	1	4
Meeting 2 2019	06:00	0	4
Meeting 3 2019	06:00	0	5
Meeting 4 2019	06:00	0	6
Meeting 5 2019	06:00	0	6
Meeting 6 2019	06:00	0	4
Meeting 1 2020	06:00	0	3
Meeting 2 2020	06:00	0	3
Meeting 3 2020	06:00	0	3
Meeting 4 2020	06:00	0	5
Meeting 5 2020	06:00	0	6
Meeting 6 2020	06:00	0	6
Meeting 1 2021	06:00	0	6

[7] Though the first meeting was conducted on 3rd October, 2016, the minutes containing the speech of members were available on public portal only from April 2017.

Meeting 2 2021	06:00	0	4
Meeting 3 2021	06:00	0	3
Meeting 4 2021	06:00	0	4
Meeting 5 2021	06:00	0	6
Meeting 6 2021	06:00	0	5
Meeting 1 2022	06:00	0	6

6.1 *Note on VADER*

An intuitive sketch of the VADER methodology goes as follows. At the first step, an exhaustive list of sentimental lexicons is created (from LIWC, ANEW, GI). This is supplemented with additional lexical features used in sentiment analysis in social media text (like emoticons, acronyms etc.). From the lexical feature "candidates" which are developed, the point estimations of sentiment valence are computed using wisdom of the crowd approach (human validated). At the next step, using data driven iterative inductive coding analysis, generalizable heuristic patterns are identified which are helpful in assessing the sentiment in text. After accounting for the impact of grammatical and syntactical rules, the sentiment intensity is computed.

VADER despite being used in the social media domain Shapiro, Sudhof and Wilson (2020)[8] demonstrates that it has performed at par with commonly used financial lexicons like HL+LM (the corpus of text used in this lexicon is specific to the domain of economics and finance). Also it has been deployed in analysing central bank communication as seen in the works of Picault, Pinter and Renault (2022)[9], Moller and Reichmann (2021)[10.] The simplicity of VADER over other sophisticated machine learning techniques merits attention.

[8] Shapiro, A. H., Sudhof, M., & Wilson, D. J. (2022). Measuring news sentiment. Journal of econometrics, 228(2), 221-243.
[9] Picault, M., Pinter, J., & Renault, T. (2022). Media sentiment on monetary policy: Determinants and relevance for inflation expectations. Journal of International Money and Finance, 124, 102626.
[10] Möller, R., & Reichmann, D. (2021). ECB language and stock returns–A textual analysis of ECB press conferences. The Quarterly Review of Economics and Finance, 80, 590-604.

For instance, a corpus that takes a fraction of a second to analyze with VADER can take hours when using complex models like SVM. Also the lexicon and rules used by VADER are accessible unlike other sentiment analysing techniques which are hidden within a machine-access only black box. Hutto and Gilbert ([11]) show that VADER has been compared with seven other well-established sentiment analysis lexicon dictionaries: Linguistic Inquiry Word Count (LIWC), General Inquirer (GI), Affective Norms for English Words (ANEW), SentiWordNet (SWN), SenticNet (SCN), Word-Sense Disambiguation (WSD) using WordNet, and the Hu-Liu04 opinion lexicon. Also the correlation coefficients of VADER (r=0.881) performs as good as the individual human rators (r=0.881) at matching ground truth, especially in analysis of the sentiment intensity of Twitter tweets. Likewise, VADER retains and at many instances improve on the traditional sentiment lexicons like LIWC (Linguistic Inquiry and Word Count). Although VADER accounts for the subjectivity in the word context and compositionality, it is still a heuristic rule-based scoring system. Natural language or communication tends to be more creative and nuanced; hence these NLP tools can only to an extent capture sentiments.

[11] Hutto, C. and Gilbert, E. (2014). Vader: A parsimonious rule-based model for sentiment analysis of social media text. In Proceedings of the international AAAI conference on web and social media, volume 8, pages 216–225.