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

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Abstract

Our study proposes a novel empirical measure to capture dissent among the committee members of the central bank of India. Using the consecutive Monetary Policy Committee (MPC) meetings of RBI we have constructed two measures of implicit dissent at the individual level as well as across groups. We have used VADER sentiment analysis, a Natural Language Processing technique, to arrive at the proposed measures and investigated their influence on anchoring the growth and inflation forecasts of the country. Our empirical findings show that discordance amongst members would invariably increase the forecast accuracy. Interestingly, our regression results have also confirmed how supply shocks increase the forecast error via the often conservative policy stance taken by the committee members.

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1 *Introduction*

In an increasingly interconnected world, policymaking and economic stability are largely influenced by how policymakers use actual words or natural language in order to convey the vision and version for the future economy. Economists and political scientists have long examined the way the masses are influenced by the anchors associated with the policy communications. Over the years their 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 diametrically opposite opinions; 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 ECB 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 having a large body of literature on the determinants of dissenting behaviour, the dearth of studies that investigated the impact of dissent on other macroeconomic variables is evident. 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) and term it as *implicit dissent*.[6] 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 internal dissent and investigated their influence on anchoring the growth and inflation forecasts of the country. Our findings highlight the importance of dissent in shaping the policies of the nation.

2 *Data and Methodology*

2.1 *Data and Sources*

For the data on qualitative communication, we have used the minutes of the bi-monthly MPC meeting . The MPC, comprising a mix of central bankers and external members, fixes the benchmark interest rate in India. The meetings are held at least 4 times a year.. The current study focuses on the MPC meetings from April 2017 till May 2022.

Our study focuses on two major macroeconomic indicators, namely the quarterly median forecasts of GDP and inflation respectively, which form the primary mandates of the monetary policy as envisioned in the Preamble to the RBI Act, 1934 . The data on these indicators are 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 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 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..[7]

[6] 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.

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

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 (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)).[8] 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 ≤ -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 shall use this technique in the creation of variables capturing the implicit dissent.

2.3 *Implicit Dissent*

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

8 See appendix for a detailed discussion on the methodology.

2.3.1 *Dissent at Individual level*

From the previous section, we use the compound score to know whether the given member's speech is positive, negative or neutral. Similarly, we look at the policy stance taken by these members with respect to interest rate tightening, loosening and status quo and assign them as positive, negative and neutral respectively. x_1 is defined as the variable capturing the sentiments obtained from the members' speeches. 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[9]. Then it follows that,

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

We then define DI that captures the concordance of his/her speech and stance. 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 speech and stance.

[9] We arbitrarily assign positive stance to contractionary policy while negative stance to expansionary policy. This assignment of stance would vary across nations based on their economic climate.
[4]See the appendix for the detailed groupings.

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 and is constructed as follows:

DG = 1 *if at least one of the members' speech, belonging to C1, is equal to at least one of the members' speech, 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 the forecaster's performance, we have taken the median GVA forecast and median CPI inflation forecast. 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.

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

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

The dependent variables in the above model are absolute deviations of the forecaster's prediction of the growth and inflation rate pertaining to the quarter vis-a`-vis the actual growth and inflation rate of that quarter. We have also considered two control variables in our framework capturing supply shock *namely* $\delta(Oilshock)$ and policy change *namely* *RepoRateDummy*.

4 *Results and Discussion*

The results in Table 1 confirm that increasing discordance in the views of the members leads to coherent estimation of the macroeconomic variable as opposed to a vague estimation. Our study tries to estimate the diversity through the presence of dissent at the individual as well as group level. To this end, our work gives an empirical estimation of dissent which is more often than not expressed implicitly, either due to institutional pressure or otherwise (Prat (2005)).

Table 1: Results of Linear Regression

	(1) **Growth Error**	(2) **Inflation error**
DG	-1.079*** (0.560)	-0.293 (0.319)
$\delta Oilshock$	0.00277 (0.0268)	0.0444** (0.0153)
DI	0.118 (0.167)	-0.207** (0.0953)
RepoRateDummy	-0.0853 (0.593)	0.625 (0.338)
Constant	1.673 (0.863)	2.078** (0.491)
N	30	30
Standard errors in parentheses $^{**}p < 0.05$, $^{***}p < 0.1$		

The presence of dissent both at an individual and at group level captures the discomfort that the committee members have with their own official stance. This would encourage forecasters to revise their forecast, as compared to a scenario where they receive a unanimous decision from a committee with aligned preferences. This reiterates the fact that heterogeneity in decision-making processes yields a better outcome.

Additionally, we also see that supply shock (i.e. $\delta OilShock$) increases the inflation forecast error. Historically, the government is often seen to take a conservative stance with regard to the effect of price change upon the economy in order to mollify any outrage from the citizens. The fact that a change in oil price widens the gap between estimation and actual realization suggests the impact of an oil shock is varied. Other policy tools are available but not used uniformly. The insignificance of the RepoRate dummy suggests that forecasters' accuracy doesn't react to the changes in monetary policy.

5 *Conclusion*

In an increasingly polarized world, where decisions are taken in the hues of binary choices, we argue that more disparate perspectives can bring about better and informed outcomes. Our results are relevant for other public policy decision-making, implying signals may become stronger if they arise from chaos.

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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[10]

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

[10] 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, generalisable 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, though used primarily in the field of social media analytics, has also been applied to analyzing speeches. Nivash et al. (2022)[11] use VADER to identify the effect of presidential speeches across the world from 1970 to 2019 on the public's mood, with positive and negative statements presented. Other studies using VADER include studies from diverse fields like - analysing legislators' speech (Kauffman et al. 2018)[12] and news

[11] Nivash, S., Ganesh, E., Harisudha, K., and Sreeram, S. (2022). Extensive analysis of global presidents' speeches using natural language. In Sentimental Analysis and Deep Learning, pages 829–850. Springer.

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media analysis Kale et al. (2019)[13]. The simplicity of VADER over other sophisticated machine learning techniques merits attention. 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 (2014)[14] 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).

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