Sentiment in RBI Financial Stability Reports

A Little Ado About Something[1]

Abstract:*An attempt is made in this article to analyse the text published in RBI Financial Stability Reports (FSRs) over the period June 2010 to December 2021 using text mining tools. We construct a Financial Stability Sentiment (FSS) Index by linking the FSR with a dictionary specially developed for capturing the sentiments published in FSRs. We find that the FSS index perfectly tracks stress episodes such as economic deceleration, Asset Quality Review(AQR) process and COVID-19 pandemic, i.e., during these periods, the value of the index increased significantly – signalling bloated stress in the financial system in India. Moreover, there is a significant negative correlation between the index and the market returns that consistently captures the large upswings and downswings in the former. Consequently, the FSS index is a reliable economic barometer as it is able to capture most of the events which had an impact on financial sector of the economy, while also having an impact on consumer perceptions.*

[1]This article is prepared by Anshuman Kamila of Indian Economic Service (2020 batch) and M. Sreeramulu of Reserve Bank Staff College, Aastha of Monetary Policy Department,Shahbaaz Khan of Department of Economic and Policy Research and Aniket Ranjan of Department of External Investments and Operations of Reserve Bank of India (RBI). Valuable inputs received from Sambhavi Dhingra and Muneesh Kapur of RBIaregratefully acknowledged.The views expressed in the article are those of the authors and do not represent the views of the institutions the authors are affiliated with. Usual disclaimers apply.

Introduction

The Global Financial Crisis (GFC) jolted the march of the global financial system which had elements of instability and systemic unsoundness built-in. The ripples of the meltdown of the financial system had reverberations across the real economy. The globally coordinated rescue efforts duly recognised the need for institutions and provisions for ensuring financial stability. The approach thereof has two legs – one, the comprehensive and continuous systemic assessment of risk build-up across the financial system; and two, having the institutional and instrumental arrangements to take effective measures to address the risks so identified. Flowing from their roles in operating monetary policy, in being the lender of the last resort and in administering the payment and settlement systems, central banks have acquired a pivotal role in the quest for financial stability. Ergo, central banks of many countries are releasing financial stability reports (FSRs) at regular intervals. Central banks generally disseminate information regarding developments, status, resilience of financial system during economic downturn and upturn through FSRs. These reports have become increasingly popular communication tools for central banks since the GFC. The text published in FSRs communicate to the public the most salient risks and vulnerabilities in the financial system and are also meant to increase central bank transparency.

To assess the health of Indian financial system with an emphasis on recognising and analysing impending risks to financial stability and carrying out stress tests, the Reserve Bank of India (RBI) set-up an inter-disciplinary unit called 'Financial Stability Unit (FSU)'. The FSU prepares and publishes FSRs on a half-yearly basis and reports continuous assessments, flagging the potential areas which need to be focussed on from a financial stability perspective. The Reserve Bank published its first report in March 2010. Analysing the FSRs has become one of the vibranttopics of research in the period following the GFC. Researchers have analysed the sentiments disseminated in FSRs from various vantage points which includes, inter alia, delineating the precise factors impinging on Financial Stability Sentiment (FSS), analysing the link between FSS and economic cycles (business, financial or credit)*etc.* For undertaking suchanalyses, researchers use a dictionary which captures the sentiment carried by words typically used in financial stability communications. This article capitalises on one such financial dictionary to compute FSS indexby using the text published in FSRs over the periodJune 2010 to December 2021. An attempt is also made in this article to capture how financial information is incorporated into FSS indexand analyse how messages conveyed in RBI's communication – particularly, that contained in FSRs – get reflected in evolution of financial sector indicators.

The rest of the article is divided into four sections. Section 2 presents a brief survey of literature on the topic, while the methodology for sentiment index for financial stability is discussed in Section 3. Results and analysis of FSS indices are presented in Section 4 and Section 5 closes the article with concluding remarks.

2. Literature Review

In the last two decades,many studies have analysed text of financial stability reports to gauge their impact on the market. One important study that surveyed these methods and its application on financial sector was conducted by Kearney & Liu (2014). They highlighted that, more precise and structured sentiment measures resulting from sophisticated textual content analysis, coupled with tailor-made dictionaries, will lead to better research in future. By using the text published in FSRs, another paper analysed the link between sentiments they convey and the financial cycle. The authors built FSS indices for 30 countries over the period of 2005-2017. They found that financial stability communications of central banks are largely driven by the developments in the banking sector. Further, the authors envisaged that the sentiment captured by FSS index elucidates movements in key indicators pertaining to the financial cycle *viz*., credit, asset prices, systemic risk, and policy rates. Finally, the paper also undertook regression analysis and confirmed that communications of central banks can be used as a useful predictor of banking crises (Correa*et al.*2020).

Another paper using similar technique investigated the impact of central bank communications on financial markets. The authors used summaries in FSRs and news articles of interviews/speeches delivered by central bank officials to check whether the tone of these communications have influence on equity prices. It was found that FSRs with positive outlook had the most significant effect on abnormal stock returns (Born *et al.*,2014). Bank of Canada (BoC) used text mining to analyse the impact of its communication on volatility/ level of returns in short-term interest rates. They established that market stories had a significant effect on volatility and returns in short term markets (Hendry, 2012). On similar lines, the US Federal Open Market Committee (FOMC) statements and the media discussions on the same were analysed using semantic orientation scores, which were found to have significant association with policy rate decisions (Lucca and Trebbi, 2009).

In Indian context, most of the studies employed language processing techniques (LPT) and analysed the sentiments in monetary policy communications. One such study used text mining to provide a measure of the degree of monetary policy transparency andexamined the impact of transparency on anchoring of inflation expectations (Samanta and Kumari, 2021). Another study analysed newsfeed from media on central banks' policy rate to gauge media sentiment with respect to the expected directional change in policy rates (Giddi and Kumari, 2020).

3. Data and Methodology

For text mining, we have considered the FSRspublished betweenJune 2010 to December 2021. An attempt is also made in this article to track the movements of FSS index with reference to key economic and financial sector indicators such as growth in bank credit, return from market (NIFTY Bank Index), RBI policy (repo) rate and consumer perceptions on economic situation. The data in respect of these indicators are collected from RBI website and data pertaining to NIFTY Bank Index is collected from National Stock Exchange (NSE) website.

3.1 Dictionary used for Financial Stability Sentiment Analysis

For sentiment analysis, this articlehas used the dictionary created by Correa *et al.* (2017), which is essentially tailored to analyse the sentiments captured in FSRs. The authors developed this dictionary by using words published in FSRs of 66 institutions over the period 2000 -2017. Overall, the authors made use of text published in 1082 FSR documents. They developed this dictionary rather than using the general dictionary since the latter may cause substantial errors while computing sentiment index, as the usage of words may have different connotations depending on the context in which they are used. According to the authors, there are three main reasons why connotations from financial stability point of view may differ from general or other finance dictionaries – (i) the word 'confined' carries almost a positive sentiment in financial stability context, while the same conveys negative connotation in other dictionaries, (ii) the words such as 'default' or 'delinquency' may indicate negative or positive connotations in other dictionaries depending on the context. However, these words are used frequently in a financial stability context invariably with a negative connotation (iii) the authors also excluded some common words used in other dictionaries which mostly represent historical events rather than any sentiment per se (for instance, the mention of the word 'crisis' after the Global Financial Crisis was in almost all cases a reference to that event).

3.2 Sentiment Index for Financial Stability

The literature on the topic displays a variety of methods and dictionaries to extract the opinion or emotion in the texts. The 'tidytext' package in R software provides access to several sentiment lexicons. All the lexicons are based on unigrams (*i.e.*, single words), containing mainly English words, and the words are classified for conveying positive/negative sentiments. The FSS index is calculated using the following formula.

$$FSS\ Index = \frac{Negative\ Words - Positive\ Words}{Total\ Words} \dots . (1)$$

where the negative or positive connotations of words are obtained from the financial stability dictionary. To compute the FSS index, the texts from FSRs are processed and individual words are extracted after removing stop words, punctuation marks, numbers, blank spaces,*etc*. Further, data stemming is used in this article, which is a technique where a set of words which have the same meaning but have some variations according to the context or sentence are normalised[2] (only root words are retained). Along with this data lemmatisation is also done, which is a text mining technique, aimed at using vocabulary and morphological analysis of words. Lemmatisation process basically aimed at eliminating inflectional endings and to return the base or dictionary form of a word. Lemmatisation does not simply cut-off inflections, it relies on lexical knowledge base like 'WordNet[3]' to obtain correct base form of words.

Any kind of differential weighting scheme is not applied to the words, since FSRs are typically long, which implies that most words in the dictionary are used in each report (Correa *et al.*, 2017). Because of the way in which FSS index is defined above, an increase in index value indicates deterioration in sentiment while a decreasing index value suggests improvement in the sentiment.

4. Results and Analysis of FSS

[2]Suppose we have three words *viz.*, rain, rained, and raining. Since the meaning for all the words is same, data stemming process retains the word 'rain'.

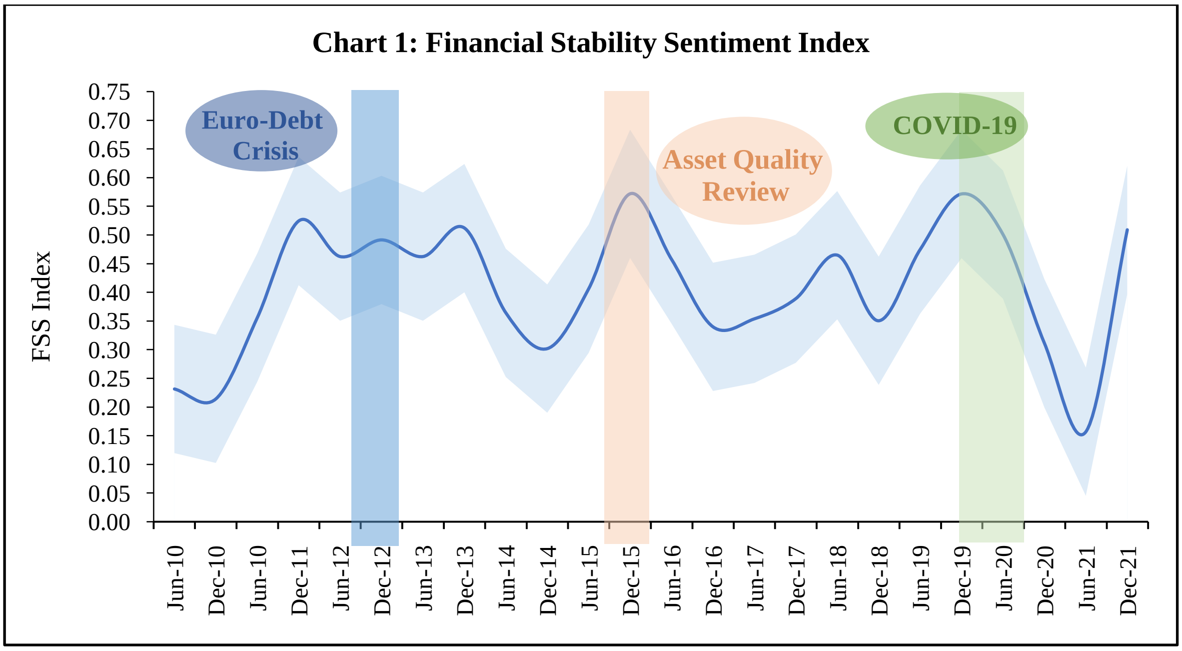
[3]WordNet is a large lexical database of English nouns, verbs, adjectives and adverbs that are grouped into sets of cognitive synonyms, each expressing a distinct concept. Synonyms are interlinked by means of conceptual-semantic and lexical relations. WordNet's structure makes it a useful tool for computational linguistics and natural language processing.

The summary statistics of FSS index for our sample of 23 FSR documents are shown in Table 1. The information regarding number of positive and negative words which are classified using the dictionary is also furnished in Annexure A2. This classification allows us to track FSS index movements across various time periods. It also increases the reliability of our empirical analysis in the paper, because some periods included in our sample witnessed excessive stress. Splitting words into these groups is also used to assess the robustness of our main empirical results.

The statistics furnished in Table 1 reveal that for all the periods considered in the study, the mean FSS index is positive, which implies that 'negative' words are used more often than 'positive' words for all the periods. This is because FSRs are written in order to highlight signs of macroeconomic stress and financial instability, which are most likely to be captured by using 'negative' words. Further, the FSS index exhibited considerable time fluctuations with standard deviation 0.111, ranging from 0.157 (December 2010) to 0.572 (December 2015). It appears that the sentiment index increased considerably (more negative sentiment) in the period around the conduct of Asset Quality Review (AQR) in 2015-16 (Chart 1).

Table 1: Descriptive Statistics

FSS Index	**Statistical Measure**
Mean	0.407
Median	0.432
Standard Deviation	0.111
Range	0.414
Minimum	0.157
Maximum	0.572

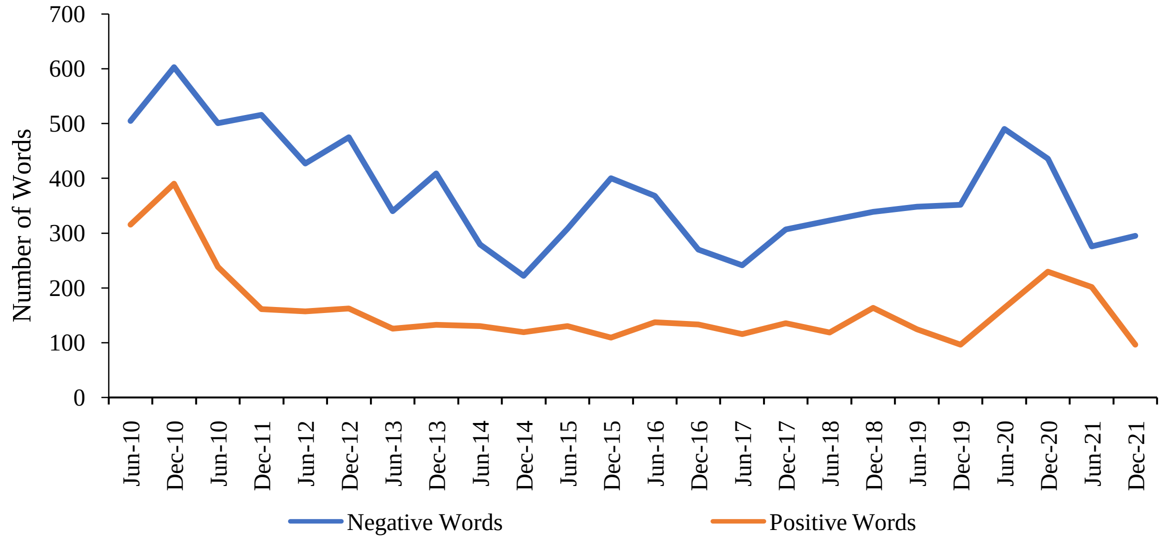


Source: Author's estimates.

4.1 Trends in Usage of Positive and Negative Words

The usage of negative words is significantly higher during three periods *viz.*, December 2011, December 2012 and June 2020. In these periods, the gap between negative and positive words is more than 300 words suggesting more negative sentiments (Chart 2). These periods have broadly highlighted sentiments in the macroeconomic environment (muted growth of components of domestic demand, elevated inflation pressures), volatility in financial markets (asset market gyrations, exchange rate volatility), *inter alia*, some episodic events also tinged the assessments of the said FSRs.For instance, in December 2011, Financial Stability Map and Indicator – quantitative tools designed to measure movements in risk dimensions affecting the entire financial system – were introduced, which pointed to heightening of risks; in December 2012, global risks remained elevated on account of delays in resolution of issues like the European sovereign debt crisis and the imminent US fiscal cliff; in December 2015, the key highlight was declining profitability, high leverage and low debt servicing capacity of the corporate sector, with attendant spillovers on the financial ecosystem. In July 2020, the landscape of the FSR was blistered with the potentially pernicious impacts of the evolving COVID-19 pandemic on the financial sector, *e.g.*, GNPA ratios, contagion losses in the banking system, *etc.*

Chart 2: Trends in Usage of Positive and Negative Words



Source: Author's estimates.

4.2 Word Cloud

Using the text mining technique, word cloud for various FSRs is generated. A compilation of most important words in terms of their sentiment across different reports is plotted, though several words are common across FSRs, it is their frequency of use that changes the sentiment (Chart 3)

Chart 3: Compilation of Word Clouds for different FSRs

FSR: December 2021

FSR: December 2019

FSR: December 2017

FSR: December 2015

FSR: December 2013

FSR: December 2011

4.3 FSS Index - Is it tracking the economic and financial conditions?

An attempt has also been made to analyse the relation between FSS index and a few economic and financial sector variables. The variables so selected represent the state of the economy and/or the financial sector and policy action. The key indicators considered for the analysis include growth in bank credit, RBI policy (repo) rate, return from stock market[4] and consumer perception on current economic situation[5].

Reserve Bank's sentiments on stability of the financial system are mostly influencedby the strength of the banking sector, understandably so in a bank-dominated financial system. Therefore, we choose bank credit believing that sentiments communicated in FSRs are likely to have some bearing on its growth thereby. The Reserve Bank policy rate has been chosen to understand the link between underlying sentiment expressed by the FSRs and the policy rate action taken by the Reserve Bank on it.[6]NIFTY Bank index has been chosen to calculate and study the relation between the return from stock market and the sentiment projected by the FSR. It is so chosen because market perspectives and resultantly, market performance of the banks' stocks is reflective of their strength and that of the financial sector. Similarly, we have chosen the consumer perception on economic situation as published in the Consumer Confidence Survey to capture the consumer sentiments about the economy of which financial sector is a major part.

To analyse the relationship, we have plotted various graphs (Annexure A1), though, we could not use any statistical tools like regression or Granger Causality test while analysing the

[4]We use Nifty Bank Index for calculating the return from market.

[5]The data regarding this indicator is extracted from 'Consumer Confidence Survey', which is a qualitative survey conducted by the RBI on a bi-monthly basis. RBI conducts these forward-looking surveys for aiding in taking a decision on policy rates.

[6]Under the current FIT framework in India, the Monetary Policy Committee determines the policy (repo) interest rate required to achieve the inflation target.

relation between FSS index and the above stated indicators owing to the limitation in the number of observations (24). Nevertheless, we have computed correlation coefficient to measure the directional relation and results are presented in Annexure A1. We found that there is negative correlation between FSS index and return from market, which is statistically significant. It can also be observed that large swings of FSS index are well captured by trends in market returns. The correlation coefficients of FSS index with other variables are not statistically significant. Besides low number of observations, the statistical insignificance of the correlation coefficients can be attributed, to domestic and international influences covered in FSR that might not exactly correspond with the movement of domestic economic indicators. Nonetheless, in spite of lack of statistical insignificance, limited trends may be observed from the charts in the Annexure A1.

To augment our previous analysis, there was a need to circumvent the problem arising out of small number of observations. To achieve this, the technique of interpolation was used, as the same is very widely used in academic literature. Essentially, whereas earlier we had data at a gap of 6 months (since FSR is released every 6 months), interpolation yields data at a quarterly frequency. The data on FSS index was interpolated using arithmetic mean and geometric mean techniques, analyses using the latter serving as a robustness check to the analyses that use the former. Growth in bank credit was calculated as earlier, namely taking a year-on-year growth of non-food bank credit in the month of consideration.Data on RBI policy rate is already available at the desired frequency. Data on return from stock market (NIFTY Bank index) is calculated for a given month using the same method as earlier, i.e., averaging daily returns over a month. Data on consumer perception on current economic situation as captured by Consumer Confidence Survey (CCS) was earlier available at the quarterly frequency since the CCS was at the quarterly frequency till September 2016, following which it has been converted to a bi-monthly survey. Thus, quarterly data on consumer perception on current economic situation has been captured by taking arithmetic mean of the value of the preceding and following month to any given month that represents a quarter (for example, for December 2016 we take the arithmetic mean of values of November 2016 and January 2017). Interpolation increases the number of observations from 23 earlier to 45. However, the correlation analysis does not yield any significant correlation between the variables under consideration, when considering the pairwise correlations between FSS indices (the arithmetic and geometric mean variants) and the other variables, except that a significant negative correlation between the FSS index and the consumer perception index (see Annexure A1). This was followed by a Granger causality analysis, which is a statistical technique for time series variables to confirm any theoretically held causal relationship between two variables. The only statistically significant relationship obtained is that FSS index is found to Granger cause consumer perception (with the causality running only in that direction). This has been found true for both the arithmetic mean as well as geometric mean variants of the FSS index (see Annexure A1). Thus, we find that FSS indexhas causal impact on consumer perception only among all other economic variables considered.

Conclusion

To extract meaningful insights from large volumes of unstructured data, text mining tools have been used. In this article an attempt is made to extract sentiments in FSRs published by Reserve Bank of India over the period of June 2010 to December 2021. Further, FSS index is computed as the ratio between 'negative words minus positive words' and 'total words' for all the time periods. It was found that FSS index is useful for financial stability analysis. The index can trackmost of the periods of economic/ financial stress. It was able to factor in the introduction of Financial Stability Map and Indicator, European sovereign debt crisis, implementation of AQR and impact of COVID-19 pandemic over different time periods. During stress periods such as economic deceleration, AQR and COVID-19 pandemic, the value of the index shot up considerably. Moreover, there is a significant negative correlation between the index and the market returns that consistently captures the large upswings and downswings in the former. Consequently, the FSS index is a reliable economic barometer as it is able to capture most of the events which had an impact on financial sector of the economy, while also having an impact on consumer perceptions.

References

Born, B., Ehrmann, M., & Fratzscher, M. (2014). Central Bank Communication on FinancialStability. *Economic Journal*.

Correa, R., Garud, K., Londono, J., & Mislang, N. (2020). Sentiment in Central Banks' Financial Stability Reports. *Oxford University Press*.

Correa, R., Garud, K., Londono-Yarce, J.-M., & Mislang, N. (2017). Constructing a Dictionary for Financial Stability. *IFDP Notes. Washington: Board of Governors of the Federal Reserve System.*

Giddi, G., & Kumari, S. (2020, August). Policy Rate Expectations in Media . *RBI Bulletin*.

Hendry, S (2012), Central Bank Communication or the Media's Interpretation: What Moves Markets?,*Bank of Canada, Working Paper*

Kearney, C. & Liu, S. (2014). Textual Sentiment in Finance: A Survey of Methods and Models. *International Review of Financial Analysis*

Lucca, D. O. and Trebbi, F. (2009), Measuring Central Bank Communication: An Automated Approach with Application to FOMC Statements, *National Bureau of Economic Research (NBER) Working Paper No. 15367*

Reserve Bank of India (2010), Financial Stability Report.

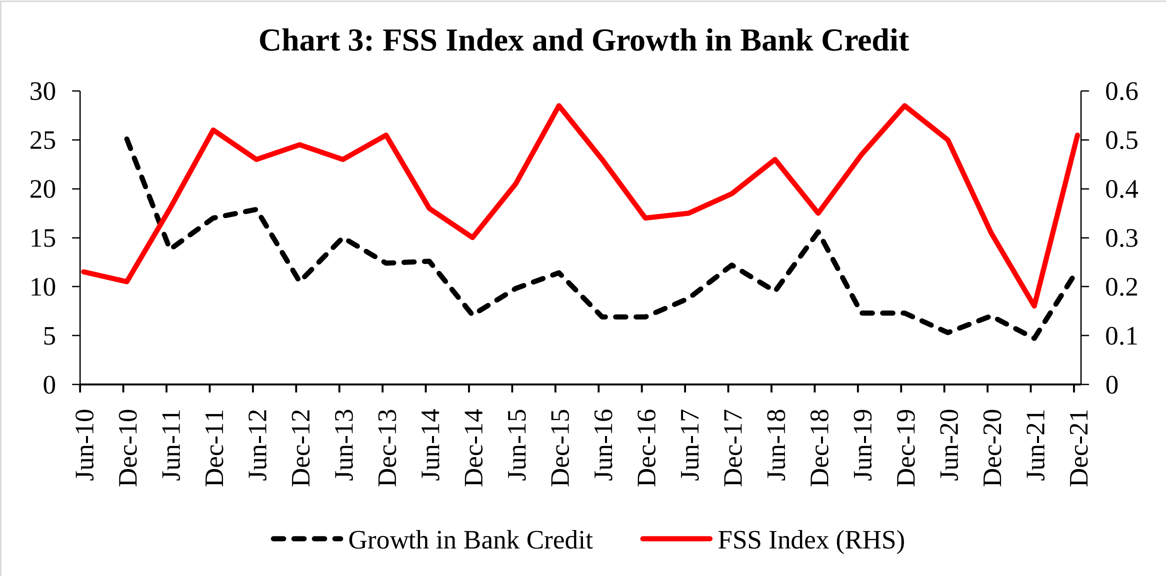
Samanta, G., & Kumari, S. (2021). Monetary Policy Transparency and Anchoring of Inflation Expectations in India. *RBI Working Paper*.

ANNEXURE A1

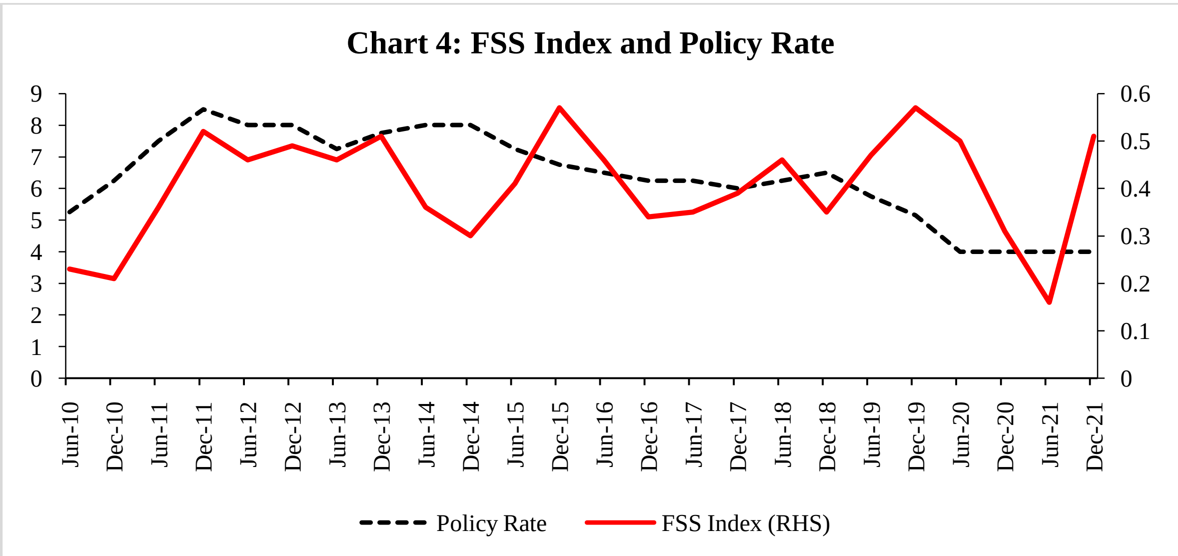
Table 1: Correlation between FSS Index and Key Variables

Correlation	**Growth in Bank Credit**	**Policy Rate**	**Return from Market**	**Consumer Perception**
FSS Index	-0.2236	0.21	-0.4540	0.2137
Note: Only correlation coefficient of Return from Market is statistically				

significant.

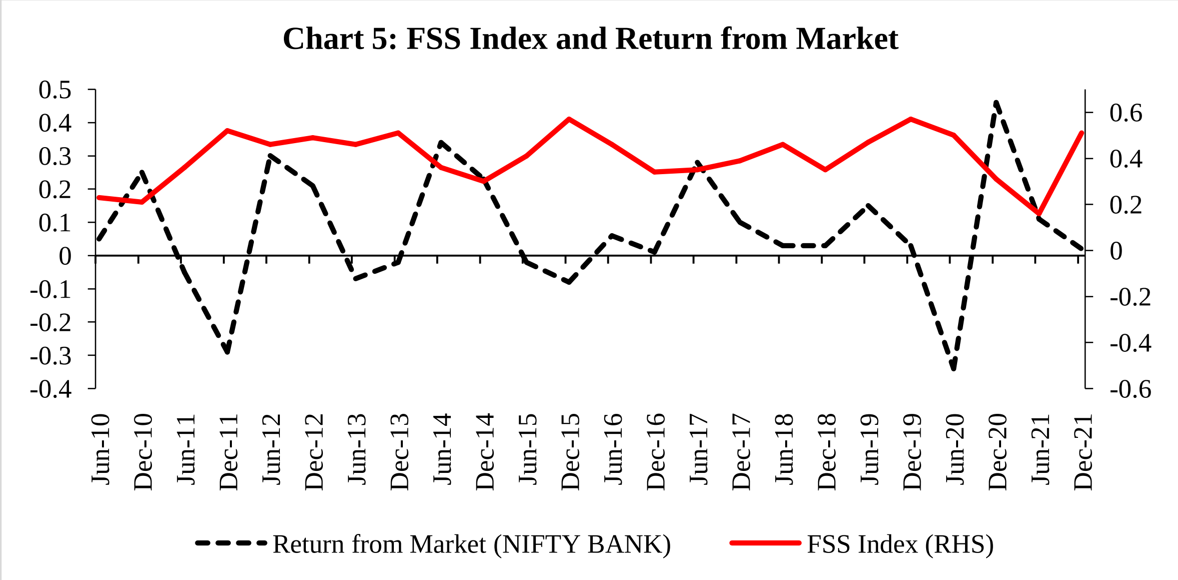


Source: Authors' estimates.

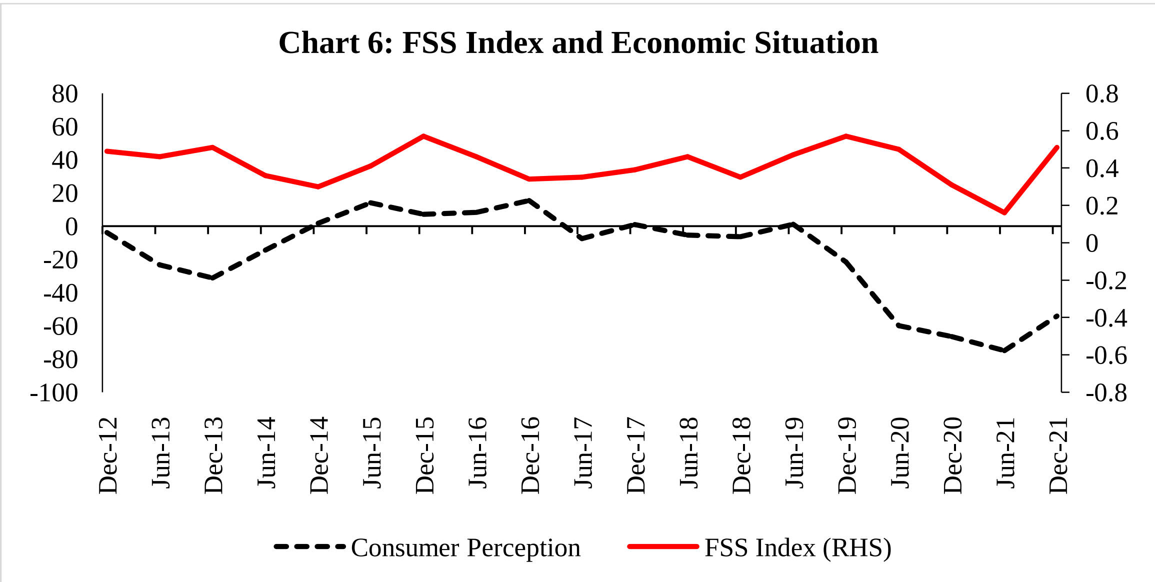


Source: Authors' estimates.

.



Source: Authors' estimates



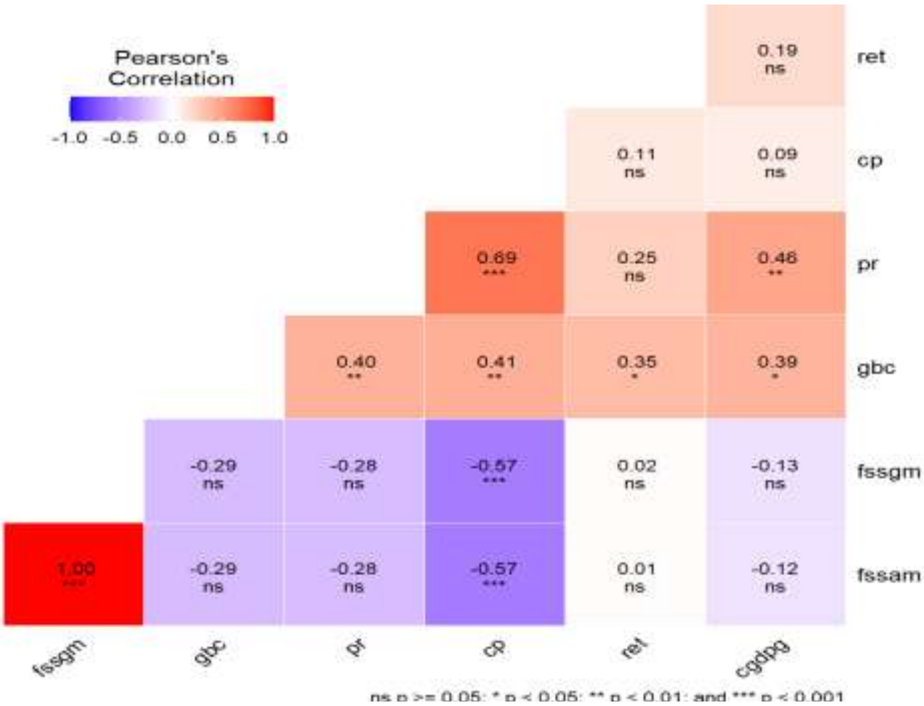
Source: Authors' estimates

Table 2: Results of Granger casualty tests

Null hypothesis	**F-statistic**	**p-value**	**Remark**
Financial Stability Sentiment Index (FSSAM)			
FSSAM does not granger cause policy rate	1.4456	0.2493	Do not reject
Policy rate does not granger cause FSSAM	0.034	0.9666	Do not reject
FSSAM does not granger cause gross bank credit	1.47	0.2438	Do not reject
Gross bank credit does not granger cause FSSAM	0.7021	0.5024	Do not reject
FSSAM does not granger cause consumer perception	3.2154	0.0522	Reject

Consumer perception does not granger cause FSSAM	0.2389	0.7888	Do not reject
FSSAM does not granger cause return (Bankex)	1.0402	0.3640	Do not reject
Return (Bankex) does not granger cause FSSAM	0.2971	0.7449	Do not reject
FSSAM does not granger cause credit to GDP gap	0.0003	0.9997	Do not reject
Credit to GDP gap does not granger cause FSSAM	1.7908	0.1818	Do not reject
Financial Stability Sentiment Index (FSSGM)			
FSSAM does not granger cause policy rate	2.2621	0.1192	Do not reject
Policy rate does not granger cause FSSAM	0.0281	0.9723	Do not reject
FSSAM does not granger cause gross bank credit	1.8547	0.1716	Do not reject
Gross bank credit does not granger cause FSSAM	0.7600	0.4752	Do not reject
FSSAM does not granger cause consumer perception	2.3718	0.1081	Reject
Consumer perception does not granger cause FSSAM	0.2758	0.7606	Do not reject
FSSAM does not granger cause return (Bankex)	07399	0.4845	Do not reject
Return (Bankex) does not granger cause FSSAM	0.2022	0.8179	Do not reject
FSSAM does not granger cause credit to GDP gap	0.0535	0.948	Do not reject
Credit to GDP gap does not granger cause FSSAM	1.6181	0.2128	Do not reject

Chart 7: Correlation Matrix



ANNEXURE A2

Table 1: Distribution of Words

Half-year	Negative Words	Positive Words	Total Words	Sentiment Index
Jun-10	505	315	820	0.232
Dec-10	603	390	993	0.215
Jun-11	501	238	739	0.356
Dec-11	516	161	677	0.524
Jun-12	427	157	584	0.462
Dec-12	475	162	637	0.491
Jun-13	340	125	465	0.462
Dec-13	409	132	541	0.512
Jun-14	279	130	409	0.364
Dec-14	222	119	341	0.302
Jun-15	308	130	438	0.406
Dec-15	400	109	509	0.572
Jun-16	368	137	505	0.457
Dec-16	270	133	403	0.340
Jun-17	241	115	356	0.354
Dec-17	307	135	442	0.389
Jun-18	323	118	441	0.465
Dec-18	339	163	502	0.351
Jun-19	348	124	472	0.475
Dec-19	352	96	448	0.571
Jun-20	490	163	653	0.501
Dec-20	436	229	665	0.311
Jun-21	276	201	477	0.157
Dec-21	295	96	391	0.509

Table 2: Definition Variables, data sources

S. No.	Variable	Description	Source
1.	Credit growth	Growth in bank credit (annualised)	RBI
2.	Consumer perceptions on current economic situation	Qualitative responses received from households through Consumer Confidence Survey (CSS)	RBI
3.	Policy rate	Repo rate	RBI
4.	Return on Stock Market	Return from Bank-NIFTY	NSE