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The impact of sentiment on emerging stock markets

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Abstract

For five leading emerging economies: China, India, Russia, Indonesia and South Korea, we show that existing sentiment variables-both direct (Consumer Confidence Index) and indirect (Baker-Wurgler Index)-are insignificant in explaining respective nations' index returns. We improve upon current techniques by using modified sentiment extraction as proposed in Anand et al. [2020] to study the impact of central bank speech sentiment on respective stock market indices. We find that central bank speeches do have a significant impact on the stock markets in our sample of emerging countries.

Keywords: Central Bank Communication, Sentiment Analysis, Text Analysis

The impact of sentiment on emerging stock markets.

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Abstract

For five leading emerging economies: China, India, Russia, Indonesia and South Korea, we show that existing sentiment variables—both direct (Consumer Confidence Index) and indirect (Baker-Wurgler Index)—are insignificant in explaining respective nations' index returns. We improve upon current techniques by using modified sentiment extraction as proposed in Anand et al. [2020] to study the impact of central bank speech sentiment on respective stock market indices. We find that central bank speeches do have a significant impact on the stock markets in our sample of emerging countries.

1 Introduction

Schmeling [2009] reports that sentiment has a significant influence on stock market returns across many industrialized countries and has a greater effect on countries which have less market integrity and more herd-like behavior—prominent characteristics observed in emerging stock markets. However due to the scarcity of studies on the impact of sentiment on a wide cross section of emerging stock markets many important questions remain unresolved; and hence a large portion of the world's economic activity has origins in countries which can be swayed significantly by changes in market sentiments. Our paper offers the first rigorous sentiment-based analysis for the stock markets of a large cross-section of leading emerging countries. We study the impact of existing measures of sentiment on the five major emerging markets: India, China, Russia, Indonesia, and South Korea, selected on the basis of their contribution to world GDP. These five nations contribute about 25% of the world's GDP as of 2019.[1]

Among the most well known sentiment measures, the Consumer Confidence Index is a widely used measure for the direct category of sentiment variables and is available for all five nations. On the other hand, Baker and Wurgler (BW) Index is the most widely used measure in the indirect sentiment index cateogory. Even though BW Index has been used in China (Zhu and Niu [2016]) and India (Dash and Mahakud [2013], Kumari and Mahakud [2015]), an exact replication, using the original six variables has not been done for any of the major emerging markets. To the best of our knowledge ours is the first paper to contribute such comprehensive cross-country evidence on the impact of sentiment on stock markets.[2]

Further, both types of existing sentiment variables have certain drawbacks. For example, as specified in Simon and Wiggins III [2001] the direct measures (survey-based: e.g. Consumer Confidence Index) might be outdated by the time they are published, as the process of surveying can take three to six months; and indirect measures (such as Baker and Wurgler Index), can suffer from a case of bi-directional causality as they are are derived from market variables and then in turn are used to predict other market variables.

We employ the modified sentiment extraction technique as proposed in

[1] A notable absence is that of Brazil which we have to drop due to the unavailability of data.

[2] Thus, we replicate the BW index with its original 6 variables for all countries except for China since the original variables such as number of IPOs and first-day return do not work in case of China as specified in Zhu and Niu [2016].

Anand et al. [2020] to analyze central bank speech sentiment. The speeches have certain unique characteristics that overcome the drawbacks of the existing sentiment variable. For example, these speeches are available almost immediately and hence can be analyzed in real-time as compared to the direct measures (Consumer Confidence Index). Also, since a vast majority of the speeches are confirmed to be delivered in advance and not in response to a specific event or crisis the probability of reverse causality is quite low in comparison to Indirect measures (BW Index).

Existing studies which use central bank communication can be divided into two categories. The first category is the set of studies in which the communication is classified categorically (e.g., +1, 0, -1) based on the subjective assessment of its content by the researcher (Guthrie and Wright [2000]). On the other hand, the second category includes studies that classify speech days as dummy variables (0 or 1) based on whether a speech was delivered on that day. (Savor and Wilson [2013]). However, there are drawbacks to both categories of studies. With respect to the first category, the classification is subjective and can vary depending upon the researcher as well as on the objective and scope of the study; whereas the second category of studies focus just on the event of speech ignoring its content and hence its impact.

The methodology of sentiment quantification which we use in this study was recently proposed in Anand et al. [2020] and overcomes these drawbacks by introducing two innovations in the field of financial text analysis. The first improvement is the usage of a sentence the unit of analysis; and the second is the use of "valence shifter"—adjectives and adverbs which amplify or dampen the sentiment of the sentence (Kennedy and Inkpen [2006], Polanyi and Zaenen [2006], Schulder et al. [2018]). The proposed methodology also marks a significant improvement over the current methods of textual analysis in finance including "bag-of-words"(Tetlock [2007], Li [2008], Tetlock et al. [2008]) and the "ngram" approach, as well as the Loughran and McDonald's

(LM) dictionary (Loughran and McDonald [2011]).

We adapt the empirical methodology in Anand et al. [2020] and divide a speech into a set of sentences and extract the sentiment for each sentence considering both the polar words (negative/positive) as well as the adverbs and adjectives (valence shifters) surrounding the polar words. Fifty-two valence shifters (for example, “ain't”, “although”, “almost”) have been classified as stopwords in the Loughran and McDonald dictionary.[3] Thus, we also improve the existing dictionary by taking these words out of the stopwords' list and giving them appropriate weightage as they can modify and/or alter the meaning of the sentence. For example, for the sentence *“The fall in unemploment rates however slow, has been steady.”*, the sentiment using LM dictionary and “bag-of-words” approach is -0.40, whereas using the modified method and valence shifters is -0.85, as the word “however” is not given appropriate weigtage in the existing method and LM dictionary. The full list of valence shifters and the weights attached to them are presented in tables 13 and 14 in the appendices. Further, since a whole sentence is considered as the primary unit to quantify sentiment, it solves the question of how many words should be considered as a cluster for sentiment extraction. This gives a superior alternative to “bag-of-words” (one word at a time) and ngram (n-words at a time) approach.

We show with a simple example, how the “bag-of-words” approach along with the LM dictionary can understate/overstate the sentiment. Additionally, we also show that, in cases where the negative valence shifters are not taken into consideration, the LM dictionary and “bag-of-words” approach can lead to incorrect sentiment.[4]

[3] Since they were classified as stopwords, they were removed from the content in the parsing process.

[4] There are 19 such negators in the list of 52 valence shifters which were classified as stopwords in the LM dictionary.

Additionally, using the updated process and dictionary we find a significant effect of speech sentiment in explaining returns for India, Indonesia and South Korea. We also show that due to its unique properties, and the drawbacks in the existing sentiment variables, speech sentiment is a more effective explanatory variable for market returns in comparison to the existing sentiment variables.

To ensure robustness we include the Economic Policy Uncertainty Index (EPUI) [Baker et al., 2016]), which is based on news coverage about policy-related economic uncertainty. Since central bank communication is bound to make news in most circumstances, this is an important control variable.

The paper is organized as follows, Section 2 is the Literature Review for central bank speeches as well as existing measures of sentiment, Section 3 specifies the methodology for sentiment calculation and analysis followed by Section 4 which lists the data sources. Section 5 presents analysis and results followed by Section 6 for the discussion of the results. Section 7 is for robustness analysis and finally, Section 8 specifies the conclusion.

2 Literature Review

The literature discussed is divided into three categories. The first is based on central bank communication, the second on text-analysis; and the third on well known methods currently in use.

2.1 Central Bank Communication

Due to the perceived importance of central bank speeches to stock markets, there have been many studies on this topic. For example, Guthrie and Wright [2000] show that instead of open market operations, central bank communication can be used to implement monetary policy measures in New Zealand. On the other hand, Kohn and Sack [2003], Demiralp and Jorda

[2004], Ehrmann and Fratzscher [2004] and Jansen and De Haan [2006] analyze the significant of central bank communication based on the dummy variable for presence/absence of speech. Jansen and De Haan [2006] categorize the comments by central bankers on the interest rate, inflation, and economic growth in Eurozone into dummies based on subjective assessment by the authors. Similarly, Gerlach et al. [2007] discusses the statements concerning interest rates made by ECB and their respective impact using subjective dummy classification. Savor and Wilson [2013] check whether macroeconomic announcements affect investors and how. He reports that the average market return and Sharpe ratio are significantly higher on days of important announcements.

2.2 Text based Measures

Antweiler and Frank [2004] analyze the impact of sentiment extracted from message activity in chat rooms on trading volume. Tetlock [2007], Engelberg [2008], Li [2008], Tetlock et al. [2008], Li [2010] are other important studies which have used the existing method of sentiment quantification ("bag-of-word") as well as Machine Learning to classify the setiment from financial texts as positive or negative. The text sources in these studies include 10-K reports, newspaper articles, message boards, and press releases. Loughran and McDonald [2011] specify a new dictionary and show its importance in comparison to the Harvard IV dictionary for analyzing financial texts. On similar lines, Garcia [2013] and Jegadeesh and Wu [2013] study the impact of sentiment calculated from news stories by using term weighing. Kearney and Liu [2014] does a survey of methods in sentiment quantification in finance. Solomon et al. [2014] shows how investors' fund allocation is affected by the media coverage of the same. Kim and Kim [2014] study the relationship between investment sentiment calculated from message postings in Yahoo! Finance and stock returns. Chen et al. [2014] analyze how the social media sentiment affects stock returns and earnings surprises. Further, Loughran and McDonald [2015] study the different dictionaries and their respective suitability for analyzing financial documents. Loughran and McDonald [2016] do a survey of the textual analysis in Accounting and Finance.

2.3 Direct and Indirect Measures

The literature for direct and indirect measures of sentiment has also evolved over the last three decades. It can be traced back to Lee et al. [1991] and Neal and Wheatley [1998] using closed-end fund rates among other variables as a proxy for an indirect measure of sentiment. Following this Baker and Stein [2004] analyze whether liquidity is a suitable indirect measure. Baker and Wurgler [2006] Baker and Wurgler [2007] are the first studies that use proxy market variables and form a sentiment index. On similar lines, Kim and Ha [2010]; Liao et al. [2011]; Baker et al. [2012], Greenwood and Shleifer [2014]; Yang and Gao [2014]; Yang and Zhou [2015] use market variables as proxies to form an indirect measure of sentiment index and test its impact on varying market variables.

Similarly, for direct variables, Otoo [1999] and Charoenrook [2005] are among the first studies which use the University of Michigan consumer survey as a direct measure of sentiment. Lee et al. [2002] calculate sentiment from the Investor Intelligence (II) survey. Jansen and Nahuis [2003] use the European Commission survey data and find the relationship between sentiment and returns to be significant. Similarly, Lemmon and Portniaguina [2006], Bergman and Roychowdhury [2008], Schmeling [2009], Zouaoui et al. [2011], Spyrou [2012], Arif and Lee [2014], Aristei and Martelli [2014] and, Szu et al. [2015] use Consumer Confidence Index (CCI) in their analysis of sentiment.

3 Methodology

3.1 Speech Sentiment

We follow Anand et al. [2020] to calculate the sentiment for each speech by treating a sentence as the base unit. Also, for instances where there are multiple speeches on the same day, the content for all is merged and is analyzed as one. The content of the speech is parsed and converted to all lower cases. Next we remove all references, footnotes, images and tables from the content and then identify all possible punctuation marks in the text. Following this, sentences are identified in three ways: between two full stops, a full stop and a question mark; and between two question marks is classified as a sentence. Thus, each speech is broken down into a collection of sentences. For each sentence, words are classified into three categories, valence shifters (adjectives and adverbs), polar words (positive/negative sentiment words) and stop words.[5] The polar words are taken from the LM dictionary. As in Anand et al. (2020), words such as "ain't", "although" and "almost" which are classified as stopwords in LM, are classified as valence shifters in this study. This is so because these words do add to the meaning of the respective sentence. Fifty-two such words are taken from the stopwords list in LM and are included in the valence shifters list. The valence shifters are further classified into four categories, i.e., amplifiers ("absolutely", "acutely", "very"), de-amplifiers ("barely", "faintly", "few"), negators ("ain't", "aren't", "cannot") and adversative conjunction ("despite", "however", "but"). The amplifiers, de-amplifiers, and adversative conjunction are given a weight a 0.8 (positive for an amplifier, negative for a de-amplifier and negative for the words before adversative conjunction and positive for the words after adversative conjunction).[6] This is done because adversative conjunction such

[5]The list of valence shifters contain each word in all possible forms (e.g. "big", "bigger", "biggest"), thus it is not required to stem the words to their basic form ("big" in this case).

[6]The weight, 0.8, is as per the existing literature (Kennedy and Inkpen [2006], Polanyi and Zaenen [2006], Schulder et al. [2018]). We verify the results by varying the weight of

as “but” will amplify the argument after it and weight down the argument before it.[7] The negators are given a value of -1. Thus, for each sentence, first, the updated stop words (updated by removing valence shifters from the LM stopwords list) are removed from a sentence. After that polar words are identified and given the weight of +1/-1, following which a set of words are identified around each polar word from the beginning till the end of the sentence. This is classified as a word cluster for each polarized word.

In comparison to the new process and updated dictionary, we show that, the existing LM dictionary and one word at a time (“bag-of-words”) approach can lead to incorrect quantification of sentiment in two ways. Firstly, by quantifying the sentiment with the correct sign but an incorrect coefficient and secondly, by quantifying with an incorrect sign (by missing the 19 negators (valence shifters) classified as stopwords). Examples for both categories are presented below:

3.1.1 Category 1: Correct Sign but Incorrect Value

The sentence below is taken from one of the speeches in our sample:

“We will not abandon our own industries to accomplish trade dominance and ensure smooth relations.”

Stop words are removed from the sentence and it transforms as below:

“We not abandon industries accomplish trade dominance ensure smooth relations”

From the above sentence, polarized words are identified (using the LM dictionary) which are “abandon” (-1), “accomplish” (+1), and “smooth”(+1).

valence shifters from 0.5 to 0.9 and our results still hold.

[7] E.g. “The fall in inflation numbers can be achieved but at the cost of unemployment.”

Next, we form a word cluster around these polar words , leading to three clusters in this sentence:[8]

1. *We not abandon*

2. *industries accomplish*

3. *trade dominance ensure smooth relations*

Further valence shifters are identified within each of these clusters, for example, "not" is a valence shifter in the first cluster. The sentiment of the cluster is then defined by the valence shifter in combination with the polar word. For example, in the first cluster "not" will multiply the sentiment of "abandon" (-1) by -1, hence the sentiment of the cluster will be -1*-1 = +1. Thus, the sentiment of the sentence will be defined by overall sentiment from all clusters divided by the number of words in that sentence. The sentiment is then averaged across sentences to get the sentiment of each speech.

The sentiment calculated using the above method is:

$$\frac{1\text{*first cluster} + 1^{*}\text{“accomplish”} + 1^{*}\text{“smooth”}}{10} = 0.33$$

Whereas using the LM method is:[9]

$$\frac{-1^{*}\text{“abandon”} + 1^{*}\text{“smooth”} + 1^{*}\text{“accomplish”}}{9} = 0.11$$

Thus the sentiment is understated by 3 times in comparison to the LM dictionary and "bag-of-words" approach.

[8]In case of adversative conjunction clusters are formed both before and after the polar word.

[9]The number of total words is one less as the stop word list is updated in this study.

3.1.2 Category 2: Incorrect Sign

The sentiment quantification for the sentence below is an example of miscalcuation of the sentiment:

"The small business owners shouldn't worry about earning their livelihood due to increased competition."

Stop words are removed from the sentence and it transforms as below:

"The small business owners shouldn't worry earning livelihood due increased competition."

Again, polarized words are identified (using the LM dictionary) which is this case is "worry" (-1). Since, there is only one polar word, word cluster constitutes everything around it.

`1.` *The small business owners shouldn't worry earning livelihood due increased competition.*

Further, valence shifters are identified in the cluster, which is only one i.e. "shouldn't"(-1). Using it the sentiment is calculated as below:

$$\frac{-1^{*}-1}{11}=0.09$$

Whereas sentiment quantified using LM dictionary and existing process is:[10]

$$\frac{-1}{10}=-0.10$$

Thus, in this case the sentence is considered as negative as per LM dictionary and existing process even though it is positive (as classified by updated process and dictionary).

[10]The number of total words (denominator) is one less since the stop word list is as per the LM dictionary.

We also find that both classes of misquantifications (sign and value) increase monotonically in degree with the presence of valence shifters as well as the length of the speech.

3.2 Baker and Wurgler Index

The Baker and Wurgler Index is replicated from Baker and Wurgler [2006]. The process is outlined below:

1. First, each of the variables is orthogonalized with respect to six macro variables to take out the macro factor effect, if any, from each of them. The six macro variables are:
   - Term Spread (Difference between the yield of 10 year and 1 year bond)
   - Short Term Rate (3 months T Bill rate)
   - Index of Industrial Production (IIP)
   - CPI
   - USD exchange rate
   - Net FII inflow

2. Then we do the principal component analysis of the orthogonalized six variables and their lags.

3. Then correlation is checked between the index formed in the second step and each of the twelve variables (constituents of the index).

4. The variable which has a higher correlation (between current and lag) is selected as the final constituent of the Index for each case.

5. Further, a correlation table is made for all six variables, and the PCA is done on this table.

6. This gives the final equation for the BW Index constituting the appropriate lag of the six variables.

- NIPO (Number of IPO)
- RIPO (First Day return of IPO)
- CEFD (Closed End Fund Discount)
- TURN (Turnover)
- P^{D-ND} (Dividend Premium)
- S (Share of Equity Issue)

An important distinction here is that in the case of China since the BW variables are different. Three variables are used to form the sentiment index in China: NIA (New Investor Account), PER (PE Ratio), and TURN (Turnover). The two variables (NIA and PE Ratio) are used instead of the traditional BW variables due to high irregularities in long term debt and IPO issue in China (Zhu and Niu [2016]).

The final equation consistent with the BW methodology for the emerging markets in our sample is:

$$\begin{aligned}\text{India} : 0.1071^{*}\text{NIPO}_t + 0.7913^{*}\text{RIPO}_{t-1} - 0.3429^{*}\text{CEFD}_{t-1} + 0.0088^{*}\text{TURN}_{t-1} \\ -0.4097^{*}\text{P}_t^{D-ND} + 0.2768^{*}\text{S}_t\end{aligned} \tag{1}$$

$$\begin{aligned}\text{Russia} : 0.4951^{*}\text{NIPO}_{t-1} + 0.4475^{*}\text{RIPO}_t - 0.3871^{*}\text{CEFD}_t + 0.0477^{*}\text{TURN}_{t-1} \\ -0.3042^{*}\text{P}_{t-1}^{D-ND} + 0.5565^{*}\text{S}_{t-1}\end{aligned} \tag{2}$$

$$\begin{aligned}\text{Indonesia} : 0.1059^{*}\text{NIPO}_{t-1} + 0.4194^{*}\text{RIPO}_t - 0.2663^{*}\text{CEFD}_{t-1} + 0.3479^{*}\text{TURN}_t \\ -0.3135^{*}\text{P}_{t-1}^{D-ND} + 0.7228^{*}\text{S}_{t-1}\end{aligned} \tag{3}$$

$$\text{South Korea} : 0.2715^{*}\text{NIPO}_{t-1} + 0.2288^{*}\text{RIPO}_{t} + 0.1565^{*}\text{TURN}_{t} - 0.8723^{*}\text{P}_{t-1}^{D-ND} + 0.2973^{*}\text{S}_{t-1} \quad (4)$$

$$\text{China} : 0.5997^{*}\text{TURN}_{t-1} + 0.4172^{*}\text{NIA}_{t-1} + 0.6828^{*}\text{PER}_{t} \quad (5)$$

For comparison the equation from Baker and Wurgler [2006].

$$0.253^{*}\text{NIPO}_{t} + 0.257^{*}\text{RIPO}_{t-1} - 0.241^{*}\text{CEFD}_{t} + 0.242^{*}\text{TURN}_{t-1} - 0.283^{*}\text{P}_{t-1}^{D-ND} + 0.112^{*}\text{S}_{t} \quad (6)$$

As can be seen, the signs of all variables are in line with Baker and Wurgler [2006]. However, the timing of the variables is different across nations. This could be due to variations in market structures and investor perceptions.

3.3 Return calculation and Analysis

Return is calculated as below:

$$R_i = \frac{P_i - P_{i-1}}{P_i}$$

Where i denotes the respective day and month.

The analysis is done for both daily and monthly frequency as all existing sentiment variables (direct and indirect) are available for the monthly frequency. With respect to speech sentiment, the monthly sentiment is calculated by summing over the sentiment for all speech days of a particular month.

A number of past studies (including Tetlock [2007]) have analyzed the relationship between sentiment and Index return using VAR (Vector Autoregression), to ascertain whether the impact reverses with subsequent lags.

However, we use OLS as the speeches are spread intermittently. Hence, there are days as well as months when there are no speeches and thus using VAR reduces the number of observations drastically. Also, since the impact of sentiment can be delayed due to socio-economic reasons, it is tested for up to three lags in accordance with Tetlock [2007].

Thus, the equation below is tested for both daily and monthly frequency:

$$R_t = a_0 + a_1 Sent_{t-n} + a_2 R_{t-1} + a_3 R_{t-2} + a_3 R_{t-3} + +a_5 Controls + \gamma_t \quad (7)$$

Where n ranges from 0 to 3 and controls include the day of the week and month dummy (for daily analysis).

4 Data

The data are acquired from an array of sources due to the varied nature of variables. All the speeches are downloaded using a link extractor from the official website of each country's central bank.[11] For China, South Korea, and Russia the official English translation is available on the respective central bank website. Five variables are extracted from the speeches; date of delivery, place of delivery, speaker, the title of the speech, and content. The index data for all countries is downloaded from Bloomberg.

Data for the existing measures of sentiment are acquired as follows:

1. Direct Measure: The Consumer Confidence Index for all five nations is

[11] One of the reasons why speeches are downloaded from the official website and not as reported in the news articles (from Reuters or Bloomberg News) is to ensure that the content is in its original form. This is so because, in most cases, news articles, in addition to the reported speech, also have the journalists' opinion which could affect the reader's perception.

downloaded from CEIC - CDM database.

2. Indirect Measure: Baker and Wurgler Index

   We replicate the BW Index from Baker and Wurgler [2006] by employing the six variables for the BW Index: Dividend Premium, Turnover, IPO Frequency, IPO first-day return, Share of Equity Issued, and Closed-End Fund Discount (CEFD)). The data for all except "Debt Issued" are obtained from Bloomberg. The Debt Issued and macroeconomic variables are downloaded from CEIC – CDM database.

3. EPUI Index: The Economic Policy Uncertainty Index (Baker et al. [2016], Baker et al. [2013]) is available on the official website `https://www.policyuncertainty.com/` for all countries in the sample except Indonesia.

5 Analysis and Result

5.1 Index Return Summary

Table 1 below shows the Index and return statistics for each country. The average number of trading days is broadly the same for all nations except Indonesia and China. For the case of China, the low number of trading days is the frequent lockdowns imposed by the government.

5.2 Existing Sentiment Variables Analysis

First, we check the impact of existing sentiment variables: both direct (Consumer Confidence Index) and Indirect (BW Index).[12] The results are re-

[12]For CCI we take change rather than level, following existing literature, thus we do not report the results for Lag 0.

Table 1: Index Return Statistics

Country	Main Index	Smallcap Index	Mean Return Main Index (Monthly)	Mean Return Smallcap Index (Monthly)	Mean Return Main Index (Daily)	Mean Return Smallcap Index (Daily)	Trading days per year
India	Nifty Index	Nifty Smallcap	0.009854	0.008333	0.0004380	0.0004301	258
China	Shanghai Composite Index	CSI smallcap 500 Shanghai Index	0.005348	0.003146	0.0002696	0.0001111	242
Russia	MOEX Index	MSCI Russia Smallcap	0.014110	-0.002313	0.0007366	-0.0002469	250
Indonesia	IDX Index	PEFINDO Index	0.010200	0.008143	0.0004849	0.0003767	243
South Korea	KOSPI Index	KOSPI Smallcap	0.005611	0.004990	0.0002512	0.0002044	246

Note: This table presents the summary statistics for return with respect to daily and monthly levels for the five nations. The data is obtained from bloomberg for each nation.

ported in tables 2 and 3 below :

Table 2: Monthly Analysis - CCI

Country/Variable	CCI Lag 1	CCI Lag 2	CCI Lag 3
India	-0.123 (0.077)	0.121 (0.099)	0.048 (0.115)
China	0.153 (0.212)	0.035 (0.221)	0.019 (0.197)
Russia	0.003 (0.003)	0.001 (0.002)	0.0003 (0.003)
Indonesia	-0.046 (0.078)	0.026 (0.083)	-0.056 (0.088)
South Korea	-0.114 (0.095)	-0.060 (0.138)	0.116 (0.126)

Note: This table presents the results from monthly regression on change in Consumer Confidence Index. The dependent variable is the monthly index return. The results are reported in line with equation 7. The standard errors (reported in parenthesis) are Heteroskedasticity and Autocorrelation (HAC) robust. The controls include three lags of return. ***, ** and * indicate that the coefficient estimate are significantly different from zero at the 1 percent, 5 percent and 10 percent levels respectively.

We find that both existing variables fail to significantly impact any emerging stock market index.[13]

[13] Except for the case of China where the BW index does have significance (similar to Zhu and Niu [2016].)

Table 3: Monthly Analysis - BW

Country/Variable	BW Lag 0	BW Lag 1	BW Lag 2	BW Lag 3
India	0.0004	0.0004	-0.0001	0.0003
	(-0.0002)	(0.0003)	(0.0003)	(0.0003
China	0.015***	0.004	0.002	0.0009
	(0.004)	(0.006)	(0.004)	(0.003)
Russia	0.0001	0.0000	0.0000	-0.0000
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Indonesia	0.0001	0.0000	-0.0000	-0.0000
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
South Korea	0.0001	-0.0000	-0.0000	-0.0000
	(0.0001)	(0.0001)	(0.0001)	(0.0001)

Note: This table presents the results from monthly regression on Baker and Wurgler index. The dependent variable is the monthly index return. The results are reported in line with equation 7. The standard errors (reported in parenthesis) are Heteroskedasticity and Autocorrelation (HAC) robust. The controls include three lags of return. ***, ** and * indicate that the coefficient estimate are significantly different from zero at the 1 percent, 5 percent and 10 percent levels respectively.

5.3 Speech Sentiment Analysis

Since CCI and BW Index are not significant in explaining the index returns for the five nations we check whether speech sentiment is an effective explanatory variable. We first look at the summary statistics for return as well as speech variables for all nations. Table 4 and 5 specify the speech statistics for each country. We get the speeches from the earliest period available from the websites of the central banks for each country. The longest time period of availability is for China and South Korea. India has the highest number of daily speeches as well as the highest number of average speeches per month. On the other hand, South Korea has the lowest number of daily speeches as well as average speeches per month. The mean and median for daily as well as monthly sentiment are negative for India, Russia, and South Korea whereas it is positive for China and Indonesia.

Figure 1a, 1b, 1c, 2a and 2b show the movement of speech sentiment and main index return across time for all five nations. It can be seen that for

Table 4: Speech Statistics

Variable/Country	Time Period	Total Number of Speeches	Daily Speeches after combining for same day	No. of Positive Sentiment Speeches (D)	No. of Negative Sentiment Speeches (D)	Total no. of months Covered by speeches	No. of Positive Sentiment (M)	No. of Negative Sentiment (M)	Avg. No. of Speeches per month
India	May 2009 - Mar 2020	695	573	190	382	142	31	111	1.6
China	Feb 2002 - Apr 2020	295	280	189	90	151	107	44	1.1
Russia	Oct 2008 - Apr 2020	167	154	14	140	69	2	67	1.1
Indonesia	Apr 2007 - Nov 2019	107	98	63	35	55	35	20	1.2
South Korea	May 2005 - Jan 2020	73	71	23	47	58	20	38	0.4

Note: This table presents the summary statistics for speech frequency with respect to daily and monthly levels for the five nations. The data is obtained from official central bank website for each nation. The 4th column shows the number of speeches after combining all speeches in a day into one.

Table 5: Speech Sentiment Statistics

Country	Time Period	Mean (Daily)	Max(daily)	Min (Daily)	Mean (Monthly)	Max (Monthly)	Min (Monthly)
India	May 2009 - Mar 2020	-0.0373	0.2218	-0.3576	-0.1527	0.2108	-0.7797
China	Feb 2002 - Apr 2020	0.0343	0.3379	-0.3188	0.0608	0.4754	-0.3640
Russia	Oct 2008 - Apr 2020	-0.06545	0.15	-0.23039	-0.14609	0.04612	-0.71541
Indonesia	Apr 2007 - Nov 2019	0.02016	0.19147	-0.20564	0.03628	0.29345	-0.33071
South Korea	May 2005 - Jan 2020	-0.04547	0.16857	-0.28964	-0.05567	0.16857	-0.57231

Note: This table presents the summary statistics for speech sentiment with respect to daily and monthly levels for the five nations. The data is obtained from official central bank website for each nation. The daily variables are reported after combining all speeches on the same day into one.

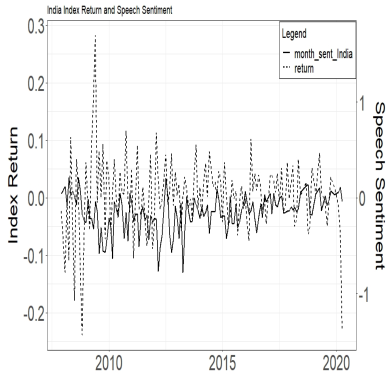
India, Indonesia, and South Korea, the speech sentiment and index return are mimicking each other's movement closely. However, the same cannot be said for China and Russia as the movement is not synchronized. Also, in the case of India, Indonesia, and South Korea, the movement of both variables is mostly contemporaneous with speech sentiment leading for certain sample durations.

Hence apriori we expect to see a significant relationship between the speech sentiment and return for India, Indonesia, and South Korea. Although, the same cannot be expected for China and Russia.

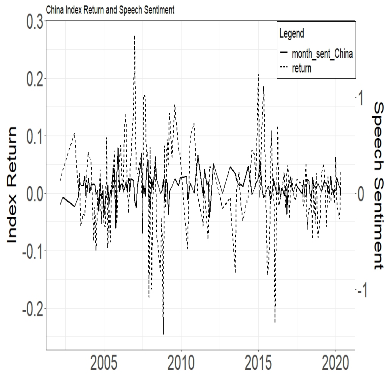
To verify the movement in figures , first, we do the daily analysis for each of the five nations.[14] The results are presented in Table 6. We find that speech sentiment significatly affects the index return of India, Indonesia, and South Korea at different lags (lag 1 for India and Indonesia, and lag 3 for South Korea). However, there is no significant result for China and Russia.

Similarly, table 7 sheds light on the monthly effect of speech sentiment for all five emerging nations. The results for India and Indonesia are in line with the daily results. We find that speech sentiment significantly impacts the index return with a lag of 1 month for these two nations. However, there

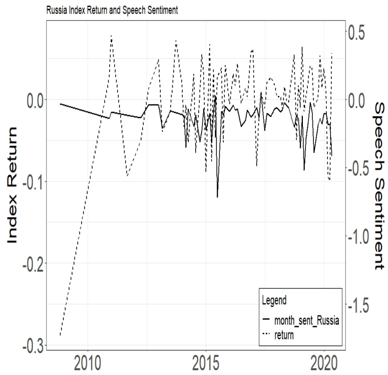
[14] All standard errors reported in this study are HAC robust.



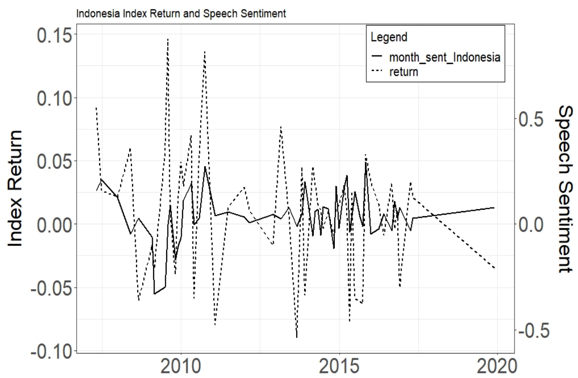
(a) The monthly return (dotted line) is for the BSE Index (India) whereas the speech sentiment (solid line) is calculated by summing up the speeches over a month and then extracting sentiment using the specified methodolgy in this study. The return is represented by the primary Y axis and the speech sentiment by the secondary Y axis.



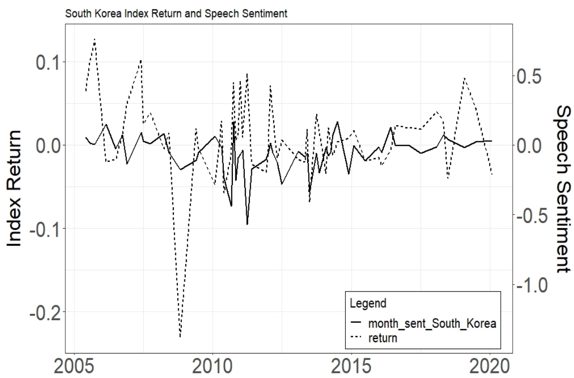
(b) The monthly return (dotted line) is for the Shanghai Composite Index (China) whereas the speech sentiment (solid line) is calculated by summing up the speeches over a month and then extracting sentiment using the specified methodolgy in this study. The return is represented by the primary Y axis and the speech sentiment by the secondary Y axis.



(c) The monthly return (dotted line) is for the MOEX Index (Russia) whereas the speech sentiment (solid line) is calculated by summing up the speeches over a month and then extracting sentiment using the specified methodolgy in this study. The return is represented by the primary Y axis and the speech sentiment by the secondary Y axis.



(a) The monthly return (dotted line) is for the IDX Index (Indonesia) whereas the speech sentiment (solid line) is calculated by summing up the speeches over a month and then extracting sentiment using the specified methodolgy in this study. The return is represented by the primary Y axis and the speech sentiment by the secondary Y axis.



(b) The monthly return (dotted line) is for the KOSPI Index (South Korea) whereas the speech sentiment (solid line) is calculated by summing up the speeches over a month and then extracting sentiment using the specified methodolgy in this study. The return is represented by the primary Y axis and the speech sentiment by the secondary Y axis.

is no significant effect for South Korea at monthly frequency. Additionally, monthly speech sentiment also affects index return significantly in China

Table 6: Speech sentiment - Daily Analysis

Country/Variable	Speech Sent Lag 0	Speech Sent Lag 1	Speech Sent Lag 2	Speech Sent Lag 3
India	-0.001 (0.011)	-0.016^{**} (0.007)	0.015^{**} (0.007)	-0.006 (0.006)
China	-0.003 (0.010)	-0.003 (0.012)	-0.000 (0.011)	-0.006 (0.012)
Russia	0.021 (0.016)	0.0005 (0.017)	0.024 (0.020)	-0.001 (0.020)
Indonesia	-0.004 (0.015)	0.025^{*} (0.014)	0.016 (0.017)	0.024 (0.016)
South Korea	-0.013 (0.013)	0.0003 (0.013)	-0.007 (0.020)	0.042^{**} (0.017)

Note: This table presents the results from daily regression on speech sentiment.The dependent variable is the daily index return. The results are reported in line with equation 7. The number of observation are the same as number of speech-days for each country. The standard errors (reported in parenthesis) are Heteroskedasticity and Autocorrelation (HAC) robust. The controls include three lags of return, day of the week and month dummy. ***, ** and * indicate that the coefficient estimate are significantly different from zero at the 1 percent, 5 percent and 10 percent levels respectively.

with a lag of 3 months. This could be due to the aggregating impact of the speeches among other factors.

Table 7: Speech sentiment - Monthly Analysis

Country/Variable	Speech Sent Lag 0	Speech Sent Lag 1	Speech Sent Lag 2	Speech Sent Lag 3
India	-0.035 (0.027)	-0.060^{**} (0.030)	-0.054^{*} (0.029)	0.028 (0.026)
China	-0.061 (0.046)	-0.023 (0.052)	-0.007 (0.056)	0.095^{*} (0.057)
Russia	-0.035 (0.058)	-0.057 (0.040)	0.001 (0.034)	-0.011 (0.053)
Indonesia	0.097 (0.059)	-0.091^{*} (0.052)	-0.132 (0.100)	-0.005 (0.064)
South Korea	0.062 (0.061)	-0.036 (0.032)	0.016 (0.031)	-0.003 (0.040)

Note: This table presents the results from monthly regression on speech sentiment. The dependent variable is the monthly index return. The results are reported in line with equation 7. The number of observation are the same as number of speech-months for each country. The standard errors (reported in parenthesis) are Heteroskedasticity and Autocorrelation (HAC) robust. The controls include three lags of return. ***, ** and * indicate that the coefficient estimate are significantly different from zero at the 1 percent, 5 percent and 10 percent levels respectively.

To further check the impact of speech sentiment we add existing sentiment variables as controls to equation 7. Thus, the equation 8 and equation 9 are specified for tables 8 and 9 respectively:

$$R_t = a_0 + a_1 Sent_{t-n} + a_2 CCI_{t-n} + a_3 R_{t-1} + a_4 R_{t-2} + a_5 R_{t-3} + a_6 Controls + \gamma_t \quad (8)$$

$$R_t = a_0 + a_1 Sent_{t-n} + a_2 BW_{t-n} + a_3 R_{t-1} + a_4 R_{t-2} + a_5 R_{t-3} + a_6 Controls + \gamma_t \quad (9)$$

where n ranges from 0 to 3.

Table 8: Monthly Analysis with Consumer Confidence Index (CCI) as Control

Independent Variables	**Lag 0**		**Lag 1**		**Lag 2**		**Lag 3**	
Country	Speech Sent	CCI	Speech Sent	CCI	Speech Sent	CCI	Speech Sent	CCI
India	−0.017 (0.025)	0.181 (0.078)	−0.073** (0.032)	−0.099 (0.087)	−0.057* (0.030)	0.142 (0.101)	0.021 (0.028)	0.120 (0.105)
China	−0.059 (0.046)	0.241 (0.272)	−0.023 (0.052)	0.143 (0.261)	−0.007 (0.056)	0.051 (0.261)	0.095* (0.057)	−0.084 (0.255)
Russia	0.029 (0.038)	0.014*** (0.002)	−0.037 (0.038)	0.010** (0.003)	0.004 (0.035)	0.002 (0.002)	−0.003 (0.051)	0.003* (0.002)
Indonesia	0.112* (0.057)	0.338** (0.133)	−0.081 (0.056)	0.140 (0.146)	−0.134 (0.107)	−0.072 (0.204)	−0.011 (0.064)	−0.134 (0.171)
South Korea	0.046 (0.059)	0.447 (0.315)	−0.035 (0.033)	−0.059 (0.191)	0.019 (0.032)	−0.134 (0.224)	−0.007 (0.039)	0.148 (0.153)

Note: This table presents the results from monthly regression on speech sentiment. The dependent variable is the monthly index return. The results are reported in line with equation **??**. The number of observation are the same as number of speech-months for each country. The standard errors (reported in parenthesis) are Heteroskedasticity and Autocorrelation (HAC) robust. The controls include three lags of return and Consumer Confidence Index (CCI) . ***, ** and * indicate that the coefficient estimate are significantly different from zero at the 1 percent, 5 percent and 10 percent levels respectively.

We find that speech sentiment results broadly remain consistent as it remains as a significant explanatory variable for India, Indonesia, and China even in the presence of CCI, whereas in the case of Russia CCI is significant with a lag of 3 months. None of the variables are significant for South Korea after addition of CCI.

In the case of the BW Index as an additional control variable, speech sentiment is not significant for any nation except Indonesia. However, BW Index is significant in the case of India, China, and Indonesia in the presence of speech sentiment.

Table 9: Monthly Analysis with Baker and Wurgler (BW) Index as Control

Independent Variables	**Lag 0**		**Lag 1**		**Lag 2**		**Lag 3**	
Country	Speech Sent	BW	Speech Sent	BW	Speech Sent	BW	Speech Sent	BW
India	-0.047 (0.046)	0.015^{***} (0.004)	0.002 (0.074)	0.004 (0.006)	-0.012 (0.061)	0.002 (0.004)	-0.016 (0.060)	0.001 (0.003)
China	-0.051 (0.046)	-0.036^{*} (0.021)	-0.024 (0.053)	0.004 (0.018)	-0.010 (0.057)	0.010 (0.019)	0.091 (0.058)	0.019 (0.020)
Russia	-0.04 (0.04)	-0.0001 (0.0000)	-0.01 (0.04)	0.0000 (0.0000)	-0.005 (0.03)	0.0000 (0.0000)	0.009 (0.05)	-0.0000 (0.0000)
Indonesia	0.08 (0.1)	-0.0004 (0.0004)	-0.062 (0.057)	-0.0000 (0.0000)	-0.133^{*} (0.066)	-0.0001^{**} (0.0000)	0.006 (0.050)	-0.0001^{**} (0.0000)
South Korea	0.056 (0.047)	0.032^{***} (0.032)	-0.049 (0.031)	-0.0000 (0.0000)	0.027 (0.035)	0.0000 (0.0000)	-0.017 (0.042)	-0.0000 (0.0000)

Note: This table presents the results from monthly regression on speech sentiment. The dependent variable is the monthly index return. The results are reported in line with equation **??**. The number of observation are the same as number of speech-months for each country. The standard errors (reported in parenthesis) are Heteroskedasticity and Autocorrelation (HAC) robust. The controls include three lags of return and Baker Wurgler (BW) Index. ***, ** and * indicate that the coefficient estimate are significantly different from zero at the 1 percent, 5 percent and 10 percent levels respectively.

Also, to ensure that speeches are not impacted by the index returns, we analyze the impact of return on speech sentiment for both daily and monthly frequency. We find that for there is no significant impact of return on speech sentiment. We present the results for monthly analysis in Table 10.

Table 10: Impact of Return on Speech

Country/Variable	Return Lag 0	Return Lag 1	Return Lag 2	Return Lag 3
India	-0.271 (0.221)	0.009 (0.245)	-0.484 (0.290)	-0.251 (0.276)
China	-0.083 (0.101)	0.215 (0.168)	0.200 (0.126)	-0.030 (0.118)
Russia	-0.027 (0.217)	0.082 (0.316)	-0.328 (0.334)	0.479 (0.401)
Indonesia	0.458 (0.350)	0.244 (0.440)	-0.022 (0.286)	0.212 (0.365)
South Korea	0.409 (0.338)	-0.061 (0.497)	-0.548 (0.405)	-0.088 (0.261)

Note: This table presents the results from monthly regression on return for the main index. The dependent variable is the monthly speech sentiment. The number of observation are the same as number speech-months for each country. The standard errors (reported in parenthesis) are Heteroskedasticity and Autocorrelation (HAC) robust. ***, ** and * indicate that the coefficient estimate are significantly different from zero at the 1 percent, 5 percent and 10 percent levels respectively.

6 Discussion of Results

We offer two possible explanations for the daily and monthly results. Both are explained in detail below:

6.1 Strength and Weight Argument

There is one theory that gives a possible explanation for the results of all five emerging nations. It can be traced back to Griffin and Tversky [1992] attempt to reconcile conservatism Edwards [1968] and representativeness Tversky and Kahneman [1974]. In Griffin and Tversky's framework, people update their beliefs based on the "strength" and the "weight" of the evidence (Barberis et al. [1998]). Griffin and Tversky use an example of a recommendation letter to explain both the attributes. The "strength" of the letter refers to how positive and warm its content is and the "weight", on the other hand, measures the credibility and stature of the letter writer.

Both these notions are in accordance with the World Economic Forum's Trustworthiness and Confidence Index presented in Figure 3 (based on the Soundness of Banks, Regulation of securities Exchange and Legal Rights Index).[15] It can be seen that the sc ore for India is highest whereas for Russia is the lowest among all nations. Whereas, the score for China, South Korea, and Indonesia is steady or falling in the specified period. Additionally, the financial market development index of the world economic forum shows a similar trend for all five nations. It can be implied from the above argument that people have placed low "weight" on the speeches in Russia even though the "strength" is high and this could be the reason for statistical insignificance. On the other hand, for India, the "weight" is high, hence speeches are significant in explaining index return, however, the "strength" is not high enough in comparison to market factors, thus speech sentiment is not a sig-

[15] The data is only available till 2016.

nificant variable in the presence of BW Index. Similarly, patterns can be observed for China, South Korea, and Indonesia.

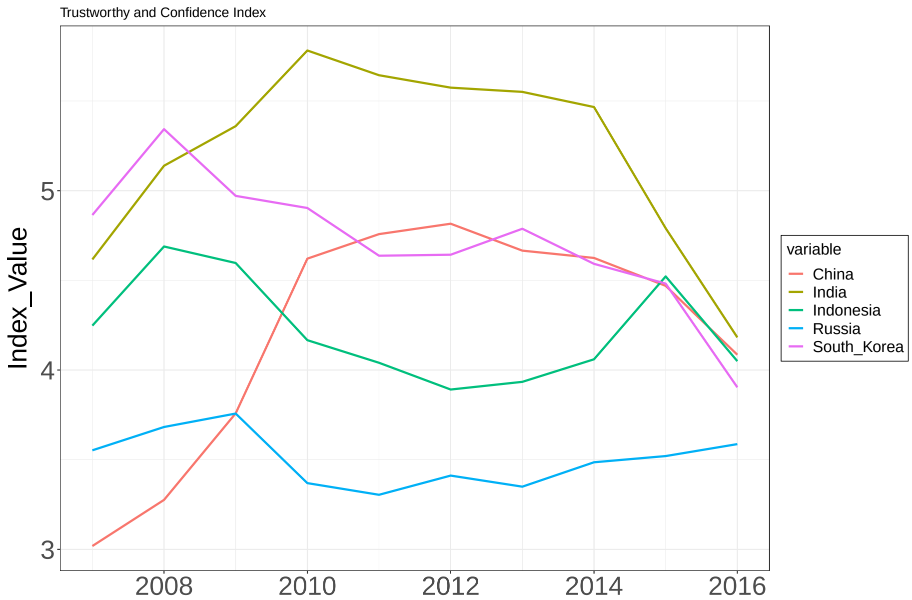


Figure 3: The figure presents the Trusthworthy and Confidence Index of the five nations from 2007 to 2016. Source : World Bank

6.2 Lost In Translation

For China, Russia, and South Korea, the speeches are translated by officials in English from the native language. This might have to lead to loss of meaning and hence incorrect quantification of sentiment, thus leading to insignificant results in respective cases.

7 Robustness

We check the robustness of our results in the presence of EPUI (Economic Policy Uncertainty Index). The index is based on news coverage about policy-related economic uncertainty. Since central bank communication is bound to make news in most circumstances, this is an important control variable. Thus, the EPUI is expected to cover the impact of speeches to a certain extent. The process is similar to BW and CCI as we add EPUI as an additional control variable. The results are presented in tables 11 and 12 below:

Table 11: Monthly Analysis - EPUI

Country/Variable	EPUI Lag 0	EPUI Lag 1	EPUI Lag 2	EPUI Lag 3
India	-0.048^{***} (0.014)	0.006 (0.016)	0.001 (0.014)	-0.005 (0.017)
China	-0.021 (0.014)	0.007 (0.012)	0.000 (0.011)	-0.001 (0.008)
Russia	-0.007 (0.006)	-0.004 (0.006)	0.001 (0.007)	-0.008 (0.005)
Indonesia	NA	NA	NA	NA
South Korea	-0.022^{**} (0.009)	-0.016 (0.011)	0.018 (0.014)	-0.007 (0.009)

Note: This table presents the results from monthly regression on EPUI. The dependent variable is the monthly index return. The results are reported in line with equation 7. The standard errors (reported in parenthesis) are Heteroskedasticity and Autocorrelation (HAC) robust. The controls include three lags of return. ***, ** and * indicate that the coefficient estimate are significantly different from zero at the 1 percent, 5 percent and 10 percent levels respectively.

We find that in the standalone case, EPUI is not a significant variable in explaining Index return. Also, as an additional control, the results remain consistent for India, whereas for China and South Korea EPUI is a significant variable (in the presence of speech sentiment). Thus, showing that speech sentiment, although not significant in itself, is an addition to the policy news in the respective nations.[16]

[16] We also repeat the analysis (as in section 5) for smallcap index for all five nations and the results stll hold. However we do not present the same due to data limitations for smallcap index for Russia, Indonesia and China.

Table 12: Monthly Analysis with EPUI Index as Control

Independent Variables	**Lag 0**		**Lag 1**		**Lag 2**		**Lag 3**	
Country	Speech Sent	EPUI	Speech Sent	EPUI	Speech Sent	EPUI	Speech Sent	EPUI
India	−0.022 (0.025)	−0.048*** (0.014)	−0.073* (0.033)	0.003 (0.018)	−0.058* (0.030)	0.005 (0.014)	0.023 (0.028)	0.011 (0.014)
China	−0.051 (0.046)	−0.036* (0.021)	−0.024 (0.053)	0.004 (0.018)	−0.010 (0.057)	0.010 (0.019)	0.091 (0.058)	0.019 (0.020)
Russia	−0.042 (0.057)	0.006 (0.005)	−0.059 (0.040)	0.002 (0.005)	−0.003 (0.033)	0.004 (0.006)	−0.004 (0.051)	−0.006 (0.005)
Indonesia	NA	NA	NA	NA	NA	NA	NA	NA
South Korea	0.074 (0.057)	0.032 (0.032)	−0.037 (0.036)	−0.003 (0.020)	0.043 (0.037)	0.058** (0.026)	0.018 (0.046)	0.042* (0.021)

Note: This table presents the results from monthly regression on speech sentiment. The dependent variable is the monthly index return. The results are reported in line with equation 8 (replacing CCI with EPUI). The number of observation are the same as number of speech-months for each country. The standard errors (reported in parenthesis) are Heteroskedasticity and Autocorrelation (HAC) robust. The controls include three lags of return and Economic Policy Uncertainity Index (EPUI) . ***, ** and * indicate that the coefficient estimate are significantly different from zero at the 1 percent, 5 percent and 10 percent levels respectively.

8 Conclusion

The study attempts to enquire about the role of sentiment variables, in five major emerging economies: India, China, Russia, Indonesia, and South Korea). This includes analyzing the role of existing sentiment variables (Direct - Consumer Confidence Index) as well as Indirect (BW Index). We are also the first to exactly replicate the BW index for the cross section of leading emerging stock markets. In addition to the existing sentiment variables, we also add a new variable based on the speeches of the central bank. The method of sentiment quantification from these speeches is also new and overcomes the existing drawbacks in Loughran and McDonald Dictionary as well as the "bag-of-words" and ngram approach. The analysis is done for both daily and monthly frequency to ensure comparison with the existing sentiment variables. It is found that speech sentiment significantly affects index returns for India, Indonesia, and South Korea in case of daily frequency. Also, for monthly frequency, the results are the same for India and Indonesia. Additionally, we also find that speech sentiment is significant in the case of China, could be due to monthly aggregation of speeches. For the explanation of results, we reply on two ideas: lost in translation argument for China, South Korea, and Russia, and the strength and weight argument for all five countries. Both these arguments can be studied in greater detail in the future to ensure unanimity and certainty. For example, the methodology used in this study can be used in the native language for non-English speaking nations (such as China, South Korea, and Russia) to resolve the lost in translation argument.

A List of Valence Shifters

The tables 13 and 14 below specifies all the valence shifters used in this study including the 52 previously classified as stopwords in the LM dictionary.

Table 13: List of Valence Shifters

Word	Classification	Weight	Word	Classification	Weight
absolutely	Amplifier	0.8	despite all that	Adversative Conjunction	0.8
acute	Amplifier	0.8	despite all this	Adversative Conjunction	0.8
acutely	Amplifier	0.8	despite that	Adversative Conjunction	0.8
ain't	Negator	-1	despite this	Adversative Conjunction	0.8
aint	Negator	-1	didn't	Negator	-1
almost	De-amplifier	0.8	didnt	Negator	-1
although	Adversative Conjunction	0.8	doesn't	Negator	-1
aren't	Negator	-1	doesnt	Negator	-1
arent	Negator	-1	don't	Negator	-1
barely	De-amplifier	0.8	dont	Negator	-1
but	Adversative Conjunction	0.8	enormous	Amplifier	0.8
can't	Negator	-1	enormously	Amplifier	0.8
cannot	Negator	-1	especially	Amplifier	0.8
cant	Negator	-1	extreme	Amplifier	0.8
certain	Amplifier	0.8	extremely	Amplifier	0.8
certainly	Amplifier	0.8	faintly	De-amplifier	0.8
colossal	Amplifier	0.8	few	De-amplifier	0.8
colossally	Amplifier	0.8	greatly	Amplifier	0.8
considerably	Amplifier	0.8	hadn't	Negator	-1
couldn't	Negator	-1	hadnt	Negator	-1
couldnt	Negator	-1	hardly	De-amplifier	0.8
daren't	Negator	-1	hasn't	Negator	-1
darent	Negator	-1	hasnt	Negator	-1
decidedly	Amplifier	0.8	haven't	Negator	-1
deep	Amplifier	0.8	havent	Negator	-1
deeply	Amplifier	0.8	heavily	Amplifier	0.8
definite	Amplifier	0.8	heavy	Amplifier	0.8

Note: This table presents the list of valence shifters along with their classification and weight.

Table 14: List of Valence Shifters

Word	Classification	Weight	Word	Classification	Weight	Word	Classification	Weight
high	Amplifier	0.8	needn't	Negator	-1	really	Amplifier	0.8
highly	Amplifier	0.8	neednt	Negator	-1	seldom	De-amplifier	0.8
however	Adversative Conjunction	0.8	neither	Negator	-1	serious	Amplifier	0.8
huge	Amplifier	0.8	never	Negator	-1	seriously	Amplifier	0.8
hugely	Amplifier	0.8	no	Negator	-1	severe	Amplifier	0.8
immense	Amplifier	0.8	nobody	Negator	-1	severely	Amplifier	0.8
immensely	Amplifier	0.8	none	Negator	-1	shan't	Negator	-1
incalculable	Amplifier	0.8	nor	Negator	-1	shant	Negator	-1
incalculably	Amplifier	0.8	not	Negator	-1	shouldn't	Negator	-1
incredibly	De-amplifier	0.8	only	De-amplifier	0.8	shouldnt	Negator	-1
isn't	Negator	-1	oughtn't	Negator	-1	significant	Amplifier	0.8
isnt	Negator	-1	oughtnt	Negator	-1	significantly	Amplifier	0.8
kind of	De-amplifier	0.8	particular	Amplifier	0.8	slightly	De-amplifier	0.8
kinda	De-amplifier	0.8	particularly	Amplifier	0.8	somewhat	De-amplifier	0.8
least	De-amplifier	0.8	partly	De-amplifier	0.8	sort of	De-amplifier	0.8
little	De-amplifier	0.8	purpose	Amplifier	0.8	sorta	De-amplifier	0.8
majorly	Amplifier	0.8	purposely	Amplifier	0.8	sparsely	De-amplifier	0.8
massive	Amplifier	0.8	quite	Amplifier	0.8	sporadically	De-amplifier	0.8
massively	Amplifier	0.8	rarely	De-amplifier	0.8	sure	Amplifier	0.8
mightn't	Negator	-1	real	Amplifier	0.8	surely	Amplifier	0.8
mightnt	Negator	-1	very	Amplifier	0.8	that being said	Adversative Conjunction	0.8
more	Amplifier	0.8	very few	De-amplifier	0.8	totally	Amplifier	0.8
most	Amplifier	0.8	very little	De-amplifier	0.8	true	Amplifier	0.8
much	Amplifier	0.8	wasn't	Negator	-1	truly	Amplifier	0.8
mustn't	Negator	-1	wasnt	Negator	-1	uber	Amplifier	0.8
mustnt	Negator	-1	weren't	Negator	-1	vast	Amplifier	0.8
whereas	Adversative Conjunction	0.8	wont	Negator	-1	wouldnt	Negator	-1
won't	Negator	-1	wouldn't	Negator	-1	werent	Negator	-1

Note: This table presents the list of valence shifters along with their classification and weight.

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