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Who moved the Market? Analyzing the role of Central Bank speeches

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“Who moved the Market”? Analyzing the role of Central Bank speeches.

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Abstract

We quantify the tone from central bank speeches of three leading English speaking developed nations (US, UK and Canada) and analyze its role in explaining the return of stock market indices for the respective nations. In this study we extend and improve upon the existing tone quantification techniques by introducing two innovations: (i) by introducing the sentence as the unit of analysis, and (ii) by introducing “valence shifters”, which assign appropriate weights to adjectives and adverbs. We use these innovations in conjunction with the “bag-of-words” and ngram approach and find that central bank communication does impact national stock market index returns significantly.

1 Introduction

The role of central banks in moderating financial stability and assisting economic growth is of prime importance and has been a focus of an array of studies in the past. Hence, central bank communication is watched very closely by all market participants. The majority of past studies have analyzed and quantified the communication from the European Central Bank (ECB) (Gerlach et al. (2007), Picault & Renault (2017)) or the Federal Open Market Committee (FOMC) (Lucca & Trebbi (2009), Hansen & McMahon (2016)).

We add to this growing literature by extracting the tone from central bank communication by the members (governors/deputy governors/board members) of three leading central banks of the United States, United Kingdom and Canada. The Loughran and McDonald dictionary (Loughran & McDonald (2011)) along with the "bag-of-words" and ngram approach have been among the prime tools in the field of financial textual analysis. In this study, the polar (positive/negative) words from the Loughran and McDonald (LM hereafter) dictionary are used in conjunction with the ngram polar phrases to reap the benefits from both sets of categorizations.

The LM list as well as ngram phrases/word list (derived from the speech text itself) have certain shortcomings. For example, the LM polar words' list does not characterize certain words, such as "increase" since their meaning is dependent upon the noun form they are used with. For example, increase used with "unemployment" has a negative connotation while its usage with "growth" carries a positive connotation. The positive/negative categorization of such verb-noun combination is taken care of in case of ngram polar phrases. For example, taking two words at time (n = 2) we can correctly assign a positive value to "increased growth"; and a negative value to "increased unemployment". On the other hand, creating new dictionaries from content derived word lists is ill-advised according to Schmeling & Wagner (2019) since it can lead to hindsight bias because the same data are used twice: first to build a dictionary and subsequently to analyze the tone and its impact. Thus, in this study we use both LM polar words and ngram phrases in conjunction with valence shifters (adverbs/adjective) which leads to more accurate quantification of tone. To the best of our knowledge this is the first instance of the usage of valence shifting in financial text analysis. This process of tone quantification, along with using the sentence as a base unit of measurement is, in our opinion, a noteworthy advanced in the framework of tone quantification of text.

The existing studies on central bank communication can be broadly classified into two categories. The first category is the set of studies in which the central bank's communications' reaction is quantified into a numeric classification (e.g., +1, 0, -1) based on either the subjective assessment of its content by the researcher or by using an objective methodology of tone extraction. For example, Guthrie & Wright (2000) use central bank communication to show how central bank statement (rather than open market operations) can be used to implement monetary policy in New Zealand. The communication is classified into categories (+1,0,-1) based on the authors' subjective assessment and it is shown that the communication, rather than open market operations causes the large changes in interest rates. On the other hand, Lucca & Trebbi (2009) use an ngram approach to quantify and analyze the impact of FOMC announcements.[1] The second category includes studies that analyze the importance of speech days based on a dummy variable for the presence/absence of the speech. For example, Savor & Wilson (2013) show that the average market return and Sharpe ratio are significantly higher on important macroeconomic announcement days.

However, there are two drawbacks to both categories of studies. Concerning the studies which involve subjective classification of the communication, it has been argued that the classification can vary depending upon the researcher as well as on the objective of the study. Thus, the results of such studies cannot be agreed upon to be standard. On the other hand, the second category of studies focus just on the event of speech, ignoring its content and hence its impact.

The use of "bag-of-words" and ngram approach helps to overcome the above drawbacks. In this study we propose extensions to the "bag-of-words" (Tetlock

[1] An ngram approach refers to identifying phrases with n number of words and categorizing them as positive/negative, e.g., ngrams with n = 3 assign values to the following phrases: "increase in employment", "decreasing output growth" etc.

(2007), Li (2008), Tetlock et al. (2008)) and ngram approach to further improve the process of tone quantification in financial texts.

We introduce two new innovations:

1. We introduce the sentence as a new unit of analysis for tone quantification thus providing an answer to the effective number of words to be treated as a unit in the ngram analysis.
2. We introduce the concept of "valence shifting" in financial text analysis (Kennedy & Inkpen (2006), Polanyi & Zaenen (2006), Schulder et al. (2018)) which are adjectives and adverbs (such as "very", "but" etc.) which modify the meaning of text but have not been employed for analyzing financial texts' tone quantification.

We divide a speech into a set of sentences and extract the tone for each sentence considering both the polar words/phrases (negative/positive) as well as the adverbs and adjectives (valence shifters) surrounding the polar words/phrases. As remarked before, valence shifters have not been used yet to classify financial texts, and as such have been not been given any weightage in the tone quantification process. Thus, we also improve the existing dictionary by giving such valence shifters appropriate weightage as they can modify and/or alter the meaning of the sentence.[2] For example, the following sentence is taken from the speech of Mark Olson, Member Federal Reserve Board of Governors, on 13-03-2006:

> "during this period, there were few issues of controversy between banks and securities firms, the most notable exception being the narrowly focused but heated disagreement as to whether banks should be allowed to underwrite revenue bonds."

The tone using LM dictionary and "bag-of-words" approach is -0.11, whereas using our modified tone extraction method it is -0.15, since the word "but"

[2] The full list of valence shifters used in the speeches is presented in A.1.

is not given appropriate weigtage in the existing method and LM dictionary.

Also, since a whole sentence is considered as a single unit to quantify tone, this solves the question of how many words should be considered as a cluster for tone extraction and thus provides an extension to the"bag-of-words" (one word at a time) and ngram (n-words at a time) approach.[3] We show with examples how the tone quantification process is improved and made more accurate by using the methodology introduced in this study, especially in the presence of various type of valence shifters. Further, using the updated process and dictionary we find a significant effect of speech tone in explaining market returns for the U.S., U.K. and Canada.

We ensure robustness of the results in several ways. First, we analyze the effect of speech tone on two of the largest English speaking emerging markets (India and South Africa) to ensure that the effect is not due to the special attributes of the developed markets. Second, we examine the impact of speech tone, quantified using the methodology introduced in this study, for an EU nation: Ireland, since it provides a special case of an English speaking nation with a national central bank as well as a supranational central bank (ECB). We also ensure robustness of results to additional macro-factors, such as term premium and inflation rate which could putatively affect national stock market indices.

The paper is organized as follows, section 2 is the literature review for central bank communication as well as that for text analysis in finance, section 3 specifies the methodology for tone calculation followed by section 4 which describes the data sources. Section 5 is for analysis and results followed by section 6 for the discussion of the results. Section 7 is for robustness analysis and finally, section 8 offers concluding remarks.

[3]This is based on the assumption that a sentence is a complete unit in itself.

2 Literature Review

The literature can be divided into two categories, firstly, on central bank communication and secondly, on text analysis in finance. Both categories are discussed below:

2.1 Central Bank Communication

Due to the perceived economic and financial importance of central banks, the work centering around them has been ample as well as diverse. For example, Guthrie & Wright (2000) study how central bank statement (rather than open market operations) can be used to implement monetary policy in New Zealand. On the other hand, Kohn et al. (2003) and Romer & Romer (2004) are two other studies which analyze central bank communication using dummy categorization and subjective assessment of the content respectively. Jansen & De Haan (2006) also study the comments by central bankers on the interest rate, inflation, and economic growth in Eurozone. The statements are categorized into dummies based on subjective analysis by the authors. Similarly, Gerlach et al. (2007) discuss the interest rate related statements made by the ECB and their respective impact using subjective dummy classification of the statement by the authors. Lucca & Trebbi (2009) use Google search and Factiva based news articles in an ngram approach to analyze FOMC annoucements. Savor & Wilson (2013) check whether investors care about macroeconomic announcements and find that the average market return and Sharpe ratio are significantly higher on important announcement days. Hansen & McMahon (2016) use a topic analysis approach on FOMC communication to analyze its impact on the market using a FAVAR framework. Picault & Renault (2017) use ngram and term weighing approach to quantify ECB communication and analyze its impact on market return and volatility. On similar lines, Smales & Apergis (2017) extract the readability of monetary policy statements using the Flesch-Kincaid index and present its impact on 10 year T-bills. Schmeling & Wagner (2019) and Apergis &

Pragidis (2019) also quantify central bank tone and analyze its impact on market return and volatility. Bennani (2020) uses media coverage of confidence in the Fed chairmen and analyzes its impact on investor tone using Baker and Wurgler index as a proxy. On related lines, Gentzkow et al. (2019) analyze the trend in partisanship of congressional speeches using machine learning and find that partisanship has increased since early 1990s.

2.2 Text based Measures

With respect to quantification of tone from financial text, Antweiler & Frank (2004) extract tone from message activity in chat rooms and analyze its impact on trading volume. Tetlock (2007), Engelberg (2008), Li (2008), Tetlock et al. (2008), Li (2010) are some of the other important studies which have used "bag-of-word" as well as machine learning approach to classify financial texts as positive or negative. These studies have used 10-K reports, newspaper articles, message boards, and press releases as sources of the text. Loughran & 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 & Wu (2013) study the impact of tone, calculated from news stories and use of term weighing for tone calculation respectively. Kearney & Liu (2014) provides a survey of methods in text tone in finance. Solomon et al. (2014) shows how media coverage of fund holdings affects investors' fund allocation. Kim & Kim (2014) study the relationship between investment tone calculated from message postings in Yahoo! Finance and stock returns. Chen et al. (2014) analyze the impact of social media calculated tone on stock returns and earnings surprises. Siganos et al. (2014) use Facebook's Gross National Happiness Index to examine relationship between daily tone and trading behavior. Further, Loughran & McDonald (2015) study the different dictionaries and their respective suitability for analyzing financial documents. Loughran & McDonald (2016) do a survey of the textual analysis in Accounting and Finance. Kostopoulos

& Meyer (2018) use acoustical analysis and Google FEARS index based on economic terms to analyze the individual investor trading behavior.

3 Methodology

3.1 Tone Quantification

We calculate the tone for each speech by classifying it as a collection of sentences. Also, for instances where there are multiple speeches on the same day, the content for all is analyzed as one. After downloading the speeches, the content is parsed and converted to all lower cases. We remove references (if any) from the content and then identify all possible punctuation marks in the text. Following this, the text between two full stops; a full stop and a question mark; and between two question marks is classified as a sentence. A complete speech is thus broken down into a collection of sentences. For each sentence, words are classified into two categories, valence shifters (adjectives and adverbs) and polar words/phrases (positive/negative tone words/phrases).

The polar words are taken from the LM dictionary and the phrases are extracted similar to Apel & Grimaldi (2012) and Apergis & Pragidis (2019). Thus phrases with a noun and a verb form such as "raise growth", "robust growth" and "rising employment" are treated as positive and others such as "increase in unemployment", "fall in output" and "decrease in growth" are categorized as negative. We further ensure that there is no duplication of polar words/phrases among LM dictionary and the ngram classification. The ngram phrases are used in conjunction with LM polar words since certain verb forms are not categorized as either positive or negative in the LM dictionary (e.g. "increase") since their meaning depends on the noun form they are used with, for example "increasing GDP growth" is positive whereas "increasing unemployment" is negative. Hence ngram phrases are used to ensure tone quantification is done appropriately for such scenarios.

The valence shifters are taken from Kennedy & Inkpen (2006), Polanyi & Zaenen (2006) and Schulder et al. (2018). These valence shifters can be further classified into four categories, i.e., amplifiers ("absolutely", "acutely", "very"), de-amplifiers ("barely", "faintly", "few"), negators ("not", "cannot") and adversative conjunction ("despite", "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.[4] This is done because adversative conjunction such as "but" will amplify the argument after it and weight down the argument before it.[5] The negators are given a value of -1.

Thus, for each sentence, first, the polar words/phrases are identified and given the weight of +1/-1, following which valence shifters are identified around each polar word/phrase from the beginning till the end of the sentence. Thus, each polar word/phrase along with its set of valence shifters are classified as a word cluster for each sentence.

We show that, in comparison to the new process and updated dictionary, the existing LM dictionary and "bag-of-words" approach can lead to incorrect quantification of tone. An example for the same is presented below:

> "a few people involved in the protected industry might benefit from the tariffs, but the economy is worse off overall."[6]

Using the "bag-of-words" approach and existing dictionary (LM) the tone of the above sentence is calculated as:

[4] The weight, 0.8, is as per the existing literature. We verify the results by varying the weight of valence shifters from 0.5 to 0.9 and our results continue to hold.

[5] E.g. "The economy is doing well but the rising prices are a concern."

[6] This sentence is taken from one of the speeches of Canada's central bank governor Stephen Poloz delivered on 4th January, 2019.

$$\frac{(+1)[=\text{benefit}] + (-1)[=\text{worse}]}{11} = 0$$

Now, using the methodology specifed in this paper, the tone is calculated as follows:

Firstly, polar words/phrases are identified from the sentence followed by valence shifters around these polar words/phrases. Thus each sentence is divided into clusters with respect to polar words/phrases such as:

1. *a* ***few*** *people involved in the protected industry might* ***benefit*** *from the tariffs*

2. ***but*** *the economy is* ***worse*** *off overall*

Thus, the above sentence is divided into two clusters with ***few*** being a valence shifter (de-amplifier) to the polar word "benefit" in the first cluster and ***but*** being a valence shifter to the word "worse" in the second cluster.

The tone calculated is as follows:

$$(-0.8)[=\text{few}] + (+1)[=\text{benefit}] = 0.2$$

$$(-0.8)[=\text{but}] + (-1)[=\text{worse}] = -1.8$$

$$\frac{(+0.2)[=\text{first cluster}] + (-1.8)[=\text{second cluster}]}{13} = -0.123$$

The number of non stop-words in the denominator is higher in case of new methodology due to the categorization and quantification of two valence shifters.

Tables 1 and 2 present the distribution and examples for the presence of various types of valence shifters in the speeches of the three nations along the difference in tone quantification using the LM method and new methodology (NM) introduced in this study.

Table 1: Valence Shifter Statistics

Country	% of Sentences containing valence shifters	% of Adversative Conjunction	% of Amplifier	% of De-amplifier	% of Negator
USA	37.91%	16.60%	53.26%	10.86%	19.26%
UK	42.26%	18.34%	47.78%	10.08%	23.04%
Canada	35.87%	17.58%	52.60%	9.91%	19.90%

Note: This table presents the distribution of valence shifters in the speeches for all three nations.

3.2 Empirical design

Return is calculated as per the formula below:

$$R_i = (P_i - P_{i-1})/P_i$$

Where i denotes the respective day.

We use central bank speech tone to explain the stock market returns of three major developed English speaking nations: US, UK, and Canada by testing their respective market indices.

A number of past studies, including Tetlock (2007), while analyzing the relationship between tone and index return have used VAR (Vector Autoregression). However, we do not employ VAR and use OLS since the speeches are delivered intermittently. Hence, there are days as well as months when there are no speeches. Thus, in this case, if we use VAR the number of observations reduces drastically.

Table 2: Speech Valence Shifters

Country	Valence Shifter Type	Valence Shifter Word	Sentence	Date and Speaker	Tone LM	Tone New Methodology	Comment
USA	Adversative Conjunction	“but”	“during this period, there were few issues of controversy between banks and securities firms, the most notable exception being the narrowly focused ***but*** heated disagreement as to whether banks should be allowed to underwrite revenue bonds.”	Mark Olson, 13-03-2006	-0.11	-0.15	The effect of the word “disagreement” is accentuated by the the presence of adversative conjunction “but” before the phrase “heated disagreement”
UK	Adversative Conjunction	“but”	“unexpected, generalised, and persistently falling prices then mean being correlated with consumption delay in japan, ***but*** the effects do not look large.”	Mark Carney, 12-03-2015	-0.24	-0.20	The “but” before the phrase “effects do not look large” decreases the negative connotation of the sentence.
USA	Amplifier	“very”	“in general, we have a ***very*** poor understanding of the forces driving speculative bubbles and the role played by monetary policy.”	Donald Kohn 16-03-2006	-0.08	-0.13	“very accentuates the impact of “poor” thus ensuring the coefficient magnitude is correct.
Canada	Adversative Conjunction	“but”	“the bank of canada’s current view is that economic growth in canada will be relatively modest in the first half of 2002—between 1 and 2 per cent, on an annualized basis—***but*** that it will accelerate in the second half—to a range of 3 to 4 per cent—and strengthen further in 2003.”	David Dodge 31-01-2002	0.04	0.08	“but” accentuates the impact of “strengthens” thus ensuring the coefficient magnitude is correct.
Canada	De-amplifier	“few”	“a ***few*** people involved in the protected industry might benefit from the tariffs, but the economy is worse off overall.”	Stephen Poloz 04-01-2019	0	-0.13	The use of “few” diminishes the impact of “benefit” and ensures correct coefficient magnitude.

Note: This table presents the examples for the four types of valence shifters for each of the four nations.

Also, since the impact of tone can be delayed due to socio-economic reasons we test it for up to five lags. The lags are kept in accordance with Tetlock (2007).

Thus, the below equation is tested for each country:

$$R_t = a_0 + \sum_{n=1}^{5} a_n Tone_{t-n} + \sum_{i=1}^{3} b_i R_{t-i} + d * \text{Controls} + \gamma_t \tag{1}$$

Where n ranges from 0 to 5 and controls include the day of the week and month dummy for time series controls; as well as average words per sentence (awps) and percentage of complex words (per_CW) as speech level controls.

The two variables of speech controls (awps and per_CW) are the main constituents of the three widely used readability measures i.e. FOG Index, Flesch Kincaid Index and SMOG Index. Thus we use these two control variables to account for the readability and complexity of speeches (Gunning et al. (1952), Li (2008), Biddle et al. (2009) and Miller (2010)).

4 Data

The data are acquired from an array of sources due to the varied nature of variables. All the speeches are downloaded automatically using a link extractor from the official website of each country's central bank.[7] These three nations are selected because of two reasons. First, these are the major English-speaking nations and second because these are among the largest countries in terms of their stock market capitalization (approximately 63%

[7]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 confound our results of speech tone quantification.

to the world's stock market capitalization as of 2020). The tone extraction methodology introduced in this study (using valence shifters) works best for the English language. This is because if the speeches are translated from any other language into English some part of the meaning might get lost due to the idiosyncratic peculiarities of that language.

The index data for all countries is downloaded from Bloomberg.

5 Analysis and Results

We first look at the summary statistics for return as well as speech variables for all nations. Table 3 and Table 4 specify the speech statistics for each country. We get the speeches from the earliest period available for each countries' official website. The longest time period of availability is for the U.K. and Canada. The U.K. also has the highest number of speeches whereas the U.S. has the highest number of average speeches per month. Also, Canada has the lowest number of average speeches per month among the three developed markets.

Table 3: Speech Statistics

Variable/Country	Time Period	Total Number of Speeches	Daily Speeches after combining for same day	No. of Positive tone Speeches (D)	No. of Negative tone Speeches (D)	Avg. No. of Speeches per month
USA	Jan 2006 - Feb 2020	797	693	146	547	4.1
UK	Apr 1996 - May 2020	1074	648	62	586	3.4
Canada	Mar 1995 - Jul 2020	568	548	202	346	1.7

Note: This table presents the summary statistics for speech frequency with respect to daily and monthly levels for the three nations. The data are obtained from the 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 below shows the index and return statistics for each country. The average number of trading days is broadly the same for all nations.

Figures 1, 2, and 3 present the movement of speech tone and the index return across time for the three nations. A cursory visual inspection shows that for all three nations the variables follow each other's movement. On

Table 4: Speech tone Statistics

Country	Time Period	Max	Min	Mean	SD
USA	Jan 2006 - Feb 2020	0.2949	-0.3403	-0.0605	0.0864
UK	Apr 1996 - May 2020	0.2892	-0.3329	-0.0589	0.0649
Canada	Mar 1995 - Jul 2020	0.2623	-0.2175	-0.0212	0.0691

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

Table 5: Index Return Statistics

Country	Main Index	Mean Return Main Index (Daily - %)	Trading days per year
USA	S&P 500 Index	0.02339	251
UK	FTSE100 Index	0.00548	252
Canada	TSX Index	0.02697	251

Note: This table presents the summary statistics for daily return the three nations. The data is obtained from Bloomberg for each nation.

this basis, we expect to see a significant relationship between speech tone and return for the three economies.

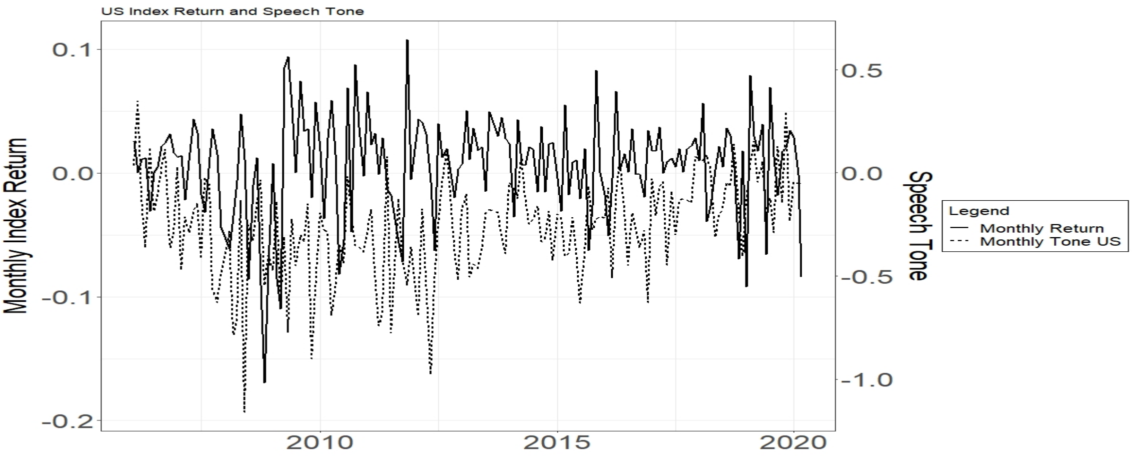

Figure 1: The monthly return (solid line) is for the S&P 500 Index (U.S.) whereas the speech tone (dotted line) is calculated by summing up the speeches over a month and then extracting tone using the specified methodolgy in this study. The return is represented by the primary Y axis and the speech tone by the secondary Y axis.

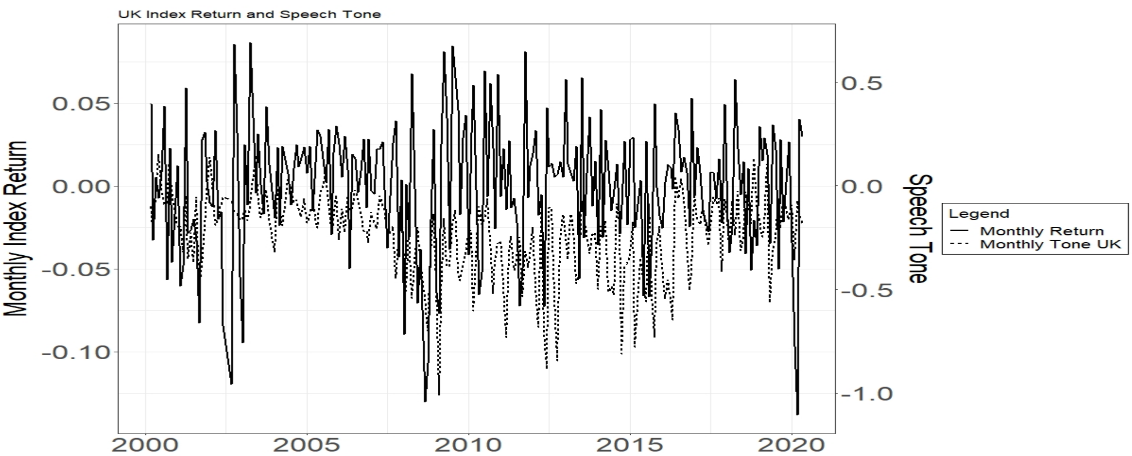

Figure 2: The monthly return (solid line) is for the FTSE Index (U.K.) whereas the speech tone (dotted line) is calculated by summing up the speeches over a month and then extracting tone using the specified methodolgy in this study. The return is represented by the primary Y axis and the speech tone by the secondary Y axis.

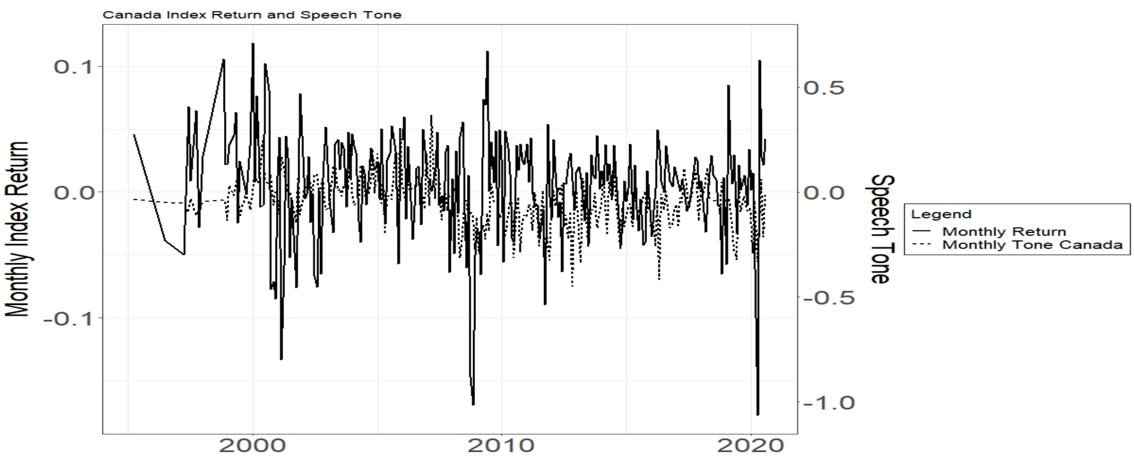

Figure 3: The monthly return (solid line) is for the TSX Index (Canada) whereas the speech tone (dotted line) is calculated by summing up the speeches over a month and then extracting tone using the specified methodolgy in this study. The return is represented by the primary Y axis and the speech tone by the secondary Y axis.

5.1 Impact of Speech tone

5.1.1 Individual Analysis

To verify the association between speech tone and index returns observed in the plots, we perform regression analysis for each of the three nations.[8] The results are presented in Table 6. We find that the speech tone significantly impacts index return for U.K. and Canada with a lag of two days (also with a lag of three days for U.K.). However, there seems to be no significant impact in case of the U.S.

The coefficient is positive for both U.K. and Canada implying that an increase in positive tone is associated with an increase in market return. Based on our results, one standard deviation change in speech tone is associated with 0.09 and 0.11 standard deviation change in daily market return for U.K. and Canada respectively.

Table 6: Daily Analysis

Country/Variable	Speech Tone Lag 0	Speech Tone Lag 1	Speech Tone Lag 2	Speech Tone Lag 3	Speech Tone Lag 4	Speech Tone Lag 5
USA	0.008 (0.005)	0.002 (0.005)	0.002 (0.005)	0.001 (0.005)	0.0007 (0.006)	0.002 (0.005)
UK	−0.0009 (0.006)	0.010 (0.006)	0.018** (0.007)	0.013* (0.006)	0.001 (0.006)	−0.002 (0.006)
Canada	0.011 (0.007)	−0.001 (0.008)	0.019** (0.009)	0.007 (0.007)	0.002 (0.007)	0.005 (0.007)
Speech Controls	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table presents the results from regressing daily index returns on lagged speech tone (and controls). The results are reported in line with equation (1). The number of observations are the same as number of speech-days for each country. The standard errors are reported in the parentheses and are all Heteroskedasticity and Autocorrelation (HAC) robust. The controls include three lags of return, day of the week, month dummy as well as speech level controls (average words per sentence and percentage of complex words). ***, ** and * indicate that the coefficient estimate are significantly different from zero at the 1 percent, 5 percent and 10 percent levels respectively.

[8] All coefficients reported in this study are HAC robust.

5.1.2 Impact of speech tone on the US stock index

For the U.S., since figure 1 suggests close association in the movement of speech tone and market return and no significant results are found for the S&P 500 index we check if speech tone impacts other market indices; or if other types of central bank communication tone are associated with the U.S. market indices.

Impact on DJIA

First, we examine the impact of central bank speech tone on another major market index i.e. the DJIA. The results are presented in table 7. We find that the speech tone impacts the DJIA index return significantly on the same day the speech is delivered.

Impact of FOMC

We analyze the impact of FOMC annoucements on both the S&P 500 and the DJIA. These annoucements are categorized by the Federal Reserve Board as 'press releases' and not speeches and hence they are not included in our initial sample for the U.S.[9]

We examine the impact of 203 FOMC statements from 1994 January to 2021 January. The results are presented in table 8. We find that for both the S&P 500 and the DJIA the FOMC statements do impact the market index significantly with a lag of 3 days. One standard deviation increase in FOMC tone is associated with a decrease of 0.251 and 0.289 standard deviation in the market return of DJIA and S&P 500 respectively.

[9]For U.K. and Canada the monetary policy annoucements are part of our database on speeches since they are categorized under speeches and not press releases by the respective central banks.

Table 7: US DJIA Analysis

Country/Variable	Coefficient	Controls	Speech Controls
Speech Tone Lag 0	0.009* (0.005)	Yes	Yes
Speech Tone Lag 1	0.002 (0.004)	Yes	Yes
Speech Tone Lag 2	0.002 (0.004)	Yes	Yes
Speech Tone Lag 3	0.002 (0.004)	Yes	Yes
Speech Tone Lag 4	0.001 (0.005)	Yes	Yes
Speech Tone Lag 5	0.001 (0.005)	Yes	Yes

Note: This table presents the results from regressing daily index returns on lagged speech tone (and controls). The dependent variable is the daily return from the DJIA Index. The results are reported in line with equation (1). The number of observations are the same as number of speech-days for each country. The standard errors are reported in the parentheses and are all Heteroskedasticity and Autocorrelation (HAC) robust. The controls include three lags of return, day of the week, month dummy as well as speech level controls (average words per sentence and percentage of complex words). ***, ** and * indicate that the coefficient estimate are significantly different from zero at the 1 percent, 5 percent and 10 percent levels respectively.

Further, we also analyze the impact of Fed speeches in light of FOMC statements to examine if the insignificance of speeches is related to FOMC statements. Thus, we examine if the impact of speeches given in the span of one week of the FOMC annoucements (i.e. 1-7 days of FOMC annoucements) are any different from the one given post one week (i.e. 8-14 days of FOMC annoucements).[10] We find that there are 154 speeches given in the span of 1-7 days of the FOMC announcements and 132 speeches given in the following one week. The results for the impact of FOMC statements on the DJIA and the S&P 500 index return are presented in table 9 and it appears that the speeches given in the immediate one week following the FOMC statements

[10] We analyze the speeches with the time of one week and not one day post FOMC announcements since the number of speeches given post one/two/three days post FOMC statements is quite small (less than 30 in most cases).

Table 8: US FOMC Analysis

Speech Tone Lag	**S&P 500**	**DJIA**	**Controls**	
Variable	Coefficient	Coefficient	Controls	Speech Controls
Speech Tone Lag 0	−0.007 (0.012)	−0.006 (0.010)	Yes	Yes
Speech Tone Lag 1	0.027 (0.017)	0.027 (0.016)	Yes	Yes
Speech Tone Lag 2	−0.010 (0.010)	−0.013 (0.010)	Yes	Yes
Speech Tone Lag 3	−0.042*** (0.014)	−0.035** (0.015)	Yes	Yes
Speech Tone Lag 4	−0.011 (0.010)	−0.006 (0.009)	Yes	Yes
Speech Tone Lag 5	0.018 (0.014)	0.019 (0.013)	Yes	Yes

Note: This table presents the results from regressing daily index returns on lagged FOMC tone (and controls). The dependent variable is the daily return from the S&P 500 Index. The results are reported in line with equation (1). The number of observations are the same as number of speech-days for each country. The standard errors are reported in the parentheses and are all Heteroskedasticity and Autocorrelation (HAC) robust. The controls include three lags of return, day of the week, month dummy as well as speech level controls (average words per sentence and percentage of complex words). ***, ** and * indicate that the coefficient estimate are significantly different from zero at the 1 percent, 5 percent and 10 percent levels respectively.

are significant in explaining index return whereas those given in the 2nd week following the statements are not. The reason for these results could be that investor attention is heightened with respect to central bank communication immediately post FOMC statements which subsequently reduces with time.

5.1.3 Panel Analysis

Next, we present a panel analysis with all three nations to analyze the impact of speech tone on market return. We employ the methodology of fixed-effects panel estimation with clustered, robust standard errors. The results are presented in table 10. It is found that the speech tone significantly impacts market return with a lag of 3 days.

Table 9: US Speech Analysis w.r.t FOMC

Speech Tone Lag	S&P 500		DJIA		Controls	
Variable	Coefficient (1 - 7 Days Post FOMC)	Coefficient (8 - 14 Days Post FOMC)	Coefficient (1 - 7 Days Post FOMC)	Coefficient (8 - 14 Days Post FOMC)	Controls	Speech Controls
Speech Tone Lag 0	0.006 (0.010)	−0.007 (0.010)	0.007 (0.010)	−0.007 (0.009)	Yes	Yes
Speech Tone Lag 1	0.004 (0.010)	0.008 (0.011)	0.001 (0.009)	0.009 (0.010)	Yes	Yes
Speech Tone Lag 2	−0.005 (0.010)	0.017 (0.011)	−0.004 (0.009)	0.015 (0.010)	Yes	Yes
Speech Tone Lag 3	0.021** (0.009)	−0.004 (0.010)	0.026*** (0.009)	−0.006 (0.010)	Yes	Yes
Speech Tone Lag 4	−0.006 (0.011)	−0.006 (0.009)	−0.005 (0.011)	−0.008 (0.009)	Yes	Yes
Speech Tone Lag 5	0.003 (0.008)	0.007 (0.010)	−0.001 (0.008)	0.009 (0.008)	Yes	Yes

Note: This table presents the results from regressing daily index returns on lagged speech tone (and controls). The dependent variable is the daily return from the S&P 500 (column 2 and 3) and DJIA Index (column 4 and 5). The results are reported in line with equation (1). The number of observations are the same as number of speech-days for each country. The standard errors are reported in the parentheses and are all Heteroskedasticity and Autocorrelation (HAC) robust. The controls include three lags of return, day of the week, month dummy as well as speech level controls (average words per sentence and percentage of complex words). ***, ** 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 the following possible explanation for the impact of central bank speech tone on market return in the U.S., U.K. and Canada. It is discussed in detail below:

6.1 Strength and Weight Argument

One framework that gives a plausible explanation for the results of the three developed nations can be traced back to the attempt by Griffin & Tversky (1992) to reconcile conservatism (Edwards (1968)) and representativeness

Table 10: Panel Analysis

Country/Variable	Coefficient	Controls	Speech Controls	Fixed Effects
Speech Tone Lag 0	0.006 (0.005)	Yes	Yes	Yes
Speech Tone Lag 1	−0.001 (0.003)	Yes	Yes	Yes
Speech Tone Lag 2	0.001 (0.004)	Yes	Yes	Yes
Speech Tone Lag 3	0.010*** (0.003)	Yes	Yes	Yes
Speech Tone Lag 4	0.001 (0.003)	Yes	Yes	Yes
Speech Tone Lag 5	0.002 (0.004)	Yes	Yes	Yes

Note: This table presents the results from panel regression on speech tone for the main index for the three nations (the U.S., U.K. and Canada). The standard errors are reported in the parentheses and are all Heteroskedasticity and Autocorrelation (HAC) robust. The controls include three lags of return, day of the week, month dummy as well as speech level controls (average words per sentence and percentage of complex words). ***, ** and * indicate that the coefficient estimate are significantly different from zero at the 1 percent, 5 percent and 10 percent levels respectively.

(Tversky & 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. Application of this framework to the impact of central bank speeches on market returns assumes that market participants analyze central bank speeches the same way readers interpret recommendation letters. Thus, before making investment decisions, they are assumed to pay attention to both the weight as well as the strength of the speeches and their possible impact on policy variables.

Both ideas are in accordance with the World Economic Forum's Trustworthiness and Confidence Index (based on Soundness of Banks, Regulation of Securities Exchange and Legal Rights Index) as shown in Figure 4.[11] It can

[11] The data are only available till 2016.

be seen that for all three nations, i.e., the U.S., U.K. and Canada the score has been higher than the world median. Also, among the three economies, Canada's score has been consistently highest and the score of U.K. has been higher in comparison to the U.S. for the majority of the time period. A conjecture can be made from the above argument that market participants have placed high "weight" on the speeches in all three nations. This combined with high "Strength" can be a plausible explanation for the statistically significant central bank tone for all three nations.

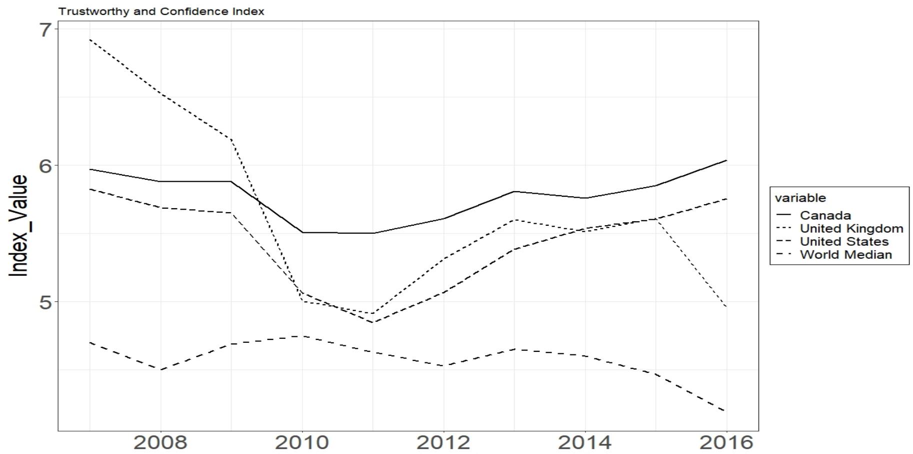

Figure 4: The figure presents the Trusthworthy and Confidence Index of the five nations from 2007 to 2016. Source : World Bank

7 Robustness

We ensure robustness in two ways. First, by examining the impact of central bank communication on English-speaking economies with differential socio-economic characterstics from the initial sample. Thus, we examine the impact of central bank communication on the emerging markets to ensure that the impact of central bank speeches is not unique to the developed markets on account of their special technological and/or socio-economic features. We also analyze the impact of central bank communication in case of an English speaking EU nation i.e. Ireland which provides for a unique case in central bank heirarchy with its own national central bank as well as a supranational central bank i.e. the ECB.

Second, we analyze the impact of central bank communication in the presence of additional macroeconomic control variables i.e. term premium, real interest rate and the inflation rate following Stambaugh et al. (2012).

7.1 The Case of India, South Africa and Ireland

One possible criticism of our results could be that the speech tone explains stock returns significantly only in the case of developed markets. In such a scenario, the results can be attributed to the economic, social, and technological advancements predominant in the developed markets. To ensure the results are not due to the special characteristics of such advanced economies we analyze the impact of speeches for two leading emerging markets where central bank speeches and communications are in the English language: India and South Africa. To further ensure robustness of the results, we analyze the impact of speech tone for Ireland, since the European Union nations provide a special case since in addition to their own national central bank they also have a supranational central bank i.e. ECB which has been known to affect the economic and financial decisions of the EU nations.

The summary statistics for speech tone and index return for India, South Africa and Ireland are presented in tables 11, 12 and 13. India has the highest number of speeches, whereas Ireland has the maximum number of average speeches per month. The mean speech tone is negative for all three nations.

The results are presented in tables 14 and 15. It can be seen that the speech tone significantly affects market return in India and South Africa with a lag of 1 day (also with a lag of 2 days for India). For the case of Ireland, it is found that the national central bank significantly impacts the speech tone as shown in column 2. However, in the presence of the ECB speeches, the national central bank speech tone impact turns insignificant.

Table 11: Speech Statistics

Variable/Country	Time Period	Total Number of Speeches	Daily Speeches after combining for same day	No. of Positive tone Speeches (D)	No. of Negative tone Speeches (D)	Avg. No. of Speeches per month
India	May 2009 - Mar 2020	695	573	190	382	1.6
South Africa	Feb 1995 - Dec 2020	444	409	136	272	1.3
Ireland	Jan 2009 - Jul 2020	553	486	126	359	3.4

Note: This table presents the summary statistics for speech frequency with respect to daily and monthly levels for the three nations. The data are obtained from the 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 12: Speech tone Statistics

Country	Time Period	Max	Min	Mean	SD
India	May 2009 - Mar 2020	0.3123	-0.6139	-0.0302	0.0802
South Africa	Feb 1995 - Dec 2020	0.2865	-0.5165	-0.0417	0.0970
Ireland	Jan 2009 - Jul 2020	0.4574	-0.3105	-0.0417	0.0787

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

Table 13: Index Return Statistics

Country	Main Index	Mean Return Main Index (Daily - %)	Trading days per year
India	Nifty Index	0.04380	258
South Africa	JSE 40 Index	0.04890	245
Ireland	ISEQ Index	0.01375	253

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

Table 14: Daily Analysis for India and South Africa

Country/Variable	Speech Tone Lag 0	Speech Tone Lag 1	Speech Tone Lag 2	Speech Tone Lag 3	Speech Tone Lag 4	Speech Tone Lag 5
India	−0.004 (0.011)	−0.018** (0.008)	0.014* (0.007)	−0.005 (0.006)	0.001 (0.007)	0.003 (0.007)
South Africa	−0.003 (0.007)	−0.011* (0.006)	0.006 (0.006)	−0.005 (0.007)	−0.005 (0.007)	−0.002 (0.006)
Speech Controls	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table presents the results from regressing daily index returns on lagged speech tone (and controls). The results are reported in line with equation (1). The number of observations are the same as number of speech-days for each country. The standard errors are reported in the parentheses and are all Heteroskedasticity and Autocorrelation (HAC) robust. The controls include three lags of return, day of the week, month dummy as well as speech level controls (average words per sentence and percentage of complex words). ***, ** and * indicate that the coefficient estimate are significantly different from zero at the 1 percent, 5 percent and 10 percent levels respectively.

Table 15: Ireland Analysis

Speech tone	**Central Bank Impact**	**Combined Impact**		**Controls**	
Lag	Central Bank Coefficient	Central Bank Coefficient	ECB Coefficient	Controls	Speech Controls
Speech Tone Lag 0	−0.010 (0.007)	−0.012 (0.009)	−0.012 (0.014)	Yes	Yes
Speech Tone Lag 1	0.002 (0.007)	−0.00007 (0.010)	0.050*** (0.015)	Yes	Yes
Speech Tone Lag 2	0.003 (0.007)	0.001 (0.008)	0.015 (0.009)	Yes	Yes
Speech Tone Lag 3	−0.012* (0.007)	−0.005 (0.008)	−0.023** (0.012)	Yes	Yes
Speech Tone Lag 4	−0.002 (0.007)	−0.001 (0.009)	0.017 (0.012)	Yes	Yes
Speech Tone Lag 5	−0.008 (0.008)	−0.010 (0.012)	0.00005 (0.013)	Yes	Yes

Note: This table presents the results from regressing daily index returns on lagged speech tone (and controls). The results are reported in line with equation (1). The number of observations are the same as number of speech-days for each country. Column 2 presents the results for the impact of central bank speech tone whereas column 3 and 4 presents the impact of both Irish central bank and the ECB on the same speech days. The standard errors are reported in the parentheses and are all Heteroskedasticity and Autocorrelation (HAC) robust. The controls include three lags of return, day of the week, month dummy as well as speech level controls (average words per sentence and percentage of complex words). ***, ** and * indicate that the coefficient estimate are significantly different from zero at the 1 percent, 5 percent and 10 percent levels respectively.

7.2 Macro variables as addtional controls

To ensure the impact of central bank communication is not due to the absence of macroeconomic variables we add real interest rate, inflation rate and term premium as additional controls to equation 1. The analysis is done for monthly frequency to ensure comparability with the frequency of the macroeconomic variables, and the monthly speech tone is calculated by summing over the tone for all speech days of a particular month. The results are presented in table 16 and we find that for all three nations the speech tone (also FOMC tone for the U.S.) is significant in explaining the variation in the respective index returns.[12]

Table 16: Robustness Analysis - Macro Variables

Speech Lag	US FOMC	US Speech	UK Speech	Canada Speech	Speech Controls	Macro Controls
Speech Tone Lag 0	0.063 (0.039)	−0.022 (0.017)	0.055** (0.022)	0.0008 (0.024)	Yes	Yes
Speech Tone Lag 1	0.022 (0.043)	0.012 (0.019)	−0.005 (0.017)	−0.004 (0.023)	Yes	Yes
Speech Tone Lag 2	0.088** (0.038)	0.036* (0.021)	0.004 (0.017)	0.033* (0.019)	Yes	Yes
Speech Tone Lag 3	0.026 (0.039)	0.021 (0.021)	0.005 (0.017)	−0.029 (0.021)	Yes	Yes
Speech Tone Lag 4	0.028** (0.050)	0.0006 (0.022)	−0.018 (0.018)	−0.017 (0.021)	Yes	Yes
Speech Tone Lag 5	0.049 (0.074)	0.024 (0.020)	−0.023 (0.021)	−0.025 (0.022)	Yes	Yes

Note: This table presents the results from regressing monthly index returns on lagged speech tone (and controls). The results are reported in line with equation (1). The number of observations are the same as number of speech-months for each country. The standard errors are reported in the parentheses and are all Heteroskedasticity and Autocorrelation (HAC) robust. The controls include speech level controls (average words per sentence and percentage of complex words). ***, ** and * indicate that the coefficient estimate are significantly different from zero at the 1 percent, 5 percent and 10 percent levels respectively.

[12] We also repeat the analysis in table 16 with the orthogonalized Baker and Wurgler Index in lieu of the macroeconomic variables for the U.S. and find that the FOMC statements and the speeches are still significant.

8 Conclusion

The study attempts to quantify the tone from the speeches of the central bank of three developed English speaking nations (US, UK, and Canada). The method of tone quantification adds to the existing Loughran and McDonald dictionary as well as the "bag-of-words" and ngram approach by using them along with "valence shifters" and by employing the sentence as the base unit of tone quantification. We find that speech tone significantly affects main index returns for the Canada, UK as well as the United States. We ensure robustness by examining the impact of central bank communication on English speaking emerging market nations i.e. India and South Aftica along with an English speaking Eurozone nation - Ireland. Further, the methodology used in this study can be developed and used in the native language for non-English speaking nations (such as Japan, Germany, and France) to analyze the impact of central bank communication in these nations.

A List of Valence Shifters

The table A.1 below specifies the valence shifters encountered in the speeches analyzed in this study.

Table A.1: List of Valence Shifters

Word	Classification	Weight	Word	Classification	Weight
almost	De-amplifier	0.8	but	Adversative Conjunction	0.8
colossal	Amplifier	0.8	enormously	Amplifier	0.8
especially	Amplifier	0.8	extremely	Amplifier	0.8
few	De-amplifier	0.8	greatly	Amplifier	0.8
high	Amplifier	0.8	little	De-amplifier	0.8
more	Amplifier	0.8	most	Amplifier	0.8
much	Amplifier	0.8	neither	Negator	-1
no	Negator	-1	never	Negator	-1
nor	Negator	-1	don't	Negator	-1
barely	De-amplifier	0.8	not	Negator	-1
quite	Amplifier	0.8	particular	Amplifier	0.8
serious	Amplifier	0.8	significant	Amplifier	0.8
sure	Amplifier	0.8	true	Amplifier	0.8
very	Amplifier	0.8	certain	Amplifier	0.8

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

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