Textual Analysis of FOMC Releases as a Tool to Gauge Uncertainty

Thomas Cunningham

Texas A&M University

Abstract

Textual analysis has been a recent area of interest in finance and economics to glean consequential information regarding underlying sentiment of various releases and publications. Research into textual analysis to understand uncertainty, however, is limited, particularly with reference to monetary policy publications. In this paper, we use textual analysis to establish a proxy to gauge macroeconomic uncertainty from the minutes of the Federal Open Market Committee (FOMC). Our research suggests that uncertainty, as measured by our established index, may be linked with market volatility and short- and medium-term Treasury yields, which can then be used as a forecasting tool for the macroeconomy. Further, our analysis of shortcomings in the existing lexical foundations and valence shifting for sentiment analysis provides a potential roadmap for continued research into uncertainty in monetary policy publications.

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INTRODUCTION

For a majority of the Federal Reserve's history, outward communication from the Federal Open Market Committee (FOMC) has been severely lacking. "*Central bankers long believed that a certain 'mystique' attached to their activities; that making monetary policy was an arcane and esoteric art that should be left solely to the initiates; and that letting the public into the discussion would only usurp the prerogatives of insiders and degrade the effectiveness of policy*." (Bernanke, 2004). The past twenty to thirty years, however, have seen a gradual yet significant openness to inner discussions and analysis by the FOMC. This revision in candor, combined with the expansion of computer-based modeling and analysis, has led to an increased focus on the language used by FOMC members in their correspondence and releases as a signal of monetary policy decisions.

Starting in the early 1990's the FOMC has been attempting to attain desired policy objectives through directed communication and signals. While not wholly transparent, FOMC public communications give insight into the inner mechanisms and choices and the short and medium term intentions of the FOMC. These indicators of future policy intentions allow the FOMC to extend their influence on long term rates, as opposed to the prevailing policy of short term interest rate targeting (Lucca & Trebbi, 2009). Long-standing financial theory shows that these short term interest rates have some linkage to long term rates (e.g. Treasury bond yields), dating back to Fisher (1896). With indications of future monetary policy decisions in place, there may exist an influence on longer term yields, as expectations of future short term yields should be a factor in these longer term yields (Bernanke, 2004). Governor Bernanke elaborates further, "*It is worth emphasizing that the predictability of monetary policy actions has both short-run and long-run aspects. A central bank may, through various means, improve the market's ability to anticipate its next policy move. Improving short-term predictability is not unimportant, because it may reduce risk premiums in asset markets and influence shorter-term yields. But signaling the likely action at the next* *meeting is not sufficient for effective policymaking. Because the values of long-term assets are affected by the whole trajectory of expected short-term rates, it is even more vital that information relevant to estimating that trajectory be communicated…This can usually be done only by providing information about the central bank's objectives, assessment of the economy, and policy strategy*."

LITERATURE REVIEW

Baker, Bloom, and Davis (2016) establish an index of uncertainty in relation to economic policy. The research finds that changes in uncertainty (as shown through an index developed for this case) "*is associated with greater stock price volatility and reduced investment and employment in policy-sensitive sectors like defense, healthcare, finance, and infrastructure construction. At the macro level, innovations in policy uncertainty foreshadow declines in investment, output, and employment."* (ibid) The index is developed by establishing a three-tier classification system to create a measure of frequency in relation to economic policy uncertainty in newspaper articles, dating back to 1900. The tier classification system is established by reviewing news articles through all of the following filters: "economic" or "economy"; "uncertain" or "uncertainty"; and "congress", "deficit", "Federal Reserve", "legislation", "regulation", or "White House". For each article that contained an item from each set of the triple, it was marked as such. The index is then derived by measuring the frequency of marked articles by month over an initial period of 1985 to 2014. This index is extended out to 1900, expanding the first term set to include "business", "industry", "commerce", and "commercial", as well as adding "war", and "tariff" to the third set of terms. This newspaper frequency index over time is then compared to other indices, such as the Federal Reserve System's Beige Book as a measure of robustness. Baker, et al.'s reasoning for such an index is based on two general foundations. First, at the firm level, past research has shown that as uncertainty increases, there are increased incentives to hold off regarding hiring and investment projects, particularly if there are significant frictions or contractual obligations involved in the commencement or termination of such projects. At the macro level, Milton Friedman (1968) posits that "*our economic system will work best when producers and consumers, employers and employees, can proceed in full confidence that the average level of prices will behave in a known way in the future – preferably that it will be highly stable.*" Baker, et. al. (2016) continue from this position, stating that uncertainty can have detrimental effects in the economic fields of monetary, fiscal, and regulatory policy, and that there are potential links between such uncertainties and stock market volatility.

Grishman (2012) gives an overview of information extraction for textual analysis. Related to this research, maximum entropy classifiers are a type of classifier in textual analysis in order to establish a probability value associated with an established indicator function. This indicator function, as with the aforementioned Baker, Bloom, & Davis (2016) research, attaches a marker to an established set of terms, and an associated weight, if chosen. For example, if, a literary work were being analyzed to parse the text into parts of speech and it was known that adverbs made up 85% of the words that end in "ly", the indicator function could mark such "ly" terms with an 85% likelihood of being an adverb. Generally, with an indicator function using a weighted classifier, one can establish a probability that the measured data set includes that intended class label (Grishman, 2012). Ke, Kelly, and Xiu (2019) extend such textual analysis foundations towards financial text data and sentiment analysis. Ke, et al. (2019) utilize a supervised approach (as discussed in Grishman (2012)) to screen for sentiment-charged terminology to establish a positive vs negative weight in financial text to measure against stock returns.

How does one quantify the attitude of the FOMC generally from text? As a whole, a lexical, or "Bag of Words" approach is a common perspective in analyzing such texts. Examples of this include dictionaries from Loughran and McDonald (2011) in which financial and economic sets of words are designated with a "negative", "positive", or "uncertainty" sentiment (Shapiro and Wilson, 2019); Hutto and Gilbert's (2014) Valence Aware Dictionary and Sentiment Reasoner (VADER), which is geared towards social media/text language, but uses helpful contextual characteristic tools to improve how accurate the measurement of sentiment can be (Shapiro and Wilson, 2019); Google's semantic orientation score in conjunction with Factiva's semantic orientation score, which can provide links between FOMC statements and news analysis to provide "hawkish" vs "dovish" recommendations (Lucca & Trebbi, 2009); and Baker et al (2016)'s lexical scope of linked terms regarding various forms of uncertainty in news articles, among others. From here, these analyses of terms are applied to the assumed model of monetary policy decisions, which has varied throughout the research.

For textual analysis of financial literature, the aforementioned Loughran-McDonald dictionary has been used across a wide set of publications. Initially developed to measure whether publicly traded company financial performance reports (10-K's) conveyed positive or negative sentiments by creating a custom set of terms associated with positivity or negativity that are commonly included in financial performance reports. This dictionary has since been expanded to include terminology associated with uncertainty and litigious language. For example, the term "favorable" would be associated with positive sentiment, "adversely" would be associated with negative, "ambiguous" with uncertainty, and "indemnify" with litigious text. Existing research using the Loughran-McDonald index include Da, Engelberg, and Gao's (2011) research surrounding negative word counts in news articles of specific stocks, Hoberg and Phillips (2016) review of unique words that firms use to describe their products, Loughran and McDonald's (2014) follow-up research into effective communication of valuation-relevant information in financial disclosures, and Engelberg, Reed, and Ringgenberg's (2012) review of profitability of short-seller's trades around negative sentiment news events.

OBJECTIVE OF STUDY

As previously mentioned, most financial text analysis allocating sentiment values has centered on assessing whether the overall optimism indicates a positive or negative tone. A key distinction to be made, in our case, is the difference between uncertainty and risk. The existing financial sentiment analyses attempt to create a positive or negative weighting of expected performance based on risk, that is, it gives us a measurement of potential outcome likelihoods, or (at a minimum) creates an index measurement from which these likelihoods can be inferred. For example, Chen, De Hu, and Hwang (2014) analyze Seeking Alpha articles, with their analysis suggesting that as the fraction of negative sentiment-associated terms increases by 1%, it follows that scaled earnings of the referenced companies are roughly .245% below market expectations (as estimated through standard forecasts). Uncertainty, on the other hand, does not have such measurable outcome likelihoods, as future probabilities contain unquantifiable factors. To delineate the differences, "*a measureable uncertainty, or 'risk' proper…is so far different from an unmeasurable one that it is not in effect an uncertainty at all*," while "true" uncertainty represents this non-quantitative factor (Knight, 1921). More clearly, risk expresses the measurement of "known-unknowns", while uncertainty constitutes the "unknown-unknowns". Particularly since the 2008 global financial crisis, there have been increasing efforts to quantify such uncertainty. Economic forecasters have created proxies for measurement of uncertainty, such as the aforementioned Baker, et al. (2016) index, Bloom's (2009) earlier uncertainty research, in which vector autoregressions of the VIX are used to measure the dissipation of the negative effects associated with uncertainty shocks, Bachmann, et al. (2013), where ex-ante forecast disagreement in survey expectations data is used to create an index of underlying uncertainty, and Jo & Sekkel (2019), in which a placeholder measurement for uncertainty is developed through measurement of ex post errors from survey forecasts. If the proxy measurement for uncertainty accurately represents underlying macroeconomic uncertainty, high levels of implied uncertainty may forecast negative consequences for policy decisions and potentially the economy at large, while low implied uncertainty is shown to forecast stable growth.

Our objective in this research is to use an assessment of FOMC minutes over time to create a similar style proxy index for economic uncertainty, and to measure whether this index provides an accurate measurement of underlying uncertainty, and the potential effects the central bank's view of uncertainty may have on the economy. From here, we would like to see whether our uncertainty index is associated with various macroeconomic indices and its potential impact on interest rates, as well as how it measures up against existing positive vs negative sentiment analyses. These positive vs negative analyses entail the creation of a sentiment index based on whether the tone of FOMC minutes leans positive or negative, and to what extent it leans in that direction (as opposed to our measurement of tone measuring uncertainty). Cannon (2015) establishes such an index measurement by marking terms associated with positive sentiment and negative sentiment and establishing a total positive count and total negative count for the measured set of text. From there, the overall tone value is determined by dividing the difference in the count of positive and negative terms by the total number of marked terms from the text.

DATA

FOMC releases come in various forms. In the most detailed sense, the Federal Reserve Board of Governors maintains a public archive of FOMC transcripts. An advantage of these transcripts is that all comments and statements from internal FOMC meetings are recorded, with clear delineations of speakers. A drawback, however, is that these records of proceedings are withheld for at least five years from the public view. Although not necessarily a timely source, the details from the transcripts can be used in conjunction with current other FOMC resources to analyze clarity of the sentiment measurement, such as using transcripts as a benchmark to measure the robustness of an index. Additional contemporary tools and data sources include FOMC's Tealbook: "Report to the FOMC on Economic and Monetary Policy", which gives insight into the various monetary policy alternatives based on current economic conditions and forecasts; FOMC Minutes, which summarize the major topics for discussion of FOMC meetings, but do not contain clear delineations by speaker/member of projections or intentions. In conjunction with the FOMC Minutes, there exists a release of the Summary of Economic Projections (SEP). The SEP gives basic statistics and visualizations of individual FOMC members on their economic projections without attributions to specific members. Lastly, the governors of the Federal Reserve Board and the presidents of the twelve regional Federal Reserve Banks will give regular speeches, which are either archived on the respective bank's website or available from the bank's libraries.

Recently, there has been a significant interest in the analysis of the specific language of the aforementioned FOMC releases. As previously stated, the information available to the public of FOMC decisions and discussions is carefully measured. Bernanke (2004) states, "*Specifying a complete and explicit policy rule, from which the central bank would never deviate under any circumstances, is impractical. The problem is that the number of contingencies to which policy might respond is effectively infinite (and, indeed, many are unforeseeable)*". That is not to say that there is not a role for FOMC language and actions being released to the public. Transparency in this limited sense can effectively allow financial markets to forecast monetary policy decisions and adjust accordingly, creating a potentially more fluid system in which policy decisions are made. A contemporary example of this is shown in a recent FOMC rate cut (25 basis point decrease, 1 August 2019), which had been largely priced into the market. Due to the limited nature of these releases, any and all insight which can be accurately gleaned from analysis of these releases can further help markets prepare for and project monetary policy decisions by the FOMC.

Our foundation for this research is to use textual analysis of FOMC minutes to establish an uncertainty index. While there are many sources of data which can be used in this case, we have decided to limit our analysis to solely minutes, as they are a set of data that is detailed enough that it contains relevant information regarding our research and current enough where we can apply our measurement techniques and index values contemporaneously with current financial data since, ultimately, the goal is to quantify the impact on markets. Additionally, the formatting of FOMC minutes is such that we can ensure that a similar grouping of text analysis be measured across time. In line with this formatting, we have limited our initial analysis to FOMC minutes from January 2009 to the present, as earlier minutes did not follow the current format. This truncated analysis was selected through hand audits of recent FOMC Minutes to ascertain which subsections of FOMC Minutes structures are forward looking. As we are attempting to measure uncertainty, this is an inherently forward-looking sentiment, and we would like to limit potential noise of backward looking sentiments. As a measure of robustness, we have additional data sets of the full FOMC Minutes text from 2009 – 2019, as well as full FOMC Minutes text from 1999 – 2019 to view the performance of such an index over a larger time period, as well as the Economic Policy Uncertainty and Monetary Policy Uncertainty Indices developed by Baker, et al (2016).

METHOD

Our project analyzed FOMC releases, focusing initially on the minutes, using textual analysis to establish an index of uncertainty, which we can, by extension, interpret how this macroeconomic uncertainty correlates macroeconomic performance. From our analysis, our model can be used as a tool to analyze the effect of uncertainty on monetary policy decisions based off of uncertainty information from the FOMC. Additionally, we measured our index against a set of interest rates, stock indices, and macroeconomic series, to measure our index against the existing Baker, et al. research and positive vs negative sentiment analyses.

Our analysis differs from existing research in several ways. Most existing research has slightly differing results, as there is no uniform baseline for the lexical “Bag of Words” nor application of sentiment values with the indicated terms from the lexical dictionary. Commonly used lexical dictionaries include the *syuzhet* R package dictionary, which was developed to provide detailed sentiment analysis, measuring how the sentiment changes as the text progresses, but is particularly directed towards prose or literary analysis; Hu and Liu's (2004) lexical dictionary developed to analyze large sets of opinion data with positive and negative sentiment, but is (as with the *syuzhet* dictionary) not focused towards financial texts; and the aforementioned Loughran-McDonald dictionary. Our initial Bag of Words foundation consisted of hand-audits of recent FOMC minutes measured against the existing Loughran-McDonald "uncertainty" classifier sub-dictionary. Our hand audits were conducted to mark terms associated with uncertainty as an unweighted binary maximum entropy classifier function would. This was compared to the Loughran-McDonald "uncertainty" classifier to determine whether the financial text lexical foundation terms matched our hand-flagged terms. After comparison of the hand-audits with the Loughran-McDonald terminology, it was determined that there was significant enough overlap to use the Loughran-McDonald dictionary as our lexical foundation.

Our research separates itself from the existing literature in the following way: Most existing literature that utilizes the Loughran-McDonald lexical foundation focuses on the positive vs negative measurement to understand optimistic/pessimistic sentiment or disagreement regarding economic performance, but little has been done to measure uncertainty. Confident that the Loughran-McDonald lexical foundation would be sufficient for our needs for this project, we used R (more specifically utilizing the *tidytext* package) to read a truncated version of each set of FOMC minutes into a text format which could then be separated by sentence. We limited the initial text analysis to the subsections of the FOMC minutes which include "Staff Economic Outlook" and "Participants' Views of Current Conditions and the Economic Outlook", as these are the subsections which are more applicable to a forward-looking scenario. Other subsections discuss pertinent economic data, but are essentially an overview of past events, rather than a forecast of what is to be. Since uncertainty is an inherently forward-looking sentiment, we hypothesized that the aforementioned "Outlook" sections would allow for a more accurate proxy to measure uncertainty, limiting potential noise from backward-looking text. We believe that a sentence-by-sentence analysis is also applicable to our situation (rather than solely the commonly used word-by-word analysis), as we are tying our text separation and lexical foundation to a weighted valence analysis. Existing word-by-word analysis is normally measured against a lexical bag of words with a Maximum Entropy Classifier, as defined earlier. Our research differs from the existing research, because it uses the foundation of the Maximum Entropy Classifier as a binary filter with which we apply a valence weighting system to after the fact. A valence weighting system reviews the words surrounding the marked text from the Maximum Entropy Classifier to analyze and designate an amplitude associated with such a sentiment. For example, solely measuring sentiment with a word by word analysis would give the sentences "A few participants noted that there remained a high level of **uncertainty** associated with international developments" and "Some participants observed that trade **uncertainties** had receded somewhat" the same impact on the total document sentiment value (uncertainty indicator term in bold). Applying a valence weighting system with a value of +/- 2 (the default value) reviews the two terms preceding and two terms following the marked term associated with uncertainty to determine whether these surrounding terms imply a large or small change in uncertainty, thus giving the former sentence a stronger valence weighted value than the second sentence.

Once the text is separated, we run a supervised model of a binary unweighted Maximum Entropy Classifier, with our indicator function referencing the "uncertainty" subsection of the Loughran-McDonald lexical foundation. To clarify, this process eliminates sentences in our subset which do not contain any of the indicator terms listed in the Loughran-McDonald "uncertainty" lexical foundation. The remaining sentences have an implied level of uncertainty, which the amplitude is measured in the following step. In order to establish a sentiment measure, we applied our existing data subset to the *sentimentr* R package to apply the language surrounding the uncertainty terms to a valence shifter. This allows us to apply a weight to scenarios which could imply increasing vs decreasing uncertainty, the strength of such an increase or decrease, and the effect of adversative conjunctions. Once this process has been run, we have a sentence by sentence uncertainty value for each set of minutes. These values are then summed, giving us a total general uncertainty for each set of minutes, which we then normalize, 100 being an existing, or natural level of uncertainty. By running this through each set of minutes from January 2009 to the present, we established a time-series against which we can measure correlation with various indices.

To summarize our analyses, we have two uncertainty values associated with each set of minutes. First, we have our "counts" measurement, which is the total number of uncertainty references using the Loughran-McDonald dictionary as our foundation. Second, we have our valence shifted "tone" measurement, which applies the aforementioned weights to each sentence associated with uncertainty through the valence shifting process, which is then summed for a total tone index.

Given as an equation, our counts measurement is given thus:

$$counts = \sum_{1}^{S} \sum_{i=1}^{N} h_i$$

(where h is the value assigned to the i^{th} indicator function (in this case either 1 or 0, i.e. unweighted), N is the number of words in the selected sentence, and S is the number of sentences in the selected text)

RESULTS and ROBUSTNESS CHECKS

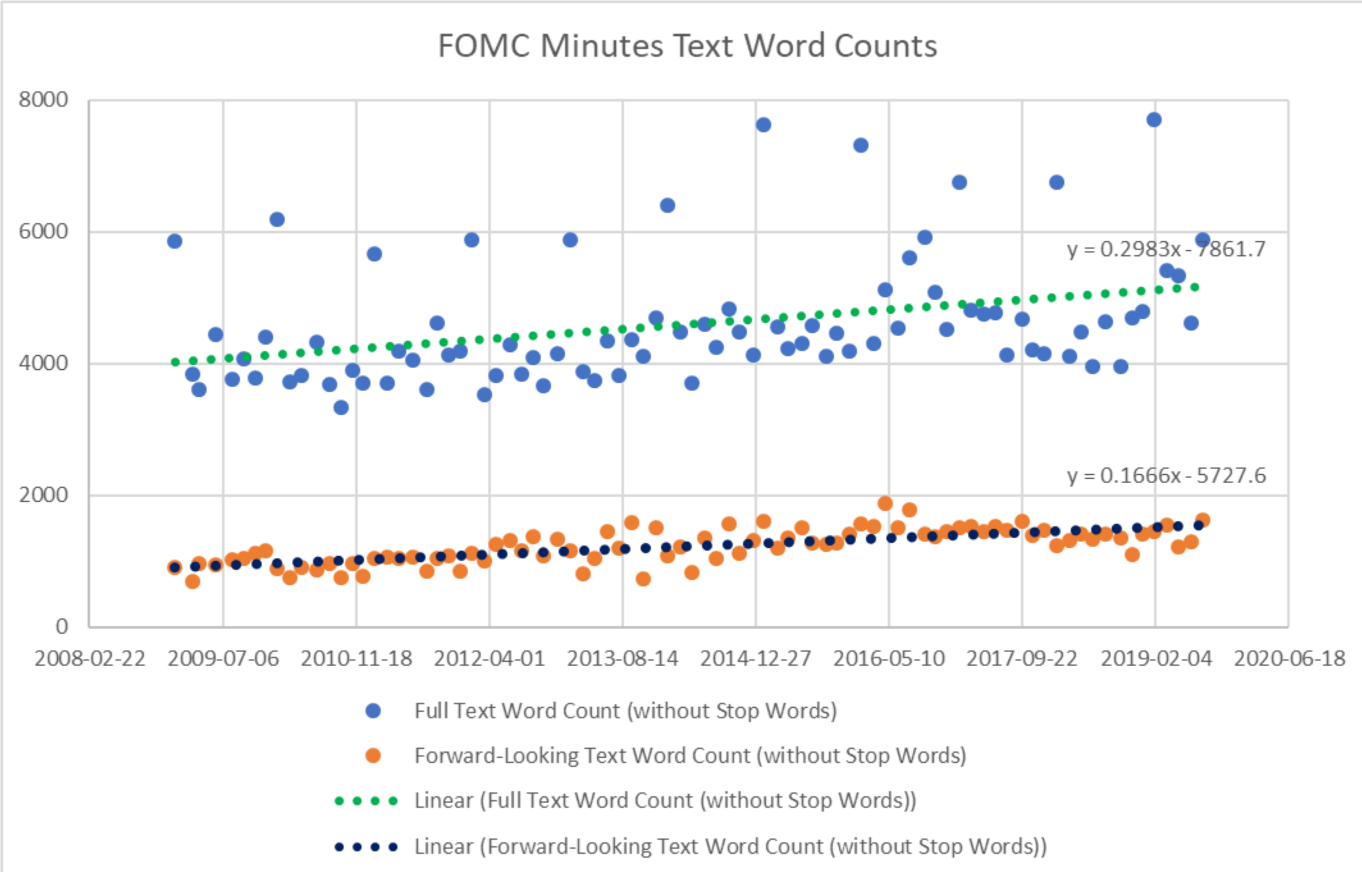
As our uncertainty analysis was based off of a two-part process (unweighted binary maximum entropy classifier, which is then applied to a weighted valence analysis), we had two measures against which we could run our robustness checks. First, we had the number of uncertainty indicated terms in each of our three data sets (forward looking 2009 – 2019 minutes, full 2009 – 2019 minutes, and full 1999 – 2019 minutes). In order to ensure that this would not be skewed by increasing total words in FOMC minutes, we calculated this as two proportions. One proportional measurement was the number of uncertainty indicated terms as a fraction of total sentiment-associated terms (positive, negative, and uncertainty), which is similar in nature to the existing positive vs negative sentiment literature. This was done to gauge overall level of uncertainty as related to sentiment, generally.

$$Uncertainty\ Sentiment\ Proportion = \frac{\#\ of\ Uncertainty\ Indicated\ Terms}{\#\ of\ Uncertainty + \#\ of\ Positive + \#\ of\ Negative\ Indicated\ Terms}$$

The existing literature (positive vs negative) measures the net number of positive minus negative terms divided by the total number of sentiment related terms. For our robustness check, the net positive/negative measure as a proportion of general sentiment is as given above, except the numerator is replaced with the difference between the number of positive indicated terms and the number of negative indicated terms.

Next, a proportional measurement was created as a fraction of total words used by the FOMC in their minutes. This was done to remove the possibility of a change in uncertainty indicated terms being solely due to an increase in the amount of words used overall. In order to weed out potential noise, we utilized *tidytext's* parsing abilities to remove "Stop Words". Stop Words are generally defined as extremely common words which do not have any valuable analytical information which can be derived from them, largely made up of prepositions. Examples include "also", "am", "an", "of", etc.

$$Uncertainty\ Word\ Proportion = \frac{\#\ of\ Uncertainty\ Indicated\ Terms}{\#\ of\ total\ words - \#\ of\ Stop\ Words}$$



Secondly, we had the valence-shifted measure of uncertainty, in which a tone sentiment was applied to the uncertainty terms. For this second analysis sample, it became apparent that the existing lexical foundations from which a valence shifting tone measurement could be applied to data was insufficient for our project needs. This is so, because the existing valence shifting analysis to apply this tone measure uses the aforementioned weighted maximum entropy classifier model, but the existing applications exist solely for positive vs negative tone measurement. Although our data samples were limited to indicators associated with uncertainty, the tone measurement creates an index measuring positive uncertainty vs negative uncertainty, rather than increasing or decreasing uncertainty. To clarify, our intention with using the valence shifted tone measurement was to measure whether the language surrounding the indicated uncertainty term implied increasing or decreasing uncertainty, and, if so, how large of an increase or decrease it is. Upon a more thorough review of the *sentimentr* valence shifting package, it became clear that the applications of weights were not applied in the manner which we intended. The existing valence shifting weights are developed around a positive vs negative sentiment lexical foundation, rather than uncertainty. The *sentimentr* package takes its weighting and text analysis from a combination of the aforementioned *syuzhet* package dictionary with the Hu and Liu dictionary, which (as previously noted) is made for positive vs negative sentiment analysis of non-financial texts. For example, the sentence "Some participants observed that trade uncertainties had receded somewhat", as mentioned earlier, would (on its face) be associated with a decrease in uncertainty. Using the *sentimentr* package, however, the indicator term is revised to "receded" (negative sentiment) with a valence shifter (de-amplifier) applied for the term "somewhat". Thus, the end sentiment value reflects a slightly negative uncertainty. Positive or negative uncertainty is essentially meaningless, however, as we are attempting to measure increasing or decreasing uncertainty. With that, we have focused our remaining analysis on the proportion of uncertainty indicator values over time. For future research, we have completed hand audits of recent FOMC minutes using a custom measurement of valence shifting to gauge increasing vs decreasing uncertainty.

Our indices were measured for contemporaneous correlation with the CBOE Volatility Index (VIX), realized volatility of the S&P500, and the average growth rate of the S&P500. In addition, we measured our indices against these benchmarks at two time periods: *during* the FOMC meeting, and *upon release* of the minutes from the respective meeting. This was done to measure whether the statements themselves could have a potential impact on these macroeconomic benchmarks or whether the indices developed from the statements reflect an underlying existing economic sentiment. Our belief was that these statements would not have a substantial effect upon release. As previously discussed, the FOMC Meeting minutes are just one of several FOMC releases. Due to the steady release of information from the FOMC and the regional banks, this allows for more smoothing of economic shocks to various perceived policy decisions. To clarify, as information (which may imply future actions), through various forms, is released to the public, markets are able to factor this information and the beliefs drawn from it to adjust their forecasts accordingly. This is not to say that the FOMC releases contain deliberate statements regarding definitive future actions, solely that the measured release of non-misleading information to the public allow markets to adjust accordingly. As mentioned earlier, take into account that the August rate change was well expected by the public.

Our correlation analysis showed mixed results. While our forward-looking and full text uncertainty indicator measure as a proportion of general sentiment reflected strong correlations with the VIX and realized volatility of the S&P500, our uncertainty indicator measure as a proportion of total words did not (shown below). Our uncertainty indicator measures as a proportion of general sentiment performed similarly to a measurement of net positive/negative indicated terms as a proportion of general sentiment; however, the net positive/negative correlations held when expanded to be a proportion of overall words. Our uncertainty indicator measure as a proportion of overall sentiment and both proportional measures of net positive/negative indicators had stronger correlations with the VIX and realized volatility of the S&P500 than the Baker, et al (2016) Economic Policy Uncertainty (EPU) and Monetary Policy Uncertainty (MPU) indices. None of the indices measured showed noticeable correlation with the average growth rate of the S&P500. We note here that, in regards to market volatility, there does not seem to be an apparent difference between our forward-looking text measurement vs the full text measurement. As believed, there was no notable difference between the correlations based on the meeting date and the release date, thus giving greater credence to our uncertainty index as a measure of underlying macroeconomic uncertainty, as well as the efficacy of FOMC releases. An item of note regarding the correlations: the uncertainty indicator measures have a negative correlation with the VIX and realized volatility of the S&P500. While on its face this may seem counterintuitive, we stress that the uncertainty indicator index is solely a count of trigger terms associated with uncertainty, but not the sentiment reflecting whether uncertainty is increasing or decreasing. We believe that these measurements still hold value, however, as our hand audits (albeit limited to recent minutes) reflect tone adjusted uncertainty measures more in-line with a positive relationship between our index and the VIX and the realized volatility of the S&P500. As an additional confirmation of this belief, prima facie one can assume that uncertainty has been decreasing since the beginning of our measurement period (January 2009), due to the global financial crisis occurring at the time. Keeping this in mind, we believe that our uncertainty indicator measures have comparable correlations with the existing positive vs negative analysis and the Baker, et al. research, accounting for revisions to sentiment with revised valence shifting.

Index/Benchmark	**VIX**	**Realized Volatility**
Uncertainty Terms as a Proportion of General Sentiment (Forward-Looking Text)	-.503	-.410
Uncertainty terms as a Proportion of General Sentiment (Full Text)	-.517	-.390
Positive-Negative Terms as a Proportion of General Sentiment (Forward-Looking Text)	-.538	-.549
Positive-Negative Terms as a Proportion of General Sentiment (Full Text)	-.624	-.592
Uncertainty Terms as a Proportion of Total Words (Forward-Looking Text)	-.135	-.111
Uncertainty Terms as a Proportion of Total Words (Full Text)	-.232	-.111
Positive-Negative Terms as a Proportion of Total Words (Forward-Looking Text)	-.602	-.604
Positive-Negative Terms as a Proportion of Total Words (Full Text)	-.620	-.609
Baker, et al EPU	.378	.317
Baker, et al MPU	.256	.275

As an extension from this we performed regression analyses to see whether the changes in these indices (i.e. how shifts in underlying macroeconomic sentiment) affected various interests rates/yields. In this case, our regressions plotted our forward-looking uncertainty indices (as a proportion of general sentiment and as a proportion of total words), positive vs negative analysis index (as a proportion of general sentiment and as a proportion of total words), the EPU, and the MPU against changes in 3 month Treasury bills, 1 year Treasury bills, and the spread between the 10 year and 2 year Treasury notes, 10 year and 1 year Treasury note/bill, respectively, and 10 year and 3 month Treasury note/bill, respectively. As previously noted, while the FOMC has the ability to revise the Targeted Federal Funds Rate (FFR), the 3 month Treasury bill and the 1 year Treasury bill yields are subject to market forces and cannot be chosen by the FOMC. Additionally, as postulated by Harvey (1986), inversions in the spread between medium term and short term Treasuries can be a harbinger of recessions in the United States. Previous research done in ECMT 674 (Economic Forecasting) showed that the 10 year – 1 year spread was the most accurate in forecasting a recession, with a one year lag, using a probit model in which a generated likelihood greater than 40% indicated a recession. The 10 year – 2 year and 10 year – 3 month spreads have been included in this research, as they are the most commonly used yield spreads used for recession forecasting analysis, and since they had generally accurate results in my previous analysis. With that, we would like to see whether the FOMC minutes accurately reflect underlying macroeconomic sentiment to the affect that changes to uncertainty sentiment (as measured by the indices) may have an effect on these Treasury bills. As shown in the appendices, changes in the forward-looking uncertainty indicator measure as a proportion of total words suggests an effect on the 3 month Treasury bill, 1 year Treasury bill, and 10 year – 3 month, 10 year – 1 year, and 10 year – 2 year spreads in Treasury yields. This is comparable to the Baker, et al (2016) Economic Policy Uncertainty Index, which suggests that changes in the EPU index have an effect on all of the above except for the 10 year – 2 year spread.

We consider this to be a validation of our results. Not only does our forward-looking uncertainty indicator measure as a proportion of total words index seem to keep pace with leading uncertainty measurement literature, but it also suggests that underlying uncertainty may be a more influential factor on Treasury yields than a majority of contemporary financial sentiment analysis. In addition, we feel that our may hold more timely and accurate long-term predictive capacity than the EPU index, as our analysis is based solely off of analysis and discussion of FOMC members. The EPU index, on the other hand, is based off of news articles which use a limited lexical foundation to garner general sentiment. Additionally, the use of news articles has an inherent delay (due to compilation of data, interpretation of such data, creation, and release) as compared to FOMC releases. If applied to other FOMC releases, such as speeches, our index could possess real-time uncertainty analysis value. For example, Fuksa and Sornette (2015) suggest that text analysis of the Beige Book provides similar results to the FOMC Minutes, but are released 3 weeks before the meeting. Lastly, because the EPU is based off of news, there is a potential for error due to bias by the news publisher, which is unlikely in FOMC minutes releases, as intentional misdirection by the FOMC (as stated earlier) could have detrimental effects to the economy.

CONCLUSION

Textual analysis of financial releases is still in its beginning stages, even more so of FOMC texts. While analysis of overall positivity is a common setup of analysis in these existing measures, measurements of uncertainty are still a new sub field of this inchoate area of research. As existing research has shown, due to the inherent unknowns involved in measuring uncertainty (i.e. the lack of ability to assign probabilities, expected outcomes, etc.) uncertainty can have (particularly in high implied levels) detrimental effects to the macroeconomy. We consider this initial exploration into FOMC text uncertainty analysis to be a baseline from which future monetary policy textual analysis can be based. Additionally, for future research, an established uncertainty-specific valence shifting sentiment score function, similar to our hand-audited scores, could provide increased accuracy in determining underlying market sentiment. All this considered, our research suggests that there exists a link between market volatility and the text of the FOMC (particularly the proportion of sentiment-charged terms associated with uncertainty) and that there may exist an influence on the 3 month Treasury bill, and 1 year Treasury bill, and the 10 year – 3 month, 10 year – 1 year, and 10 year – 2 year Treasury yield spreads (more specifically with regards to the overall proportion of uncertainty-associated terms). Future analysis, particularly with a valence-adjusted sentiment applied to uncertainty measures may allow for further understanding of the effect of uncertainty on bond yields and macroeconomic performance.

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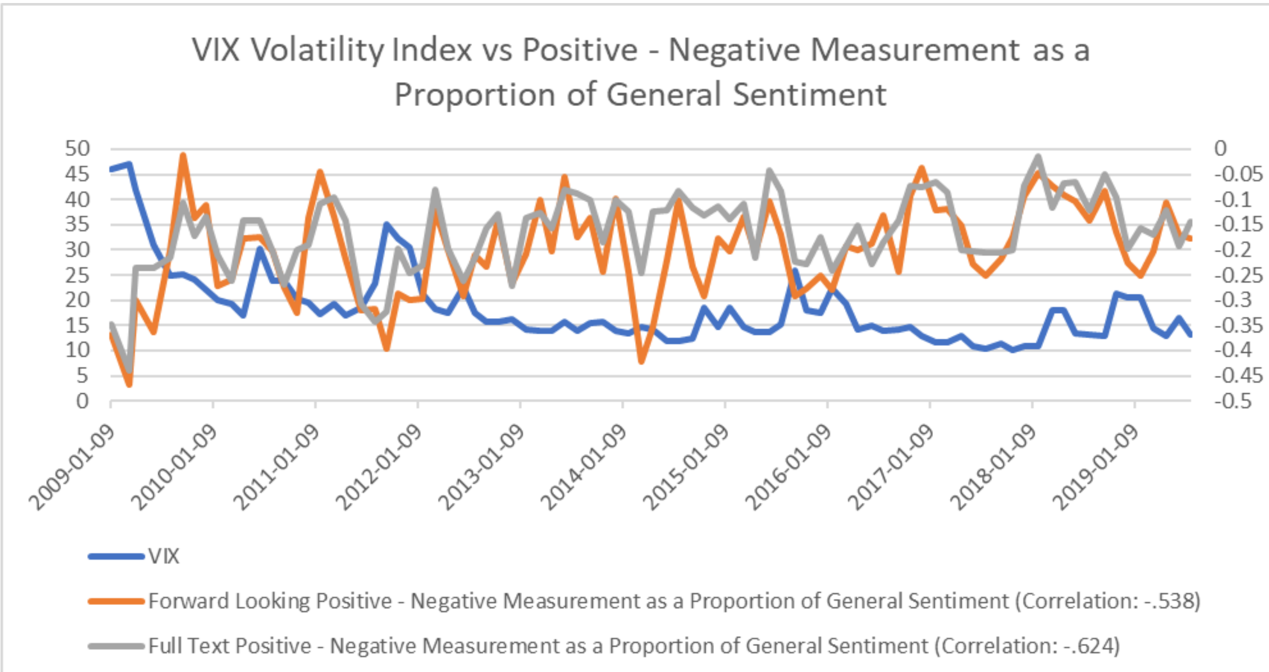
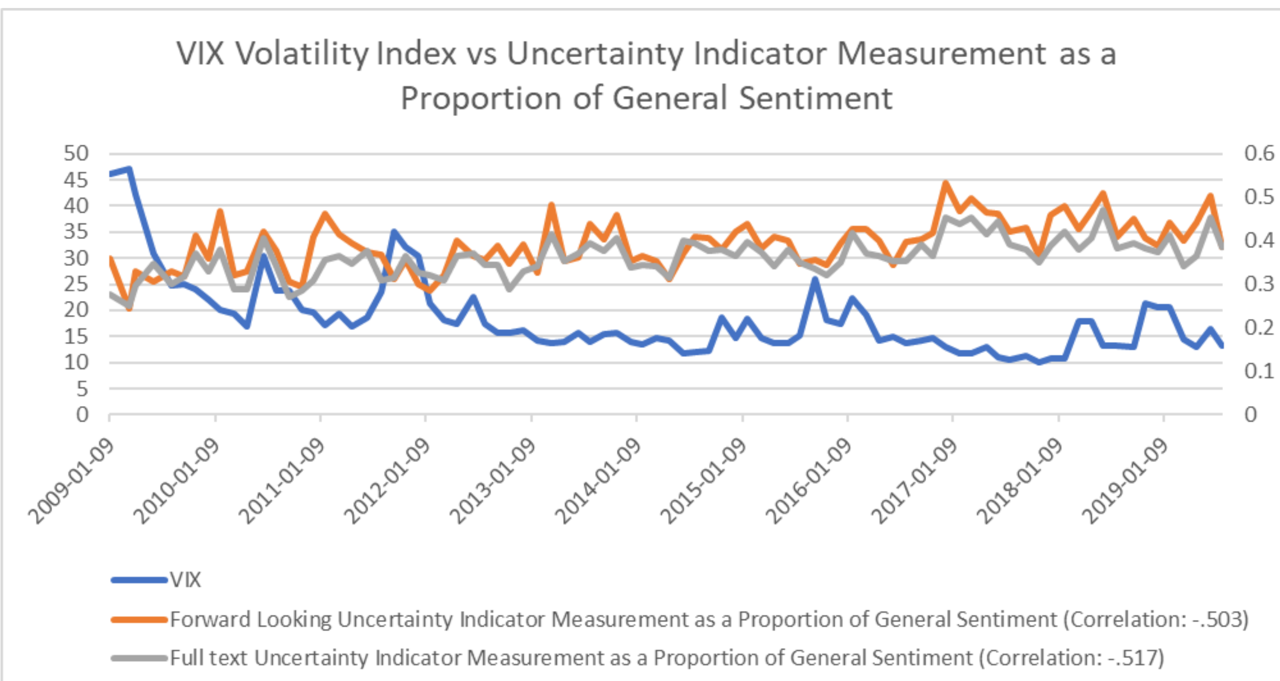
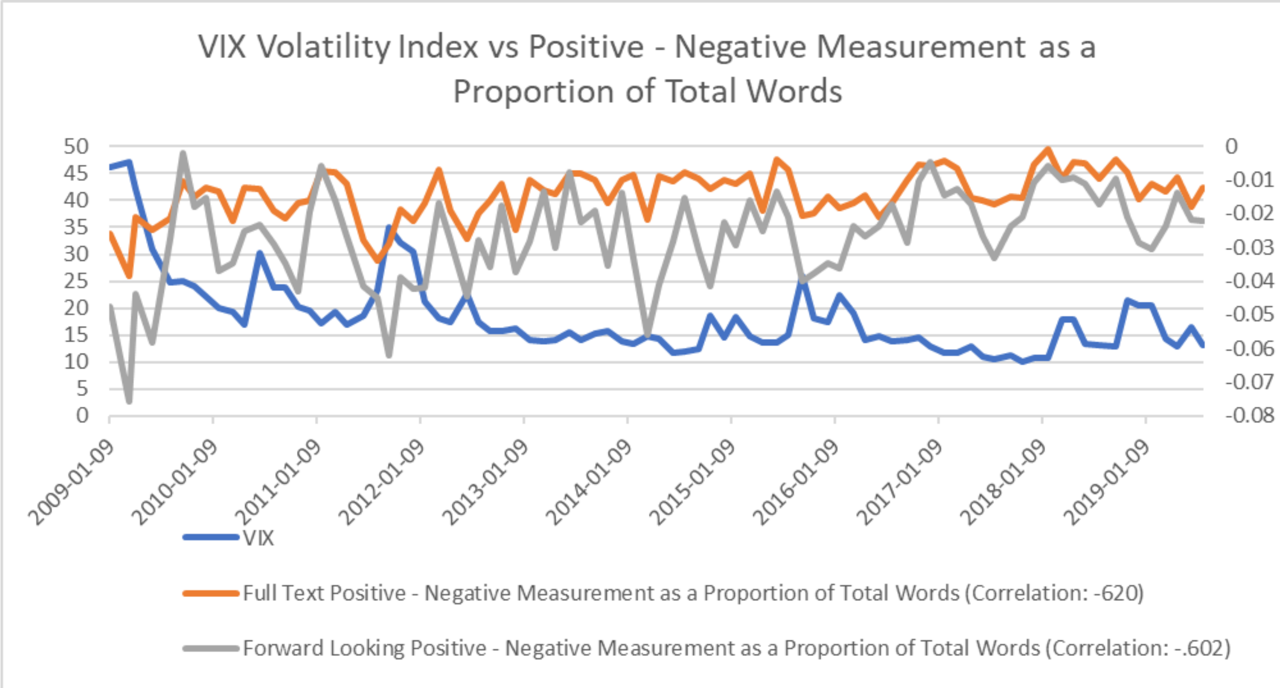
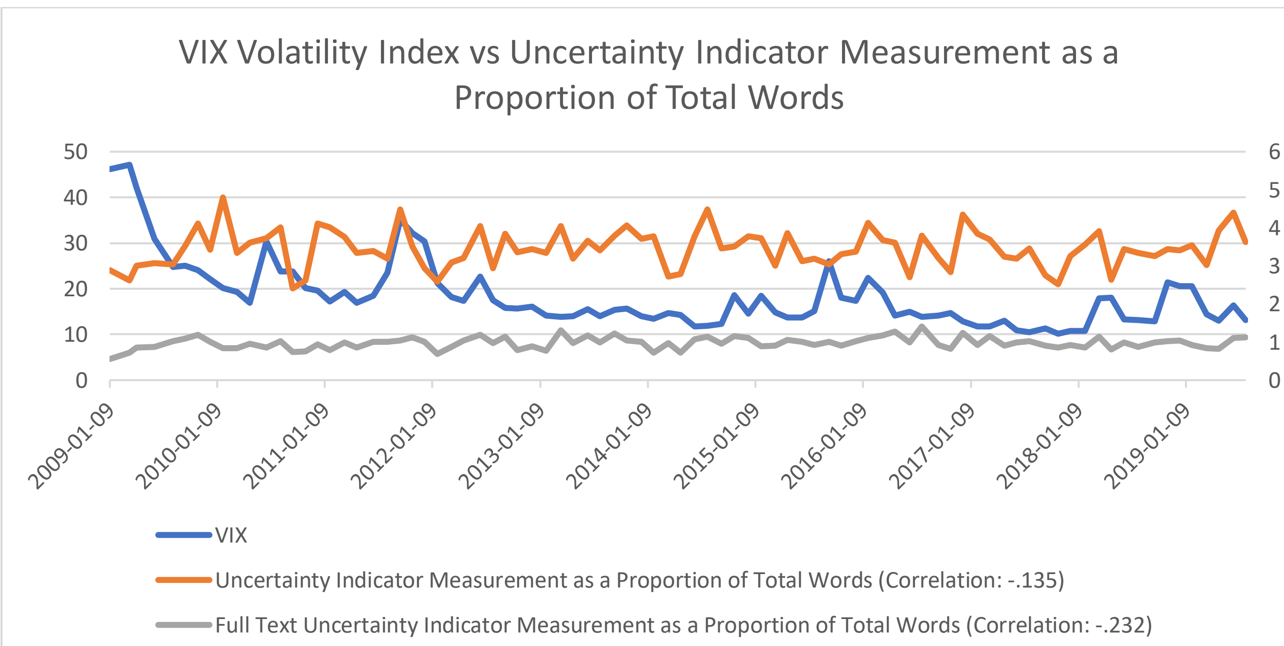
Appendix A

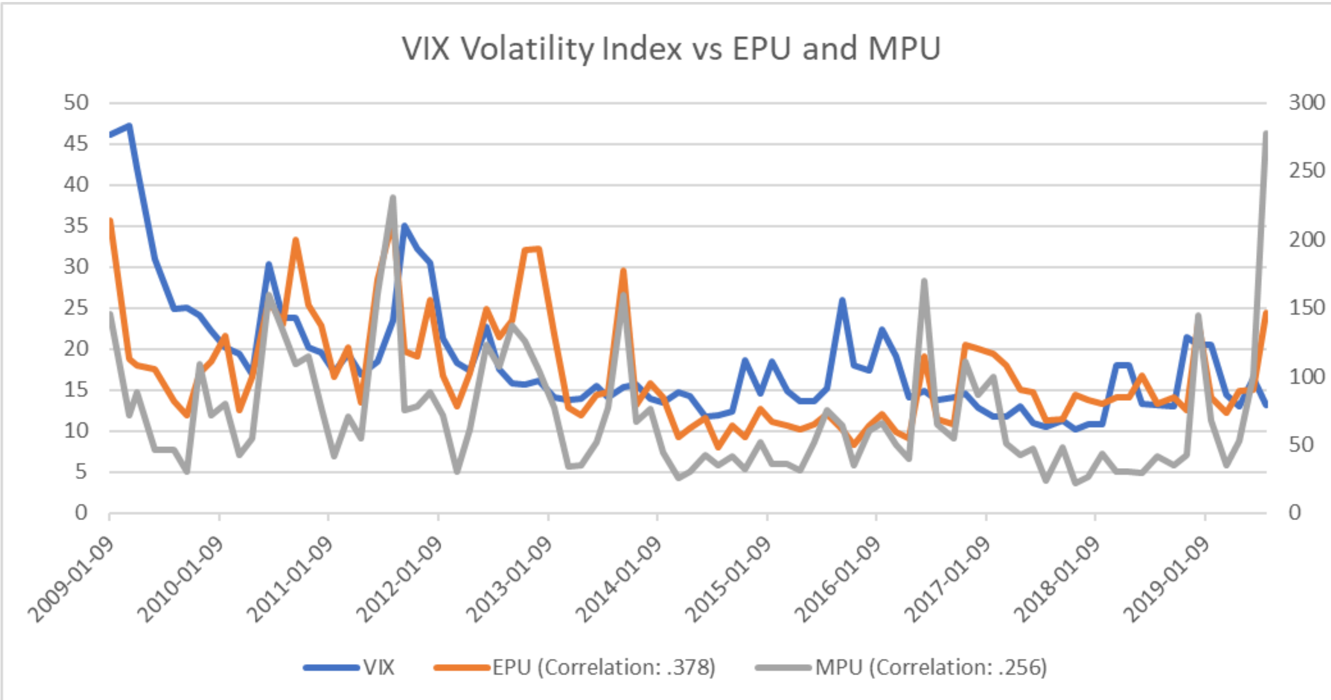
Correlation Graphs



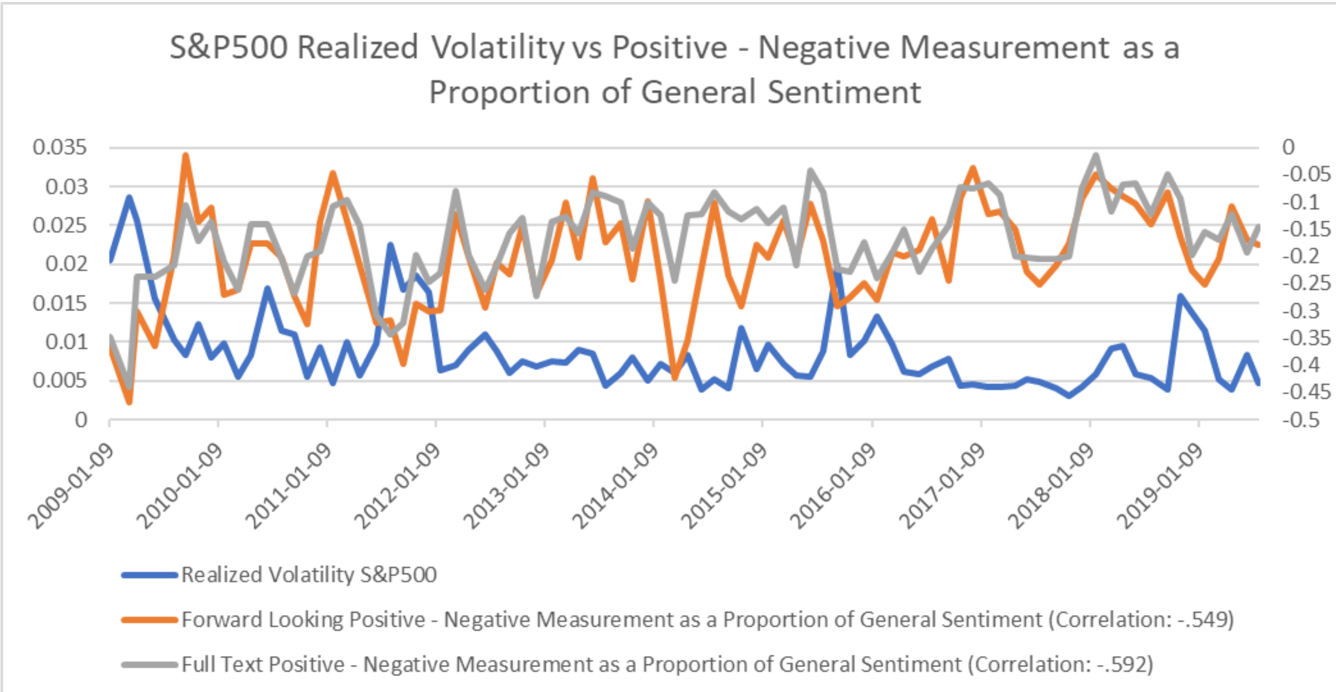


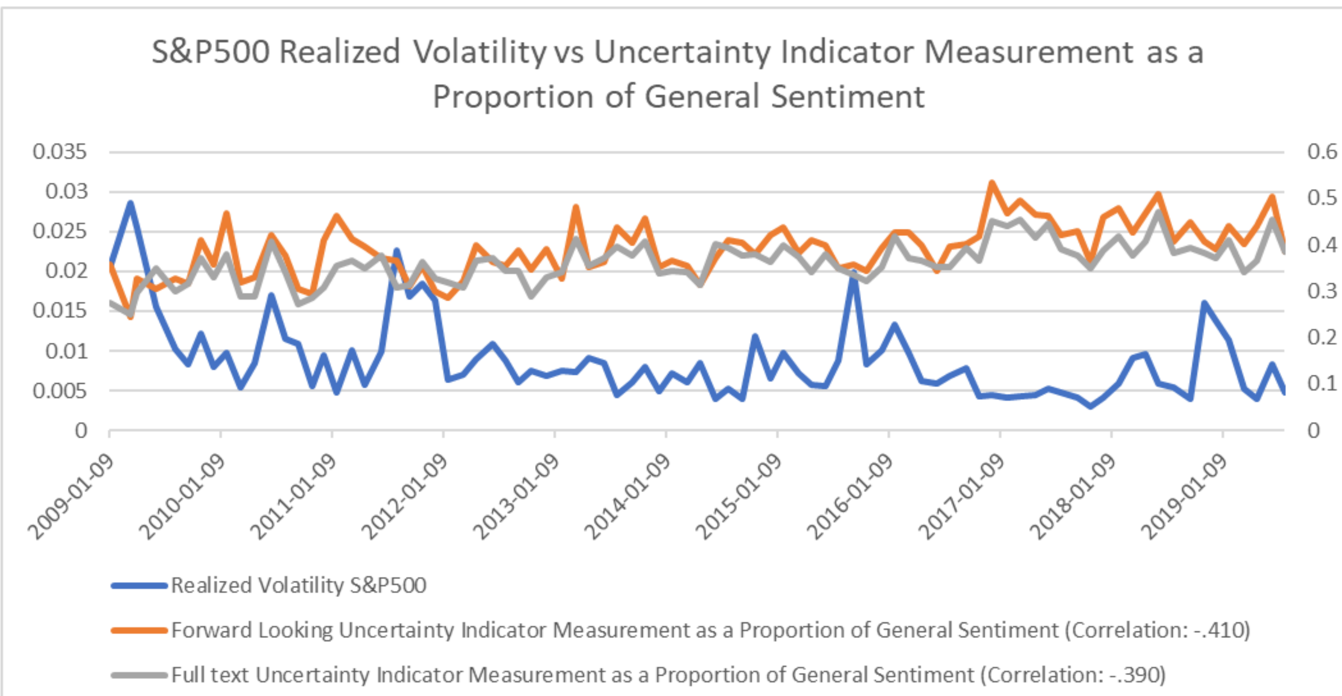

VIX Volatility Index vs Positive - Negative Measurement as a Proportion of Total Words
50
45
40
35
30
25
20
15
10
5
0
0
-0.01
-0.02
-0.03
-0.04
-0.05
-0.06
-0.07
-0.08
2009-01-09
2010-01-09
2011-01-09
2012-01-09
2013-01-09
2014-01-09
2015-01-09
2016-01-09
2017-01-09
2018-01-09
2019-01-09
VIX
Full Text Positive - Negative Measurement as a Proportion of Total Words (Correlation: -620)
Forward Looking Positive - Negative Measurement as a Proportion of Total Words (Correlation: -.602)

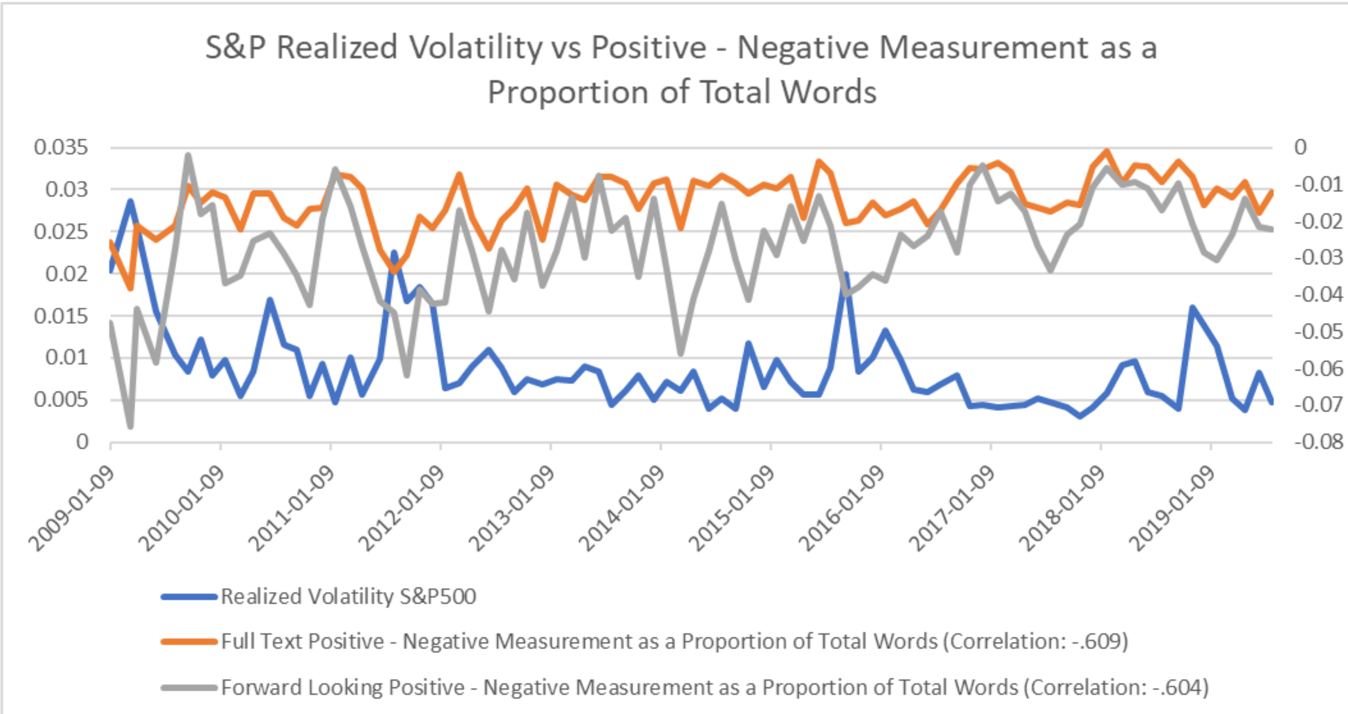

VIX Volatility Index vs Uncertainty Indicator Measurement as a Proportion of Total Words
50
40
30
20
10
0
6
5
4
3
2
1
0
2009-01-09
2010-01-09
2011-01-09
2012-01-09
2013-01-09
2014-01-09
2015-01-09
2016-01-09
2017-01-09
2018-01-09
2019-01-09
VIX
Uncertainty Indicator Measurement as a Proportion of Total Words (Correlation: -.135)
Full Text Uncertainty Indicator Measurement as a Proportion of Total Words (Correlation: -.232)

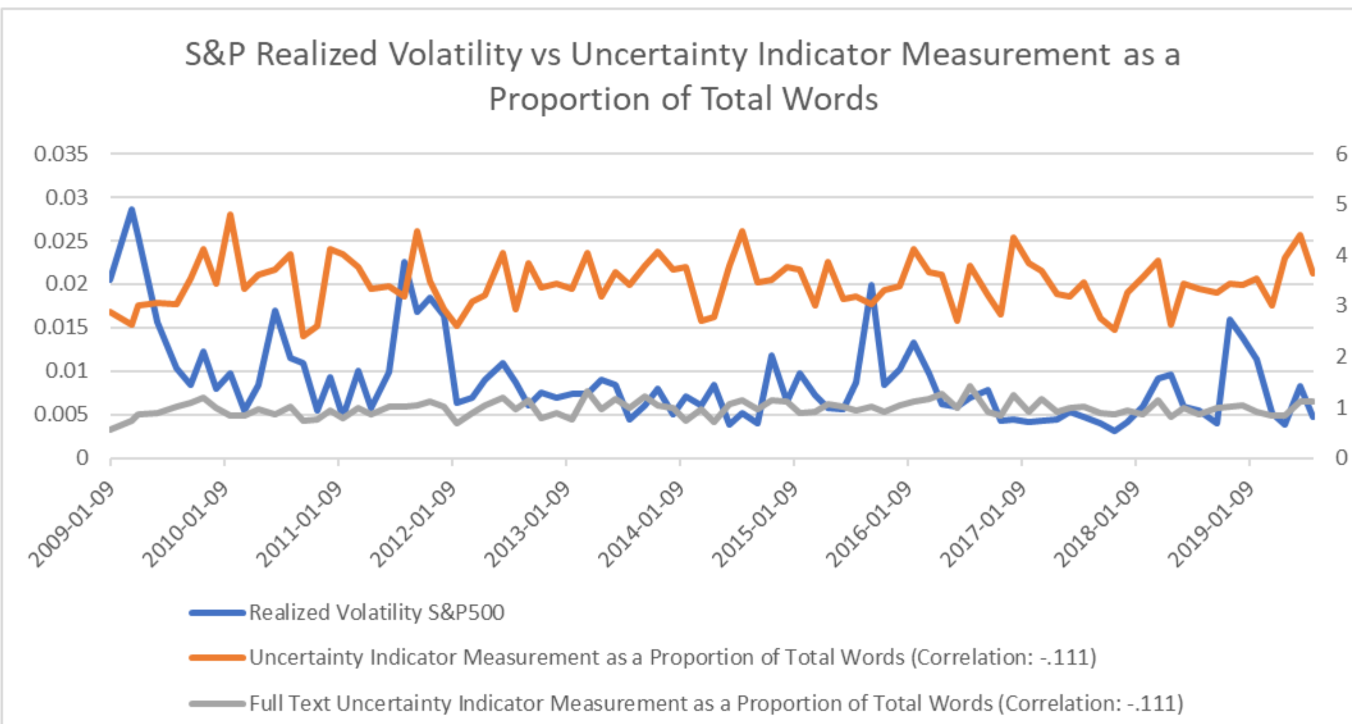


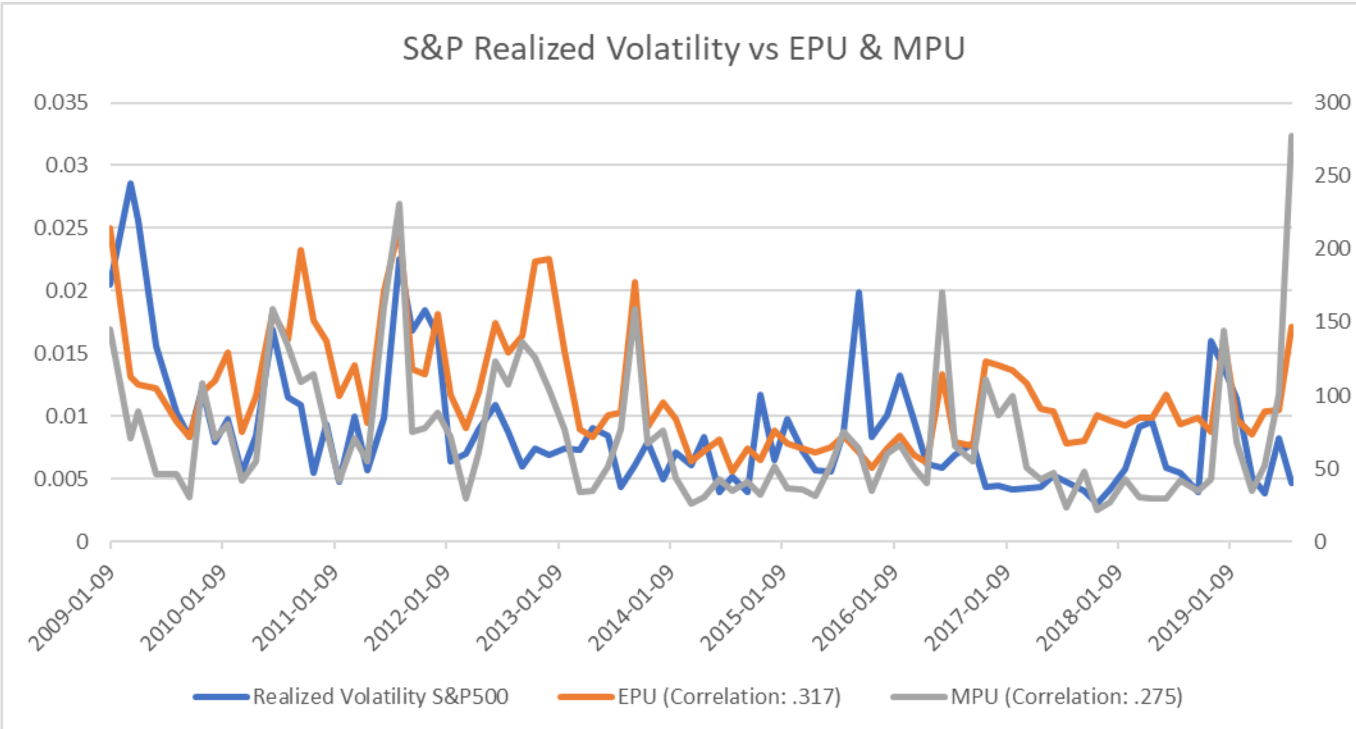
VIX Volatility Index vs EPU and MPU
50
45
40
35
30
25
20
15
10
5
0
300
250
200
150
100
50
0
2009-01-09
2010-01-09
2011-01-09
2012-01-09
2013-01-09
2014-01-09
2015-01-09
2016-01-09
2017-01-09
2018-01-09
2019-01-09
VIX
EPU (Correlation: .378)
MPU (Correlation: .256)


S&P500 Realized Volatility vs Positive - Negative Measurement as a Proportion of General Sentiment
0.035
0.03
0.025
0.02
0.015
0.01
0.005
0
0
-0.05
-0.1
-0.15
-0.2
-0.25
-0.3
-0.35
-0.4
-0.45
-0.5
2009-01-09
2010-01-09
2011-01-09
2012-01-09
2013-01-09
2014-01-09
2015-01-09
2016-01-09
2017-01-09
2018-01-09
2019-01-09
Realized Volatility S&P500
Forward Looking Positive - Negative Measurement as a Proportion of General Sentiment (Correlation: -.549)
Full Text Positive - Negative Measurement as a Proportion of General Sentiment (Correlation: -.592)


S&P500 Realized Volatility vs Uncertainty Indicator Measurement as a Proportion of General Sentiment
0.035
0.03
0.025
0.02
0.015
0.01
0.005
0
0.6
0.5
0.4
0.3
0.2
0.1
0
2009-01-09
2010-01-09
2011-01-09
2012-01-09
2013-01-09
2014-01-09
2015-01-09
2016-01-09
2017-01-09
2018-01-09
2019-01-09
Realized Volatility S&P500
Forward Looking Uncertainty Indicator Measurement as a Proportion of General Sentiment (Correlation: -.410)
Full text Uncertainty Indicator Measurement as a Proportion of General Sentiment (Correlation: -.390)


S&P Realized Volatility vs Positive - Negative Measurement as a Proportion of Total Words
0.035
0.03
0.025
0.02
0.015
0.01
0.005
0
0
-0.01
-0.02
-0.03
-0.04
-0.05
-0.06
-0.07
-0.08
2009-01-09
2010-01-09
2011-01-09
2012-01-09
2013-01-09
2014-01-09
2015-01-09
2016-01-09
2017-01-09
2018-01-09
2019-01-09
Realized Volatility S&P500
Full Text Positive - Negative Measurement as a Proportion of Total Words (Correlation: -.609)
Forward Looking Positive - Negative Measurement as a Proportion of Total Words (Correlation: -.604)


S&P Realized Volatility vs Uncertainty Indicator Measurement as a Proportion of Total Words
0.035
0.03
0.025
0.02
0.015
0.01
0.005
0
6
5
4
3
2
1
0
2009-01-09
2010-01-09
2011-01-09
2012-01-09
2013-01-09
2014-01-09
2015-01-09
2016-01-09
2017-01-09
2018-01-09
2019-01-09
Realized Volatility S&P500
Uncertainty Indicator Measurement as a Proportion of Total Words (Correlation: -.111)
Full Text Uncertainty Indicator Measurement as a Proportion of Total Words (Correlation: -.111)



S&P Realized Volatility vs EPU & MPU
0.035
0.03
0.025
0.02
0.015
0.01
0.005
0
300
250
200
150
100
50
0
2009-01-09
2010-01-09
2011-01-09
2012-01-09
2013-01-09
2014-01-09
2015-01-09
2016-01-09
2017-01-09
2018-01-09
2019-01-09
Realized Volatility S&P500
EPU (Correlation: .317)
MPU (Correlation: .275)

Appendix B

Regression Results

Forward-Looking Uncertainty Indicator Measurement as a Proportion of Total Words

Three Month T-Bill (Variables: Indicator, Inflation Rate, Unemployment Rate, Target Federal Funds Rate)

```
Call:
lm(formula = data$ThreeMonthTBill.zoo ~ data$uncertaintyindicator.zoo +
    InflationRate.zoo + UnemploymentRate.zoo + TargetFederalFundsRate.zoo)

Residuals:
     Min       1Q   Median       3Q      Max 
-0.34006 -0.02816  0.00478  0.03129  0.20107 

Coefficients:
                               Estimate Std. Error t value Pr(>|t|)    
(Intercept)                    0.987915   0.258303   3.825 0.000258 ***
data$uncertaintyindicator.zoo -0.032501   0.015931  -2.040 0.044644 *  
InflationRate.zoo             -0.004717   0.001123  -4.199  6.9e-05 ***
UnemploymentRate.zoo          -0.151731   0.255936  -0.593 0.554956    
TargetFederalFundsRate.zoo     1.103530   0.018186  60.681  < 2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.07237 on 80 degrees of freedom
Multiple R-squared:  0.9913,	Adjusted R-squared:  0.9909 
F-statistic:  2279 on 4 and 80 DF,  p-value: < 2.2e-16
```

One Year T-Bill (Variables: Indicator, Inflation Rate, Unemployment Rate, Target Federal Funds Rate)

```
Call:
lm(formula = data$OneYearTBill.zoo ~ data$uncertaintyindicator.zoo +
    InflationRate.zoo + UnemploymentRate.zoo + TargetFederalFundsRate.zoo)

Residuals:
     Min       1Q   Median       3Q      Max 
-0.66259 -0.09548 -0.00880  0.09224  0.35638 

Coefficients:
                               Estimate Std. Error t value Pr(>|t|)    
(Intercept)                    1.669515   0.616420   2.708  0.00827 ** 
data$uncertaintyindicator.zoo -0.094609   0.038019  -2.488  0.01491 *  
InflationRate.zoo             -0.005939   0.002681  -2.215  0.02958 *  
UnemploymentRate.zoo           0.271349   0.610771   0.444  0.65804    
TargetFederalFundsRate.zoo     1.131974   0.043399  26.083  < 2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.1727 on 80 degrees of freedom
Multiple R-squared:  0.9537,	Adjusted R-squared:  0.9514 
F-statistic: 412.2 on 4 and 80 DF,  p-value: < 2.2e-16
```

Ten Year – 3 Month Yield Spread (Variables: Indicator, Inflation Rate, Unemployment Rate, Target Federal Funds Rate)

```
Call:
lm(formula = data$TenYr3MoSpread.zoo ~ data$uncertaintyindicator.zoo +
    InflationRate.zoo + UnemploymentRate.zoo + TargetFederalFundsRate.zoo)

Residuals:
     Min       1Q   Median       3Q      Max
-0.98429 -0.35058  0.07657  0.31676  0.83495

Coefficients:
                               Estimate Std. Error t value Pr(>|t|)
(Intercept)                   12.725360   1.565257   8.130 4.50e-12 ***
data$uncertaintyindicator.zoo  0.180046   0.096540   1.865  0.06585 .
InflationRate.zoo             -0.047349   0.006807  -6.956 8.62e-10 ***
UnemploymentRate.zoo          -1.807803   1.550912  -1.166  0.24722
TargetFederalFundsRate.zoo    -0.370649   0.110202  -3.363  0.00118 **
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.4386 on 80 degrees of freedom
Multiple R-squared:  0.7729,  Adjusted R-squared:  0.7616
F-statistic: 68.08 on 4 and 80 DF,  p-value: < 2.2e-16
```

Ten Year – 1 Year Yield Spread (Variables: Indicator, Inflation Rate, Unemployment Rate, Target Federal Funds Rate)

```
Call:
lm(formula = data$TenYr1YrSpread.zoo ~ data$uncertaintyindicator.zoo +
    InflationRate.zoo + UnemploymentRate.zoo + TargetFederalFundsRate.zoo)

Residuals:
     Min       1Q   Median       3Q      Max
-0.96544 -0.31606 -0.00903  0.31722  0.93531

Coefficients:
                               Estimate Std. Error t value Pr(>|t|)
(Intercept)                   12.025128   1.510633   7.960 9.67e-12 ***
data$uncertaintyindicator.zoo  0.230845   0.093171   2.478 0.015332 *
InflationRate.zoo             -0.045863   0.006569  -6.981 7.70e-10 ***
UnemploymentRate.zoo          -2.271360   1.496789  -1.517 0.133085
TargetFederalFundsRate.zoo    -0.402663   0.106356  -3.786 0.000295 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.4233 on 80 degrees of freedom
Multiple R-squared:  0.7877,  Adjusted R-squared:  0.7771
F-statistic: 74.21 on 4 and 80 DF,  p-value: < 2.2e-16
```

Ten Year – 2 Year Yield Spread (Variables: Indicator, Inflation Rate, Unemployment Rate, Target Federal Funds Rate)

```
Call:
lm(formula = data$TenYr2YrSpread.zoo ~ data$uncertaintyindicator.zoo +
    InflationRate.zoo + UnemploymentRate.zoo + TargetFederalFundsRate.zoo)

Residuals:
     Min       1Q   Median       3Q      Max 
-0.95108 -0.19022 -0.02089  0.20525  0.85705 

Coefficients:
                              Estimate Std. Error t value Pr(>|t|)    
(Intercept)                   10.51729    1.28994   8.153 4.05e-12 ***
data$uncertaintyindicator.zoo  0.19822    0.07956   2.491 0.014789 *  
InflationRate.zoo             -0.04015    0.00561  -7.156 3.55e-10 ***
UnemploymentRate.zoo          -2.18107    1.27812  -1.706 0.091800 .  
TargetFederalFundsRate.zoo    -0.35793    0.09082  -3.941 0.000173 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.3614 on 80 degrees of freedom
Multiple R-squared:  0.7973,	Adjusted R-squared:  0.7872 
F-statistic: 78.69 on 4 and 80 DF,  p-value: < 2.2e-16
```

Economic Policy Uncertainty Index

Three Month T-Bill (Variables: EPU, Inflation Rate, Unemployment Rate, Target Federal Funds Rate)

```
Call:
lm(formula = data$ThreeMonthTBill.zoo ~ data$EPU.zoo + InflationRate.zoo +
    UnemploymentRate.zoo + TargetFederalFundsRate.zoo)

Residuals:
     Min       1Q   Median       3Q      Max 
-0.32492 -0.02828 -0.00368  0.02799  0.21994 

Coefficients:
                             Estimate Std. Error t value Pr(>|t|)    
(Intercept)                 1.1280627  0.2920104   3.863 0.000226 ***
data$EPU.zoo               -0.0003910  0.0002284  -1.712 0.090728 .  
InflationRate.zoo          -0.0056494  0.0012457  -4.535    2e-05 ***
UnemploymentRate.zoo       -0.1146802  0.2576325  -0.445 0.657427    
TargetFederalFundsRate.zoo  1.1126899  0.0190271  58.479  < 2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.07291 on 80 degrees of freedom
Multiple R-squared:  0.9912,	Adjusted R-squared:  0.9907 
F-statistic:  2246 on 4 and 80 DF,  p-value: < 2.2e-16
```

One Year T-Bill (Variables: EPU, Inflation Rate, Unemployment Rate, Target Federal Funds Rate)

```
Call:
lm(formula = data$OneYearTBill.zoo ~ data$EPU.zoo + InflationRate.zoo + 
    UnemploymentRate.zoo + TargetFederalFundsRate.zoo)

Residuals:
     Min       1Q   Median       3Q      Max 
-0.62751 -0.09235 -0.01411  0.10096  0.43118 

Coefficients:
                            Estimate Std. Error t value Pr(>|t|)    
(Intercept)                2.2773138  0.6870238   3.315  0.00138 ** 
data$EPU.zoo              -0.0014597  0.0005373  -2.717  0.00807 ** 
InflationRate.zoo         -0.0093862  0.0029307  -3.203  0.00195 ** 
UnemploymentRate.zoo       0.3892177  0.6061416   0.642  0.52263    
TargetFederalFundsRate.zoo  1.1658773  0.0447659  26.044  < 2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.1715 on 80 degrees of freedom
Multiple R-squared:  0.9544,	Adjusted R-squared:  0.9521 
F-statistic: 418.1 on 4 and 80 DF,  p-value: < 2.2e-16
```

Ten Year – 3 Month Yield Spread (Variables: EPU, Inflation Rate, Unemployment Rate, Target Federal Funds Rate)

```
Call:
lm(formula = data$TenYr3MoSpread.zoo ~ data$EPU.zoo + InflationRate.zoo + 
    UnemploymentRate.zoo + TargetFederalFundsRate.zoo)

Residuals:
     Min       1Q   Median       3Q      Max 
-0.85801 -0.33231 -0.02477  0.28703  0.99052 

Coefficients:
                           Estimate Std. Error t value Pr(>|t|)    
(Intercept)               15.850368   1.695278   9.350 1.81e-14 ***
data$EPU.zoo              -0.004112   0.001326  -3.102  0.00266 ** 
InflationRate.zoo         -0.056510   0.007232  -7.814 1.87e-11 ***
UnemploymentRate.zoo      -1.817509   1.495696  -1.215  0.22788    
TargetFederalFundsRate.zoo -0.280046   0.110463  -2.535  0.01319 *  
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.4233 on 80 degrees of freedom
Multiple R-squared:  0.7885,	Adjusted R-squared:  0.7779 
F-statistic: 74.56 on 4 and 80 DF,  p-value: < 2.2e-16
```

Ten Year – 1 Year Yield Spread (Variables: EPU, Inflation Rate, Unemployment Rate, Target Federal Funds Rate)

```
Call:
lm(formula = data$TenYr1YrSpread.zoo ~ data$EPU.zoo + InflationRate.zoo +
    UnemploymentRate.zoo + TargetFederalFundsRate.zoo)

Residuals:
     Min       1Q   Median       3Q      Max
-0.86213 -0.29280  0.00177  0.29067  0.99330

Coefficients:
                            Estimate Std. Error t value Pr(>|t|)
(Intercept)                14.760186   1.697544   8.695 3.49e-13 ***
data$EPU.zoo               -0.003226   0.001327  -2.430  0.01734 *
InflationRate.zoo          -0.052940   0.007241  -7.311 1.78e-10 ***
UnemploymentRate.zoo       -2.347542   1.497695  -1.567  0.12096
TargetFederalFundsRate.zoo -0.332568   0.110611  -3.007  0.00353 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.4238 on 80 degrees of freedom
Multiple R-squared:  0.7871,	Adjusted R-squared:  0.7765
F-statistic: 73.95 on 4 and 80 DF,  p-value: < 2.2e-16
```

Ten Year – 2 Year Yield Spread (Variables: EPU, Inflation Rate, Unemployment Rate, Target Federal Funds Rate)

```
Call:
lm(formula = data$TenYr2YrSpread.zoo ~ data$EPU.zoo + InflationRate.zoo +
    UnemploymentRate.zoo + TargetFederalFundsRate.zoo)

Residuals:
     Min       1Q   Median       3Q      Max
-0.95248 -0.23835 -0.05071  0.21408  0.86825

Coefficients:
                            Estimate Std. Error t value Pr(>|t|)
(Intercept)                12.073421   1.487413   8.117 4.77e-12 ***
data$EPU.zoo               -0.001495   0.001163  -1.285  0.20247
InflationRate.zoo          -0.043312   0.006345  -6.826 1.53e-09 ***
UnemploymentRate.zoo       -2.286204   1.312302  -1.742  0.08533 .
TargetFederalFundsRate.zoo -0.326450   0.096919  -3.368  0.00117 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.3714 on 80 degrees of freedom
Multiple R-squared:  0.786,	Adjusted R-squared:  0.7753
F-statistic: 73.47 on 4 and 80 DF,  p-value: < 2.2e-16
```