Exploration in Automated Systems for Analyzing Public Policy Documents[*]

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Abstract. Speeches given by decision makers within Central Banks are subject to frequent and careful analysis. However, a systematic process for their evaluation has remained elusive. This paper introduces a methodology for a systematic process in the form of a semantic network that can be used to augment existing approaches. The approach suggests a correlation between the new systematic method and public market securities data.

Keywords: Monetary policy, Semantic Network, Computational Linguistics.

1 Introduction

Broadcast and written about widely, pronouncements by Central Bankers may not be the average government official speech. The public announcements of U.S. Central Bankers has been studied widely [1]. Controlling a balance sheet of a little over $2 Trillion, the words and phrases in speeches given by members of the Federal Open Market Committee are dissected carefully for meaning [2], but systematic approaches remain elusive. With the trend toward decision making transparency being an invention only since 1996, the language of the bankers themselves has evolved from being intentionally vague to today's more clear speeches [3]. The conclusions of earlier studies of central bank speeches has also evolved from tenuous links between the speeches and actual monetary policy to more sophisticated analysis that can classify the sentiment and find some correlation to actual monetary policy [4]. There are many studies that attempt to find a correlation between the public pronouncements and monetary policy or the U.S. Treasury Yield curve [5], [6], [7]. The study of these speeches are interesting for at least a few reasons: (i) They are already widely followed by the public; (ii) The subject matter of the speeches lends itself to study because they are tightly

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constrained around U.S. Monetary Policy[1]; (iii) The speeches are given at regular intervals; (iv) The speeches are given by a small and predictable group that make up the membership of the Fed Governing Body [8]; (v) The group itself looks to understand the characteristics of the speeches' impact. [9]; and (vi) There are related or tangential policy bodies against which future research may apply findings [10], [11]. Some approaches in computational linguistics such as Latent Semantic Analysis have been applied to central bank speeches, but the results are "nuanced," [12]. This paper concerns itself with establishing a system for analyzing the texts that can be routinely applied to speeches given by the central bank officials. Using just the public speeches, the approach seeks to find a correlation with security prices.

2   Background

2.1   US Federal Reserve

The Central Bank of the United States is the US Federal Reserve ("The Fed"). The Fed is comprised of twelve regional Banks and a central administrative body based in Washington. The decision making body of the Fed is the Federal Open Market Committee ("FOMC") whose annually rotating voting membership is comprised of a combination of seven presidential appointees (known as Fed Governors, the posts for which are not always full as they require Senate approval) who work from the Washington Headquarters and five of the twelve regional Fed Presidents [8]. The members of the Fed give public speeches at regular intervals throughout the year (see appendix I) [8]. As opposed to FOMC meeting minutes, the speeches are intended to provide security market participants some insight into the direction of Monetary Policy [4]. The Fed has many mechanisms for expressing Monetary Policy and many studies have been done on the degree of efficacy of these actions [6]. The primary vehicle for expressing monetary policy remains the setting interest the Fed Funds rate around which many other interest rates are linked [8].

2.2   Financial Data

Some research suggests that the degree to which The Fed is effective in setting expectations on Monetary Policy is the extent to which the Treasury Yield curve retains an upward sloping shape [13]. Changes in the Fed Funds rate has the biggest effect on the securities with the shortest maturities, or at the 'short end of the curve' [14], [13]. The Fed Funds rate itself is expressed as a target rate around which little fluctuation occurs. For purposes of this research, it is treated as a fixed rate that changes only in increments of 25 basis points. Investors can express views on the probability of a change in the Fed Funds through a mechanism of Fed Funds Futures. These are contracts traded publicly that come into existence each month with a two-year expiration. Using a variety of techniques, communications from the Fed have been studied in many different from the

degree of correlation to Bond prices [6], to the volume of trading in the debt market [15], to how the voting within the FOMC effects prices [12], [16]. Other linguistic approaches have been brought to bear on the analysis of FOMC speeches from innovations in the application [17] to innovations in the processing of text itself [18], [19]. Some of this work centers on the feedback loop of the announcements changing response to the markets which itself has an impact on the markets [20], [3]. The analysis of the speeches themselves is against a backdrop of a tension within the FOMC to focus on strict rules of market engagement versus more subtle actions [21], [22]. While some research has attempted to develop a sophisticated interpretation of a systemic analysis such 'a term structure of announcements' [5], other research takes a large data set of speeches from many different speakers and concludes that the results are 'nuanced' [12].

2.3 *Semantic Networks and Sentiment Classifiers*

While many explore ways to make market bets on sentiment [23], [17] or other forms of analysis [24] of qualitative Central Bank communications, the results have not been strong [11], [10]. Some difficulty in sentiment classification in this domain [25], [26], [27], [28] is from the confusion among domain experts [29]. A different approach could be useful. Semantic network analysis is the use of network analytic techniques on paired associations based on shared meaning as opposed to paired associations of behavioral or perceived communication links [30]. Semantic Networks have been applied been explored in a variety of circumstances from large-scale news [31] reporting to email [7], [32], [33]. The approaches in Semantic Network Analysis vary depending upon the research question. For some applications, the appropriate methodology is to tag the words as having characteristics such as people or places [33]. Other approaches use the method of looking at the relationship of words to each other [30]. The analysis of Semantic Networks itself getting richer with analytical tools to measure the network [34]. This richness combined with the relational dependence inherent in Semantic Networks suggests a better path toward a systematic analysis of public policy speeches.

3 Methodology

The approach we take toward developing a systematic method of evaluating public policy speeches is to develop a semantic network for a select group of speeches. These network measures from generating a semantic network are then compared to financial data around which the speeches most related. The speeches collected are from the FOMC in two select years since the speeches have become public. These are compared to various public market interest rate indicators around which the FOMC speeches most directly influence. Since its creation in 1913, The Fed did not release qualitative information about Monetary Policy until 1996. However, only since the Chairmanship of The Fed transferred to the current Chair, Ben Bernanke, in February of 2006, did The Fed express a willingness to

become more transparent in its communications. We therefore use the years from 2006-2007 to generate a semantic network from the speeches given by FOMC members. Measurements of the semantic network are then compared to quantitative financial data to determine if there is a relationship and if so, the nature of the relationship. First, qualitative data is collected in the form of speeches. Speeches by FOMC members have the benefit of being most clearly labeled in the body of the text for date, location, speaker, and topic. Some texts are excluded from this study: prepared congressional testimony, answers under congressional questioning, FOMC board meeting minutes, and speeches given about bank regulatory matters. Second, financial data is collected in the form of the full U.S. Treasury Yield curve and two Fed Funds Futures contracts: those expiring in December 2007 and December 2008 because they may be considered the most traded instruments of their kinds in this time [35]. The speeches are first acquired through publicly available data from the US Federal Reserve. The public data includes information beyond the speech itself. For this study, the standard disclaimers given by The Fed, the information on the person making the speech as well as the venue are stripped out. Using the software tools available through Automap [36], a list of common words (a 'delete list', see Appendix III) is then mapped onto the collection of speeches. In automap, punctuation is removed, lowercase is forced, then a thesaurus is mapped to avoid duplication of similar words (see thesaurus used in appendix IV). With only those words in the thesaurus remaining, a semantic network is created using a bi-directional window size of seven. For those days where multiple speeches are given, the network measures are averaged. For those dates that occur when there are no financial data available (e.g., when the bond market is closed), the next day is used.

4   Results and Conclusion

Our analysis gives us both the degree to which any independent variables are correlated to any combination of dependent variables, but also the combination of variables themselves. We first present the detail of each analysis and then summarize both R^2 and the independent variables found. Among the 1728 combinations, we take the four models with R^2 above 0.40. Each of the models created in the CART analysis have a different set of dependent and independent variables. Each of the models also has a different set of dependent variables. Each model splits the independent variables differently. The approach presented in this paper is a systematic analysis of public policy speeches given by central bankers in the U.S. The analysis suggests some correlation between relevant financial data and the semantic networks approach presented. Between the two different approaches for analyzing the correlation and the combinations of twelve dependent variables, there appears to be some consistency in the independent variables. For example, Network Centralization (Column Degree) is an independent variable in nine cases in the regression analysis. Among the four models of the CART analysis, only five independent variables are unique to one model. There is also some consistency of results among the multiple analysis methodologies. Average Distance played a part in seven of the Regression models

and half of the CART models. Together, the results suggest that in some circumstances, there exists a correlation between financial data and a systematic approach using semantic networks to analyzing public policy speeches. However, the conclusions are limited in several ways. First, the speeches are for those by U.S. Central Bankers. These have benefits as outlined earlier, but the conclusions may prove difficult to generalize to other Central Banks and the public policy pronouncements of other officials. Second, while there are many documents produced by the U.S. Central Bank, this research looks at only the speeches as stated earlier. The minutes of the FOMC board meeting minutes could be another study. Third, this study only covers the years 2006-2007. While there are good reasons for this limitation as described earlier, the effectiveness of the conclusions may vary over other years. Fourth, this correlation does not predict the outcomes of the results in any way. Prediction of any sort, for example, either binary (i.e., the numbers will go up or down) or in direction (i.e., the numbers will stop going up) would be very interesting research by itself. Others have begun to explore this [37], [24], [14]. Fifth, the results of a Semantic Network approach are inherently impacted by qualitative decisions made early in the process such as the development of the delete list and the Thesaurus. Sixth, there are other dependent variables that could be included in further study such as U.S. GDP growth or the 34 other Fed Funds Futures expiring between 2007 and 2008. Treatment of dependent variables could also vary such as normalization to equity prices or equity derivatives.

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