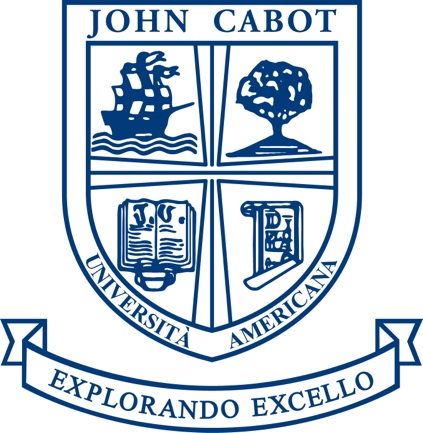
Moving Markets: The Impact of ECB’s Statements on Equity Market’s Volatility

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Table of Contents

[Abstract 3](#_Toc132643758)

[Introduction and Motivation 4](#_Toc132643759)

[Literature Review 5](#_Toc132643760)

[Research Question and Hypotheses 9](#_Toc132643761)

[Methodology and Data Sources 9](#_Toc132643762)

[Description of the Variables 11](#_Toc132643763)

[Regression Analysis 12](#_Toc132643764)

[Preliminary Multiple Linear Models 12](#_Toc132643765)

[Diagnostics of Preliminary Models. 13](#_Toc132643766)

[Final Model 13](#_Toc132643767)

[Interpretation of the Regression Results 13](#_Toc132643768)

[Did COVID change how Statements are perceived? 14](#_Toc132643769)

[GARCH Model. 15](#_Toc132643770)

[Limitations of the Study 17](#_Toc132643771)

[Conclusion 18](#_Toc132643772)

[References 19](#_Toc132643773)

[Appendix 20](#_Toc132643774)

[Tables 20](#_Toc132643775)

[Figures 22](#_Toc132643776)

Abstract

This study analyzes the impact of European Central Bank’s statements and surprise monetary policies on the equity market’s volatility of the Eurozone using data from 2015 to Q1 2023. Moreover, it investigates the role of the COVID-19 pandemic in shaping investors’ perception of public information. The main findings include a statistically significant relationship between all variables of interest and volatility. A GARCH model is employed to model volatility and understand to which extent the pandemic period affected how the tone of a given statement is perceived by the main actors in the equity market. The results suggest that COVID-19 exacerbated how negatively statements are perceived, thus promoting more volatility in the equity market of the Eurozone.

Keywords: sentiment analysis, central bank statements, volatility, surprise interest rate changes, GARCH model

JEL Classification: G14, G41, E52, E58, E71

Moving Markets: The Impact of ECB’s Statements on Equity Market’s Volatility

# Introduction and Motivation

Understanding fluctuations in the equity market is a relevant part of the job of any investment analyst and, in general, of every educated investor. Considering that the rational investor always seeks strategies to attain the highest possible profit, it is clear that they would at least try to come up with an explanation as to why the expected return of a stock is so variable and what are the factors influencing volatility. This paper tries to answer this question and focuses on the importance that unexpected changes in monetary policy and central bank statements have on the volatility of the stock market. The motivation behind it is to explore which factors can be viewed as significant predictors of higher volatility and in which market circumstances they are exacerbated. The relevance and usefulness of such inquiry resides in the possibility to unveil systematic responses from the equity market to events such as the public disclosure of information from a central bank. The paper is, therefore, focused on the analysis of the European Central Bank (ECB) and the reactions that statements issued by it cause in the Eurozone equity market at a specific time. Understanding the impact of written statements, given their importance when communicating policy changes, is a fundamental part for every central bank that wants to contain the exuberance of markets. The results provided by a study like this can be translated into a collection of best practices for central banks that can be followed to alleviate any undesired effect on markets. For instance, considering the cognitive limitations that every investor has and how their rationality is bounded by the information they possess, it would be a good practice to keep the statements as short as possible and avoid employing a tone that is too emotionally charged. Kahneman (2003) discusses extensively the impact of how information is presented on how it is cognitively processed and perceived. Discussions on the most prominent cognitive biases have led behavioral economists to question the extent to which the rationality assumptions used in economic theory are coherent with reality. For example, Kahneman (2003) points out that most choices not only originate from limited information but that information can also be interpreted in a misleading way. Indeed, it was shown how more salient stimuli are remembered and retrieved more easily compared to their less emotional counterpart. Therefore, it would be coherent to assume that rationality principles do not hold well when the available information is communicated in an emotionally charged fashion. Such approach runs the risk of making readers disregard the underlying meaning of the communication and promote impulsive responses. Most importantly, studies have shown how exogenous shocks inducing fears in markets can lead to severely adverse choices that challenge any possible rational explanation (Ortmann et al., 2020). For this reason, the current study will include a section devoted entirely to how COVID-19 affected market participants’ perception of ECB’s statements.

# Literature Review

The topic of central bank’s statement and disclosure of public information has been studied by many, especially after observing that the role of central banks started to become less independent from governments. Previous studies included considerations on the timing of central bank’s statement, the divergence between private and public information, how long it takes to incorporate newly issued information into asset prices, and the effect of unexpected changes in monetary policies on equity markets. In this section, the main findings from this vast body of literature will be summarized to explain and highlight some of the components that are important for the current study.

Amato and collaborators (2002) studied the effects of newly issued public information and how it affects both market participants’ reactions and expectations as well as impacting the market for private information. They explain that public information is attached a heavier weight when it comes to influencing expectations compared to private information. It follows that central banks have enough leverage to sway the opinions of markets; but with that comes a great responsibility as also real and *perceived* errors will be largely amplified when absorbed by market participants. This calls for the need of a decision-making structure that allows central banks to be as transparent as possible while not flooding the markets with unnecessary or ambiguous information. Committing errors under the form of disclosing ambiguous information comes at the cost of inefficiencies in the adjustment of the market’s long-run expectations, thus directly diminishing the efficacy of monetary policies. At the same time, given the smaller weight that private information holds in forecasting future outcomes, such information undergoes a process of devaluation which leads fewer and fewer people to rely on this data, especially if it is costly to acquire.

However, perverse effects can still arise in the moment when actors’ previous expectations are not reflected 1-to-1 in monetary policies. In his 2001 paper, Kuttner puts forth a technique to decompose the interest rate change into its expected and unexpected components. The technique he proposes is quite simple and is employing short-term interest rate futures to measure the expectations of the market.

Equation 1: Decomposition of Unexpected Interest Rate Change with Daily Data

According to this equation, the unexpected component of monetary policy changes ( is the difference between the future-implied interest rate in month *s* on the day of the event (*t*) and the previous day (*t-1*). The factor multiplying this difference can be interpreted as a scaling factor necessary to reflect the number of days remaining in the month that are affected by the change. Briefly, using this decomposition, the results pointed at a strong correlation between the surprise component and market interest rates, concluding that unforeseen policies have a larger magnitude in shaping interest rates at longer maturities.

Kuttner’s analysis was also proposed in other studies that went beyond the bond market and analyzed the equity market. Bernanke and Kuttner (2005) tried to understand the mechanisms through which the equity market reacted to FED’s policy by employing both daily and monthly data. For the purpose of this paper, the rationale behind the monthly analysis will be explained more in-depth, but it suffices to say that it has the same power to detect effects that the daily framework has. With monthly data, the surprise component is isolated in a similar way to daily data. The decomposition is as follows:

Equation 2: Decomposition of Unexpected Change in Interest Rates with Monthly Data

The interpretation here can also be provided in a straightforward manner: the average of the short-term interest rate *r* over month *t* should be the correct price of the futures contract for month *t*, by computing the difference with the actual price on the last day *D* of the previous month *t-1*, it is possible to get a grasp of the unexpected component of monetary policies. This operationalization of the surprise component of monetary policies is fundamental for this current study. However, Bernanke and Kuttner’s contribution stretches beyond the construction of a way to measure unexpected policies in a monthly framework; their findings also shed light on how changing expectations on excess returns and dividends mediate the impact on the equity market more than the effect of the sole interest rate change.

As mentioned before, the timing of the statement also matters and Ehrmann and Fratzscher (2005) look exactly at that to determine whether there is a pattern in how often and when central banks release statements. They conclude that the ECB does not increase the frequency of issued statements before the decision to change interest rates, a feature that sets it apart from the FED and the Bank of England. This means that for the Eurozone market participants are often left with less guidance compared to the US or the UK. One possible implication of this behavior from the ECB is enhanced volatility in the equity markets.

However, the issue of how long it takes for market participants to incorporate new information into their expectations is left to address. A paper by Rosa (2011) includes a high-frequency analysis to determine how much volatility is generated after an FOMC meeting. Employing a GARCH (Generalized Autoregressive Conditional Heteroskedasticity) model, he unveils how higher volatility is present in the 40-minute time window after the FOMC is concluded. The main conclusion in this study is that, at least following the FED’s communication schedule, one could expect market participants to push for a market correction, reflecting the most recent and available public information, in less than an hour from the release of such information. Moreover, his analysis also manages to find further support for the fact that the unexpected component accounts for most of the volatility observed after the meeting.

The last relevant piece of literature for this current study introduces an algorithm-based classification technique. In an attempt to improve on human-based tone classification tasks, whose outcomes could be influenced by cognitive biases thus leading to harder-to-replicate results, Chadha et al. (2020) present a Machine Learning algorithm which extracts the meaning of a text file and classify it as either dovish, neutral, or hawkish. This approach was applied to a corpus of central banks’ documents to find the latent tone of the statement and create a categorical variable out of it. This is a massive improvement from previous human-based classification tasks since it allows the analysis to be more reliable, less biased, and much more generalizable. The present study borrowed the lists of words they used to classify statements as either dovish or hawkish and implemented those terms in a frequential Python-based algorithm. The details of the algorithm will be presented in the methodology section of the paper. The full code is available on GitHub for replicability purposes.[[1]](#footnote-2)

# Research Question and Hypotheses

The underlying question to this current study is: how do ECB’s statements affect the volatility in the European equity market? Specifically, how do the surprise policy change and the tone of the statement reinforce volatility? Have there been any changes in how statements are perceived by investors after the COVID-19 pandemic?

The following analysis hypothesized that hawkish statements are going to influence volatility more than dovish statements. This directly stems from the liquidity preference theory asserting that in a liquid market there are many buyers and sellers willing to trade an asset, which makes it easier to buy or sell at a fair price. On the other hand, in a market with less liquidity, there are fewer buyers and sellers, which makes it harder to execute trades at a fair price. As a result, this can lead to wider bid-ask spreads which in turn can lead to larger price swings as buyers and sellers adjust their prices to match each other, resulting in higher volatility (Amihud et al., 1990).

A second hypothesis is that unexpected changes in interest rates promote more volatility regardless of the nature of the statement. This hypothesis is important to test as it directly relates to how market agents form expectations for long-run interest rates based on central bank’s interventions on short-term rates. The rationale behind this is that every public information that was not considered at time *t* (i.e., unexpected change) will be incorporated into prices leading to a market correction at time *t+1*, assuming that markets are efficient. This market correction is expected to be the source of increased volatility.

# Methodology and Data Sources

Being particularly focused on text-analysis and on the re-elaboration of specific variables, this methodology section will outline how the entire empirical analysis has been carried out. The first challenge of this study is the creation of a dummy variable categorizing a given ECB statement as either employing a positive (dovish) or negative (hawkish) tone. Contrary to previous studies relying on human categorization, as also pointed out above, this study expands on the literature of Natural Language Processing (NLP) algorithms to provide an unbiased categorization of the statements. The algorithm developed carries out the task by computing the frequency of occurrence of specific words that belong to either a pre-specified list of hawkish or dovish words[[2]](#footnote-3). Documents have been downloaded directly in PDF format from the ECB website, converted into txt files to perform the analysis, and inputted into the categorization algorithm. The algorithm reduced words to their root form and counted their occurrences in the text; then compared whether there were more words belonging to the dovish or hawkish dictionary and assigned a score of 1 (hawkish) or 0 (dovish).

The second challenge that the current study had to face was the creation of a variable capable of measuring the unexpected component of monetary policies. The creation of such variable follows Bernanke and Kuttner’s decomposition with monthly data presented in *equation 2*. Therefore, the unexpected component was operationalized as the difference between the average of the short-term interest rate (i.e., the ECB deposit facility rate) in a specific month and the interest rate implied by a similar futures contract on short-term rates (EURIBOR) on the last day of the preceding month.

All other variables have been obtained from reliable databases such as the [ECB Data Warehouse](https://sdw.ecb.europa.eu/) or from the [FRED](https://fred.stlouisfed.org/) website. Moreover, the dataset underwent cleaning procedures to facilitate the analysis and make it more solid. The procedures focused on removing outliers and, therefore, observations above the VSTOXX’s 95th percentile have been dropped, resulting in a sample reduction of three datapoints. They were observations from the months of March, April, and May 2020 when the COVID pandemic started to shake markets. Outliers have been retained only for the analysis employing the GARCH model to assess how well it would deal with such extreme values.

# Description of the Variables

**VSTOXX**: the main dependent variable employed in the study. It is an index of the implied volatility obtained from trading options having as underlying stock prices of the top 50 public companies by market capitalization in the Eurozone.

**D\_v\_H**: a dummy variable capturing the tone of the statement obtained through the classification algorithm introduced in the previous section. It is one of the most important variables in the study since it relates to the first hypothesis. It takes value 1 when the statement is categorized as hawkish and value 0 when the statement is categorized as dovish.

**Unexpected Interest Rate**: a variable generated following *equation 2* that measures the extent to which market’s expectations were met. A value of 0 means no surprise at all, whereas both positive and negative nonzero values indicate an unanticipated interest rate component that was not foreseen by market participants. Another useful interpretation is: the higher the absolute value, the higher the surprise component. This is the second most important variable as it explicitly relates to the second hypothesis.

**HCPI Change**: a variable measuring the change in inflation over months. It is operationalized as the difference in HCPI from the previous month and expressed in percentage terms.

**COVID**: a dummy variable signaling the presence in the economy of the homonymous pandemic. It takes value 1 from January 2020 to December 2022.

**Germany Manufacturing PMI**: a variable measuring the producers’ confidence in the Eurozone economy. It is obtained through a survey and measured on a monthly basis. Values above 50 signal confidence in the economy, whereas values below this threshold signal a recession.

**D\_Contraction**: A dummy variable measuring the presence of a contraction in the economy. It takes value 1 for the month in which the PMI is less than 50 and value 0 otherwise.

# Regression Analysis

This section will outline the main models employed in the analysis, the reason why they were included and an interpretation of the regression coefficients.

## Preliminary Multiple Linear Models

The first model, shown in the first column of *table 1*, attempts to grasp the relationship between volatility and the tone of the statement. As it can be observed from the negative coefficient, the hypothesis that the more hawkish a statement is the more volatility will be generated in the market does not find support in this model. The negative coefficient is retained throughout all linear models. A follow-up analysis will show how it interacts with the COVID-19 period, but for now let us focus on the other variable of interest: the unexpected change in interest rate.

Contrary to the first hypothesis, the second one is supported when looking at the regression results. Indeed, the statistically significant coefficient associated with surprise interest rate changes hints at a positive relationship between the unexpected component of interest rates and equity market volatility, as measured by the VSTOXX index. Also in this case, the positive relationship is retained across models.

Models from 3 to 5 analyze the impact of macro fundamentals such as inflation (HCPI) and control for investors’ expectations on the economy through the PMI index. From model 5 it is learned that inflation is inversely correlated to volatility. Despite being beyond the scope of the current study, this result can be interpreted as further empirical evidence of the price stickiness theory first suggested by Ball and Mankiw (1995). According to this theory, prices take a longer time to adjust to shifts of the demand and supply curves and, therefore, inflation in one period might not necessarily imply huge price swings. On the other hand, PMI is not a statistically significant predictor of volatility.

Diagnostics of Preliminary Models. Despite the consistent results obtained across models they all suffered from residual autocorrelation. As it can be observed from *Figure 2*, there is a significant positive autocorrelation between residuals up to the 6th lag. However, this trend seems to get weaker the higher the number of lags. For this reason, the following models provide autocorrelation-robust standard errors computed following the Newey-West correction with a lag of 1.

## Final Model

The final model, shown in column 5 of *table 2*, corrects for autocorrelation and all previously significant coefficient remain so also in this specification. When adjusting for autocorrelation the hawkishness of the statement remains negatively correlated to volatility. The surprise component of monetary policies is still a positive and highly significant predictor of volatility.

## Interpretation of the Regression Results

The OLS estimates yielded the following coefficients:

Considering only statistically significant coefficients, their interpretation from the final linear model would be as follows:

**Constant**: On average, when all other predictors take value 0, the VSTOXX amounts to 17.91.

**Unexpected Change in Interest Rate**: a unit change in this variable would imply that markets’ expectations were 100% wrong. However, since this is a very unlikely scenario, let us interpret the coefficient with the more likely 25 bp surprise change in interest rates. Considering this value, and keeping everything else constant, the VSTOXX would increase by 4.56 on average.

**Tone of the Statement**: keeping everything else constant, a hawkish statement is associated to a change of -2.757 in the VSTOXX index on average.

**Inflation (HCPI)**: keeping everything else constant, a unit change in inflation from the previous month is associated to a change in the VSTOXX of -2 on average.

**COVID**: keeping everything else constant, a pandemic-like period is expected to increase the VSTOXX by 7.619 compared to a pandemic-free period on average.

## Did COVID change how Statements are perceived?

Following the interpretation of the regression results, it would be interesting to understand whether the COVID-19 pandemic is associated to the public perception of ECB’s statements. In other words, the aim of the upcoming analysis is to investigate whether markets started building expectations from ECB’s statements differently from what they had been doing before the advent of the global pandemic. To test this hypothesis, an interaction term between the tone of the statement and the COVID-19 period is introduced. Moreover, not requiring data on interest rate futures, the following analysis can be conducted on the whole sample ranging from April 2015 to February 2023.

From *table 3* it is possible to see that the interaction term has a positive coefficient which, however, is not statistically significant. A possible explanation for the statistical insignificance might reside in the lack of power of the model that is introducing too much noise to detect the presence of a possible significant effect when there is one – a potential case of type II error. To test for the possible lack of power of the model, a correlation between its squared residuals was run. The rationale for this test was that if the residuals showed a correlation pattern among them, and that was not captured in the model, then the model lacked power to detect main effects. Therefore, the model could be improved by controlling for patterns in the error term. *Figure 3* shows that there is unmodeled volatility in the error term up to 10 time lags with the bulk of it occurring at lags of 1 and 2. Partial autocorrelation is also observed, particularly at lag 1. Partial autocorrelation is important to take into account since it measures the amount of correlation that is not explained by previous time lags. Combining these findings provides useful insights that can be leveraged employing a model that takes them into account.

GARCH Model. This section explores how a GARCH (*p, q*) model is best suited to model volatility levels that are conditional on time. The order of the GARCH term (*p*) is obtained from the lag with the highest partial autocorrelation, while that of the ARCH term (*q*) is determined based on the lags presenting the most significant autocorrelation. From the previous analysis on residuals, sensible values for *p* and *q*, respectively, are 1 and 2. GARCH models are the most employed in the current literature exploring volatility as they provide very consistent results and allow for more robust models that can adjust for shocks over time. The power of a GARCH model is better understood when it is presented in its mathematical formulation. It is important to keep in mind that the main aim of such model is to help with the decomposition of the error term into a predictable (deterministic) and a stochastic component, so that only random processes are contained in the error term. This relies on the assumption that the error term can be decomposed as:

with being the deterministic component and representing white noise, which is nonpredictable by definition. This results in the formulation of the conditional variance and conditional mean equations.

The conditional variance equation explains how the variance of the series depends on the squared error term from the previous periods and a lagged autoregressive term. The former is also known as the ARCH term. The coefficients measure the magnitude of the effect of squared errors on the conditional volatility. The remaining term is an autoregressive one showing the relationship of the dependent variable with a lagged version of itself. Similarly, here the coefficient quantifies the importance of such effect. When controlling for these terms in the conditional variance equation, the conditional mean equation has more power to detect main effects of predictors. In this equation, represents the expected value that the dependent variable would take if all other predictors were to be set equal to zero. On the other hand, represents a matrix of coefficients multiplying a vector of independent variables at time *t*. It is now possible to substitute into the conditional mean equation the estimated coefficients obtained through maximum likelihood estimation. From *table 4* column 1 the coefficients for the conditional mean equation are:

The interpretation of the coefficients is as follows:

**Constant**: On average, when all other predictors take value 0, the VSTOXX amounts to 16.04.

: On average, and holding everything else constant, a hawkish statement is associated with a change in volatility for the period of -1.391.

: On average, and holding everything else constant, the COVID period is associated with a change in volatility for the period of 5.824 compared to non-COVID periods.

: On average, and holding everything else constant, the co-occurrence of COVID and a hawkish statement is linked to an increase in volatility for the period of 5.676.

From the analysis, it can be concluded that when controlling appropriately for explicit patterns of the error term, the coefficient of the interaction term becomes positive and statistically significant at the .01 significance level. This might indicate a reversal in how hawkish statements started to be perceived after the COVID-19 pandemic. Indeed, if before hawkish statements were associated with a decrease in volatility, during the COVID-19 period they became highly associated with an increase in equity market’s volatility.

# Limitations of the Study

The main limitations of the current study are reflected in data on futures contracts whose availability could not cover the entire period of the analysis. This caused a sample reduction when analyzing the surprise component of monetary policies and did not allow for the introduction of the interaction term between COVID and the tone of the statement. This was mainly because until December 2021 there was no co-occurrence of COVID-19 and a hawkish statement, making the introduction of an interaction term useless.

Moreover, while the GARCH model solved some of the issues of previous linear models by correcting for conditional volatility, it still presents some issues when it undergoes further diagnostics. For instance, from *Figure 4* it is possible to see that the mean of the residuals obtained from the GARCH model is not 0, thus suggesting that it does not closely mirror normally distributed white noise centered about 0. Although this is a violation of one of the assumptions of the GARCH model, no other pattern seems to be emerging from the residuals signaling that most of their predictable power has been included in the conditional variance equation.

Lastly, all models presented in this study were not tested on an out-of-sample basis and, therefore, their true forecasting power cannot be determined. This approach could be improved by either using Machine Learning algorithms coupled with validation processes or by leaving out a test portion of the dataset. Given the small size of this dataset, leaving a test portion out would have represented a significant drawback of the analysis and, therefore, it was not performed. Advanced methods that would be also useful to improve on the current study would require the implementation of appropriately trained Recurrent Neural Networks (RNNs). The ability of such machine learning algorithms to automatically determine optimal synaptic weights could dramatically enhance the forecast outcomes (Di-Giorgi et al., 2023). Together all those suggestions can be considered in future studies to improve upon the outcomes of the present analysis.

# Conclusion

To sum up, this study found evidence supporting the hypothesis that volatility in equity markets is significantly related to the tone of central banks’ statements and the surprise component of interest rate changes. Specifically, it concluded that, based on a sample from 2015 to 2021, a 25 bp unexpected change in interest rate would lead to an increase in volatility of 4.57 - about a 25% increase when considering the average volatility in this time window. Although in a first model the hawkishness of the tone was found to be significantly negatively correlated to volatility, another model considering the interaction of the hawkishness of the statement with the COVID-19 period returned a significant and positive coefficient. This finding highlights how the pandemic period is linked to a reversal in equity markets’ perception of hawkish statements, with them being now perceived as an indicator of higher risk and, therefore, relating positively to volatility.

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Appendix

# Tables



Table 2 Autocorrelation-adjusted Linear Models

Table 1 First Linear Models



Table 5 Full Sample Summary Statistics

Table 4 GARCH Model

Table 3 Interaction between COVID and Statement's Tone

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Figure 3 Correlation of Squared Residuals from Linear Interaction Model

Figure 2 Residuals Correlation from Linear Models

Figure 1 Classification Table from Chadha et al. (2020)

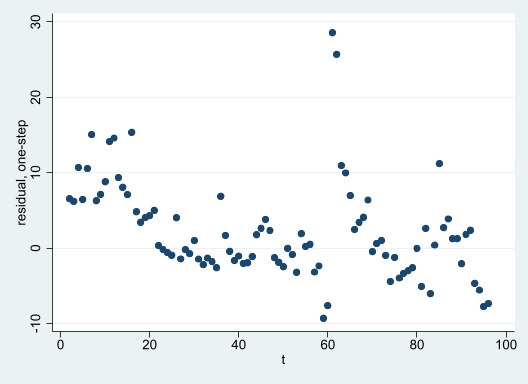


Figure 4 Residuals from GARCH Model plotted over Time

1. The repository with the full code employed in the analysis is available at the following link: <https://github.com/tricarico672/Capstone_Text_Analysis> [↑](#footnote-ref-2)
2. See Figure 1 in the appendix for reference on which words were included for the classification of each tone. [↑](#footnote-ref-3)