Applied Data Science

Final Project

Paper replication of

The Similarity of ECB'S communications

paper by

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replicated by

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1. Introduction

According to the efficient market hypothesis, one cannot outperform the market as stock prices incorporate all public information available about a company (according to the strong efficient market, stock prices incorporate both public and private information but this theory has been discredited) (Fama et al, 1970).Those theories have been put into question and new researches have shed the light on new methods (cointegration), that, if validated, can allow one to make stock prices predictions. However, others still expect stock prices to incorporate relevant information regarding the state of a company. That information can also encompass economic previsions and therefore announcements from major European entities.

For instance, Funke and Matsuda (2006) proved that ECB monetary policy announcements can potentially impact stock prices as they encompass transparent and accurate information regarding future shifts in economies, such as interest rate and exchange rate. Other authors align with those statements: for instance Schmeling and Wagner (2019) demonstrated that a higher positive tone employed in ECB speech is associated with higher equity market returns and that tone impacts stock prices through risk premium (Baranowski et al, 2023). In the same vein, Amaya and Filbien (2015) found that investors increasingly extracted information from ECB announcements and more especially from ECB MRO rate announcements. They incorporated them into their valuation models. They also found that since investors consider more information from monetary policy announcements, they gained less abnormal returns, also proving that stock markets could better predict ECB movements.

In this paper, we will therefore analyze ECB communication and its shift over time. We will employ the same methodology used by Amaya and Filbien and will extend the study time until December 2022. We will first measure the similarity of ECB statements at press conferences and its evolution over time, and then we will measure the market's reaction to ECB communication announcements. Finally, we will investigate the association between similarity of ECB announcements and market reaction. We will use the study of Amaya and Filbien as a proxy and will compare our results to theirs. This study aims to investigate whether similarity of ECB statements has changed since 2013 and whether market's reactions have also changed accordingly.

2. Data

We collected the date and the content from every ECB press conference from the 9th of June 1998 to the 15th December 2022, directly from the ECB's website using a web scraping method. Then a series of manipulations (the NLP pipeline) had to be applied to the content of each announcement to prepare them for the sentiment analysis. We first cleaned the dataset by removing introductions, and the conclusions repeating each time unnecessary for the analysis, as well as the contractions and the digits. We kept Q&A as we thought that it could provide more insight on the sentiment of the announcement. Then, the text was normalized, tokenized and the English stop words were removed. The collection methods and the sources of the other variables used in the analysis can be seen in the Appendix. We also collected the Euro Stoxx 50 Index Closing Price from Google Finance. Regarding control variables, we collect MRO change directly from the ECB website. We collected monthly HICP data from Eurostat. We collected the output gap (yearly data) from Ameco Online database. Finally, we gathered positive words and negative words from Opinion Lexicon, which directly took those lists from previous studies (Liu et al.., 2005).

3. The Similarity of ECB Statements

3.1. The similarity of ECB announcements

We computed the similarity between two consecutive ECB statements. We employed the same methodology used by Tetlock (2011) and by Amaya and Filbien (2014). We first converted each content of the conference into bigrams, or " two words coming together in the corpus". Then, we used the following formula to find the level of similarity across statements:

$$Similarity_i = \frac{Bigrams_i \cap Bigrams_{i-1}}{Bigrams_i \cup Bigrams_{i-1}}$$

We first looked at common bigrams presented in each two consecutive speeches. Then, we computed the number of unique bigrams present in the union of the two texts (or total bigrams in a speech i - common bigrams + total bigrams in a speech i+1 - common bigrams + common bigrams). By using this ratio, we could compare the evolution of similarity across time. A value close to 1 means that the speeches are highly similar and present common expressions, whereas small values (next to 0) mean that statements are completely different. We then plotted the results and the results can be seen in Figure 1 in the Empirical Results section. While Amaya and Filbien also compared this ratio to other similarity measures, such as cosine coefficient or correlation, we decided to only focus on it as we thought it was already a good proxy to emphasize similarity across speeches.

After computing the similarity score for each ECB speeches, we performed the same regression than that of Amaya and Filbien to investigate on linear trends in similarity score across time:

$$logSimilarity_i = \alpha_0 + \alpha_1 logTime_i + \beta' Control_i + \epsilon_i,$$

Our vector controls encompass output gap, change in MRO and inflation. This vector will be reused in other regressions. To replicate closely the results of Amaya and Filbien, we matched changes in MRO to the closest speech announcement. However, we could not find quarterly output gaps as Amaya and Filbien did, so we therefore resorted to yearly data and matched each conference of a given year to the corresponding output gap.

3.1.2. Measuring market's reaction to ECB communication announcements

We firstly collected daily stock prices from Dow Jones Euro Stoxx 50, or the referential index for euro one. We could then compute the daily return or the logarithm of the ratio of the Price at i,t on the Price at i, t-1. We also estimated constant mean return as we wanted to compute abnormal returns, which can be defined as followed:

$$AR_{i,t} = R_{i,t} - \overline{R}_{i,t}$$

One has to subtract daily returns from average index returns to find abnormal returns, that is, unexpected large profit or losses from a specific investment or portfolio (Barone, 2021). In line with Amaya and Filbien, we used Fama methodology to find those returns, that is constant mean returns, or the most appropriate model when one is working with stock market index data. Indeed, Fama looked at abnormal behavior in returns of stocks during specific events to investigate the speed of adjustment of stock prices to new specific information release. The average index return can be computed as followed:

$$\bar{R}_i = \frac{1}{T_1 - T_0} \sum_{t \in [T_0, T_1]} R_{it}.$$

Similarly to Amaya and Filbien, we used an estimation window that covers 250 days to 50 days before the announcement date. In our case T1 is equivalent to 250 and T0 to 50. Finally, we summed those abnormal returns to find cumulative abnormal returns, which can defined as followed:

$$CAR_i = \sum_{t=-5}^{5} AR_{i,t}.$$

Cumulative return is the total sum of abnormal returns and is frequently used to measure the effects of specific events on stock prices. We used here an estimation wisdom that includes the returns 5 days before the announcement dates to the returns 5 days after the announcement dates.

3.1.3 Similarity of ECB announcements and market reaction

Following the methodology employed by Amaya and Filbien, we computed the pessimism score for each ECB speech. We did so to analyze informational content of each speech, and to test whether the ECB Speech similarity is related to a decrease in market's reaction. We define the variable "Pessimism" following Ferguson et al. and Garcia (2013):

$$Pessimism_i = \frac{NegativeWords_i - PositiveWords_i}{TotalWords_i}$$

The higher the value, the higher the level of pessimistic content in the announcement. Since almost all our pessimism variables are negative, the closer the value to one, the higher the level of pessimistic content in the announcement. Moreover, regarding negative words and positive words, we did not take the same exact list as that of Amaya and Filbie, who used the Loughran and McDonald Dictionary. The list we took also incorporated financial specific words. We could then input the pessimism variable in the following regression:

$$|CAR_i| = \gamma_0 + \gamma_1 logSimilarity_i * Pessimism_i + \alpha' Control_i + \eta_i,$$

Similarly to Amaya and Fabien, we were interested in estimating the effect of similarity of ECB speeches (combined with the variable pessimism) on cumulative abnormal returns. We used the same vector control as Amaya and Fabien.

3.2. Empirical Results

3.2.1. Descriptive Statistics

We summarized descriptive statistics for our variables as shown below:

	count	mean	std	min	25%	50%	75%	max
CAR	268	0.00173928	0.0455982	-0.314637	-0.018556	0.00764478	0.0263905	0.154176
CARAbs	268	0.0318075	0.0326608	0.00110192	0.0119063	0.0247791	0.0406667	0.314637
SentimentScore	268	-0.0332636	0.0151196	-0.0893204	-0.0415526	-0.0328374	-0.0226687	0.00178944
similarity	268	0.12057	0.0378219	0.0110069	0.0949599	0.122828	0.148354	0.195546
OutputGap	268	-0.433582	2.0847	-6.2	-2.2	0	1.3	2.8
InflationRate	268	0.1819	0.410062	-1.27204	-0.0164624	0.179854	0.386507	2.38451
MROchange	268	-0.000932836	0.156294	-0.75	0	0	0	0.75

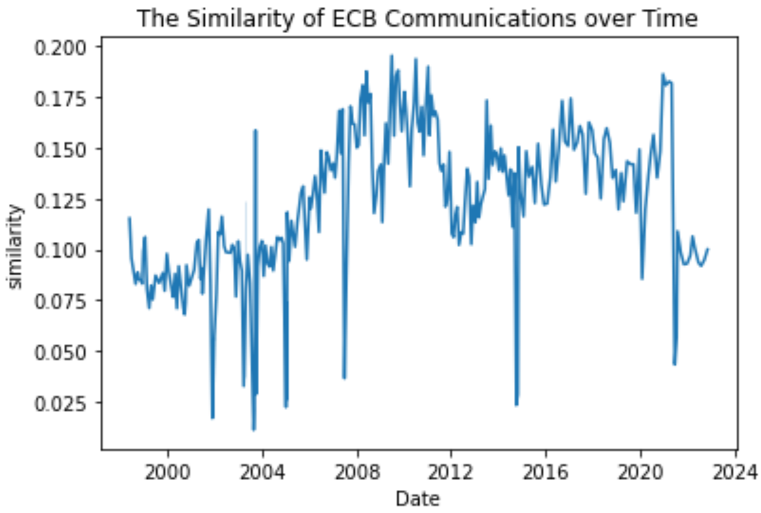
The Sentiment Score corresponds here to the pessimism score (or the imbalance between the number of negative words to positive words as a proportion of the total number of words in the *i*th announcement). In line with Amaya and Filbien's results (who found an average level of pessimism equal to -0.26%), our average level of pessimism is very close to 0, proving that the average level of pessimism slightly increased over time (by comparison with Amaya and Filbien studies). However, one can still note that ECB rather employs a neutral tone as the percentage is still very low.

Moreover, our output gap is slightly negative during the study period. This result is not surprising as a negative output gap occurs generally in a period of recession, which happened in 2020 during the COVID outbreak.

About CAR variables, the mean abnormal stock market reaction to ECB MRO rate announcement, has a mean around 0.0017 which is superior compared to Amaya and Filbien's results and, especially, positive. On the other hand, The distribution of absolute CAR seems equivalent to the paper. Regarding similarity, the mean is lowered by roughly 50%, which means less similarity between ECB communication is our sample period.. Finally, our average MRO delta is very similar to that of the authors, proving that in the long run, shifts in MRO rates compensate with each other.

3.2.2. Similarity of ECB communication across time

In line with Amaya and Filbien's results, we found an increase in similarity of ECB communications over time for the same sample as theirs. Nevertheless, one has to note that this increase is valid until 2008, after which the similarity in ECB communications started decreasing and showing a higher volatility. The results of our analysis can be seen in the figure below.



However, our results differ from those of Amaya and Filbien when considering the scale of the similarity measure of the ECB's communications. Even though we followed as closely as possible the methodology employed by Tetlock (2011) and Jaccard (1901) to compute similarity across bigrams, the maximum of the percentage of bigrams similarity reached up to 55% in the initial paper, while in this study the maximum level of similarity is around 20%. This difference could be explained by content taken during the analysis, as well as the longer timeframe. For instance, Amaya and Filbien might have included the introductory part of the statements (e.g. the title, the salutations, etc.) and removed the Q&A in their analysis, which could increase the similarity ratio.

We also could notice some periods in which the similarity ratio decreases sharply. For instance, in October 2014, the similarity ratio plunged to 0.023. Actually, on 2 October 2014, ECB released new details regarding covered bond purchase programmes and asset-backed securities (ECB, 2014). This period matches exactly the decrease in similarity ratio, which occurrs between the speech on 9 September and 2 October. This new speech on introduction on asset purchases programs explains the sharp decrease in the similarity ratio. Besides, in September 2003, the similarity ratio reached its lowest level or 0.021. In this same period, ECB released an exclusive speech regarding inflation differentials in the euro area and its potential causes and implications. Finally, in June 2021, the similarity ratio between the speech of 22 April and that of 10 June reached 0.04. At this time, the ECB announced new economic measures regarding the pandemic (continuity of asset purchases, refinancing operations..).

3-3 Regression Analysis

All results of regression can be found in Appendices. In some regressions, we found mixed results compared to those of Amaya and Filbien. For instance, and regarding the OLS regression that explains the similarity with Time **(Appendix 1**), our logTime coefficient is positive (0,12) and significant(as the p-value is very close to 0), aligning with results of the authors. However our Beta 1 coefficient is still less important than that of the author (0.463), meaning that similarity cannot be directly explained by time. Those findings are consistent with our graph above, which shows that there is a higher variation in the similarity between announcements after 2008. This higher volatility might be partly explained by emergence of unexpected events (such as covid outbreak and Ukraine crisis during 2020-2022). Moreover, shifts in our control variables do not seem to have an impact on similarity over ECB statements, differing with results of Amaya and Filbien who found that, for instance, shift in inflation partially explained similarity as the coefficient equaled -0.17. Thus, our result could be explained by the fact that the ECB introduces new monetary subjects in its statements and therefore has expanded the scope of its subjects from 2008 to 2022.

Additionally, we also assessed the market's reaction to the informational content of announcements. Results are put in **Appendix 2.** Our beta1 coefficient (0.27) is relatively closed to that found by the authors, but still lower. It seems that a shift in pessimism will impact less the absolute CAR when we extend the period of the study. In other terms, the market still reacts to negative announcements but in lower proportions. Those results are consistent with those of the authors as it proves that investors react less to negative contents as they might already expect those measures. Moreover, if we look at other potential drivers of CAR, which are control variables (**Appendix 3),** we can notice that those variables are still not useful to explain markets' reactions when we perform the regression. Those results are aligned with Amaya and Filbien's statements who proved that the Eurozone stocks markets are unresponsive to these control variables.

In the last two regressions **(Appendix 4 and Appendix 5**), we performed regression to try to explain first absolute cumulative abnormal returns with the interaction between similarity and sentiment score and then absolute cumulative abnormal returns with those same variables and control variables (output gap, MRO delta and inflation).The first regression shows the effect of ECB communication resemblance on markets' reaction, with a condition on the level of similarity of communication statement. In both regressions, the coefficient of interaction is not significant compared to that of the authors as they had a coefficient up to -26% for the first of those regressions. So similarities between ECB's communication isn't significantly modulating the impact of pessimism score on markets' reaction. If we include control variables (**Appendix 5**), the interaction between similarity and sentiment store accounts slightly increases. As in the original paper, no control variables seem to impact the absolute CAR as each coefficient is not significant, confirming the statement that investors react increasingly less to ECB monetary announcements. Other drivers seem to influence the absolute CAR.

So we can assess that ECB similarities in their communications isn't reducing the effect of pessimism score on markets' reaction. This isn't logical because if the new conference from ECB is similar to the previous one, markets shouldn't react since ECB is keeping the same objectives as before.

4. Conclusion

While Amaya and Filbien contributed to the existing literature on ECB communication by proving that similarity over ECB monetary policy statements has increased over time, our results are more mitigated and even though we detected a linear trend in similarity until 2008, no clear tendency regarding similarity between ECB speeches can be perceived after this time. This phenomenon might be explained by the introduction of new contents in ECB speeches, and those contents might be directly related to new monetary measures. For instance in 2015, ECB resorted to unconventional monetary tools: quantitative easing.

Moreover, our summary statistics indicate that the distribution of variables (CAR, Pessimism..) has changed over time. As we extended the sample period, we captured new types of events that implied new reactions from ECB. For instance, the Covid-19 crisis has made the prospects unclear on every market, even with ECB communications and interventions. But we can also mention the 2022 year with the Russo -Ukrainian war. Obviously, those events only occur in a small time frame (from 2020 to 2022) and therefore can only partially explain the shift in distribution.

Nevertheless, our results still align with those of authors in some ways. First, we also found that pessimism in speeches still has an impact on market reactions, but at a lower proportion than that found in Amaya and Filbien. Since the average level of pessimism has slightly increased, we can suppose that investors generally react less to pessimism in announcements. Moreover, in all regressions, our variable controls are not significant, meaning that investors do not take into consideration change in those variables, probably because they already expect changes before announcements. However, one has to note that pessimism is the only variable that still explains relatively small changes in absolute CAR, even though the coefficient in the regression is small.

Regarding future research, one could, for instance, examine to what extent the use of unconventional monetary tools influence the level of similarity across ECB statements or examine whether the last events of the last decade (with a particular focus of the last two years with the outbreak and the Ukraine crisis) has pushed ECB to review the format of its speech.

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Appendix

Data Collection

Data	Frequency	Method	Source	Useful for
ECB press conferences	every conference since 1998 to 2022	Web Scraping	ECB Website	Calculation of Sentiment Score and Similarity variable
Euro Stoxx 50 Index Closing Price	daily	Downloaded series as Google sheets and imported as csv	Google Finance	Calculation of the Cumulative Abnormal Return (CAR) variable
MRO change	every MRO change with respective date	Python list of dates and respective changes	ECB website	Control variable
Harmonized Index Consumer Price	monthly	Parsed the data directly from website	Eurostat	Control variable (proxy for inflation_
Output Gap	yearly	Downloaded the data and imported the csv	Ameco Online database	Control variable
Positive Negative Words	NA	Import data from text file	Bing Liu, Minquing Hu and Junsheng Cheng	Pessimism Score

Regression Analysis

Appendix 1: Similarity of ECB communications over time

The screen below shows the results of the regression below, which identifies any linear trend in the similarity of ECB statements across time.We used 268 ECB speeches from 1998 to 2022, therefore extending the timeframe of the study of Amaya and Filbien. Except for Log time, all our control variables are not significant, differing from the author's results.

$$logSimilarity_i = \alpha_0 + \alpha_1 logTime_i + \beta' Control_i + \epsilon_i$$

```
                            OLS Regression Results
==============================================================================
Dep. Variable:          logSimilarity   R-squared:                       0.129
Model:                            OLS   Adj. R-squared:                  0.116
Method:                 Least Squares   F-statistic:                     9.723
Date:                Thu, 05 Jan 2023   Prob (F-statistic):           2.38e-07
Time:                        11:58:21   Log-Likelihood:                -140.77
No. Observations:                 268   AIC:                             291.5
Df Residuals:                     263   BIC:                             309.5
Df Model:                           4
Covariance Type:            nonrobust
=================================================================================
                    coef    std err          t      P>|t|      [0.025      0.975]
---------------------------------------------------------------------------------
Intercept        -3.2143      0.206    -15.629      0.000      -3.619      -2.809
logTime           0.1263      0.026      4.864      0.000       0.075       0.177
OutputGap        -0.0180      0.013     -1.348      0.179      -0.044       0.008
MROchange        -0.1241      0.166     -0.748      0.455      -0.451       0.203
InflationRate     0.0486      0.063      0.766      0.444      -0.076       0.174
==============================================================================
Omnibus:                      163.820   Durbin-Watson:                   1.015
Prob(Omnibus):                  0.000   Jarque-Bera (JB):             1058.144
Skew:                          -2.511   Prob(JB):                    1.69e-230
Kurtosis:                      11.339   Cond. No.                         67.1
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
```

Appendix 2: CAR and Sentiment Score

Explaining absolute cumulative abnormal returns with the variable pessimism score. The dependent variable is CAR and the independent variable, pessimism score. The sample consists of 268 ECB speeches from 1998 to 2022.

$$|CAR_i| = \beta_0 + \beta_1 Pessimism_i + \eta_i.$$

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                 CARAbs   R-squared:                       0.016
Model:                            OLS   Adj. R-squared:                  0.012
Method:                 Least Squares   F-statistic:                     4.354
Date:                Tue, 03 Jan 2023   Prob (F-statistic):             0.0379
Time:                        22:29:04   Log-Likelihood:                 538.76
No. Observations:                 268   AIC:                            -1074.
Df Residuals:                     266   BIC:                            -1066.
Df Model:                           1
Covariance Type:            nonrobust
==================================================================================
                     coef    std err          t      P>|t|      [0.025      0.975]
----------------------------------------------------------------------------------
Intercept          0.0409      0.005      8.497      0.000       0.031       0.050
sentimentScore     0.2748      0.132      2.087      0.038       0.016       0.534
==============================================================================
Omnibus:                      250.031   Durbin-Watson:                   2.007
Prob(Omnibus):                  0.000   Jarque-Bera (JB):             6698.622
Skew:                           3.707   Prob(JB):                         0.00
Kurtosis:                      26.343   Cond. No.                         66.3
==============================================================================
```

Appendix 3: CAR and control variables (Output gap, MRO change, inflation)

Explaining absolute cumulative abnormal returns according to control variables (output gap, inflation and delta MRO).The sample consists of 268 ECB speeches from 1998 to 2022.

$$|CAR_i| = \gamma_0 + \alpha' Control_i + \eta_i$$

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                 CARAbs   R-squared:                       0.024
Model:                            OLS   Adj. R-squared:                  0.013
Method:                 Least Squares   F-statistic:                     2.169
Date:                Thu, 05 Jan 2023   Prob (F-statistic):             0.0921
Time:                        12:01:33   Log-Likelihood:                 540.47
No. Observations:                 268   AIC:                            -1073.
Df Residuals:                     264   BIC:                            -1059.
Df Model:                           3
Covariance Type:            nonrobust
=================================================================================
                    coef    std err          t      P>|t|      [0.025      0.975]
---------------------------------------------------------------------------------
Intercept         0.0305      0.002     13.726      0.000       0.026       0.035
OutputGap        -0.0014      0.001     -1.433      0.153      -0.003       0.001
MROchange        -0.0253      0.013     -1.943      0.053      -0.051       0.000
InflationRate     0.0036      0.005      0.724      0.470      -0.006       0.013
==============================================================================
Omnibus:                      243.134   Durbin-Watson:                   1.982
Prob(Omnibus):                  0.000   Jarque-Bera (JB):             5878.986
Skew:                           3.592   Prob(JB):                         0.00
Kurtosis:                      24.791   Cond. No.                         14.1
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
```

Appendix 4: CAR and interaction between log similarity and sentiment score

Explaining absolute cumulative abnormal returns with the interaction between similarity and pessimism score.The sample consists of 268 ECB speeches from 1998 to 2022.

$$|CAR_i| = \gamma_0 + \gamma_1 logSimilarity_i * Pessimism_i + \eta_i.$$

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                 CARAbs   R-squared:                       0.012
Model:                            OLS   Adj. R-squared:                  0.008
Method:                 Least Squares   F-statistic:                     3.223
Date:                Tue, 03 Jan 2023   Prob (F-statistic):             0.0737
Time:                        22:32:34   Log-Likelihood:                 538.20
No. Observations:                 268   AIC:                            -1072.
Df Residuals:                     266   BIC:                            -1065.
Df Model:                           1
Covariance Type:            nonrobust
================================================================================================
                                   coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------------------------
Intercept                        0.0384      0.004      9.139      0.000       0.030       0.047
sentimentScore:logSimilarity    -0.0913      0.051     -1.795      0.074      -0.192       0.009
==============================================================================
Omnibus:                      250.405   Durbin-Watson:                   2.004
Prob(Omnibus):                  0.000   Jarque-Bera (JB):             6682.877
Skew:                           3.718   Prob(JB):                         0.00
Kurtosis:                      26.306   Cond. No.                         25.7
==============================================================================
```

Appendix 5: CAR and Similarity/Sentiment score interaction and controls

Explaining absolute cumulative abnormal returns with interaction between similarity and pessimism (sentiment score) and control variables.The sample consists of 268 ECB speeches from 1998 to 2022.

$$|CAR_i| = \gamma_0 + \gamma_1 logSimilarity_i * Pessimism_i + \alpha' Control_i + \eta_i$$

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                 CARAbs   R-squared:                       0.034
Model:                            OLS   Adj. R-squared:                  0.019
Method:                 Least Squares   F-statistic:                     2.280
Date:                Thu, 05 Jan 2023   Prob (F-statistic):             0.0611
Time:                        12:03:28   Log-Likelihood:                 541.78
No. Observations:                 268   AIC:                            -1074.
Df Residuals:                     263   BIC:                            -1056.
Df Model:                           4
Covariance Type:            nonrobust
================================================================================================
                                coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------------------------
Intercept                     0.0367      0.004      8.302      0.000       0.028       0.045
logSimilarity:SentimentScore -0.0818      0.051     -1.605      0.110      -0.182       0.019
OutputGap                    -0.0012      0.001     -1.256      0.210      -0.003       0.001
MROchange                    -0.0243      0.013     -1.864      0.063      -0.050       0.001
InflationRate                 0.0030      0.005      0.597      0.551      -0.007       0.013
==============================================================================
Omnibus:                      242.924   Durbin-Watson:                   2.019
Prob(Omnibus):                  0.000   Jarque-Bera (JB):             5940.231
Skew:                           3.582   Prob(JB):                         0.00
Kurtosis:                      24.924   Cond. No.                         55.3
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
```