How does European Central Bank's Communication affect yield curves?

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The research aims to analyze the response of yield curves against ECB's communication from 2018 until May 2021. The analysis is executed for the monthly and daily data. The data published by ECB regarding Euro area government bonds yield of 3-month, 1-year, 2-year, 5-year, and 10-year maturity are aggregated. In addition, all speeches which are official released by ECB are collected as well. By applying natural language processing techniques, text mining and sentimental analysis in particular, the collection of speeches are converted into a monthly time series. After that, in order to observe the yield curves' reaction to communication of ECB, multiple OLS regression models are alternately executed on both daily and monthly dataset. The result appears that short-term yield curves, particularly 3-month maturity and 1-year maturity, are influenced by ECB's communication when the model applied on monthly frequency data. Besides, regardless of data frequency, there is no signals indicating the relationship between ECB's communication and 2-year, 5-year, 10-year maturity yields curves.

Keywords: Narative Economy, NLP, Text Mining, Sentimental Analysis, OLS Regression

1. INTRODUCTION

This paper focuses on observing the influence of the Central Bank's communication on the fluctuation of yield curves. In some cases, Central bank communication would be unnecessary for predictability, especially when markets sufficiently comprehend the reaction function of central bank. However, central bank communication may become more essential in periods of raising uncertainty. It is because conveying policy-makers' risk assessment influences expectations. The communication of Central Bank is underlined by adopting a two-pillar monetary policy strategy to assess risks to price stability in the euro area (Bernanke, Boivin and Eliasz, 2005). Thus, analysing the communication of Central Bank could helps in term of knowing its important and its impact on other Economy indicators.

The literature has shown that communication by policy-makers carry information relating the current assessment of macroeconomic and financial developments of central bank', its risk assessment as well as possible policy reactions at next meetings (Égert and Kočenda, 2014). The near-term predictability of interest rate decisions is enhanced by major central banks through official communication (Jansen and Haan, 2009). The results is confirmed by some other papers in which they applied linguistic algorithms to measure the sentiment of policy deliberations with quantitative communication indicators of central bank communication. (Cayla, Maizi and Marchand, 2011).

In this paper, I would like to combine several natural language processing techniques in order to analyse the impact of European Central bank communication on yield curves using the most recently data.

2. DATA

In order to answer the research question, we first need to measure two main entities which are the communication of European Central Bank and yield of short term bonds as well as intermediate-term bonds.

Yield Curves Yield curves data are aggregated for five different maturity period including 3-month, 1-year, 2-year, 5-year, and 10-year maturity. The data is collected as daily data then processed into monthly and daily data. The process can be observed in figure 1, the algorithm diagram. Yield curves data includes spot rates corresponding to the certain date.

ECB's Communication Figure 1 also reveals the data used for measuring ECB's communication. It is official speeches of Central Bank. Besides, the dates on which each speech is released are also collected.

Frequency and Period Yield curves data and ECB's speeches are collected entirely with daily frequency for the period from January 2018 to May 2021.

3. MODELING METHOD

The purpose of this research is to investigate whether the communication of ECB influences yield curves. Thus, an Ordinary Least Squared regression, in which yields is dependent variables and ECB's communication is independent variables, will be executed on the data achieved from section 2. Since OLS method can be exclusively applied on numerical data, converting text from released speeches into numerical values is a crucial step in order to achieve the input for OLS regression. On the whole, section 3 will include three main parts. First, Natural Language Processing techniques that help converting speeches into time series will be introduced. Also, how it is converted into daily and monthly data will be explained. Second, the brief description on how the yield curves are aggregated will be interpreted. Thirdly, a short introduction on regression equations will be clarified in this section as well.

3.1. Natural Language Processing

Topic Extraction
Extracting and selecting macroeconomics-relating topics
As its name, topic extraction is a technique for extracting the main topics indicated in the corpus. In particular, Latent Dirichlet Allocation (LDA) will be applied on the speeches data in order to extracting 15 main topics. LDA is an approach based on probabilistic vectors of words, which indicate their relevance to the text corpus. Ten representative words whose the highest probability of each

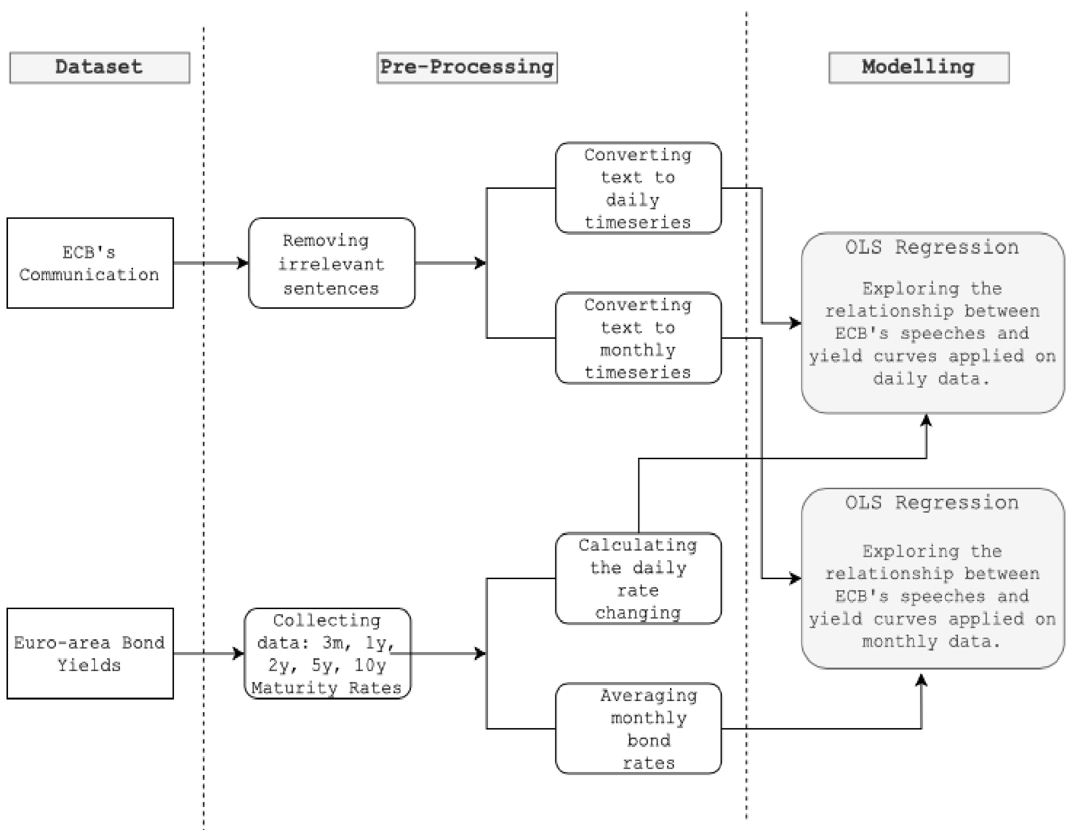

Figure 1. Algorithm for modelling the effects of ECB's communication on yield curves

topic will be listed. Based on the listed vocabularies, certain macroeconomics-relating topics will be selected for the next step of sentimental analysis whereas irrelevant topics will not be taken into consideration. At this stage, there is nothing has changed in our data set. The only insights we have are fifteen extracted topics and selected ones.

Removing irrelevant sentences After determining selected topics, each sentence in each speech will be assigned to one of fifteen extracted topics. After that, all sentences that are assigned to the unselected topics will be eliminated. The remained data included economics-related sentenced and its released date. Monthly and daily data will be aggregated separately for the sentimental analysis step.

Sentimental Analysis
As the result of LDA analysis, our data now includes macroeconomics-topic-relating corpus. These corpus are the result of joining remained sentences according to to each day. By joining sentences of the same month, we will have also monthly corpus. In each corpus, sentences are split into single words. Each word will be assign multiple score values including positive score, negative score, neutral score and compound score. Finally, all speeches are converted into multi monthly time series and multi daily day time series. An example of how a text can be converted to multiple indexes:

mm	sent	topic	neg	neu	pos	compound
2019-07-01	Text	1	0.169	0.725	0.106	-0.6557

Text in the previous table is: *To a significant extent, this sequence of low inflation rates reflects the prolonged adjustment dynamics that characterise the aftermath of a major global financial crisis, together with a substantial downward shift in the realisation of shocks to inflation that we have observed in recent years.*

3.2. Yield Curves

Daily Time Series Yield curves data includes five daily time series maturity period including 3-month, 1-year, 2-year, 5-year, and 10-year maturity. In this research, we aim to know whether the ECB's communication influences daily yield curves. Thus, in stead of using the daily bond rates of each day, we will find the different of rate between two days.

$$Dif_i = Rate_{i+1} - Rate_i$$

In which, Dif_i is the rate changing of the date i^{th}; $Rate_i$, $Rate_{i+1}$ are respectively the bond rate on the i^{th} and $(i+1)^{th}$ day. In the OLS regression, we will get to know whether the speeches on i^{th} day has any relationship with the $Diff_i$ index.

	Term per Topic
Topic1	legislative, buy, resort, wholesale, leaning, weight, risen, lender, permanent, resulted, highlighted, understood, determining, modern, interface
Topic2	difficulty, triggered, integrity, standardised, successfully, equal, aftermath, fsb, dealing, equivalent, mitigating, described, tangible, accepted, hole
Topic3	tariff, shadow, yves, virtual, meant, concrete, prudent, vc, partner, skill, exit, outflow, reliable, genuine, otherwise
Topic4	diversification, contributes, incident, anticipated, simulation, emerged, strategic, complexity, utilisation, narrow, warrant, rose, heightened, weather, patience
Topic5	balanced, ec, aligned, store, surrounding, diffusion, characterised, indicated, break, tends, prevented, precisely, fragmented, brief, taylor
Topic6	continuing, fear, anchored, revolution, actor, drive, redemption, raised, trough, organisation, seek, planning, reversal, separate, resolved
Topic7	converge, moderation, bear, signalling, accept, boom, outright, creates, encouraging, safeguarding, regional, turned, amid, occasion, anticipate
Topic8	bubble, harmonisation, statute, contained, ground, fluctuation, argument, box, bund, democracy, belief, proper, phenomenon, prepare, applies
Topic9	surprise, application, counterparty, floor, deutsche, pick, thinking, delay, peak, conditional, caput, automation, recognition, track, geopolitical
Topic10	sensitivity, ssm, mortgage, albeit, stood, costly, anchoring, commerce, complementary, spirit, adopt, coordinated, backdrop, lecture, passed
Topic11	const, psd, search, recovered, perceived, category, room, shortcoming, safer, muted, enabling, ecrb, proportionate, appreciation, acceptance
Topic12	ester, presentation, frontier, bottom, picture, fair, pursuit, serious, discipline, materialise, showed, cumulative, foresee, complemented, reflection
Topic13	rating, platform, obstacle, decrease, surplus, undermine, systemically, sized, try, protracted, persistently, legitimacy, eased, exist, ledger
Topic14	svensson, peer, deleveraging, compensation, employed, sudden, depositor, concerning, author, eurozone, inflationary, grown, disaster, notable, guide
Topic15	praet, claim, constant, concentrated, whose, granted, srf, peter, construction, widespread, communicate, assistance, reap, issuing, property

Figure 2. Extracted topics from ECB's speeches

Monthly Time Series Monthly yield curves data includes five monthly time series. Values of each month are the average daily rate of that month.

3.3. Ordinary Least Squares Regression

Ordinary least squares (OLS) regression is a statistical method of analysis that estimates the relationship between one or more independent variables and a dependent variable. In this research, we will apply it on different maturity yield data and time series data that extracted as well as converted from ECB's official speeches The method estimates the relationship by minimizing the sum of the squares in the difference between the observed. General regression equation:

$$yield_i = \alpha + \beta * Communication_{narrative} + \epsilon$$

In particular, $yield_i$ is one of five bond rates' types while $Communication_{narrative}$ are the positive score, negative score and compound score.

4. RESULTS

4.1. Daily Data

Topic extraction The keywords, i.e. tokens, in total fifteen topics are presented in figure 2. Six topics are selected because they mentioned about different economic-related concerns. The selected topics are:

- Topic 1: A topic about lender and liquidity.
- Topic 3: A topic mentioned about tariff.
- Topic 7,8: Two topics about the risk of the economy.
- Topic 10: A topic which is focusing on mortgage.
- Topic 14: The last topic covering legislative and yield curves with Svensson model.

Figure 3. Topic 1 Word-Cloud

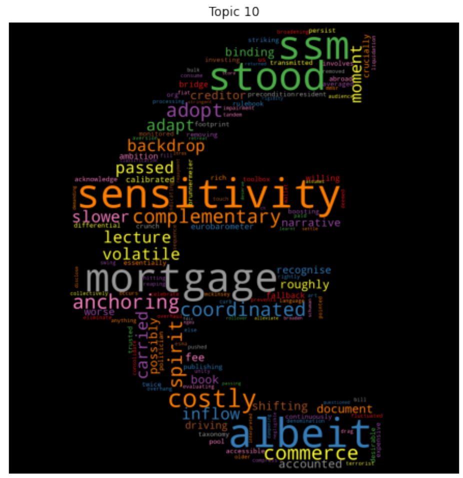

Figure 4. Topic 10 Word-Cloud

Figure 3 and figure 4 are world-cloud visualizations of 150 representative words corresponding to topic 1 and topic 10 in table 2.

Dropping irrelevant sentences After having selected topics, we will eliminate all irrelevant sentences regarding other nine unselected topics. Figure 5 shows the number of the sentences that are assigned to all fifteen topics. Meanwhile, we can see in figure 6 the distribution of sentences on selected topics after deleting all noise corpus.

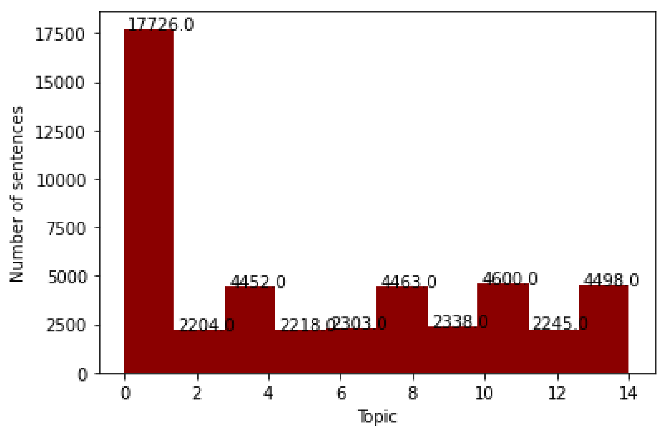

Figure 5. Topic distribution before elimination

Sentimental analysis Our data in this stage is still text. However, it is more selective than the original speeches data. By applying sentimental analysis, we will convert these selective corpus into numerical values using **VADER Lexicon** dictionary from **nltk** library. On the

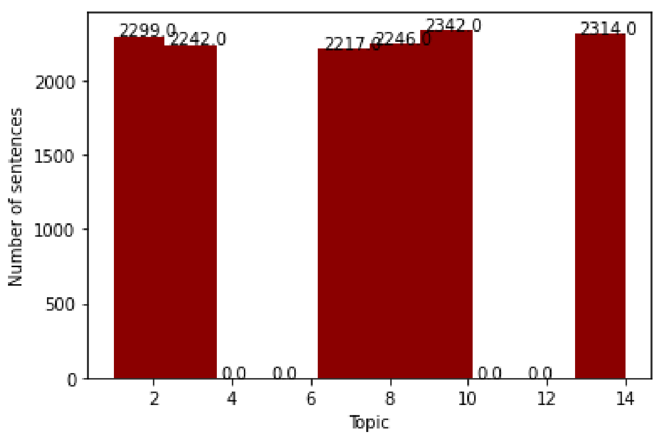

Figure 6. Topic distribution after elimination

whole, our text data is converted into multiple daily time series including positive scores, negative score, neutral score and compound score time series. In this paper, I will use only three of them, which are positive, negative and compound values, in order to run the OLS regression model.

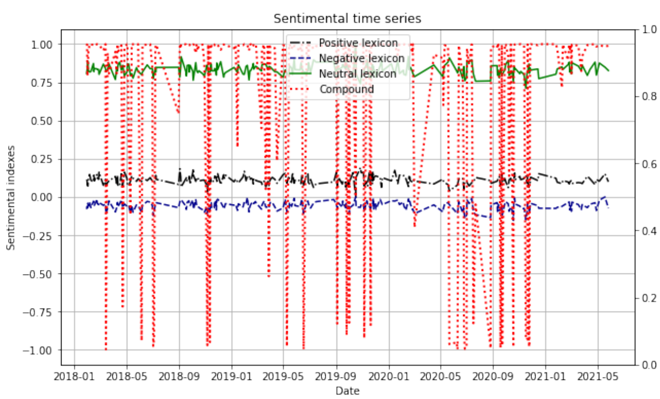

Figure 7. Sentimental timeseries converted from speeches

OLS Regression In this section, we will run OLS regression multiple times. We repeated the regression by remaining independent variables which is visualized in 7 and replacing one by one dependent variable as in 8. Besides, OLS regression will be executed with and without intercept. We have two regression equations as following:

$$yield_i = \beta_0 + \beta_1 * x_{pos} + \beta_2 * x_{neg} + \beta_3 * x_{compound} + \epsilon \quad (1)$$

$$yield_i = \beta_1 * x_{pos} + \beta_2 * x_{neg} + +\beta_3 * x_{compound} + \epsilon \quad (2)$$

Executing OLS regression for all five yield curves, we have the OLS model summary in in Apendix A 5. The regression results show that P-values of all five models using equation 1 are not significantly. Therefore, it is impossible to conclude any insights about relationship of ECB's communication and yield curves. Moreover, after running the same experiment on the same data set using regression equation 2, p-value are much higher than the significant level of 95%. Thus, the model is not significant and we can not conclude about the instant influences of ECB's speeches on yield curves using daily data.

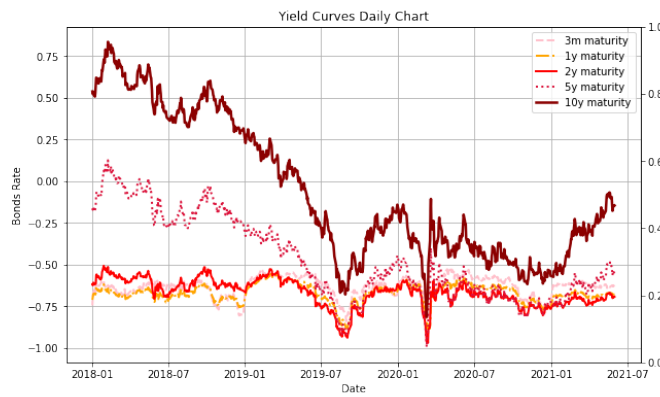

Figure 8. Yield curves

4.2. Monthly Data

In this section, we will execute the identical process as in the section 4.1. The unique feature that is different is that we will use monthly data for both yield curves and sentimental time series converted from monthly speeches.

Topic extraction The tokens of fifteen topics are presented in figure 9. Six economy-related topics are selected from 15 topics. They are:

- Topic 1: A topic about lender and liquidity.
- Topic 3: A topic which is focusing on mortgage.
- Topic 11: A topic concerning inflation.
- Topic 12: A topic about the risk of the economy.
- Topic 13: Another topic mentioned about tariff.
- Topic 14: The last topic covering legislative and yield curves with Svensson model.

Figure 10 and figure 11 are world-cloud visualizations of 150 representative words corresponding to topic 1 and topic 10 in table 9. Topic 1 shows the topic about lender of last resort. A lender of last resort is the institution provides of liquidity to a financial institution which is unable to obtain it. Meanwhile, topic 14 concerns Svensson model which stipulates that the shape of the yield curve.

	Term per Topic
Topic1	const, resort, harmonisation, wholesale, leaning, risen, lender, compensation, floor, fluctuation, depositor, permanent, belief, grown, reflection
Topic2	difficulty, standardised, successfully, equal, aftermath, decrease, concerning, strategic, fsb, reap, dealing, equivalent, mitigating, tangible, accepted
Topic3	psd, sensitivity, converge, shadow, virtual, deleveraging, mortgage, constant, meant, concrete, prudent, outflow, reliable, genuine, otherwise
Topic4	contributes, incident, anticipated, emerged, granted, fair, complementary, complexity, narrow, raised, rose, database, separate, journey, calculated
Topic5	buy, weight, balanced, frontier, stood, costly, recovered, aligned, store, surrounding, diffusion, characterised, break, tends, indicated
Topic6	diversification, continuing, fear, anchored, revolution, backdrop, enabling, acceptance, understood, trough, fragmented, planning, determining, disinflationary, feed
Topic7	ssm, yves, accept, simulation, author, outright, creates, safeguarding, regional, delay, amid, turned, proportionate, consistently, automation
Topic8	statute, triggered, employed, contained, ground, argument, boom, box, democracy, proper, prepare, emir, described, shifting, challenged
Topic9	application, counterparty, bear, deutsche, anchoring, pick, signalling, thinking, discipline, peak, caput, issuing, conditional, appreciation, recognition
Topic10	surprise, albeit, commerce, spirit, coordinated, lecture, passed, adapt, slower, volatile, inflow, carried, parameter, multiple, reversal
Topic11	search, platform, perceived, obstacle, category, room, inflationary, systemically, shortcoming, safer, pursuit, resulted, adopt, muted, assistance
Topic12	bubble, moderation, picture, encouraging, bund, sized, materialise, showed, phenomenon, foresee, occasion, redemption, warrant, complemented, precisely
Topic13	tariff, ester, presentation, rating, sudden, vc, surplus, undermine, srf, partner, exit, try, protracted, persistently, legitimacy
Topic14	svensson, legislative, peer, integrity, eurozone, skill, serious, actor, cumulative, highlighted, moved, crypto, failed, durable, notable
Topic15	praet, claim, concentrated, ec, bottom, whose, peter, construction, communicate, widespread, property, kind, applies, disaster, tackle

Figure 9. Extracted topics from ECB's speeches

Dropping irrelevant sentences In this stage, we remove irrelevant sentences concerning other irrelevant topics. Figure 12 shows the number of the sentences that are assigned to all fifteen topics while figure 13 reveals the distribution of sentences on selected topics after deleting unimportant contents.

Sentimental analysis As the same previous execution on daily data, our data in this step is more selective than the original speeches data. We will convert these selective text

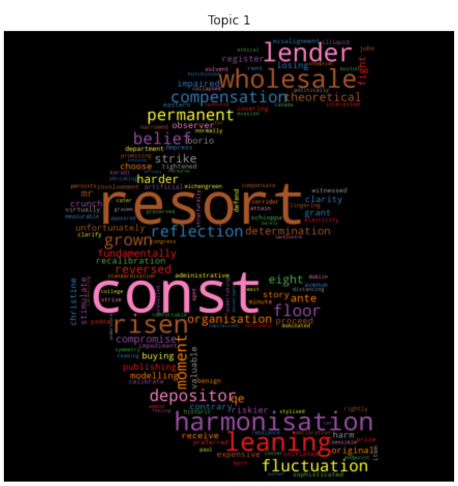

Figure 10. Topic 1 Word-Cloud

Figure 11. Topic 14 Word-Cloud

into numerical values using **VADER Lexicon** dictionary from **nltk** library. On the whole, our text data is converted into multiple monthly time series including four time series. I will use three of them in this paper, which are positive, negative and compound values, in order to run the OLS regression model.

OLS Regression By applying OLS regression model using monthly data. We repeated the regression by remaining independent variables which is visualized in 14 and

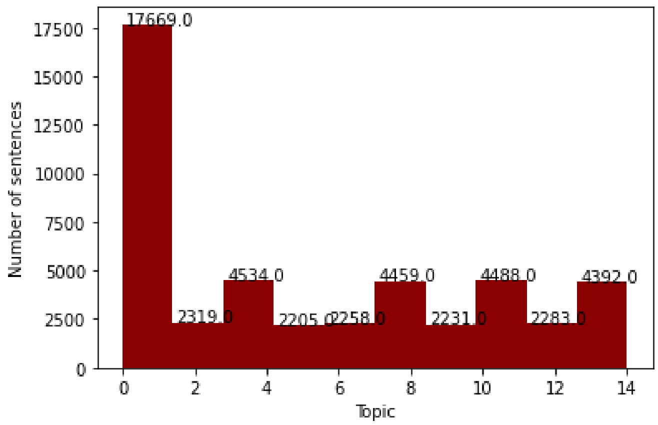

Figure 12. Topic distribution before elimination

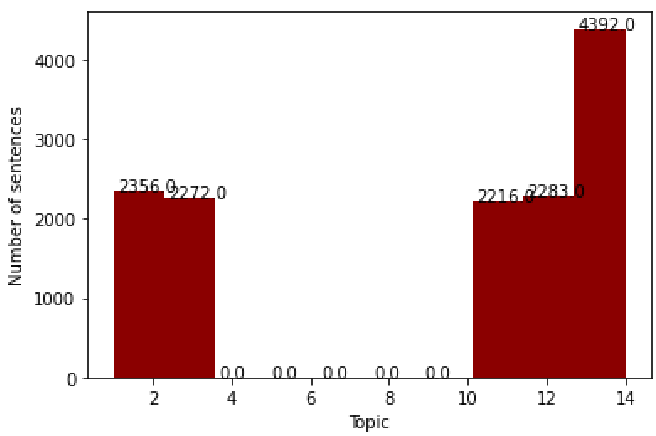

Figure 13. Topic distribution after elimination

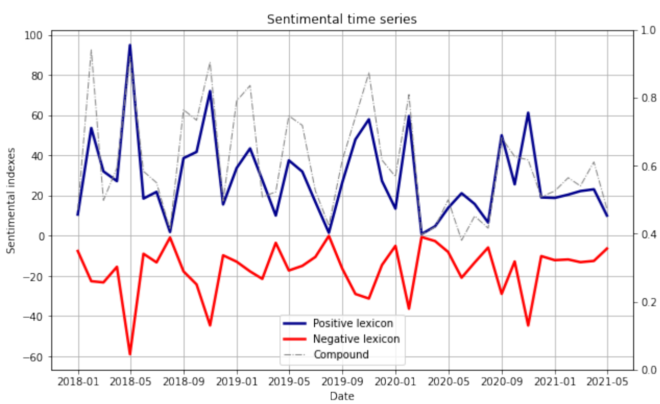

Figure 14. Sentimental timeseries converted from speeches

replacing one by one dependent variable as in 15. OLS regression will be executed alternately with and without intercept. We continuously use two regression equations which are equation 1 and equation 2 Executing OLS regression for five yield curves, we have the summary of OLS models in Appendix B 5. Five regression models using equation 1 show that p-values are not significantly. Therefore, it is impossible to conclude any insights about relationship of ECB's communication and yield curves. However, after running the same experiment on the same data set using regression equation 2, there are two models that are significant at level of 95%.

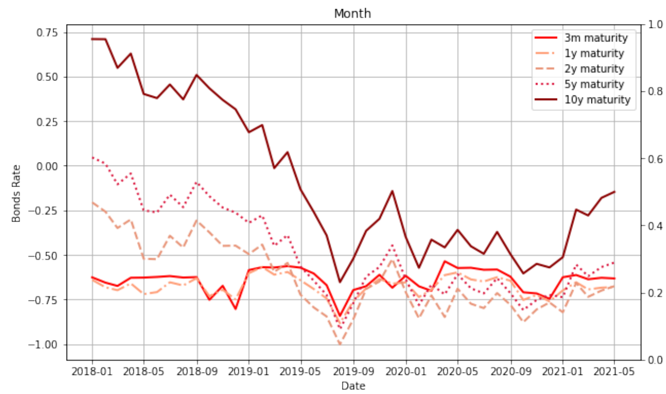

Figure 15. Yield curves

Model using 3-month maturity bond as responding variable applied equation 2 give significant p-value < 0.5. Table 4.2 is the OLS model summary with 3-month maturity bond rate dependent variable. A similar positive result is also achieved from the OLS regression model using 1-year maturity bond. We have two regression equations:

$$yield_{3m} = 0.0714x_{pos} - 0.0914x_{neg} - 0.0275x_{compound} \quad (3)$$

$$yield_{1y} = 0.0773x_{pos} - 0.0989x_{neg} - 0.0294x_{compound} \quad (4)$$

Last but not least, model applied on 2-year, 5-year, 10-year maturity bond data are not significant. Therefore, we can not conclude about the relationship between them in these cases. Appendix b 5 includes all OLS regression model outputs.

5. DISCUSSION

Applying machine learning techniques for textual materials is a new method. Inheriting its power, researchers

Table 1. Model using 3-month maturity bond as dependent variable and applied equation 2

Dep. Variable:	3m	**R-squared (uncentered):**	0.702			
Model:	OLS	**Adj. R-squared (uncentered):**	0.679			
Method:	Least Squares	**F-statistic:**	29.90			
Date:	Wed, 23 Jun 2021	**Prob (F-statistic):**	4.23e-10			
No. Observations:	41	**Log-Likelihood:**	-15.377			
Df Residuals:	38	**AIC:**	36.75			
Df Model:	3	**BIC:**	41.89			
Covariance Type:	nonrobust					
	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
pos	0.0714	**0.040**	1.770	0.085	-0.010	0.153
neg	-0.0914	0.045	-2.027	0.050	-0.183	-0.000
compound	-0.0275	0.012	-2.255	0.030	-0.052	-0.003

can efficiently discover how the linguistic communication affects to numerical values. In this paper, corpus with relevant topics are extracted and converted into numerical values. Several insights are draw out from the analysis:

First, Central Bank's communication does not instantly affects to yield curves regardless of different maturity types. The non-significant models regressed on daily data and sentimental time series converted from text strongly proved this statement.

Second, Short-term yield curves, 3-month maturity and 1-year maturity in particular, are influenced by ECB's communication with monthly frequency. Equation 3 and 4 show that both 3-month maturity yield and 1-year maturity yield are changing proportionally to the positive sentimental of ECB's speeches. On the contrary, they are in inverse ratio to the negative and neutral sentimental of ECB's speeches.

Third, Longer-period yield curves are not responded to the sentiment lexicons of ECB's speeches. In fact, the model regressed on 2-year, 5-year and 10-year maturity yields curves is not robust at the significant level. Thus, we can not withdraw conclusion about their mutual impact.

Limitation In the context of attention-raising for natural language processing minor major, a more efficient lexicon library exclusively built for Economics terms could be an important mean in order to achieved a better results. Beside, a research with a longer-period data could enhance the analysis even thought it requires powerful computers together with huge storage capacities.

DATA SOURCE

ECB (2021). Speeches dataset, https://www.ecb.europa.eu/press/key/html/downloads.en.html.

ECB (2021). Yield curves, https://www.ecb.europa.eu/stats/financial_markets_and_interest_rates/euro_area_yield_curves/html/index.en.html

CODE SOURCE

All collected data and code files applied on this paper can be easily downloaded from the following link:https://github.com/jyanqa/Narative-Economy
VADER lexiconhttps://www.nltk.org/_modules/nltk/sentiment/vader.html

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APPENDIX A 5 - DAILY DATA

OLS Regression Results

Dep. Variable:	3m	**R-squared (uncentered):**	0.013
Model:	OLS	**Adj. R-squared (uncentered):**	0.001
Method:	Least Squares	**F-statistic:**	1.118
Date:	Sun, 04 Jul 2021	**Prob (F-statistic):**	0.343
Time:	09:16:59	**Log-Likelihood:**	757.83
No. Observations:	250	**AIC:**	-1510.
Df Residuals:	247	**BIC:**	-1499.
Df Model:	3		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
neg	-0.0144	0.027	-0.532	0.595	-0.068	0.039
pos	0.0269	0.022	1.217	0.225	-0.017	0.070
compound	-0.0014	0.002	-0.897	0.371	-0.005	0.002

Omnibus:	11.548	**Durbin-Watson:**	2.019
Prob(Omnibus):	0.003	**Jarque-Bera (JB):**	19.249
Skew:	0.255	**Prob(JB):**	6.61e-05
Kurtosis:	4.260	**Cond. No.**	43.4

OLS Regression Results

Dep. Variable:	1y	**R-squared (uncentered):**	0.006
Model:	OLS	**Adj. R-squared (uncentered):**	-0.006
Method:	Least Squares	**F-statistic:**	0.5205
Date:	Sun, 04 Jul 2021	**Prob (F-statistic):**	0.669
Time:	09:19:16	**Log-Likelihood:**	804.36
No. Observations:	250	**AIC:**	-1603.
Df Residuals:	247	**BIC:**	-1592.
Df Model:	3		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
neg	0.0231	0.022	1.027	0.305	-0.021	0.067
pos	-0.0155	0.018	-0.846	0.399	-0.052	0.021
compound	0.0012	0.001	0.887	0.376	-0.001	0.004

Omnibus:	16.925	**Durbin-Watson:**	1.943
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	36.074
Skew:	0.303	**Prob(JB):**	1.47e-08
Kurtosis:	4.760	**Cond. No.**	43.4

OLS Regression Results

Dep. Variable:	2y	**R-squared (uncentered):**	0.010
Model:	OLS	**Adj. R-squared (uncentered):**	-0.002
Method:	Least Squares	**F-statistic:**	0.8353
Date:	Sun, 04 Jul 2021	**Prob (F-statistic):**	0.476
Time:	09:19:36	**Log-Likelihood:**	731.43
No. Observations:	250	**AIC:**	-1457.
Df Residuals:	247	**BIC:**	-1446.
Df Model:	3		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
neg	0.0464	0.030	1.544	0.124	-0.013	0.106
pos	-0.0365	0.025	-1.484	0.139	-0.085	0.012
compound	0.0021	0.002	1.197	0.233	-0.001	0.006

Omnibus:	13.639	**Durbin-Watson:**	1.952
Prob(Omnibus):	0.001	**Jarque-Bera (JB):**	26.464
Skew:	0.250	**Prob(JB):**	1.79e-06
Kurtosis:	4.513	**Cond. No.**	43.4

OLS Regression Results

Dep. Variable:	5y	**R-squared (uncentered):**	0.004
Model:	OLS	**Adj. R-squared (uncentered):**	-0.008
Method:	Least Squares	**F-statistic:**	0.3592
Date:	Sun, 04 Jul 2021	**Prob (F-statistic):**	0.783
Time:	09:19:49	**Log-Likelihood:**	623.62
No. Observations:	250	**AIC:**	-1241.
Df Residuals:	247	**BIC:**	-1231.
Df Model:	3		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
neg	0.0478	0.046	1.033	0.303	-0.043	0.139
pos	-0.0330	0.038	-0.871	0.385	-0.107	0.042
compound	0.0017	0.003	0.611	0.542	-0.004	0.007

Omnibus:	7.215	**Durbin-Watson:**	1.994
Prob(Omnibus):	0.027	**Jarque-Bera (JB):**	8.183
Skew:	0.274	**Prob(JB):**	0.0167
Kurtosis:	3.697	**Cond. No.**	43.4

OLS Regression Results

Dep. Variable:	10y	**R-squared (uncentered):**	0.001
Model:	OLS	**Adj. R-squared (uncentered):**	-0.011
Method:	Least Squares	**F-statistic:**	0.1176
Date:	Sun, 04 Jul 2021	**Prob (F-statistic):**	0.950
Time:	09:20:02	**Log-Likelihood:**	564.84
No. Observations:	250	**AIC:**	-1124.
Df Residuals:	247	**BIC:**	-1113.
Df Model:	3		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
neg	0.0262	0.059	0.448	0.655	-0.089	0.142
pos	-0.0194	0.048	-0.405	0.686	-0.114	0.075
compound	0.0016	0.003	0.475	0.635	-0.005	0.008

Omnibus:	3.965	**Durbin-Watson:**	1.944
Prob(Omnibus):	0.138	**Jarque-Bera (JB):**	4.428
Skew:	0.126	**Prob(JB):**	0.109
Kurtosis:	3.602	**Cond. No.**	43.4

OLS Regression Results

Dep. Variable:	3m	**R-squared:**	0.004
Model:	OLS	**Adj. R-squared:**	-0.008
Method:	Least Squares	**F-statistic:**	0.3494
Date:	Sun, 04 Jul 2021	**Prob (F-statistic):**	0.790
Time:	09:17:43	**Log-Likelihood:**	757.93
No. Observations:	250	**AIC:**	-1508.
Df Residuals:	246	**BIC:**	-1494.
Df Model:	3		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
const	0.0017	0.004	0.449	0.654	-0.006	0.009
neg	-0.0238	0.034	-0.695	0.488	-0.091	0.044
pos	0.0183	0.029	0.627	0.531	-0.039	0.076
compound	-0.0016	0.002	-0.985	0.326	-0.005	0.002

Omnibus:	12.120	**Durbin-Watson:**	2.011
Prob(Omnibus):	0.002	**Jarque-Bera (JB):**	20.286
Skew:	0.271	**Prob(JB):**	3.93e-05
Kurtosis:	4.286	**Cond. No.**	60.5

OLS Regression Results

Dep. Variable:	1y	**R-squared:**	0.006
Model:	OLS	**Adj. R-squared:**	-0.006
Method:	Least Squares	**F-statistic:**	0.5177
Date:	Sun, 04 Jul 2021	**Prob (F-statistic):**	0.670
Time:	09:18:05	**Log-Likelihood:**	804.79
No. Observations:	250	**AIC:**	-1602.
Df Residuals:	246	**BIC:**	-1587.
Df Model:	3		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
const	0.0029	0.003	0.922	0.357	-0.003	0.009
neg	0.0071	0.028	0.249	0.804	-0.049	0.063
pos	-0.0301	0.024	-1.242	0.215	-0.078	0.018
compound	0.0008	0.001	0.597	0.551	-0.002	0.004

Omnibus:	17.983	**Durbin-Watson:**	1.931
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	37.891
Skew:	0.335	**Prob(JB):**	5.92e-09
Kurtosis:	4.785	**Cond. No.**	60.5

OLS Regression Results

Dep. Variable:	2y	**R-squared:**	0.010
Model:	OLS	**Adj. R-squared:**	-0.002
Method:	Least Squares	**F-statistic:**	0.8296
Date:	Sun, 04 Jul 2021	**Prob (F-statistic):**	0.479
Time:	09:18:24	**Log-Likelihood:**	731.46
No. Observations:	250	**AIC:**	-1455.
Df Residuals:	246	**BIC:**	-1441.
Df Model:	3		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
const	0.0011	0.004	0.257	0.798	-0.007	0.009
neg	0.0405	0.038	1.063	0.289	-0.035	0.115
pos	-0.0419	0.033	-1.290	0.198	-0.106	0.022
compound	0.0020	0.002	1.077	0.283	-0.002	0.006

Omnibus:	13.856	**Durbin-Watson:**	1.949
Prob(Omnibus):	0.001	**Jarque-Bera (JB):**	26.771
Skew:	0.259	**Prob(JB):**	1.54e-06
Kurtosis:	4.517	**Cond. No.**	60.5

OLS Regression Results

Dep. Variable:	5y	**R-squared:**	0.004
Model:	OLS	**Adj. R-squared:**	-0.008
Method:	Least Squares	**F-statistic:**	0.3704
Date:	Sun, 04 Jul 2021	**Prob (F-statistic):**	0.774
Time:	09:18:38	**Log-Likelihood:**	623.66
No. Observations:	250	**AIC:**	-1239.
Df Residuals:	246	**BIC:**	-1225.
Df Model:	3		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
const	-0.0018	0.006	-0.280	0.779	-0.015	0.011
neg	0.0578	0.059	0.987	0.325	-0.058	0.173
pos	-0.0238	0.050	-0.476	0.635	-0.122	0.075
compound	0.0019	0.003	0.663	0.508	-0.004	0.007

Omnibus:	7.121	**Durbin-Watson:**	1.999
Prob(Omnibus):	0.028	**Jarque-Bera (JB):**	8.050
Skew:	0.272	**Prob(JB):**	0.0179
Kurtosis:	3.691	**Cond. No.**	60.5

OLS Regression Results

Dep. Variable:	10y	**R-squared:**	0.001
Model:	OLS	**Adj. R-squared:**	-0.011
Method:	Least Squares	**F-statistic:**	0.09681
Date:	Sun, 04 Jul 2021	**Prob (F-statistic):**	0.962
Time:	09:18:55	**Log-Likelihood:**	564.89
No. Observations:	250	**AIC:**	-1122.
Df Residuals:	246	**BIC:**	-1108.
Df Model:	3		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
const	0.0026	0.008	0.314	0.754	-0.014	0.019
neg	0.0120	0.074	0.162	0.872	-0.134	0.158
pos	-0.0324	0.063	-0.512	0.609	-0.157	0.092
compound	0.0013	0.004	0.369	0.712	-0.006	0.008

Omnibus:	4.050	**Durbin-Watson:**	1.939
Prob(Omnibus):	0.132	**Jarque-Bera (JB):**	4.568
Skew:	0.126	**Prob(JB):**	0.102
Kurtosis:	3.613	**Cond. No.**	60.5

APPENDIX B 6 - MONTHLY DATA

OLS Regression Results

Dep. Variable:	3m	**R-squared (uncentered):**	0.702
Model:	OLS	**Adj. R-squared (uncentered):**	0.679
Method:	Least Squares	**F-statistic:**	29.90
Date:	Sun, 04 Jul 2021	**Prob (F-statistic):**	4.23e-10
Time:	11:37:19	**Log-Likelihood:**	-15.377
No. Observations:	41	**AIC:**	36.75
Df Residuals:	38	**BIC:**	41.89
Df Model:	3		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
pos	0.0714	0.040	1.770	0.085	-0.010	0.153
neg	-0.0914	0.045	-2.027	0.050	-0.183	-0.000
compound	-0.0275	0.012	-2.255	0.030	-0.052	-0.003

Omnibus:	2.703	**Durbin-Watson:**	1.542
Prob(Omnibus):	0.259	**Jarque-Bera (JB):**	1.715
Skew:	0.466	**Prob(JB):**	0.424
Kurtosis:	3.367	**Cond. No.**	64.1

OLS Regression Results

Dep. Variable:	1y	**R-squared (uncentered):**	0.704
Model:	OLS	**Adj. R-squared (uncentered):**	0.681
Method:	Least Squares	**F-statistic:**	30.19
Date:	Sun, 04 Jul 2021	**Prob (F-statistic):**	3.72e-10
Time:	11:37:38	**Log-Likelihood:**	-17.413
No. Observations:	41	**AIC:**	40.83
Df Residuals:	38	**BIC:**	45.97
Df Model:	3		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
pos	0.0773	0.042	1.823	0.076	-0.009	0.163
neg	-0.0989	0.047	-2.087	0.044	-0.195	-0.003
compound	-0.0294	0.013	-2.297	0.027	-0.055	-0.003

Omnibus:	3.205	**Durbin-Watson:**	1.430
Prob(Omnibus):	0.201	**Jarque-Bera (JB):**	2.156
Skew:	0.529	**Prob(JB):**	0.340
Kurtosis:	3.376	**Cond. No.**	64.1

OLS Regression Results

Dep. Variable:	2y	**R-squared (uncentered):**	0.601
Model:	OLS	**Adj. R-squared (uncentered):**	0.569
Method:	Least Squares	**F-statistic:**	19.04
Date:	Sun, 04 Jul 2021	**Prob (F-statistic):**	1.06e-07
Time:	11:37:55	**Log-Likelihood:**	-22.069
No. Observations:	41	**AIC:**	50.14
Df Residuals:	38	**BIC:**	55.28
Df Model:	3		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
pos	0.0825	0.048	1.738	0.090	-0.014	0.179
neg	-0.1065	0.053	-2.007	0.052	-0.214	0.001
compound	-0.0285	0.014	-1.989	0.054	-0.058	0.001

Omnibus:	2.187	**Durbin-Watson:**	0.870
Prob(Omnibus):	0.335	**Jarque-Bera (JB):**	1.329
Skew:	0.416	**Prob(JB):**	0.515
Kurtosis:	3.291	**Cond. No.**	64.1

OLS Regression Results

Dep. Variable:	5y	**R-squared (uncentered):**	0.492
Model:	OLS	**Adj. R-squared (uncentered):**	0.452
Method:	Least Squares	**F-statistic:**	12.28
Date:	Sun, 04 Jul 2021	**Prob (F-statistic):**	9.20e-06
Time:	11:38:09	**Log-Likelihood:**	-19.675
No. Observations:	41	**AIC:**	45.35
Df Residuals:	38	**BIC:**	50.49
Df Model:	3		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
pos	0.0721	0.045	1.608	0.116	-0.019	0.163
neg	-0.0935	0.050	-1.867	0.070	-0.195	0.008
compound	-0.0233	0.014	-1.719	0.094	-0.051	0.004

Omnibus:	1.252	**Durbin-Watson:**	0.622
Prob(Omnibus):	0.535	**Jarque-Bera (JB):**	0.984
Skew:	0.375	**Prob(JB):**	0.611
Kurtosis:	2.879	**Cond. No.**	64.1

OLS Regression Results

Dep. Variable:	10y	**R-squared (uncentered):**	0.061
Model:	OLS	**Adj. R-squared (uncentered):**	-0.013
Method:	Least Squares	**F-statistic:**	0.8205
Date:	Sun, 04 Jul 2021	**Prob (F-statistic):**	0.491
Time:	11:38:21	**Log-Likelihood:**	-22.280
No. Observations:	41	**AIC:**	50.56
Df Residuals:	38	**BIC:**	55.70
Df Model:	3		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
pos	0.0384	0.048	0.804	0.426	-0.058	0.135
neg	-0.0523	0.053	-0.980	0.333	-0.160	0.056
compound	-0.0071	0.014	-0.493	0.625	-0.036	0.022

Omnibus:	6.956	**Durbin-Watson:**	0.178
Prob(Omnibus):	0.031	**Jarque-Bera (JB):**	3.575
Skew:	0.495	**Prob(JB):**	0.167
Kurtosis:	1.945	**Cond. No.**	64.1

OLS Regression Results

Dep. Variable:	3m	**R-squared:**	0.012
Model:	OLS	**Adj. R-squared:**	-0.068
Method:	Least Squares	**F-statistic:**	0.1531
Date:	Sun, 04 Jul 2021	**Prob (F-statistic):**	0.927
Time:	11:38:38	**Log-Likelihood:**	54.263
No. Observations:	41	**AIC:**	-100.5
Df Residuals:	37	**BIC:**	-93.67
Df Model:	3		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	-0.6401	0.020	-32.686	0.000	-0.680	-0.600
pos	0.0009	0.008	0.110	0.913	-0.015	0.017
neg	-0.0017	0.009	-0.198	0.844	-0.020	0.016
compound	5.713e-05	0.002	0.024	0.981	-0.005	0.005

Omnibus:	11.122	**Durbin-Watson:**	1.301
Prob(Omnibus):	0.004	**Jarque-Bera (JB):**	10.694
Skew:	-1.068	**Prob(JB):**	0.00476
Kurtosis:	4.301	**Cond. No.**	113.

OLS Regression Results

Dep. Variable:	1y	**R-squared:**	0.037
Model:	OLS	**Adj. R-squared:**	-0.041
Method:	Least Squares	**F-statistic:**	0.4774
Date:	Sun, 04 Jul 2021	**Prob (F-statistic):**	0.700
Time:	11:38:54	**Log-Likelihood:**	59.174
No. Observations:	41	**AIC:**	-110.3
Df Residuals:	37	**BIC:**	-103.5
Df Model:	3		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	-0.6760	0.017	-38.914	0.000	-0.711	-0.641
pos	0.0028	0.007	0.402	0.690	-0.011	0.017
neg	-0.0042	0.008	-0.541	0.592	-0.020	0.012
compound	-0.0003	0.002	-0.152	0.880	-0.005	0.004

Omnibus:	14.143	**Durbin-Watson:**	1.058
Prob(Omnibus):	0.001	**Jarque-Bera (JB):**	17.484
Skew:	-1.075	**Prob(JB):**	0.000160
Kurtosis:	5.369	**Cond. No.**	113.

OLS Regression Results

Dep. Variable:	2y	**R-squared:**	0.100
Model:	OLS	**Adj. R-squared:**	0.027
Method:	Least Squares	**F-statistic:**	1.373
Date:	Sun, 04 Jul 2021	**Prob (F-statistic):**	0.266
Time:	11:39:06	**Log-Likelihood:**	10.981
No. Observations:	41	**AIC:**	-13.96
Df Residuals:	37	**BIC:**	-7.107
Df Model:	3		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	-0.6858	0.056	-12.186	0.000	-0.800	-0.572
pos	0.0069	0.022	0.310	0.759	-0.038	0.052
neg	-0.0105	0.025	-0.416	0.680	-0.062	0.041
compound	0.0010	0.007	0.140	0.889	-0.013	0.015

Omnibus:	1.881	**Durbin-Watson:**	0.488
Prob(Omnibus):	0.391	**Jarque-Bera (JB):**	1.774
Skew:	0.469	**Prob(JB):**	0.412
Kurtosis:	2.604	**Cond. No.**	113.

OLS Regression Results

Dep. Variable:	5y	**R-squared:**	0.104
Model:	OLS	**Adj. R-squared:**	0.031
Method:	Least Squares	**F-statistic:**	1.427
Date:	Sun, 04 Jul 2021	**Prob (F-statistic):**	0.250
Time:	11:39:21	**Log-Likelihood:**	-0.038040
No. Observations:	41	**AIC:**	8.076
Df Residuals:	37	**BIC:**	14.93
Df Model:	3		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	-0.5676	0.074	-7.709	0.000	-0.717	-0.418
pos	0.0095	0.029	0.324	0.748	-0.050	0.069
neg	-0.0140	0.033	-0.423	0.675	-0.081	0.053
compound	0.0012	0.009	0.129	0.898	-0.017	0.020

Omnibus:	2.972	**Durbin-Watson:**	0.343
Prob(Omnibus):	0.226	**Jarque-Bera (JB):**	2.760
Skew:	0.577	**Prob(JB):**	0.252
Kurtosis:	2.467	**Cond. No.**	113.

OLS Regression Results

Dep. Variable:	10y	**R-squared:**	0.106
Model:	OLS	**Adj. R-squared:**	0.033
Method:	Least Squares	**F-statistic:**	1.460
Date:	Sun, 04 Jul 2021	**Prob (F-statistic):**	0.241
Time:	11:39:37	**Log-Likelihood:**	-20.427
No. Observations:	41	**AIC:**	48.85
Df Residuals:	37	**BIC:**	55.71
Df Model:	3		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	-0.2265	0.121	-1.871	0.069	-0.472	0.019
pos	0.0134	0.048	0.279	0.782	-0.084	0.111
neg	-0.0206	0.054	-0.378	0.708	-0.131	0.090
compound	0.0026	0.015	0.177	0.861	-0.028	0.033

Omnibus:	4.097	**Durbin-Watson:**	0.279
Prob(Omnibus):	0.129	**Jarque-Bera (JB):**	3.244
Skew:	0.566	**Prob(JB):**	0.197
Kurtosis:	2.213	**Cond. No.**	113.