Revista de Ciencias Económicas 42-N°2: julio-diciembre 2024 / e60583 / ISSN: 0252-9521 / ISSN: 2215-3489
Abre 1 de julio y cierra 31 de diciembre de 2024
https://revistas.ucr.ac.cr/index.php/economicas

Similarity of European Central Bank communications and its impact on financial markets: and extension[1]

CAMILO SALDARRIAGA[2];

Recibido: Aprobado:

Resumen

El presente estudio replica, actualiza y amplía la metodología implementada por Amaya y Filbien en su artículo 'La similitud de la comunicación del BCE' (Amaya y Filbien, 2015). En el artículo original, los autores aplicaron técnicas de procesamiento del lenguaje natural para medir la similitud y el sentimiento de las conferencias de prensa del Banco Central Europeo y su impacto en los mercados financieros entre enero 1999 y diciembre 2013. El presente estudio replica la metodología entre enero de 1999 y diciembre de 2023, y la amplía evaluando el impacto que tuvieron diferentes presidencias del BCE en el rendimiento anormal del mercado.

PALABRAS CLAVE: Política monetaria, zona euro, procesamiento del lenguaje natural, tasas de interés, rendimientos de mercado.

RANGO ACADÉMICO

JEL: G1, G280, E580.

Abstract

The present study replicates, updates, and extends the methodology implemented by Amaya and Filbien in their paper The similarity of ECB's communication (Amaya and Filbien, 2015). In the original paper, the authors applied natural language processing techniques to measure the similarity and sentiment of the European Central Bank press conferences and their impact on financial markets between January 1999 and December 2013. The present study replicates the methodology, and extends it by evaluating the impact that different ECB. The article concludes that the similarity in ECB communications increased with time in the period of study when controlled for several macro variables. This growing similarity mitigates the impact that different levels of pessimism of the ECB communications have on abnormal returns. It was also found that during the Presidency of Christine Lagarde the similarity of ECB communications decreased considerably. Finally the study does not find significant evidence that the different presidency

[1] The whole code with the estimations can be accessed in the GitHub repository.

[2] Msc. In Economics and Msc. In Financial Economics from the École d'Économie de la Sorbonne, Université Paris 1 Panthéon-Sorbonne. E-mail: jcamsalda@gmail.com

periods changed the way in which the pessimism in ECB communications affected the market´s abnormal returns.

KEYWORDS: Monetary policy, euro-zone, natural language processing, interest rates, abnormal returns.

ACADEMIC RANK

JEL: G1, G280, E580.

I. INTRODUCTION:

In their original paper, Amaya and Filbien (2015) use textual analysis to evaluate how the similarity of European Central Bank communications has evolved over the years. The authors measure the similarity between the ECB communications and evaluate the abnormal returns generated by these communications on financial markets. They conclude that similarity increased between 1999 and 2013 and that this similarity mitigated the impact on market abnormal returns of certain ECB decisions and messages. The present paper evaluates if these conclusions hold during the last decade when the Covid crisis and the posterior inflationary crisis pushed central banks all over the world to implement strong shifts in monetary policy. It also extends the original article by analyzing the effects of different ECB presidencies on abnormal returns.

The paper replicates the methodology used by Amaya and Filbien (2015) updating it with the most recent data. To do this, I developed an automatized process to extract the text of the European Central Bank press conferences between January 1999 and December 2023 and applied natural language processing techniques to measure the similarity and pessimism of each communication. I also extended the original article by analyzing how the similarity, pessimism and abnormal returns changed during the mandate of the different ECB presidents.

The article found that the main results of Amaya and Filbien (2015) still hold true when controlling for macroeconomic variables. The similarity of ECB communications has grown over time and the effect of its interaction with the pessimism of communications has remained negative. A possible interpretation for this is that the increasing similarity of communications has helped investors set their expectations, reducing surprises that generate abnormal returns.

Regarding the different presidencies, the article concludes that during the Presidency of Christine Lagarde the similarity of ECB communications decreased considerably. Finally, the study does not find significant evidence that the different presidency periods changed the way in which the pessimism in ECB communications affected the market´s abnormal returns.

II. LITERATURE REVIEW:

With the development of computational capacities, the 2000s experienced the appearance of several studies applying textual analysis to financial economics. In his groundbreaking article, Tetlock (2007) applied content analysis software to obtain a measure of the sentiment of relevant Wall Street Journal columns between the period 1984 to 1999. The author studied the relationship between news tone—particularly negative tone—and market outcomes such as stock prices, trading volumes, and volatility. To do it, he constructs a measure of investor sentiment based on the frequency of negative words.

The author found that increased negativity in media sentiment is generally associated with a decline in stock prices, suggesting that negative media tone has a measurable, short-term impact on market behavior. Specifically, the study finds that pessimistic language in the news tends to predict lower returns on the day of publication, though this effect reverses slightly in the following days.

In similar research, Tetlock, Saar-Tsechansky, and Macskassy (2008) applied a sentiment analysis measure to articles from the Wall Street Journal and the Dow Jones Institutional News Service between 1980 and 2004 to determine if there was a relation between the tone and content of news reports and companies' future earnings. After analyzing 350 000 stories the authors concluded that negative words present on firm-specific stories can forecast low firm earnings. Surprisingly, the authors did not find the same relation for positive words, something they associate with previous literature on psychology that shows the greater impact of negative information on decision-making processes.

Tetlock (2011) develops a measure of similarity to determine if news stories provide new or old information. The measure consists of obtaining the number of unique words present in both articles (the intersection) and dividing it by the number of unique words present in the union of both articles. The author evaluates the similarity measure in articles from November 1996 to October 2008 in the Dow Jones Newswire. Then, he measures how the level of similarity with previous stories affects the market reaction using the event study methodology on the respective asset return. The author concludes that higher similarity increases the return reversal after the event, which implies that investors may fail to distinguish new information from old one.

Loughran and McDonald (2011) conducted a review of previous textual analyses developed until that date and found that most of the analyses used as base for word classification the Harvard-IV-4 TagNeg (H4N) dictionary. The authors analyzed the word classification of the dictionary and concluded that three-fourths of words classified in the dictionary as negative are not necessarily negative in a financial context. As an alternative, the authors built the Loughran and McDonald Master Dictionary, which since then has been constantly updated and widely used in the financial-economic analysis context.

Related to the European Central Bank and the reaction of European markets to monetary policy, Filbien, J. Y., & Labondance (2013) evaluate how abnormal returns around ECB press conferences have evolved through time. Using the DJ Eurostoxx50 Index they evaluated the abnormal returns around all the ECB press conferences between January 1999, to December 2008. The authors found that the market's abnormal returns decreased over time. Finally, the authors introduced a dummy variable corresponding to the presidency period of Willem Frederik Duisenberg to determine if his presidency affected abnormal returns. They found that Duisenberg's presidency did not have a significant impact on market abnormal returns.

In the last few years, several studies using more complex language processing techniques have emerged. For example, Shapiro and Wilson (2022) used sentiment analysis the estimate the FED´s Federal Open Market Committee objective function. Oshima and Matsubayashi (2018) use sentiment analysis to evaluate the impact on financial markets of Bank of Japan Board meeting minutes. While Gorodnichenko, Pham, and Talavera (2023) developed a deep-learning model to detect emotions and tones in the Federal Open Market Committee press conferences and evaluate the impact on markets. They conclude that a positive tone on the Federal Reserve´s conference is associated with significant increases in share prices.

III. METHODOLOGY

Text scrapping and cleaning

First, I scraped all the conference texts from the ECB webpage. To do this, I used Beautiful Soup Python package (Richardson, L. 2023). I extracted the ECB communication texts and condensed them into a CSV table with 268 conference texts between January 1999 and December 2023. After a manual review, I discovered that four meeting dates were omitted by the ECB webpage as they did not have a press conference. I omit them from the analysis as the original paper only considers conferences. The four meetings without press conferences were held on:

- 16 March 2000
- 31 August 2000
- 17 September 2001
- 08 October 2008

Additionally, the manual review allowed to identify that the ECB webpage includes two conferences that were not related to monetary policy meetings. These are also omitted from the analysis. The conferences that were held on:

- 13 October 2003
- 20 January 2005

Then, all the text that is associated with the webpage format was also removed. Expressions like "Click here for the transcript of questions and answers" are removed from the file. This is important because the Beautiful Soup package (Richardson, L. 2023) includes this kind of expression in the scrapped text, and they are clearly not part of the message from the monetary authorities. The resulting clean text is used to obtain the bigrams and calculate the measures of similarity and pessimism.

Measuring similarity

To measure the similarity of the ECB communications, the present article uses the definition proposed by Tetlock (2011) and used by Amaya and Filbien (2015). This definition decomposes the texts into bigrams, which are expressions composed of two words. Then, it measures the number of bigrams in each communication separately and the bigrams present in both communications. Therefore, the similarity between communication i and communication $i-1$ is defined as:

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

In other words, similarity is measured as the share of bigrams present in both communications. As explained by Amaya and Filbien: "This similarity measure provides a general idea about the amount of redundant information in two successive ECB statements" (2015). The value of the similarity measure oscillates between 0 and 1. I obtained the bigrams from the cleaned text we

To evaluate the behavior of similarity measure through time the next regression is estimated using ordinary OLS:

$$ln(Similarity_i) = \alpha_0 + \alpha_1 log(time_i) + \beta' control_i + \epsilon_i \quad \textbf{(Equation 1)}$$

With $time_i$ a time trend variable measured in days between the day of the press conference and the first day of analysis. $control_i$ is the setoff control variables: quarterly output gap, the change in the MRO rate (Main Refinancing Operations rate), and the Harmonised Index Consumer Prices (HICP). To obtain the trend component of GDP in order to estimate the output gap the Hodrick–Prescott filter is used.

The different specifications of equation 1 to estimate are:

$$ln(Similarity_i) = \alpha_0 + \beta_1 \, \Delta\text{MRO} + \beta_2 \text{Inflation} + \beta_3 \text{ output\_gap\_quart } + \epsilon_i \quad \underline{\textbf{(specification 1, equation 1)}}$$

$$ln(Similarity_i) = \alpha_0 + \alpha_1 log(time_i) + \epsilon_i \quad \underline{\textbf{(specification 2, equation 1)}}$$

$$ln(Similarity_i) = \alpha_0 + \alpha_1 log(time_i) + \beta_1 \, \Delta\text{MRO} + \beta_2 \text{Inflation} + \beta_3 \text{ output\_gap\_quart} + \epsilon_i \quad \underline{\textbf{(specification 3, equation 1)}}$$

$$ln(Similarity_i) = \alpha_0 + \alpha_1 \text{Time count} + \beta_1 \text{ Delta MRO} + \beta_2 \text{Inflation} + \beta_3 \text{ output\_gap\_quart} + \epsilon_i \quad \underline{\textbf{(specification 4, equation 1)}}$$

Impact of similarity on financial markets

To evaluate the impact of ECB's communications on financial markets I use the DJEurostoxx50 as Amaya and Filbien (2015). The DJEurostoxx50 which is used to follow the general trends in the European market, is calculated with the Laspeyres formula, and is composed of 50 companies from 11 countries in the eurozone. The return of the index is measured by $R_{i,t} = ln\left(\frac{P_{i,t}}{P_{i,t-1}}\right)$ and the abnormal returns are measured around the event window with the constant mean return model as proposed by Fama, Fisher, Jensen, and Roll (1969) and Brown and Warner (1985) in their classical articles.

This way, I first use a rolling window to estimate the return average in the period comprising 250 days before the event and 50 days before the event:

$$\overline{R_{i,t}} = \sum_{t=-250}^{-50} \frac{R_{i,t}}{201}$$

Then, I calculate the abnormal returns for the 5 days after and before the events:

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

Finally, I obtain the cumulative abnormal return for each event (CAR_i):

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

Measuring communications pessimism

To evaluate the pessimism of ECB communications I take the clean text, and then classify all the words between negative and positive using the Loughran and McDonald Master Dictionary With Sentiment Word Lists (Loughran and McDonald 2024). Contrary to other commonly used dictionaries, the Loughran and McDonald Master Dictionary With Sentiment Word Lists has been adjusted to correctly classify the sentiment of words in the context of financial markets, as explained in Loughran and McDonald (2011). Once all the words are classified, I use them to estimate the pessimism measure for every period with the next formula:

$$Pessimism_i = \frac{Number\ of\ negative\ words_i - Number\ of\ Positive\ words_i}{Number\ of\ total\ words_i}$$

To evaluate the impact of ECB communications on financial markets, the regression proposed by Amaya and Filbien (2015) is estimated:

$$|CAR_i| = \gamma_0 + \gamma_1 log(Similarity_i) * Pessimism_i + \alpha' Control_i + \mu_i \quad \textbf{(Equation 2)}$$

Where $Control_i$ corresponds to the variables: output gap, Harmonised Index Consumer Prices (HICP), and change in the MRO. In addition, to the mentioned variables, Amaya and Filbien (2015) present one additional specification including a Surprise MRO variable obtained from analysts' predictions. I do not include this variable in the analysis due to access costs. The variable $Pessimism_i$ corresponds to an indicator of the pessimism in ECB communications, therefore γ_1 provides the effect of the interaction between similarity and pessimism.

The different specifications of equation 2 to estimate are:

$$|CAR_i| = \gamma_0 + \gamma_3 Pessimism_i + \mu_i \ \underline{\textbf{(specification 1, equation 2)}}$$

$$|CAR_i| = \varphi_0 + \gamma_1\ \Delta\text{MRO} + \gamma_2\ \text{Inflation} + \gamma_5 \text{output\_gap\_quart} + \mu_i \ \underline{\textbf{(specification 2, equation 2)}}$$

$$|CAR_i| = \gamma_0 + \gamma_4 \text{Pessimism x log\_similarity} + \mu_i \ \underline{\textbf{(specification 3, equation 2)}}$$

$$|CAR_i| = \varphi_0 + \gamma_1 \Delta\text{MRO} + \gamma_2\ \text{Inflation} + \gamma_4 \text{Pessimism x log\_similarity} + \gamma_5 \text{output\_gap\_quart} + \mu_i \ \underline{\textbf{(specification 4 equation 2)}}$$

Impact of ECB Presidencies

As an extension of the original paper, I analyze how the different presidency periods affected the relations previously described. First, I would like to evaluate the impact of presidencies on the similarity of ECB communications. To do this, I use a set of dummy variables corresponding to the presidency periods. Which derives in the equations:

$$ln(Similarity_i) = \alpha_0 + \alpha_1 log(time_i) + \beta_1\ \Delta\text{MRO} + \beta_2 \text{Inflation} + \beta_3\ \text{output\_gap\_quart} + \theta_1 dummy_1 + \theta_2 dummy_2 + \theta_3 dummy_3 + \epsilon_i \ \underline{\textbf{(specification 3.1, equation 1)}}$$

$$ln(Similarity_i) = \alpha_0 + \alpha_1 \text{Time count} + \beta_1\ \Delta\text{MRO} + \beta_2 \text{Inflation} + \beta_3\ \text{output\_gap\_quart} + \theta_1 dummy_1 + \theta_2 dummy_2 + \theta_3 dummy_3 + \epsilon_i \ \underline{\textbf{(specification 4.1, equation 1)}}$$

Where the reference or base category corresponds to the presidency of Willem F. Duisenberg, $dummy_1$ to Jean Claude Trichet's presidency, $dummy_2$ to Mario Draghi's and $dummy_3$ to Christine Lagarde's until the end of 2023.

Then, I evaluate how the impact of pessimism in abnormal returns changes during each presidency. For this, I introduce an interaction term between the presidencies dummies and the pessimism variable, obtaining the equations:

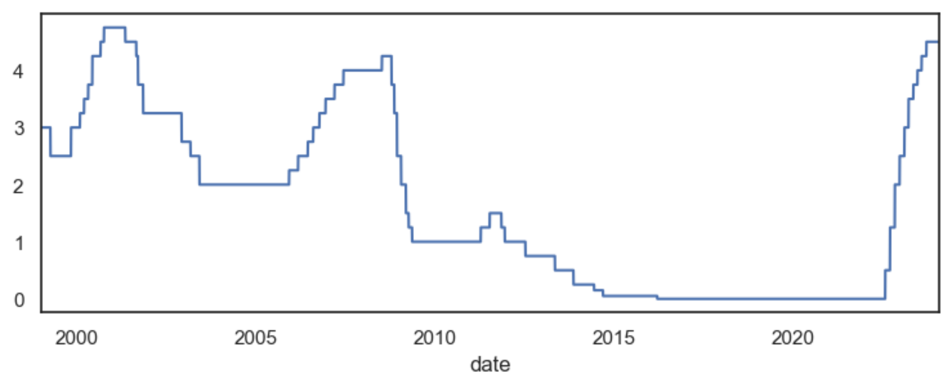
$$|CAR_i| = \varphi_0 + \gamma_1 \Delta\text{MRO} + \gamma_2 \text{ Inflation} + \gamma_5 \text{output\_gap\_quart} + + \theta_1 dummy_1 * Pessimism_i + \theta_2 dummy_2 * Pessimism_i + \theta_3 dummy_3 * Pessimism_i + \mu_i$$ **(specification 2.1, equation 2)**

$$|CAR_i| = \varphi_0 + \gamma_1 \Delta\text{MRO} + \gamma_2 \text{ Inflation} + \gamma_4 \text{Pessimism x log\_similarity} + \gamma_5 \text{output\_gap\_quart} + \theta_1 dummy_1 * Pessimism_i + \theta_2 dummy_2 * Pessimism_i + \theta_3 dummy_3 * Pessimism_i + \mu_i$$ **(specification 4.1, equation 2)**

IV. DATA AND DESCRIPTIVE STATISTICS:

The policy rate used for the analysis is the ECB Main Refinancing Operations rate (MRO), which was obtained from the ECB website (European Central Bank, 2024). Graph 1 presents the behavior of MRO rates during the analysis period.

Graph 1. ECB MRO rate between January 1999 and December 2023



Source: European Central Bank(2024)

As a first step every change in the MRO rate was associated with its corresponding meeting press conference. A summary table of the number of conferences and MRO rate changes per year is presented in Table 1. Table 1 has a difference from the original paper in the number of meetings registered for the year 2000. After a manual review, it was confirmed that the ECB authorities held 13 press conferences during that year, which means that the table presented here is right. One factor explaining the difference is that Amaya and Filbien (2015) did not count the extraordinary ECB meetings held in Paris on October 19, 2000 and in Madrid on March 30, 2000. These two press conferences were included as they contained announcements regarding monetary policy and interest rates.

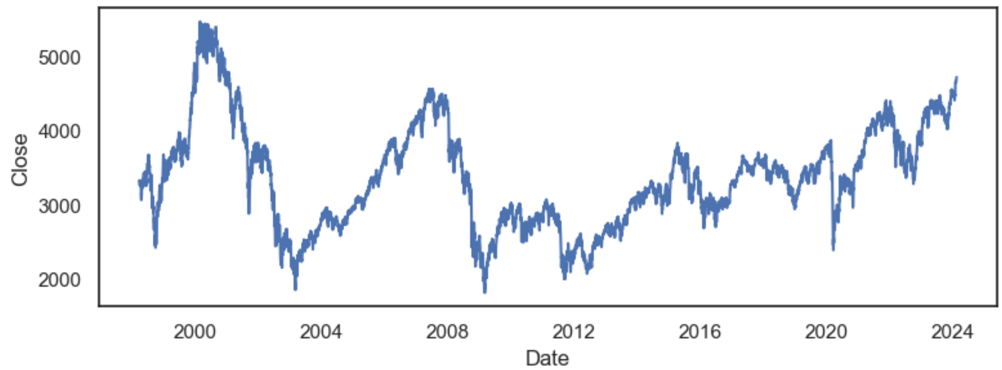
Table 1. ECB press conferences and MRO rate changes per year

	MRO rate change									
Year	**-0.75**	**-0.5**	**-0.25**	**-0.1**	**-0.05**	**0**	**0.25**	**0.5**	**0.75**	**Total changes**
1999	0	1	0	0	0	9	0	1	0	11
2000	0	0	0	0	0	10	2	1	0	13
2001	0	1	2	0	0	8	0	0	0	11
2002	0	1	0	0	0	10	0	0	0	11
2003	0	1	1	0	0	9	0	0	0	11
2004	0	0	0	0	0	11	0	0	0	11
2005	0	0	0	0	0	10	1	0	0	11
2006	0	0	0	0	0	7	5	0	0	12
2007	0	0	0	0	0	9	2	0	0	11
2008	1	2	0	0	0	8	1	0	0	12
2009	0	2	2	0	0	8	0	0	0	12
2010	0	0	0	0	0	12	0	0	0	12
2011	0	0	2	0	0	8	2	0	0	12
2012	0	0	1	0	0	11	0	0	0	12
2013	0	0	2	0	0	10	0	0	0	12
2014	0	0	0	2	0	10	0	0	0	12
2015	0	0	0	0	0	8	0	0	0	8
2016	0	0	0	0	1	7	0	0	0	8
2017	0	0	0	0	0	8	0	0	0	8
2018	0	0	0	0	0	8	0	0	0	8
2019	0	0	0	0	0	8	0	0	0	8
2020	0	0	0	0	0	8	0	0	0	8
2021	0	0	0	0	0	8	0	0	0	8
2022	0	0	0	0	0	4	0	2	2	8
2023	0	0	0	0	0	1	4	2	0	7

Source: own elaboration with data from the European Central Bank (2024)

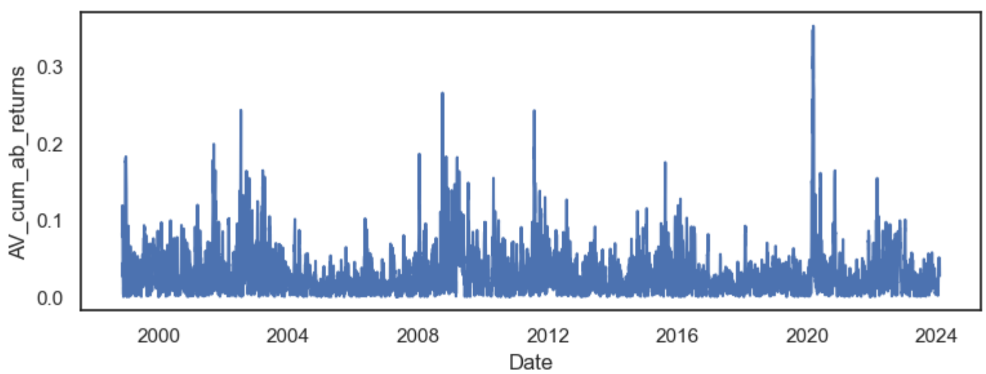
The data from the European stock index STOXX 50 was downloaded from Google Finance. The respective behavior of the variable time series is presented in Graph 2. Using the index data I calculated the daily returns as explained in section III. Then, for every day I calculated the abnormal cumulative return in a ten-day window (five days before and five days after) and obtained its absolute value. The cumulative abnormal return absolute value through the period of study is presented in Graph 3.

Graph 2. STOXX 50 index between January 1999 and December 2023.



Source: Own elaboration with data from Google Finance EURO STOXX 50. (2024).

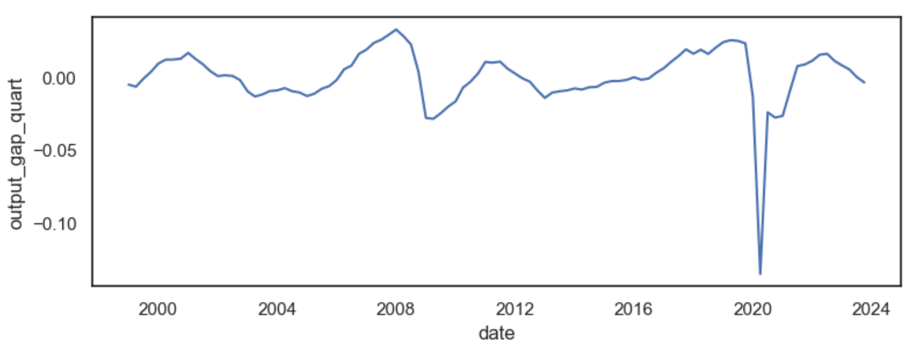
Graph 3. STOXX 50 index cumulative abnormal return absolute value between January 1999 and December 2023.



Source: Own elaboration with data from Google Finance EURO STOXX 50. (2024).

The information from the Quarterly GDP of the Eurozone was obtained from the Federal Reserve Economic Data Base (Eurostat, 2024). To extract the trend component and obtain the quarterly gap, I used the Hodrick-Prescott filter (Hodrick and Prescott, 1997). The output gap variable is presented in Graph 4.

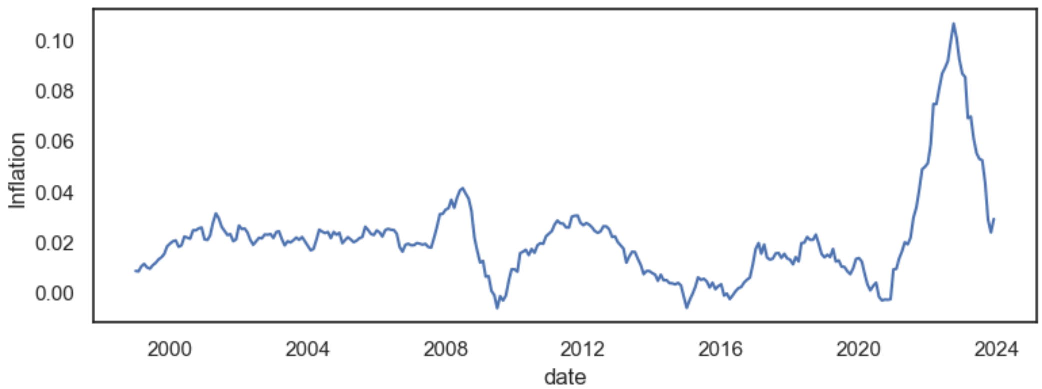
Graph 4. Output gap for the eurozone between January 1999 and December 2024



Source: Own elaboration with data from Eurostat, 2024.

Then, I obtained the Harmonised Index Consumer Prices (HICP) from the FRED repository (Eurostat, 2024). I applied the log transformation and then the first difference transformation to obtain the inflation rate in the Eurozone. The inflation variable is presented in Graph 5.

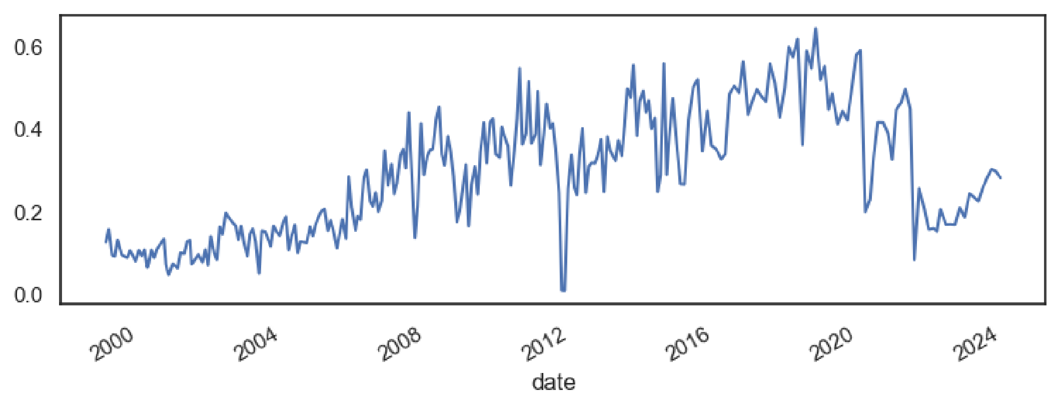
Graph 5. Inflation in the Eurozone between January 1999 and December 2024



Source: Own elaboration with data from Eurostat, 2024.

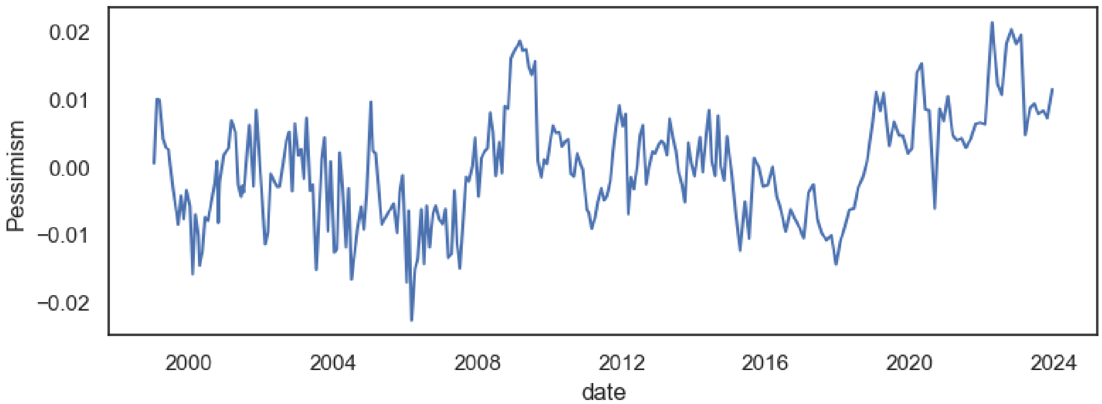
Graphs 6 and 7 present respectively the similarity and pessimism variables through time. The increasing trend of similarity observed by Amaya and Filbien (2013) in their original paper continued until the Covid pandemic when the Eurozone experienced a severe decrease in the GDP, followed by a strong inflationary episode as can be seen in graphs 5 and 4 respectively. As expected, the macroeconomic turbulences experienced by the whole world between 2020 and 2023 required changes in the monetary policy of the ECB, something that is translated into the similarity measure. The impact of these turbulences is also reflected in the pessimism indicator which remained relatively stable between 2013 and 2019, just to experience an important increase after 2020.

Graph 6. Similarity measure of ECB communications between January 1999 and December 2024



Source: Own elaboration.

Graph 7. Pessimism measure of ECB communications between January 1999 and December 2024



Source: Own elaboration.

Finally, Table 2 presents all the main descriptive statistics of the analyzed variables.

Table 2. Descriptive statistics for analyzed variables between January 1999 and December 2024

	count	mean	std	min	25%	50%	75%	max
Cumulative_ab_returns	256	0.000	0.046	-0.339	-0.021	0.003	0.026	0.124
Absolute_value_cumulative_ab_returns	256	0.032	0.033	0.000	0.013	0.024	0.042	0.339
Pessimism	256	0.000	0.008	-0.023	-0.006	0.000	0.005	0.021
Similarity	256	0.284	0.148	0.006	0.155	0.281	0.401	0.642
output_gap_quart	256	0.000	0.018	-0.136	-0.009	0.000	0.011	0.033
Inflation	256	0.021	0.017	-0.006	0.012	0.020	0.025	0.106
Delta MRO	256	0.005	0.164	-0.750	0.000	0.000	0.000	0.750

Source: Own elaboration.

V. RESULTS AND ANALYSIS:

Evolution of similarity

First, I estimate the different specifications of equation 1, which analyzes the similarity of ECB communications. The summary of the results is presented in Table 3. The detailed tables of every regression are presented in Annex 1. Specifications 2, 3, and 4 include a time variable, their significant and positive coefficients show that when controlling for macro factors, the similarity of ECB communications has been increasing over time.

It is important to underscore that this conclusion holds even when including the covid crisis period and the posterior inflationary episode when the value of the similarity variable decreased. This is consistent with the findings of Amaya and Filbien (2015) and shows that the pattern they identified is still valid even in times of strong macroeconomic shocks. Therefore, it is possible to conclude that on average the ECB communications' similarity has been increasing during the last decades, despite the events of the last 3 years.

Table 3. Summary of regression results for different specifications of Equation 1

	Specification			
Variable	1	2	3	4
R2	0.088	0.352	0.494	0.509
const	-1.147***	-2.109***	-1.815***	-1.878***
Delta MRO	0.710**		0.262	0.272
Inflation	-14.281***		-17.761***	-16.661***
Time		0.0002***	0.0002***	
Time count				0.006***
output_gap_quart	3.327		6.401***	6.177**

Source: Own elaboration.

* Statistical significance at the 10% level,**Statistical significance at the 5% level,***Statistical significance at the 1% level.

Impact of similarity on financial markets

Now, I present the results of estimating the different specifications of Equation 2. These specifications show the impact of pessimism in the market abnormal returns, and how similarity affects this relation. Specification 1 shows that there is a positive and significant effect of ECB pessimism and the market's abnormal returns. This can be explained by the fact that pessimism might be higher in sessions preceding interest rate reductions and other expansionary policy measures.

Consistently with the findings of Amaya and Filbien (2015), I found that the interaction term between pessimism and the logarithm of similarity is negative and significant, which means that similarity helps to attenuate the effect of pessimism on abnormal returns. Therefore, higher levels of similarity add predictability of ECB decisions help markets price pessimism in advance. As expected the effect of the change in the monetary policy rate is negative.

Table 4. Summary of regression results for different specifications of Equation 2

	Specification			
Variable	1	2	3	4
R2	0.028	0.029	0.024	0.041
const	0.032***	0.028***	0.032***	0.031***
Delta MRO		-0.033**		-0.025*
Inflation		0.171		0.047
Pessimism	0.696**			
Pessimism x log_similarity			-0.405**	-0.326*
output_gap_quart		-0.165		-0.096

Source: Own elaboration.

* Statistical significance at the 10% level,**Statistical significance at the 5% level,***Statistical significance at the 1% level.

Impact of ECB Presidencies

In this section, I extend the work of Amaya and Filbien (2015) by analyzing the impact that different presidencies have had on the relations studied. First, the results of estimating specifications 3.1 and 4.1 of Equation 1 are presented in Table 5. I include for comparison the results from specifications 3 and 4, which do not include the presidency dummies.

The results show that in comparison with the base scenario (which is the presidency of Willem F. Duisenberg), during the presidency of Jean Claude Trichet there was an increase in the level of similarity of the ECB communications, while in the case of Mario Dragui´s period, there are not significant differences in the level of similarity of the base scenario. The most interesting case is definitely the period of Christine Lagarde´s presidency, where a strong and significant decrease in the similarity measure is observed. This means that the ECB reacted to the macroeconomic shocks of the pandemic and the posterior inflationary period, not only with changes in the conventional monetary policy tools but also with an important change in the tone of its communications.

Table 5. Summary of regression results for specifications 3.1 and 4.1 of Equation 1

	Specification			
Variable	**3**	**4**	**3_1**	**4_1**
R2	0.494	0.509	0.592	0.595
const	-1.815***	-1.878***	-2.227***	-2.252***
Delta MRO	0.262	0.272	0.349*	0.361**
Inflation	-17.761***	-16.661***	-12.170***	-11.925***
Time	0.0002***		0.0004***	
Time count		0.006***		0.009***
output_gap_quart	6.401***	6.177**	2.257	2.630
President_Christine Lagarde			-0.731***	-0.702**
President_Jean Claude Trichet			0.287**	0.244**
President_Mario Draghi			-0.072	-0.156

* Statistical significance at the 10% level,**Statistical significance at the 5% level,***Statistical significance at the 1% level.

Now, to understand the effect of different presidencies on how abnormal returns change with pessimism, I present in Table 6 the summary results of estimating specifications 2.1 and 4.1 of equation 2. For comparison, I included the results for specifications 2 and 4. Interestingly, the interaction term between the presidency dummies and similarity is not significant for all the cases except for the case of Christine Lagarde´s presidency on specification 2.1, which is significant for a 10% level of significance. This means that there is no significant evidence that the different presidency periods changed the way in which the pessimism in ECB communications affected the market´s abnormal returns.

Table 6. Summary of regression results for specifications 2.1 and 4.1 of Equation 2

	Specification			
Variable	**2**	**4**	**2_1**	**4_1**
R2	0.029	0.041	0.054	0.054
const	0.028***	0.031***	0.033***	0.033***
Delta MRO	-0.033**	-0.025*	-0.031**	-0.032**
Inflation	0.171	0.047	-0.113	-0.112
Pessimism x log_similarity		-0.326*		0.026**
output_gap_quart	-0.165	-0.096	0.010	0.011**
pessimis_Christine Lagarde			1.612*	1.658
pessimis_Jean Claude Trichet			0.629	0.663
pessimis_Mario Draghi			0.236	0.256

* Statistical significance at the 10% level,**Statistical significance at the 5% level,***Statistical significance at the 1% level.

VI. CONCLUSIONS:

This study applies and updates the methodology of Amaya and Filbien (2015) by incorporating recent data. An automated process was developed to extract text from European Central Bank (ECB) press conferences held between January 1999 and December 2023, enabling the use of natural language processing techniques to evaluate the tone and thematic consistency of ECB communications over time. Additionally, this research extends prior findings by examining variations in communication style, tone, and abnormal returns across the tenures of different ECB presidents.

The findings confirm that Amaya and Filbien's (2015) results persist when controlling for macroeconomic factors. Specifically, the similarity of ECB communications has increased through time , and the negative impact of tone when paired with high communication similarity remains significant. One interpretation is that the increased uniformity in ECB messaging has allowed investors to adjust their expectations, thereby reducing the likelihood of unexpected market reactions.

When analyzing presidencies individually, the study finds a marked decrease in communication consistency during Christine Lagarde's tenure. However, there is no significant evidence that presidential transitions substantially alter the relationship between ECB communication tone and market abnormal returns.

VII. REFERENCES:

Amaya, D., & Filbien, J. Y. (2015). The similarity of ECB's communication. Finance Research Letters, 13, 234-242.

Brown, S. J., & Warner, J. B. (1985). Using daily stock returns: The case of event studies. Journal of financial economics, 14(1), 3-31.

Eurostat. (2024). Harmonized Index of Consumer Prices: All Items for Euro area (19 countries) [CP0000EZ19M086NEST], retrieved from FRED, Federal Reserve Bank of St. Louis. Accessed on January 28 2024 from: https://fred.stlouisfed.org/series/CP0000EZ19M086NEST.

Eurostat. (2024). Real Gross Domestic Product (Euro/ECU Series) for Euro Area (19 Countries) [CLVMEURSCAB1GQEA19], retrieved from FRED, Federal Reserve Bank of St. Louis. Accessed on January 28 2024 from: https://fred.stlouisfed.org/series/CLVMEURSCAB1GQEA19.

EURO STOXX 50. (2024). EURO STOXX 50 (EURO STOXX 50), stock quote. Google Finance. Accessed on January 28 2024 from: https://www.google.com/finance/quote/SX5E:INDEXSTOXX.

European Central Bank (2024). Key ECB interest rates [Data set]. Frankfurt, Germany. Accessed on January 2024 from: https://data.ecb.europa.eu/main-figures/ecb-interest-rates-and-exchange-rates/key-ecb-interest-rates.

Fama, E. F., Fisher, L., Jensen, M. C., & Roll, R. (1969). The adjustment of stock prices to new information. International economic review, 10(1), 1-21.

Garcia, D. (2013). Sentiment during recessions. The journal of finance, 68(3), 1267-1300.

Gorodnichenko, Y., Pham, T., & Talavera, O. (2023). The voice of monetary policy. American Economic Review, 113(2), 548-584.

Hodrick, R. J., & Prescott, E. C. (1997). Postwar US business cycles: an empirical investigation. Journal of Money, credit, and Banking, 1-16.

Jaccard, P. (1901). Distribution de la flore alpine dans le bassin des Dranses et dans quelques régions voisines. Bull Soc Vaudoise Sci Nat, 37, 241-272.

Loughran, T., & McDonald, B. (2011). When is a liability not a liability? Textual analysis, dictionaries, and 10-Ks. The Journal of Finance, 66(1), 35-65.

Loughran, T., & McDonald, B. (2020). Measuring firm complexity. Journal of Financial and Quantitative Analysis, 1-55.

Loughran, T., & McDonald, B. (2024). Loughran-McDonald Master Dictionary with Sentiment Word Lists. University of Notre Dame. Accessed on January 2024 from https://sraf.nd.edu/loughranmcdonald-master-dictionary/

Oshima, Y., & Matsubayashi, Y. (2018). Monetary policy communication of the bank of Japan: Computational text analysis. Graduate School of Economics Working paper.

Shapiro, A. H., & Wilson, D. J. (2022). Taking the fed at its word: A new approach to estimating central bank objectives using text analysis. The Review of Economic Studies, 89(5), 2768-2805.

Richardson, L. (2023). Beautiful Soup (Version 4.12.2) [Software]. Crummy, LLC. https://www.crummy.com/software/BeautifulSoup/

Tetlock, P. C. (2007). Giving content to investor sentiment: The role of media in the stock market. The Journal of Finance, 62(3), 1139-1168.

Tetlock, P. C., Saar-Tsechansky, M., & Macskassy, S. (2008). More than words: Quantifying language to measure firms' fundamentals. The journal of finance, 63(3), 1437-1467.

Tetlock, P. C. (2011). All the news that's fit to reprint: Do investors react to stale information? The Review of Financial Studies, 24(5), 1481-1512.

ANNEX I:

Table 7. Regression result for specification 1 of Equation 1

Dep. Variable:		Similarity		R-squared:		0.088
Model:		OLS		Adj. R-squared:		0.077
Method:		Least Squares		F-statistic:		8.119
No. Observations:		256		Prob (F-statistic):		3.50E-05
Df Residuals:		252		Log-Likelihood:		-253.68
Df Model:		3		AIC:		515.4
Covariance Type:		nonrobust		BIC:		529.5
	coef	std err	t	P>|t|	[0.025	0.975]
const	-1.1466	0.073	-15.797	0	-1.29	-1.004
output_gap_quart	3.3271	2.404	1.384	0.168	-1.407	8.062
Inflation	-14.281	2.914	-4.9	0	-20.02	-8.541
Delta MRO	0.7098	0.279	2.543	0.012	0.16	1.259
Omnibus:		92.154		Durbin-Watson:		0.537
Prob(Omnibus):		0		Jarque-Bera (JB):		287.687
Skew:		-1.566		Prob(JB):		3.38E-63
Kurtosis:		7.143		Cond. No.		76.3

Source: Own elaboration.

Table 8. Regression result for specification 2 of Equation 1

Dep. Variable:		Similarity		R-squared:		0.402
Model:		OLS		Adj. R-squared:		0.352
Method:		Least Squares		F-statistic:		0.349
No. Observations:		256		Prob (F-statistic):		1.38E+02
Df Residuals:		254		Log-Likelihood:		1.05E-25
Df Model:		1		AIC:		-210.02
Covariance Type:		nonrobust		BIC:		424
	coef	std err	t	P>|t|	[0.025	431.1
const	-2.1095	0.067	-31.627	0	-2.241	-1.978
Time	2.00E-04	1.37E-05	11.738	0	0.00E+00	0.00E+00
Omnibus:		177.648		Durbin-Watson:		0.679
Prob(Omnibus):		0		Jarque-Bera (JB):		2199.754
Skew:		-2.619		Prob(JB):		0
Kurtosis:		16.372		Cond. No.		9.44E+03

Source: Own elaboration.

Table 9. Regression result for specification 3 of Equation 1

Dep. Variable:		Similarity		R-squared:		0.494
Model:		OLS		Adj. R-squared:		0.485
Method:		Least Squares		F-statistic:		61.15
No. Observations:		256		Prob (F-statistic):		5.21E-36
Df Residuals:		251		Log-Likelihood:		-178.4
Df Model:		4		AIC:		366.8
Covariance Type:		nonrobust		BIC:		384.5
	coef	std err	t	P>|t|	[0.025	0.975]
const	-1.8147	0.072	-25.265	0	-1.956	-1.673
Time	2.00E-04	1.25E-05	14.175	0	0.00E+00	0.00E+00
output_gap_quart	6.4006	1.808	3.54	0	2.839	9.962
Inflation	-17.7613	2.19	-8.11	0	-22.074	-13.448
Delta MRO	0.2619	0.211	1.242	0.215	-0.153	0.677
Omnibus:		209.319		Durbin-Watson:		0.929
Prob(Omnibus):		0		Jarque-Bera (JB):		4252.609
Skew:		-3.089		Prob(JB):		0.00E+00
Kurtosis:		21.987		Cond. No.		3.76E+05

Source: Own elaboration.

Table 10. Regression result for specification 4 of Equation 1

Dep. Variable:	Similarity			R-squared:		0.509
Model:		OLS		Adj. R-squared:		0.501
Method:		Least Squares		F-statistic:		65.11
No. Observations:		256		Prob (F-statistic):		1.04E-37
Df Residuals:		251		Log-Likelihood:		-174.38
Df Model:		4		AIC:		358.8
Covariance Type:		nonrobust		BIC:		376.5
	coef	std err	t	P>|t|	[0.025	0.975]
const	-1.8776	0.073	-25.723	0	-2.021	-1.734
Time count	0.0061	0.00E+00	14.675	0	0.005	0.007
output_gap_quart	6.1769	1.778	3.474	0.001	2.676	9.678
Inflation	-16.6609	2.148	-7.755	0	-20.892	-12.43
Delta MRO	0.2722	0.207	1.313	0.19	-0.136	0.68
Omnibus:		222.646		Durbin-Watson:		0.955
Prob(Omnibus):		0		Jarque-Bera (JB):		5311.103
Skew:		-3.326		Prob(JB):		0.00E+00
Kurtosis:		24.3		Cond. No.		1.13E+04

Source: Own elaboration.

ANNEX II:

Table 11. Regression result for specification 1 of equation 2

Dep. Variable:		AV_cum_ab_returns		R-squared:		0.028
Model:		OLS		Adj. R-squared:		0.025
Method:		Least Squares		F-statistic:		7.43
No. Observations:		256		Prob (F-statistic):		0.00686
Df Residuals:		254		Log-Likelihood:		512.94
Df Model:		1		AIC:		-1022
Covariance Type:		nonrobust		BIC:		-1015
	coef	std err	t	P>|t|	[0.025	0.975]
const	0.0318	0.002	15.532	0	0.028	0.036
Pessimism	0.6962	0.255	2.726	0.007	0.193	1.199
Omnibus:		257.832		Durbin-Watson:		1.945
Prob(Omnibus):		0		Jarque-Bera (JB):		9318.849
Skew:		4.005		Prob(JB):		0
Kurtosis:		31.451		Cond. No.		125

Source: Own elaboration.

Table 12. Regression result for specification 2 of equation 2

Dep. Variable:	AV_cum_ab_returns	R-squared:	0.029
Model:	OLS	Adj. R-squared:	0.017
Method:	Least Squares	F-statistic:	2.505
No. Observations:	256	24 Feb 2024	0.0597
Df Residuals:	252	Log-Likelihood:	513.01
Df Model:	3	AIC:	-1018
Covariance Type:	nonrobust	BIC:	-1004

	coef	std err	t	P>|t|	[0.025	0.975]
const	0.0283	0.004	7.802	0	0.021	0.035
output_gap_quart	-0.1648	0.12	-1.37	0.172	-0.402	0.072
Inflation	0.1707	0.146	1.17	0.243	-0.117	0.458
Delta MRO	-0.0326	0.014	-2.334	0.02	-0.06	-0.005

Omnibus:	269.377	Durbin-Watson:	1.993
Prob(Omnibus):	0	Jarque-Bera (JB):	11479.61
Skew:	4.231	Prob(JB):	0
Kurtosis:	34.695	Cond. No.	76.3

Source: Own elaboration.

Table 13. Regression result for specification 3 of equation 2

Dep. Variable:	AV_cum_ab_returns	R-squared:	0.024
Model:	OLS	Adj. R-squared:	0.02
Method:	Least Squares	F-statistic:	6.301
No. Observations:	256	Prob (F-statistic):	0.0127
Df Residuals:	254	Log-Likelihood:	512.39
Df Model:	1	AIC:	-1021
Covariance Type:	nonrobust	BIC:	-1014

	coef	std err	t	P>|t|	[0.025	0.975]
const	0.0319	0.002	15.53	0	0.028	0.036
Pessimism x similarity	-0.405	0.161	-2.51	0.013	-0.723	-0.087

Omnibus:	257.477	Durbin-Watson:	1.939
Prob(Omnibus):	0	Jarque-Bera (JB):	9246.391
Skew:	3.999	Prob(JB):	0
Kurtosis:	31.335	Cond. No.	78.6

Source: Own elaboration.

Table 14. Regression result for specification 4 of Equation 2

Dep. Variable:	AV_cum_ab_returns	R-squared:	0.041
Model:	OLS	Adj. R-squared:	0.026
Method:	Least Squares	F-statistic:	2.704
No. Observations:	256	Prob (F-statistic):	0.031
Df Residuals:	251	Log-Likelihood:	514.65
Df Model:	4	AIC:	-1019
Covariance Type:	nonrobust	BIC:	-1002

	coef	std err	t	P>|t|	[0.025	0.975]
const	0.031	0.004	7.93	0	0.023	0.039
Pessimism x similarity	-0.3263	0.181	-1.798	0.073	-0.684	0.031
output_gap_quart	-0.0963	0.126	-0.766	0.444	-0.344	0.151
Inflation	0.0471	0.161	0.293	0.77	-0.269	0.363
Delta MRO	-0.0254	0.014	-1.753	0.081	-0.054	0.003

Omnibus:	260.692	Durbin-Watson:	1.997
Prob(Omnibus):	0	Jarque-Bera (JB):	9970.554
Skew:	4.052	Prob(JB):	0
Kurtosis:	32.48	Cond. No.	105

Source: Own elaboration.

ANNEX III:

Table 14. Regression result for specification 3.1 of Equation 1

Dep. Variable:		log_Similarity		R-squared:		0.592
Model:		OLS		Adj. R-squared:		0.581
Method:		Least Squares		F-statistic:		51.49
Date:		Tue 12 Nov 2024		Prob (F-statistic):		6.79e-45
Time:		9:51:22		Log-Likelihood:		-150.61
No. Observations:		256		AIC:		317.2
Df Residuals:		248		BIC:		345.6
Df Model:		7				
Covariance Type:		nonrobust				
	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
const	-2.2273	0.086	-25.99	0	-2.396	-2.059
Time	0.0003	3.87e-05	6.475	0	0	0
output_gap_quart	2.2567	1.909	1.182	0.238	-1.502	6.016
Inflation	-12.17	2.41	-5.05	0	-16.917	-7.423
Delta MRO	0.3487	0.191	1.824	0.069	-0.028	0.725
President_Christine Lagarde	-0.7305	0.323	-2.259	0.025	-1.368	-0.093
President_Jean Claude Trichet	0.2873	0.12	2.402	0.017	0.052	0.523
President_Mario Draghi	-0.0718	0.213	-0.337	0.737	-0.492	0.348
Omnibus:		289.146		Durbin-Watson:		1.148
Prob(Omnibus):		0		Jarque-Bera (JB):		14978.87
Skew:		-4.685		Prob(JB):		0
Kurtosis:		39.283		Cond. No.		4.76e+05

Source: Own elaboration.

Table 15. Regression result for specification 4.1 of Equation 1

Dep. Variable:		log_Similarity		R-squared:		0.595
Model:		OLS		Adj. R-squared:		0.584
Method:		Least Squares		F-statistic:		52.08
Date:		Tue 12 Nov 2024		Prob (F-statistic):		2.98E-45
Time:		9:51:22		Log-Likelihood:		-149.75
No. Observations:		256		AIC:		315.5
Df Residuals:		248		BIC:		343.9
Df Model:		7				
Covariance Type:	nonrobust					
	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
const	-2.2524	0.087	-25.964	0	-2.423	-2.082
Time count	0.0087	0.001	6.624	0	0.006	0.011
output_gap_quart	2.6297	1.885	1.395	0.164	-1.083	6.342
Inflation	-11.925	2.405	-4.958	0	-16.662	-7.188
Delta MRO	0.3607	0.191	1.893	0.06	-0.015	0.736
President_Christine Lagarde	-0.702	0.313	-2.243	0.026	-1.318	-0.086
President_Jean Claude Trichet	0.2438	0.123	1.982	0.049	0.002	0.486
President_Mario Draghi	-0.1564	0.221	-0.708	0.479	-0.591	0.278
Omnibus:		295.959		Durbin-Watson:		1.154
Prob(Omnibus):		0		Jarque-Bera (JB):		16388.46
Skew:		-4.849		Prob(JB):		0
Kurtosis:		40.979		Cond. No.		1.44E+04

Source: Own elaboration.

ANNEX IV:

Table 16. Regression result for specification 2.1 of Equation 2

Dep. Variable:		AV_cum_ab_returns		R-squared:		0.054
Model:		OLS		Adj. R-squared:		0.032
Method:		Least Squares		F-statistic:		2.384
Date:		Tue 12 Nov 2024		Prob (F-statistic):		0.0294
Time:		9:51:22		Log-Likelihood:		516.4
No. Observations:		256		AIC:		-1019
Df Residuals:		249		BIC:		-994
Df Model:		6				
Covariance Type:		nonrobust				

	coef	std err	t	P>|t|	[0.025	0.975]
const	0.0328	0.004	7.915	0	0.025	0.041
output_gap_quart	0.0102	0.142	0.072	0.943	-0.27	0.29
Inflation	-0.1125	0.203	-0.555	0.58	-0.512	0.287
Delta MRO	-0.0313	0.015	-2.084	0.038	-0.061	-0.002
pessimis_Christine Lagarde	1.6122	0.875	1.842	0.067	-0.112	3.336
pessimis_Jean Claude Trichet	0.6295	0.411	1.531	0.127	-0.18	1.439
pessimis_Mario Draghi	0.2359	0.622	0.379	0.705	-0.988	1.46

Omnibus:	243.759	Durbin-Watson:	1.995
Prob(Omnibus):	0	Jarque-Bera (JB):	7487.615
Skew:	3.722	Prob(JB):	0
Kurtosis:	28.427	Cond. No.	439

Source: Own elaboration.

Table 17. Regression result for specification 4.1 of Equation 2

Dep. Variable:		AV_cum_ab_returns		R-squared:		0.054
Model:		OLS		Adj. R-squared:		0.028
Method:		Least Squares		F-statistic:		2.036
Date:		Tue 12 Nov 2024		Prob (F-statistic):		0.0512
Time:		9:51:22		Log-Likelihood:		516.4
No. Observations:		256		AIC:		-1017
Df Residuals:		248		BIC:		-988.4
Df Model:		7				
Covariance Type:		Non-robust				

	coef	std err	t	P>|t|	[0.025	0.975]
const	0.0328	0.004	7.818	0	0.025	0.041
Pessimism x log_similarity	0.0256	0.279	0.092	0.927	-0.524	0.575
output_gap_quart	0.0108	0.143	0.076	0.94	-0.27	0.292
Inflation	-0.1118	0.203	-0.55	0.583	-0.512	0.289
Delta MRO	-0.0317	0.015	-2.044	0.042	-0.062	-0.001
pessimis_Christine Lagarde	1.6579	1.008	1.645	0.101	-0.328	3.643
pessimis_Jean Claude Trichet	0.6634	0.554	1.198	0.232	-0.427	1.754
pessimis_Mario Draghi	0.2564	0.662	0.387	0.699	-1.047	1.56

Omnibus:	243.763	Durbin-Watson:	1.995
Prob(Omnibus):	0	Jarque-Bera (JB):	7488.842
Skew:	3.722	Prob(JB):	0
Kurtosis:	28.43	Cond. No.	520

Source: Own elaboration.