

NEUMANN JÁNOS EGYETEM
MNB INTÉZET: FENNTARTHATÓ PÉNZÜGYEK KÖZPONT
NEMZETKÖZI GAZDASÁG ÉS GAZDÁLKODÁS MESTERSZAK



**Van-e a jegybanki kommunikáció tónusának hatása a Fama-French
faktorok hozamaira?
Szentiment elemzés alkalmazása a Federal Reserve beszédeire**

**Does central bank tone matter for Fama-French factor returns? an
application of sentiment analysis on the Federal Reserve speeches**

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Abstract

A large part of monetary policy related information comes from the communication of central bank. Specifically, within the field of communication, speeches have played an increasingly important role in recent times, especially after the 2008-2009 global financial crisis. The tone and the environment in which certain words are expressed has a predictive effect on future path of monetary policy and on financial market developments, therefore it is crucial to understand and quantify as precise as possible the sentiment of central banks. In this paper I estimate whether the tone of Fed speeches has an impact on the Fama-French five factors and on the momentum factor. By retrieving all the speeches from the Federal Reserve webpage, I construct four different types of sentiment indicators to measure the tone of the Fed speeches. These indices differ in terms of their complexity – whether they capture single-word or multi-word contexts – and to what extent the indicator was created for a monetary policy context. Based on the results of this research, it can be concluded that the tone of Fed communication has a substantial effect on the momentum, high minus low and conservative minus aggressive factors. In general, the results support the argument that the speeches have a significant content of information for investors, thus the tone of central banks can shape market expectations. In addition, the research also contributes to the literature by finding that in a rising interest rate environment, shares overvalued compared to their real value may perform worse compared to shares that are much closer or in fact even lower than their intrinsic value.

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1. Introduction

“Monetary policy is 98 percent talk and only two percent action.” (Bernanke, 2015). This is how Ben Bernanke sometimes perceived the Fed's monetary policy moves during his time at the Federal Reserve. Even if this statement is probably a bit of an exaggeration, it is indisputable that communication has become a crucial tool of central banks especially after the 2008-2009 global financial crisis. The communication of central banks communication has become so versatile that it covers lots of topics for instance monetary policy, monetary policy strategy, financial stability, economic outlook, and future policy decisions.

By the fact that the central bank talks about such a wide variety of topics, speeches have a significant content of information for investors, thus the tone of central banks can shape market expectations (Schmeling and Wagner, 2015). Wecken and Büchsenmann (2019) argue that due to the key role of central bank communication, policymakers should be well aware of the intended and unintended impact of words in public central bank statements and speeches have on financial assets. According to the efficient market hypothesis only unexpected announcements, statements or tone can have significant effect on the financial market. However, in many cases, the opposite was observed and several find that market participants are not fully rational and therefore irrational behaviours can lead to mispricing of assets on the financial markets (Andersen et al., 2007; Savor and Wilson, 2013; Kurov et al., 2016; Hu et al., 2017). With respect to stock markets, several studies concluded that the sentiment of central bank communication has a significant impact on equity returns (Schmeling and Wagner, 2015; Sadique et al., 2013).

As both the financial market players and researchers realized that central bank communication can have a very large impact on financial markets, extracting the tone of speeches or texts through text analysis received significant focus in recent years in the field of behavioral economics and asset pricing. By applying text analysis to speeches or press releases, researchers can understand the variation of factor returns even more precisely. An area on the field of text analysis is the sentiment analysis, which is a widely used concept to measure the tone (positive/negative) of financial texts. Castillo et al. (2018) point out central bank statements with positive (negative) tone are expected to be a reliable proxy for the degree of hawkishness (dovishness) of the central bank on economic and financial conditions.

In this research I focus whether the tone of the Federal Reserve speeches has on impact on the well-known Fama-French five factors and the momentum factor. Hubert and Fabian (2017) highlights that in addition to FOMC minutes, other interventions in the press, speeches

at conferences or during political events like the testimony to the US congress may also convey central bank sentiment. Based on this motivation, I gather these speeches from the Federal Reserve page with the help of webscraping technique and estimate whether more hawkish tone of the Federal Reserve can have a substantial effect on the factor returns.

To assess the impact of Fed speeches on the Fama-French five factors and the momentum factor I first retrieve all the speeches from the Federal Reserve page. Then to convert it to a numerical indicator, I estimate four different types of sentiment indicators based on the Loughran-McDonald (2011), Bennani-Neunkirch (2017), Apel and Blix-Grimeldi (2012) and another approach proposed as a mixture of the last two dictionaries. Using four different types of sentiment indicators can be beneficial from a robustness perspective as the indicators differ in terms of their complexity – whether they capture single-word or multi-word contexts – and to what extent the dictionary was created for a monetary policy context. Then focusing on the daily data downloaded from the Fama-Kenneth library, I estimate OLS regressions between the factor returns and the different types of sentiment indicators. The significant effect Fed speeches on factor returns may indicate that the investors closely follow not only the FOMC minutes but other speeches made by decision makers and therefore every word can be crucial from an asset pricing point of view.

I find that as central bank communication becoming more hawkish the momentum factor returns likely to decrease. In other words, central bank communication implying a rising interest rate policy causes stocks that performed well in the past are likely to gain low returns in the future compared to stocks who performed weak in the past. Controlling for the speaker of the speech – Chairman or Chair – the momentum effect remains significant and even gets stronger. In this case, other factors, the high minus low (HML) and conservative minus aggressive investment (CMA) factors, are also significant. For the CMA factor, those companies that invested more conservatively (and thus became less indebted) are expected to outperform the companies that invested strongly in the past and therefore are expected to be more indebted when the central bank communication indicating a stricter interest rate policy. The result of the HML factor is also consistent with the findings in the literature (da Silva Ramos, 2021) and the industry (Goldman Sachs, 2023): growth stocks, especially with high valuation multiples are vulnerable to high inflation rates (and high interest rates), while value stocks become attractive during high inflationary times since they trade much closer or in fact even lower than their intrinsic value. With respect to the different types of sentiment indicators, those indicators significantly explained the factor returns that were proposed specifically for a monetary context, namely the BN dictionary and the ABG dictionary. This result suggests that

it indeed matters what method is used to capture the tone of the central bank's communication and therefore it is beneficial creating more indexes to explain the movement of factor returns.

This paper can provide several implications for the literature. The first contribution of this research is that it quantifies the tone of Fed speeches by four different types of sentiment indicators which covers both financial and monetary policy context. By creating more than just one type of sentiment index, it is possible to compare which of the sentiment indicators have a substantial effect on the factor returns. Second, the results of the study confirm that central bank communication significantly influences the expectations of market participants, thereby the tone of speeches can influence the pricing of assets. All of this suggests that market participants pay close attention to the central bank's speeches and that the tone of communication can be at least as important as changes in certain monetary policy instruments. Finally, with respect to the factor returns, the results of this paper support the argument that as central bank speeches become more hawkish growth and aggressive investment portfolios underperform compared to value and conservative investment portfolios respectively.

The rest of the paper continues as follows. In the second section, I describe the related literature discussing the importance of monetary policy communication, the techniques that can measure the sentiment with respect to communication and the relationship of sentiment and financial markets. The third section presents the data section focusing on the textual data and the factor returns. In the fourth section, I give an overview of the applied modelling methodology. In the fifth section I present the main empirical findings of this research. The final section discusses the main findings of the paper.

2. Related literature

In this chapter, I divide the literature overview into three distinct parts to review the importance of monetary policy communication and the arising techniques in the literature that can quantify the tone of the central banks. In the first part, I present why is the communication of central banks so closely monitored these days by financial market participants. In the second part, I list some of the methods presented in the literature that can capture the tone of the central banks. Last but not least the relationship of central bank sentiment and equity markets are going to be discussed.

2.1. The importance of monetary policy communication

In the last three decades there has been a remarkable shift in the communication practices of the central banks. According to Wecken and Büchsenmann (2019) prior to the 1990s central banks were characterized by low transparency and very cryptic statements informing the public only to the very minimum. Indeed, some even thought that the effective monetary policy sometimes includes surprises for financial market participants (Kahveci and Odabaş, 2016). Fawley and Neely (2014) highlight that the Fed has modified its procedures in communication practices over time to become more transparent.

According to Haan et al. (2007) the central bank communication represents the public provision of information on topics of monetary policy, monetary policy strategy, the economic outlook, and future policy decisions. In practice this means that central banks convey signals to prepare market participants for certain monetary policy actions. Speeches are an important tool for central bankers to convey views on the preferred policy stance. Issing (2005) argues central bank signalling can significantly increase the effectiveness of monetary policy actions. In consistent with this Blinder et al. (2008) argue that communication helps central banks achieve their objectives and that it can move markets.

After the 2008-2009 global financial crisis several central banks reached the lower zero bound (ZLB) of interest rates. The ZLB restricted central banks to lose further the interest rates with conventional monetary policy tools. As a result, the communication of central banks has become an even more important tool of their monetary policy toolkit. Communication has emerged to fill the role of strategically shaping market expectations and thus became a crucial toolkit for central bankers to implement monetary policy (Woodford, 2005; de Haan et al., 2007). Hansen and McHahon (2016) point out in addition to conventional monetary policy tools, central bank communication is considered to add two new tangible dimensions of information, namely forward guidance and the state of the economy. Gürkayanak et al. (2005) find both monetary policy actions and statements have important but differing effects on asset prices, with statements having a much greater impact on longer-term Treasury yields. Measuring the tone of central banks can be also add explanatory power to predict future rates. With the exception of Jansen and De Haan (2009), several studies find that the extracting the tone of the ECB is an important explanatory variable of future changes in the ECB's policy rate. This means that in addition to developments in macroeconomic variables, the communication of the ECB can add complementary information about future interest rates.

2.2. Measuring central bank sentiment

The central bank communication is closely followed by market participants, extensively covered in the financial press. In order to assess the effectiveness of their communications central banks also evaluate the media coverage of their statements and press releases. These processes inevitable caused researchers in the field of behavioural economics and asset pricing to extract the tone of communication through text analysis in recent years. In general, textual analysis aims to convert qualitative information into quantitative information (Loughran and McDonald, 2011).

Sentiment analysis is a widely used concept to measure the tone (positive/negative) of financial texts. Castillo et al. (2018) point out central bank statements with positive (negative) tone are expected to be a reliable proxy for the degree of hawkishness (dovishness) of the central bank on economic and financial conditions. This is due to the fact that majority of vocabulary-based dictionaries assign terms like increase/grow/rise can be to positive category while decrease/fall/decline terms are classified to negative category. In terms of the monetary policy direction the former list of words indicates hawkish, while the latter indicates dovish tone from the central bank. Apel and Blix-Grimeldi (2012) define two general concepts of analysing text in the field of sentiment analysis, namely manual content analysis, and computational linguistics.

Based on the manual content analysis the texts are classified according to its content and coded on a numerical scale. Wecken and Büchsenmann (2019) argue that manually coding statements based on their content yields a few drawbacks. First, the risk of misclassifications emerges in the texts as the assessment of human coding inevitably characterized by subjectivity. Second, as the communication quantified ex-post, it is unsure how the financial market participants perceived the information at the time when the text has been published or the speech has taken place.

As an alternative method we can also quantify qualitative informative with the so-called computational linguistics approach. Within this approach we can use either machine learning or automated “search-and-count-words” methods. Loughran and McDonald (2015) state that despite the machine learning methods make relatively few errors when operating properly, understanding the results is challenging due to the complexity of these approaches. In addition, it should be also noted that the training of these ML algorithms requires a lot of capacity in order for the algorithm to learn the hidden relationships on the largest possible amount of data.

For this reason, within the field of sentiment analysis researchers mostly apply the bag-of-words method. In this case one can use a computer programme to count how frequently certain words in a text. Based on a pre-defined list of words or dictionary we can assign the words in either to positive (hawkish) or negative (dovish) category. The most frequently stated arguments behind usage of the bag-of-words method are the simplicity behind the method and the risk arising from subjectivity is much more moderate. According to Hubert and Fabien (2017), one advantage of these methods on the field of sentiment analysis is that it is fully automated and replicable, which remove the subjectivity of human-reading coded indices.

In recent years, many bag-of-words-based sentiment indices have been developed (Loughran and McDonald, 2011; Apel and Blix-Grimeldi, 2012; Bennani and Neunkirch, 2017). Within the field of financial research, lexicon proposed by Loughran and McDonald (2011) (henceforth LM dictionary) is the most widely used dictionary. The LM dictionary is an extension of the General Inquirer's Harvard dictionary, and it reflects the tone of financial texts in a more precise manner. Based on their assessment, almost three-fourths of negative words in the Harvard dictionary are not negative in a financial context. Wecken and Büchsenmann (2019) list several advantages of the usage of LM dictionary. First, one can propose a new statistical dictionary or manually classify tone of central bank texts. Both approaches are, however, very likely to raise the concerns of subjectivity and also can be very time consuming. Second, LM represents the latest and most widely used candidate in this field of research. Third, despite the fact the LM dictionary might lack explanatory power in a monetary policy context, as of today, alternatives with a monetary policy focus – e.g., the dictionary by Picault and Renault (2017) – are still very new, and their practicality is not widely confirmed yet.

However, despite its popularity, recently several criticized the LM dictionary functioning in the economic studies, especially in the context of central bank communication (Picault and Renault, 2017; Kearney and Liu, 2013; Kahveci and Odabaş, 2016). The biggest argument against the LM dictionary is that since monetary policy communication has a very specific vocabulary and practical application, the LM dictionary may not be able to accurately capture the tone of central bank communication. In order to grasp the tone of monetary political communication as accurate as possible, Apel and Blix-Grimaldi introduce a 'hawkish' and 'dovish' word list in 2012 (henceforth ABG dictionary). Unlike the LM dictionary ABG dictionary uses the frequency of two-word combinations rather than a single word. Despite it fails to capture the negative tone following crisis (Picault and Renault, 2017), researchers still prefer this dictionary when estimating the tone of central bank communication (Hansen and

McMahon, 2016). Similar to Apel and Blix Grimaldi (2012), Bennani and Neuenkirch (2017) sorted keywords into two categories depending on whether they indicate a more hawkish tone or a more dovish tone in a monetary policy context.

In this study, I quantify the tone of Fed speeches with some of sentiment indices proposed by the related literature. Therefore, in the data chapter of this research, I will detail the practical differences of these indices. By understanding the differences between the sentiment indices, one can interpret and understand the impact of the Fed sentiment quantified by different methods on the Fama-French five factor regressions more precisely. In addition, the use of several indices is also beneficial in terms of examining the robustness of the results.

2.3. The relationship of central bank tone and financial markets

This study examines whether the tone of the Fed communication influences the five factors defined by Fama and French (2015). Since I study the financial market effects, a comprehensive review of the literature on the impact of monetary policy communication on financial markets can put my later results into context.

There is a general consensus in the literature since Blinder et al. (2008), that central bank communication has an effect on financial markets, however it is still uncertain the exact transmission mechanism through which central bank sentiments affect financial markets (Hubert and Fabian, 2017). Within the context of monetary policy and financial markets, according to the efficient market hypothesis, an announcement or statement by central banks can either meet market expectations or not. Consequently, only unexpected announcements, statements or tone can have significant effect on the financial markets. Despite the hypothesis assumes that market participants can incorporate the new information into their decisions quickly, several find that market participants are not fully rational and therefore irrational behaviours can lead to mispricing of assets on the financial markets (Andersen et al., 2007; Savor and Wilson, 2013; Kurov et al., 2016; Hu et al., 2017).

Antweiler and Frank (2004) and Das and Chen (2007) are among the first who publish results related to the qualitative content and stock valuations. Schmeling and Wagner (2015) find that ECB tone has a statistically and economically significant effect on equity and government bond prices on the day of the press conference. The effect propagates beyond the release day through the cycle to the next ECB press conference. They argue that ECB tone moves assets through risk premia required by market participants.

Wecken and Büchsenmann (2019) confirm the positive (negative) relationship between ECB tone and equity (bond) returns. It is worth to note however, by further specifying different financial market shocks, evidence shows that the impact on equity returns is weakened, disappears, or, in some cases, even reversed when central bankers use forward guidance in their communication. Sadique et al. (2013) provide such results that the Federal Reserve Beige Book tone drives volatility and trading volume in the stock market. Similar results are estimated by Jegadeesh and Wu (2017), who employ Latent Dirichlet Allocation (LDA) topic model and confirm that the tone of FOMC minutes affects stock market returns and volatility. Wecken and Büchsenmann (2019) emphasize stock returns and government bond yields, over the last two decades, have typically co-moved positively in response to economic activity and changes in investor's risk appetite, however monetary policy shocks usually resulted lower stock returns. Based on the theoretical framework proposed by Wecken and Büchsenmann (2019) four shocks can be identified which can influence the movement of stocks and bonds, namely the monetary policy, economic and risk-premium shocks.

Most researchers usually find significant effect between central bank communication and financial markets, however Kurihara (2014) argues that this is not always the case. Kurihara (2014) studies whether the tone of ECB communication has an effect on stock returns in the Euro area. Based on his findings, the effect of such announcements on stock returns has not been significant.

3. Data

In this chapter I present the data I use to estimate the tone of Fed speeches on the Fama French five factor and the momentum factor returns. First, I describe the Fama-French five factors and the momentum factor and their importance in the field of asset pricing. In the second section, different types sentiment indices proposed by the related literature are going to be discussed.

3.1 Fama-French five factors and momentum factor

Even prior 2000's several pointed out the price anomalies which arises questions with respect to the efficient market hypothesis when searched for an adequate asset pricing model (Basu, 1977; Banz, 1981; Haugen and Baker, 1996). Partly based on the emergence of various price anomalies and major irregularities in the efficient market hypothesis Fama and French (1993) first proposed then constantly developed a new stock anomaly theory.

The Fama and French (1993) three-factor model aims to estimate the relationship between average return and size of an equity and the relationship between average return and price related ratios such as book-to market (B/M). They point out that at the time of the paper were published, these two factors thought to add relevant explanatory power to the well-known CAPM model (Sharpe, 1964; Lintner, 1965). Fama and French (1993) described the three-factor model as follows:

$$R_{it} = a_i + b_i RMFT_t + s_i SMB_t + h_i HML_t + e_{it} \quad (1)$$

, where R_{it} refers to the excess return of portfolio i at time t . $RMFT_t$ denotes the excess return of the market return over the risk-free rate at time t . SMB_t is the size factor, which gives the difference between the return of a portfolio of small stocks minus the return of a portfolio of large stocks. HML_t captures the value factor, which is the return difference of a portfolio with high book-to-market ratio (high B/M ratio) and a portfolio with low book-to-market ratio (low B/M ratio).

Later, questions were also raised about the strength of the three-factor model as it fails to explain variation in average returns related to profitability and investment (Novy-Marx, 2013; Titman, Wei, and Xie, 2004). As a result, Fama and French (2015) added the profitability and investment factors to the three-factor model in order to explain the variation in excess return to an even greater extent:

$$R_{it} = a_i + b_i RMFT_t + s_i SMB_t + h_i HML_t + r_i RMW_t + c_i CMA_t + e_{it} \quad (2)$$

, where RMW_t refers to the difference between portfolios of stocks with robust and weak profitability, and CMA_t is the investment factor (conservative minus aggressive) which is calculated by the difference between the portfolio returns of stocks with low and high investment propensity.

The Fama-French five factor model was tested both in the Japanese (Kubota and Takehara, 2018) and Australian (Chiah et al., 2016) markets. Zaremba and Czapkiewicz (2017) market and it was concluded that the Fama-French five factor model outperforms and explains portfolio returns by a greater extent compared the CAPM and Fama-French three factor models.

Similarly to Dirkx and Peter (2020), in addition to the five factors proposed by Fama and French (2015), I also include the momentum factor in my research. Their results show that the momentum factor shows the highest return after the market factor, which is also statistically significant. The momentum effect has an outstanding and robust track record of risk-adjusted performance (Asness et al., 2014; Geczy and Samonov, 2016). The momentum effect captures the phenomenon according to assets that performed well (weak) in the past are likely to gain high (low) returns in the future. Ehsani and Linnainmaa (2022) argue that momentum factor

raises questions with respect to the efficient market hypothesis in its weakest form. Based on this, past returns should not predict future returns if asset prices incorporate the new information immediately.

Artmann et al. (2012) perform estimations on the German stock market with different types of factor models. They emphasize that construction and sorting procedure of the portfolios makes the factor results very sensitive. Based on this consideration, I do not estimate factors for the US market on equity level data, but will use data on a daily frequency estimated by Fama and French.¹ Data downloaded from the Fama-French library shows the following descriptive statistics for the Fama-French five factors and the momentum factor between 2006 and 2023:

Variable	Rm-Rf	SMB	HML	RMW	CMA	MOM
Min	-12	-4.55	-5.02	-2.72	-2.73	-14.4
Max	11.4	5.7	6.73	4.2	2.46	7.12
Mean	0.041	0.001	-0.004	0.016	0.004	0.001
Median	0.07	0	-0.03	0.01	-0.01	0.06
Std. dev	1.26	0.64	0.83	0.46	0.38	1.09

1. Table: Summary statistics of the Fama-French five factors and the momentum factor

This table lists the summary statistics for Fama-French five factors plus the momentum factor. The data was retrieved from the Fama-French data library on a daily frequency. The observed period is from January 2006 to December 2023. Fama and French explained in detail how the portfolios are exactly constructed: Rm-Rf includes all NYSE, AMEX, and NASDAQ firms. SMB, HML, RMW, and CMA for July of year t to June of t+1 include all NYSE, AMEX, and NASDAQ stocks for which we have market equity data for December of t-1 and June of t, (positive) book equity data for t-1 (for SMB, HML, and RMW), non-missing revenues and at least one of the following: cost of goods sold, selling, general and administrative expenses, or interest expense for t-1 (for SMB and RMW), and total assets data for t-2 and t-1 (for SMB and CMA).

Source: Fama-French library, own calculation

Based on the summary statistics shown above it can be concluded that on a daily average the market has an excessive return of 0.041% on the risk-free return, which is one-month Treasury bill rate in this case. As for the average factor returns, with the exception of the HML factor, we can see positive returns in case of the Fama-French factors in the examined period. Looking at the extreme values, the MOM factor shows a value of -14.4%, meaning that two low prior return portfolios minus the two high prior return portfolios resulted 14.4%. This remarkable difference was calculated on the 9th of November 2020. The maximum value of the excess return on the market was 11.4% which was observed on the 13th of October 2008. Considering the standard deviation of the factors, the excess return on the market shows the

¹ https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/f-f_5_factors_2x3.html

largest, while the CMA (conservative minus aggressive) factors shows the smallest standard deviation between 2006 and 2023.

3.2 Data for the Federal Reserve speeches

There is a general consensus in the literature that communication related to interest rate decisions has an impact on financial markets (Schmeling and Wagner, 2015; Wecken and Büchsenmann, 2019). Hubert and Fabian (2017) capture the sentiment of FOMC minutes, however argue that other interventions in the press, speeches at conferences or during political events like the testimony to the US congress may also convey central bank sentiment.

Partially based on this argument, in my research I quantify whether, in addition to communication related to monetary policy decisions, other speeches made by decision makers or speeches at conferences also have a significant effect on the financial markets. The site of Federal Reserve contains Fed speeches starting from 2006 until today and it is updated with the latest speeches on a weekly basis. Both the speeches made by Governors, Vice Chairman, Vice Chairs, Chairmen and Chairs can be found on this page. One of the advantages of this site is that, with the exception of the speeches of 2006, the specific date (hour and minute) of the speeches is also available, which creates the possibility to exclude those speeches that took place after the market closed. Therefore, I only estimate the effect of the speeches that happened on the day when the markets were open.

Using webscraping method, I retrieve all the speeches from page of the Federal Reserve from 2006 to the end of 2023. The database contains the title, the content, the date (year, month, day, hour and minute) and the speaker of the speech. The following table presents the number of speeches and the share of speeches made by Chairmen and Chairs in different years.

Year	Number of speeches	Share of Chairmen and Chairs
2006	73	33%
2007	73	32%
2008	72	32%
2009	54	39%
2010	60	43%
2011	48	38%
2012	42	38%
2013	53	32%
2014	41	37%
2015	54	20%
2016	43	12%
2017	55	24%
2018	44	25%
2019	78	22%

2020	53	11%
2021	68	13%
2022	46	13%
2023	95	9%

2. Table: Number of speeches and share of speeches made by Chairmen and Chairs in different years

The table shows descriptive statistics about the webscraped data for the Fed speeches between 2006 and 2023. The above statistics are based on yearly grouped values. The second column of the table presents the number of speeches in the given year, while the third column refers to the share of speeches made by Chairmen or Chairs in a specific year.

Source: Federal Reserve official webpage, own calculation

Based on the table above no clear trend emerges in terms of the number of speeches. Most speeches are available for the year 2023, while in the two years following the crisis, in 2011 and in 2022, the Fed's decision-makers made relatively few speeches 48 and 42, respectively. However, in terms of the share of speeches made by Chairs and Chairmen there is a clear decreasing trend: before and immediately after the 2008-2009 global financial crisis 30-40 percent of the speeches could be linked to speeches of Chairs and Chairmen, while following the recovery in the economy the share fell to 10-20 percent. All this leads to the conclusion that, although the number of speeches did not change substantially during the observed period, the Chairs and Chairmen give quite a few speeches other than the regular interest rate decisions.

3.3 Estimating the tone of Fed communication with several sentiment indices

In this research I use four different types of dictionaries (methods) that aim to capture the tone of the Fed communication. The presented indices can be grouped along two dimensions: in terms of their complexity – whether they capture single-word or multi-word contexts – and to what extent the dictionary was created for a monetary policy context.

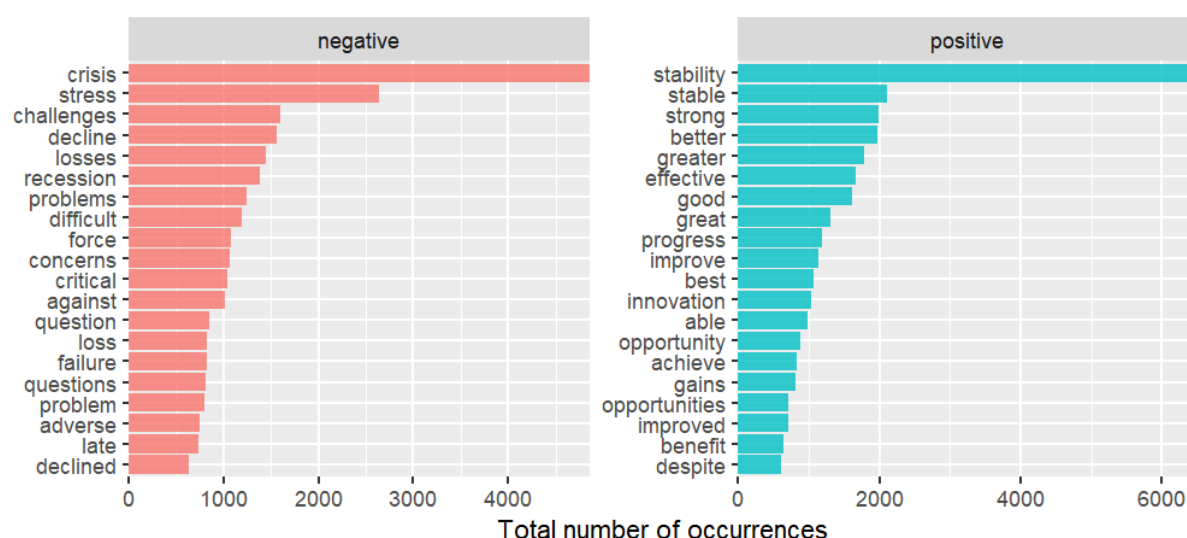
Firstly, I describe the sentiment indices generated based on the one-word dictionaries, namely the Loughran and McDonald (2012) and Bennani and Neunkirch (2017) dictionaries. Following the one-word based dictionaries I present more complex methods which, although increases the accuracy when capturing the tone of sentences, at the same time the risk arising from subjectivity also rises somewhat.

3.3.1 Dictionaries based on one-word expressions

Loughran and McDonald (2011) research concluded that a more general sentiment lexicon – such as the Harvard IV-4 – was not a good fit for analysing the sentiment of financial texts. Therefore, they expanded the existing dictionaries in such a way that it can be applied specifically to the financial area. As I have already presented above, although the LM dictionary

method has received more and more criticism in the field of text and sentiment analysis recently, due to its simplicity and comparability, it is still one of the most widely used methods for sentiment analysis of financial texts. The LM dictionary includes seven sentiment category identifiers where the individual words are classified: negative, positive, uncertainty, litigious, strong modal, weak modal, and constraining. In contrast to the Harvard dictionary, based on their assessment the term of „risk” not necessarily arises in a negative context, therefore they classify this word to the uncertainty category.

In general, when calculating sentiment/tone of a speech or a text we subtract the negative (dovish) words/terms from the positive (hawkish) words/terms and divide by the all possible negative and positive words. Thus, despite the fact that Loughran and McDonald (2011) also identify other categories in addition to positive and negative categories, due to comparability with other indices and due the function of this research – to estimate whether the tone of Fed communication has an impact on the Fama-French five factors and the momentum factor –, in the rest of the paper I will only focus on positive (hawkish) and negative (dovish) expressions. The following figure shows the most common negative and positive words in the Fed speeches based on the Loughran-McDonald dictionary between 2006 and 2023.



1. Figure: The most common negative and positive words in the Fed speeches based on the Loughran-McDonald dictionary

Source: Federal Reserve official webpage, own calculation

Based on the LM dictionary it can be concluded that crisis, stress and challenges contributed the most to the negative sentiment. The term crisis was used nearly 5,000 times in Fed speeches between 2006 and 2013. As for the positive expressions, stability, stable and strong contributed the most to the positive sentiment of the Fed communication.

Bennani and Neunkirch (2017) employ an automated text linguistic approach to create an indicator that measures the tone of more than 1500 speeches delivered by members of the Governing Council during the period 1999M1–2014M4. The advantage of the dictionary is that the keywords they searched for can be used as indirect indicators of monetary policy inclination via the economic outlook. The keywords were categorised depending whether they capture a more dovish or a more hawkish tone. The hawkish terms include high*, strong*, increas*, and fast*, while words like low*, weak*, decreas*, and slow* indicate a more dovish tone.² Similarly to the LM dictionary, the tone of the given speech is obtained as follows:

$$tone_{i,t} = \frac{hawkish_{i,t} - dovish_{i,t}}{hawkish_{i,t} + dovish_{i,t}} \quad (3)$$

With this calculation method I quantify a continuous variable $tone_{i,t}$ for the speech i on day t . The variable can have a value between -1 to 1 depending on how dovish or hawkish the tone of the speech is.

3.3.2 Methods capturing combinations of words

With respect to the single word-based dictionaries however one could argue that policymakers could use a combination of positive and negative words together for instance ‘solid decrease’ or another example would be the word “recovery” in isolation appears to carry a positive message, but the phrase “sluggish recovery” does not. Another bias could be that policymakers use a negation to reverse the meaning of the message such as with “not improving” versus “worsening”. The methodologies capturing several words or phrases were proposed to mitigate the possible distorting effects stemming from that the semantic meaning of single words often is ambiguous and depends on the context in which they are used.

Apel-Grimaldi (2012) point out searching for combinations of words rather than for single words increases the precision of the search despite these methods are less popular in the field of economics. They tried to capture the tone of the Riksbank minutes with regard to its dovishness or hawkishness. Based on 82 Riksbank policy meetings between January 2000 and February 2011 two quantitative measures were proposed, namely a dovish and a hawkish one.

² The full list of keywords indicating more hawkish monetary policy is as follows: accelerat*, betttter, boom*, emerg*, expansion, fast*, favo(u)rabl*, firm*, great*, high*, improv*, increas*, larger, posiiitive, rais*, ris*, stabili*, stable, strengthen*, strong*, subdued, unsustainable, upside, upswing, upturn, upward*. The list of dovish keywords is: collaps*, contraction, dampen*, decelerat*, declin*, decreas*, delay*, depression, destabili*, deteriorat*, difficul*, diminish*, disappear*, downside, downswing, downturn, downward*, fall*, fragil*, low*, negative, poor, recession*, slow*, sluggish, small*, struggling, sustainable, unfavo(u)rabl*, unstable, weak*, worse.

The designed context specific list includes of combinations of a noun and an adjective. By this method one can capture a combination of words for instance ‘higher growth’, ‘lower inflation’ or ‘rising employment’.

The ABG dictionary covers relatively few (4) adjectives per category. Presumably the communication of Federal Reserve decision makers is broader and covers more adjectives. To capture the tone of as many texts as possible and therefore to give a comprehensive assessment of the Fed communication tone, in addition to the ABG dictionary, I also propose a new dictionary which is a mixture between the ABG and BN dictionary. For the nouns I search for keywords that are relevant from a monetary policy perspective for instance GDP, output and price. As for the adjectives I use the hawkish and dovish words from the BN dictionary. The following comparison table shows the nouns and adjectives used in the two types of multi-word dictionaries.

Apel-Grimaldi (ABG) dictionary			Own Dictionary		
Nouns	Hawkish	Dovish	Nouns	Hawkish	Dovish
inflation, cyclical position, growth, price, wages, oil price, development	high*, strong*, increas*, fast	low*, weak*, decreas*, slow	gdp, output, inflation, price, employment	accelerat*, bettter, boom*, emerg*, expansion, fast*, favo(u)rabl*, firm*, great*, high*, improv*, increas*, larger, positiive, rais*, ris*, stabili*, stable, strengthen*, strong*, subdued, unsustainable, upside, upswing, upturn, upward*.	collaps*, contraction, dampen*, decelerat*, declin*, decreas*, delay*, depression, destabili*, deteriorat*, difficul*, diminish*, disappear*, downside, downswing, downturn, downward*, fall*, fragil*, low*, negative, poor, recession*, slow*, sluggish, small*, struggling, sustainable, unfavo(u)rabl*, unstable, weak*, worse

3. Table: Comparison of the more complex dictionaries

The table shows the multi-word dictionaries namely the Apel-Grimaldi (ABG) dictionary and the one proposed as a mixture of the ABG and BN dictionaries. In both cases the first column presents the nouns used in the given dictionary. Second and third columns are the hawkish and dovish adjectives that were assigned to the nouns.

Based on the table, there is some overlap between the two dictionaries in case of both the nouns and the adjectives. Nevertheless, the own method finds more expressions due to the larger set of adjectives. To measure the tone of the speeches as accurately as possible, I made some corrections for both of the dictionaries.

First, in contrast to the Apel-Grimaldi method, I do not examine direct two-word combinations (bigrams), but capture entire sentences. This is necessary because the adjective often does not appear directly next to the noun. Second, if the given sentence contained both

adjectives hawkish and dovish adjectives, then I decided depending on quantity base which category dominated the sentence more. Last, similarly to Bennani and Neunkirch (2017) to avoid extreme values for the sentiment indicator, I exclude speeches from the analysis that contain less than 3 occurrences of the above mentioned two-word combinations. After running the different dictionaries on the Fed speeches and carrying out the necessary data correction steps, the sentiment indices become comparable. The following table shows the pairwise correlations for different types of sentiment indices.

Full sample					Jan 2020 to Dec 2023			
Index	BN	LM	OWN	ABG	BN	LM	OWN	ABG
BN	1.00	0.23	0.60	0.45	1.00	0.29	0.65	0.58
LM	0.23	1.00	0.25	0.06	0.28	1.00	0.33	0.05
OWN	0.60	0.25	1.00	0.42	0.66	0.33	1.00	0.63
ABG	0.45	0.06	0.42	1.00	0.58	0.05	0.63	1.00

4. Table: Pearson correlations for the content of Fed speeches

This table presents the Pearson correlations for the different sentiment indices capturing the tone of the Fed speeches between January 2006 and December 2023. The correlation matrices are grouped depending on the size of the sample. The first sample shows the pairwise correlations for the full sample, while the other sample is a sub-sample for the period after the COVID 19.

Source: Federal Reserve official webpage, own calculation

On the overall sample the correlations range from 0.06 to 0.60, while on the sub-sample they elevated from 0.05 to 0.66. Although significant difference in terms of minimum and maximum values cannot be observed between the two samples, on average, the co-movement between indices is stronger in the period after the COVID 19. The correlations are positive in all cases, therefore in general it can be concluded that if one of the sentiment measures is expecting a hawkish sentiment, the other sentiment also measures a hawkish tone in the Federal Reserve communication.

As it was already discussed in the literature review and the data chapter focused on the different types of sentiment measures, the LM dictionary captures more efficiently the information content related to the economic outlook, while the other three indicators extracting more the tone of monetary policy content of the Fed speeches. The Pearson correlation values confirm this statement, since the LM dictionary shows a very weak correlation with the other indicators (0.06 to 0.25), while the co-movement of the other indicators focusing more on the stance of monetary policy is quite strong (0.23 to 0.60). It is desirable from an estimation point of view because the regressions can separate the impact of different channels – the change in

monetary policy stance and the variation of the risk premium stemming from the changing economic environment resulting from the positive economic environment – on the Fama-French five factors and its extension by the momentum factor.

4. Estimation Strategy

To measure how the factors generated by Fama and French respond to the content of Fed speeches, the following analysis relies on Ordinary Least Square (OLS) estimations. To be the most efficient linear unbiased estimator, the OLS model is based on three underlying assumptions: explanatory variable and the error term should be independent, the error term not autocorrelated and homoscedastic with mean 0 and variance of σ^2 and the explanatory variables are linearly independent (Wooldridge, 2012).

Using OLS we might face some limitations which is due the omitted variable bias – disregarded explanatory variable correlates with one of the independent variables or if it is a determinant of the dependent variable – or from reverse causality, which means in this case that the variation of Fama-French factors affects the tone of the Fed speeches. In particular, the omitted variable bias stems from the fact that variables that are not in the scope in this study explain the factor returns by a great extent. In this study, I consider only the factor returns taken into account on the day of the speech. Indeed, with the availability of very high frequency data – having data for the hour and minutes of the given speech – I also have the option to ignore speeches after the financial markets have closed. In addition, in order to really capture as much as possible the effect of the speeches not related to the interest rate decision but other interventions in the press, speeches at conferences or during political events, I also excluded the observations of the days on which the interest rate decision took place. With these preliminary steps the estimation risk of other major influences on asset prices is minimized. The reverse causality bias is present when not only the communication of the central bank has an impact on the financial market, but the effect is also existing in reverse, that is the development of stock markets influences how the central bank communicates about monetary policy and economic prospects. Although in the case of emerging banks, it is common for the central bank to gently comment on financial market processes – via increased risk aversion and rising volatility resulting weakening exchange rates – however, a central bank of an advanced country rather comments more on the economic outlook and thereby also hints at the future monetary policy path.

I describe the impact of Fed sentiment on the Fama-French five factors and on the momentum factor with the following equation:

$$R_i = a_i + b_i \text{tone}_i + e_i \quad (3)$$

, where R_i refers to returns factor I , which includes $R_m - R_f$ (excess return on market), SMB (small minus big), HML (high-low), RMW (robust minus weak), CMA (conservative minus aggressive) and MOM (two high prior return portfolios minus the average return on the two low prior return portfolios) factors. tone_i is the tone of Fed speeches measured by 4 types of sentiment indicators, namely the LM (Loughran-McDonald), BN (Bennani-Neunkirch), ABG (Apel and Grimaldi) and another dictionary proposed in this paper, while e_i is the error term in the OLS model.

5. Results

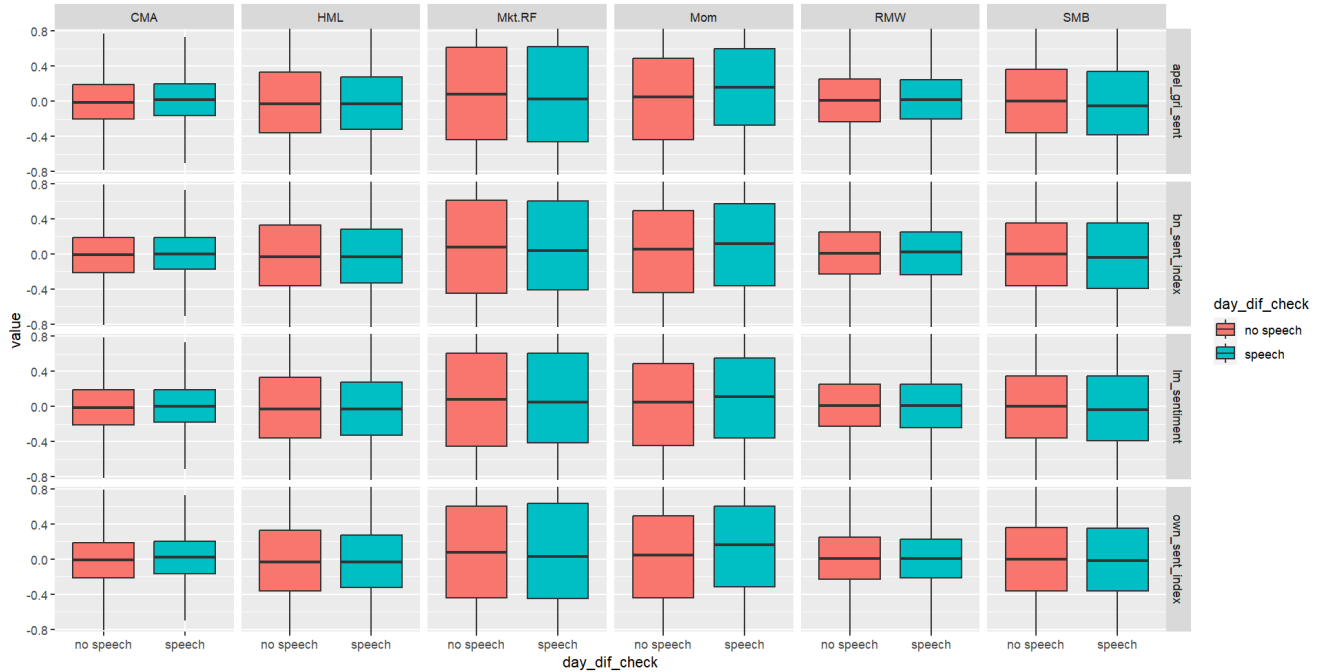
The results section of this research is divided into three sub-sections. First, I quantify whether on the days when the Fed speech took place, do the factor returns differ from the days when no Fed speeches were observed. Second, I run the OLS regression between the Fama-French five factors and the momentum factor and the different type of sentiment indicators. Third, I estimate other control regressions by splitting the sample to several sub-samples depending on the speaker of the speeches.

5.1 Compare the returns on Fed speech days and on non-speech days

Before estimating the impact of Fed sentiment on factor returns, I estimate whether significant differences can be observed in the factor returns on days when Fed speech took place and on days when the Federal Reserve decision makers did not make any speech. With this type of analysis, we can have a guess whether the speeches can be expected to have any effect during the subsequent OLS runs.

In general, when assessing the impact of the communication of central banks on financial markets one can compare the difference of returns or volatility on the days when central bank speech took place and on days when no speech was observed. Schmeling and Wagner (2015) assess the fundamental relevance of ECB press conferences by comparing equity market developments during event windows on press conference days (PC Thursday) compared to non-press conference days (non-PC Thursday). Based on their results both cumulative returns and average market volatility substantially differ on an intraday basis compared to returns on non-PC Thursdays. In this research I first visually compare the average returns on Fed speech days with non-Fed speech days. After that I estimate with two-sample t-tests whether the average factor returns significantly differ. Figure 2 shows the different box

plots calculated according to which sentiment indicator were taken into account and which factor type was examined.



2. Figure: Box plots of Fama-French factors and momentum factor on Fed speech days and on non-speech days

The figure presents boxplots of Fama-French factors, and the momentum factor returns on days when a Fed decision maker made a speech versus days when no speeches were observed. The box plots are grouped across two dimensions. On the horizontal dimension the plots are separated based on the factor return, namely the conservative minus aggressive (CMA), high minus low (HML), excess return over market (Mkt.RF), Mom (two high prior return portfolios minus the average return on the two low prior return portfolios), robust minus aggressive (RMW) and small minus big (SMB). On the vertical dimension the factor returns are calculated based on the sentiment indicator samples.

Source: Federal Reserve official webpage, Fama-French library, own calculation

Comparing the size of boxplots returns vary to the greatest extent in the case of excess return over the market and the momentum factor. This is in line with the figures on table 1, where these two factors show the highest standard variation. As for the riskiness of the factors, the returns of the CMA and RMW factors show the smallest variance. Looking at the returns on the days with Fed speeches and days without Fed speeches, a substantial difference in returns is clearly visible only in the case of momentum factor. The difference can be detected for all sentiment indicator sub-samples and the sign of the difference of the means is positive, meaning that the momentum factor results higher return when Fed speeches are observed. When no Fed speeches took place the average return of the momentum factor is around 0%, while on days with Fed speeches the return is 0.15-0.2% depending which sentiment indicator sample is analysed. Other than the momentum, although to a much lesser extent, a difference can be also

observed in the average returns in case of the sample calculated for the own index. After the visual analysis, I use the two-sample Welsch test to check whether the average of the factor returns differs significantly. I only show the cases where the p value of the two-sample test is below 30 percent.

Sentiment indicator	Factor	Estimation	T statistics	P value
own_sent_index	Mom	-0,138	-2,72	0,01 (***)
apel_gri_sent	Mom	-0,141	-2,55	0,01 (***)
bn_sent_index	Mom	-0,081	-1,96	0,05 (*)
lm_sentiment	Mom	-0,075	-1,81	0,07 (*)
own_sent_index	CMA	-0,021	-1,22	0,22
own_sent_index	HML	0,045	1,22	0,22
apel_gri_sent	Mkt.RF	0,081	1,18	0,24
apel_gri_sent	HML	0,046	1,11	0,27

3. Figure: Two sample Welch t-test for factor returns on Fed speech days and on non-speech days

The table shows the results of the two sample Welch's t-tests. The first sample includes the days when Fed speeches were observed, while the second sample refers to days without Fed speeches. The first column of the table names the observations from the speeches are calculated. The second column presents the factor returns for which the t - statistic tests are fitted. The third column shows the difference between the average factor returns in the two sample. Fourth column gives the test results of the Welch t-test, while the last column demonstrates the corresponding p values for the test statistics. Significance levels are determined as follows: * $p < .10$, ** $p < .05$, *** $p < .01$.

Source: Federal Reserve official webpage, own calculation

The results of the Welch t-tests confirm my previous findings made on the basis of the previous boxplot figures. Momentum factor returns significantly – the statistical power depending on which sub-sample we calculate as a basis of the Fed speeches – differ on days when there was a Fed speech compared to days when there was no speech. For instance, taking into account the observations of the own sentiment indicator and the ABG dictionary, even at the 1 percent significance level, the average of the returns calculated from the momentum factor is statistically different on Fed-speech days versus non-Fed speech days. As for the other factors, although no significant difference can be shown in a statistical sense, the average returns differ in case of the conservative minus aggressive (CMA), high minus low and the excess return over market factors (Mkt.RF).

5.2 Relationship between the tone of Fed speeches and factor returns

According to the results of the previous chapter, the factor returns differ significantly on the days when there was a Fed speech compared to the days when there was no speech. This preliminary result suggests that it is worthwhile to examine the effect of the tone of the Fed speeches in more depth, as investors also closely monitor the content of other interventions in

the press or speeches at conferences. These speeches that are not directly related to interest rate decisions may also convey central bank sentiment. As a first step, I run the bivariate (one explanatory variable) OLS regressions for all possible factors and sentiment indicators. Given the fact I investigate 6 factors and 4 explanatory sentiment indicators, I run a total of 24 regressions. Figure 5 presents the bivariate OLS regressions results for all possible factors and sentiment indicators.

Dependent variables:		Independent variables:			
Factor returns		Sentiment indicators			
	Tone_BN	Tone_LM	Tone_ABG	Tone_OWN	
CMA	-0,06 (-1.36)	-0,06 (-1.50)	0,02 (0.56)	-0,03 (-0.69)	
HML	0,12 (1.32)	-0,01 (-0.15)	0,08 (0.90)	-0,06 (-0.74)	
Mkt.RF	0,00 (-0.03)	0,04 (0.30)	-0,17 (-1.16)	-0,12 (-0.84)	
Mom	-0,22 (*) (-1.78)	-0,12 (-0.97)	-0,07 (-0.62)	0,02 (0.13)	
RMW	0,04 (0.69)	0,06 (1.08)	0,03 (0.56)	0,04 (0.79)	
SMB	0,01 (0.18)	-0,11 (-1.34)	-0,06 (-0.86)	-0,06 (-0.79)	
N	814	810	416	498	

5. Table: Bivariate OLS regression results to estimate the impact of Fed speeches on Fama-French five factors and on the momentum factor

On each day when I estimate a sentiment index with one of the above presented methods, I run a regression between the Fama-French five factors and the momentum factor and the Fed sentiment. The table shows the regression results between Fed sentiment and Fama-French five factors and the momentum factor returns. From the regressions, I present the coefficients of the variables and the t-statistics in parentheses. The last row of the table demonstrates the number of observations in the given sentiment indicator sample. The significance levels are reported next to the coefficients as follows: * $p < .10$, ** $p < .05$, *** $p < .01$. OLS coefficients significant at the 1, 5 and 10 percent significance levels are highlighted in bold.

Source: Federal Reserve official webpage, Fama-French library, own calculation

Looking at the number of observations they range from 416 to 814 depending on which type of sentiment indicator sample is used for the OLS regression. Unsurprisingly, the BN and LM dictionary methods that capture unigrams in the texts have more than 800 observations, while the OLS regressions that are based on more complex sentiment indicators – both adjectives and verbs have to be present in the text – are estimated with less than 500 observations. In general, the coefficients of the sentiment indicators extracted from the OLS regressions do not show clear evidence with respect to the relationship of the tone of Fed

speeches and the factor returns. The corresponding t-statistics vary between -0.03 (Mkt.RF) to -1.78 (Mom). Nevertheless, the sentiment of Fed speeches measured with the BN dictionary method has a significant impact on the momentum factor on 10 percent significance level. The negative sign of the BN coefficient indicates as central bank communication becoming more hawkish the momentum factor returns likely to decrease. In other words, central bank communication implying a rising interest rate policy causes stocks that performed well in the past are likely to gain low returns in the future compared to stocks who performed weak in the past. The fact that tone has a substantial effect on portfolios formed from past returns can be explained by the precautionary motive and the change in risk aversion of the financial market participants.

There may be several reasons why the bivariate OLS regressions – which capturing the sensitivity of factor returns with the change of Fed tone in speeches – on the entire sample only show significant results for the momentum factor. First, as the proposed sentiment indicators grasp the tone of the texts from a different perspective both in terms of content and complexity, similarity is not necessarily expected in the case of different sentiment indicators. Second, the financial market impact of the speeches may differ substantially depending on who gives the speech. For instance, a greater impact is expected if a Chair or Chairman makes the speech. This is due to the fact that date of the speech is already known to the investors in advance, therefore they make expectations with respect to the content and tone of the speech. To address these effects, in the next chapter I run different regressions depending on the speaker of the speech.

5.3 Robustness tests: Controlling for the speaker of the speech

The impact of the Fed sentiment on the factor returns can be influenced by several factors. Therefore, in the following, I run different regressions considering who was the speaker of the speech. Figure 6 presents the bivariate OLS regressions results for all possible factors and sentiment indicators controlling for the speaker – Chairmen and Chairs or other speakers which can include Governors and Vice Chairs – of the speech.

Speaker	Chairs	Other	Chairs	Other	Chairs	Other	Chairs	Other
	Tone_BN		Tone_LM		Tone_ABG		Tone_OWN	
CMA	0.06 (0.73)	-0.10(**) (-2.05)	0.05 (0.70)	-0.12(**) (-2.26)	0.23(***) (3.13)	-0.05 (-1.12)	0.18(**) (1.99)	-0.08(*) (-1.77)
HML	0.49(***) (2.38)	-0.01 (-0.13)	0.27 (1.38)	-0.14 (-1.36)	0.20 (1.12)	0.03 (0.31)	0.24 (1.14)	-0.14 (-1.46)
Mkt.RF	-0.21 (-0.60)	0.07 (0.46)	-0.00 (-0.01)	0.09 (0.57)	-0.41 (-1.13)	-0.09 (-0.59)	-0.06 (-0.14)	-0.14 (-0.94)
Mom	-0.51(**) (-1.98)	-0.11 (-0.81)	-0.34 (-1.38)	-0.02 (-0.13)	0.05 (0.20)	-0.11 (-0.82)	-0.26 (-0.97)	0.08 (0.58)
RMW	0.05 (0.48)	0.03 (0.52)	0.12 (1.25)	0.03 (0.45)	-0.01 (-0.16)	0.04 (0.72)	-0.00 (-0.01)	0.05 (0.85)
SMB	-0.12 (-0.78)	0.07 (0.72)	-0.12 (-0.83)	-0.11 (-1.16)	-0.07 (-0.52)	-0.06 (-0.67)	-0.16 (-0.99)	-0.04 (-0.43)
N	212	602	210	600	113	303	129	370

6. Table: Bivariate OLS regression results to estimate the impact of Fed speeches on Fama-French five factors and on the momentum factor controlling for the speaker

On each day when I estimate a sentiment index with one of the above presented methods, I run a regression between the Fama French five factors and the momentum factor and the Fed sentiment. The table shows the regression results between Fed sentiment and Fama-French five factors and the momentum factor returns. From the regression, I present the coefficients of the variables and the t-statistics in parentheses. The last row of the table demonstrates the number of observations in the given sentiment indicator sample. The significance levels are reported next to the coefficients as follows: * p<.10, ** p<.05, *** p<.01. OLS coefficients significant at the 1, 5 and 10 percent significance levels are highlighted in bold.

Source: Federal Reserve official webpage, Fama-French library, own calculation

The number of observations in the OLS regressions range from 113 (ABG dictionary with Chairs and Chairmen as speakers) to 602 (BN dictionary with other speakers including Governors and Vice Chairs).

Looking at the conservative minus aggressive factor (CMA) overall it can be concluded that the tone of Fed speeches has a significant impact on the returns. Nevertheless, the speeches have different effect both in terms of the magnitude and the direction on the CMA factor depending on the speaker of the speeches. Assessing the coefficients for regressions with Chairmen or Chairs as speakers the direction of the relationship between the tone of Fed and the CMA return is positive and statistically significant for ABG and OWN indicators on 1 and 5 percent, respectively. Both indicators focus on expressions related to the direction of monetary policy, therefore they can be treated as a proxy of hawkishness or dovishness of the speeches. Accordingly, based on these results a more hawkish tone results the CMA factor return to increase. The CMA factor generated by Fama-French refers to the average return on

the two conservative investment portfolios minus the average return on the two aggressive investment portfolios. This means that a more positive return for CMA factor corresponds to conservative investment portfolio earn higher returns compared to aggressive investment portfolios. The positive relationship for this factor is consistent with economic intuition: as central bank communication indicating a stricter interest rate policy (more hawkish tone of Federal Reserve), those companies that invested more conservatively (and thus became less indebted) are expected to outperform the companies that invested strongly in the past and therefore are expected to be more indebted. It is important to note however, that the relationship in case of the speaker was not a Chairmen or a Chair is opposite, meaning that the more hawkish tone corresponds to lower CMA factor return. As far as the direction of monetary policy is concerned, investors tend to pay more attention to the speeches of the highest decision maker. This is confirmed by the higher t-statistics for samples when the speaker was a Chair or a Chairman.

Other than CMA factor, HML factor also show significant results with respect to the tone of the Fed. Looking at the high minus low factor regressions results with speakers either was a Chair or a Chairman the coefficients vary from 0.20 (tone_ABG) to 0.49 (tone_BN). The positive coefficients indicates that with as the tone of Fed speeches becomes more hawkish, the HML factor return increases and it is statistically significant on 5 percent significance level in case of the BN sentiment. The HML factor is the average return on the two value portfolios minus the average return on the two growth portfolios. In general, growth stocks, especially with high valuation multiples are vulnerable to high inflation rates (and high interest rates), while value stocks become attractive during high inflationary times since they trade much closer or in fact even lower than their intrinsic value. This is due to the fact that the forecasted earnings are dependent on the distant future cash-flows and are discounted to net present value with a discount rate which are usually bonds yields. More hawkish tone of central bank communication implies bond yields and discount rates to rise, which reduces their net present value of future cash flows. On the other hand, value stocks also have a strong cash flow and not heavily dependent on the distant future cash-flow, which makes them more attractive during high inflationary times unlike growth stocks. The results of this research indicate a similar conclusion since more hawkish tone results the value portfolios outperform the growth portfolios.

These results are in line with the findings of da Silva Ramos (2021) as they point out that with increasing inflationary expectations and accordingly more hawkish tone causes

growth stocks to significantly underperform compared to value stocks. Besides, an analysis from Goldman Sachs (2023) ³ is also consistent with the findings of this research as it states that value stocks dominance tends to perform well when inflation is high, economic growth is strong and rates are elevated. By contrast, growth stocks often outperform value stocks when inflation is low, economic growth is relatively weak and rates are low and falling.

Last but not least, similar to the previous section of the paper – when the regressions were not distinguished based on the speaker of the speech – the tone of the Fed speeches has a substantial impact on the momentum factor. Most of the cases the sign of the coefficient is negative, and it is statistically significant on a 5 percent significance level for the tone calculated by the BN approach. Based on the OLS regression it can be said that when the tone become more hawkish, the momentum effect weakens. Accordingly in these periods those stocks that performed well in the past likely to underperform compared to stocks that gained relatively low return. In other words, the phenomena according to the tendency of winning stocks to continue performing well in the near term weakens significantly. This result is somewhat related to the cautionary motive of investors that also appears in the HML factor, i.e., when rising interest rates are expected in parallel with the hawkish communication of central banks investors may prefer to buy stocks that have not been overvalued compared to their real intrinsic value.

6. Conclusion

In this research I estimate whether the tone of Fed speeches has a significant impact on the Fama-French five factor returns and the on the momentum factor returns. Several studies highlighted the importance of FOMC meetings, however there are few studies which deal with the effect of other communication practices such interventions in the press, speeches at conferences. By proposing different types of sentiment indicators, I quantify whether these speeches can significantly explain the variation of factor returns and therefore understand the behaviour of market participants under different sentiment levels of the Fed speakers.

To estimate the effect of the Fed sentiment on the factor returns first I gathered all the speeches from the Federal Reserve site. Then as a next step I created four different types of explanatory variables with the help of sentiment analysis. The sentiment indicators captured the tone of Fed speeches by calculating all the hawkish and dovish words in the speeches. Finally,

³ <https://www.gsam.com/content/gsam/us/en/institutions/market-insights/gsam-insights/perspectives/2023/growth-vs-value-re-think-your-investment-style.html>

I estimated OLS regressions between the factor returns and the different types of sentiment indicators.

Based on the results of this paper more hawkish tone from the Federal Reserve results the momentum factor returns to decrease. This means that communication implying higher interest rates causes stocks that performed well in the past are likely to gain low returns in the future compared to stocks who performed weak in the past. This result became even more robust after controlling for speeches where the speaker was either a Chair or Chairman. Besides, controlling for the speaker, the conservative minus aggressive investment (CMA) factor is also significantly explained by the tone of the Fed speeches. Based on the results of this paper companies that invested more conservatively (and thus became less indebted) are expected to outperform the companies that invested strongly in the past when the central bank applies more hawkish communication in the speeches. Last but not least the sentiment of the Federal Reserve speeches also significantly affects the high minus low (HML) factor returns: growth stocks underperform in periods with high inflation rates (and high interest rates) compared to value stocks which become attractive during these times since they trade much closer or in fact even lower than their intrinsic value. These results were consistent with the findings of the industry and the literature (da Silva Ramos, 2021; Goldman Sachs, 2023).

7. Literature overview

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