MASTERARBEIT | MASTER'S THESIS

Titel | Title

Machine learning, sentiment and the Bank of England: investigating the impact of central bank communications on the financial market

verfasst von | submitted by

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angestrebter akademischer Grad | in partial fulfilment of the requirements for the degree of

Master of Science (MSc)

Wien | Vienna, 2024

Studienkennzahl lt. Studienblatt | Degree programme code as it appears on the student record sheet:	UA 066 913
Studienrichtung lt. Studienblatt | Degree programme as it appears on the student record sheet:	Masterstudium Applied Economics
Betreut von | Supervisor:	Assoz. Prof. Mag. Dr. Paul Pichler Privatdoz.
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Abstract

Central bank communication has become a critical tool in modern monetary policy, moving from minimal disclosure to full transparency to manage market expectations. This thesis explores the impact of the Bank of England's communications on the UK financial market, a relatively understudied area compared to the U.S. Federal Reserve and the European Central Bank. Leveraging CentralBankRoBERTa, a state-of-the-art machine learning model, this thesis quantifies the sentiment of central bank statements and integrates these findings with the UK Monetary Policy Event-Study Database (UKMPD), a novel dataset tracking intraday monetary policy surprises in the UK. The analysis reveals that market reactions—specifically in the UK fixed income, overnight index swaps, and exchange rate markets—are significantly influenced by the maturity of the dependent variable, the magnitude of the monetary policy surprise, and prevailing sentiment. The thesis demonstrates a fundamental relationship between sentiment targeted at specific audiences and financial market movements, contributing new insights to the understanding of monetary policy's effects in the UK context.

Kurzfassung

Die Kommunikation von Zentralbanken ist zu einem entscheidenden Instrument moderner Geldpolitik geworden, um Markterwartungen zu steuern, welches sich von minimaler Offenlegung hin zu voller Transparenz entwickelt hat. Diese Arbeit untersucht den Einfluss der Kommunikation der Bank of England auf den britischen Finanzmarkt, der im Vergleich zur US-Notenbank und der Europäischen Zentralbank relativ wenig erforscht wurde. Mithilfe von CentralBankRoBERTa, einem hochmodernen Machine-Learning-Modell, quantifiziert diese Arbeit die Stimmung in den Erklärungen der Zentralbank und integriert diese Erkenntnisse mit der UK Monetary Policy Event-Study Database (UKMPD), einem neuartigen Datensatz, der intratägliche geldpolitische Überraschungen in Großbritannien verfolgt. Die Analyse zeigt, dass Marktreaktionen – insbesondere auf den britischen Renten-, Overnight-Index-Swap- und Devisenmärkten – erheblich durch die Laufzeit der abhängigen Variablen, das Ausmaß der geldpolitischen Überraschung und die vorherrschende Stimmung beeinflusst werden. Diese Thesis legt eine grundlegende Beziehung zwischen der auf bestimmte Zielgruppen gerichteten Stimmung und den Bewegungen auf den Finanzmärkten dar und liefert neue Erkenntnisse zum Verständnis der Auswirkungen von Geldpolitik im britischen Kontext.

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1. Introduction

"*Irrational exuberance*" – a seemingly innocuous phrase with a somewhat peculiar sound. This same expression caused significant declines in stock markets worldwide when mentioned on December 5 1996 by Alan Greenspan who was back then the chairman of the Federal Open Markets Committee (FOMC). His words were interpreted as a signal that stock markets were overvalued (Born et al., 2014). This is just one example out of many, when central banks' announcements have triggered market reactions. Since then, views on central bank communication practices have undergone substantial changes. A few decades ago, the prevailing practice by central bankers was to minimize communication. However, nowadays, managing expectations through full decision transparency has become a central tenet of monetary policy (Blinder et al., 2008). This phenomenon is highlighted by the famous economist Ben Bernanke in his blog where he writes:

"*When I was at the Federal Reserve, I occasionally observed that monetary policy is 98 percent talk and only two percent action. The ability to shape market expectations of future policy through public statements is one of the most powerful tools the Fed has*" Bernanke (2015).

Central banks usually communicate through official statements and speeches. As a result, they showcase the main central banking operations. Consequently, they aim to increase financial stability by providing market participants with knowledge on economic topics and medium term predictions (Petropoulos and Siakoulis, 2021).

Academia has increasingly recognized the importance of studying monetary policy, especially forward guidance, to better understand the financial market. Early research often relied on lexicon-based natural language processing (NLP) to quantify central bank statements, but these methods struggled to capture contextual nuances (Niţoi et al., 2023). Recently, there has been a significant shift towards using machine learning and deep learning techniques for more advanced textual analysis (Pfeifer and Marohl, 2023). For instance, Pfeifer and Marohl (2023) apply large language models (LLMs) to central bank communications, developing CentralBankRoBERTa—a state-of-the-art economic agent classifier that distinguishes five basic macroeconomic agents and a binary sentiment classifier that identifies the emotional content of sentences.

Research on the impacts of monetary policy has predominantly focused on the United States and the Euro Area due to the global influence of the Fed and ECB and the availability of systematic intraday financial market data for these regions (Braun et al., 2023). However, the Bank of England's announcements and their effects on the UK financial market are also noteworthy. In "Bank of England Staff Working Paper No. 1050" Braun et al. (2023) introduce the UK Monetary Policy Event-Study Database (UKMPD), a high-frequency dataset that tracks intraday monetary policy surprises in the UK. This dataset enables the authors to estimate the effects of rate decisions, forward guidance and quantitative easing on UK financial markets and macroeconomic indicators, offering new insights into market reactions to the Bank of England's communication strategies.

This thesis makes three key contributions. First, it focuses on the Bank of England, which has been relatively overlooked in academic literature compared to the Federal Reserve (FED) and the European Central Bank (ECB). Second, it implements a new machine learning technique, CentralBankRoBERTa, to quantify central bank communications. Third, by integrating the sentiment analysis output with the UKMPD—a novel dataset of intraday monetary policy surprises for the UK—it provides a detailed analysis of the impact channels of monetary policy on the UK financial market. Finally, the results show that the reactions of the UK fixed income, overnight index swaps, and exchange rate markets are influenced by factors such as the maturity of the dependent variable, the magnitude of the monetary policy surprise, and prevailing sentiment. Additionally, the analysis establishes a fundamental relationship between audience-targeted sentiment and financial market movements.

The remainder of the thesis is organized as follows: Chapter 2 reviews the relevant literature related to the topic and positions the thesis within this context. Chapter 3 outlines the methodologies employed in the study. Chapter 4 describes the data used for the machine learning model and the regressions. Chapter 5 presents the empirical results, analyzing how the UK financial market reacts to monetary policy surprises and the quantified (audience targetted) sentiment of the Bank of England. Finally, Chapter 6 concludes the thesis.

2. Literature Review

The body of literature examining the effects of monetary policy on financial markets is extensive. There are few papers that are foundational building blocks in this area. An early example is Gürkaynak et al. (2004), which implements a high-frequency event-study analysis to investigate the effects of U.S. monetary policy on the stock market, finding that both the current federal funds rate target and the future path of policy, particularly Federal Open Market Committee statements, significantly influence bond yields and asset prices.

Later, Swanson (2017) extends these methods by also identifying surprise changes in large-scale asset purchases (LSAPs), which significantly affect Treasury yields, corporate bond yields, stock prices, and exchange rates. Similarly, Altavilla et al. (2019) carry this out for the European Central Bank's policy communication and find that the same three factors capture a significant amount of the variation in the yield curve. Other notable papers for the Euro Area (EA) are Brand et al. (2010) and Jarociński and Karadi (2020).

Until recent years, most studies focusing on the United Kingdom lacked systematic analyses of financial market reactions to monetary policy shocks and predominantly relied on a single measure of monetary policy surprises. Examples of such studies include Miranda-Agrippino (2016), Gerko and Rey (2017), and Cesa-Bianchi et al. (2020). Recently, Kaminska and Mumtaz (2022) have identified four interacting channels during Quantitative Easing: action (operating through effective policy rates), signaling (affecting expected policy rates), policy uncertainty, and QE-specific bond supply (both influencing term premia).

Introducing the UK Monetary Policy Event-Study Database (UKMPD) to address the literature gap for the United Kingdom, Braun et al. (2023) facilitate the computation of intraday surprises surrounding the Bank of England's Monetary Policy Committee announcements and accompanying Monetary Policy Report press conferences. They study the causal effects of rate decisions and forward guidance on the UK financial market and macroeconomic aggregates.

Although insightful, none of these studies incorporate a textual analysis of the content of central bank announcements. In their paper "Central Bank Communication and Monetary Policy: A Survey of Theory and Evidence," Blinder et al. (2008) emphasize the significance of communication in the realm of monetary policy, exploring how specific word choices by central bankers have impacted economic indicators through time. Subsequently, researchers have increasingly endeavored to quantify central bank communication. The most common approach is by grading monetary policy sentences based on whether they are positive or negative (hawkish or dovish). For instance, Musard-Gies (2006), Rosa and Verga (2007), and Heinemann and Ullrich (2007) manually code these statements for the ECB and find that they possess predictive abilities.

While hand-coding is straightforward to implement, its subjectivity can present disadvantages to the end results (Picault and Renault, 2017). Consequently, researchers have begun to adopt alternative methodologies. One such methodology is dictionary-based. By measuring the frequency of the keyword "vigilance," Jansen and De Haan (2007) find evidence of a negative relationship between the European Central Bank (ECB) communication about risks to price stability and changes in euro area break-even inflation. Another approach to quantifying words is the word-count technique. Early research in this area includes Romer and Romer (2004), who use a narrative approach to identify monetary policy shocks from central bank documents. Lucca and Trebbi (2009) analyze the content of FOMC statements using semantic orientation scores derived from extensive data obtained via search engines. Later, Picault and Renault (2017) argue that quantifying central bank communication with a non-specific lexicon might fail to capture all dimensions of sentiment. Hence, they develop a field-specific dictionary to quantify ECB communication, which significantly outperforms others like the Loughran-McDonald and the Apel-Blix Grimaldi.

Most recently, Niţoi et al. (2023) point out the primary limitation of dictionary-based approaches, namely their inability to account for the context of keywords. Therefore, finance researchers have been increasingly adopting machine learning and deep learning techniques for textual analysis, which can learn sentiment weights for words and sentences, thereby capturing the sentiment of entire expressions. In 2014, Moniz and De Jong (2014) apply Naive Bayes, a supervised machine learning method, to categorize sentences from the Bank of England's MPC minutes by topic, however they then infer sentiment using a dictionary-based approach.

The superiority of machine learning techniques even when compared to domain-specific lexicons, is shown in recent research papers like Purda and Skillicorn (2015) and Frankel et al. (2022). Moreover, Swanson (2021) shows that deep-learning models (also called large language models or LLMs) are better than non-deep-learning models for textual analysis in finance. Usually, such large language models are pre-trained on a large text corpus and then fine-tuned for specific tasks, enabling them to extrapolate sentiment for new data Pfeifer and Marohl (2023). In that regard in 2023, Pfeifer & Marohl utilize LLMs for analyzing central bank communications. They create CentralBankRoBERTa, an advanced economic agent classifier capable of identifying five fundamental macroeconomic agents, as well as a binary sentiment classifier that detects the emotional tone of sentences within central bank communications. This model is the inspiration for this analysis.

Finally, the thesis contributes to the existing literature on the relationship between central bank communications and the financial market in three key areas. First, it implements a large language model specifically designed to quantify central bank sentiment. Second, it focuses on the Bank of England and the UK, a relatively understudied area. Third, it assesses the influence of monetary policy shocks and the sentiment of communications on gilt yields, overnight index swaps, and exchange rates.

3. Methodology

3.1. Natural Language Processing for Central Banks

According to Bholat et al. (2015), a focal point in the quantification of text, particularly in the context of central bank communication, is natural language processing (NLP), also known as text mining or computational linguistics. NLP involves extracting meaning from strings of letters. There are several advantages to implementing this process with computers. First, computers are significantly faster than human readers and can process far more information. Second, computers can identify meanings and patterns that might be missed by humans.

Furthermore, Bholat et al. (2015) emphasize that, unlike fields such as political science and marketing, text mining has not been a prominent technique in economics, particularly within central banks. This represents a potential gap in scientific research, as NLP can be a valuable tool. For a central bank, the data can consist of either a single document or a corpus of documents. For example, in the case of the Bank of England, the relevant corpus could include all Monetary Policy Committee speeches, staff notes, and field reports.

Text mining is the process of creating a comprehensive synthesis of the corpus to efficiently perform valuable tasks such as categorizing text into semantic groups, evaluating the distribution of word frequency, and verifying the overall statistical features of the given text. Subsequently, sentiment analysis aims to design automatic procedures for discovering and summarizing opinions from textual information. A precise definition of sentiment analysis is the computational study of opinions and emotions expressed in textual documents (Bruno, 2016).

Sentiment data can be valuable for addressing various issues in econometrics across multiple fields, including economics, finance, accounting, marketing, psychology, and computer science. The choice of analysis methods depends on the specific goals. A fundamental step in econometrics applied to sentiment analysis is measuring sentiment. The discussion includes the use of qualitative sentiment data in applied economic theory and its role as an information source for nowcasting and forecasting economic variables (Algaba et al., 2020).

Hence, sentiment analysis should be understood as a specific application within text mining that focuses on determining the sentiment expressed in a piece of text. There are various text mining techniques. As already mentioned, some intuitive approaches include dictionary and Boolean techniques, which utilize a deductive knowledge-making approach. Therefore, the process begins with a general theory and employs datasets to test its validity (Bholat et al., 2015). For simplicity, Boolean techniques are not going to be discussed here.

In their 2020 paper, Frankel et al. (2022) compare the effectiveness of dictionary-based and machine-learning methods in capturing sentiment in corporate disclosures during 10-K filings and conference call dates. Their findings indicate that machine-learning methods significantly outperform dictionary-based methods in explaining returns, with the added advantage of simplicity in implementation. Additionally, Pfeifer and Marohl (2023) point out that most studies in central bank communication utilize NLP algorithms that follow a bag-of-words approach, treating text as collections of individual, context-independent words. However, advancements in computational linguistics have introduced deep-learning-based NLP algorithms known as large language models (LLMs), which possess billions of parameters. These advanced algorithms can learn syntactic and semantic relationships from vast text datasets, allowing them to incorporate context into their analysis.

In contrast to deduction-based techniques, abduction-based methods like Latent Semantic Analysis, Latent Dirichlet Allocation, and Descending Hierarchical Classification are unsupervised machine learning techniques. They aim to infer the best explanation for an event based on its data without attempting to generate a generalizable theory (Bholat et al., 2015). However, these are not large language models and have their weaknesses. For instance, such models show connections within document term matrices and do not directly provide an interpretable sentiment. Moreover, these data-driven methods lack comparability between different data sets, meaning the clustering provided by a topic model is only relevant within the context of its specific data set. This limitation makes it challenging to generalize empirical findings about the contents of central bank communications (Pfeifer and Marohl, 2023).

3.2. Machine Learning

Hubert and Fabien (2017) discuss the application of machine learning algorithms in natural language processing to analyze large unstructured text databases, such as central bank communications. By quantifying the content of raw text data, these algorithms offer advantages such as automation and replicability, reducing the subjectivity inherent in human reading and coded indices. However, a significant challenge lies in converting raw policy statements into measurable quantities for systematic analysis, particularly in capturing intangible concepts like "waves of optimism and pessimism" in central bank communication.

Therefore, one of the objectives of this thesis is to explore the potential of machine learning in quantifying textual data.

The CentralBankRoBERTa is introduced by Pfeifer and Marohl (2023) as a modern pre-trained model, designed to provide an accessible and standardized tool for scholars studying central bank communications. It consists of two key classifiers: an **economic agent classifier** that distinguishes five basic macroeconomic agents, and a **binary statement classifier** that identifies emotional content in sentences.

It is important to note that CentralBankRoBERTa is a fine-tuned version of RoBERTa, which itself is an improved iteration of BERT, known for its superior performance in common benchmarks like GLUE [1] and SQuAD[2].

In 2019, Devlin et al. introduced BERT, standing for Bidirectional Encoder Representations from Transformers. The model's design focuses on pre-training deep bidirectional representations from unlabeled text, considering both left and right context in all layers. Subsequently, the pre-trained model can be fine-tuned with just one additional output layer to excel across various tasks, including question answering and language inference, without necessitating significant task-specific architecture modifications. Hence, BERT is renowned for its simplicity of use and empirical power.

Later in that year, Liu et al. (2019) highlight that BERT was significantly undertrained, leading to the proposal of RoBERTa. This replication study meticulously evaluates the impact of various key hyperparameters and training data sources. RoBERTa can equal or surpass the performance of all post-BERT methods. Its modifications include longer training duration with larger batches and more data, removal of the next sentence prediction objective, training on longer sequences, and dynamic adjustment of the masking pattern in training data. The enhanced approach outperforms BERT in both GLUE and SQuAD when controlling for training data.

Figure 3.1 depicts the architecture of the CentralBankRoBERTa, clearly illustrating the connection of the training pipeline and RoBERTa.

3.3. The CentralBankRoBERTa

This section is based on Pfeifer and Marohl (2023).

The corpus on which the model is trained, includes speeches from the three largest English-speaking databases of central banks: BIS (1998–2022), Fed (1948–2022), and ECB (1999–2022). The BIS dataset comprises 10,211 speeches, the Fed dataset has 6,765 speeches, and the ECB dataset contains 2,405 speeches. Unlike traditional NLP

[1] GLUE benchmark is a collection of resources for training and evaluating natural language understanding systems, comprising nine diverse tasks and a diagnostic dataset. Its goal is to drive research in developing general and robust NLP models. (Wang et al., 2018)

[2] The Stanford Question Answering Dataset (SQuAD) is a reading comprehension dataset containing questions formulated by crowd workers based on a collection of Wikipedia articles. (Rajpurkar et al., 2016)

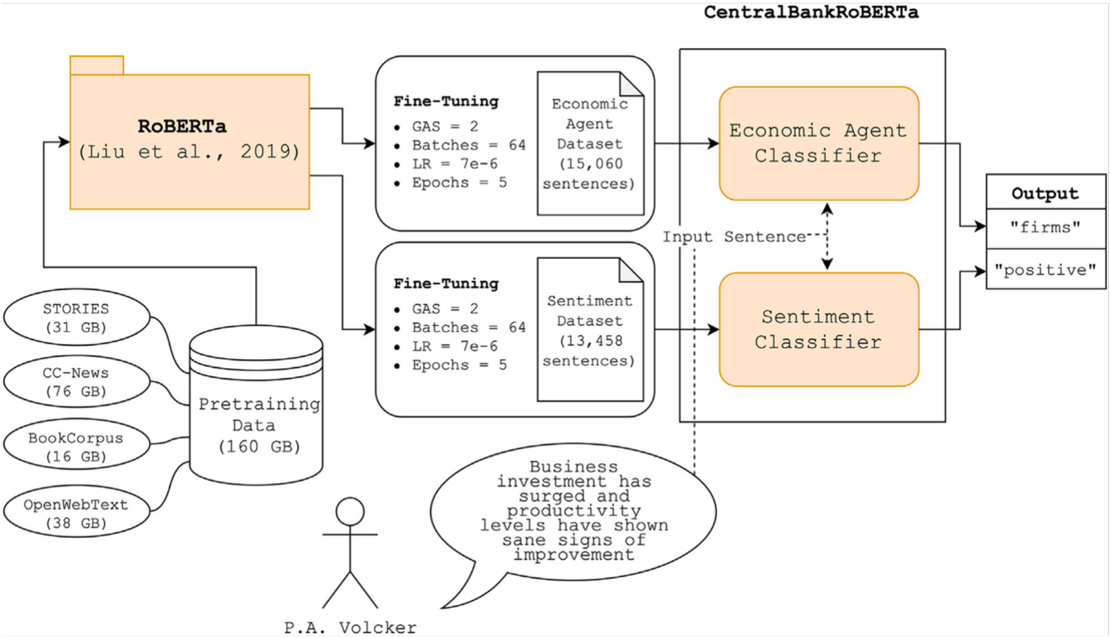

Figure 3.1.: CentralBankRoBERTa architecture, taken from Pfeifer and Marohl (2023).

algorithms, deep-learning algorithms like BERT do not need preprocessed inputs. Instead, entire raw sentences are used as inputs. Preprocessing is minimized by only separating speeches into individual sentences with at least 20 characters.

To determine the most suitable NLP algorithm for classifying central bank communications, various deep learning models and other machine learning algorithms are fine-tuned using prelabeled training data. The limited text data in central bank communications presents unique challenges for developing effective text mining systems. Therefore, creating high-quality datasets and testing appropriate models for domain-specific classification tasks can help address these challenges. Although accurate labeling requires specialized knowledge and is time-consuming, it remains essential for benchmarking most machine and deep learning tasks.

For the economic agent classifier, RoBERTa, BERT, and XLNet large language models are fine-tuned, with all three achieving an accuracy of 90% or higher. However, RoBERTa scores overall better than the other models for sentences labeled as financial sector and government.

Similarly, for the sentiment classifier, the same LLMs, including FinBERT, are fine-tuned. Additionally, deep learning approaches such as Long Short-Term Memory (LSTM), Support Vector Machine (SVM), Random Forest, and Naïve Bayes (NB) are tested due to their prominence in sentiment analysis. However, the LLMs outperform them, with RoBERTa again achieving the best performance. Consequently, Pfeifer and Marohl (2023) release the CentralBankRoBERTa.

As previously mentioned, CentralBankRoBERTa has two functions: the **economic agent classifier** and the **sentiment classifier**. Below is a detailed explanation of their construction and functions.

3.3.1. The Economic Agent Classifier

The importance of the economic agent classifier is stressed with the fact that a significant theoretical literature highlights the heterogeneity of audiences in central bank communication (e.g. Blinder et al. (2022)), with studies suggesting that households, firms, and financial markets form inflation expectations differently, necessitating more audience-specific communications. However, empirical analyses often lack audience-specific data, focusing mainly on the listeners rather than the speakers. For instance, the announcement of lower interest rates may benefit households but disadvantage banks.

For the training of the Agent Classifier, Pfeifer and Marohl (2023) manually labeled 6205 randomized sentences from the Fed database, grouping them into households, the financial sector, the government, or the central bank. However, they report that sentences, targeting the central bank itself significantly reduced the accuracy of the model, hence they were excluded. Since sentences about the central bank often include technical or operational statements, they may be unfitting for binary classification. For this reason, sentences categorized as central bank targeted are also left out from this analysis.

They emphasize the challenges that arise with categorization due to potential ambiguities. For example, discussions about mortgages could be relevant to all types of economic agents, but the meaning for each agent could differ depending on the context. When the central bank addresses mortgages in its announcements, the information might be relevant to households interested in home loans, businesses looking for commercial loans, the financial sector originating such loans, or the public sector when discussing government-backed loans. Hence, the authors label only sentences where it is objectively clear that only one of the economic agents is addressed. Furthermore, sentences including more than one agent receive only one label.

3.3.2. The Sentiment Classifier

For this classifier, the training dataset includes 6,683 manually prelabeled sentences from the Fed database, labeled as either positive (1) or negative (0). These labels apply only to sentences addressing a single economic agent, excluding those about the central bank itself. Both descriptive and prescriptive sentences are included in the sentiment labels. Pfeifer and Marohl (2023) explain that the data shows a higher proportion of negative labels, contradicting earlier studies that reported more positive central bank communications (e.g. Bennani and Neuenkirch (2017)). This suggests that while overall communications might be positive, targeted communications towards specific economic agents are more negative. This nuance may have been missed by traditional bag-of-words NLP methods.

To gain a better understanding of the labeling, the authors show the following sentences:

1. *Our homeowners are thus less burdened with their housing predicament and better positioned as consumers.*

2. *Continued success on the economic front depends largely on political reform, namely constitutional reforms that will help restrain fiscal spending.*

During manual labeling, the first sentence is categorized as targeted at households and received a positive sentiment. The second sentence, however, is targeted at the government and received a negative sentiment.

Furthermore, Pfeifer and Marohl (2023) augment the training data by generating two extra sets of pseudo-labels from the BIS and ECB datasets for each classifier. Pseudo-labeling involves integrating confidently predicted test data into the training set. They set high confidence thresholds (77% for BIS, 79% for ECB) to produce these labels, resulting in 4,804 additional labels for the BIS and 4,051 labels for the ECB in the economic agents classifier, and 2,563 additional labels from the ECB and 4,212 from the BIS in the sentiment classifier. This yields a total of 15,060 labels for economic agents and 13,458 labels for sentiment classification. The breakdown includes 7,730 negative and 5,728 positive labels for sentiment.

4. Data

This section provides a detailed description of the data used for the empirical analysis. Two data groups are employed: **text-based data** and **financial market data**. The **text-based data** consists of the communication records of the Bank of England. The **financial market data** includes the calculated intraday surprises and resulting monetary policy factors around the Bank of England's Monetary Policy Committee (MPC) announcements, as well as the press conferences that accompany the publication of the quarterly Monetary Policy Report from the UKMPD.

4.1. History of the Meeting Schedule of the Bank of England

The Bank of England has been an independently operating central bank since 1997. Initially, the Monetary Policy Committee met monthly and used the Bank Rate as the sole instrument to control inflation. Announcements, concerning the monetary policy decisions were typically made at 12:00 noon local time, accompanied by a brief statement. Additionally, every quarter, in February, May, August and November, the BOE published its Inflation Report (IR)[1], which included official forecasts and was released a week after the Bank Rate announcement at 10:30 local time, followed by a 1-hour press conference. This conference allowed the Monetary Policy Committee to discuss key projections, issues, and the rationale behind their decisions. Minutes of each MPC meeting were published two weeks after each announcement at 9:30 local time. For instance, the old schedule is displayed in Table 4.1.

[1] The name "Inflation Report" was changed to "Monetary Policy Report" starting in 2020. Hence, the latter is used in this analysis.

Month	MPC Meetings	Minutes Publication	Inflation Report Publication
January	Wed 9 / Thu 10	Wed 23	
February	Wed 6 / Thu 7	Wed 20	Wed 13
March	Wed 5 / Thu 6	Wed 19	
April	Wed 9 / Thu 10	Wed 23	
May	Wed 7 / Thu 8	Wed 21	Wed 14
June	Wed 4 / Thu 5	Wed 18	
July	Wed 9 / Thu 10	Wed 23	
August	Wed 6 / Thu 7	Wed 20	Wed 13
September	Wed 3 / Thu 4	Wed 17	
October	Wed 8 / Thu 9	Wed 22	
November	Wed 5 / Thu 6	Wed 19	Wed 12
December	Wed 3 / Thu 4	Wed 17	

Source: The Bank of England official website. (BOE, 2007)

Table 4.1.: Official MPC dates for 2008, released by the Bank of England on 19 September 2007.

Month	MPC Meetings	MPR Publication	Super Thursday
February	Thu 4	Thu 4	yes
March	Thu 18		
May	Thu 6	Thu 6	yes
June	Thu 24		
August	Thu 5	Thu 5	yes
September	Thu 23		
November	Thu 4	Thu 4	yes
December	Thu 16		

Source: The Bank of England official website. (BOE, 2020)

Table 4.2.: Official MPC dates for 2021, released by the Bank of England on 17 September 2020.

Braun et al. (2023) note that during the initial years, the significance of the minutes' information was somewhat diminished due to the delay in their public release. Additionally, their publication often coincided with other data releases, such as the Labour Force Survey or statistics on money, lending activities, and GDP figures, which could significantly impact markets. Due to these constraints, the release of the minutes is not considered among the policy-relevant events in this earlier part of the sample for the UKMPD.

A significant change was made in August 2015, when the monetary policy cycle of the BOE was made to follow a six-week schedule, reducing decision meetings from twelve to eight annually. To enhance transparency, the Monetary Policy Committee revised its communication flow, eliminating delays in publishing the Inflation Report and minutes. Now, monetary policy decisions, statements, and minutes are released together on Thursdays at 12:00 local time. The quarterly Monetary Policy Report (MPR) is published with the policy decision, accompanied by a press conference from 12:30 to 13:30, creating what is known as the BOE's "Super Thursday"[2] (Table 4.2).

In this thesis, the influence of both events is analyzed. Firstly, the impact of MPC meetings on the financial market is investigated using summaries and minutes from these meetings. Secondly, the impact of the "Super Thursdays" is examined by focusing specifically on days when both MPC meetings and the publication of the Monetary Policy Report (MPR) occur. For this part, summaries and minutes of the MPC meetings, along with the governor's opening remarks and transcripts of the press conferences, are required.

4.2. Text-based Data

The text corpus consists of the summaries and minutes of the MPC meetings, the governor's opening remarks, and the transcripts of the press conferences following the publication of the Monetary Policy Reports. Since the aim of the analysis is to investigate the communications of the Bank of England, only the governor's answers in the press conferences are filtered and used in the text corpus, rather than the entire transcripts.

[2] Also referred to as the Monetary Event.

Event	Doc. type	Start date	End date	No. of documents	Words per sentente	Sentences per doc.	Flesch-Kincaid grade
MPC meetings	Summaries	2015-08-06	2023-06-22	69	20.5	74.7	12.9
MPC meetings	Minutes	2015-08-06	2023-06-22	69	21.5	339.4	11.9
Monetary Events (Super Thursdays)	Opening remarks by the Governor	2015-08-06	2023-05-11	32	22.42	70.9	12.1
Monetary Events (Super Thursdays)	Governor's answers in the press conferences	2015-08-06	2023-05-11	32	23.4	330.4	10.4

Table 4.3.: Descriptive statistics of the Bank of England text corpus.

The Bank of England provides all these documents in the "News and Publications" section of its official website. Almost all of them are web-scraped with the Selenium and Requests packages in Python. However, some documents are downloaded manually due to issues with the HTML code.

As a result of the scattered nature of the schedule and the lesser importance of forward guidance in the BOE's communications before August 2015, the analysis is limited to the period between August 2015 and 2023 (22nd of June for the MPC Meetings and 11th of May for the Monetary Events).

Table 4.3 presents descriptive statistics for four sections of the central bank's corpus: summaries, minutes, opening remarks by the governor and press conferences. As expected, summaries are the shortest in length, while minutes are the longest, based on the average number of sentences per document. Additionally, summaries have the fewest average words per sentence, which is intuitive given their need to be concise while conveying crucial information. Furthermore, the Flesch-Kincaid grade score, calculated in Python to assess readability in terms of years of education required, reveals an interesting finding: summaries have the highest scores, indicating they are the most challenging to comprehend. In contrast, the press conferences have the lowest score (10.4), which is intuitive since they are not scripted, and the language used is more colloquial. Hence, it is interesting to see how and if the readability of these texts has some impact on the reaction of the financial market.

4.3. Financial Market Data

Braun et al. (2023) note that the empirical literature on the effects of monetary policy focuses almost exclusively on the ECB and the Federal Reserve. One reason for this is unquestionably their significant global role. Another reason is the simple fact that the required data to perform an analysis on the effects of monetary policy has not been available. Hence, the Bank of England (BOE) introduces the UK Monetary Policy Event-Study Database (UKMPD) to fill the gap in the literature, which is utilized as the financial market data in this analysis. The UKMPD tracks high-frequency fluctuations in asset prices surrounding MPC announcements and the publications of the Monetary Policy Report since 1997[3]. The database incorporates structural elements to encompass various facets of UK monetary policy.

The following sections provide a detailed description of the elements of the UKMPD, constructed by Braun et al. (2023).

4.3.1. High-Frequency Monetary Policy Surprises

Following the methodology outlined by Gürkaynak et al. (2004), monetary policy surprises are defined as high-frequency revisions in asset prices surrounding monetary policy events. These surprises are calculated within narrow time windows surrounding the announcements, representing the difference between prices before and after the event. Specifically, for monetary policy decisions, a 30-minute measurement window is utilized, spanning from 10 minutes before to 20 minutes after the announcement. To ensure accuracy and consistency, the pre-event price is determined as the median quote between 11:40 and 11:50, while the post-event price is the median quote between 12:20 and 12:30 (see 4.1).

For press conferences following the release of the Monetary Policy Report, a 90-minute measurement window is employed, which guarantees that price changes and the resulting factor changes quantify the length to which the decision was interpreted as a surprise by

[3] As previously mentioned, this analysis is confined to the period from August 2015 to June 2023.

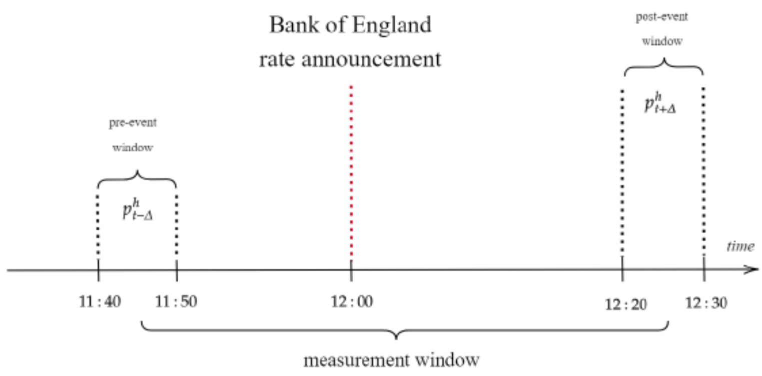

Figure 4.1.: Measuring monetary policy surprises, taken from Braun et al. (2023).

the market.

In light of the distinct characteristics of the BOE communication framework, two versions of the dataset are provided. The first version comprises surprises computed solely around MPC decision announcements (and minutes). The second version incorporates high-frequency market reactions surrounding both MPC decisions and press conferences. Starting from the first Super Thursday in August 2015, surprises in the latter version of the dataset are calculated within a 90-minute window encompassing both events.Both versions of the database are utilized in this thesis.

The UKMPD offers insights into various high-frequency asset prices, reflecting market-based expectations regarding policy trajectories. Specifically, it provides surprises in assets like Overnight Index Swaps (OIS) and interest rate futures, directly linked to market sentiments about policy directions. Additionally, the UKMPD incorporates gilt yields (UK Treasury) to evaluate medium to long-term interest rate expectations, focusing on 1, 2, 5, and 10-year reference bonds. The database also includes high-frequency surprises in the stock market, encompassing FTSE 100, FTSE 250, and futures on the FTSE 100, alongside bilateral exchange rates with the Euro and the US dollar, which demonstrate market responses to policy decisions.

Due to the extensive number of variables, only the most relevant results are presented and interpreted, specifically for gilt yields, overnight index swaps, and exchange rates.

	Target	Path	QE
count	69	69	69
mean	0.00073	0.00116	-0.00362
std	0.04063	0.02944	0.04394
min	-0.15972	-0.07820	-0.13951
25%	-0.00873	-0.01042	-0.02444
50%	0.00125	0.00190	-0.00449
75%	0.00796	0.00714	0.01944
max	0.18849	0.11398	0.12919

Table 4.4.: Summary statistics of the monetary policy factor surprises from August 2015 to June 2023.

The remaining results are included in the Appendix A.

4.3.2. High-Frequency Monetary Policy Factors

Given that physical currency offers no nominal return, setting the short-term nominal interest rate significantly below zero is practically unfeasible for a central bank using conventional monetary policy instruments. This constraint, known as the zero lower bound (ZLB), has compelled numerous central banks to adopt unconventional monetary policies to spur economic growth following the global financial crisis of 2007–09 (Swanson, 2017).

Likewise, when the UK Bank Rate reached its effective lower bound, the MPC has employed various monetary policy tools tailored to influence specific segments of the yield curve. Braun et al. (2023) estimate these UK-specific monetary policy components, by utilizing the model in Swanson (2021). The estimation involves two steps. Firstly, principal components summarize common variation in the first four short sterling futures and the 2, 5, and 10-year gilt yields. Secondly, additional constraints are applied to identify structural factors. Only the first factor (Target) loads on the first short sterling futures. The second (Path) and third (Quantitative Easing) factors are differentiated by minimizing the variance of the latter over the pre-2009 sample. The factors are constructed to be orthogonal to each other.

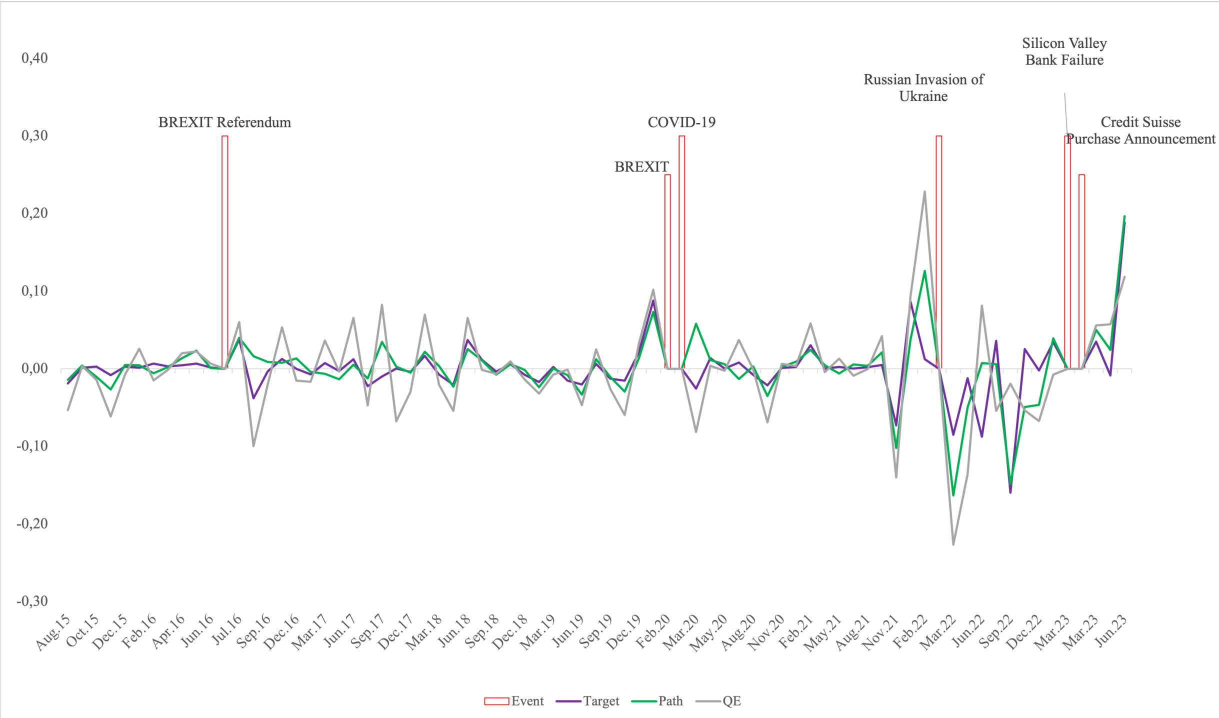

Figure 4.2.: Visualization of the calculated Target, Path and Quantitative Easing factors between August 2015 and June 2023 and major world events.

4.3.3. Correspondence of Factors to Notable BOE Announcements

Figure 4.2 presents a time visualization of the calculated monetary policy factors spanning from August 2015 to June 2023, encompassing all MPC meetings and Super Thursdays. The gray line depicts the QE factor, the green line represents the Path factor, and the purple line indicates the Target factor. Additionally, significant events that occurred during this period are highlighted in red, dividing the history of monetary policy decisions into three major periods. In this section the most interesting occurrences throughout the sample are discussed. The chronological analysis of events is based solely on the summaries, minutes and Monetary Policy Reports published by the Bank of England. For detailed sources, please refer to the bibliography (BOE, 2016), (BOE, 2020), (BOE, 2021), (BOE, 2022).

The first period of monetary policy factor volatility is marked by Brexit, which began in June 2016 after the United Kingdom vote to leave the European Union. Following, the exchange rates declined, and the growth outlook weakened in the short and medium term. In response, the Bank of England's Monetary Policy Committee decided on August 3, 2016, to implement a package of measures aimed at supporting growth and ensuring inflation returns to the target sustainably. These measures included a 25-basis point cut in the Bank Rate to 0.25%, a new Term Funding Scheme to reinforce the pass-through of the rate cut, the purchase of up to £10 billion of UK corporate bonds, and an expansion of the asset purchase scheme for UK government bonds by £60 billion, bringing the total to £435 billion. These measures received a negative response from market participants, resulting in a significant volatility of the factor surprises.

While the Bank Rate rose slowly to 0.75% during this period, the Committee voted repeatedly to maintain the stock of sterling non-financial investment grade corporate bond purchases, financed by the issuance of central bank reserves, at £10 billion and maintain the stock of UK government bond purchases, at £435 billion. The decisions were continuously based on assumptions of the outcomes of the negotiations between the UK and the EU on trade agreements. With the official Brexit on the 1st of February 2020 and the agreement on free trade, this period ended.

The second period is marked by the COVID-19 pandemic and is a significant topic in the MPC meeting summaries and minutes. During this time, the Bank Rate was mostly kept constant at 0.1%. However, the Committee gradually increased the total target stock of asset purchases to £895 billion by November 2020. As can be seen in Figure 4.2, this was a positive surprise for market participants, following the strong volatility resulting from the virus outbreak.

The year 2021 experienced heightened turbulence. Notably, the announcement in November 2021 caused a major negative surprise across all three factors, with the QE factor being the most dominant. Since there were no new announcements, market participants might have been disappointed by the lack of changes in monetary policy instruments. In December 2021, the Bank of England eventually increased the Bank Rate by 0.15 percentage points, to 0.25%. This announcement resulted in the largest (positive) volatility of factors, which is also the most striking observation in Figure 3 by far.

Only two months later, the Russian invasion of Ukraine caused extreme turbulence in financial markets, followed by long-lasting inflation due to increases in global energy and tradable goods prices. The war and its consequences mark the third main period in the sample. Following, in March 2022, the Committee voted to increase Bank Rate by 0.25 percentage points, to 0.75%, resulting in a drop of over 160% in all three surprise factors. The Bank continued increasing the Bank Rate and in June 2023 it had reached 5%.

5. Empirical Analysis

This section provides a detailed explanation of the steps taken to implement the machine learning model on the text data, followed by a presentation of the high-frequency event regression results.

5.1. Implementing CentralBankRoBERTa

For the implementation of the model, the original code published by Pfeifer and Marohl (2023) on GitHub is used in Google Colab, as it requires GPUs.

Since the model works on a sentence basis, each text unit in the corpus is split into individual sentences. Afterwards, the CentralBankRoBERTA code is run on each sentence. Following, each sentence has a predicted sentiment S that can be either 0 or 1, where $S = 0$ indicates negative sentiment, and $S = 1$ indicates positive sentiment. The sentence is also associated with probabilities of sentiment: $P(S = 0)$ for negative sentiment and $P(S = 1)$ for positive sentiment.

Additionally, each sentence has a predicted agent A, which can take on one of five values: $A = 0$ for households, $A = 1$ for firms, $A = 2$ for the financial sector, $A = 3$ for the government, and $A = 4$ for the central bank. The sentence is associated with probabilities for each type of agent: $P(A = 0)$ for households, $P(A = 1)$ for firms, $P(A = 2)$ for the financial sector, $P(A = 3)$ for the government, and $P(A = 4)$ for the central bank.

Pfeifer and Marohl (2023) argue that sentences targeting the central bank itself could introduce bias due to their technical nature. Therefore, such sentences are removed from the dataframes before further manipulation. Subsequently, the sentences are aggregated back into their original texts (summaries, minutes, opening remarks by the governor, and

Date	Speech	WASI	AASI: Fin. Sector	AASI: Firms	AASI: Households	AASI: Gov.
2015-08-06	The Bank of England's Monetary Policy ...	-0.47	-0.25	-0.32	-0.29	-0.10
2015-09-10	The Bank of England's Monetary Policy ...	-0.68	-0.53	-0.39	-0.51	-0.52
2015-11-05	The Bank of England's Monetary Policy ...	-0.51	-0.39	-0.39	-0.29	-0.67

Table 5.1.: Example of the final summaries dataframe.

answers of the governor in the press conferences) based on the date of each event. To facilitate calculation, all "0" values in the predicted sentiment columns are replaced with "-1". By aggregating these, two indices are created:

1. Weighted Average Sentiment Index (WASI):

$$WASI = \frac{\sum_{i=1}^{n} \cdot (S_i \cdot P(S_i))}{\sum_{i=1}^{n} \cdot P(S_i)} \tag{5.1}$$

2. Average Audience Sentiment Index (AASI):

$$AASI = 1/n \cdot \sum_{i=1}^{n} \cdot (S_i \cdot P(S_i) \cdot P(A_j)) \tag{5.2}$$

This process results in four dataframes: summaries, minutes, opening remarks by the governor, and transcripts of the governor's answers during press conferences. Table 5.1 shows an example of the final summary dataframe after classification and index calculation (the other three data frames have the exact same format).

5.2. Visualization of Sentiment

Figure 5.1 and Figure 5.2 visualize the sentiments of the summaries and minutes from the Monetary Policy Committee meetings, presenting both the Weighted Average Sentiment Index and the four types of Average Audience Sentiment Index.

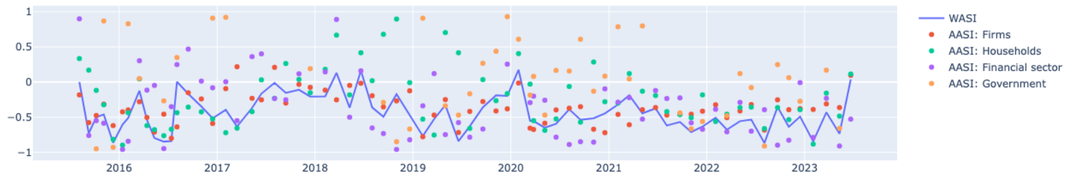

Figure 5.1.: Sentiment of the summaries of the MPC meetings.

It is evident from the plots that the overall sentiment is negative. This trend aligns with the findings of Pfeifer and Marohl (2023), who observed more negative labels during the manual labeling process of the classifiers training. Their findings contradict earlier studies like Apel and Blix (2014) and Bennani and Neuenkirch (2017), which noted more positive central bank communications.

Furthermore, when comparing the Average Audience Sentiment Index to the Weighted Average Sentiment Index, it is apparent that the central bank indeed addresses different agents in the economy differently. For instance, targeting government and households in both figures tends to have higher overall sentiment compared to the financial sector and firms.

Another observation is that the minutes appear more concise in targeting, while the summaries exhibit a larger variation in sentiment. This could be attributed to the fact that summaries and minutes differ substantially in purpose and length. While minutes provide more detailed and balanced content, summaries focus on key points from the meetings, which in some cases could amplify certain sentiments.

The pattern is similar for the documents from the press conferences. Figure 5.3 and Figure 5.4 show the WASIs and the AASIs for the governor's opening remarks and his answers during the press conferences. Here again, the overall sentiment is negative. In addition to the positive sentiment when addressing households and the government, the sentiment towards firms tends to be higher in the press conference answers. This is intuitive for two reasons: first, because the press conferences are generally addressed to

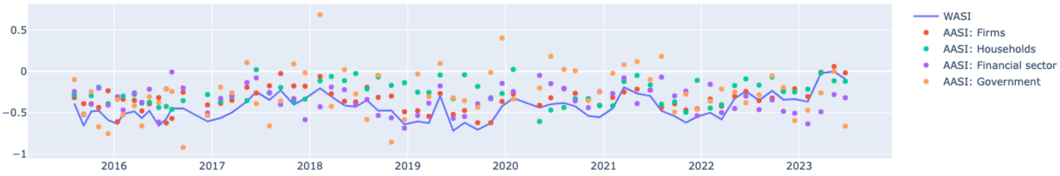

Figure 5.2.: Sentiment of the minutes of the MPC meetings.

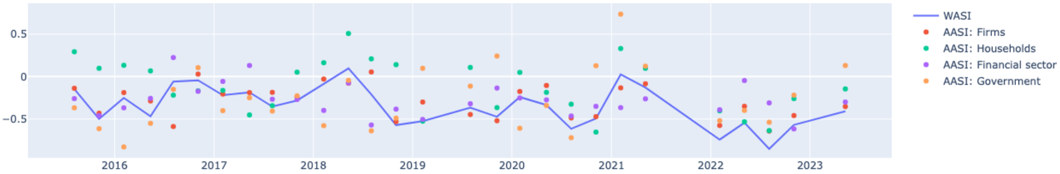

Figure 5.3.: Sentiment of the opening remarks before press conferences.

a broader public than the MPC meetings, and second, because the governor needs to convey a sense of stability to his listeners.

Regarding the variation of sentiment in both figures, the governor's answers during the press conferences seem more concise than the opening remarks. This can once again be attributed to the length and purpose of both types of documents. The opening remarks are brief and therefore highlight the most important topics regarding the Bank's decisions and projections. Consequently, this could result in the amplification of specific sentiments.

5.3. High Frequency Event Regression

To assess the relation between the information content of the central bank communications and financial variables, the explanatory power of the two indicators is tested empirically. More precisely, the following equations are considered:

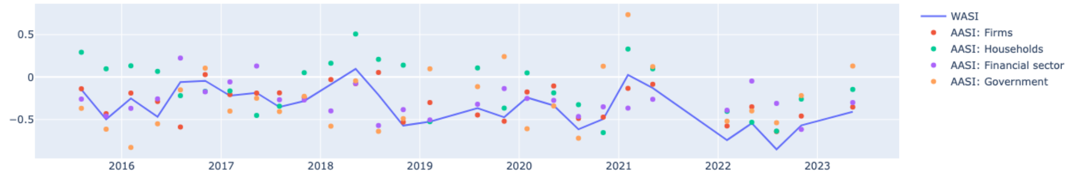

Figure 5.4.: Sentiment of the Governor's answers in the press conferences.

$$y_t = \alpha + \beta_1 \cdot Target_t + \beta_2 \cdot Path_t + \beta_3 \cdot QE_t + WASI_{t,k} + \epsilon_t \tag{5.3}$$

where, y_t is the financial market variable at interest. $Target_t$ is the Bank Rate policy suprise. $Path_t$ is the forward guidance policy surprise. QE_t is the quantitative easing policy surprise. $WASI_{t,k}$ is the Weighted Average Sentiment Index. Heteroscedastic Robust Standard Errors (ϵ_t) are implemented to avoid large fluctuations, typical for finance data series. Time is t and document type is k, which can be "S" for summaries, "M" for minutes, "OR" for opening remarks by the governor and "PA" for answers in the press conference.

Generally, positive signs for β_1, β_2, β_3 are expected, the logic being that a positive surprise results in a positive movement of market variables.

$$y_t = \alpha + \beta_1 \cdot Target_t + \beta_2 \cdot Path_t + \beta_3 \cdot QE_t + AASI_{t,k,j} + \epsilon_t \tag{5.4}$$

Equation 5.4 is the same as Equation 5.3, only substituting the $WASI_{t,k}$ with the $AASI_{t,k,j}$. The latter is the Average Audience Sentiment Index at time t, for document type k, and audience type j, which are firms, households, the financial sector and the government (the central bank is excluded).

5.4. Empirical Findings

5.4.1. Fixed Income

MPC Meetings

	$GB1YTRR_t$	$GB2YTRR_t$	$GB5YTRR_t$	$GB10YTRR_t$
	(1)	(2)	(3)	(4)
const	0.003	-0.005**	0.002	-0.002
	(0.005)	(0.002)	(0.002)	(0.001)
$Target_t$	0.514***	0.503***	0.364***	0.240***
	(0.059)	(0.014)	(0.020)	(0.016)
$Path_t$	0.194***	0.198***	0.029	-0.213***
	(0.060)	(0.033)	(0.045)	(0.040)
QE_t	0.818***	0.912***	1.012***	0.992***
	(0.048)	(0.028)	(0.017)	(0.019)
$WASI_{t,S}$	0.001	0.003	0.000	-0.002
	(0.005)	(0.003)	(0.002)	(0.002)
$WASI_{t,M}$	0.003	-0.009*	0.007*	-0.001
	(0.008)	(0.005)	(0.004)	(0.003)
Observations	62	62	62	62
R^2	0.945	0.988	0.991	0.992
Adjusted R^2	0.940	0.987	0.991	0.991
Residual Std. Error	0.010 (df=56)	0.005 (df=56)	0.004 (df=56)	0.004 (df=56)
F Statistic	151.680*** (df=5; 56)	502.506*** (df=5; 56)	936.334*** (df=5; 56)	894.671*** (df=5; 56)

Note: *p<0.1; **p<0.05; ***p<0.01

Table 5.2.: MPC Meetings: Gilt Yields & WASI

Table A.9 reports the responses of 1-year, 2-year, 5-year, and 10-year gilt yields to changes in the Bank Rate, forward guidance, quantitative easing, and the Weighted Average Sentiment Index for the summaries and minutes from August 2015 to June 2023. Similar to the results of Braun et al. (2023), a positive Bank Rate surprise, or equivalently, an unexpected increase in the Bank Rate, causes the entire nominal gilt yield curve to shift upwards, with the impact decreasing as the maturity lengthens. In contrast to the Bank Rate surprise, changes in the quantitative easing factor cause the impact to increase as the maturity lengthens. The MPC's forward guidance appears to be very informative for short-term maturities. Although the effect on the 5-year gilt yield is not significant, for the 10-year gilt yield, the coefficient sign changes, indicating that forward guidance has a slight negative effect on long-term maturities for this period.

The sentiment of the MPC summaries of the announcements has no significant effect on the UK fixed income market, which is not surprising given their structure and length. However, a small effect is observed in the minutes, which are longer and more informative. The 2-year gilt yield reacts negatively, likely indicating that the minutes contain reassuring information about near-term economic conditions. Conversely, the 5-year gilt yield reacts positively, suggesting that the sentiment points to potential economic growth or inflationary pressures in the medium term. Investors might interpret this as an indication that the MPC could raise rates more significantly in the future, leading to higher yields on medium-term gilts. Hence, it is interesting to observe the outcomes of the fixed income market when the AASI is implemented.

Table 5.3 replaces the WASI with the Average Audience Sentiment Index (AASI). In this case, it can be observed how the market reacts to targeted sentiment. The effects of the factor surprises remain unchanged. Once again, the minutes have a greater impact on the dependent variables compared to the summaries.

The most notable observation is the significant effect of household targeting in the summaries. A one-unit higher sentiment results in a 1.5 basis points increase in the 5-year gilt yield, on average. This coefficient changes direction in the 10-year gilt yield and loses significance.

Overall, the reported R-squared and Adjusted R-squared are very high, indicating that the independent variables explain a substantial portion of the variation in the dependent variable.

Monetary Events

Generally, the Weighted Average Sentiment Index tends to underperform. One possible explanation is that it is overly generalized and fails to capture the subtleties of sentiment. Therefore, for the remainder of this empirical analysis, only OLS results incorporating the AASI will be included. All remaining WASI results can be found in the Appendix A.

Table 5.4 presents the reactions of gilt yields to monetary policy surprise factors and sentiment, focusing exclusively on Super Thursdays, which include the governor's opening remarks and answers in the press conferences, and excluding dates with only MPC

	$GB1YTRR_t$	$GB2YTRR_t$	$GB5YTRR_t$	$GB10YTRR_t$
	(1)	(2)	(3)	(4)
const	0.002	-0.005**	0.001	-0.002
	(0.006)	(0.003)	(0.002)	(0.002)
$Target_t$	0.509***	0.509***	0.361***	0.240***
	(0.057)	(0.013)	(0.021)	(0.017)
$Path_t$	0.194***	0.193***	0.041	-0.218***
	(0.059)	(0.032)	(0.042)	(0.038)
QE_t	0.816***	0.916***	1.003***	0.997***
	(0.045)	(0.028)	(0.017)	(0.021)
$AASI_{t,S,Firms}$	0.005	0.000	-0.002	0.001
	(0.006)	(0.003)	(0.002)	(0.002)
$AASI_{t,S,Households}$	-0.003	0.002*	-0.001	-0.001
	(0.003)	(0.001)	(0.001)	(0.001)
$AASI_{t,M,Firms}$	-0.013	-0.010*	0.001	0.003
	(0.008)	(0.006)	(0.004)	(0.003)
$AASI_{t,M,Households}$	0.018	-0.005	0.015***	-0.008*
	(0.011)	(0.005)	(0.005)	(0.005)
$AASI_{t,M,FinSector}$	0.005	0.004	-0.000	-0.002
	(0.010)	(0.004)	(0.003)	(0.003)
$AASI_{t,M,Government}$	-0.007	-0.001	-0.001	0.001
	(0.006)	(0.002)	(0.002)	(0.001)
Observations	62	62	62	62
R^2	0.952	0.989	0.993	0.993
Adjusted R^2	0.943	0.987	0.991	0.991
Residual Std. Error	0.010 (df=52)	0.005 (df=52)	0.004 (df=52)	0.004 (df=52)
F Statistic	97.396*** (df=9; 52)	316.231*** (df=9; 52)	623.112*** (df=9; 52)	556.589*** (df=9; 52)
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 5.3.: MPC Meetings: Gilt Yields & AASI

	$GB1YTRR_t$	$GB2YTRR_t$	$GB5YTRR_t$	$GB10YTRR_t$
	(1)	(2)	(3)	(4)
const	0.048	0.064	-0.016**	-0.024
	(0.036)	(0.058)	(0.008)	(0.020)
$Target_t$	0.375***	0.390**	0.469***	0.332***
	(0.110)	(0.179)	(0.033)	(0.061)
$Path_t$	0.153**	0.296**	0.299***	-0.093**
	(0.076)	(0.126)	(0.030)	(0.042)
QE_t	0.927***	0.992***	1.066***	0.963***
	(0.104)	(0.092)	(0.030)	(0.031)
$AASI_{t,S,Firms}$	0.026	-0.019	-0.025***	0.021***
	(0.021)	(0.022)	(0.004)	(0.007)
$AASI_{t,S,Households}$	0.001	0.013	0.009***	-0.009***
	(0.010)	(0.010)	(0.003)	(0.003)
$AASI_{t,M,Firms}$	0.010	0.044	-0.028***	-0.003
	(0.051)	(0.041)	(0.010)	(0.013)
$AASI_{t,M,Households}$	-0.062**	-0.023	0.012	-0.000
	(0.029)	(0.046)	(0.008)	(0.016)
$AASI_{t,M,FinSector}$	0.124***	0.060*	-0.003	-0.019*
	(0.030)	(0.034)	(0.008)	(0.011)
$AASI_{t,M,Government}$	-0.012	-0.014	0.012***	-0.001
	(0.014)	(0.013)	(0.003)	(0.004)
$AASI_{t,OR,Firms}$	-0.033	0.015	-0.002	-0.008
	(0.028)	(0.024)	(0.005)	(0.008)
$AASI_{t,OR,Households}$	-0.007	-0.010	0.013***	-0.002
	(0.012)	(0.012)	(0.003)	(0.004)
$AASI_{t,OR,FinSector}$	-0.063***	0.006	0.004	-0.008
	(0.024)	(0.026)	(0.008)	(0.009)
$AASI_{t,OR,Government}$	-0.009	0.001	-0.002	0.002
	(0.011)	(0.009)	(0.004)	(0.003)
$AASI_{t,PA,Firms}$	-0.033	0.006	-0.035**	0.015
	(0.047)	(0.077)	(0.015)	(0.026)
$AASI_{t,PA,Households}$	0.045*	0.037	-0.032***	0.002
	(0.026)	(0.024)	(0.006)	(0.008)
$AASI_{t,PA,FinancialSector}$	0.081***	0.090	0.021**	-0.044**
	(0.031)	(0.060)	(0.009)	(0.021)
$AASI_{t,PA,Government}$	0.076***	0.039***	0.015***	-0.023***
	(0.016)	(0.013)	(0.004)	(0.004)
Observations	21	21	21	21
R^2	0.996	0.995	1.000	0.999
Adjusted R^2	0.977	0.969	0.999	0.995
Residual Std. Error	0.010 (df=3)	0.011 (df=3)	0.002 (df=3)	0.004 (df=3)
F Statistic	730.708*** (df=17; 3)	2959.884*** (df=17; 3)	3298.565*** (df=17; 3)	17791.218*** (df=17; 3)
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 5.4.: Monetary Events: Gilt Yields & AASI

meetings. Initially, it appears that Monetary Events have a more pronounced impact on the fixed income market compared to regular MPC meetings, as evidenced by several significant effects in this table. However, summaries and minutes also show noteworthy effects. One interpretation could be that due to their prominence, Super Thursdays attract a larger audience than regular MPC meetings, thereby amplifying the impact of Monetary Policy Committee publications.

All three monetary policy factors are highly significant, with the 5-year yield showing the strongest response. Consistent with previous findings, a positive surprise in forward guidance leads to a negative reaction in the 10-year government bond yield, underscoring how central bank communications can yield different outcomes depending on the timeframe.

Additionally, targeted sentiment exerts a notably stronger influence, with coefficients displaying varying signs based on bond maturity and document type. This observation supports Pfeifer and Marohl (2023) assertion that central banks tailor their messages to economic agents differently. Ultimately, press conference responses have the most significant impact, which aligns with the intuitive notion that these events are unscripted and likely involve emotionally charged answers, in contrast to prepared statements.

5.4.2. Overnight Index Swaps

Braun et al. (2023) contend that Overnight Index Swaps (OIS) and interest rate futures reflect expectations about monetary policy. They propose that sudden changes in these instruments at high frequencies can effectively gauge how market expectations of policy trajectories are influenced by monetary policy events. Therefore, in this section the effects of monetary policy surprise factors and sentiment on overnight index swaps are analyzed (the interest rate futures output can be found in the Appendix A).

MPC Meetings

Table 5.5 reports the results for the overnight index swaps during the MPC meetings. Among the three factors analyzed, the Target factor has the strongest influence on

	$GBP2MOIS_t$	$GBP3MOIS_t$	$GBP1YOIS_t$	$GBP2YOIS_t$
	(1)	(2)	(3)	(4)
const	-0.007	-0.006	-0.003	-0.007
	(0.006)	(0.006)	(0.003)	(0.005)
$Target_t$	1.056***	1.066***	0.889***	0.661***
	(0.075)	(0.070)	(0.033)	(0.053)
$Path_t$	0.199*	0.325***	0.949***	0.787***
	(0.106)	(0.106)	(0.074)	(0.068)
QE_t	-0.069	-0.021	0.394***	0.769***
	(0.055)	(0.047)	(0.059)	(0.058)
$AASI_{t,S,Firms}$	-0.001	0.002	-0.001	0.003
	(0.007)	(0.006)	(0.004)	(0.005)
$AASI_{t,S,Households}$	-0.000	0.002	0.004*	0.009***
	(0.004)	(0.004)	(0.002)	(0.003)
$AASI_{t,M,Firms}$	-0.020	-0.022*	-0.013	-0.010
	(0.014)	(0.012)	(0.009)	(0.008)
$AASI_{t,M,Households}$	0.005	0.002	-0.007	-0.014
	(0.018)	(0.017)	(0.009)	(0.014)
$AASI_{t,M,FinSector}$	-0.007	-0.004	0.010	0.008
	(0.012)	(0.011)	(0.008)	(0.008)
$AASI_{t,M,Government}$	0.006	0.008	0.003	-0.002
	(0.007)	(0.007)	(0.003)	(0.004)
Observations	62	62	62	62
R^2	0.899	0.915	0.971	0.964
Adjusted R^2	0.882	0.900	0.966	0.958
Residual Std. Error	0.016 (df=52)	0.015 (df=52)	0.009 (df=52)	0.010 (df=52)
F Statistic	33.536*** (df=9; 52)	36.329*** (df=9; 52)	165.843*** (df=9; 52)	90.535*** (df=9; 52)

Note: *p<0.1; **p<0.05; ***p<0.01

Table 5.5.: MPC Meetings: OIS & AASI

overnight index swaps (OIS), with its impact diminishing as maturity increases. In contrast, the Path factor starts with a weaker influence but gains strength with increasing maturity. The QE surprise factor is significant only for the 1-year and 2-year OIS, indicating that quantitative easing program shocks have a more pronounced long-term effect. Notably, only household-targeted sentiment in the summaries influenced the OIS, with the highest significance observed at the 2-year maturity. Here can be argued that since financial markets closely monitor household sentiment as an indicator of future economic performance, strong household sentiment can lead to market expectations of rising interest rates, affecting medium-term OIS rates.

Monetary Events

The picture changes considerably when implementing the Super Thursday dataset (Table 5.6). The publication of the Monetary Policy Report and the accompanying press conferences appear to induce a strong effect. The Target factor is significant only for the first three maturities, with the strongest coefficient at the 3-month level. Changes in forward guidance influence the 3-month and 1-year levels. The Quantitative Easing effect persists in the long term and becomes stronger compared to the MPC meetings.

The sentiment analysis of this dataset reveals a significant impact, particularly evident in the household and government targeting coefficients, which consistently show negative signs. This suggests that positive sentiment is associated with a negative reaction in OIS rates, and vice versa. One plausible explanation is that positive sentiment may indicate a reduced likelihood of future Bank Rate cuts or an increased possibility of rate hikes, thereby negatively affecting OIS rates. Alternatively, excessive optimism could be interpreted as a warning signal, prompting cautious market behavior and leading to lower OIS rates.

Interpreting sentiment clearly allows for diverse viewpoints. For instance, while household sentiment in the governor's opening remarks tends to be negative, it often turns positive during press conference responses. This initial contrast may seem contradictory but can be explained by considering the context, tone, and specific content of these

	$GBP2MOIS_t$	$GBP3MOIS_t$	$GBP1YOIS_t$	$GBP2YOIS_t$
	(1)	(2)	(3)	(4)
const	0.094**	0.084***	0.049*	0.105
	(0.037)	(0.018)	(0.028)	(0.074)
$Target_t$	0.651***	0.747***	0.722***	0.192
	(0.153)	(0.067)	(0.097)	(0.301)
$Path_t$	0.180	0.341***	0.720***	0.447
	(0.151)	(0.060)	(0.077)	(0.300)
QE_t	-0.005	-0.025	0.550***	1.048***
	(0.127)	(0.051)	(0.068)	(0.226)
$AASI_{t,S,Firms}$	0.015	0.013*	0.025**	0.006
	(0.017)	(0.008)	(0.012)	(0.031)
$AASI_{t,S,Households}$	-0.004	-0.003	-0.013**	-0.008
	(0.011)	(0.004)	(0.005)	(0.016)
$AASI_{t,M,Firms}$	0.036	0.028	0.041	0.092
	(0.042)	(0.018)	(0.027)	(0.083)
$AASI_{t,M,Households}$	0.085**	0.081***	0.012	-0.011
	(0.037)	(0.015)	(0.023)	(0.069)
$AASI_{t,M,FinSector}$	0.075**	0.081***	0.036**	0.049
	(0.032)	(0.013)	(0.017)	(0.055)
$AASI_{t,M,Government}$	-0.013	-0.011**	-0.012*	-0.018
	(0.011)	(0.005)	(0.007)	(0.022)
$AASI_{t,OR,Firms}$	0.013	0.007	0.017	0.063
	(0.024)	(0.010)	(0.017)	(0.053)
$AASI_{t,OR,Households}$	-0.046***	-0.041***	-0.026***	-0.035
	(0.015)	(0.006)	(0.007)	(0.030)
$AASI_{t,OR,FinSector}$	-0.021	-0.034**	-0.000	0.048
	(0.036)	(0.014)	(0.018)	(0.064)
$AASI_{t,OR,Government}$	-0.016	-0.011**	-0.010	-0.025
	(0.015)	(0.005)	(0.006)	(0.022)
$AASI_{t,PA,Firms}$	0.159**	0.139***	0.073*	0.082
	(0.066)	(0.028)	(0.038)	(0.117)
$AASI_{t,PA,Households}$	0.061**	0.050***	0.052***	0.117**
	(0.028)	(0.012)	(0.017)	(0.060)
$AASI_{t,PA,FinancialSector}$	-0.004	0.008	0.008	0.056
	(0.043)	(0.017)	(0.026)	(0.077)
$AASI_{t,PA,Government}$	0.034**	0.025***	0.002	0.005
	(0.017)	(0.007)	(0.008)	(0.028)
Observations	21	21	21	21
R^2	0.985	0.997	0.998	0.990
Adjusted R^2	0.897	0.983	0.989	0.931
Residual Std. Error	0.010 (df=3)	0.004 (df=3)	0.006 (df=3)	0.019 (df=3)
F Statistic	137.180*** (df=17; 3)	1172.942*** (df=17; 3)	1890.022*** (df=17; 3)	66.827*** (df=17; 3)
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 5.6.: Monetary Events: OIS & AASI

communications.

Opening remarks typically take a cautious and broad approach, possibly emphasizing risks, whereas press conference answers tend to provide detailed, reassuring, and positive insights that impact market sentiment differently. This nuanced interpretation underscores the varied effects of sentiment on OIS rates, highlighting the complexity involved in analyzing its impact.

5.4.3. Exchange Rates

Table 5.7 presents the regression output for the EUR/GBP and GBP/USD exchange rates during the MPC meetings. Notably, the Path factor is not significant, suggesting that surprises in the central bank's forward guidance do not impact these exchange rates. This lack of significance can be attributed to the multitude of factors influencing exchange rates, such as structural factors, market sentiment, risk appetite, and both global and domestic economic conditions. These broader influences likely overshadow any surprises in forward guidance.

In contrast, the Target factor shows a similar magnitude for both currency ratios but with opposite signs. This indicates that changes in the Bank Rate significantly affect the Forex market. Specifically, an increase in the Bank Rate leads to a decrease in the EUR/GBP exchange rate and an increase in the GBP/USD exchange rate, suggesting an appreciation of the GBP relative to both the EUR and the USD. This effect can be explained by the higher interest rates attracting foreign investors seeking better returns, thereby increasing demand for the GBP.

The impact of the QE factor is even more pronounced. For EUR/GBP, the negative effect (-7.794) indicates that QE leads to the depreciation of the EUR relative to the GBP. Conversely, the positive effect (7.676) on GBP/USD suggests that QE contributes to the appreciation of the GBP relative to the USD. This discrepancy may be due to differing reactions to QE policies in the Eurozone and the UK.

Interestingly, only the sentiment targeting households in the summaries has a significant impact. Household sentiment affects consumer spending, a major component of economic

	EUR/GBP_t	GBP/USD_t
	(1)	(2)
const	0.189*	-0.200*
	(0.112)	(0.102)
$Target_t$	-4.589***	4.865***
	(0.885)	(0.951)
$Path_t$	1.212	-1.157
	(1.762)	(1.378)
QE_t	-7.794***	7.676***
	(0.839)	(0.792)
$AASI_{t,S,Firms}$	0.026	-0.065
	(0.199)	(0.192)
$AASI_{t,S,Households}$	-0.164*	0.194**
	(0.090)	(0.078)
$AASI_{t,M,Firms}$	-0.018	-0.016
	(0.305)	(0.269)
$AASI_{t,M,Households}$	0.367	-0.298
	(0.262)	(0.236)
$AASI_{t,M,FinSector}$	0.171	-0.189
	(0.191)	(0.161)
$AASI_{t,M,Government}$	0.050	-0.064
	(0.104)	(0.091)
Observations	62	62
R^2	0.687	0.739
Adjusted R^2	0.633	0.694
Residual Std. Error	0.257 (df=52)	0.229 (df=52)
F Statistic	16.126*** (df=9; 52)	21.627*** (df=9; 52)
Note:		*p<0.1; **p<0.05; ***p<0.01

Table 5.7.: MPC Meetings: Exchange Rates & AASI

activity. Positive sentiment can boost consumer spending and economic growth, while negative sentiment can have the opposite effect. Given that exchange rates are sensitive to economic performance, changes in household sentiment can directly influence currency values.

The lack of effect from the MPC minutes can be attributed to several factors. The minutes often provide detailed discussions of the committee's decision-making process rather than new policy actions or changes. If the minutes do not reveal significant new information or shifts in policy stance, their impact on exchange rates may be limited. Additionally, the detailed debates included in the minutes might not translate into actionable information for investors. Typically, the key market-moving information is derived from actual decisions and forward guidance rather than the detailed discussions found in the minutes.

Monetary Events

Table 5.8 reports the results for the Monetary Events. Consistent with previous findings, the sentiment from Super Thursdays has a much larger impact on the financial markets. The magnitude of the Target factor is significant for both exchange rates during these monetary events, with a notably greater effect on EUR/GBP. This can be attributed to the different economic relationships - the Eurozone and the UK have highly integrated economies, causing changes in the UK Bank Rate to have a more pronounced impact on the EUR/GBP exchange rate compared to GBP/USD.

In contrast, the QE factor has a more profound effect on the GBP/USD relationship than on EUR/GBP. This can be explained by the USD's status as the world's primary reserve currency. Actions by the UK's central bank through QE significantly influence investor behavior regarding the USD. QE in the UK can lead to changes in global liquidity and capital flows, thereby impacting the GBP/USD exchange rate more than EUR/GBP.

As before, the Path factor does not impact exchange rates. However, sentiment variables—particularly those reflected in the summaries and minutes regarding immediate decisions—are influential. Additionally, notable effects arise from the governor's opening

	EUR/GBP_t	GBP/USD_t
	(1)	(2)
const	1.649**	-1.138
	(0.679)	(0.887)
$Target_t$	-10.674***	7.458**
	(2.339)	(3.198)
$Path_t$	-1.461	-1.162
	(1.792)	(2.349)
QE_t	-5.369***	9.164***
	(2.003)	(3.060)
$AASI_{t,S,Firms}$	0.693**	-0.741
	(0.351)	(0.506)
$AASI_{t,S,Households}$	-0.395**	0.206
	(0.197)	(0.302)
$AASI_{t,M,Firms}$	0.748	-0.269
	(0.762)	(1.035)
$AASI_{t,M,Households}$	1.190**	-1.280
	(0.526)	(0.880)
$AASI_{t,M,FinSector}$	1.253**	-0.969
	(0.539)	(0.792)
$AASI_{t,M,Government}$	-0.517**	0.582**
	(0.218)	(0.265)
$AASI_{t,OR,Firms}$	0.049	-0.195
	(0.392)	(0.478)
$AASI_{t,OR,Households}$	-0.352*	0.316
	(0.201)	(0.217)
$AASI_{t,OR,FinSector}$	-0.075	0.154
	(0.516)	(0.791)
$AASI_{t,OR,Government}$	-0.149	-0.233
	(0.215)	(0.397)
$AASI_{t,PA,Firms}$	2.244**	-1.809
	(1.061)	(1.507)
$AASI_{t,PA,Households}$	-0.009	0.303
	(0.433)	(0.528)
$AASI_{t,PA,FinancialSector}$	0.899	-0.169
	(0.584)	(1.019)
$AASI_{t,PA,Government}$	-0.330	0.606
	(0.294)	(0.389)
Observations	21	21
R^2	0.985	0.974
Adjusted R^2	0.901	0.829
Residual Std. Error	0.177 (df=3)	0.258 (df=3)
F Statistic	117.035*** (df=17; 3)	255.637*** (df=17; 3)
Note:		*p<0.1; **p<0.05; ***p<0.01

Table 5.8.: Monetary Events: Exchange Rates & AASI

remarks and responses during press conferences. Overall, Bank of England sentiment appears to have a stronger effect on the EUR/GBP relationship, likely due to the economic interdependence between the UK and the Eurozone. Both firm and household targeting are significant but affect the exchange rate differently. This supports Pfeifer and Marohl (2023) argument that the central bank's target audience matters and leads to varying outcomes.

The most striking observation is the strong effect of 2.224 from the sentiment targeting firms in the governor's press answers. This significant impact on the EUR/GBP exchange rate can be attributed to several factors: the close economic ties between the UK and the Eurozone, market sensitivity to business conditions, immediate reactions to real-time information, and implications for monetary policy and economic outlook. Positive sentiment towards firms boosts confidence in the UK economy, resulting in a stronger GBP relative to the EUR.

6. Conclusion

This thesis introduces Natural Language Processing (NLP), text mining, and sentiment analysis, with a focus on machine learning techniques. CentralBankRoBERTa emerges as a key methodology, used to quantify sentiment in the Bank of England's announcement corpus. The indices derived from this sentiment analysis, combined with data from the UKMPD, facilitate the construction of regression models that examine the impact of monetary policy channels on the UK financial market, particularly fixed income, overnight index swaps, and foreign exchange.

The analysis reveals that the UK financial markets react to various influencing factors, including the maturity of the dependent variable, the magnitude of the monetary policy surprise, and prevailing sentiment. Notably, the Bank Rate factor generally exerts a stronger influence in the short term, with its impact diminishing as the maturity lengthens. In contrast, the QE factor tends to have a more prolonged effect. The Path factor's significance is less consistent and harder to interpret.

Additionally, Super Thursdays have a greater impact than regular MPC meetings, and the minutes from these meetings are more significant than the summaries. Household sentiment targeting appears to have the most substantial and enduring effect on financial variables.

These findings align with the argument of Pfeifer and Marohl (2023), reinforcing the fundamental relationship between targeted sentiment and financial market movements. This nuanced understanding could enhance forecasting accuracy and provide valuable insights for investment and policymaking decisions. Recognizing these dynamics can help stakeholders navigate the complexities of the financial landscape more effectively and assess whether these results possess predictive abilities.

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A. Appendix

	$FFIc1_t$	$FTSE_t$	$FTMC_t$	$FTAS_t$
	(1)	(2)	(3)	(4)
const	-0.032	-0.040	-0.118**	-0.052
	(0.098)	(0.096)	(0.058)	(0.085)
$Target_t$	-2.937***	-2.854***	-2.205***	-2.673***
	(0.626)	(0.622)	(0.525)	(0.565)
$Path_t$	2.263	2.194	2.531***	2.156
	(1.583)	(1.564)	(0.811)	(1.369)
QE_t	-5.450***	-5.276***	-2.668***	-4.702***
	(1.159)	(1.138)	(0.595)	(1.006)
$WASI_{t,S}$	0.028	0.028	0.077	0.038
	(0.127)	(0.122)	(0.077)	(0.106)
$WASI_{t,M}$	-0.064	-0.081	-0.260*	-0.112
	(0.229)	(0.223)	(0.145)	(0.200)
Observations	62	62	62	62
R^2	0.513	0.510	0.508	0.524
Adjusted R^2	0.470	0.466	0.464	0.482
Residual Std. Error	0.248 (df=56)	0.242 (df=56)	0.159 (df=56)	0.214 (df=56)
F Statistic	7.487*** (df=5; 56)	7.213*** (df=5; 56)	7.345*** (df=5; 56)	7.445*** (df=5; 56)
Note:				*p<0.1; **p<0.05; ***p<0.01

Table A.1.: MPC Meetings: Stock Market & WASI

	$FFIc1_t$	$FTSE_t$	$FTMC_t$	$FTAS_t$
	(1)	(2)	(3)	(4)
const	0.051	0.042	-0.111	0.017
	(0.101)	(0.099)	(0.070)	(0.088)
$Target_t$	-2.380***	-2.323***	-1.961***	-2.202***
	(0.572)	(0.556)	(0.527)	(0.506)
$Path_t$	2.453	2.364	2.589***	2.283*
	(1.498)	(1.481)	(0.941)	(1.304)
QE_t	-5.752***	-5.566***	-2.710***	-4.934***
	(1.012)	(0.999)	(0.604)	(0.892)
$AASI_{t,S,Firms}$	0.061	0.059	0.030	0.048
	(0.129)	(0.126)	(0.075)	(0.108)
$AASI_{t,S,Households}$	-0.126	-0.126	0.021	-0.095
	(0.085)	(0.083)	(0.052)	(0.072)
$AASI_{t,M,Firms}$	-0.512*	-0.518*	-0.403**	-0.484*
	(0.296)	(0.290)	(0.182)	(0.261)
$AASI_{t,M,Households}$	0.322	0.327	0.003	0.258
	(0.255)	(0.252)	(0.221)	(0.231)
$AASI_{t,M,FinSector}$	0.343*	0.334*	0.106	0.297*
	(0.207)	(0.201)	(0.147)	(0.177)
$AASI_{t,M,Government}$	0.164	0.149	0.022	0.121
	(0.103)	(0.096)	(0.073)	(0.087)
Observations	62	62	62	62
R^2	0.610	0.607	0.542	0.614
Adjusted R^2	0.542	0.539	0.462	0.548
Residual Std. Error	0.230 (df=52)	0.225 (df=52)	0.159 (df=52)	0.200 (df=52)
F Statistic	5.767*** (df=9; 52)	5.534*** (df=9; 52)	5.522*** (df=9; 52)	5.557*** (df=9; 52)

Note: *p<0.1; **p<0.05; ***p<0.01

Table A.2.: MPC Meetings: Stock Market & AASI

	$FFIc1_t$	$FTSE_t$	$FTMC_t$	$FTAS_t$
	(1)	(2)	(3)	(4)
const	0.124	0.131	0.103	0.112
	(0.758)	(0.759)	(0.403)	(0.669)
$Target_t$	-5.624*	-5.495*	-5.013***	-5.307*
	(3.240)	(3.213)	(1.825)	(2.838)
$Path_t$	0.920	0.836	2.439**	1.016
	(2.677)	(2.632)	(1.113)	(2.275)
QE_t	-4.562	-4.300	-2.546*	-3.910
	(2.790)	(2.762)	(1.505)	(2.449)
$WASI_{t,S}$	0.591	0.571	0.408	0.535
	(0.507)	(0.500)	(0.286)	(0.442)
$WASI_{t,M}$	0.048	0.065	0.006	0.039
	(0.940)	(0.946)	(0.421)	(0.819)
$WASI_{t,OR}$	-0.075	-0.059	0.045	-0.053
	(0.466)	(0.455)	(0.275)	(0.404)
$WASI_{t,PA}$	-0.520	-0.526	-0.080	-0.446
	(1.315)	(1.303)	(0.812)	(1.160)
Observations	21	21	21	21
R^2	0.497	0.482	0.684	0.512
Adjusted R^2	0.226	0.204	0.514	0.249
Residual Std. Error	0.432 (df=13)	0.427 (df=13)	0.229 (df=13)	0.377 (df=13)
F Statistic	2.686* (df=7; 13)	2.470* (df=7; 13)	4.085** (df=7; 13)	2.615* (df=7; 13)
Note:				*p<0.1; **p<0.05; ***p<0.01

Table A.3.: Monetary Events: Stock Market & WASI

	$FFIc1_t$	$FTSE_t$	$FTMC_t$	$FTAS_t$
	(1)	(2)	(3)	(4)
const	0.480	0.424	-0.290	0.293
	(2.132)	(2.170)	(0.918)	(1.919)
$Target_t$	-2.330	-2.142	-1.684	-2.065
	(7.127)	(7.254)	(2.965)	(6.384)
$Path_t$	2.532	2.454	2.412	2.275
	(5.108)	(5.244)	(1.936)	(4.568)
QE_t	-6.599	-6.380	-3.576	-5.744
	(6.432)	(6.436)	(2.910)	(5.700)
$AASI_{t,S,Firms}$	-0.309	-0.329	-0.205	-0.298
	(1.168)	(1.169)	(0.546)	(1.041)
$AASI_{t,S,Households}$	0.420	0.421	0.360	0.399
	(0.642)	(0.642)	(0.291)	(0.569)
$AASI_{t,M,Firms}$	-1.080	-1.098	-1.001	-1.022
	(2.561)	(2.556)	(1.236)	(2.281)
$AASI_{t,M,Households}$	0.853	0.829	-0.102	0.624
	(1.636)	(1.661)	(0.710)	(1.467)
$AASI_{t,M,FinSector}$	2.186	2.123	1.099	1.877
	(1.736)	(1.747)	(0.778)	(1.549)
$AASI_{t,M,Government}$	0.434	0.477	0.465	0.449
	(0.722)	(0.725)	(0.339)	(0.645)
$AASI_{t,OR,Firms}$	-0.374	-0.398	-0.761	-0.446
	(1.300)	(1.302)	(0.631)	(1.162)
$AASI_{t,OR,Households}$	0.390	0.415	0.445	0.403
	(0.628)	(0.635)	(0.281)	(0.562)
$AASI_{t,OR,FinSector}$	-0.999	-1.004	-0.566	-0.883
	(1.610)	(1.619)	(0.699)	(1.427)
$AASI_{t,OR,Government}$	0.299	0.282	0.167	0.251
	(0.694)	(0.691)	(0.314)	(0.612)
$AASI_{t,PA,Firms}$	0.286	0.214	-0.593	0.094
	(3.269)	(3.319)	(1.358)	(2.923)
$AASI_{t,PA,Households}$	-1.350	-1.349	-0.727	-1.182
	(1.384)	(1.391)	(0.639)	(1.233)
$AASI_{t,PA,FinancialSector}$	1.229	1.199	0.364	1.022
	(1.762)	(1.810)	(0.712)	(1.593)
$AASI_{t,PA,Government}$	-0.515	-0.511	0.219	-0.393
	(0.959)	(0.960)	(0.437)	(0.852)
Observations	21	21	21	21
R^2	0.797	0.784	0.907	0.794
Adjusted R^2	-0.350	-0.439	0.380	-0.374
Residual Std. Error	0.571 (df=3)	0.574 (df=3)	0.259 (df=3)	0.509 (df=3)
F Statistic	12.952** (df=17; 3)	10.753** (df=17; 3)	43.690*** (df=17; 3)	14.831** (df=17; 3)
Note:				*p<0.1; **p<0.05; ***p<0.01

Table A.4.: Monetary Events: Stock Market & AASI

	$IRF1_t$	$IRF2_t$	$IRF3_t$	$IRF4_t$
	(1)	(2)	(3)	(4)
const	-0.003*	-0.002	-0.001	-0.006***
	(0.001)	(0.003)	(0.002)	(0.002)
Target	0.969***	1.100***	0.828***	0.690***
	(0.012)	(0.030)	(0.014)	(0.014)
Path	-0.013	0.813***	1.049***	1.005***
	(0.021)	(0.055)	(0.040)	(0.030)
QE	0.005	0.395***	0.682***	0.856***
	(0.013)	(0.031)	(0.025)	(0.017)
S: WASI	0.004	-0.009	-0.002	0.004
	(0.003)	(0.006)	(0.002)	(0.004)
M: WASI	-0.005	0.010	0.006	-0.007
	(0.005)	(0.010)	(0.004)	(0.006)
Observations	62	62	62	62
R^2	0.994	0.980	0.994	0.994
Adjusted R^2	0.993	0.978	0.994	0.993
Residual Std. Error	0.003 (df=56)	0.008 (df=56)	0.004 (df=56)	0.005 (df=56)
F Statistic	1489.956*** (df=5; 56)	286.931*** (df=5; 56)	1720.085*** (df=5; 56)	871.578*** (df=5; 56)
Note:				*p<0.1; **p<0.05; ***p<0.01

Table A.5.: MPC Meetings: IRFs & WASI

	$IRF1_t$	$IRF2_t$	$IRF3_t$	$IRF4_t$
	(1)	(2)	(3)	(4)
const	-0.002	-0.003	-0.001	-0.005**
	(0.002)	(0.004)	(0.002)	(0.002)
$Target_t$	0.969***	1.100***	0.825***	0.689***
	(0.013)	(0.030)	(0.014)	(0.015)
$Path_t$	-0.019	0.826***	1.049***	0.997***
	(0.024)	(0.060)	(0.037)	(0.032)
QE_t	0.006	0.393***	0.684***	0.857***
	(0.014)	(0.035)	(0.026)	(0.020)
$AASI_{t,S,Firms}$	0.002	-0.005	0.003	0.001
	(0.002)	(0.005)	(0.003)	(0.004)
$AASI_{t,S,Households}$	0.002	-0.005*	0.000	0.001
	(0.001)	(0.002)	(0.001)	(0.002)
$AASI_{t,M,Firms}$	-0.002	0.006	0.007*	-0.002
	(0.004)	(0.010)	(0.004)	(0.005)
$AASI_{t,M,Households}$	-0.004	0.008	-0.005	-0.003
	(0.005)	(0.010)	(0.005)	(0.007)
$AASI_{t,M,FinSector}$	0.004	-0.009	-0.002	0.004
	(0.002)	(0.006)	(0.003)	(0.003)
$AASI_{t,M,Government}$	-0.002*	0.005*	0.001	-0.002
	(0.001)	(0.002)	(0.002)	(0.001)
Observations	62	62	62	62
R^2	0.994	0.981	0.995	0.994
Adjusted R^2	0.993	0.977	0.994	0.992
Residual Std. Error	0.004 (df=52)	0.008 (df=52)	0.004 (df=52)	0.005 (df=52)
F Statistic	1478.646*** (df=9; 52)	191.644*** (df=9; 52)	1079.544*** (df=9; 52)	543.881*** (df=9; 52)
Note:				*p<0.1; **p<0.05; ***p<0.01

Table A.6.: MPC Meetings: IRFs & AASI

	$IRF1_t$	$IRF2_t$	$IRF3_t$	$IRF4_t$
	(1)	(2)	(3)	(4)
const	0.006	-0.031	-0.009	-0.014
	(0.012)	(0.025)	(0.018)	(0.019)
$Target_t$	0.888***	1.288***	1.001***	0.669***
	(0.071)	(0.148)	(0.081)	(0.112)
$Path_t$	-0.039	0.699***	0.989***	0.880***
	(0.043)	(0.091)	(0.068)	(0.078)
QE_t	0.023	0.319***	0.634***	0.932***
	(0.034)	(0.067)	(0.045)	(0.073)
$WASI_{t,S}$	0.006	-0.014	-0.005	0.004
	(0.006)	(0.014)	(0.008)	(0.009)
$WASI_{t,M}$	0.003	-0.013	0.013	-0.010
	(0.016)	(0.034)	(0.020)	(0.025)
$WASI_{t,OR}$	0.009	-0.019	-0.019	0.008
	(0.008)	(0.017)	(0.012)	(0.012)
$WASI_{t,PA}$	0.008	-0.027	0.004	-0.017
	(0.021)	(0.043)	(0.032)	(0.035)
Observations	21	21	21	21
R^2	0.968	0.965	0.991	0.988
Adjusted R^2	0.952	0.946	0.987	0.982
Residual Std. Error	0.006 (df=13)	0.013 (df=13)	0.008 (df=13)	0.011 (df=13)
F Statistic	41.180*** (df=7; 13)	36.780*** (df=7; 13)	184.481*** (df=7; 13)	437.789*** (df=7; 13)
Note:				*p<0.1; **p<0.05; ***p<0.01

Table A.7.: Monetary Events: IRFs & WASI

	$IRF1_t$	$IRF2_t$	$IRF3_t$	$IRF4_t$
	(1)	(2)	(3)	(4)
const	0.044	-0.109**	-0.044	0.037
	(0.027)	(0.046)	(0.057)	(0.052)
$Target_t$	0.744***	1.563***	1.139***	0.427*
	(0.109)	(0.181)	(0.217)	(0.219)
$Path_t$	-0.130	0.889***	1.082***	0.773***
	(0.108)	(0.174)	(0.201)	(0.232)
QE_t	0.100	0.180	0.509***	1.058***
	(0.082)	(0.134)	(0.157)	(0.172)
$AASI_{t,S,Firms}$	0.000	0.001	0.013	0.014
	(0.011)	(0.019)	(0.023)	(0.022)
$AASI_{t,S,Households}$	-0.001	-0.001	-0.000	-0.013
	(0.006)	(0.010)	(0.012)	(0.013)
$AASI_{t,M,Firms}$	0.042	-0.086*	-0.029	0.057
	(0.029)	(0.048)	(0.056)	(0.062)
$AASI_{t,M,Households}$	-0.001	0.000	0.011	0.003
	(0.025)	(0.040)	(0.048)	(0.055)
$AASI_{t,M,FinSector}$	0.016	-0.049	-0.002	-0.013
	(0.020)	(0.033)	(0.039)	(0.044)
$AASI_{t,M,Government}$	-0.013*	0.027**	0.009	-0.020
	(0.008)	(0.013)	(0.016)	(0.016)
$AASI_{t,OR,Firms}$	0.028	-0.052*	-0.031	0.049
	(0.018)	(0.030)	(0.035)	(0.039)
$AASI_{t,OR,Households}$	-0.018*	0.036**	0.010	-0.030
	(0.011)	(0.017)	(0.020)	(0.024)
$AASI_{t,OR,FinSector}$	0.025	-0.041	-0.039	0.053
	(0.024)	(0.038)	(0.044)	(0.050)
$AASI_{t,OR,Government}$	-0.007	0.011	0.010	-0.016
	(0.008)	(0.013)	(0.015)	(0.019)
$AASI_{t,PA,Firms}$	0.030	-0.051	-0.028	0.066
	(0.043)	(0.072)	(0.088)	(0.088)
$AASI_{t,PA,Households}$	0.042**	-0.085**	-0.030	0.064
	(0.021)	(0.034)	(0.040)	(0.044)
$AASI_{t,PA,FinancialSector}$	0.018	-0.056	-0.019	-0.028
	(0.028)	(0.046)	(0.055)	(0.064)
$AASI_{t,PA,Government}$	0.009	-0.026	-0.011	-0.012
	(0.010)	(0.017)	(0.020)	(0.021)
Observations	21	21	21	21
R^2	0.990	0.994	0.995	0.995
Adjusted R^2	0.936	0.957	0.963	0.966
Residual Std. Error	0.007 (df=3)	0.011 (df=3)	0.014 (df=3)	0.014 (df=3)
F Statistic	272.112*** (df=17; 3)	123.014*** (df=17; 3)	110.513*** (df=17; 3)	120.246*** (df=17; 3)
Note:				*p<0.1; **p<0.05; ***p<0.01

Table A.8.: Monetary Events: IRFs & AASI

	$GB1YTRR_t$	$GB2YTRR_t$	$GB5YTRR_t$	$GB10YTRR_t$
	(1)	(2)	(3)	(4)
const	0.003	-0.005**	0.002	-0.002
	(0.005)	(0.002)	(0.002)	(0.001)
$Target_t$	0.514***	0.503***	0.364***	0.240***
	(0.059)	(0.014)	(0.020)	(0.016)
$Path_t$	0.194***	0.198***	0.029	-0.213***
	(0.060)	(0.033)	(0.045)	(0.040)
QE_t	0.818***	0.912***	1.012***	0.992***
	(0.048)	(0.028)	(0.017)	(0.019)
$WASI_{t,S}$	0.001	0.003	0.000	-0.002
	(0.005)	(0.003)	(0.002)	(0.002)
$WASI_{t,M}$	0.003	-0.009*	0.007*	-0.001
	(0.008)	(0.005)	(0.004)	(0.003)
Observations	62	62	62	62
R^2	0.945	0.988	0.991	0.992
Adjusted R^2	0.940	0.987	0.991	0.991
Residual Std. Error	0.010 (df=56)	0.005 (df=56)	0.004 (df=56)	0.004 (df=56)
F Statistic	151.680*** (df=5; 56)	502.506*** (df=5; 56)	936.334*** (df=5; 56)	894.671*** (df=5; 56)
Note:				*p<0.1; **p<0.05; ***p<0.01

Table A.9.: MPC Meetings: Gilt Yields & WASI

	$GB1YTRR_t$	$GB2YTRR_t$	$GB5YTRR_t$	$GB10YTRR_t$
	(1)	(2)	(3)	(4)
const	0.010	0.019	-0.002	-0.014
	(0.033)	(0.026)	(0.011)	(0.014)
$Target_t$	0.523***	0.473***	0.433***	0.305***
	(0.191)	(0.119)	(0.060)	(0.068)
$Path_t$	0.462***	0.429***	0.272***	-0.131*
	(0.140)	(0.101)	(0.064)	(0.068)
QE_t	0.877***	0.927***	1.027***	1.021***
	(0.115)	(0.071)	(0.051)	(0.043)
$WASI_{t,S}$	0.020	0.013	-0.002	-0.003
	(0.019)	(0.015)	(0.008)	(0.009)
$WASI_{t,M}$	-0.013	0.007	0.004	-0.005
	(0.049)	(0.035)	(0.014)	(0.018)
$WASI_{t,OR}$	0.005	0.018	0.012	-0.015
	(0.026)	(0.020)	(0.008)	(0.011)
$WASI_{t,PA}$	0.028	0.037	0.003	-0.014
	(0.054)	(0.040)	(0.019)	(0.023)
Observations	21	21	21	21
R^2	0.928	0.972	0.991	0.987
Adjusted R^2	0.889	0.957	0.986	0.980
Residual Std. Error	0.022 (df=13)	0.013 (df=13)	0.008 (df=13)	0.008 (df=13)
F Statistic	25.862*** (df=7; 13)	80.193*** (df=7; 13)	465.125*** (df=7; 13)	453.047*** (df=7; 13)
Note:				*p<0.1; **p<0.05; ***p<0.01

Table A.10.: Monetary Events: Gilt Yields & WASI

	$GBP2MOIS_t$	$GBP3MOIS_t$	$GBP1YOIS_t$	$GBP2YOIS_t$
	(1)	(2)	(3)	(4)
const	-0.007	-0.005	-0.002	-0.009*
	(0.005)	(0.005)	(0.003)	(0.005)
$Target_t$	1.045***	1.052***	0.868***	0.658***
	(0.072)	(0.065)	(0.034)	(0.050)
$Path_t$	0.175*	0.296***	0.944***	0.793***
	(0.091)	(0.092)	(0.075)	(0.070)
QE_t	-0.058	-0.006	0.397***	0.774***
	(0.060)	(0.050)	(0.060)	(0.052)
$WASI_{t,S}$	-0.000	0.004	0.010**	0.016***
	(0.009)	(0.008)	(0.005)	(0.005)
$WASI_{t,M}$	-0.014	-0.014	-0.012*	-0.025**
	(0.012)	(0.011)	(0.007)	(0.011)
Observations	62	62	62	62
R^2	0.897	0.912	0.970	0.967
Adjusted R^2	0.888	0.904	0.968	0.964
Residual Std. Error	0.016 (df=56)	0.014 (df=56)	0.009 (df=56)	0.010 (df=56)
F Statistic	59.219*** (df=5; 56)	69.647*** (df=5; 56)	309.358*** (df=5; 56)	155.012*** (df=5; 56)
Note:				*p<0.1; **p<0.05; ***p<0.01

Table A.11.: MPC Meetings: OIS & WASI

	$GBP2MOIS_t$	$GBP3MOIS_t$	$GBP1YOIS_t$	$GBP2YOIS_t$
	(1)	(2)	(3)	(4)
const	0.057**	0.055**	0.014	0.012
	(0.029)	(0.022)	(0.012)	(0.030)
$Target_t$	0.911***	0.943***	0.896***	0.532***
	(0.131)	(0.113)	(0.081)	(0.149)
$Path_t$	0.183**	0.331***	0.813***	0.696***
	(0.085)	(0.070)	(0.061)	(0.105)
QE_t	-0.045	-0.023	0.507***	0.901***
	(0.084)	(0.073)	(0.060)	(0.089)
$WASI_{t,S}$	0.011	0.007	0.000	0.013
	(0.015)	(0.015)	(0.011)	(0.013)
$WASI_{t,M}$	0.043	0.046*	0.012	-0.004
	(0.031)	(0.024)	(0.015)	(0.035)
$WASI_{t,OR}$	-0.016	-0.019	-0.001	0.025
	(0.016)	(0.015)	(0.011)	(0.019)
$WASI_{t,PA}$	0.107*	0.107**	0.037	0.021
	(0.057)	(0.045)	(0.024)	(0.054)
Observations	21	21	21	21
R^2	0.865	0.908	0.986	0.974
Adjusted R^2	0.792	0.858	0.979	0.960
Residual Std. Error	0.015 (df=13)	0.013 (df=13)	0.009 (df=13)	0.014 (df=13)
F Statistic	16.452*** (df=7; 13)	37.189*** (df=7; 13)	327.194*** (df=7; 13)	75.280*** (df=7; 13)
Note:				*p<0.1; **p<0.05; ***p<0.01

Table A.12.: Monetary Events: OIS & WASI

	EUR/GBP_t	GBP/USD_t
	(1)	(2)
const	0.115	-0.117
	(0.102)	(0.102)
$Target_t$	-4.640***	4.961***
	(0.825)	(0.916)
$Path_t$	1.305	-1.285
	(1.643)	(1.341)
QE_t	-7.684***	7.574***
	(0.776)	(0.775)
$WASI_{t,S}$	-0.155	0.137
	(0.118)	(0.118)
$WASI_{t,M}$	0.279	-0.264
	(0.202)	(0.215)
Observations	62	62
R^2	0.674	0.715
Adjusted R^2	0.645	0.690
Residual Std. Error	0.252 (df=56)	0.231 (df=56)
F Statistic	27.073*** (df=5; 56)	34.586*** (df=5; 56)
Note:		*p<0.1; **p<0.05; ***p<0.01

Table A.13.: MPC Meetings: Exchange Rates & WASI

	EUR/GBP_t	GBP/USD_t
	(1)	(2)
const	0.358	0.064
	(0.603)	(0.581)
$Target_t$	-6.186*	5.640**
	(3.179)	(2.771)
$Path_t$	-0.627	0.393
	(2.656)	(2.481)
QE_t	-7.377***	8.949***
	(2.096)	(1.854)
$WASI_{t,S}$	0.156	-0.391
	(0.395)	(0.365)
$WASI_{t,M}$	0.192	0.154
	(0.689)	(0.667)
$WASI_{t,OR}$	-0.294	0.436
	(0.387)	(0.410)
$WASI_{t,PA}$	0.344	0.463
	(1.208)	(1.055)
Observations	21	21
R^2	0.744	0.802
Adjusted R^2	0.606	0.695
Residual Std. Error	0.352 (df=13)	0.344 (df=13)
F Statistic	13.538*** (df=7; 13)	27.943*** (df=7; 13)
Note:		*p<0.1; **p<0.05; ***p<0.01

Table A.14.: Monetary Events: Exchange Rates & WASI