Budapesti Corvinus Egyetem

"How can a Fed Chair not be an actor?"

Effects of verbal and non-verbal FOMC communication on asset prices

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Abstract

This paper investigates how different verbal and non-verbal dimensions of Federal Open Market Committee (FOMC) communication affect asset prices in narrow windows on policy announcement days. I develop a novel framework based on large language models to construct four textual tone indices from FOMC statements and press conference transcripts, capturing the Fed's hawkish-dovish stance, Fed's economic sentiment, and monetary policy and economic uncertainty conveyed in the texts. In addition, I extract emotional tone from the Fed Chair's voice during press conferences using state-of-the-art Speech Emotion Recognition models. With event study regressions controlling for monetary policy stance and macroeconomic conditions, I present three main findings. First, a more hawkish-than-expected tone raises equity prices, and this effect operates through a decrease in discount rate risk premia. Second, a better-than-expected economic sentiment in statements has broad expansionary effects across asset classes, driven by a lowered hedging risk premia. Third, a more positive voice tone by the Fed Chair at press conferences has effects similar to a monetary easing: it raises stock prices, lowers Treasury yields, and also helps predict future policy rate cuts. The results suggest that central bank tone conveys additional information beyond standard numerical data releases and policy decisions. Both what is said and how it is said play an important role in explaining market reactions.

Contents

List of Figures

List of Tables

I Introduction

Central bank communication has become an increasingly important policy tool, particularly after the global financial crisis. As Blinder et al. (2024) put it: “When central bankers talk, financial markets listen — intently.” Communication practices have expanded substantially, with central banks regularly publishing minutes, hosting press conferences, and issuing forward guidance. This trend reflects both the increased complexity of monetary policy and the critical role of expectation management. Understanding the mechanism through which different aspects of communication affect markets is essential to evaluate optimal communication strategies.

“How can a Fed Chair not be an actor?”[1] - ask Gorodnichenko et al. (2023) in their study published in the American Economic Review, after showing that the tone of the Fed Chair’s voice during FOMC[2] press conferences significantly affects stock price movements. Their findings implicate that the non-verbal component is a potentially important channel of central bank communication, which is also supported by the research of Curti and Kazinnik (2023) and Alexopoulos et al. (2024), who find similar effects for facial expressions. These findings serve as a key motivation for my work. In this paper, I apply state-of-the-art deep learning Speech Emotion Recognition techniques to further examine the impact of vocal tone at FOMC press conferences, providing an extension of the work of Gorodnichenko et al. (2023).

In addition, a growing literature documents that the sentiment of central bank statements and press conference speeches strongly affects financial markets (Hansen and McMahon, 2016; Parle, 2022; Baranowski et al., 2023; Chau et al., 2025; Schmeling and Wagner, 2025). Besides quantifying vocal tone, this paper constructs four textual sentiment indices from FOMC statements and accompanying press conferences. To do so, I propose a novel framework to separate texts related to monetary policy stance from those evaluating the economic outlook, using a fine-tuned large language model (LLM) for topic classification. This makes it possible to quantify the sentiment in the two topics separately. Using fine-tuned LLMs, I quantify Fed’s hawkish-dovish sentiment from monetary texts and Fed’s economic sentiment

[1] This question paraphrases Ronald Reagan’s famous remark: “How can a president not be an actor?”

[2] Abbreviation for Federal Open Market Committee, the branch of the U.S. Federal Reserve (Fed in short) responsible for setting monetary policy.

from economic texts. I also construct two text-based uncertainty indices using dictionary methods.

By constructing one vocal and four verbal communication indices, I aim to identify which specific aspects of central bank communication influence financial markets and how the effects of different tonal elements vary. Additionally, measuring multiple components of communication enables the estimation of the ceteris paribus effects of distinct verbal sentiments and the vocal tone.

What matters for financial markets on announcement days is not the tone of the FOMC itself (which is already partly known or predictable), but the unexpected changes in the tone of communication. To capture surprises in FOMC's tone, I extract the unexpected components of the verbal and vocal tone indices - those not predicted by the previous tone, recent economic developments, or the prevailing monetary policy stance, building upon Hubert and Labondance (2021).

The analysis covers FOMC statement releases and subsequent press conferences from 2011 to 2025. I investigate the effects of surprises in FOMC tone on narrow-window asset price changes separately around the two types of events. To isolate the impact of communication beyond actual policy decisions made on the day, I control for the policy actions announced in the statement and various macroeconomic and financial indicators.

Relatedly, recent literature emphasized that the Fed affects markets beyond providing news about the expected path of the target rate. Literature on the "Fed information effect" (e.g. Romer and Romer (2000); Nakamura and Steinsson (2018); Jarociński and Karadi (2020)) argues that financial markets respond not only to changes in policy rates but also to the information conveyed in FOMC communication about the economic outlook and future policy intentions. Another strand of studies highlights that monetary policy actions transmit through a risk-taking channel (e.g. Borio and Zhu (2012); Hanson and Stein (2015); Bauer et al. (2023)), by changing perceived uncertainty, risk-taking and therefore risk premia embedded in asset prices. Another innovation of my study is the direct linkage between tone surprises in FOMC communication and the underlying transmission channels of monetary policy. To achieve this, I adopt the methodology of Cieslak and Pang (2021) to decompose narrow-window asset price changes into orthogonal structural components representing classical monetary policy shocks, information effects, and the risk-taking channel. Then, I estimate whether tone surprises generate responses in these structural asset-price shocks, providing insight into the mechanisms through which communication affects financial markets.

This paper complements the existing literature in four ways.

The first is a methodological contribution. Unlike most studies, I measure multiple dimensions of information contained in FOMC communication, instead of relying on one single indicator of tone. I propose a novel framework, based on an LLM topic classifier to separate information contained in FOMC texts and use distinct measures, with distinct economic interpretations to quantify their tone. This extends the recent literature that employed LLMs to analyze central bank communication (Shah et al., 2023; Hilscher et al., 2024; Kim et al., 2024).

Secondly, I extend the branch of studies that estimate central bank tone surprises, instead of relying simply on the level of tone indices (Hubert and Labondance, 2021; Schmeling and Wagner, 2025). A novelty of my study compared to the existing literature is that I directly link tone surprises to the transmission channels of monetary policy by disentangling asset price responses into structural components, enabling the direct investigation of the mechanism through which different dimensions of central bank tone affect markets.

Third, I provide support for recent studies which argue that textual sentiment affects financial markets primarily by changing risk premia. I show that a better-than-expected economic sentiment in FOMC statements has wide-ranging effects across asset classes, raising stock prices, lowering VIX and Treasury yields of different maturities, and these effects are driven by reduced hedging risk premia, as suggested by Schmeling and Wagner (2025) and Chau et al. (2025). Furthermore, I complement the recent work of Cieslak and McMahon (2023) by showing that a surprisingly hawkish (dovish) tone by the Fed can stabilize (increase) discount rate risk premia, and therefore raise (lower) equity returns. This implies that central bank tone may be an important element in the risk-taking channel of monetary policy transmission (Borio and Zhu, 2012). I further argue that hawkish-dovish tone surprises can be interpreted by markets as a "policy mistake" of the Fed, signaling that Fed's views on ideal monetary policy stance differ from those of the markets. Markets therefore price a "policy mistake premium", conditional on the Fed's hawkish-dovish tone (Caballero and Simsek, 2022). This phenomenon is present after both statements and press conferences.

Finally, but importantly, I demonstrate that the voice tone of the Fed Chair during press conferences has significant effects on asset prices. A one standard deviation positive voice tone surprise raises E-mini S&P500 Futures returns by 17 basis points, even after controlling for the sentiment in the text of the press conference. I complement previous findings of Gorodnichenko et al. (2023) by showing that voice tone primarily carries information about monetary policy stance and a positive (negative) voice tone has equivalent effects to a monetary easing (tightening). Additionally, as suggested by their research, I also present evidence that the chair's voice tone has similar properties to a forward guidance, and helps predict future Fed Funds Rate decisions.

The remainder of the paper is structured as follows. Section II explores three strands of literature relevant to the paper: Fed's effects on long-term Treasury yields and risky asset prices, information and risk-taking channels of monetary policy, and the literature on the effects of central bank communication, especially that of the Fed and ECB. Sections III and Section IV outline the identification of textual sentiment and voice tone indices. Section V describes the identification of unexpected surprises in tone indices, while VI describes how I measure high-frequency asset price changes and construct structural shocks. Section VII estimates the incremental effects of tone surprises on asset price surprises in narrow windows around FOMC statements and press conferences and shows that different aspects of communication affect financial markets in different manners. Section VIII concludes and provides implications.

II Literature review

In this section, I review three key strands of literature relevant to my work. First, I provide an overview of studies that examine the Federal Reserve's role in influencing Treasury term premia, risk-taking, and risky asset prices. Second, I discuss the most recent methodologies used to identify structural asset price surprises on FOMC announcement days, which aim to capture the multifaceted effects of FOMC decisions on both the stock market and the entire yield curve. Lastly, in Section II.3, I review the literature on measuring the sentiment of central bank communication and its impact on asset prices. In the latter section, I also recognize the lack of studies aiming to establish a link between the multi-dimensional aspects of the language of the FOMC and asset price surprises generated on FOMC announcement days.

II.1 Fed's impact beyond short-term yields

A large and growing literature has documented the impact of Federal Reserve policy decisions on financial markets. Although the influence of monetary policy on short-term interest rates is well established, numerous empirical studies have found that long-term Treasury yields respond more strongly to policy announcements than predicted by standard macro-finance models. This discrepancy has become a central focus in the analysis of monetary transmission mechanisms. Cochrane and Piazzesi (2002) were among the first to highlight this empirical regularity, showing that a 100 basis point surprise in the Federal Funds Rate leads to an increase of approximately 52 basis points in 10-year nominal Treasury yields. Hanson and Stein (2015) extend their finding to real interest rates, ruling out the role of inflation expectations. They show that policy shocks induce strong responses in 10-year real yields. Crucially, their analysis attributes this sensitivity primarily to movements in the term premium, rather than to revisions in the expected future path of the short-term policy rate. Further support for the role of term premia comes from Gertler and Karadi (2015) and Gilchrist et al. (2015), who argue that monetary policy significantly affects credit market conditions through its influence on term premia and credit spreads.

In their seminal paper, Borio and Zhu (2012) highlight the underexplored link between monetary policy and the perception and pricing of risk. They introduce the concept of the "risk-taking channel of monetary policy," which posits that low interest rates incentivize financial institutions and investors to take on greater risk in search of higher returns. They argue that the transformation of the global financial landscape has altered the transmission of monetary policy since the 1980s, requiring central banks to account for the behavior of risk-driven investors and large financial intermediaries. Empirical studies on the risk-taking channel have shown that monetary policy significantly influences risky asset prices and risk premia across financial markets. Bernanke and Kuttner (2005) demonstrate that monetary easing increases stock prices, increases expected future dividends, and also reduces the risk premium investors demand for holding stocks. Bekaert et al. (2013) decompose the VIX index into risk aversion and uncertainty components and find that easier monetary policy lowers both. Lastly, Bauer et al. (2023) develop a novel index of risk appetite and find that US monetary policy exerts strong and persistent effects on it. They interpret these effects as evidence that shifts in risk appetite represent an important channel through which monetary policy is transmitted to financial markets. In terms of global effects, Rey (2015) and Miranda-Agrippino and Rey (2020) argue that US monetary policy is one of the most important drivers of risky asset prices worldwide.

Additionally, studies have recently underlined that Federal Reserve statements on monetary policy communicate more than only policy choices; they also reflect the central bank's view of the economy. Understanding monetary policy transmission has increasingly centered on this wider route of communication called the "central bank information effect" or the "information channel of monetary policy transmission". Pioneers in the field, Romer and Romer (2000), argue that the Fed can provide private knowledge about the condition of the economy, which was previously unknown to professional forecasters. In a similar vein, Nakamura and Steinsson (2018) find that rate hikes are generally seen as a sign of Fed's confidence in the strength of the economy and cause forecasters to revise their growth projections upwards. Hansen et al. (2019) systematize this channel by describing the signaling effects of central banks. Their findings show that changes in expectations about economic fundamentals explain a major share of the market reaction to FOMC announcements, and this change in expectations can be explained by central banks' communication about uncertainty. More recent studies emphasize the need to distinguish between information effects and pure policy shocks. For instance, Miranda-Agrippino and Ricco (2021) demonstrate that neglecting to control for the information content of Fed communication results in skewed estimates of the impacts of monetary policy and price puzzle phenomena. Jarociński and Karadi (2020) and Jarociński

(2022) construct central bank information surprises and show that these information-type interest hikes have expansionary effects on the economy.

In sum, the impact of Fed monetary policy extends across various asset classes and may come from various type of information released on FOMC days. Beyond the conventional short-rate expectations channel, central banks can also affect markets through risk premia and the release of economic information. As will be seen in Section II.3, the tone of FOMC communication may help explain these effects on risk-taking and economic expectations. However, we should note that the precise mechanisms through which monetary policy influences risky asset prices and long-term rates remain debated in the existing literature.

II.2 Identifying announcement day surprises from asset prices

In light of Section II.1, new empirical methods are necessary to accurately quantify the multifaceted narrow-window effects of monetary policy, as standard monetary shocks, measured by interest rate changes surrounding announcements, may be confounded with other information regarding economic and financial conditions (Cieslak and Schrimpf, 2019). In this section, I briefly review the literature that aims to identify structural asset price surprises, with particular attention to Cieslak and Schrimpf (2019) and Cieslak and Pang (2021), whose methodology will be adopted in this study.

The early literature has sought to identify FOMC-day monetary policy surprises from high-frequency changes in short-term Fed Funds Rate Futures. The influential paper of Kuttner (2001) argues that the simple change in the target rate in a window around an FOMC announcement is unable to disentangle expected and unexpected policy actions. He proposes a measure of monetary policy surprises based on the change in one-year ahead Fed Funds Rate Futures in a narrow window around FOMC announcements. Gürkaynak et al. (2005) dismiss the idea that variations in Fed Funds Rate Futures on announcement days may be adequately explained by one factor. They estimate a "path factor" and a "target factor" using factor analysis on intraday short- to mid-term Fed Funds Rate Futures data to identify monetary policy shocks within a 30-minute window surrounding the announcement. Swanson (2021) identifies a third category of monetary policy shocks, namely the LSAP surprise to account for the presence of unconventional monetary policy tools after the global financial crisis. A critique of these approaches comes from Cieslak and Pang (2021) who argue that path and LSAP shocks might result from a combination of numerous correlated information, since news about growth, news about the future course of policy, and shocks to risk premia all influence rates at longer maturities.

Given the information content of Fed announcements and its large effects on risk premia, several studies leverage information outside the yield curve to dissect high-frequency announcement day asset price changes into structural policy shocks (Matheson and Stavrev, 2014; Jarociński and Karadi, 2020; Cieslak and Schrimpf, 2019; Cieslak and Pang, 2021). For example, the maturity dimension of the yield curve, together with the correlation between yields and equities, has proven to be effective in distinguishing between economically distinct structural shocks.

Matheson and Stavrev (2014) and Jarociński and Karadi (2020) employ two assets (the S&P 500 and a singular selected bond yield) to differentiate between information shocks and monetary policy surprises. Cieslak and Schrimpf (2019) also identify a third risk premium shock, in addition to economic and monetary policy shocks. Their identified shocks correspond to three primary channels of monetary policy transmission discussed in Section II.1: the conventional monetary news channel, the Fed information effect, and the risk premium channel.

Cieslak and Pang (2021) go even further and dissect the complete maturity of the yield curve and the S&P 500 index into four orthogonal components with structural interpretation: monetary policy shocks, growth shocks, common premium shocks, and shocks to the hedging premium. Their identification strategy consists of two sets of restrictions on the structural form residuals of a VAR(1) model: one on the comovement between stocks and bond yields and one on the impact various shocks have on the yield curve across maturities. Their methodology is described in detail in Section VI. Growth news affects investors' cash flow expectations, by changing economic expectations. Good growth news raises stock prices and bond yields. Monetary news reflect surprises in the expected path of the risk-free rate. Easier monetary news raises stock prices but lowers yield. Since equities and bonds are susceptible to pure discount rate risk, a positive common premium news raises equity and bond risk premia, reflected in decreasing stock prices higher long-term yields. A positive hedging premium shock raises stock risk premia but decreases bond risk premia since bonds hedge stock cash flow risk.

Cieslak and Pang (2021) provide a distinguished view of how the Fed affects stocks and bonds. Through variance decompositions of daily nominal yield changes and stock market returns, they demonstrate that from 1983 to 2017, approximately 80% of the variance in 2-year yield changes is attributed to monetary and growth news, each contributing similar proportions. Meanwhile, in case of changes in the 10-year yield, 80% of the variance is accounted for by premium shocks, divided into contributions of 45% from the common premium and 35% from the hedging premium. Risk premium shocks are also the main drivers of the variation in stock returns.

As will be seen in section II.3, very few studies have aimed to explain either monetary news or non-monetary news (i.e. growth shocks and risk premium shocks) generated on FOMC announcement days by the central bank's textual and spoken communication. According to Cieslak and Schrimpf (2019), however, there is a clear difference in what types of shocks are generated on different FOMC events. Using high-frequency data, they show that monetary news dominates monetary policy announcements. Information about economic growth is extracted primarily during press conferences and other communication events aimed at elucidating the context of policy decisions. Risk premium shocks have nonlinear impacts on asset prices, with their relevance growing since the adoption of unconventional monetary policies. In this paper, my aim is to shed light on whether structural policy shocks are attributable to different aspects of communication by the FOMC. I hypothesize that the way the FOMC communicates its monetary policy intentions, economic outlook, and their perception of uncertainty plays a crucial role in explaining the structural shocks the Fed generates.

II.3 Effects of FOMC communication

"Monetary policy is 98 percent talk and 2 percent action" - said Nobel Prize winner and former Chairman of the Federal Reserve Ben Bernanke in 2022.[3] Indeed, the words of central banks are closely monitored by financial market participants and have demonstrated a significant influence on market movements (Ehrmann and Talmi, 2020). Central bank communication has also become an even more important tool in the post-GFC era, as policy rates were at zero lower bound and unconventional tools were necessary to conduct meaningful monetary policy and guide the expectations of market participants (Hagedorn et al., 2019).

The way central banks communicate matters. Naturally, FOMC releases contain various "numerical" information, such as decisions made on FOMC days (e.g. changes in open market operations, LSAP purchases or the target rate), and the FOMC's forecasts and evaluation of the economy (e.g. Survey of Economic Projections published every second meeting). However, central bank readers and listeners receive numerical decisions through written texts and spoken speeches. The tone of the statement and the following press conferences may merely echo the numerical information or, as suggested by recent research, may communicate other signals that are not officially revealed by the numerical decisions announced. The tone may disclose information consistent with confidential Greenbook projections, which are published with a five-year delay, or internal discussions only revealed in the Minutes three weeks later (Hubert and Labondance, 2021). In favor of the additional disclosure hypothesis, both verbal and non-verbal elements of statements and press conferences have been demonstrated to strongly influence asset prices, even after controlling for numerical decisions made on FOMC days. In this chapter, I will review the literature that quantifies verbal and non-verbal communication's role in monetary policy transmission.

FOMC statements are released shortly after the end of the generally two-day FOMC meetings. These statements are relatively short, usually consisting of 3-6 paragraphs, and follow a fairly consistent structure. They include a brief assessment of current economic conditions, a description of the monetary policy decisions taken at the meeting, and often a more or

[3] https://www.brookings.edu/events/ben-bernanke-the-fed-from-the-great-inflation-to-covid-19/

less explicit indication of future policy direction. The structured nature of these statements makes them particularly suitable for computational linguistic analysis. A growing body of literature has employed natural language processing (NLP) and computational linguistic methods to extract sentiment and tone from FOMC statements. Lucca and Trebbi (2009) were the first to suggest that communication is a more important driver of Treasury rates than contemporaneous policy rate decisions. Hansen and McMahon (2016) apply topic modeling based on Latent Dirichlet Allocation (Blei et al., 2003) and dictionary methods to quantify statements' sentiment about economic topics. They also manually flag statements containing forward guidance and find that shocks to forward guidance affect market and real variables more than communication of current economic conditions. Doh et al. (2021) show that qualitative evaluations of economic conditions and risks in FOMC statements can influence bond prices as much as changes in the policy rate. These evaluations can meaningfully shift the perceived policy tone and affect financial markets even without a policy change. Hubert and Labondance (2021) compute FOMC statement tone by counting positive and negative words. Similarly to the present study, they aim to directly explain narrow-window asset price surprises generated on FOMC days They find that the sentiment of the statement explains monetary surprises beyond other announcement-day information, such as forecasts and votes, and that its impact is stronger around turning points in the monetary policy cycle. In addition, Ehrmann and Talmi (2020) demonstrate that even minor changes in the language of central bank statements can surprise financial markets.

Since the FOMC began holding press conferences (PCs) in 2011, they have provided a new avenue for communication beyond written statements. These conferences offer both prepared remarks and spontaneous responses, providing a richer context for interpreting the monetary policy stance. Between 2011 and 2018, FOMC press conferences followed only meetings with a Summary of Economic Projections (SEP). In June 2018, Chair Powell announced that, starting January 2019, PCs would follow every meeting, with the aim of enhancing transparency and fostering public understanding of the Fed's actions.[4] Close to the present

[4]De Pooter (2021) argue that PCs generally provide meaningful signals and move asset prices strongly. Especially, when no SEP is released, the press conference has a greater impact on near-term rates, as investors look to it for guidance. Stock price reactions to press conferences can be large and even opposite in direction to the statement, highlighting their importance.

study, Gorodnichenko et al. (2023) build a large language model (LLM) to measure the hawkishness/dovishness of PC texts. Hilscher et al. (2024) and Kim et al. (2024) use a fine-tuned version of FinBERT LLM, developed for sentiment analysis of economic and financial news to quantify the sentiment of ECB press conferences and FOMC minutes, and find that central bank sentiment predicts policy rates. Baranowski et al. (2023) quantify hawkish and dovish words at ECB press conferences, showing that a more hawkish tone raises stock prices, and Introductory Remarks are more influential than the Q&A part.

Related to my paper, recent studies investigated the non-verbal content of CB communication. Gorodnichenko et al. (2023), for the first time in the literature, analyze the voice tone of the chair during PCs, showing that a more positive voice tone significantly raises stock prices, while they find no similar effects in the case of text-based indicators. Curti and Kazinnik (2023) show that financial markets respond negatively to negative facial expressions during the FOMC press conference, even after accounting for the verbal content and other controls. Alexopoulos et al. (2024) measure the voice tone and facial expressions of the Fed Chair and Congress members during congressional testimonies. A positive change in the chair's voice, or facial emotion indices during testimonies correlates with an increase in the S&P 500 index and a decrease in the VIX, especially when discussing monetary policy actions.

Most of the studies mentioned above shrink verbal and non-verbal communication information into one single variable. This is problematic, as FOMC texts cover multiple different topics and multidimensional information. As exceptions, Picault and Renault (2017) construct economy and monetary policy-related dictionaries for the ECB, and analyze the two topics' sentiment separately. They show that markets are more volatile on the day after an ECB press conference with a negative tone about the economic outlook of the euro area. Hansen et al. (2019) and Chau et al. (2025) use topic modeling and evaluate the tones of different topics.

In this study, my direct aim is to evaluate how different dimensions of verbal and non-verbal FOMC communication effect financial markets. I propose a new and effective methodology to separate FOMC texts into three topics: monetary policy stance, economic outlook, and financial developments. I create four indices of textual data: economic sentiment, a hawkish-dovish index, and similarly to Ying et al. (2025) I compute a measure of the uncertainty in the texts. Following Gorodnichenko et al. (2023), I also measure the positive and negative emotions in the chairs' voice in order to capture the beyond-words dimension of FOMC communication.

Although the effects of CB communication are backed by considerable evidence, a natural follow-up to ask is through what mechanisms these effects operate. In Section II.2, I discussed two unconventional aspects of monetary policy transmission: the Fed's information effects by revealing its economic assessment to the public, and the Fed's role to drive the risk premia of assets and the risk aversion of investors. Although this question is often overlooked in the literature, some studies suggest that communication plays an important role through information and risk-based channels.

Parle (2022) argues, that consistent with the literature on the information channel of monetary policy, a more hawkish (dovish) tone in ECB press conferences has a significant positive (negative) impact on stock prices, and suggest that markets interpret the tone as a signal of the ECB's private information about the economic outlook, rather than as an indication of future interest rate changes.

Hansen et al. (2019) show that central bank communication - Bank of England's Inflation Reports' - affects market beliefs about long-run uncertainty. According to Ying et al. (2025), the uncertainty of monetary policy, derived from short-term interest rate options, is related to textual uncertainty measures in the FOMC statements. Schmeling and Wagner (2025) find that a more positive tone at ECB press conferences decreases stock market volatility and credit spreads and highlight that policy communication matters for asset prices through a risk-based channel, as a tone surprise conveys news not captured by standard measures of monetary policy shocks. Dossani (2021) show that the hawkishness measured in press conferences of five large central banks is associated with a decrease in the variance risk premium and an increase in option-implied risk aversion. Similarly, Cieslak and McMahon (2023) show that a more hawkish (dovish) stance of FOMC predicts reductions (increases) in risk premia.[5] In light of these studies, another novelty of my study is that I directly link the informational and risk-related transmission mechanisms of FOMC to multidimensional indicators of textual and audio indicators. I aim to answer the question of how different verbal and non-verbal aspects of FOMC communication affect asset prices, and via what kind of mechanisms.

III Textual analysis

My primary objective in this chapter is to create four indices from the textual data of FOMC days. The underlying assumption is that FOMC communication encompasses multidimensional information, that cannot be captured by one single index, which is what most of the previous literature has aimed to do. I capture first-moment tone by analyzing sentiments regarding monetary policy and economic stance, and second-moment tone by quantifying uncertainty in texts that discuss either monetary policy or the economic outlook.

III.1 Data

The textual data spans from January 2011 to January 2025, covering:

- FOMC Statements: The Committee issued eight statements per year, except for 2020. Three statements between March 3, 2020 and March 23, 2020 are dropped, as they were either unscheduled/irregular. This results in a total number of 110 statements in the dataset.
- FOMC Press Conferences: Between 2011 and 2018, press conferences were held at every second announcement, while since 2019, they have been held after every meeting. I again exclude two irregular PCs held after the outbreak of Covid-19 pandemic in 2020, resulting in a sample of 80 conferences.

[5]Relatedly, Cieslak et al. (2023) argue that the FOMC's forward-looking stance, revealed through private deliberations, predicts lower risk premia between meetings. This effect goes beyond the official statement, highlighting the importance of intermeeting communication in guiding market perceptions.

I download all FOMC statements and transcripts of FOMC press conferences from the Federal Reserve website in PDF format. Using the PdfParser Python package, I extract the paragraphs from each statement. For press conferences, I extract the paragraphs from the chair's opening statement and their responses to each press question.

FOMC statements typically consist of 3 to 6 paragraphs. During press conferences, the chairs answered between 18 and 38 questions. Chair Bernanke and Chair Yellen generally answered fewer questions but provided more detailed responses, whereas Chair Powell tends to take more questions but keeps his responses shorter.

III.2 Topic classification

Before beginning to analyze the sentiment of the FOMC texts, I map each sentence to a topic. During a single conference, the chair moves between discussions on the economic outlook, financial market conditions, and the stance of monetary policy. Given that topics change throughout the conference, a single sentiment-classifier model is not well-suited across the entire text. My approach differs from most of the literature in this respect. Most previous work handles FOMC texts as one, without distinguishing between the topics discussed (e.g. Hubert and Labondance (2021); Gorodnichenko et al. (2023); Hilscher et al. (2024)). Others have used LDA topic modeling (Hansen and McMahon, 2016; Hansen et al., 2019; Chau et al., 2025). In contrast, I use a large language model classifier that offers a more direct and interpretable mapping from text to topic. Although LDA-based topic models can be effective in uncovering latent topical structures, they are overly high-dimensional and often produce topics that are difficult to interpret or require subjective judgment.

To train an LLM for topic classification, I leverage the structured format of the FOMC Minutes[6], which are published three weeks after each FOMC meeting. The FOMC Minutes are structured into several distinct sections. The sections cover discussions about three recurring topics:

- Economic Outlook (sections Staff Review of the Economic Situation, Staff Economic

[6]FOMC minutes are detailed records of the Fed's policy meetings, providing insights into the economic outlook, monetary policy discussions, and the rationale behind interest rate decisions.

Outlook, Participants' Views on Current Conditions and the Economic Outlook)

- Conduct of monetary policy (section Committee Policy Actions)
- Financial developments (section Staff Review of the Financial Situation)

The clear distinction between topics, along with the strong similarity between topics covered in the Minutes, statements and press conferences, allow me to create a dataset from FOMC Minutes sentences for fine-tuning a large language model that is able to classify sentences into these three categories.

To build the training dataset, I take a sample of 2,000 sentences from the FOMC Minutes dataset compiled by Acosta (2023). I then label each sentence according to the topic of the section in which it appears. Each sentence is classified into one of "monetary policy stance", "economic conditions", "financial conditions" categories based on the corresponding sections of the FOMC Minutes listed above. Since discussions sometimes overlap, I manually correct some labels to improve accuracy.[7] Next, I randomly divide the labeled dataset into three subsets: 80% of the sentences are allocated to the training set, while the remaining 20% form the test set. Then another 10% of the training set is separated as the evaluation dataset for the fine-tuning procedure.

Three common LLMs are fine-tuned on the labeled Minutes training dataset and tested on the test set. I employ the BERT Base, RoBERTa Base, and FinBERT models. BERT Base, created by Google, is a bidirectional transformer model that has been trained on extensive English corpora, and functions as a foundational model for various NLP tasks. BERT leverages attention mechanisms to process language. Specifically, BERT employs "soft attention" to dynamically weigh contextual information, allowing it to emphasize relevant cues while attenuating less informative elements (Vaswani et al., 2017). RoBERTa Base is an optimized version of BERT, created by Facebook AI, which has been trained on a larger dataset and employs dynamic masking to improve performance. FinBERT, introduced by Araci (2019), derived from BERT, is fine-tuned for economic and financial-specific sentiment analysis. As

[7] For example, the stance of the economy is sometimes discussed in the Policy Actions section, or real economy is discussed in sections about the financial situation. These cases are not overly common; manually corrected sentences take up about 5% of the training data.

a benchmark, I also prompt OpenAI's ChatGPT-4o mini (the best free unlimited version of ChatGPT as of early 2025) to classify sentences into the three specified categories. Fine-tuning is carried out using the Hugging Face Train Interface, a no-code platform designed for the fine-tuning of large-language models for downstream applications. The fine-tuning procedure and the ChatGPT prompting strategy are discussed in the Appendix sections A.1 and A.2.

Table 1: Performance metrics of the LLMs fine-tuned/prompted for topic classification

Model	Train Loss	Val Loss	Test Loss	Accuracy	Macro F1
Fine-tuned RoBERTa Base	0.30	0.26	0.36	**90.18 %**	**0.87**
Fine-tuned BERT Base	**0.13**	0.22	0.37	88.92 %	0.84
Fine-tuned FinBERT	0.16	**0.19**	**0.61**	89.17 %	0.86
ChatGPT-4o mini	—	—	—	87.35 %	0.83

Notes: This table presents five performance metrics of the LLMs used to classify FOMC sentences into discussions of monetary policy, economic conditions, and financial developments. The loss values represent the cross-entropy loss, which measures the divergence between predicted and true class distributions; lower values indicate better model fit. Accuracy denotes the proportion of correctly classified sentences. The macro F1 score, which equally weights precision and recall across all classes, provides a balanced assessment of performance. Numbers in bold indicate the best performing model by the given metric.

Table 1 contains the performance of the four models on the training, evaluation and test sets. Overall, the models prove to be similarly effective in distinguishing between the three predefined topics. The fine-tuned RoBERTa Base model achieves the best out-of-sample accuracy (90.18 %) and Macro F1 score (0.87) , while other models seem to be slightly over-fitted on the training data.

Finally, I apply the fine-tuned RoBERTa Base model[8] to the sentences collected from FOMC-day statements and press conference transcripts. Since a single paragraph or a Q&A answer can cover multiple topics, it is important to classify the texts at the sentence level instead of the paragraph level. Therefore, I first split my textual dataset into individual sentences, resulting in 28373 sentences altogether. Before applying the topic-classifier LLM, I also identify 6312 "filler" sentences, those that have lost meaningful economic context due to the

[8]The fine-tuned model is available at https://huggingface.co/kissmarci00/autotrain-roberta-base-topic

sentence segmentation.[9]

In most cases, the fine-tuned LLM performs sentence classification as expected. Section A.3 in the Appendix contains two examples of the topic classification output. Occasional misclassifications occur. For instance, sentences with "the Committee" as the subject are often labeled as policy actions, even when they primarily convey economic assessments. This likely reflects biases in the training data constructed from FOMC Minutes sentences, where such constructions are more frequently associated with policy decisions. The proposed method could be improved with cleaner, fully human-annotated data. However, the method offers advantages over LDA topic models, which assign topics based solely on word distributions. Additionally, my approach required far fewer subjective decisions compared to other topic modeling techniques.

III.3 Measuring hawkish-dovish sentiment

In the previous section, I have distinguished between texts related to monetary policy and those focused on economic and financial conditions. With this separation, we now have a set of sentences suited for conducting sentiment analysis on monetary policy.

A self-explanatory scale to assess the sentiment of monetary policy is the hawkish-dovish scale. A hawkish stance involves a focus on controlling inflation and may involve tightening monetary policy, typically through interest rate hikes. In contrast, a dovish stance emphasizes stimulating economic growth, often by adopting more accommodative policies, such as interest rate cuts.

I follow the branch of literature that measures hawkish-dovish stance using NLP techniques. Traditional computational linguistics models, which categorize text as simply positive or negative, fall short when it comes to identifying monetary policy stances (Shah et al., 2023). These models often misinterpret key economic terms due to their context-agnostic nature.

[9]"Fillers" are particularly common in the unscripted Q&A part of press conferences. To identify "filler" sentences, I collect the 500 most common words (excluding stopwords) in the FOMC Minutes dataset. From these 500, I delete words that do not contain any economic meaning, resulting in 420 words altogether. Finally, I mark sentences as "filler" in my FOMC-day sentence dataset if they do not contain any of the 420 words.

For instance, the word "increase" could indicate either a hawkish or dovish sentiment depending on the accompanying term. An "increase in unemployment" generally reflects a weak economy and might lean dovish, while an "increase in inflation" signals economic overheating, often prompting a hawkish response. Shah et al. (2023) construct a large human-annotated dataset of hawkish-dovish sentences. They also propose a fine-tuned RoBERTa model for classification, which will serve as my benchmark model. Similarly, Gorodnichenko et al. (2023) fine-tune the BERT Base model using human-annotated sentences from FOMC statements and PC transcripts and achieve 81 % accuracy. Niţoi et al. (2023) develop a fine-tuned LLM for policy stance evaluation of CEE central banks, and find that their measure has a higher predictive power in anticipating policy rates changes than other lexicon-based sentiment indicators.

I obtain the training dataset for fine-tuning from Gorodnichenko et al. (2023). They developed a training dataset comprising 1242 sentences contained within FOMC statements between 1997 and 2010 and classified them as hawkish, dovish, or neutral according to the assessments of multiple human annotators. I select 80% of the sentences for training data and use the remaining 20% for testing purposes.

I run a horse race of four fine-tuned LLMs and ChatGPT 4o-mini. Fine-tuning is implemented through Hugging Face's Train API.[10] The results of the horse race are shown in Table 2. The fine-tuned BERT Base model[11] comes out as the winner according to all test metrics. In particular, this model significantly outperforms the FOMC RoBERTa model of Shah et al. (2023) and is also able to slightly beat the ChatGPT-4o mini. The model achieves an overall accuracy score of 80,8 % and recalls hawkish, dovish, and neutral sentiments at 80 %, 84 %, and 78 %, respectively.

Before applying the fine-tuned BERT Base model to the monetary policy-related sentences in the textual dataset, I perform an additional pre-processing step to enhance contextual coherence. Specifically, I concatenate consecutive monetary policy sentences within each statement/introductory remarks paragraph and Q&A answer to form more semantically complete

[10] Fine-tuning and prompting strategies are described in sections A.1 and A.2 in the Appendix.

[11] The fine-tuned model is available at https://huggingface.co/kissmarci00/autotrain-bert-base-uncased-bs8-e3-ms256

Table 2: Performance metrics of the LLMs fine-tuned/prompted for hawkish-dovish classification

Model	Train Loss	Val Loss	Test Loss	Accuracy	Macro F1
Fine-tuned RoBERTa Base	0.69	0.65	0.62	73,1 %	0.71
Fine-tuned BERT Base	0.47	**0.58**	**0.60**	**80,8 %**	**0.81**
Fine-tuned FinBERT	**0.40**	0.63	0.61	77.9 %	0.78
FOMC RoBERTa (Shah et al. 2023)	—	—	0.62	67.5 %	0.68
ChatGPT-4o mini	—	—	—	77.1 %	0.79

Notes: This table presents five performance metrics of the LLMs used to classify FOMC sentences about the monetary policy stance into discussions hawkish/dovish/neutral categories. The loss values represent the cross-entropy loss, which measures the divergence between predicted and true class distributions; lower values indicate better model fit. Accuracy denotes the proportion of correctly classified sentences. The macro F1 score, which equally weights precision and recall across all classes, provides a balanced assessment of performance. Numbers in bold indicate the best performing model by the given metric.

units. Additionally, I merge adjacent "filler" sentences into these units — those not explicitly classified as monetary policy text but appearing in close proximity[12] — as they may provide relevant contextual information or help clarify the policy stance. The purpose of this strategy is to enhance the model's ability to capture nuanced language by leveraging the contextual awareness of the BERT embedding architecture.[13]

I calculate the Hawkish-Dovish Sentiment for each statement and press conference separately using the following formula:

$$\text{HDS} = \frac{\#\text{Hawkish} - \#\text{Dovish}}{\#\text{Hawkish} + \#\text{Dovish}} ,$$

where #Hawkish and #Dovish denote the number of sentence sequences of hawkish and dovish tone on each occasion. A higher value of HDS indicates a more hawkish policy stance. The HDS time series are plotted on the left panel of Figure 1.

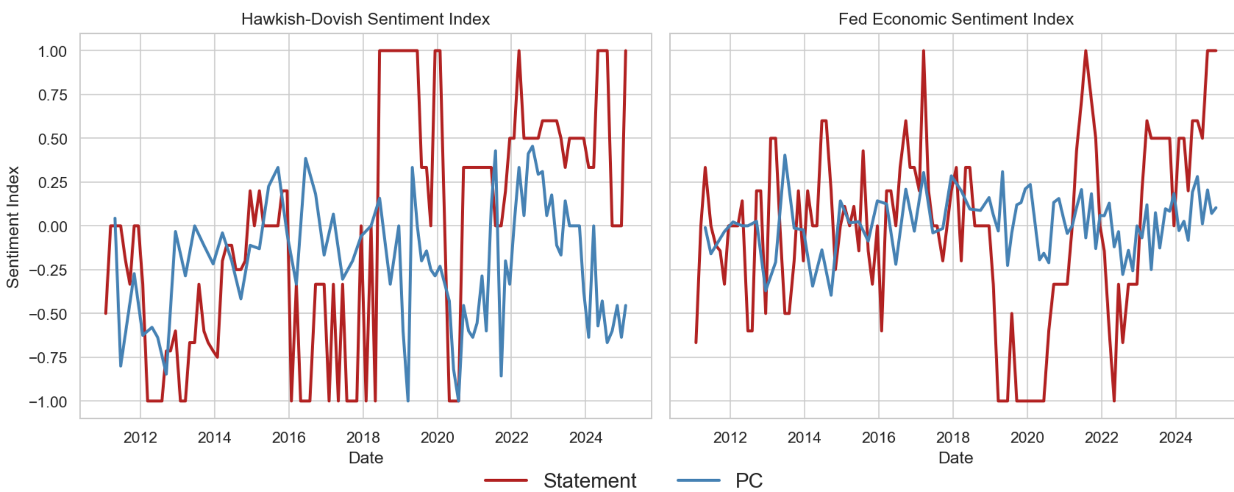
To assess the validity of the Hawkish-Dovish Sentiment Index (HDS) as a measure of mone-

[12]Specifically, each "filler" is merged into a unit of monetary policy text if it directly precedes or follows the unit.

[13]I also experiment with an alternative approach in which sentences are treated as separate units for sentiment classification. The two methods produce highly correlated results. However, the approach based on sentence sequences, as adopted in this study, demonstrates more statistically significant results in Section VII. This improvement may be attributed to improved information processing, as the sequential format likely provides the model with a more comprehensive contextual framework to interpret monetary policy sentiment accurately.

tary policy sentiment, I examine its correlation with key economic and financial indicators. The HDS of the statement is correlated (0.54) with the level of the Federal Funds Rate, indicating alignment with the actual policy position. It is negatively correlated (-0.30) with changes in business confidence since the previous FOMC meeting, suggesting that improved economic expectations are followed by more dovish language. HDS also shows negative correlations with changes in VIX, financial stress, and inflation expectations, consistent with a more hawkish tone in response to increasing uncertainty or inflationary pressures. These indicate that at least some of the tone in the FOMC statements is highly predictable by economic conditions and does not come as a surprise to markets. I address this question in more detail in Section V.[14] Interestingly, the correlation between the HDS of statements and subsequent press conferences is low (0.12), pointing to differences in tone across communication channels.

Figure 1: Sentiment indices in FOMC statements and press conferences



Notes: The figure displays the Hawkish-Dovish Sentiment index (HDS, left panel) and the Fed Economic Sentiment index (FES, right panel) derived from FOMC statements and press conferences by own calculation. HDS indices are based on a BERT Base large language model fine-tuned to classify monetary policy stance. FES indices are computed using FOMC-FinBERT, a fine-tuned model for central bank communication. The red line represents sentiment extracted from official statements, while the blue line corresponds to sentiment in press conference transcripts. Both indices range between −1 (most negative/dovish) and +1 (most positive/hawkish) by construction.

[14] I also provide regression estimates and data description in Section V.

III.4 Measuring Fed economic sentiment

In Section III.2, I have separated a set of sentences that discuss the FOMC's economic outlook. To measure economic sentiment in these texts, I follow Hilscher et al. (2024) and employ FOMC-FinBERT, a domain-specific adaptation of the FinBERT LLM model[15], specifically fine-tuned for central bank communication. Developed by Gössi et al. (2023), FOMC-FinBERT is trained on financial texts published in the FOMC Minutes, to better capture the linguistic nuances of Fed's economic discourse. Building on the original FinBERT framework, they improved the model using a sentence-filtering (SF) approach during fine-tuning. Their results demonstrate a notable improvement in classification accuracy when using the SF-enhanced FOMC-FinBERT compared to the original FinBERT model. As with its predecessor, FOMC-FinBERT classifies texts into one of three categories: positive, negative, or neutral.

As in Section III.3, I construct sentence sequences by concatenating neighboring economic sentences and "fillers". I employ the FOMC-FinBERT model on sentence sequences. Then I calculate the Fed Economic Sentiment index by the following formula:

$$\text{FES} = \frac{\#\text{Positive} - \#\text{Negative}}{\#\text{Positive} + \#\text{Negative}} ,$$

where #Positive and #Negative denote the number of sentence sequences of positive and negative tone on each occasion. A higher value of FES indicates a more positive tone regarding economic conditions.[16] The Fed Economic Sentiment time series are plotted on the right panel of Figure 1. Without comprehension, the FES index is weakly positively correlated with the change in economic news sentiment (Shapiro et al., 2022) and business confidence since the last announcement and negatively correlated with the change in unemployment forecasts in the Survey of Professional Forecasters.

[15] The original FinBERT model was developed by Araci (2019), and is pre-trained on a large corpus of financial texts, enabling it to capture the nuanced language and sentiment commonly found in economic and financial texts.The model has proven effective in extracting sentiment from central bank documents, outperforming traditional tools such as the Loughran and McDonald dictionary and aspect-based sentiment – widely used in monetary policy analysis – as well as other machine learning approaches (Huang et al. (2022); Kim et al. (2024).

[16] Note that we remain agnostic about whether the sentiment is regarding current conditions or future expectations.

III.5 Quantifying uncertainty in text

In addition to analyzing economic and monetary policy sentiment, I quantify textual uncertainty in FOMC communications. Uncertainty in central bank language reflects ambiguity or lack of clarity about the economic outlook or policy path and has been shown to influence financial markets and perceptions of risk (Hansen and McMahon, 2016; Ying et al., 2025). Elevated uncertainty in Fed communications can affect expectations independently of sentiment or hawkish-dovish orientation, potentially raising volatility or weakening the clarity of policy signals. Controlling for textual uncertainty is therefore critical to isolate the distinct effects of sentiment and policy stance on market outcomes and macroeconomic expectations. It also helps to unravel whether market reactions are driven by tone or by the perceived lack of informational clarity in the Fed's message.

Due to the current lack of large language models (LLMs) specifically trained to quantify textual uncertainty with high reliability, this study follows the approach of Ying et al. (2025) and employs the Loughran-McDonald (LM) dictionary to calculate uncertainty in FOMC texts (Loughran and McDonald, 2011). The dictionary contains 80000+ words and abbreviations, and among other features, each word is labeled whether it conveys uncertain sentiment.

After removing stopwords, I calculate the Textual Monetary Policy Uncertainty (on monetary policy texts) and Textual Fed Economic Uncertainty (on economic texts) indices for each statement and PC through the following formulae:

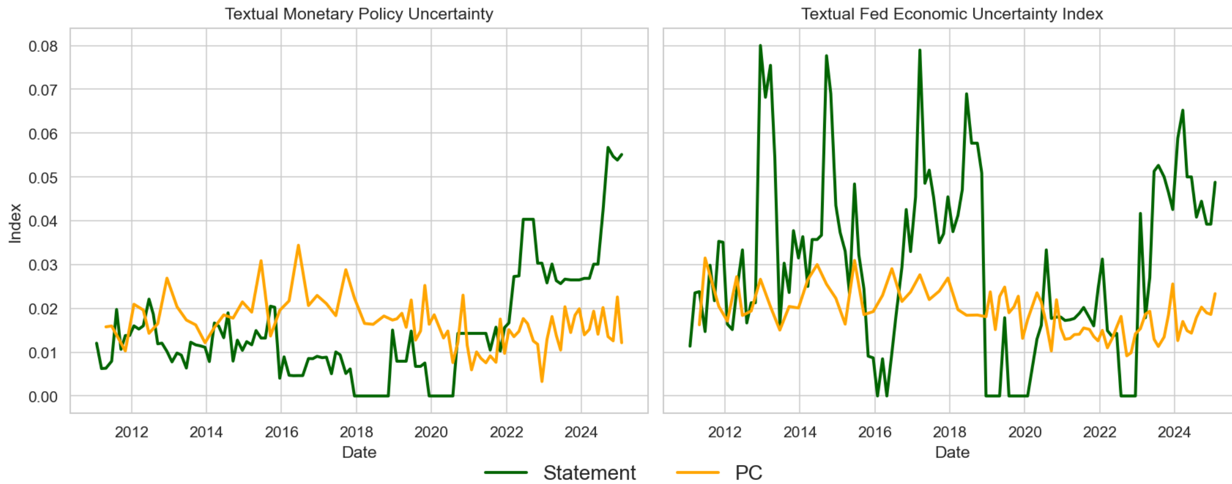
$$\text{TMPU} = \frac{\#\text{Uncertain Words}_{MP}}{\#\text{All Words}_{MP}},$$

$$\text{TFEU} = \frac{\#\text{Uncertain Words}_{EC}}{\#\text{All Words}_{EC}},$$

where #Uncertain Words denotes the number of words that carry uncertain sentiment according to the LM dictionary, and #Total Words is the number of words in the given PC transcript/statement, excluding stopwords.

Textual Monetary Policy Uncertainty (TMPU) and Textual Fed Economic Uncertainty (TFEU) indices are shown in Figure 2. TMPU in statements has reached historically elevated levels

Figure 2: Textual Uncertainty in FOMC statements and press conferences



Notes: This figure presents two indices of textual uncertainty derived from FOMC statements and press conferences. The left panel shows the Textual Monetary Policy Uncertainty (TMPU) index, while the right panel displays the Textual Fed Economic Uncertainty (TFEU) index. Both indices are constructed using the Loughran and McDonald (LM) dictionary, based on the frequency of uncertainty-related terms in each document, stopwords excluded. The green line represents statements, and the orange line corresponds to press conference transcripts. Higher values indicate greater uncertainty expressed in the respective communication channel.

since 2022, while TFEU declined between 2019 and 2022 before rising again more recently. Press conferences under Chair Powell (since 2018) exhibit slightly lower levels of uncertainty in both dimensions compared to those under his predecessors. Notably, TMPU measures in both statements and press conferences are strongly correlated with the hidden dissent index derived from FOMC Minutes (Tsang and Yang, 2024; $r = 0.40$ and $r = 0.42$, respectively), suggesting that greater internal disagreement between FOMC members is associated with more uncertain communication. In addition, TMPU is strongly correlated with market-based measures of monetary policy uncertainty as in Bauer et al. (2022), with correlations of 0.75 (statements) and 0.80 (press conferences).

In contrast, TFEU does not exhibit strong intuitive correlations. While it is weakly positively associated with forecast disagreement among FOMC members (measured as the range between the highest and lowest projections for inflation and unemployment), it shows weak and negative correlations with broader indicators such as the VIX and the Economic Policy Uncertainty index (Baker et al., 2016).

IV Voice tone analysis

To capture the impact of beyond-words communication on FOMC press conferences, I analyze the emotions in the voice of chairs during press conferences. As of my knowledge, Gorodnichenko et al. (2023) were the only authors to conduct similar analysis on FOMC press conferences. They find that positive emotions in the chair's voices at FOMC press conferences lead to large and significant increases in share prices. My aim is to try to validate their surprising result with deep learning models different from those used in their paper.

My approach differs from that of Gorodnichenko et al. (2023) in one important way. They train a neural network based on manually extracted specific features - such as frequency and amplitude - from the waveform audio representations of emotional speech datasets TESS and RAVDESS. In contrast, I apply pre-trained models available on the Hugging Face platform, specifically those based on the Wav2Vec 2.0 architecture, which was developed by Facebook AI Research (Baevski et al., 2020). This architecture, designed to improve speech recognition quality through self-supervised learning, has been shown to achieve better performance than non-Wav2vec models in various speech tasks, including emotion recognition (Wang et al., 2022; Pepino et al., 2021).

IV.1 Speech data

Official videos of FOMC press conferences are available on the Federal Reserve's YouTube channel. To isolate the chair's voice, all FOMC press conferences from April 2011 to January 2025 are manually timestamped to identify segments where the chair was holding the opening statement or answering a press question. This task was carried out with the help of four fellow students.[17] Opening statements typically include prepared remarks that summarize recent decisions in economic and monetary policy. Q&A responses consist of unscripted responses to the questions posed by the press. I ensure that only the chair's voice is audible during the time-stamped intervals. I download the audio for all PCs and extract segments corresponding

[17] I extend my gratitude to Ádám Balogh, Flóra Flink, Eszter Nagy, and Anna Szőnyi for their contributions.

to the recorded timestamps using the librosa package (McFee et al., 2015) in Python.

Table 3 contains summary statistics for the voice segments extracted in the described way. Chair Yellen's press conferences were characterized by long opening statements and less but longer Q&A answers compared to Chair Bernanke and Chair Powell. Chair Powell's conferences in the past seven years include shorter and more concise responses, and considerably more questions per conference than previous events.

Table 3: Summary statistics of speech segments

Chair	**Type**	**Number**	**Mean length (sec)**
Ben Bernanke	Opening statements	12	560
	Q&A answers	261	96
Janet Yellen	Opening statements	16	777
	Q&A answers	296	113
Jerome Powell	Opening statements	54	464
	Q&A answers	1334	73
Total	Opening statements	82	539
	Q&A answers	1891	82

Notes: This table presents summary statistics for speech segments extracted from FOMC press conferences held between April 2011 and January 2025. Each chair's speaking time is divided into two categories: *Opening statements*, which consist of prepared statements typically outlining recent monetary policy decisions and economic assessments; and *Q&A Answers*, which include spontaneous verbal responses to questions posed by members of the press. These categories are manually timestamped to ensure that only the Chair's voice is included, and that overlapping or unclear speech is excluded. Source of audio data: Federal Reserve YouTube Channel

IV.2 Speech Emotion Recognition using Wav2vec 2.0

Recent advancements in Speech Emotion Recognition (SER) use deep learning techniques to extract emotional signals from raw audio data. These techniques utilize end-to-end structures that learn expressive representations directly from waveforms of audio files.

In this paper, I employ the Wav2vec 2.0 architecture developed by Facebook AI (Baevski et al., 2020). Wav2vec 2.0 is a state-of-the-art framework for speech representation learning. The model consists of a multi-layer convolutional (CNN) feature encoder that transforms raw waveform audio into latent speech representations.[18] During pretraining, spans of these latent

[18]This essentially means that the model's input is a one-dimensional array representing the raw audio waveform, which is subsequently encoded to capture relevant features. As a result, there is no need for prior feature extraction (e.g., pitch, volume) before entering the audio into the model.

features are masked, following a masked modeling strategy similar to the one used in BERT (Devlin et al., 2019). The masked representations are then passed to a Transformer network, which builds contextualized embeddings over the full sequence. The model is trained with a contrastive loss, where some parts of the input are masked, and the model learns to predict the masked parts by distinguishing between the true representation and distractors. Baevski et al. (2020) published several versions of Wav2vec 2.0 models trained on unlabeled or labeled data. The Wav2vec 2.0 Base model consists of 12 transformer layers, with 768-dimensional hidden representations and 8 attention heads. In contrast, the Wav2vec 2.0. Large model is deeper and more expressive, using 24 transformer layers, 1024-dimensional representations, and 16 attention heads.

Fine-tuning Wav2vec 2.0 models for speech emotion recognition involves adapting the pre-trained model — originally trained to capture general speech patterns — to the specific task of identifying emotional states in speech. This is typically done by adding a lightweight classification head on top of the model's transformer-based architecture, allowing it to map speech embeddings to discrete emotion categories. Fine-tuned Wav2vec 2.0 models have demonstrated efficacy in Speech Emotion Recognition, outperforming conventional models on benchmark datasets including IEMOCAP and RAVDESS (Pepino et al., 2021).

To assign emotions to FOMC audio segments, I use three models based on Wav2vec 2.0 Base that have been fine-tuned for emotion recognition. I opt for Wav2vec 2.0 Base models, as they can outperform Wav2vec 2.0 Large models on SER tasks, while also offering the advantage of significantly lower computational and memory requirements (Pepino et al., 2021). The three models employed in this paper are available at the AI community platform Hugging Face:[19]

- Yang et al. (2021) fine-tune the Wav2vec 2.0. Base on the IEMOCAP speech emotion dataset, achieving 63.43% out-of-sample accuracy.
- Gautam (2024) fine-tune on four SER datasets (TESS, RAVDESS, CREMA-D, SAVEE), achieving 0.80 as accuracy score, and 0.79 as Macro F1 Score.

[19]The models are selected based on citations and reported evaluation metrics, and are available on the following URLs at Hugging Face:
https://huggingface.co/superb/wav2vec2-base-superb-er,
https://huggingface.co/Dpngtm/wav2vec2-emotion-recognition,
https://huggingface.co/DunnBC22/wav2vec2-base-Toronto_emotional_speech_set.

- Dunn (2023) employs the TESS dataset and realizes 88% accuracy on their test set.

IV.3 Voice Tone Score

To extract emotional content from press conference audio, each segment—either the introductory remarks or individual Q&A responses—is processed in three steps:

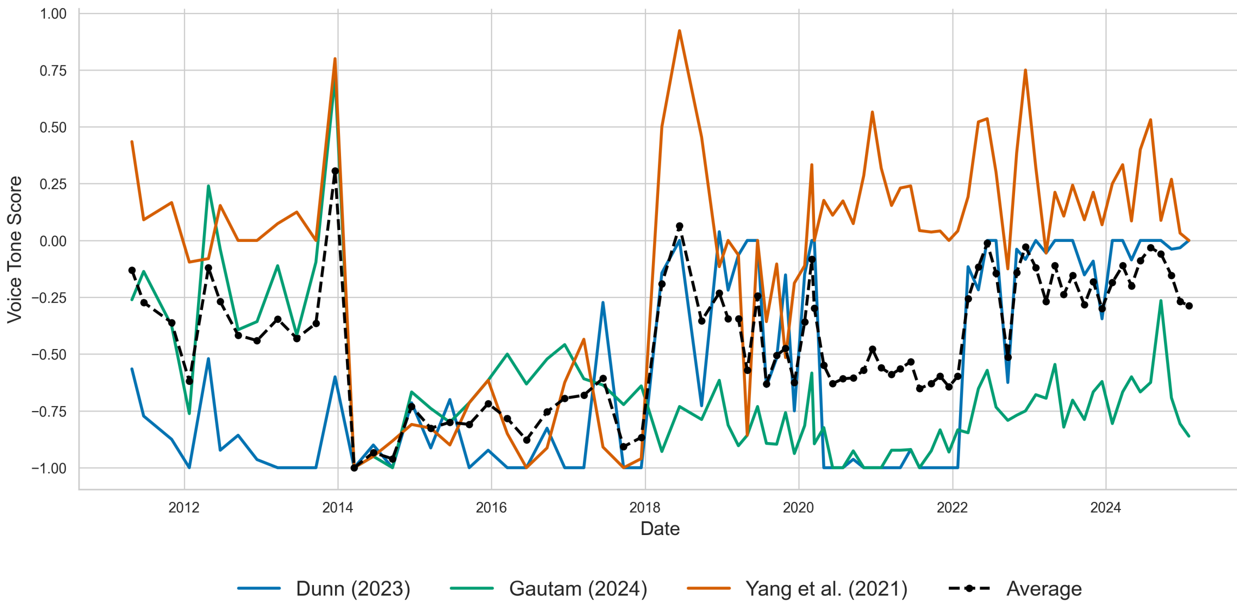
1. Each audio segment is divided into sub-segments lasting no more than 60 seconds. This is necessary as the models are trained on short, less-than-a-minute audio files.
2. Emotion recognition models are applied to each sub-segment, and predicted class probabilities are averaged across all sub-segments within the segment.
3. The emotion with the highest average probability is assigned to the full segment.

To construct a conference-level Voice Tone Score (VTS), predicted emotions are grouped into positive, neutral, and negative categories. While all models include a ”neutral” class, the other emotion labels differ slightly. The following mapping is applied: ’happy’, ’pleasantly surprised’, and ’calm’ are classified as positive, while ’angry’, ’disgust’, ’fear’ and ’sad’ are classified as negative. The VTS for each conference is then computed as:

$$\text{VTS} = \frac{\#\text{Positive segments} - \#\text{Negative segments}}{\#\text{All segments}}$$

Figure 3 plots the VTS derived from the three models, along with their average. Notably, the average tone is consistently negative throughout the sample, and Chair Yellen’s presidency between 2014 and 2018 is characterized by the most negative tone. The average VTS is modestly correlated (0.16) with the tone measure in Gorodnichenko et al. (2023). To avoid model selection bias, I rely on the average VTS throughout the paper and refer to it simply as the Voice Tone Score.

Figure 3: Voice Tone Scores across different SER models



Notes: The figure shows Voice Tone Scores calculated from FOMC press conference audio files, based on three different Speech Emotion Recognition models. The lines correspond to VTS calculated based on the SER models of Dunn (2023), Gautam (2024) and Yang et al. (2021) and the simple average across all three models. Higher values indicate a more confident or positive tone, while lower values reflect a more cautious or negative tone.

V Measuring surprises in FOMC communication

FOMC verbal and non-verbal communication tones are most likely endogenous to the prevailing economic and financial conditions. For example, as seen in Section III.3, the Hawkish-Dovish-Sentiment index is correlated with the level of the Fed Funds Rate and the change in economic conditions in the near past. Since my objective is to assess whether FOMC tone induces surprises in financial markets, it is essential to isolate the component of tone that is unexpected. The predictable component of the tone may already be incorporated into asset prices, and thus carry limited informational value. Moreover, even if the level of the FOMC tone remains unchanged between meetings, changing macroeconomic conditions can cause market participants to interpret the same tone differently (Hubert and Labondance, 2021). For example, a status quo policy decision (tone) in worsening economic conditions will likely be interpreted as a contractionary monetary policy (tone) shock.

Therefore, similarly to Hubert and Labondance (2021) and Schmeling and Wagner (2025), I isolate the unexpected component of the verbal and non-verbal tone indices, unexplained by prior economic and financial conditions, which I refer to as the tone shock / tone surprise. Tone shocks capture deviations from what market participants expected given the current economic conditions and recent developments. An HDS surprise can be viewed as FOMC's intentional verbal signal on the shift of its monetary policy position. From the markets's perspective, an HDS surprise can also be interpreted as a policy mistake of the Fed, as it diverges from the markets' estimated appropriate monetary policy stance. An FES shock may indicate the release of FOMC's private economic information previously unknown to market participants. Surprises in TMPU and TFEU indicate shifts in the clarity of language regarding monetary policy actions and economic assessments.

To identify tone surprises in FOMC statements and press conferences, I build on the methodology of Hubert and Labondance (2021), who carry out the same task for FOMC statements. For statements, I construct tone surprises in the four textual indices. For press conferences, tone surprises are derived from all five verbal and non-verbal communication tone indices introduced in Section III.

$$\text{Tone}_t^{ST} = \alpha + \beta_1 \,\text{Tone}_{t-1}^{ST} + \beta_2 \,\text{Tone}_{t-1}^{PC} + \beta_3 \,\mathbf{X_{t-1}} + \beta_4 \,\Delta\mathbf{Z_{t/t-1}} + \varepsilon_{\text{Tone}_t}^{ST} \tag{1}$$

$$\text{Tone}_t^{PC} = \alpha + \beta_1 \,\text{Tone}_t^{ST} + \beta_2 \,\text{Tone}_{t-1}^{PC} + \beta_3 \,\mathbf{X_{t-1}} + \beta_4 \,\Delta\mathbf{Z_{t/t-1}} + \beta_5 \,\Delta\mathbf{X_{t/t-1}} + \varepsilon_{\text{Tone}_t}^{PC} \tag{2}$$

Equation (1) illustrates the estimation of tone surprises in FOMC statements. Tone_t^{ST} denotes the level of a given tone index in the statement on announcement day t. I regress this on the tone of the previous FOMC statement at $t-1$ and, if applicable, the tone of the preceding press conference at $t-1$. The control matrix $\mathbf{X_{t-1}}$ includes the policy variables observed on the previous FOMC date, that is, the Federal Funds Rate, news to unconventional monetary policies, as well as the level and dispersion of FOMC forecasts in the latest SEP release. The matrix $\Delta\mathbf{Z_{t/t-1}}$ captures changes in key financial and macroeconomic indicators between the previous statement date ($t-1$) and the day before the current FOMC statement. In detail, $\mathbf{Z_t}$ includes the VIX, Economic Policy Uncertainty of Baker et al. (2016), Economic News Sentiment of Shapiro et al. (2022), United States Business Confidence of OECD, the St. Louis FRED Financial Stress index, and the dispersion and median in the 4-quarters ahead unemployment, growth forecasts and 1- and 5-year ahead inflation forecasts of the Survey of Professional Forecasters, released quarterly. Table 12 in the Appendix contains descriptions of the variables used and their respective sources.

Equation (2) outlines the estimation of tone surprises in FOMC press conferences. Each tone variable is regressed on its own lag from the preceding statement and press conference. The sets of controls in $\mathbf{X_{t-1}}$ and $\Delta\mathbf{Z_{t/t-1}}$ are exactly the same as in Equation (1). Additionally, $\Delta\mathbf{X_{t/t-1}}$ captures changes in the Fed Funds Rate and unconventional monetary policy stance between FOMC events, reflecting the idea that the tone of the press conference may respond to the decisions announced earlier the same day.

The residuals $\varepsilon^{ST}_{\text{Tone}}$ and $\varepsilon^{PC}_{\text{Tone}}$ correspond to the unexpected component of tone variables. Table 4 reports the R^2 values for all specifications, showing that tone is significantly predictable from observable variables. This highlights the need to focus on tone surprises rather than tone levels. Interestingly, the predictable component is larger for statements than for press conferences, suggesting that the conference tone is more likely to deviate from expectations.

Table 4: Explained portion of FOMC communication tone indices

Event	Statistics	*HDS*	*FES*	*TMPU*	*TFEU*	*VTS*
Statements	R^2	0.51	0.56	0.89	0.66	—
	Adjusted R^2	0.42	0.48	0.87	0.59	—
	p-value	0.00	0.00	0.00	0.00	—
Press conferences	R^2	0.43	0.39	0.39	0.61	0.61
	Adjusted R^2	0.23	0.19	0.17	0.49	0.48
	p-value	0.01	0.03	0.04	0.00	0.00

Notes: This table reports model fit statistics from regressions estimating tone surprises in FOMC statements anc press conferences, as defined in Equations (1) and (2). The five indices—Hawkish-Dovish Sentiment (HDS), Fed Economic Sentiment (FES), Textual Monetary Policy Uncertainty (TMPU), Textual Fed Economic Uncertainty (TFEU), Voice Tone Score (VTS) — are regressed on prior tone, FOMC policy stance, and recent changes in economic, and financial variables. Reported p-values are from F-tests of joint significance for the explanatory variables.

Descriptive statistics of the identified tone shocks are reported in Appendix Tables 13 and 14. Statement tone shocks exhibit substantially larger standard deviations than their press conference counterparts. This reflects the nature of the tone measurement methodology: press conference shocks are derived from a much larger volume of text—approximately 40 times more—resulting in smoother, less volatile measures. Accordingly, direct comparisons of magnitudes between statement and press conference tone shocks are not meaningful. Notably, the correlation between statement and subsequent press conference tone shocks is close to zero, suggesting that the chair does not systematically reinforce or offset the tone conveyed in the statement during the press conference.

VI Measuring surprises in asset prices

In this section, I first describe the methodology used to measure high-frequency changes in asset prices around FOMC statements and press conferences. While examining the direct impact of tone shocks on asset prices is informative, it does not reveal the underlying mechanisms driving these responses. To address this, Section VI.2 outlines the identification strategy used to isolate structural components of surprises in asset price movements.

VI.1 Changes in asset prices

To measure high-frequency changes in asset prices, I follow Cieslak and Schrimpf (2019) and focus on five instruments: changes in 2-, 5-, and 10-year Treasury note futures, E-mini S&P 500 futures, and VIX futures. Futures markets are highly liquid, making them well-suited for capturing immediate market responses. One-minute tick data are obtained from FirstRate Data.

Between 2011 and 2012, FOMC statements were released at 12:30 PM EST on days when a press conference was scheduled, which began at 2:15 PM EST. On non-conference days, statements were released at 2:15 PM EST. Since 2013, the standard schedule has been a 2:00 PM statement release, followed by a press conference starting at 2:30 PM EST. For FOMC statements, I measure price changes from 10 minutes before to 20 minutes after the release; for press conferences, I use a window from 10 minutes before the start until 20 minutes after the end of the conference.

Price changes are computed as log differences. For bond futures, these are scaled by the negative of their duration to approximate yield changes. Duration estimates are obtained from Bloomberg at the daily frequency, using futures-equivalent duration based on notional amounts. Descriptive statistics are reported in Appendix Tables 15 and 16. Notably, asset price changes around press conferences show both higher standard deviations and greater absolute means, suggesting that press conferences are a significant channel for monetary policy communication.

VI.2 Estimating structural shocks

To identify structural surprises generated on FOMC announcement days, I implement the methodology of Cieslak and Pang (2021). The benefit of employing their methodology instead of relying only on simple changes in asset prices is that it allows me to analyze asset-price surprises with structural interpretation. For example, consider the changes in long-term bond yields and stock prices after FOMC announcements. They may emerge from a combination of various types of information, including news on economic expansion, expected monetary policy, and changes in risk premiums (Cieslak and Schrimpf, 2019). An analysis limited to simple changes in stock prices and long-term rates would leave us uninformed about the type of information that influenced the reaction. By recovering pieces of information that have structural interpretation and are orthogonal to each other, we are able to analyze more closely what drives the response of asset prices on FOMC days.

In this section, I describe how I identify four interpretable structural shocks according to Cieslak and Pang (2020) and Cieslak and Pang (2021). Asset price changes are dissected into four components: changes attributable to monetary policy news, growth news, common premium news and hedging premium news. To implement the identification procedure, I use the publicly available code for Cieslak and Schrimpf (2019) and extend it to the four-variable case. Four asset price changes are used to estimate the four surprises, including the narrow-window changes in three future Treasury note yields and S&P 500 E-mini futures returns, as described in Section VI.1. Structural shocks around statements and press conferences are estimated using separate models, as the underlying dynamics are likely to differ across these two settings.

A widely used framework in asset pricing models represents transformed asset prices $\mathbf{Y_t}$ as an affine function of state variables $\mathbf{F_t}$ for each t:

$$\mathbf{Y_t} = a + \mathbf{A}\mathbf{F_t}, \quad \text{with} \quad \text{rank}(\mathbf{A}) = \text{rank}(\mathbf{F_t}), \tag{3}$$

where the state variables follow an autoregressive process:

$$\mathbf{F_t} = \mu_F + \mathbf{\Phi}\mathbf{F_{t-1}} + \mathbf{\Sigma_F}\omega_t, \quad \text{where} \quad \omega_t \sim \mathcal{N}(0, \mathbf{I}) \text{ and } \quad \mathbf{\Sigma_F} \text{ is diagonal.} \tag{4}$$

The factors in $\mathbf{F_t}$ are not directly observable, so for estimation one should make use of the observation equation, which we again assume to be an AR(1) process:

$$\mathbf{Y_t} = \mu_Y + \mathbf{\Theta}\mathbf{Y_{t-1}} + u_t \quad \text{, where } u_t \sim \mathcal{N}(0, \mathbf{\Sigma_u}). \tag{5}$$

Given that we have four observed variables and four factors in our model, $\mathbf{Y_t}$, $\mathbf{F_t}$, ω_t and u_t are 4×1 vectors, while $\mathbf{A}$, $\mathbf{\Phi}$, $\mathbf{\Sigma_F}$, $\mathbf{\Sigma_u}$ and $\mathbf{\Theta}$ are 4×4 matrices. In our setting, $\mathbf{Y_t} = (\Delta 2Y_t, \Delta 5Y_t, \Delta 10Y_t, \Delta S\&P_t)'$, the narrow window changes in asset prices around statements or PCs. Residuals ω_t are called structural-form residuals. These are orthogonal to each other, each of them affects only one factor contemporaneously, making it possible to be given economic interpretation. u_t meanwhile are called reduced-form residuals, which are potentially correlated with each other and have no straightforward interpretation. Combining equations (3)-(5), we have the following relationship between reduced-form and structural-form residuals:

$$u_t = \tilde{\mathbf{A}}\omega_t, \quad \text{where} \quad \tilde{\mathbf{A}} = \mathbf{A}\mathbf{\Sigma_F}. \tag{6}$$

Let us note that $\tilde{\mathbf{A}}$ directly captures how structural shocks ω_t affect $\mathbf{Y_t}$. Although there are an infinite number of different $\tilde{\mathbf{A}}$ and ω_t that would provide consistent results in the system, by imposing restrictions on $\tilde{\mathbf{A}}$ - that match how we expect these structural shocks to affect $\mathbf{Y_t}$ - we can reduce the set of possible solutions to economically meaningful ones.

What shocks do we consider economically meaningful? As described in Section II.2, we aim to explain announcement day shocks by four factors: monetary news, growth/economic news, common premium news and hedging premium news. Cieslak and Pang (2021) show evidence from empirical asset pricing to justify the following restrictions.

Sign restrictions:

1. A positive growth news ω_t^g raises stock prices and yields, consistently with the information shocks of monetary policy described by Nakamura and Steinsson (2018) and Jarociński and Karadi (2020). This response reflects improved expectations about future economic activity, which boosts anticipated earnings for equities and anticipates an upward revision in the expected path of interest rates.

2. A positive monetary news shock ω_t^m raises yields and lowers stock prices. This is intuitive as positive monetary news signal a rise in current and expected risk-free rates.

3. News indicating a rise in the common risk premium ω_t^{cp} tends to raise both equity and bond risk premia, as both asset classes are sensitive to changes in discount-rate risk. An increase in common premia results in lowered stock prices and higher bond yields.

4. An increase in the hedging premium ω_t^{hp} raises equity premia while lowering bond premia, since bonds serve as a hedge against stock cash-flow risk.

Between-asset restrictions:

1. The impact of monetary news decreases with the maturity of the yield curve. This is consistent with the standard expectation hypothesis.

2. The opposite holds for common and hedging risk premium news. Their effect increases with the maturity of yields, as the term premium part of yields grows compared to the expectations component, amplifying the sensitivity of longer-term bonds to such news.

3. Growth news has larger effects on short-to-intermediate maturity yields than long-term yields, as they primarily influence mid- and short-term growth expectations and expectations about the path of monetary policy.

To apply these restrictions on $\tilde{\mathbf{A}}$, I follow four steps, based on Cieslak and Pang (2021) who implement the Householder algorithm described in Kilian and Lütkepohl (2017, Ch. 13).

1. Take the Cholesky decomposition of the covariance matrix of reduced-form shocks u_t. $\mathbf{\Sigma_u} = \mathbf{PP'}$, where $\mathbf{P}$ is lower triangular. Then u_t can be written as $u_t = \mathbf{P}\omega_t^*$, where ω_t^* is a set of uncorrelated shocks, where $\omega_t^* \sim \mathcal{N}(0,1)$ (Kilian and Lütkepohl, 2017, Ch. 13).

2. ω_t^* shocks are recursively identified and have no useful interpretation to us. However we can obtain an identical set of reduced-form shocks by having an orthonormal rotation matrix $\mathbf{Q_i}$, which satisfy $\mathbf{Q_i'Q_i} = \mathbf{I}$, and therefore

$$u_t = \mathbf{PQ_i'Q_i}\omega_t^*. \tag{7}$$

   Since $\mathbf{Q_i}\omega_t^*$ shocks are still uncorrelated, they are candidates for our structural shocks. Combining equations 6 and 7, we arrive at $\tilde{\mathbf{A}} = \mathbf{PQ_i}$ and $\omega_t = \mathbf{Q_i}\omega_t^*$, meaning the restrictions we want to see on $\tilde{\mathbf{A}}$ can be directly applied to $\mathbf{PQ_i}$ and $\omega_t = \mathbf{Q_i}\omega_t^*$ will be our structural shocks.

3. Next, we simulate $\mathbf{Q_i}$ rotation matrices following Rubio-Ramirez et al. (2010) via QR decomposition. We keep 1000 different $\mathbf{Q_i}$ matrices for which the restrictions on $\mathbf{PQ_i}$ are satisfied.

4. From our 1000 possible solutions for ω_t we take the median target (MT) solution (Fry and Pagan, 2011).

The structural shocks identified above exhibit empirically consistent properties in Cieslak and Pang (2020). Growth shocks are closely associated with real GDP forecast revisions, while monetary policy shocks correlate strongly with measures from Gürkaynak et al. (2005)

and Swanson (2021). Shocks to common and hedging premia align with known patterns in bond and equity risk premia indices.

The presently identified shocks also show favorable external validity. Statement-related growth shocks correlate at 65% with the information shocks of Jarociński and Karadi (2020), while monetary policy shocks show an 88% correlation with the target surprise measure of Bauer and Swanson (2023).

In theory, heightened monetary policy uncertainty (MPU) should raise required risk compensation for holding Treasuries that are subject to discount rate risks, reflected in higher common premia. Empirically, the common premium shocks around statements and press conferences exhibit 48% and 63% correlation, respectively, with two-day changes in MPU around FOMC days, as measured by Bauer et al. (2022). In contrast, a higher MPU can increase the demand for hedging assets, compressing the hedging premium. This is supported by the data, as two-day MPU changes are negatively correlated with hedging premium shocks (-0.13 and -0.47).

Table 5 reports the results of the historical variance decomposition of the asset price changes into structural shocks. Monetary news is the dominant source of market reactions in our event windows, as expected. However, premium shocks account for more than 50% of variation in ten-year yield changes, and explain a significant portion of changes in equity prices. When comparing the two premiums, common premium shocks seem to be more dominant drivers of asset prices than hedging premium shocks at both events, especially around statements.

VII Do tone surprises cause asset price surprises?

I now turn to the central question of the paper: How do different dimensions of verbal and non-verbal tone surprises affect asset prices? As an illustrative example, Figure 4 plots the average cumulative return on E-mini S&P 500 futures on FOMC announcement days, separated into days when Fed Economic Sentiment surprises were positive or negative in both the statement and the press conference.

Days characterized by positive FES surprises tend to end with higher overall equity returns.

Table 5: Variance decomposition of statement and press conference asset price changes

(a) Statement changes					**(b) Press conference changes**				
	ω_t^{mp}	ω_t^{g}	ω_t^{cp}	ω_t^{hp}		ω_t^{mp}	ω_t^{g}	ω_t^{hp}	ω_t^{cp}
Δ2Y	0.62	0.25	0.11	0.02	Δ2Y	0.63	0.24	0.09	0.04
Δ5Y	0.35	0.24	0.34	0.07	Δ5Y	0.44	0.16	0.24	0.16
Δ10Y	0.29	0.14	0.38	0.20	Δ10Y	0.33	0.13	0.32	0.22
ΔS&P	0.52	0.11	0.24	0.14	ΔS&P	0.56	0.08	0.24	0.11

Notes: Each cell reports the share of explained variance in narrow window asset price changes on FOMC days attributable to each of the four structural shock dimensions: monetary policy (ω_t^{mp}), growth (ω_t^{g}), common premium (ω_t^{cp}), and hedging premium (ω_t^{hp}). Results are reported separately for statement and press conference windows.

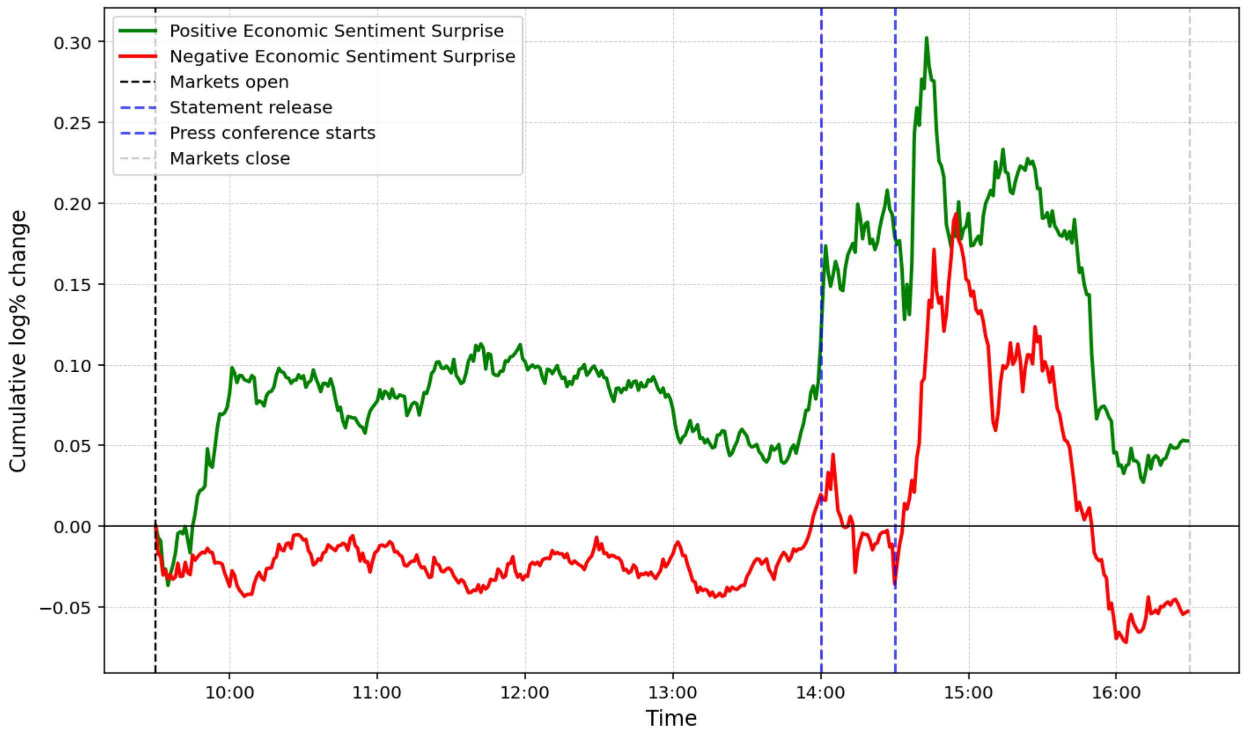
There is some indication that these surprises are at least partially anticipated, as reflected in marginally higher returns even before the announcement. Around the statement release, one can observe a notable jump in returns, consistent with markets reacting to unexpected positive tone. At the beginning of the press conference, there is also an unconditional increase, although this effect appears to even out over time. On average, days with positive tone surprises close with cumulative returns roughly 10 basis points higher than their negative counterparts.

That said, Figure 4 should be interpreted with caution. The observed return patterns may be confounded by prevailing macroeconomic conditions, current monetary policy actions and surprises in other tone dimensions. While the plot is suggestive, it does not offer conclusive evidence of causal relationships.

In this section, I formally test whether the identified multi-dimensional tone shocks have causal effects on asset prices. I investigate statements and press conferences separately to account for their potentially distinct informational roles.

In both of the following subsections, I begin by assessing whether asset prices respond to tone surprises, beyond the numerical information released on the day. Upon finding meaningful effects, I then investigate the channels through which these effects operate, by focusing on the structural asset price shocks identified in the previous section.

Figure 4: Cumulative returns of S&P 500 futures on FOMC day with positive or negative economic sentiment surprises



Notes: This figure shows the average cumulative log% returns of E-mini S&P 500 futures on FOMC announcement days when press conferences were held. FOMC days prior to 2013 are excluded due to differences in the timing of statement releases and press conferences. The green (red) line represents average cumulative returns on days when both the statement and the press conference conveyed a positive (negative) surprise in Federal Economic Sentiment, as identified in Sections III and V. All times are shown in Eastern Standard Time (EST).

VII.1 Statement surprises

Equation (8) outlines the regression specification used to estimate the effects of tone surprises in FOMC statements.[20] The dependent variable, ΔY_t^{ST}, denotes the change in the given asset price or structural shock within a 30-minute window around statement releases. The matrix $\Delta \mathbf{X_t}$ includes changes in numerical policy indicators released in the statement: changes in the target rate, changes in unconventional policy actions (coded as 1 if hawkish, 0, or –1 if dovish), number of dissenting votes, and changes in the longer run forecasts for inflation and unemployment if the SEP is released at announcement t. For regressions with asset

[20]The specification builds on Hubert and Labondance (2021), but extends it by incorporating multiple tone dimensions and a broader set of asset price responses.

price changes as dependent variables, I additionally control for monetary policy surprises, capturing the unexpected part of shifts in short-term interest rates.

The matrix $\mathbf{\Omega_t}$ includes controls for financial and economic conditions: the levels of Economic Policy Uncertainty, Business Confidence, the VIX, and the Fed Funds Rate.[21] Structural shocks have zero mean and unit variance by construction, while tone shocks are identified as residuals and thus have zero mean. For consistency and comparability, I standardize all variables so that they have zero mean and unit standard deviation across all regressions.

$$\Delta Y_t^{ST} = \alpha + \beta_1 \varepsilon^{ST}_{\mathrm{HDS,t}} + \beta_2 \varepsilon^{ST}_{\mathrm{FES,t}} + \beta_3 \varepsilon^{ST}_{\mathrm{TMPU,t}} + \beta_4 \varepsilon^{ST}_{\mathrm{TFEU,t}} + \beta_5 \mathbf{\Delta X_t} + \beta_6 \mathbf{\Omega_t} + \epsilon_t \tag{8}$$

The coefficients of interest are β_1, β_2, β_3 and β_4 that capture the ceteris paribus effects of tone surprises beyond numerical policy surprises and macro-financial information. Table 6 contains the estimated coefficients and standard errors when the outcome variables are asset price changes.

Table 6: Effect of statement tone surprises on asset prices

	$\Delta 2Y$	$\Delta 5Y$	$\Delta 10Y$	$\Delta S\&P$	ΔVIX
Hawkish-dovish Sentiment shock ($\varepsilon^{ST}_{\mathrm{HDS}}$)	-0.06	-0.10	-0.08	0.11**	-0.05
	[0.06]	[0.07]	[0.06]	[0.05]	[0.06]
FED Economic Sentiment shock ($\varepsilon^{ST}_{\mathrm{FES}}$)	0.09*	0.12*	0.14*	0.13**	-0.12*
	[0.05]	[0.07]	[0.07]	[0.06]	[0.06]
Textual MPU shock ($\varepsilon^{ST}_{\mathrm{TMPU}}$)	-0.03	-0.05	-0.05	0.05	-0.09
	[0.06]	[0.08]	[0.08]	[0.06]	[0.07]
Textual Economic Uncertainty shock ($\varepsilon^{ST}_{\mathrm{TFEU}}$)	-0.02	-0.02	-0.01	0.02	0.02
	[0.04]	[0.08]	[0.03]	[0.02]	[0.04]
R-squared	0.76	0.51	0.44	0.69	0.50
N	112	112	112	112	112

Notes: This table reports standardized OLS regression coefficients where the dependent variables are yield changes in 2-Year, 5-year, 10-year Treasury Note Futures (CBOT) and returns in E-mini S&P500 Futures and VIX Futures, measured in -10, +20 minutes window around statement releases. The specification corresponds to Equation (1), from which coefficient β_1-β_4 are reported. Independent variables are four tone surprise dimensions extracted from FOMC statements. Control variables are indicators of macroeconomic and FOMC policy stance, and changes in economic and financial conditions since the last announcement day, listed in Appendix Table 12. All models use heteroskedasticity-robust standard errors (HC1). Standard errors are in brackets. * p<0.1, ** p<0.05, *** p<0.01.

[21] Detailed descriptions and data sources are provided in Appendix Table 12.

A surprise in the Fed's economic sentiment has broad effects across financial markets (second row). A positive (negative) surprise — signaling a better (worse) than expected economic outlook — raises (lowers) equity returns and bond yields, while decreasing (increasing) the VIX. For instance, a one standard deviation positive sentiment shock increases S&P 500 futures by 0.13 standard deviations (approximately 6 basis points). These findings are consistent with prior works. Schmeling and Wagner (2025) show that a positive tone surprise in ECB communication increases stock prices and interest rates in. Similarly, Picault and Renault (2017) document declines in the VSTOXX (the "European VIX") following announcements with a positive tone on euro area economic outlook. For the FOMC, Hubert and Labondance (2021) find that positive (negative) tone in statements is associated with increases (decreases) in short-term yields. Chau et al. (2025) show that optimistic Fed tone reduces option-implied volatility and risk aversion.

Surprises in hawkish-dovish sentiment also have significant effects on equities (first row). A one standard deviation hawkish tone shock raises E-mini S&P 500 futures by 0.11 standard deviations (around 5 basis points).

Why would a hawkish (a.k.a. tightening) tone boost risky assets, like stocks? This phenomenon has recently received attention in the literature. Two main views attempt to explain it, represented by Cieslak and McMahon (2023) and Parle (2022).

Parle (2022) argue that the ECB reveals "private information" about the economy via its hawkish-dovish stance. Markets may interpret hawkish (dovish) communication as good (bad) news about the future state of the economy, rather than as a signal of tighter (looser) future monetary policy. This perspective aligns with the literature on central bank information effects (Nakamura and Steinsson, 2018; Jarociński and Karadi, 2020), where asset price reactions reflect the perceived economic outlook embedded in central bank policy signals.

In contrast, Cieslak and McMahon (2023) offer a risk-based explanation. They argue that a hawkish (dovish) tone may decrease (increase) risk premia in asset prices. Consequently, a decrease (increase) in risk premia results in higher (lower) stock returns. They propose empirical evidence on this phenomenon, based on the theoretical model of Caballero and Simsek (2022), where the Fed and the markets disagree on the appropriate monetary policy stance, and the markets will price a "policy-mistakes" premium. Cieslak and McMahon (2023) argue that a too dovish tone can be interpreted by markets as a "policy mistake", signaling markets that the Fed is unwilling to stabilize markets in the future, resulting in higher risks of overheating the economy. A higher uncertainty is then priced in higher risk premiums on both stocks and bonds, i.e. the common premium. An excess hawkish tone can, on the other hand, stabilize risk premia.

To decide between the two proposed explanations, the structural shocks come in handy. If the rise in stock prices after a hawkish tone surprise is attributable to a perceived positive information about the economy, one would expect to see HDS shocks inducing growth shocks, which primarily operate through short- or mid-term future expectations. However, if the response of stock prices is transmitted through risk-taking channels, one would expect to see a drop in discount rate risk premia after excess hawkishness.

Table 7: Effect of statement tone surprises on structural shocks

	ΔMP	ΔG	ΔCP	ΔHP
Hawkish-dovish Sentiment shock ($\varepsilon^{ST}_{\text{HDS}}$)	0.18	-0.01	-0.19***	-0.11
	[0.11]	[0.11]	[0.07]	[0.08]
FED Economic Sentiment shock ($\varepsilon^{ST}_{\text{FES}}$)	-0.01	0.13	-0.00	-0.24**
	[0.07]	[0.10]	[0.09]	[0.11]
Textual MPU shock ($\varepsilon^{ST}_{\text{TMPU}}$)	-0.00	-0.01	-0.09	-0.03
	[0.10]	[0.10]	[0.09]	[0.11]
Textual Economic Uncertainty shock ($\varepsilon^{ST}_{\text{TFEU}}$)	0.01	-0.03	-0.03	-0.04
	[0.09]	[0.10]	[0.10]	[0.14]
R-squared	0.19	0.15	0.22	0.19
N	112	112	112	112

Notes: This table reports standardized OLS regression coefficients where the dependent variables are monetary policy surprises ($\omega^{mp} = \Delta$ MP), growth surprises($\omega^{g} = \Delta$ G), common premium surprises ($\omega^{cp} = \Delta$ CP) and hedging premium surprises ($\omega^{hp} = \Delta$ HP) in a [-10,+20] window around the FOMC statement release, identified in Section VI.2. The regression specification corresponds to Equation (1), from which coefficient β_1-β_4 are reported. Independent variables are four tone surprise dimensions extracted from FOMC statements. Control variables are indicators of macroeconomic and FOMC policy stance, and changes in economic and financial conditions since the last announcement day, listed in Appendix Table 12. All models use heteroskedasticity-robust standard errors (HC1). Standard errors are in brackets. * p<0.1, ** p<0.05, *** p<0.01.

Table 7 presents the estimated regression coefficients of Equation 8 on structural shocks. The first row provides clear evidence that the changes we have seen in stock prices are primarily driven by changes in the common premium. This finding supports the recent findings of Cieslak and McMahon (2023) that a hawkish (dovish) tone can lower (increase) common risk premium. Cieslak and McMahon (2023) argue that this phenomenon is mostly observable during inter-meeting periods, but my results shed light that it is present on announcement days as well.

Cieslak and McMahon (2023) argue that FOMC tone can convey a form of conditional policy commitment. A hawkish surprise may signal the Fed's readiness to tighten policy if necessary, effectively communicating a contingency plan to stabilize financial premia. Conversely, an overly dovish tone may raise concerns in markets if it suggests that the Fed is overly reactive or even behind the curve in its assessment of financial conditions. These dynamics point to a potential information asymmetry between the Fed and market participants, where markets' and Fed's views about ideal monetary policy are in disagreement, resulting in perceived "policy mistakes".

As discussed in Section V, the Hawkish-Dovish Sentiment (HDS) surprises in this paper can indeed be interpreted as policy mistakes. By construction, they reflect deviations in tone that cannot be predicted from prior FOMC communication or prevailing macro-financial conditions. This makes the identified HDS surprises an ideal tool for testing the narrative of Cieslak and McMahon (2023).

Table 7 have provided evidence that if the Fed's communication signals intentions that diverge from market expectations — e.g. when the tone is too dovish — this misalignment may lead to increased uncertainty and elevated risk premia. The results thus suggest that overly dovish surprises are not uniformly perceived as positive.

Notably, common premium is the only significant channel through which HDS affects markets around statements. An HDS shock also decreases the hedging premium and seems to induce positive monetary policy surprises as expected, but these results are statistically insignificant. The effects on growth-type shocks are essentially zero.

The second row of Table 7 shows that the effect of Fed's economic sentiment on asset prices seen in Table 6 is also primarily driven by a risk-based channel. A positive economic tone surprise decreases the hedging premium. This is consistent with previous literature that argued that a positive central bank tone in general decreases risk premia embedded in risky asset prices (Schmeling and Wagner (2025) for the ECB, Chau et al. (2025) for the Fed). The results stand in contrast to those of Hubert and Labondance (2021), who find that positive tone surprises generate growth-type shocks. While a slight, though statistically insignificant, positive effect on growth shocks can be observed, the findings suggest that even economic tone surprises operate primarily through risk-based channels. This discrepancy likely stems from differences in tone shock identification. Whereas Hubert and Labondance (2021) do not distinguish between topics discussed in FOMC statements and rely only on a net count of positive versus negative words, the approach in the present paper is more fine-grained and based on state-of-the-art large language models.

Interestingly, the textual uncertainty shocks do not have significant effects on asset prices. This finding contrasts with Hansen and McMahon (2016), who argue that central bank communication about uncertainty in economic fundamentals influences long-term yields. There are two possible explanations for this discrepancy. First, the method of identifying uncertainty — scoring the frequency of uncertain words — may lack the nuance needed to fully capture the underlying meaning. Second, textual uncertainty might not be a strong explanatory factor when other variables are controlled for. It is also possible that first-moment sentiment measures already contain information related to economic uncertainty. Future methodological improvements could aim to orthogonalize first- and second-moment textual indicators to isolate the distinct effects of textual uncertainty.

VII.2 Press conference surprises

Press conferences differ from policy statements in both format and informational content. While statements are pre-written, concise, and carefully worded to minimize ambiguity, press conferences are live and unscripted. This setting allows for more elaboration on particular policy considerations. Moreover, as we have seen in II.3, the tone and body language of the chair may influence market perceptions, making the press conference a qualitatively distinct communication tool. I now analyze whether verbal and non-verbal communication induce changes in asset prices and what channels these changes work through.

Equation (9) presents the regression setup used to estimate the effects of press conference communication, closely mirroring the approach employed in the previous section. Since markets may continue processing statement information during the press conference, it is essential to control for numerical changes in policy stance announced in the statement ($\Delta\mathbf{X_t}$), similarly as in Equation (8). I also experiment with including tone shocks, asset price changes, and structural shocks from the statement window in $\Delta\mathbf{X_t}$, as these effects may persist into the conference. However, they prove to be insignificant predictors, and their inclusion does not materially change the estimates of the coefficients of interest, so I omit them to preserve degrees of freedom. The vector $\mathbf{\Omega_t}$ includes the same set of controls capturing prevailing economic and financial conditions as before.[22] The main coefficients of interest are β_1–β_4, which show the ceteris paribus effects of verbal tone shocks during the press conference, and γ, which captures the impact of voice tone surprises. Note that when constructing conference tone shocks, we have already controlled for the tone in the preceding statements, so these effects purely capture the additional tone surprise compared to the statements.

$$\Delta Y_t^{ST} = \alpha + \beta_1\varepsilon^{PC}_{\text{HDS,t}} + \beta_2\varepsilon^{PC}_{\text{FES,t}} + \beta_3\varepsilon^{PC}_{\text{TMPU,t}} + \beta_4\varepsilon^{PC}_{\text{TFEU,t}} + \gamma\varepsilon^{PC}_{\text{VTS,t}} + \beta_5\Delta\mathbf{X_t} + \beta_6\mathbf{\Omega_t} + \epsilon_t \quad (9)$$

Table 8 contains the effects of PC tone shocks on asset prices based on regression (9). Although less significant, an HDS shock behaves the same way as seen in the statement window, a hawkish surprise raises equity returns and lowers the VIX, consistently with the findings of Parle (2022) and Baranowski et al. (2023) for ECB press conferences.[23] Interestingly, FES shocks lose their significance, suggesting that markets do not pay attention to the chair's economic assessments, which contradicts previous findings for ECB press conferences (e.g. Schmeling and Wagner (2025)). In general, the chair's words appear to matter less than the words of the preceding statement, suggesting that the chair largely echoes the statement's tone rather than (successfully) attempting to surprise markets.

[22] As Fed Chairs changed two times during the 14 years of the investigated time period, I also included dummies for each chair's time. However, these dummies showed no explanatory effects, even when using them as interaction variables. Therefore I omitted them to preserve degrees of freedom.

[23] Additionally, we can observe that HDS shocks show similar patters at PCs as we have seen at statements (Table 9, first row), by a hawkish (dovish) surprise (lowering) raising common risk premia). This implies that the same mechanism is applicable to chair's PC speeches, further backing the study of Cieslak and McMahon (2023).

Table 8: Effect of press conference tone surprises on asset prices

	$\Delta 2Y$	$\Delta 5Y$	$\Delta 10Y$	$\Delta S\&P$	ΔVIX
Hawkish-dovish Sentiment shock ($\varepsilon^{PC}_{\text{HDS}}$)	-0.08	-0.09	-0.10	0.15*	-0.15*
	[0.09]	[0.09]	[0.08]	[0.08]	[0.09]
FED Economic Sentiment shock ($\varepsilon^{PC}_{\text{FES}}$)	0.15	0.20	0.19	-0.16	0.12
	[0.12]	[0.13]	[0.13]	[0.12]	[0.12]
Textual MPU shock ($\varepsilon^{PC}_{\text{TMPU}}$)	-0.16	-0.10	-0.06	0.10	-0.12
	[0.10]	[0.10]	[0.10]	[0.11]	[0.12]
Textual Economic Uncertainty shock ($\varepsilon^{PC}_{\text{TFEU}}$)	-0.13	-0.15	-0.14	0.06	0.10
	[0.16]	[0.16]	[0.17]	[0.14]	[0.10]
Voice Tone shock ($\varepsilon^{PC}_{\text{VTS}}$)	-0.21**	-0.19*	-0.18*	0.22**	-0.26**
	[0.09]	[0.10]	[0.11]	[0.10]	[0.11]
R-squared	0.28	0.27	0.24	0.22	0.27
N	80	80	80	80	80

Notes: This table reports standardized OLS regression coefficients where the dependent variables are yield changes in 2-Year, 5-year, 10-year Treasury Note Futures (CBOT) and returns in E-mini S&P500 Futures and VIX Futures, measured in [-10, +20] minutes window around the duration of FOMC press conferences. The specification corresponds to Equation (2), from which coefficient β_1-β_4 and γ are reported. Independent variables are four tone surprise dimensions extracted from FOMC PC transcripts and the surprise in the Voice Tone Score. Control variables are indicators of macroeconomic and FOMC policy stance, and changes in economic and financial conditions since the last announcement day, and policy changes in the statement before the PC, listed in Appendix Table 12. All models use heteroskedasticity-robust standard errors (HC1). Standard errors are in brackets. * p<0.1, ** p<0.05, *** p<0.01.

Remarkably, voice tone shocks show strong and broad effects across asset classes. A one standard deviation positive voice tone surprise increases equity returns by approximately 17 basis points. This finding is consistent with Gorodnichenko et al. (2023), the only prior study examining the effects of vocal tone in FOMC press conferences. My results reinforce their conclusion that the tone in the Fed Chair's voice can have a substantial influence on financial markets, exceeding the informational content conveyed through the Fed's actions and words. Unlike Gorodnichenko et al. (2023), I also find a significant impact of voice tone on Treasury yields, suggesting that the mechanism which vocal cues influence markets extends beyond equity risk, affecting even traditionally safer asset classes.

Why would the tone of voice affect asset prices? Gorodnichenko et al. (2023) remain agnostic about the precise informational content of the voice tone. They suggest two mechanism that could be at work. First, they note that the effects of voice tone on assets resemble those of forward guidance, signaling a predictable path of future monetary policy. Second, they link voice tone to information effects (Romer and Romer, 2000): a confident or upbeat tone may indicate satisfaction with inflation dynamics and the pace of recovery, thereby boosting stock markets and reducing uncertainty.

Table 9: Effect of press conference tone surprises on structural shocks

	ΔMP	ΔG	ΔCP	ΔHP
Hawkish-dovish Sentiment shock ($\varepsilon^{PC}_{\text{HDS}}$)	-0.10	0.07	-0.14*	-0.01
	[0.09]	[0.09]	[0.08]	[0.09]
FED Economic Sentiment shock ($\varepsilon^{PC}_{\text{FES}}$)	0.14	-0.00	0.17	-0.06
	[0.12]	[0.13]	[0.12]	[0.13]
Textual MPU shock ($\varepsilon^{PC}_{\text{TMPU}}$)	-0.18	-0.12	0.05	-0.09
	[0.13]	[0.09]	[0.11]	[0.10]
Textual Economic Uncertainty shock ($\varepsilon^{PC}_{\text{TFEU}}$)	-0.09	-0.12	-0.05	0.06
	[0.07]	[0.08]	[0.04]	[0.11]
Voice Tone shock ($\varepsilon^{PC}_{\text{VTS}}$)	-0.23**	-0.01	-0.13	-0.02
	[0.09]	[0.09]	[0.11]	[0.13]
R-squared	0.25	0.25	0.11	0.21
N	80	80	80	80

Notes: This table reports standardized OLS regression coefficients where the dependent variables are monetary policy surprises ($\omega^{mp} = \Delta$ MP), growth surprises($\omega^{g} = \Delta$ G), common premium surprises ($\omega^{cp} = \Delta$ CP) and hedging premium surprises ($\omega^{hp} = \Delta$ HP) in a [-10,+20] window around the duration of FOMC press conferences, identified in Section VI.2. The specification corresponds to Equation (2), from which coefficient β_1-β_4 and γ are reported. Independent variables are four tone surprise dimensions extracted from FOMC PC transcripts and the surprise in the Voice Tone Score. Control variables are indicators of macroeconomic and FOMC policy stance, changes in economic and financial conditions since the last announcement day, and policy changes in the statement before the PC, listed in Appendix Table 12. All models use heteroskedasticity-robust standard errors (HC1). Standard errors are in brackets. * p<0.1, ** p<0.05, *** p<0.01.

To take a stand between the two possible explanations, Table 9 sheds light on the mechanisms behind asset price changes during PCs. The table contains OLS regression estimates of tone surprise coefficients in Equation (9), with structural shocks as dependent variables. Notably, voice tone shocks affect assets primarily by generating a monetary policy surprise. Essentially, a positive (negative) voice tone has similar effects to a monetary easing (tightening) during the press conference. A one standard deviation of tone surprise induces 0.23 standard deviation of monetary policy surprises. This suggests that the chair's voice tone carries information primarily about monetary policy stance rather than the chair's perceived economic outlook.[24]

[24] I also experimented with including interaction terms between voice tone and textual shocks, to find out whether the effect of voice tone is dependent on the sentiment of the texts being delivered. I find no significant interaction between vocal and textual shocks, suggesting that voice tone acts as an independent communication channel.

To further investigate the informational content of voice tone during FOMC press conferences, I conduct a forecasting exercise. The challenge faced by market participants in real time is to form expectations about the Fed's next policy decision. Accordingly, I test whether voice tone provides incremental predictive power for future monetary policy actions, beyond what is already captured by current economic and financial conditions, as well as the contemporaneous policy stance.

Specifically, I estimate Equation (10), which models the change in the Federal Funds Rate at announcement $t + j$ as a function of information available at time t, when the press conference takes place. The set of predictors includes the Fed's policy decisions at time t, denoted $\Delta\mathbf{X}_t$. This contains changes in the Federal Funds Rate, changes in the median and dispersion of inflation and unemployment forecasts, the number of dissenting FOMC votes, and changes in unconventional monetary policy measures at time t. To control for financial market responses, I also include the change in two-year Treasury yields and equity returns on the day of the FOMC announcement at $\Delta\mathbf{X}_t$.

$$\Delta FFR_{t+j} = \alpha + \beta_1 \varepsilon^{PC}_{\text{VTS,t}} + \beta_2 \Delta\mathbf{X_t} + \beta_3 \Delta\mathbf{Z_{t/t-1}} + \beta_4 \mathbf{\Omega_t} + \epsilon_t \tag{10}$$

Additionally, $\Delta\mathbf{Z}_{t/t-1}$ captures recent changes in broader economic conditions between announcements $t-1$ and t, such as shifts in Business Confidence, the Economic Policy Uncertainty (EPU) index, and the VIX. The vector $\mathbf{\Omega}_t$ includes level controls for these indicators, as well as the current policy rate and median projections for inflation and unemployment.

Textual tone shocks are excluded from the regression due to their negligible effect on the estimates. Furthermore, to improve model fit, I restrict the sample to the post-2014 period, omitting years in which the policy rate remained unchanged and explicit forward guidance was in place.

The significant coefficients of the estimated forecasting regression are presented in Table 10. As shown in the first row, voice tone surprises indeed contain meaningful information about future policy decisions. This is in line with the findings of Gorodnichenko et al. (2023), who suggest that voice tone may act as a form of forward guidance. Specifically, a more positive tone is associated with a higher likelihood of a rate cut at the subsequent FOMC announcement. This signaling effect diminishes with longer forecast horizons, as shown in columns 2-3.

Table 10: Forecasting power of voice tone surprises

	ΔFFR_{t+1}	ΔFFR_{t+2}	ΔFFR_{t+3}
Voice Tone shock ($\varepsilon^{PC}_{\text{VTS,t}}$)	-0.28**	0.02	-0.12
	[0.13]	[0.25]	[0.15]
Unemployment median forecast at t	-0.34**	-0.01	-0.16
	[0.15]	[0.24]	[0.21]
ΔFFR_t	0.73***	0.67***	0.43***
	[0.00]	[0.01]	[0.10]
VIX level at t	0.013***	0.01	0.02*
	[0.00]	[0.01]	[0.01]
BCI level at t	0.01**	0.00	0.01
	[0.00]	[0.01]	[0.01]
N	63	63	63
R^2	0.81	0.69	0.64

Notes: This table reports standardized OLS regression coefficients where the dependent variables are the change in the Fed Funds Rate at different horizons. Sample only contains FOMC days with PCs after 2014. Only variables that significantly explain the $t+1$ horizon are reported. Explanatory variables are information available at t: the surprise in the Voice Tone Score at time t, indicators of macroeconomic and FOMC policy stance, changes in economic and financial conditions between the last announcement and t, monetary policy surprise and equity price change on announcement day t, and policy changes at t, listed in Appendix Table 12. Standard errors are in brackets. * p<0.1, ** p<0.05, *** p<0.01.

In sum, the above findings on voice tone suggest two key insights. First, financial markets closely monitor the chair's vocal tone, responding immediately. Second, vocal tone in fact conveys information beyond the explicit hawkish or dovish content of the statement. A positive (negative) tone is an indication of an increased likelihood of monetary easing (tightening).

Explaining why voice tone transmits monetary policy signals remains a challenge. One possible interpretation is that tone serves as an implicit signal of the chair's overall assessment of the success of monetary policy. A calm and positive tone, for instance, may unintentionally convey confidence in economic conditions, which markets interpret as a sign that future policy may lean more accommodative. Alternatively, tone may be used strategically. The chair may modulate their vocal tone intentionally to manage expectations and guide market reactions. In this view, the tone becomes part of the broader communication toolkit - subtle but meaningful. Regardless of intent, the empirical evidence suggests that markets react to tone as if it contains valuable information about future policy.

VIII Conclusion

This paper has shown that both the words used in FOMC communication and the voice tone in press conferences contain valuable information for financial markets. Using advanced deep learning models, I found that different aspects of communication affect asset prices in different ways. A more hawkish (dovish) tone tends to increase (decrease) stock prices, mostly through common premia, as found in Cieslak and McMahon (2023). A better (worse) than expected economic sentiment has expansionary (contractionary) effects on markets, and this operates through changes in hedging premia. I also provide additional support for the findings of Gorodnichenko et al. (2023), showing that the voice tone of the Fed Chair during press conferences has a strong impact on equities and Treasuries and helps predict the future path of interest rates.

The results have at least three implications for future researchers in the field:

1. The findings highlight the importance of analyzing multi-dimensional information in FOMC communication. The economic sentiment and the hawkish-dovish tone of the Fed affect markets in different ways. Methods that rely on a one-dimensional indicator of tone (e.g., only count positive or negative words) may miss these important differences. In addition, ignoring one type of tone may lead to incorrect estimates of the effects of another.

2. The finding that textual sentiment surprises affect asset prices primarily through risk premium channels suggests that FOMC's tone may be an important driver of the widely documented risk-taking transmission channel of monetary policy (Borio and Zhu, 2012; Bauer et al., 2023). It seems a promising avenue for further research to explore the relationship between central bank communication, investor risk perceptions, and risk premia. While this paper shows narrow windows effects, it remains an open question

whether these effects persist beyond announcement days or whether they tend to mean-revert over time. Investigating the longer-horizon dynamics of these tone-driven shifts in risk premia would provide a deeper understanding of how monetary policy affects financial markets.

3. The results confirm that there is potential in using advanced deep learning and large language models to analyze both verbal and non-verbal central bank tone. In line with Curti and Kazinnik (2023), Gorodnichenko et al. (2023) and Alexopoulos et al. (2024), non-verbal aspects of the Fed Chair's speeches have information that can be extracted by academic research and are most likely already extracted by markets. The voice tone probably - regardless of whether it is deliberate or unintentional - already acts as an additional channel of monetary policy, with forward-looking properties similar to those of formal forward guidance. Future research should continue to explore the role of non-verbal cues in influencing macroeconomic and financial market variables.

There are also practical lessons for central bankers. It seems that markets play close attention to shifts in Fed's hawkish-dovish tone and economic evaluations beyond the policy decisions and numerical forecast information that is regularly provided. A surprise in tone can have surprising consequences: for example, a dovish surprise in the Fed's tone may not always be taken as good news - it can increase uncertainty and risk premia. Furthermore, FOMC members should be aware that markets likely respond not just to the content of their messages, but also to the tone in which they deliver them.

Disclosure of AI tools

This paper benefited from the use of AI-assisted tools, including Writefull and Quillbot AI, to improve the clarity and readability of the text. OpenAI's ChatGPT was employed in Sections III and IV to suggest coding solutions for various data transformation and data preprocessing tasks. In addition, ChatGPT was used to support the design of figures and tables throughout the paper. All AI-generated suggestions were carefully reviewed by the author. All interpretations, decisions, and final content are the sole responsibility of the author.

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A Appendix

A.1 Fine-tuning procedure

I fine-tuned transformer-based language models from the Hugging Face `transformers` library to perform text classification. This involves adapting a general-purpose pretrained model (FinBERT, BERT, RoBERTa) to the specific task by training it further on a labeled dataset. The architecture consists of a pre-trained transformer encoder with an added linear classification head, where the number of output units corresponds to the number of target categories. Text inputs were tokenized using the BERT tokenizer, by default.

Training Configuration:

Fine-tuning was carried out using the Hugging Face `Trainer` API. Table 11 contains the standard values of main hyperparameters used. I also experimented with alternative hyperparameter sets, but it did not improve the models' predictive performance.

Table 11: Hyperparameter values for fine-tuning

Hyperparameter	**Value**	**Description**
`learning_rate`	5×10^{-5}	Learning rate for the AdamW optimizer.
`epochs`	3	Number of epochs over the training set.
`batch_size`	8	Training batch size per device.
`weight_decay`	0.00	No L2 regularization used.
`warmup_ratio`	0.1	Fraction of total training steps used for linear warm-up.
`max_seq_length`	128 / 256	Maximum sequence length for input tokenization. Longer sequences are truncated. I use 256 as sequence length for the hawkish-dovish classification model as it is applied on longer texts.

Training was performed using the AdamW optimizer with a linear learning rate schedule and warm-up. Early stopping was employed to avoid overfitting, based on the cross-entropy loss function.

A.2 ChatGPT prompts

The following prompt was given to ChatGPT-4o mini to classify FOMC Minutes sentences in the test dataset into topics.

> "Discard all previous instructions. You are a financial language expert specializing in Federal Reserve communications. Your task is to classify a sentence from an FOMC statement into one of the following three categories. Respond with the category name only.
>
> 1. Monetary Policy Stance Sentences that describe the current or future path of monetary policy tools. This includes references to interest rates (e.g., the federal funds rate), quantitative easing or tightening, balance sheet policy, forward guidance, or any decisions or intentions about adjusting policy to achieve economic goals.
>
> 2. Economic Conditions Sentences that assess or describe the state of the broader U.S. or global economy. This includes mentions of inflation, employment, GDP growth, productivity, consumption, supply and demand dynamics, or international economic developments.
>
> 3. Financial Market Developments Sentences that describe financial market behavior or conditions. This includes references to stock markets, bond yields, credit conditions, liquidity, banking system stability, asset prices, or volatility in financial instruments.
>
> Classify the following sentence into one of the above categories."

The following prompt was given to ChatGPT-4o mini to classify monetary policy related sentences, based on Shah et al. (2023, p. 6).

> "Discard all the previous instructions. Behave like you are an expert sentence classifier. Classify the following sentence from FOMC into 'hawkish', 'dovish', or 'neutral' class. Label 'hawkish' if it is corresponding to tightening of the monetary policy, 'dovish' if it is corresponding to easing of the monetary policy, or 'neutral' if the stance is neutral."

A.3 Examples of topic classification output

FOMC statement on October 24, 2012:

> "Information received since the Federal Open Market Committee met in September suggests that economic activity has continued to expand at a moderate pace in recent months. Growth in employment has been slow, and the unemployment rate remains elevated. Household spending has advanced a bit more quickly, but growth in business fixed investment has slowed. The housing sector has shown some further signs of improvement, albeit from a depressed level. Inflation recently picked up somewhat, reflecting higher energy prices. Longer-term inflation expectations have remained stable.
>
> Consistent with its statutory mandate, the Committee seeks to foster maximum employment and price stability. The Committee remains concerned that, without sufficient policy accommodation, economic growth might not be strong enough to generate sustained improvement in labor market conditions. Furthermore, strains in global financial markets continue to pose significant downside risks to the economic outlook. The Committee also anticipates that inflation over the medium term likely would run at or below its 2 percent objective.
>
> To support a stronger economic recovery and to help ensure that inflation, over time, is at the rate most consistent with its dual mandate, the Committee will continue purchasing additional agency mortgage-backed securities at a pace of $40 billion per month. The Committee also will continue through the end of the year its program to extend the average maturity of its holdings of Treasury securities, and it is maintaining its existing policy of reinvesting principal payments from its holdings of agency debt and agency mortgage-backed securities in agency mortgage-backed securities. These actions, which together will increase the Committee's holdings of longer-term securities by about $85 billion each month through the end of the year, should put downward pressure on longer-term interest rates, support mortgage markets, and help to make broader financial conditions more accommodative.
>
> The Committee will closely monitor incoming information on economic and financial developments in coming months. If the outlook for the labor market does not improve substantially, the Committee will continue its purchases of agency mortgage-backed securities, undertake additional asset purchases, and employ its other policy tools as appropriate until such improvement is achieved in a context of price stability. In determining the size, pace, and composition of its asset purchases, the Committee will, as always, take appropriate account of the likely efficacy and costs of such purchases.
>
> To support continued progress toward maximum employment and price stability, the Committee expects that a highly accommodative stance of monetary policy will remain appropriate for a considerable time after the economic recovery strengthens. In particular, the Committee also decided today to keep the target range for the federal funds rate at 0 to 1/4 percent and currently anticipates that exceptionally low levels for the federal funds rate are likely to be warranted at least through mid-2015."

Blue color marks sentences about the economic outlook.

Red color marks sentences classified as monetary policy action.

Green color marks sentences about financial developments.

Press conference answer from Chair Powell on July 31, 2024:

> ”Yeah, I can’t really say that, honestly. You know, we’re—we—we’ve seen significant movement in the labor market, and, you know, we’re very mindful of this question of, is it just normalization or is it more? We think it’s just normalization, but we want to be in a position to, to support the labor market. At the same time, we’re seeing progress on inflation. So, you know, we actually got to this—we raised rates a year ago at the July meeting. And if you look at the situation in the economy a year ago, unemployment—sorry, inflation was over 4 percent. It was a completely different economy. Now we’ve made a lot of progress, and the labor market—I think unemployment was in the 3s, mid-3s, so it’s a different economy. And I think it’s time, it’s coming to be time, to adjust that so that we support this continued process. The thing we’re trying to do is—you know that we have, we’ve had this really significant decline in inflation, and unemployment has remained low. And this is a really unusual and historically, historically unusual and such a welcome outcome for the people we serve. What we’re thinking about all the time is, how do we keep this going? And this is—this is part of that. We think we don’t need to be 100 percent focused on inflation because of the progress we’ve made: 12-month headline at $2\frac{1}{2}$, core at 2.6. You know, it’s way down from where it was. The job is not done on inflation, but, nonetheless, we can afford to begin to dial back the restriction in our policy rate. And I think we’re just—it’s part of a process. In terms of what that looks like, I mean, I think most rate—you would think, in a base case, that policy rates would move down from here, but I don’t want to try to give specific forward guidance about when that might be, the pace at which it might happen, because I think that’s really going to depend on the economy, and that’s highly uncertain.”

Blue color marks sentences about the economic outlook.

Red color marks sentences classified as monetary policy action.

Uncolored sentences denote ”fillers”.

A.4 Data and data sources

Table 12: Summary of data used

Description	Source	Regressions
Control Variables		
Median of 4-quarters ahead unemployment forecasts of the Survey of Professional Forecasters	Federal Reserve Philadelphia	(1)(2)
Median of 4-quarters ahead PCE forecasts of the Survey of Professional Forecasters	Federal Reserve Philadelphia	(1)(2)
Median of 4-quarters ahead economic growth forecasts of the Survey of Professional Forecasters	Federal Reserve Philadelphia	(1)(2)
Median of 5-year ahead CPI forecasts of the Survey of Professional Forecasters	Federal Reserve Philadelphia	(1)(2)
Dispersion of 4-quarters ahead unemployment forecasts of the Survey of Professional Forecasters (3rd quartile - 1st quartile)	Federal Reserve Philadelphia	(1)(2)
Dispersion of 4-quarters ahead PCE forecasts of the Survey of Professional Forecasters (3rd quartile - 1st quartile)	Federal Reserve Philadelphia	(1)(2)
Dispersion of 4-quarters ahead economic growth forecasts of the Survey of Professional Forecasters (3rd quartile - 1st quartile)	Federal Reserve Philadelphia	(1)(2)
Dispersion of 5-year ahead CPI forecasts of the Survey of Professional Forecasters (3rd quartile - 1st quartile)	Federal Reserve Philadelphia	(1)(2)
Median Longer Run FOMC Summary of Economic Projections for the Civilian Unemployment Rate	Federal Reserve St. Louis	(1)(2), (8)(9)(10)
Median Longer Run FOMC Summary of Economic Projections for the Personal Consumption Expenditures Inflation Rate	Federal Reserve St. Louis	(1)(2), (8)(9)(10)
Dispersion of Longer Run FOMC Summary of Economic Projections for the Civilian Unemployment Rate (Max - Min)	Federal Reserve St. Louis	(1)(2), (8)(9)(10)
Dispersion of Longer Run FOMC Summary of Economic Projections for the Personal Consumption Expenditures Inflation Rate (Max - Min)	Federal Reserve St. Louis	(1)(2), (8)(9)(10)
Effective Fed Funds Rate	Federal Reserve St. Louis	(1)(2), (8)(9)(10)
St. Louis Fed Financial Stress Index	Federal Reserve St. Louis	(1)(2)
CBOE Volatility Index: VIX	Federal Reserve St. Louis	(1)(2), (8)(9)(10)
Economic Policy Uncertainty Index for United States (Baker et al., 2016)	Federal Reserve St. Louis	(1)(2)(10), (8)(9)
Business confidence index (BCI)	OECD	(1)(2), (8)(9)(10)
Daily News Sentiment Index (Shapiro et al., 2022)	Federal Reserve San Francisco	(1)(2)
Number of dissenting votes on FOMC Meetings (Thornton and Wheelock, 2014)	Federal Reserve St. Louis	(8)(9)(10)
News regarding unconventional monetary policies (LSAP and FG) - 1 if hawkish, -1 if dovish news, 0 if no change	Cieslak and Schrimpf (2019) until 2017, own coll. afterw.	(1)(2), (8)(9)(10)
Asset Price Data		
Historical 1-min fr. price of 2-Year Treasury Note Futures (CBOT) (ZT)	FirstRate Data	(5), (8)(9)(10)

Historical 1-min fr. price of 5-Year Treasury Note Futures (CBOT) (ZF)	FirstRate Data	(5), (8)(9)
Historical 1-min fr. price of 10-Year Treasury Note Futures (CBOT) (ZN)	FirstRate Data	(5), (8)(9)
Historical 1-min fr. price of E-Mini S&P 500 Futures (CME) (ES)	FirstRate Data	(5), (8)(9)
Historical 1-min fr. price of VIX Futures (CBOE) (VX)	FirstRate Data	(5), (8)(9)(10)

A.5 Descriptive statistics

Table 13: Descriptive Statistics for Statement Tone Surprise Measures

	Mean	Std. Dev.	Min	25th Pctl	Median	75th Pctl	Max
Hawkish-dovish Sentiment shock ($\varepsilon^{ST}_{\text{HDS}}$)	0.000	0.438	-1.652	-0.218	0.008	0.302	1.326
FED Economic Sentiment shock ($\varepsilon^{ST}_{\text{FES}}$)	-0.000	0.485	-1.342	-0.364	0.043	0.374	0.980
Textual MPU shock ($\varepsilon^{ST}_{\text{TMPU}}$)	0.000	0.004	-0.011	-0.003	-0.000	0.003	0.011
Textual Economic Uncertainty shock ($\varepsilon^{ST}_{\text{TFEU}}$)	0.000	0.012	-0.046	-0.006	-0.000	0.005	0.048

Table 14: Descriptive Statistics for Conference Tone Surprise Measures

	Mean	pcd. Dev.	Min	25th Pctl	Median	75th Pctl	Max
Voice Tone shock ($\varepsilon^{PC}_{\text{VTS}}$)	-0.000	0.173	-0.441	-0.100	0.006	0.085	0.725
Hawkish-dovish Sentiment shock ($\varepsilon^{PC}_{\text{HDS}}$)	-0.000	0.286	-0.673	-0.207	-0.016	0.184	0.625
FED Economic Sentiment shock ($\varepsilon^{PC}_{\text{FES}}$)	-0.000	0.213	-0.543	-0.136	0.013	0.139	0.648
Textual MPU shock ($\varepsilon^{PC}_{\text{TMPU}}$)	0.000	0.004	-0.010	-0.003	-0.001	0.002	0.011
Textual Economic Uncertainty shock ($\varepsilon^{PC}_{\text{TFEU}}$)	0.000	0.003	-0.007	-0.002	-0.000	0.002	0.007

Table 15: Descriptive Statistics for Asset Price Changes around statements (basis points)

	Mean	Abs. Mean	Std. Dev.	Min	25th Pctl	Median	75th Pctl	Max
Change in 2-year yields	-0.162	2.926	4.310	-14.736	-1.482	0.000	1.808	11.975
Change in 5-year yields	-0.149	3.192	4.425	-14.314	-1.908	0.069	2.227	9.404
Change in 10-year yields	-0.052	2.237	3.058	-11.817	-1.362	0.000	1.692	6.195
Change in equity returns	3.153	31.207	43.082	-133.010	-18.027	8.499	24.772	149.781
Change in VIX futures	-57.086	124.871	149.722	-467.914	-122.432	-64.238	24.232	280.348

Table 16: Descriptive Statistics for Asset Price Changes around PCs (basis points)

	Mean	Abs. Mean	Std. Dev.	Min	25th Pctl	Median	75th Pctl	Max
Change in 2-year yields	-0.886	3.314	4.803	-15.470	-2.926	-0.738	1.021	15.580
Change in 5-year yields	-0.843	3.430	4.520	-12.203	-3.128	-1.436	1.138	12.774
Change in 10-year yields	-0.641	2.590	3.256	-8.295	-2.644	-1.008	1.175	8.690
Change in equity returns	1.834	56.569	78.048	-248.416	-39.245	10.242	41.684	270.652
Change in VIX futures	-0.429	210.905	290.778	-927.061	-159.036	-9.288	149.283	1104.756