PERCEIVING CENTRAL BANK COMMUNICATIONS THROUGH PRESS COVERAGE

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Abstract

We present evidence suggesting that a simple measure of central bank communication tone, as perceived and interpreted by the media, correlates with the performance of financial assets and market participants' expectations. This correlation appears even stronger than that of indices constructed using more complex models, such as a large language models like BERT. We employ a straightforward quantitative index, inspired by the well-known Baker, Bloom and Davis (2016) paper, using a "bag of words" approach and semantic orientation to measure this media-perceived tone orientation in terms of dovishness or hawkishness. Our approach, which emphasises the perception by the press media, contrasts with previous research that focused primarily on central bank minutes or speeches. Our preliminary findings reveal a statistically significant correlation with the movements of 2, 5 and 10-year US Treasury yields, with reactions being faster and more pronounced for shorter maturities. Our index also shows a leading correlation with some measures of inflation expectations, investor sentiment proxies, the stock market and the dollar. Additionally, to account for the impact of COVID-19, we propose the use of Google search trends as a proxy variable.

Keywords: central bank communication, natural language processing, market perception, monetary policy, inflation expectations, bond yields, investor sentiment.

JEL classification: E50, E52, E58, G14, G17, C45, C81, D83.

Resumen

En este documento presentamos una evidencia empírica que sugiere que una medida simple del tono de la comunicación del banco central, tal como es percibida por los medios de comunicación, se correlaciona con la evolución de los tipos de interés y las expectativas de los inversores en renta fija. Esta interrelación parece ser incluso más fuerte que la de los índices construidos usando modelos más complejos, como los grandes modelos de lenguaje tipo BERT. Utilizamos un índice cuantitativo sencillo, inspirado en el reconocido trabajo de Baker, Bloom and Davis (2016), y empleamos un enfoque de diccionario y orientación semántica para medir el tono percibido por los medios en términos de inclinación *dovish* (acomodaticia) o *hawkish* (restrictiva). Nuestro enfoque, que pone el énfasis en la percepción de los medios de comunicación, contrasta con investigaciones previas que se centran, de forma principal, en los mensajes oficiales (incluidos en las actas o discurso) y no en la interpretación de los medios. Nuestros hallazgos preliminares revelan una correlación estadísticamente significativa con los movimientos de los tipos de interés de Estados Unidos a dos, cinco y diez años, y las reacciones más rápidas y pronunciadas se producen en los tramos de la curva más cortos. Además, nuestro índice también se corresponde de forma anticipada con algunas medidas de las expectativas de inflación, *proxies* del sentimiento de los inversores, la bolsa y el dólar. Asimismo, para tener en cuenta el impacto del COVID-19, proponemos el uso de las búsquedas de Google como una variable *proxy.*

Palabras clave: comunicación de los bancos centrales, procesamiento de lenguaje natural, percepción del mercado, política monetaria, expectativas de inflación, tipos de interés, sentimiento del inversor.

Códigos JEL: E50, E52, E58, G14, G17, C45, C81, D83.

1 Introduction

In recent years, central bank communication has emerged as an indispensable tool within the framework of monetary policy[1]. Its purpose has been to enhance transparency and clarity, helping to align market expectations more effectively with the central bank's policy decisions and orientation. This approach aims to avoid potential painful shocks and market distortions. Back in 2013, Mr. Ben S. Bernanke emphasized this importance in his speech titled "Communication and monetary policy" commenting that the "the Fed's monetary policy communications have proved far more important ... enhanced transparency is increasing the effectiveness of monetary policy". Furthermore, in 2016 the Jerome H Powell 's speech titled "Understanding Fedspeak" explained further the role of communication: "The Federal Open Market Committee's (FOMC) public communications are designed to serve three important purposes. The first is to provide the transparency... The second is to enhance the effectiveness of monetary policy...And the third is to show the full range of FOMC participants' views".

The European Central Bank also recognizes the critical role of communication in shaping effective monetary policy. In its website, the ECB highlights how "clear and effective communication is very important to us. Our monetary policy becomes more effective when our decisions are better understood". Moreover, the ECB emphasises the importance of media in the proper understanding of expectations in terms of monetary policy: "The media play an important role in this process and help keep us accountable to the European public."

Central bank communication plays a pivotal role in financial markets, as demonstrated by numerous studies using natural language processing (NLP) to analyze the impact of official statements, press conferences, and speeches. While these studies have established central bank communication as a market driver, they predominantly focus on direct analysis of official communications. Our research takes a different approach. While acknowledging the rapid advancements in complex text mining methodologies, we explore a simpler, semantically-oriented method applied to a broader corpus of media coverage. We hypothesize that this simpler method, applied to a richer dataset of media interpretations, can yield comparable or even superior correlations with financial asset movements. This is because we suspect that media interpretations, often overlooked, may provide a more accurate reflection of market sentiment and subsequent asset repricing. Specifically, we aim to determine whether media reporting on all forms of central bank intervention (statements, minutes, press conferences, speeches, interviews, etc.) correlates with—and potentially leads or lags—financial asset price changes.

In a first step, we create our "Dovishness Index" using a simple, intuitive, and easily replicable semantic rule applied to media articles sourced from FACTIVA by Dow Jones. This index aims to quantify the perceived tone of central bank communication feedback, ranging from dovish (accommodative, positive signal) to hawkish (restrictive, negative signal). We anticipate that these signals can be used to monitor financial asset market repricing associated with shifts in perceived tone of central bank communications, considering both direction and magnitude. Our study focuses on Fed communication and US financial markets, but the methodology is adaptable to other central banks.

In a second stage, we assess the added value of our media-based index compared to existing metrics derived from official communication, specifically the JP Morgan Hawk-Dove Score Index (HDS). This comparison will be conducted in two ways. First, we will examine the correlation between our Dovishness Index and various financial variables, particularly sovereign fixed income across different time frames. Second, we will directly compare the performance of our index with the JP Morgan HDS Index, to isolate the potential informational value added by media interpretation. This comparison will allow us to differentiate between market reactions attributable to the "official message" (captured by the JP Morgan HDS Index) and those stemming from "media interpretation" (captured by our

[1] As such, an important monetary policy instrument that has gained prominence is "forward guidance". Forward guidance is a tool used by the central bank to provide indications about its monetary policy intentions, including orientation for the expected future path of its key interest rates. This tool allows the central bank to influence short, medium and long-term interest rates. It is also highly valuable in relation to other monetary policy instruments, such as asset purchases, proving to be particularly useful when interest rates are close to their lower bound, i.e., when there is little scope to reduce them any further. The Federal Open Market Committee (FOMC) began using forward guidance in its post-meeting statements in the early 2000s. The European Central Bank (ECB) began using forward guidance in July 2013, when the Governing Council announced that interest rates were expected to remain low for an extended period of time.

Dovishness Index), effectively controlling for the underlying message conveyed by the central bank. We also incorporate a proxy to control for the effects of the COVID-19 shock.

Our findings indicate that the media interpretation of central bank messages has a significant impact on financial markets, providing valuable insights that complement existing measures based only on official communications. We conclude that the Dovish Index has predictive power over several financial indicators, especially for fixed income assets with higher price impact in the shorter part of the curve, as evidenced by a positive correlation, which seems a logical result. Additionally, it also shows short term inflation expectation predicting capabilities. Although the predictive power fades compared to fixed income, it is still relevant for equity and the dollar although in an inverse manner (positive for equity). Compared to a more complex index like the JP Morgan HDS Index, it also provides additional value in terms of predictive potential for the performance of several financial assets.

Finally, our study contributes to the existing literature by demonstrating that a simple measure of central bank communication tone, as perceived and interpreted by the media, correlates with financial asset performance and market expectations. This correlation is robust, even exceeding that of more complex models. The strength of this correlation suggests that the media's interpretation of central bank messaging, rather than just the merely capturing the official tone, is key for predicting market reactions. Our novel approach analyzes all forms of central bank communication, offering a continuous and readily replicable measure. This provides a new, transparent methodology for researching the impact of central bank communication on markets using readily available data.

The structure of the study is as follows: the second section provides a comprehensive review of the existing literature on measuring the tone of central bank communications. The third section details the data sources utilized in this study, along with a discussion of alternative sources. The fourth section describes the methodology employed to calculate the index. The fifth sections summarizes the statistical properties of the Dovishness Index in relationship to the performance of several financial assets, survey indexes, and the JP Morgan HDS Index. To conclude, the final section encapsulates the key findings of our study.

2 Literature

While the increasing use of sophisticated natural language processing techniques and large language models has significantly advanced the analysis of central bank communications, less attention has been paid to the potential of simpler, semantically-driven approaches applied to a broader range of media sources. This paper addresses this gap by exploring whether a simplified keyword-based approach, applied to a wider corpus of news articles and analyst reports, can yield comparable or even superior insights into market sentiment and its impact on various financial assets. This focus on simplicity and broader media sources offers advantages in terms of interpretability and replicability, allowing for a more transparent understanding of the relationship between media sentiment and market movements. Furthermore, analyzing a broader media landscape provides a more holistic view of market sentiment, capturing not only the direct impact of official pronouncements but also the subsequent interpretation and dissemination of central bank communication by key intermediaries. To highlight our contributions within this context, we structure this review by first examining the literature employing dictionary-based methods for sentiment analysis. Subsequently, we discuss studies utilizing more complex models, such as deep learning and LLMs, often applied to official central bank statements. Next, we review research that incorporates broader data sources beyond official communications, exploring the use of news articles and alternative data. Finally, we review studies that investigate the relationship between sentiment derived from central bank communication and market outcomes, highlighting the ongoing efforts to understand and potentially predict financial market movements based on textual analysis. Our work contributes to this body of research by examining the performance of a simpler, keyword-driven approach applied to a broader range of media in predicting movements in specific asset classes, including equities, fixed income, and foreign exchange.

Early work on sentiment analysis in central bank communication often utilized dictionary-based methods. Picault and Renault (2015), for example, developed a weighted lexicon to categorize ECB monetary policy statements. Similarly, Tadle (2022) explored a dictionary-based approach for analyzing FOMC minutes. Building on this, Parle (2022) introduced a "Dictionary Hawk-Dove Index" based on ECB press conferences, using a four-category dictionary and incorporating a dynamic topic model to capture evolving language. These studies demonstrate the value of dictionary-based approaches but predominantly focus on official central bank communications. However, we argue that analyzing a broader range of media sources, including news articles and analyst reports, can provide a richer understanding of market sentiment. To this end, we employ a simplified keyword-based dictionary applied to this wider corpus, hypothesizing that media interpretations can reveal nuances not captured by analyses of official statements alone.

Furthermore, while recent research has increasingly focused on complex deep learning and large language models (LLMs), our work explores the efficacy of a simpler approach. For instance, Niţoi et al. (2023), Bertsch et al. (2022), and Mahdavi Ardekani et al. (2023) utilize fine-tuned BERT models and even ChatGPT (Hansen and Kazinnik (2023)) adaptations for analyzing central bank communication and economic sentiment. Other studies have explored novel data sources, such as Gorodnichenko et al. (2023) who analyze voice tone in FOMC press conferences. While acknowledging the potential of these sophisticated techniques, we question whether a simpler, semantically-driven approach can offer comparable insights, particularly when applied to a broader media dataset. Commercial indexes, such as those from Bloomberg (Alex Montiel (2021)) and JP Morgan Hawk-Dove Score (Joseph Lupton (2023)), also employ complex methodologies like transfer learning and BERT models, primarily focusing on official Fed communications. We use the JP Morgan Hawk-Dove Score as a key benchmark, given its sophisticated methodology and daily updates, allowing for a direct comparison with our simpler approach.

The focus on a broader range of media sources aligns with studies like Shapiro and Wilson (2022) and Tobback et al. (2017), who utilized newspaper articles and Factiva data, respectively. Although alternative sources like GDELT have been employed (Consoli et al. (2021); Blanqué et al. (2022)), we chose Factiva for its extensive historical coverage. In terms of semantic orientation, the work of Tobback et al. (2017) is the most closely related to our study. They analyzed media reports to construct a "hawkish" vs. "dovish" index by examining the relative frequency of related terms, employing a Support Vector Machine for classification. Like them, we focus on media perceptions of central bank communication. However, a key distinction of our research is that we demonstrate a simpler approach can achieve comparable results. Specifically, we generated over 900 different combinations of keywords, effectively exploring subsets of the terms identified by them, and found that a carefully selected subset offers similar performance to their more complex model.

Finally, a key objective of sentiment analysis is to assess its predictive power. Existing research has explored the impact of central bank communication sentiment on various outcomes, including financial asset prices (Bertsch et al. (2022); Blanqué et al. (2022)), monetary policy decisions (Parle (2022); Tobback et al. (2017)), and market uncertainty (Niţoi et al. (2023)). Our work contributes to this literature by examining the predictive power of our simpler, media-based sentiment index across a broader range of asset classes (equities, fixed income, foreign exchange and survey-based indexes). We also benchmark our index's performance against the more complex JP Morgan Hawk-Dove Score, which employs BERT, providing a direct comparison between our streamlined approach and a more complex model.

3 Data sources

We primarily relied on the Dow Jones's FACTIVA service as our primary database for sourcing global press media content regarding the FED communication tone. FACTIVA Dow Jones provides information sources in 30 different languages, but 63% of the more than 18,000 sources are in English. In our study, we focused only on English-language articles, mainly from Dow Jones Newswires (59%) and Reuters (22%). Although the available data from FACTIVA spans from January 1981, our final dataset begins in June 2008 due to the availability constraints of other economic and financial variables. While we initially explored the GDELT (Global Database of Events, Language and Tone) project database with similar results, we encountered limitations related to the lack of data availability before January 2017. Consequently, we transitioned to FACTIVA to extend the time frame for our study. FACTIVA also offers the advantage of being able to select specific data sources, for example concentrating only on the most reliable newspapers reporting economic data.[2]

[2]While our study did not incorporate Bloomberg text mining resources to extract tone data, it could be considered as an alternative. The three data sources describe above, FACTIVA, GDELT and Bloomberg exhibit a strong correlation among themselves (as shown in Figure 1). This high degree of consistency provides flexibility for researchers to replicate the methodology, adapting their models based on the the data source that best aligns with their specific needs.

In order to assess the properties of an index that measures the tone of a central bank, we examined the correlation with a wide range financial assets and market indexes aiming to incorporate a wide range of of categories, all based in the US market. These categories include the performance of fixed income, equity, foreign exchange, inflation expectations and market sentiment surveys. The variables selected for fixed income assets are the sovereign 2-year, 5-year, and 10-year generic constant maturity U.S. Treasury bond yields. In foreign exchange we used the dollar index against a basket of major currencies (Euro, British pound, Canadian dollar, Japanese yen, Swiss franc, Swedish krona). Regarding inflation, we incorporated the constant maturity 2-year break-even rate, the 5-year forward 5-year inflation swap as market indicators and the monthly survey from the University of Michigan to household regarding the inflation expectation for the next year, as proxies for inflation expectations in both the short and mid term. On the macroeconomic front, we used the Citi's Economic Surprise Index for the US, which measures the degree of data surprises relative to market expectations and is constructed using weighted historical standard deviations of surprises (difference between actual releases and Bloomberg surveys) for different macroeconomic indicator where the weights depend on the announcement's effect on the foreign exchange markets. Additionally. we incorporated a proxy for the term premium on UST securities according to the Adrian Crump and Moench 10 year Treasury Term Premium Model. Regarding market sentiment, we included the weekly survey data published by JP Morgan of fixed-income investors, regarding their investment stance on Treasury debt compared to their benchmarks. To assess the impact of COVID-19 on our variables of interest, we employed Google Trends to extract search data related to COVID-19, using it as a proxy variable to gauge its influence. The justification for the inclusion of this variable lies in the fact that various studies (see Mangono et al. (2021)) point out that people tend to search for information on the internet when they begin to experience symptoms of a disease. Therefore, searches become a leading variable for infection rates. Finally, all time series represent monthly or monthly averages of daily data.

In our effort to identify additional information beyond the currently available indexes, we have identified three models that quantify central bank speeches: The Morgan Stanley Sentiment Score of the FOMC Statements, The Bloomberg Intelligence Fixed Income Fed Policy Sentiment and The JP Morgan Hawk-Dovish Score Index. To verify if our Dovishness Index can provide additional insights, we will compare it with the JP Morgan HDS Index. The latter is a comprehensive and sophisticated model that employs the latest Natural Language Processing techniques and predictive capabilities. It is a model based on the BERT-based NLP methodology fined-tuned with extensive training. Common features with the Dovishness Index are the systematic quantitative approach to central bank communication, the daily updates and the easy to understand outcome. In contrast to our Dovishness Index, it is based on official speeches and statements. The score is calculated on the opposite direction to our Dovishness Index, with positive values indicating a hawkish stance. It's important to note that the JP Morgan HDS Index is calculated as a three-month average. For comparison, our index is also calculated as a three-month average. (table 1 provides a summary of several dovish/hawkish indexes)

4 Methodology

Our Dovishness Index is constructed monthly using daily data and a straightforward methodology designed to capture the media's interpretation of central bank communication and its potential impact on market sentiment. This includes coverage of official FOMC communications, as well as news reports and analysis of speeches, interviews, and other public statements made by Federal Reserve Governors, even outside the context of formal FOMC meetings. It is not directly tied to FOMC meetings, but rather reflects the sentiment expressed in news published each day, providing a continuous measure of market perception regarding the stance of monetary policy. Inspired by the Economic Policy Uncertainty Index developed by Baker et al. (2016), our approach applies a text query, rule filter, and counting methodology to the FACTIVA database. To quantify our Dovishness Index, we aggregate the number of articles mentioning "dovish" or "less hawkish" and subtract the number of articles mentioning "hawkish" or "less dovish." In both cases, the mention of the Federal Reserve must appear, the articles must be in English and published in the United States. This difference is then divided by the total number of English-language articles published in the United States. This index is subsequently standardized to express values in standard deviations from the historical mean of the index.

$$Dovish\_Index_t = \frac{dove_t - hawk_t}{TotalNews_t}. \tag{1}$$

Where:

$dove_t$ are the articles that meet the following criteria in FACTIVA: (fed or federal w/1 reserve) and (dovish or less w/1 hawkish) and re=usa and la=en [3]

$hawk_t$: fed or federal w/1 reserve) and (hawkish or less w/1 dovish) and re=usa and la=en
$TotalNews_t$: re=usa and la=en.

Frequently, when the tone of a central bank is dovish, press headlines mentioning a "dovish" stance tend to outnumber articles mentioning a "hawkish" bias. Therefore, by applying a semantic orientation analysis and calculating the difference between dovish and hawkish articles, we aim to capture the dovish bias as interpreted by the press. Our index is based on the assumption that analysts often assess the tone of central bank communication based on the prevailing narrative in news headlines and articles (figure 2). This shared interpretation, stemming from convergent media messaging, provides a valuable indicator of market expectations.

To analyze the impact or the significance of our index, we examine different lags and leads in the following regression, using all variables as month-over-month changes:

$$y_t = \alpha + \sum_{i=1}^{k} \beta_i y_{t-i} + \gamma_1 DovishIndex_{t+\ell} + \gamma_2 JPmorganHawks_{t+\ell} + \gamma_3 COVID_Search_{t+\ell} + \epsilon_t \quad (1)$$

Where:

- y_t is the dependent variable at time t.
- k is the lag length of the dependent variable, chosen to ensure no autocorrelation in residuals.
- $DovishIndex_{t+\ell}$ is our Dovishness Index at time $t+\ell$.
- $JPmorganHawks_{t+\ell}$ is the J.P. Morgan HDS Index at time $t+\ell$.
- $COVID_Search_{t+\ell}$ is the number of COVID searches at time $t+\ell$.
- $\ell \in \{-24, -23, ..., 0, ..., 23, 24\}$ represents the lead/lag structure.

As a reminder, the variables that we will use as dependent variables are:

- **Fixed Income Assets**:
  - Sovereign 2-year, 5-year, and 10-year generic constant maturity U.S. Treasury bond yields.
- **Foreign Exchange**:
  - Dollar index against a basket of major currencies (Euro, British pound, Canadian dollar, Japanese yen, Swiss franc, Swedish krona).
- **Inflation Expectations**:
  - Constant maturity 2-year break-even rate.
  - 5-year forward 5-year inflation swap rate.
  - Monthly survey from the University of Michigan regarding household inflation expectations for the next year.
- **Macroeconomic Indicators**:
  - Citi's Economic Surprise Index for the US.
  - Proxy for the term premium on UST securities according to the Adrian Crump and Moench 10y Treasury Term Premium Model.

[3] These are search parameters used in the FACTIVA database: re specifies the region (e.g., re=usa for the United States); la indicates the language (e.g., la=en for English). The w/1 is a proximity operator. For example, federal w/1 reserve finds items containing "federal" within one word of "reserve"

- **Market Sentiment**:
  - Weekly survey data published by JP Morgan to fixed-income investors regarding their investment stance on Treasury debt compared to their benchmarks.

We estimate four specifications for each dependent variable:

1. **A model with only our Dovishness Index**: This specification may be impacted by the structural change due to COVID-19, so we include COVID-19 searches in the next specification to minimize this potential endogenous variable.
2. **A model including our Dovishness Index and a COVID-19 proxy**: This helps to account for the structural changes brought by the pandemic.
3. **A model adding the J.P. Morgan HDS Index**: By including the J.P. Morgan model, which uses BERT, we expect that if our index does not provide additional information, its significance will drop drastically. Alternatively, if they are highly correlated, neither index will be statistically significant.
4. **A model identifying the optimal lead/lag structure (up to 24 months) for the J.P. Morgan HDS Index**: Optimality is defined as a model that eliminates autocorrelation from the residuals and demonstrates statistical significance for the J.P. Morgan HDS Index. We use the Durbin-Watson and Ljung-Box tests to confirm the absence of autocorrelation and the presence of significance.

This entire process, including considering lags and leads up to 24 months for all explanatory variables, is repeated for each dependent variable. We focus on the sign, significance, and magnitude of coefficients across the different lead/lag specifications.

To ensure robustness and address subjectivity concerns, we conduct a robustness check by generating 962 random combinations of dovish/hawkish words identified by Tobback et al. (2017) (table 2) and comparing our simple index against the median of these randomly generated indices using the Diebold-Mariano test. A preliminary lag selection analysis is also performed. For each of the 962 indices, we estimate regressions for each dependent variable, regressing its monthly change on its own first lag, the contemporaneous COVID-19 search index change, and the specific dovish index change lagged from 0 to 12 months:

$$y_t = \alpha + \beta y_{t-1} + \gamma DovishIndex_{t-\ell} + \delta COVID_Search_{t-\ell} + \epsilon_t \tag{2}$$

where $\ell \in 0, 1, ..., 12$. We compute the 95% confidence interval for γ and record its significance. This process allows us to identify the lag structure that maximizes the number of statistically significant γ coefficients across the 962 dovish indices and informs the lag selection for Equation 1. Furthermore, this analysis helps us determine which specific combination of search terms yields the most robust dovish index, as indicated by the highest overall significance across lags and dependent variables. This ensures we use the most informative index for the main analysis.

If our Dovish Index has statistically significant effects while the J.P. Morgan HDS index (BERT-derived) does not, even after optimizing its lead/lag structure, it suggests our index captures unique information, reflecting broader market perceptions beyond direct interpretations of Fed communications.

Theoretically, we consider several economic and financial mechanism that could impact the coefficients estimated in regression (1). A dovish stance by the central bank can influence various aspects of the market, leading to specific outcomes in bond yields, currency strength, macroeconomic surprises, investment sentiment, equity performance, and inflation expectations. These impacts are detailed below:

- **Lower Yields (especially short-term)**:
  - A dovish stance by the central bank typically signals lower interest rates or a delay in rate hikes, which could directly impact short-term bond yields. Investors anticipate lower returns on short-term bonds, leading to a decline in yields.
  - Lower yields on short-term bonds can also result from increased demand for these securities as investors seek safer assets.

- **Weaker Dollar**:
  - A dovish central bank stance often leads to a depreciation of the domestic currency. Lower interest rates reduce the return on investments denominated in that currency, making it less attractive to foreign investors.
  - A weaker dollar can also be a result of expectations of prolonged monetary easing, or an increase in the money supply.
- **Reduced Positive Macroeconomic Surprises**:
  - Dovish signals may indicate concerns about economic growth, leading to lower expectations for positive macroeconomic data. This can result in fewer positive surprises relative to market expectations.
  - Investors might adjust their forecasts downward, anticipating weaker economic performance and thus reducing the likelihood of positive surprises.
- **Cautious Investment Sentiment**:
  - A dovish stance can lead to increased caution among investors, as it may signal underlying economic weaknesses or uncertainties. This can result in a more conservative approach to investment, with a preference for lower-risk assets.
  - Cautious sentiment can also be driven by expectations of higher volatility, uncertainty or lower future returns, prompting investors to seek stability rather than high-risk, high-reward opportunities.
- **Positive Equity Performance**:
  - Lower interest rates reduce borrowing costs for companies, potentially boosting profitability and supporting higher equity prices.
  - A dovish stance can also increase liquidity in the financial system, providing more capital for investment in equities and potentially driving up stock prices.
- **Contained Inflation Expectations**:
  - Dovish policies often aim to support economic growth without triggering high inflation. By signaling a commitment to maintaining low and stable inflation, central banks can anchor inflation expectations.
  - Contained inflation expectations help maintain the purchasing power of fixed-income investments, making them more attractive to investors.
  - Stable inflation expectations are also indicative of confidence in monetary policy.

5 Preliminary results

The Dovishness Index proposed in this paper is shown in figure 3. The index appears to capture periods where the Fed adopted a more dovish or hawkish stance reasonably well. For instance, the index spikes upwards around March 2019, coinciding with news reports suggesting a dovish turn in monetary policy driven by growth concerns, mild inflation data, discussions around a dovish Fed nominee, and possible White House pressure (under the Trump administration). Similarly, in early May 2016, the index reflects a more dovish bias consistent with news about bond traders pushing back rate forecasts and uncertainty surrounding the “Brexit” vote. Conversely, the index turns sharply negative around February 2022, capturing the hawkish shift as the Fed began to grapple with rising inflation and the war in Ukraine. Finally, the index shows a hawkish peak around October 2022, reflecting expectations of an assertive and dynamic rate hike cycle, amid signs of economic strength and persistence of core inflation.

The econometric analysis underscores the relationship between our Dovishness Index and several market variables, even after controlling for the impact of the COVID-19 pandemic. Of all the variables analyzed, the strongest relationship is observed, as expected, with Treasury bond yields. A more dovish tone (a higher value on our Dovishness Index) is associated with lower Treasury bond yields across maturities. This negative relationship is statistically significant both contemporaneously and as a leading indicator (tables 3, 4, and 5).

Specifically, our Dovishness Index exhibits a significant contemporaneous and negative correlation with the two-year maturity generic bond yield (table 3). This aligns with the anticipated market reaction to dovish signals, where expectations of lower future interest rates drive down short-term bond yields. The index also acts as a leading indicator for longer-term maturities, specifically the five (table 4) and ten-year Treasury bonds (table 5), leading by three months. The magnitude of the coefficient decreases as maturity lengthens, suggesting that the impact of dovish sentiment is more pronounced on shorter-term yields.

In contrast, the JP Morgan HDS displays significant lagging properties for these same two, five, and ten-year maturity reference bonds (third and fourth columns in tables 3, 4, and 5). It lags the two-year bond by one month and the five and ten-year bonds by one quarter. This difference in lead/lag structure suggests our index captures the immediate market interpretation of news and sentiment, while the JP Morgan HDS, which analyzes the tone of official FOMC communications, reflects either the central bank's reaction to evolving financial conditions or the delayed market processing of official statements. This lag could be attributed to the time it takes for markets to fully digest and react to the nuances of official communications.

Our analysis also reveals a relationship between our Dovishness Index and investor sentiment, as measured by the weekly JP Morgan fixed-income investor survey. A dovish reading on our index precedes a bullish turn in investor sentiment by two months (table 6). This suggests our index captures shifts in market sentiment before they are reflected in investor surveys. Conversely, the JP Morgan HDS lags investor sentiment; a bullish sentiment precedes a dovish shift in the JP Morgan HDS by three months. This lag may be due to investors incorporating macroeconomic information into their outlook before it is fully reflected in official communications. For example, investors might interpret emerging macroeconomic weakness as favorable for fixed income (bullish) which, in turn, could lead to more dovish commentary from FOMC members in subsequent periods. This reinforces the observation that the JP Morgan HDS often reflects the central bank's reaction to evolving macroeconomic and market conditions, rather than anticipating them. The contrasting lead/lag relationships between our index, the JP Morgan HDS, and investor sentiment highlight the unique and timely information captured by our Dovishness Index.

We also examined the relationship between our Dovishness Index and various measures of inflation expectations. We find a significant, negative correlation between our index and the University of Michigan one-year horizon inflation expectation survey, with our index leading by one month (table 7). This suggests our index captures evolving sentiment about near-term inflation before it is reflected in consumer surveys.

In contrast, the relationship between our index and market-based measures of longer-term inflation expectations, such as the five-year inflation swap five-years forwards (5y5y) (table 8) and the two-year breakeven inflation rate (table 9), is less pronounced and exhibits a different lead/lag structure. Specifically, we observe a negative correlation with 5y5y forwards two months after the forward expectation is observed, and a positive correlation with the two-year breakeven rate six months after observation. The JP Morgan HDS also exhibits a lagged response to both the 5y5y and the two-year breakeven rate. This aligns with the typical behavior of central banks, which monitor and react to shifts in market-based inflation expectations when setting monetary policy. For instance, higher inflation expectations may prompt a more hawkish policy stance. The observed lag in the JP Morgan HDS likely reflects this reactive nature of central bank communications. Therefore, while our Dovishness Index appears to anticipate short-term consumer inflation expectations, market-based measures of longer-term inflation expectations appear to precede shifts in both the Dovishness Index and the JP Morgan HDS, likely reflecting the central bank's response to these market signals.

Our analysis of equity markets and the US dollar reveals movements consistent with expectations. As anticipated, a dovish tone, as captured by our index, is associated with a rise in the S&P 500 (table 10) and a decline in the US dollar (table 11) one month later. We also find a negative relationship between our Dovishness Index and economic surprises, although with a lag of three quarters (table 12). This lagged relationship could reflect the time it takes for monetary policy to affect the real economy, rather than simply influencing expectations. Specifically, a dovish tone appears to precede negative economic surprises three quarters later. Finally, we found no significant relationship between our Dovishness Index and the 10-year term premium (table 13).

The JP Morgan HDS, in contrast, exhibits a different dynamic. It shows a lagged, dovish response to US dollar appreciation (three quarters later), and a lagged, hawkish response to increases in the 10-year term premium (two months later). Interestingly, the JP Morgan HDS appears to lead S&P 500 returns, with the market turning positive one quarter after a hawkish signal. It also leads economic surprises, with surprises declining two months after a hawkish reading.

As demonstrated in the preceding analysis, the media reporting encapsulated by the Dovishness Index seems to reflect a valuable and precise representation of the general market's interpretation of central bank communications, exhibiting significant statistical properties in terms of financial asset performance. Additionally, the Dovishness Index appears to have a more significant impact on certain economic and financial variables than the tone of the official communication itself. This is particularly evident in the case of US Treasury yields. The Diebold-Mariano test results (table 14) confirm this observation, showing that our simpler index, based on media interpretation, produces significantly more accurate forecasts for 2, 5, and 10-year Treasury yields than the more complex JP Morgan HDS index, which uses a BERT-type LLM to analyze the full text of FOMC statements and press conferences. Specifically, our index leads to statistically significant lower forecast errors at the 1-month horizon for the 2-year yield and at the 3-month horizon for the 5- and 10-year yields.

To assess the robustness and address potential subjectivity concerns regarding our simplified Dovishness index, we benchmarked its performance against indices derived from a broader lexicon. Using the word set from Tobback et al. (2017) (table 2), we generated 962 indices by randomly sampling subsets of these terms. We then compared the predictive accuracy of our simplified index against the median of these 962 random indices across our set of dependent variables. A Diebold-Mariano test (table 6) revealed no statistically significant difference, suggesting our simplified index captures similar sentiment dynamics without the added complexity of a larger lexicon. Furthermore, we compared our index against the best-performing randomly generated index, based on the number of statistically significant predictors (table 6). Again, the Diebold-Mariano test (table 6) showed no statistically significant difference in predictive accuracy, further supporting the effectiveness of our simplified approach.

6 Conclusion

This paper evaluates the efficacy of a simple Dovishness Index in capturing media interpretations of central bank communication and its leading correlation over various financial assets. Our findings underscore the importance of considering not just the tone of official pronouncements, but also how these pronouncements are interpreted and disseminated by the press. Market expectations are ultimately shaped by this interpretive layer, which our Dovishness Index effectively captures.

Our analysis reveals a statistically significant leading relationship between the Dovishness Index and several key financial variables. Most notably, the index anticipates movements in 2, 5, and 10-year US Treasury yields, with shorter maturities exhibiting a more pronounced and rapid response. This leading relationship is further validated by Diebold-Mariano tests, demonstrating that our simpler, media-based index provides significantly more accurate forecasts of Treasury yields than a more complex index based on LLMs models applied to FOMC communications. This superior predictive power highlights the value of incorporating media sentiment into the analysis of monetary policy expectations.

Furthermore, the Dovishness Index anticipates short-term consumer inflation expectations (University of Michigan survey) and, as expected, leads movements in equity markets (S&P 500) and the US dollar. Interestingly, the index also exhibits a lagged relationship with economic surprises, suggesting a potential link between dovish monetary policy and subsequent real economic developments.

Comparisons with the JP Morgan HDS index, which focuses on the tone of official communications, reveal important distinctions. While the JP Morgan HDS often exhibits a lagged response to market developments, probably reflecting a reactive nature of central bank policy, our Dovishness Index demonstrates a leading relationship with several key variables, capturing the market's forward-looking interpretation of monetary policy signals.

The robustness of our simple Dovishness Index is supported by comparisons with a large set of alternative indices constructed using a broader, randomly generated lexicon. Diebold-Mariano tests show no statistically significant difference in predictive accuracy, confirming that our simplified approach effectively captures market sentiment dynamics.

In conclusion, our Dovishness Index provides a valuable new tool for understanding how media interpretation shapes market expectations and influences asset prices. By capturing the market's real-time processing of central bank communication, our index offers a unique and timely perspective on monetary policy sentiment. Future research could explore refining the index methodology, expanding its application to other central banks and asset classes, and investigating the specific mechanisms through which media interpretation influences market behavior. Such research promises to further enhance our understanding of the complex interplay between central bank communication, media narratives, and financial market dynamics.

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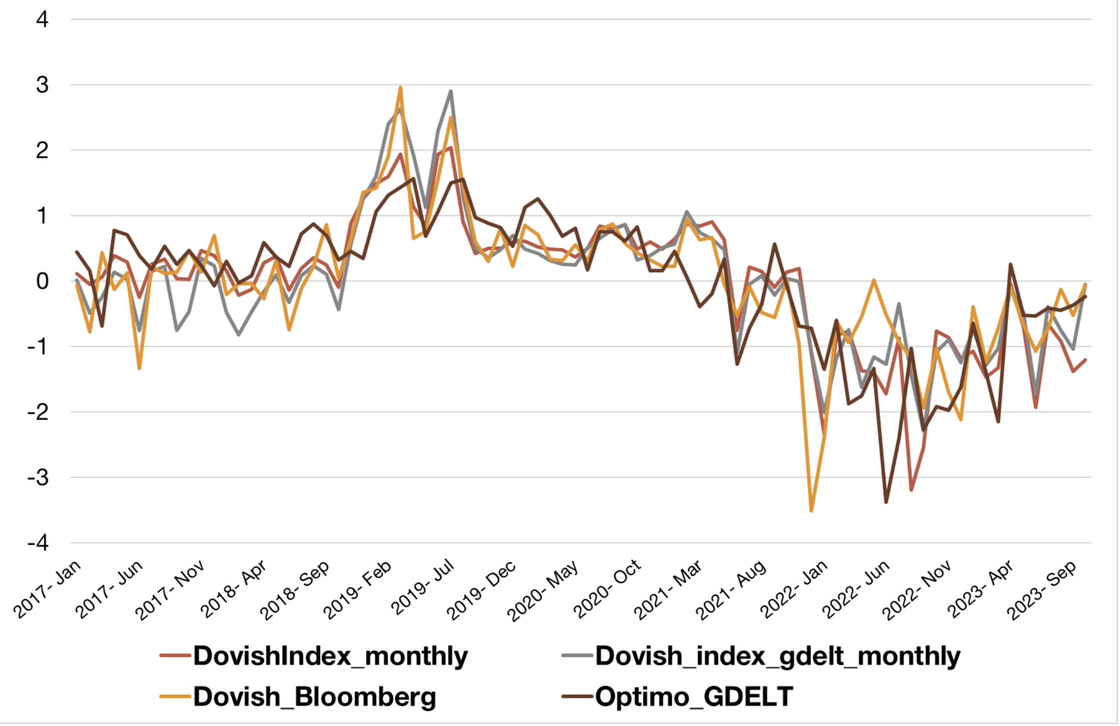
Annex

Figure 1: Comparison of Generated Indices Based on Multiple Data Sources



Source: FACTIVA, Bloomberg, GDELT and own calculations

Figure 2: News headlines

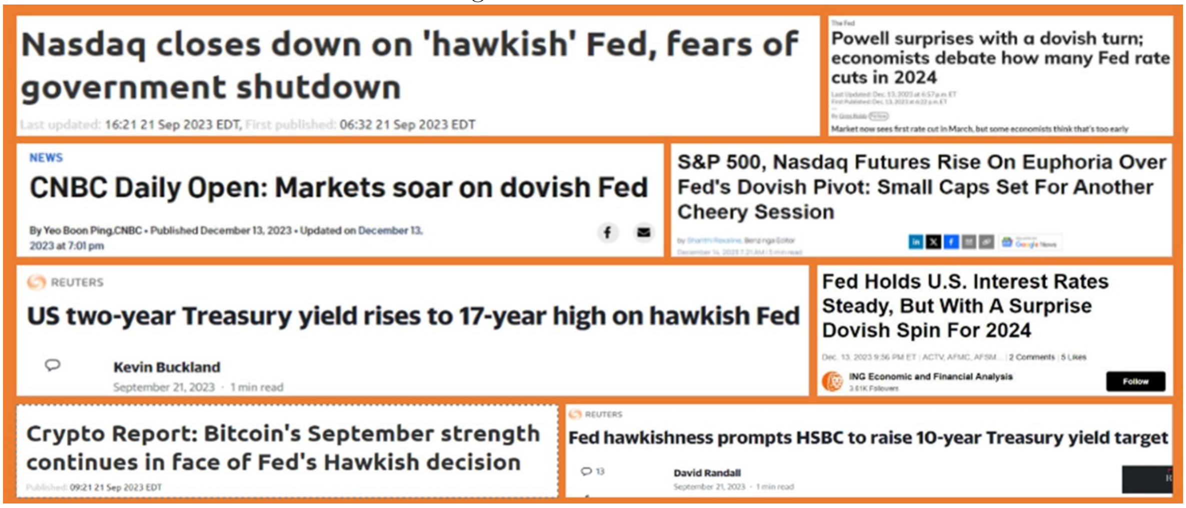
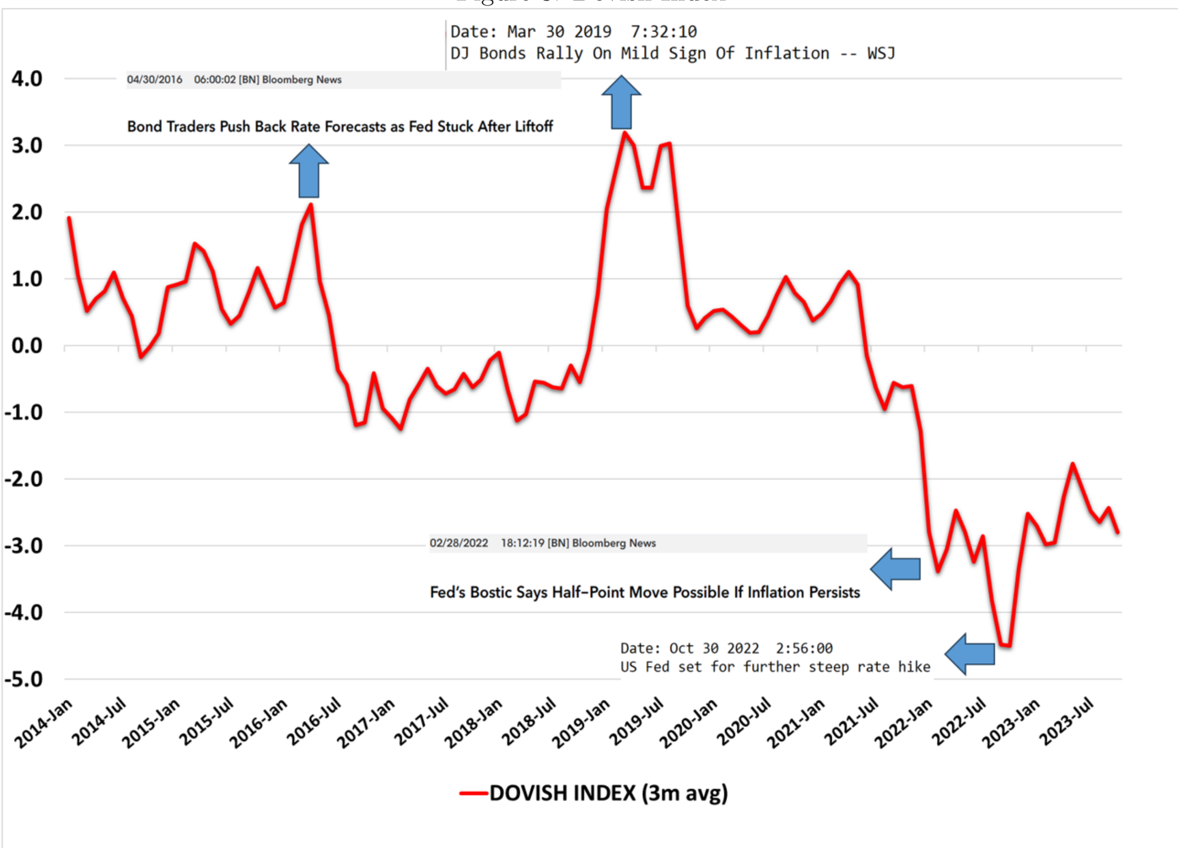


Figure 3: Dovish Index



Source: Own calculations

Table 1: Models Brief Summary

	BARCLAYS, BLOOMBERG, JPM, OTHERS	**MORGAN STANLEY**	**BLOOMBERG**	**JP MORGAN**
AUTHORS		A. Jaime, J. Lin, M. Hombach, V. Tirupattur (2021)	A. Montiel, I.F. Jersey, W. Hoffman (2023)	J. Lupton, D. M Atlas, D. Weitzenfeld (04/2023)
CODE		MNLFEDS	BIFIFEDA (minutes) BIFIOSA (statements)	JLGPUSCH (statements) JLGPUSPH (speeches)
METHOD	RULE BASED/DICTIONARIES/ TOPIC SHIFT Bag of Words, Dictionaries, TF-IDF	DEEP LEARNING CNN	LLM BERT	LLM BERT upgrading to GPT
	1.- Automatic Topic detection (inflation, labour, economic growth, financial conditions) and importance assignment (e.g., TF-IDF) 2.- Sentiment extraction and measure for a given topic, generating sentiment scores for each topic (e.g., Loughran-McDonald) 3.- Weighting and aggregation, generating an overall score	1.- Word embedding (Word2Vec and Sentence2Vec) 2.- CNN training on text labelled by own research analyst into categories (Hawkish, Neutral, Dovish) 3.- Fuzzy match to algorithm to increase accuracy adjusted to central bank communication 4.- Index created by the average of the probability/scoring assigned to each sentence	1.- Transfer learning, retraining BERT on individual manually labelled sentences for central bank's 5 categories: Dove, Dove-Neutral, Neutral, Neutral-Hawk, Hawk (acceptable accuracy 68%) 2.- Score: weighted ratio of # hawkish sentences minus # dovish sentences to total # of sentences 3. Minutes Index: scores from "consensus weights"	1.- Rule Based Filter. Sentence as unit of analysis. Inventory hierarchically classified concept (82) filtering and eliminating non-relevant information (46%) 2.- Relevance Classifier Model, key words matching (232 rules) generating a relevance weight for each sentence 3.- HS Model, hawkishness/dovishness determination, trained with 4,000 user-tagged sentences. Noise removal with 3 month moving avg
INPUT	FOMC statements	FOMC statements initially. Expansion to minutes, speeches, analyst reports	FOMC minutes, post-meeting press conference, FED member speeches, interviews	FOMC statement, FED member speeches
STATE	US	US	US	US
DATE	1993	1999	1993	1998
FREQUENCY	Monthly (FOMC meetings)	Monthly (FOMC meetings)	Monthly (FOMC meetings)	Monthly (FOMC meetings) and Daily (speeches)
INDEX Dovish to +100/Hawkish Neutral to +100 Hawkish Dovish" to +100 for "Most Hawkish"	Range: -100 Dovish, 0 = Range: -100 for "Most	Probability range: -100/		

Table 2: Hawkish and dovish words used to calculate random combinations of keywords

Hawkish (H)		Dovish (D)	
Raise	Lift	Cut	Loosen
Increase	Boost	Decrease	Slice
Go up	Bump up	Go down	Shave
Tighten	Augment	Ease	Trim
Head up	Higher	Head down	Lower
Hike	Climb	Slash	Drop
Move up	Hawkish	Move down	Dovish
Put up	Tight	Put down	Loose
Rise	Accommodation	Reduce	Accommodative

Source: Tobback et al. (2017)

Table 3: Regression Results - US 2-Year Treasury Yield (MoM Change)

	(1) DI	(2) DI + Covid	(3) DI + Covid + JPM	(4) DI + Covid + JPM (Optimal)
UST 2Y MoM (1-month lag)	0.463***	0.436***	0.406***	0.378***
	(0.065)	(0.063)	(0.066)	(0.067)
DovishIndex MoM	-209.297***	-226.150***	-209.859***	-197.105**
	(80.387)	(77.659)	(78.455)	(78.286)
JPM MoM (1-month ahead)			0.004	0.007**
			(0.003)	(0.003)
CovidSearch MoM		-0.004***	-0.004***	-0.004***
		(0.001)	(0.001)	(0.001)
Constant	0.007	0.008	0.008	0.008
	(0.011)	(0.011)	(0.011)	(0.011)
N	182	182	182	181
R^2	0.254	0.309	0.316	0.330
Adj. R^2	0.245	0.298	0.301	0.314
DW	2.160	2.209	2.172	2.160
DW p-value	0.848	0.913	0.857	0.836
Box-Ljung χ^2	1.908	3.381	2.148	2.184
Box-Ljung p-value	0.592	0.337	0.542	0.535

This table presents results of regressions explaining the MoM change in the US 2-year Treasury yield. Each column represents a different set of explanatory variables. (1) Dovishness Index (DI). (2) DI + Covid Search (Covid). (3) DI + Covid + JP Morgan (JPM). (4) DI + Covid + JPM, including JPM only when significant and the model has no significant correlated errors. Standard errors are in parentheses below the coefficients. Lags/leads used are indicated in parentheses after the variable names. *p<0.1; **p<0.05; ***p<0.01.

Table 4: Regression Results - US 5-Year Treasury Yield (MoM Change)

	(1) DI	(2) DI + Covid	(3) DI + Covid + JPM	(4) DI + Covid + JPM (Optimal)
UST 5Y MoM (1-month lag)	0.327***	0.305***	0.307***	0.263***
	(0.070)	(0.069)	(0.069)	(0.067)
DovishIndex MoM (3-month lag)	-139.298*	-124.880*	-128.772*	-118.090*
	(71.313)	(70.035)	(71.324)	(67.804)
JPM MoM (3-month lag)			-0.001	
			(0.002)	
JPM MoM (3-month ahead)				0.011***
				(0.003)
CovidSearch MoM		-0.003***	-0.002**	
		(0.001)	(0.001)	
Constant	0.003	0.003	0.003	-0.001
	(0.010)	(0.010)	(0.010)	(0.009)
N	179	179	179	176
R^2	0.135	0.174	0.175	0.259
Adj. R^2	0.125	0.160	0.156	0.241
DW	1.983	2.033	2.038	2.176
DW p-value	0.434	0.569	0.563	0.858
Box-Ljung χ^2	1.438	1.806	1.907	3.104
Box-Ljung p-value	0.697	0.614	0.592	0.376

This table presents results of regressions explaining the MoM change in the US 5-year Treasury yield. Each column represents a different set of explanatory variables. (1) Dovishness Index (DI). (2) DI + Covid Search (Covid). (3) DI + Covid + JP Morgan (JPM). (4) DI + Covid + JPM, including JPM only when its coefficient is statistically significant and the model has no significant correlated errors. Standard errors are in parentheses below the coefficients. Lags/leads used are indicated in parentheses after the variable names. *p<0.1; **p<0.05; ***p<0.01.

Table 5: Regression Results - US 10-Year Treasury Yield (MoM Change)

	(1) DI	(2) DI + Covid	(3) DI + Covid + JPM	(4) DI + Covid + JPM (Optimal)
UST 10Y MoM	0.346***	0.312***	0.314***	0.265***
(1-month lag)	(0.07)	(0.069)	(0.069)	(0.068)
DovishIndex MoM	-110.203**	-100.264**	-102.575**	-96.318**
(3-month lag)	(50.62)	(49.628)	(50.548)	(48.272)
JPM MoM			-0.0005	0.007***
(3-month lag)			(0.002)	(0.002)
JPM MoM				
(3-month ahead)				
CovidSearch MoM		-0.002***	-0.002***	-0.002***
		(0.001)	(0.001)	(0.001)
Constant	0.001	0.001	0.001	-0.002
	(0.007)	(0.007)	(0.007)	(0.007)
N	179	179	179	176
R^2	0.152	0.193	0.193	0.263
Adj. R^2	0.142	0.179	0.175	0.246
DW	1.878	1.905	1.909	2.009
DW p-value	0.192	0.247	0.240	0.486
Box-Ljung χ^2	1.430	0.985	0.999	1.807
Box-Ljung p-value	0.698	0.805	0.802	0.614

This table presents results of regressions explaining the MoM change in the US 10-year Treasury yield. Each column represents a different set of explanatory variables. (1) Dovishness Index (DI). (2) DI + Covid Search (Covid). (3) DI + Covid + JP Morgan (JPM). (4) DI + Covid + JPM, including JPM only when its coefficient is statistically significant and exhibits no correlated errors. Standard errors are in parentheses below the coefficients. Lags/leads used are indicated in parentheses after the variable names. *p<0.1; **p<0.05; ***p<0.01.

Table 6: Regression Results - Investor Sentiment Index (MoM Change)

	(1) DI	(2) DI + Covid	(3) DI + Covid + JPM	(4) DI + Covid + JPM (Optimal)
Investor sentiment MoM	-0.210***	-0.230***	-0.230***	-0.222***
(1 month lag)	(0.072)	(0.073)	(0.073)	(0.073)
DovishIndex MoM	16475.480**	15834.770**	16058.880**	15113.540**
(2 months lags)	(6755.301)	(6734.445)	(6863.325)	(6777.502)
JLGPUSPH MoM			0.044	
(two months lags)			(0.238)	
JLGPUSPH MoM				-0.420*
(3 months ahead)				(0.251)
CovidSearch MoM		0.165	0.163	0.142
		(0.100)	(0.101)	(0.101)
Constant	0.115	0.105	0.100	0.171
	(0.927)	(0.923)	(0.926)	(0.927)
N	180	180	180	177
R^2	0.079	0.092	0.093	0.105
Adj. R^2	0.068	0.077	0.072	0.085
DW	2.048	1.996	1.999	1.996
DW p-value	0.623	0.484	0.474	0.466
Box-Ljung χ^2	4.285	4.721	4.803	5.218
Box-Ljung p-value	0.232	0.193	0.187	0.157

This table presents results of regressions explaining the MoM change in the Investor Sentiment Index. Each column represents a different set of explanatory variables. (1) Dovishness Index (DI). (2) DI + Covid Search (Covid). (3) DI + Covid + JP Morgan (JPM). (4) DI + Covid + JPM, including JPM only when its coefficient is statistically significant and exhibits no correlated errors. Standard errors are in parentheses below the coefficients. Lags/leads used are indicated in parentheses after the variable names. *p<0.1; **p<0.05; ***p<0.01.

Table 7: Regression Results - INFLATION EXPECTATIONS (MoM change)

	(1) DI	(2) DI + Covid	(3) DI + Covid + JPMorganDovish	(4) DI + Covid + JPMorganDovish Optimal
Inflation expectations MoM (1 month lag)	-0.137*	-0.139*	-0.142*	-0.156**
	(0.074)	(0.074)	(0.075)	(0.075)
Inflation expectations MoM (4 months lag)			-0.209***	
			(0.075)	
DovishIndex MoM (1 month lag)	-457.054**	-434.333**	-376.714**	-425.986**
	(179.653)	(179.925)	(179.662)	(177.457)
JLGPUSPH MoM (one month lag)			0.013**	
			(0.006)	
JLGPUSPH MoM (one month ahead)				0.011*
				(0.006)
CovidSearch MoM		-0.004		-0.003
		(0.003)		(0.003)
CovidSearch MoM (2 months lags)			0.006**	
			(0.003)	
Constant	-0.004	-0.003	-0.005	-0.011
	(0.025)	(0.025)	(0.024)	(0.024)
N	181	181	180	180
R^2	0.052	0.062	0.120	0.082
Adjusted R^2	0.041	0.046	0.095	0.061
DW Statistic	1.993	2.004	2.049	2.086
DW p-value	0.476	0.503	0.608	0.698
Box-Ljung Chi-Squared	1.726	1.419	3.380	2.164
Box-Ljung p-value	0.631	0.701	0.337	0.539

This table presents results of regressions explaining the MoM change in the Inflation Expectations. Each column represents a different set of explanatory variables. (1) Dovishness Index (DI). (2) DI + Covid Search (Covid). (3) DI + Covid + JP Morgan (JPM). (4) DI + Covid + JPM, including JPM only when its coefficient is statistically significant and exhibits no correlated errors. Standard errors are in parentheses below the coefficients. Lags/leads used are indicated in parentheses after the variable names. *p<0.1; **p<0.05; ***p<0.01.

Table 8: Regression Results - Forward Inflation Expectation 5y5y (MoM change)

	(1) DI	(2) DI + Covid	(3) DI + Covid + JPMorganDovish	(4) DI + Covid + JPMorganDovish Optimal
Forward inflation expectation 5y5y MoM (1 month lag)	0.049	0.075	0.083	0.050
	(0.075)	(0.073)	(0.074)	(0.074)
Forward inflation expectation 5y5y MoM (3 months lags)	-0.097		-0.044	
	(0.074)		(0.077)	
Forward inflation expectation 5y5y MoM (2 months lags)		-0.192***	-0.187**	
		(0.073)	(0.074)	
DovishIndex MoM (1 month lag)			41.218	
			(59.479)	
DovishIndex MoM (2 months ahead)	-135.337**	-136.039**		-109.760*
	(58.160)	(57.698)		(59.471)
JLGPUSPH MoM (1 month lag)			-0.002	
			(0.002)	
JLGPUSPH MoM (3 months ahead)				0.005**
				(0.002)
CovidSearch MoM (1 month lag)				-0.0001
				(0.001)
CovidSearch MoM		-0.001		
		(0.001)		
Constant	-0.001	-0.002	0.001	-0.002
	(0.008)	(0.008)	(0.008)	(0.008)
N	179	180	181	180
R^2	0.044	0.083	0.060	0.066
Adjusted R^2	0.027	0.062	0.028	0.045
DW Statistic	1.989	1.997	2.012	1.978
DW p-value	0.457	0.480	0.502	0.413
Box-Ljung Chi-Squared	5.768	0.887	0.197	9.668
Box-Ljung p-value	0.123	0.829	0.978	0.022

This table presents results of regressions explaining the MoM change in the Forward Inflation Expectation 5y5y. Each column represents a different set of explanatory variables. (1) Dovishness Index (DI). (2) DI + Covid Search (Covid). (3) DI + Covid + JP Morgan (JPM). (4) DI + Covid + JPM, including JPM only when its coefficient is statistically significant and exhibits no correlated errors. Standard errors are in parentheses below the coefficients. Lags/leads used are indicated in parentheses after the variable names. *p<0.1; **p<0.05; ***p<0.01.

Table 9: Regression Results - BREAKEVEN 2Y (MoM change)

	(1) DI	(2) DI + Covid	(3) DI + Covid + JPMorganDovish	(4) DI + Covid + JPMorganDovish Optimal
Breakeven 2Y MoM	0.300***	0.336***	0.329***	0.289***
(1 month lag)	(0.070)	(0.069)	(0.069)	(0.066)
Breakeven 2Y MoM	-0.184***	-0.176***	-0.206***	-0.173***
(3 months lags)	(0.069)	(0.067)	(0.070)	(0.064)
Breakeven 2Y MoM	0.072	0.081*	0.085*	0.095**
(11 months lags)	(0.045)	(0.044)	(0.044)	(0.042)
DovishIndex MoM	384.525**	357.809**	388.582**	293.182*
(6 months ahead)	(159.298)	(155.178)	(156.137)	(149.557)
JLGPUSPH MoM			0.009	
(1 month lag)			(0.006)	
JLGPUSPH MoM				0.026***
(3 months ahead)				(0.006)
CovidSearch MoM		0.007***	0.008***	0.007***
(2 months lags)		(0.002)	(0.002)	(0.002)
Constant	0.015	0.013	0.011	0.009
	(0.022)	(0.021)	(0.021)	(0.020)
N	173	173	173	170
R^2	0.183	0.231	0.241	0.328
Adjusted R^2	0.163	0.208	0.213	0.303
DW Statistic	1.909	2.023	2.031	1.980
DW p-value	0.237	0.514	0.521	0.385
Box-Ljung Chi-Squared	1.570	0.984	0.752	2.385
Box-Ljung p-value	0.666	0.805	0.861	0.496

This table presents results of regressions explaining the MoM change in the BREAKEVEN 2Y. Each column represents a different set of explanatory variables. (1) Dovishness Index (DI). (2) DI + Covid Search (Covid). (3) DI + Covid + JP Morgan (JPM). (4) DI + Covid + JPM, including JPM only when its coefficient is statistically significant and exhibits no correlated errors. Standard errors are in parentheses below the coefficients. Lags/leads used are indicated in parentheses after the variable names. *p<0.1; **p<0.05; ***p<0.01.

Table 10: Regression Results - S&P500 (MoM change)

	(1) DI	(2) DI + Covid	(3) DI + Covid + JPMorganDovish	(4) DI + Covid + JPMorganDovish Optimal
S&P500 MoM	0.121	0.118	0.116	0.060
(1 month lag)	(0.074)	(0.074)	(0.074)	(0.070)
S&P500 MoM	-0.161**	-0.156**	-0.156**	-0.130**
(6 months lags)	(0.063)	(0.062)	(0.063)	(0.059)
DovishIndex MoM	2.848	3.304	2.989	5.353**
(1 month lag)	(2.504)	(2.494)	(2.531)	(2.377)
JLGPUSPH MoM			-0.0001	
(1 month lag)			(0.0001)	
JLGPUSPH MoM				0.0005***
(3 months lags)				(0.0001)
CovidSearch MoM	-0.0001*	-0.0001**	-0.0001	
	(0.00004)	(0.00004)	(0.00003)	
Constant	0.001***	0.001***	0.001***	0.001***
	(0.0004)	(0.0004)	(0.0004)	(0.0003)
N	178	178	178	175
R^2	0.056	0.077	0.080	0.205
Adjusted R^2	0.040	0.055	0.053	0.181
DW Statistic	1.964	1.945	1.944	1.970
DW p-value	0.383	0.337	0.317	0.382
Box-Ljung Chi-Squared	3.578	3.286	2.892	3.059
Box-Ljung p-value	0.311	0.350	0.409	0.383

This table presents results of regressions explaining the MoM change in the S&P500 (MoM change). Each column represents a different set of explanatory variables. (1) Dovishness Index (DI). (2) DI + Covid Search (Covid). (3) DI + Covid + JP Morgan (JPM). (4) DI + Covid + JPM, including JPM only when its coefficient is statistically significant and exhibits no correlated errors. Standard errors are in parentheses below the coefficients. Lags/leads used are indicated in parentheses after the variable names. *p<0.1; **p<0.05; ***p<0.01.

Table 11: Regression Results - DOLLAR INDEX (MoM change)

	(1) DI	(2) DI + Covid	(3) DI + Covid + JPMorganDovish	(4) DI + Covid + JPMorganDovish Optimal
Dollar index MoM (1 month lag)	0.321***	0.321***	0.265***	0.338***
	(0.070)	(0.071)	(0.069)	(0.070)
Dollar index MoM (5 months lags)			-0.039	
			(0.064)	
DovishIndex MoM (1 month lag)	-10.970	-10.995	-16.788**	-10.904
	(8.870)	(8.934)	(8.164)	(8.955)
JLGPUSPH MoM (6 months lags)			0.001***	
			(0.0003)	
JLGPUSPH MoM (9 months leads)				-0.001***
				(0.0003)
CovidSearch MoM		0.0000		
		(0.0001)		
CovidSearch MoM (1 month lag)			-0.0002*	-0.0003*
			(0.0001)	(0.0001)
Constant	0.001	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)
N	181	181	178	172
R^2	0.114	0.114	0.198	0.180
Adjusted R^2	0.104	0.099	0.174	0.161
DW Statistic	1.959	1.958	1.932	1.977
DW p-value	0.371	0.369	0.281	0.401
Box-Ljung Chi-Squared	1.534	1.537	0.316	0.937
Box-Ljung p-value	0.675	0.674	0.957	0.817

This table presents results of regressions explaining the MoM change in the DOLLAR INDEX. Each column represents a different set of explanatory variables. (1) Dovishness Index (DI). (2) DI + Covid Search (Covid). (3) DI + Covid + JP Morgan (JPM). (4) DI + Covid + JPM, including JPM only when its coefficient is statistically significant and exhibits no correlated errors. Standard errors are in parentheses below the coefficients. Lags/leads used are indicated in parentheses after the variable names. *p<0.1; **p<0.05; ***p<0.01.

Table 12: Regression Results - ECONOMIC SURPRISE INDEX (MoM change)

	(1) DI	(2) DI + Covid	(3) DI + Covid + JPMorganDovish	(4) DI + Covid + JPMorganDovish Optimal
Economic surprise MoM (1 month lag)	0.349*** (0.068)	0.370*** (0.069)	0.536*** (0.064)	0.215*** (0.069)
Economic surprise MoM (2 months lags)			-0.508*** (0.065)	
Economic surprise MoM (5 months lags)			-0.132** (0.060)	
DovishIndex MoM (9 months lags)	-60552.700*** (15827.230)	-58874.220*** (15763.440)	-37789.520*** (12968.070)	-45321.570*** (14829.980)
JLGPUSPH MoM (one month lag)			-1.703*** (0.502)	
JLGPUSPH MoM (two months lags)				-2.563*** (0.580)
CovidSearch MoM		-0.397* (0.228)	-0.567*** (0.188)	
CovidSearch MoM (one month lag)				-0.917*** (0.213)
Constant	-0.281 (2.154)	-0.256 (2.141)	0.746 (1.740)	0.703 (1.988)
N	173	173	173	173
R^2	0.212	0.226	0.503	0.344
Adjusted R^2	0.203	0.213	0.485	0.328
DW Statistic	1.585	1.615	2.118	1.612
DW p-value	0.003	0.005	0.735	0.004
Box-Ljung Chi-Squared	45.389	41.512	1.950	39.279
Box-Ljung p-value	<0.001	<0.001	0.583	<0.001

This table presents regression results explaining the month-over-month (MoM) change in the Economic Surprise Index. Each column represents a different model specification: (1) uses the Dovishness Index (DI, t-9) as the explanatory variable; (2) adds the Covid Search Index (MoM) to the DI; (3) incorporates the JPMorgan hawkishness measure (JPM, t-1); and (4) includes the JPMorgan hawkishness (t-1) measure only when its coefficient is statistically significant and exhibits no correlated errors. The Economic Surprise Index is also used with lags (t-1, t-2, and t-5). Standard errors are in parentheses. *p<0.1; **p<0.05; ***p<0.01.

Table 13: Regression Results - 10-Year Term Premium (MoM Change)

	(1) DI	(2) DI + Covid	(3) DI + Covid + JPMorganDovish	(4) DI + Covid + JPMorganDovish Optimal
Term premium 10Y MoM (1 month lag)	0.360*** (0.070)	0.352*** (0.076)	0.443*** (0.078)	0.319*** (0.069)
Term premium 10Y MoM (2 months lags)	-0.386*** (0.074)	-0.341*** (0.076)	-0.271*** (0.083)	-0.413*** (0.071)
Term premium 10Y MoM (3 months lags)	0.199*** (0.074)	0.160** (0.077)	0.127* (0.072)	0.199*** (0.072)
Term premium 10Y MoM (4 months lags)	-0.150** (0.071)		-0.109 (0.068)	-0.156** (0.070)
DovishIndex MoM (1 month lag)	-15.350 (106.490)	62.896 (115.700)		
DovishIndex MoM (6 months lags)			163.356 (99.944)	
DovishIndex MoM (2 months ahead)				130.336 (106.881)
JLGPUSPH MoM (1 month lag)			0.002 (0.004)	
JLGPUSPH MoM (2 months ahead)				0.010*** (0.004)
CovidSearch MoM (1 month lag)		-0.0002 (0.002)	0.0010 (0.001)	
CovidSearch MoM (2 months lags)				0.0005 (0.002)
Constant	-0.014 (0.015)	-0.006 (0.016)	-0.008 (0.014)	-0.022 (0.014)
N	180	181	176	178
R^2	0.189	0.157	0.191	0.230
Adjusted R^2	0.166	0.133	0.157	0.199
DW Statistic	1.899	1.800	1.947	1.987
DW p-value	0.233	0.082	0.321	0.424
Box-Ljung Chi-Squared	3.606	0.903	0.155	3.485
Box-Ljung p-value	0.307	0.825	0.985	0.323

This table presents regression results explaining the month-over-month (MoM) change in the 10-Year Term Premium. Each column represents a different model specification: (1) uses the Dovishness Index (DI) with lags; (2) adds the Covid Search Index to the DI; (3) incorporates the JPMorgan hawkishness measure (JPM); and (4) includes the JPMorgan measure only when statistically significant and exhibits no correlated errors. Lags and leads are indicated in parentheses. Standard errors are in parentheses below the coefficients. *p<0.1; **p<0.05; ***p<0.01.

Table 14: Diebold-Mariano Test Results - Simplified Index vs. BERT-based Model

Maturity	DM Statistic	p-value	Forecast Horizon
2 Years	-2.4415	0.0098	1
5 Years	-1.7702	0.0426	3
10 Years	-1.7995	0.0402	3

The table presents the results of the Diebold-Mariano test comparing the forecast accuracy of two models: one using our proposed index and the other using the JP Morgan index. The test evaluates whether the forecast errors of our model are significantly smaller than those of the JP Morgan model (alternative hypothesis: "less"). A negative DM statistic and a p-value below the significance level (e.g., 0.05) indicate that our model provides significantly more accurate forecasts. As shown in the table, our index outperforms the JP Morgan index for 2, 5, and 10-year maturities, with statistically significant results at a 5% significance level.

Table 15: Hawkish and Dovish Search Terms Ranked by Counts of Significance

Rank	Counts of Sig.	ID	Hawkish Search Terms	Dovish Search Terms
1	52	934	(FED OR “Federal Reserve”) (Tighten OR “Go up” OR Lift OR Boost OR Hawkish)	(FED OR “Federal Reserve”) (Slice OR Drop OR “Put down” OR “Move down” OR Decrease)
2	52	754	(FED OR “Federal Reserve”) (Tighten OR “Go up” OR Lift OR Boost OR Hawkish)	(FED OR “Federal Reserve”) (Lower OR Ease OR Decrease OR “Head down” OR Drop)
3	52	684	(FED OR “Federal Reserve”) (Tighten OR “Move up” OR “Head up” OR Rise OR Augment)	(FED OR “Federal Reserve”) (“Head down” OR Drop OR Decrease OR Shave OR Accommodative)
4	51	866	(FED OR “Federal Reserve”) (Rise OR Augment OR Tight OR Lift OR Hawkish)	(FED OR “Federal Reserve”) (Accommodative OR “Go down” OR “Head down” OR Drop OR Lower)
5	51	624	(FED OR “Federal Reserve”) (Tighten OR “Move up” OR “Head up” OR Rise OR Augment)	(FED OR “Federal Reserve”) (Slice OR Drop OR “Put down” OR “Move down” OR Decrease)
6	51	445	(FED OR “Federal Reserve”) (Rise OR Augment OR Tight OR Lift OR Hawkish)	(FED OR “Federal Reserve”) (Shave OR “Head down” OR “Go down” OR Lower OR Decrease)
7	51	184	(FED OR “Federal Reserve”) (Tighten OR “Go up” OR Lift OR Boost OR Hawkish)	(FED OR “Federal Reserve”) (Accommodative OR “Go down” OR “Head down” OR Drop OR Lower)
8	50	786	(FED OR “Federal Reserve”) (Accommodation OR Climb OR Boost OR Tighten OR Hawkish)	(FED OR “Federal Reserve”) (Shave OR “Head down” OR “Go down” OR Lower OR Decrease)
9	50	664	(FED OR “Federal Reserve”) (Tighten OR “Go up” OR Lift OR Boost OR Hawkish)	(FED OR “Federal Reserve”) (Cut OR Lower OR “Move down” OR “Go down” OR Drop)
10	50	644	(FED OR “Federal Reserve”) (Rise OR Climb OR “Bump up” OR Augment OR Tighten)	(FED OR “Federal Reserve”) (Decrease OR Slice OR “Go down” OR Lower OR Slash)
11	50	530	(FED OR “Federal Reserve”) (Accommodation OR Boost OR Augment OR Lift OR “Head up”)	(FED OR “Federal Reserve”) (Decrease OR Cut OR Drop OR Shave OR “Head down”)
12	50	414	(FED OR “Federal Reserve”) (Tighten OR “Move up” OR “Head up” OR Rise OR Augment)	(FED OR “Federal Reserve”) (Shave OR “Head down” OR “Go down” OR Lower OR Decrease)
13	50	334	(FED OR “Federal Reserve”) (Tighten OR “Go up” OR Lift OR Boost OR Hawkish)	(FED OR “Federal Reserve”) (Decrease OR Slice OR “Go down” OR Lower OR Slash)
14	50	55	(FED OR “Federal Reserve”) (Rise OR Augment OR Tight OR Lift OR Hawkish)	(FED OR “Federal Reserve”) (Decrease OR Slice OR “Go down” OR Lower OR Slash)
15	49	956	(FED OR “Federal Reserve”) (Rise OR Augment OR Tight OR Lift OR Hawkish)	(FED OR “Federal Reserve”) (“Put down” OR “Head down” OR “Move down” OR Slash OR Lower)
16	49	655	(FED OR “Federal Reserve”) (Rise OR Augment OR Tight OR Lift OR Hawkish)	(FED OR “Federal Reserve”) (Slice OR Drop OR “Put down” OR “Move down” OR Decrease)
17	49	475	(FED OR “Federal Reserve”) (Rise OR Augment OR Tight OR Lift OR Hawkish)	(FED OR “Federal Reserve”) (Lower OR Ease OR Decrease OR “Head down” OR Drop)
18	49	424	(FED OR “Federal Reserve”) (Tighten OR “Go up” OR Lift OR Boost OR Hawkish)	(FED OR “Federal Reserve”) (Lower OR Drop OR Ease OR Trim OR “Go down”)
19	49	24	(FED OR “Federal Reserve”) (Tighten OR “Move up” OR “Head up” OR Rise OR Augment)	(FED OR “Federal Reserve”) (Decrease OR Slice OR “Go down” OR Lower OR Slash)
20	49	3	(FED OR “Federal Reserve”) (Tighten OR “Go up” OR Lift OR Boost OR Hawkish)	(FED OR “Federal Reserve”) (Decrease OR Cut OR Drop OR Shave OR “Head down”)

Table 16: Diebold-Mariano Test - Simple Keyword Search Proves Robust

Compared Model	DM Statistic	p-value (one-sided)	p-value (two-sided)	Conclusion ($\alpha = 0.05$)
Median of 962 random indices	-0.938	0.1755	0.351	No significant difference
Best-performing randomly generated index	-1.093	0.139	0.279	No significant difference

Note: The best-performing text: (FED OR "Federal Reserve") [(Tighten OR "Go up" OR Lift OR Boost OR Hawkish) - (Slice OR Drop OR "Put down" OR "Move down" OR Decrease)].

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