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Agree to disagree: Measuring hidden dissent in FOMC meetings ☆

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ABSTRACT

Using FOMC transcripts and customized deep learning models, we quantify “hidden dissent”, or disagreement in the FOMC that is unobserved in formal votes. We find hidden dissent to be prevalent and systematically driven by macroeconomic conditions like inflation and unemployment. It strongly correlates with divergent member projections (SEP) and measures of policy sub-optimality, reflecting heterogeneity among members in policy preferences. Furthermore, we show that the financial markets respond to the hidden dissent implied in FOMC minutes.

1. Introduction

Statements, minutes, speeches, and other texts released by the Federal Reserve have been scrutinized extensively using techniques ranging from simple word clouds to advanced machine learning models. However, the transcripts of Federal Open Market Committee (FOMC) meetings—word-for-word records of members’ views—have been less studied. This is partly due to the five-year delay in their release, but also because of the difficulty in analyzing the vast volume of text produced by over a hundred past FOMC members.

This paper begins by evaluating each member’s position during meetings, using data (i.e., NO votes) to identify language that indicates strong disagreement with policy actions. The total percentage of NO votes from 1976 to 2018 is 6.93%. In Fig. 1, we show the annual counts of YES and NO votes, which reveal minimal variation over time.

While NO votes are rare, they provide enough data to train a deep learning model. Using members’ words, our model accurately predicts whether a member voted to dissent, allowing us to assess hidden dissent that may not have led to a NO vote. We demonstrate that Fig. 1 creates a misleading impression of consensus among FOMC members, and show that the level of hidden dissent measured by our model aligns with economic conditions more consistently than the voting outcomes.

Consider two examples that illustrate our main idea. In the FOMC meeting on May 19, 1998, President Minehan of the Federal Reserve Bank of Boston raised concerns about inflation and proposed a less accommodating policy, and she said:

“Mr. Chairman, at our last meeting I expressed concern that, even in the absence of clear indications that inflation was rising, both the strength of the domestic economy and the frothiness in financial markets required some policy tightening to reduce the risk that even more tightening might be needed later…”

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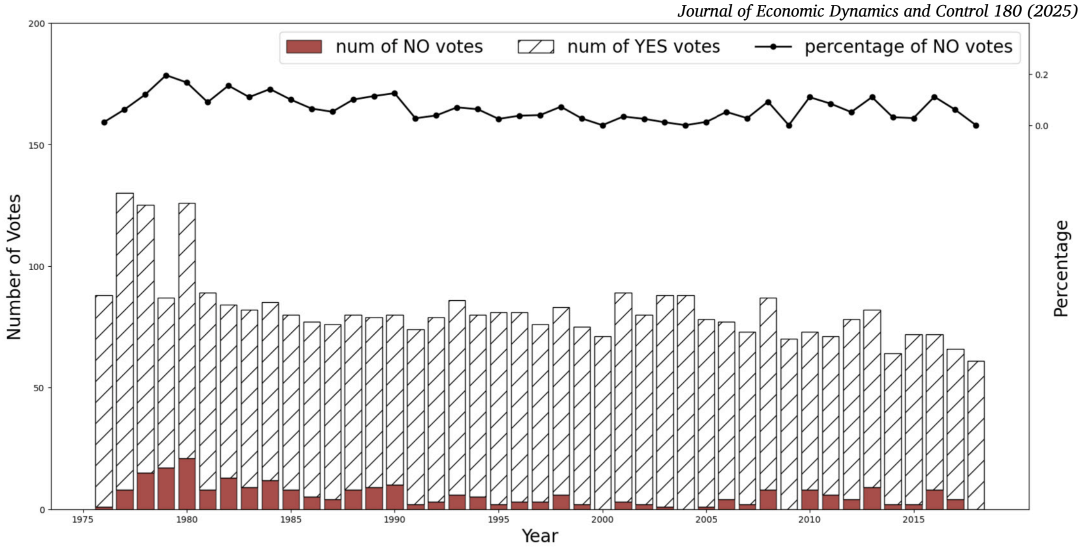

Fig. 1. Number of YES and NO Votes in Each Year. *Note:* The bar chart illustrates the annual distribution of YES and NO votes by FOMC members. Solid red bars indicate NO votes, while transparent striped bars represent YES votes. The dotted line shows the annual percentage of NO votes. (For interpretation of the colors in the figure(s), the reader is referred to the web version of this article.)

Other members, like Presidents Jordan, Poole and Broaddus shared Minehan's concerns. Even though Broaddus was not invited to vote in that meeting, he commented that:

"Mr. Chairman, if it were my choice, I would still prefer to make a small move today for many of the reasons that Cathy Minehan and Bill Poole have adduced here...So, to paraphrase Governor Kelley, I would say that if we sit still, I hope we will at least sit uptight. [Laughter]"

Eventually the Committee seeks to maintain the federal funds rate unchanged at an average of around 5-1/2 percent, and President Minehan, despite her concerns, voted YES.

Another example comes from the FOMC meeting on April 24, 2012. Governor Raskin voted for the final decision (no action), but the governor also raised concerns:

"Thank you, Mr. Chairman. I, too, support alternative B, but not without a vague sense that the actions taken today, i.e., no action, could be eventually interpreted by markets as being contractionary, an interpretation that could eventually effectively make them contractionary...Analogously, if our statement today sends a signal that we are content with the current path of the economy, this could work like contractionary policy—the last thing we need right now in my view. I hope that is not the message the public takes from our meeting today."

These examples suggest that some members voiced disagreements that were not reflected in their votes. In this paper, we introduce a hidden dissent measure based on a customized deep learning model, ranging from 0 (strong support) to 1 (substantial opposition). We also aggregate these individual measures to derive the level of hidden dissent for each FOMC meeting.

To validate the relevance of our measure, we regress it on two sets of explanatory variables at both individual and meeting levels. The first set includes current or projected targets under the dual mandate: inflation and unemployment rates. The second set comprises member characteristics like age, gender, political ideology, and education. Our results show that hidden dissent is strongly correlated with economic conditions, increasing when inflation rises or unemployment falls. This correlation suggests that members have more reservations when there seems to be a need for "cooling down" the economy, and members are more in unison when the economy is in a downturn. Among characteristics, we find that only education background has consistent explanatory power.

We also present evidence showing that hidden dissent is driven by members' differing policy preferences and economic projections. First, using data from the Summary of Economic Projections (SEP), we show that disagreements over the trajectory of monetary policy and projections for macroeconomic variables have roughly equal explanatory power. We also find evidence that the disagreement on monetary policy contains information beyond the disagreement on economic outlook, and this information is correlated with our measure of hidden dissent. Second, we observe a strong correlation between hidden dissent and the optimal policy perturbation (OPP) proposed by Barnichon and Mesters (2023). Since OPP can be driven by variations in loss functions or impulse responses, we again conclude that both forms of heterogeneity are important.

Finally, we investigate the real-world relevance of this hidden dissent by examining its impact on financial markets. While previous research has focused heavily on the sentiment conveyed in central bank communications (e.g., overall hawkishness or dovishness), we hypothesize that the degree of internal hidden disagreement represents a distinct and previously under-explored information channel. Using FOMC minutes for timeliness, we demonstrate that our hidden dissent measure provides information beyond simple sentiment, triggering significant and unique reactions in stock and bond markets.

1.1. Related papers

Central bank communication is a well-researched field, with numerous studies exploring various aspects (Born et al., 2014; Hansen and McMahon, 2016; Tobback et al., 2017; Hansen et al., 2019; Husted et al., 2020; Lunsford, 2020; Leombroni et al., 2021; Malmendier et al., 2021). Among central banks, the Federal Reserve has received the most attention due to its detailed communication records. Researchers have studied statements, minutes, speeches, news articles, press conferences, testimonies, and even facial expressions to understand Federal Reserve communication (Handlan, 2020; Arismendi-Zambrano et al., 2021; Shapiro et al., 2022; Gorodnichenko et al., 2023; Curti and Kazinnik, 2023; Alexopoulos et al., 2024). Recently, there has been growing interest in the less-explored FOMC meeting transcripts. Romer and Romer (2008) pioneered this area by manually examining transcripts from three FOMC meetings to show the link between forecast differences and policy actions. However, the release of transcripts, containing over three million words, makes manual analysis challenging. Advances in natural language processing (NLP) now enable researchers to apply sophisticated machine learning methods to analyze this large volume of text (Jurafsky and Martin, 2023). For example, Hansen et al. (2018) applied an LDA model to FOMC transcripts to study transparency policies, while Cieslak et al. (2021) and Shapiro and Wilson (2022) used Bag of Words models to measure members' sentiment. More recently, Shah et al. (2023) trained a BERT-based model to gauge monetary policy stance using FOMC speeches, meeting minutes, and press conference transcripts.

In this study, we develop a customized deep learning model leveraging transfer learning and the self-attention mechanism to analyze FOMC transcripts and uncover nuanced shifts in hidden dissent. We further aggregate these individual-level measures to construct a meeting-level hidden dissent score for each meeting. Additionally, we explore how this measure relates to economic conditions, members' personal characteristics and the factors contributing to hidden dissent. Finally, we investigate how financial markets respond to this new hidden dissent measure.

Our research contributes to the literature characterizing FOMC members' policy preferences through various forms of communication. For instance, Kahn and Oksol (2018) examined the Compilation and Summary of Individual Economic Projections to study how hawks and doves in the FOMC differed in their views of appropriate monetary policy, while Apel et al. (2022) used minutes and transcripts to measure participants' "hawkishness" and found it improves forecasting of future policy. Bertsch et al. (2022) employed a BERT-based model to analyze speeches, focusing on non-dual mandate concerns that influenced policy. Similarly, Bordo and Istrefi (2023) used a hawk-dove measure to study how members' personal characteristics shaped their preferences.

Our paper moves beyond traditional static classifications by using FOMC transcripts, which provide a more detailed record of members' views. By applying our deep learning model to the full content of transcripts, we construct a hidden dissent score at the individual-meeting level rather than the individual level, allowing members' policy preferences to fluctuate over time rather than categorically labeling them as hawks or doves. This method provides a more flexible and granular view compared to assigning fixed labels, capturing the nuances of policy deliberation. We also show that hidden dissent is closely related to current economic conditions, with little influence from personal characteristics.

In addition, our work connects to the literature examining explicit voting dissent as an information channel in monetary policy. Studies like Riboni and Ruge-Murcia (2014) demonstrate that dissenting votes can predict future policy actions, while Madeira et al. (2023) link dissent frequency to specific economic conditions, such as supply shocks that create policy trade-offs. However, a key limitation of focusing solely on recorded votes is their rarity. In contrast, our hidden dissent measure proves to be more prevalent and, as we demonstrate, shows a closer connection with the macroeconomic situation and tangible influences on financial markets, complementing the insights gained from studying explicit dissent.

Furthermore, we also apply our deep learning model to FOMC meeting minutes to derive a more timely assessment of hidden dissent. This approach takes advantage of our model's ability to capture nuanced dissent, offering a consistent, data-driven index that can be utilized soon after meetings, rather than waiting for the five-year lagged release of transcripts.

This paper is structured as follows. We lay out the various variables and data sources in section 2. Then section 3 describes the customized deep learning model and the generation of hidden dissent scores. In section 4 we discuss our empirical strategies and examine the economic meaning of the hidden dissent measure. And section 5 concludes.

2. Data

The data used in this study fall into four categories: (1) personal characteristics of FOMC members, (2) FOMC communication materials and voting outcomes, and (3) macroeconomic and financial market data.

2.1. Personal characteristics

Personal characteristics for each FOMC member come from multiple sources, including the Federal Reserve History website, members' Wikipedia entries and related news articles. The list of variables we collect is shown in Table 1.

When categorizing the hometown region of each FOMC member, we follow the practice established by the Bureau of Labor Statistics and divide the U.S. into four regions: Northeast (NE), Midwest (MW), South and West. We base the hometown classification on the location where a member was raised rather than their birthplace and we use "OTH" to represent hometowns outside of the U.S. Similarly, the school regions where members attained their highest degree are classified in the same fashion.

To measure the political ideology of FOMC members, we employ two different methods due to the different appointment procedures for governors and presidents. Members of the Board of Governors are appointed by the President of the United States (POTUS) and confirmed by the U.S. Senate. However, the POTUS and Senate are not directly involved in picking presidents of the twelve regional Federal Reserve Banks. Based on the information on the Board of Governors of the Federal Reserve website, presidents are chosen by their own boards of directors and confirmed by the Board of Governors. Accordingly, we use the party affiliation of the incumbent POTUS at the time of each governor's appointment as a proxy for their political ideology. For the presidents of the regional Federal Reserve Banks, we proxy their ideology based on the party that won the most recent presidential election in the state where

Table 1
FOMC Member Personal Information.

Collected Information	Description
Birth Date	Date of birth of the FOMC member
Gender	Gender of the FOMC member
Hometown Region	Geographic region of the member's hometown
Term Starts	Year the member began serving as governor or president
Term Ends	Year the member left their current position
School Region	Region of the institution granting the member's highest degree
School Wealth	Endowment per student at the institution granting the highest degree
Degree Major	Major field of the member's highest degree
Great Depression	Equals 1 if the member experienced the Great Depression
Great Inflation	Equals 1 if the member experienced the Great Inflation
WWII	Equals 1 if the member experienced World War II
Party	(1) Party of the sitting U.S. President (for governors) or (2) Party of the state-level presidential election winner (for presidents)

Note: This table describes the personal information collected for each FOMC member, sourced from the Federal Reserve History website, Wikipedia, and various news articles.

Table 2
Summary Statistics of Selected FOMC Member Characteristics.

Personal Char.	Count	Proportion (%)
Hometown		
Northeast	32	32.99
Midwest	23	23.71
South	22	22.68
West	13	13.40
Other	7	7.22
School		
Northeast	43	44.33
Midwest	26	26.80
South	18	18.56
West	10	10.31
Experience		
WWII	52	53.61
Great Depression	41	42.26
Great Inflation	43	44.33
Other Char.		
Female	14	14.43
Economics Major	69	71.13
Appt. Democrat	44	45.36

Note: This table displays the distribution of selected characteristics of FOMC members. “Hometown Other” indicates members who grew up outside the U.S., and “Appt. Democrat” counts members appointed by a Democratic president or from states that voted Democratic in presidential elections.

the respective bank is located. For example, President Jeffrey M. Lacker assumed the role of president at the Federal Reserve Bank of Richmond in 2004, so we use the presidential election result in Virginia in 2004; President Dennis P. Lockhart was appointed as the president of the Federal Reserve Bank of Atlanta in 2007, we use the presidential election result in Georgia in 2008 rather than 2004. The state level presidential election data after 1976 is downloaded from MIT Election Data and Science Lab, and earlier data is downloaded from the Election Statistics published by the U.S. House of Representatives.

We also collect the significant events experienced by FOMC members in their early ages. Following Bordo and Istrefi (2023), we collect information related to three major events: the Great Depression (1929-1939), World War II (1939-1945), and the Great Inflation (1965-1982). If a FOMC member experienced one of these events before turning 21, we count the corresponding variable as one.[1] Eventually, we collect the personal information of FOMC members who cast votes in meetings from 1976 to 2018, a selective description of the personal characteristics information can be found in Table 2.

[1] We choose to not include World War I (1914-1918) because only nine FOMC members experienced WWI in our sample, and this number is significantly smaller than that in other events. We also look at the active periods of these nine members and find that they only served on the FOMC from 1976 to 1986. In contrast, members who experienced the Great Depression can be found from 1976 to 2008, members who experienced the Great Inflation can be found from 1982 to 2018, and members who experienced WWII were on the FOMC throughout the entire data sample. Furthermore, given that some macroeconomic data used in our later study is only available after 1986, we choose to focus on the listed three events.

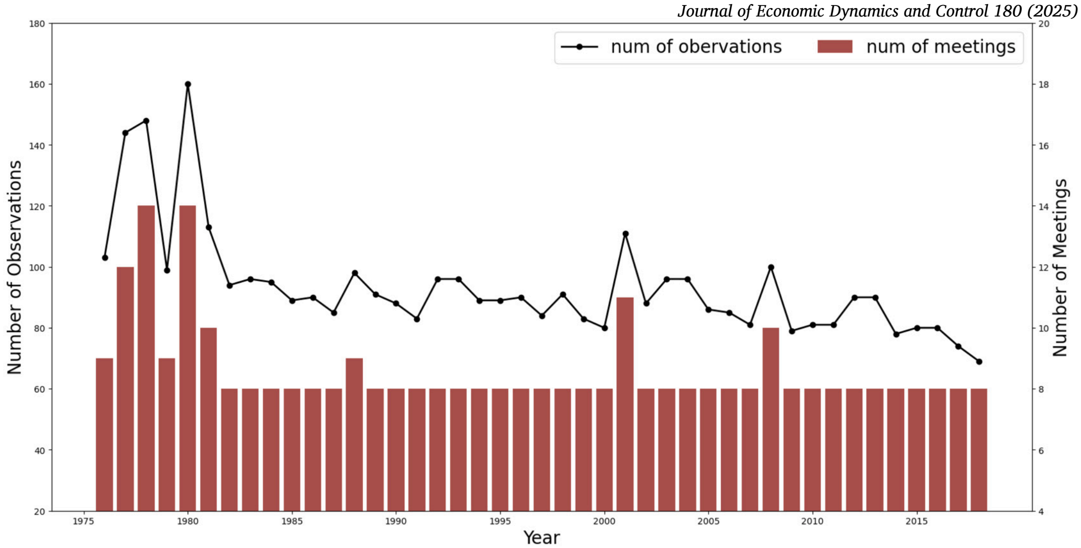

Fig. 2. Numbers of Observations and Meetings in Each Year. *Note:* The bar chart displays the annual count of FOMC meetings, with the black dotted line showing the number of voting members (observations) per year. While the number of meetings remains relatively stable in recent years, slight fluctuations in observations reflect varying attendance across meetings.

2.2. Communication materials and voting outcomes

How FOMC communicates its monetary policies changes over time, and Todd (2016) gives a detailed discussion on this topic. In this study, we download the available transcripts spanning from March 29, 1976 to the end of 2018, remove all the content from Fed staff, and only keep the transcripts related to the members who cast votes at the end of meetings. These transcripts are then disassembled and re-clustered at the meeting-person level. For example, suppose ten FOMC members attended a FOMC meeting, combining the transcript with the members' voting records resulted in the creation of ten labeled observations. And, to reduce the data processing time, we also remove irrelevant sentences like "Thank you, Chair", "Thank you, President", "Good morning..." etc. To remove them, we follow the method in Shapiro and Wilson (2022) and use the Oxford Dictionary of Economics and the Oxford Dictionary of Finance and Banking to filter out sentences that do not contain any economics-related terms.

The FOMC meeting minutes were introduced in 1993 to provide the public with "a timely summary of significant policy issues addressed by meeting participants." Initially, the minutes were released approximately three days after the subsequent Committee meeting. However, since December 2004, the release schedule has been moved up to three weeks following the meeting. Prior to 1993, the content of the current minutes was available in two separate documents: the *Record of Policy Actions* and the *Minutes of Actions*. In this study, we consider these two documents as substitutes for the current meeting minutes for the period before 1993. Corresponding documents are available on the Board of Governors of the Federal Reserve website, from which we compile meeting minutes data spanning from 1976 to 2024.

The voting records we have extracted are cross-checked with the FOMC Dissents data maintained by Thornton and Wheelock (2014) to ensure accuracy. By pairing individual-level transcripts with their respective voting records, we process data from 370 FOMC meetings and a set of 3,950 labeled observations was assembled for the training of our NLP model.[2] The distributions of meeting and observation counts per year are shown in Fig. 2.

2.3. Macroeconomic and financial markets data

Macroeconomic data mainly comes from the Tealbook (formerly Greenbook) data set maintained by the Federal Reserve Bank of Philadelphia. Tealbook is prepared by the Board of Governors' staff in preparation for each regularly scheduled FOMC meeting. Tealbook contains in-depth analysis of the U.S. and international economy. Additionally, staff at the Board of Governors also prepare projections for the U.S. economy using an assumption about monetary policy. We use the unemployment and core CPI data from the Tealbook to measure the dual mandate, and the core CPI data only became available after the FOMC meeting on February 12, 1986. Meanwhile, all financial markets data unitized in this study is openly accessible on Yahoo Finance.

2.4. Transformation of meeting-level variables

Combining the macroeconomic variables with personal characteristics, we create a list of variables at the FOMC meeting level, and they are summarized in Table 3.

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[2] We include conference calls as long as they contain voting records. If not, we discard the corresponding transcripts.

Table 3
FOMC Meeting Information.

Variable	Description
Macro-level Variables	
Unemployment Trend	Trend in unemployment data from the Tealbook
Unemployment S.D.	Standard deviation of unemployment data from the Tealbook
CPI Trend	Trend in core CPI data from the Tealbook
CPI S.D.	Standard deviation of core CPI data from the Tealbook
Meeting-level Variables	
Experience S.D.	Standard deviation of members' experience
Age S.D.	Standard deviation of members' ages
School Wealth S.D.	Standard deviation of endowments per student
Hometown Div.	Diversity of members' hometown regions
School Div.	Diversity of regions where members earned their highest degrees
Major Pct.	Percentage of members with an economics-related highest degree
Gender Pct.	Percentage of female members present at a meeting
Great Depression Pct.	Percentage of members who experienced the Great Depression
Great Inflation Pct.	Percentage of members who experienced the Great Inflation
World War II Pct.	Percentage of members who experienced World War II
Appt. Democrat Pct.	Percentage of members appointed by a Democratic president
Incumbent Democrat	Dummy variable for the incumbent president's party; 1 if Democrat

Note: Meeting-level data is derived from FOMC members' personal information, while macro-level economic data is sourced from the Tealbook (formerly the Greenbook).

A member's experience is calculated based on the start date of their term and the date of each meeting.[3] Similarly, a member's age at a certain FOMC meeting is calculated based on the birth date and the corresponding meeting date. To measure the diversity in a meeting, we employ the concept of Shannon entropy and calculate:

$$H = -\sum_{i=1}^{n} p_i \log_b p_i$$

where n is the number of elements in the system, p_i is the frequency of element i, and b is the base of the logarithm.

In the case of quantifying the diversity of hometowns among meeting participants, we count the numbers of members whose hometown locates in the northeast (NE) region, the midwest (MW) region, the south region, the west region, and outside of the U.S. (OTH). It is then fed into the aforementioned entropy function with a base of five to standardize the entropy value. Shannon entropy reaches its maximum value when all elements have equal probability, implying that greater diversity in hometown distribution corresponds to a higher entropy value. Consequently, value 0 indicates minimal diversity of hometowns, while a value of 1 signifies the highest level of diversity on hometowns. The same approach is applied to calculate the school diversity.

For the macroeconomic variables, unemployment and inflation, we use corresponding five data points: *Variable_B2*, *Variable_B1*, *Variable_F0*, *Variable_F1* and *Variable_F2* from the Tealbook to calculate both trend and standard deviation for these two variables. The trend value is determined by the slope obtained from a first-degree polynomial regression applied to the five data points. And the standard deviation is also calculated based on these five data points, which measures the uncertainty faced by FOMC members.

3. Natural language processing

With the continued evolution of deep learning, a multitude of NLP tasks are seeing improving outcomes (Kamath et al., 2019; Lauriola et al., 2022). In this section, we present the architecture of our customized deep learning model, which is built on the self-attention mechanism. We implement the model on FOMC communication materials. For background information on the application of deep learning models in NLP, please refer to Appendix A. A more detailed discussion can be found in Dell (2024).

3.1. A customized deep learning model

Our primary goal is to quantify the extent of disagreement expressed by FOMC members during meetings. To achieve this, we develop a deep learning model designed to analyze the textual content of members' statements. Since computers process numerical data rather than raw text, the first step involves converting the language used by members into a format the model can understand. We employ a state-of-the-art technique based on Sentence-BERT (Reimers and Gurevych, 2019) to transform each sentence within a member's transcript into a numerical representation, known as a sentence embedding. This process captures the semantic meaning

[3] For members like Governor Janet Yellen who served as the president of the Federal Reserve Bank of San Francisco first (2004-2010), then joined the Federal Reserve Board (2010-2018), we count her term started in 2004 as the president.

Table 4
Hyperparameter Value Search Space.

Variable	Value Search Space
Number of MHSA Modules in Chair Section	[1, 12], step = 1
Number of MHSA Modules in Member Section	[1, 12], step = 1
Number of MHSA Heads in Chair Section	[4, 12], step = 4
Number of MHSA Heads in Member Section	[4, 12], step = 4
Dropout Rate	[0.4, 0.8], step = 0.005
Initial Learning Rate	$[1e^{-3}, 1e^{-6}]$

Note: The learning rate is sampled from a specified range in the logarithmic domain, and a learning rate scheduler is applied throughout the model training process.

Table 5
Summary Statistics for Hidden Dissent Measures.

Measure	Mean	S.D.	Min	Max	Count
Individual Level					
hd_{ij}	0.3235	0.2282	0.0000	0.8464	3523
v_{ij}	0.0693	0.2539	0.0000	1.0000	3523
Meeting Level					
HD_i	0.3207	0.1513	0.0209	0.7095	370
V_i	0.0693	0.0993	0.0000	0.6667	370

Note: This table presents summary statistics for the hidden dissent measures used in this study. The variable x_{ij} represents hidden dissent values directly derived from our deep learning model, while X_i denotes the aggregated hidden dissent level based on x_{ij}.

of the sentences. For technical consistency, we ensure all these numerical representations have a uniform size through the padding process.[4]

The core of our approach lies in comparing each member's statements against those of the FOMC chair. Given the Chair's consistent record of voting with the majority to implement the final policy decision, we use their transcript as a proxy for the meeting's ultimate policy stance or consensus view. Our customized model architecture, inspired by the self-attention mechanism prevalent in modern NLP (Vaswani et al., 2017), is specifically designed for this comparison. Intuitively, the self-attention mechanism allows the model to weigh the importance of different parts of the text, focusing on the segments most relevant for gauging agreement or disagreement. The model processes the numerical representations of both the member's and the chair's transcripts, identifies the key differences in their expressed views, and uses these differences to predict the member's likely voting outcome (YES = 0 or NO = 1). Fig. 3 provides a schematic overview of this architecture.

Training such a model requires careful consideration of the data and methodology. We optimize the model's configuration by fine-tuning its hyperparameters, such as the complexity of its internal layers and the learning rate, using the *optuna* framework developed by Akiba et al. (2019) to find the best settings (details in Table 4). A key challenge is the inherent imbalance in the voting data: dissenting (NO) votes are rare compared to assenting (YES) votes.[5] To prevent the model from simply learning to always predict YES, we employ an over-sampling technique, effectively showing the model an equal number of YES and NO vote examples during training. Furthermore, we incorporate standard deep learning practices like learning rate scheduling (gradually adjusting the learning rate during training) and early stopping (halting training when performance on unseen data stops improving) to enhance training efficiency and, crucially, to prevent overfitting—ensuring the model generalizes well to new, unseen transcripts rather than just memorizing the training data.

The optimally configured model achieves high accuracy in predicting actual votes on both the training data (85.88%) and unseen test data (84.20%). While the model is trained to predict a binary outcome (0 or 1), the underlying prediction is a probability score between 0 and 1, indicating the likelihood of a member dissenting (voting NO). We leverage this probability directly as our measure of *hidden dissent*. We denote this score as hd_{ij} for member j in meeting i. A score close to 0 signifies strong agreement with the chair's position, while a score close to 1 indicates substantial disagreement, reflecting a high probability of the model predicting a NO vote. Summary statistics for these hidden dissent measures are reported in Table 5. This continuous measure allows us to capture nuances

[4] Specifically, using Sentence-BERT, each sentence is converted into a 768-dimension vector. We then group these sentence vectors for each member's transcript in a meeting and pad them to a standard size of (256, 768) before feeding them into our model. This standardization aids the model training process.

[5] After filtering out observations that contain fewer than five sentences, the final dataset contains 3,523 observations. Among these, only 244 (6.9%) are linked with NO votes, compared to 3,279 with YES votes. This severe imbalance poses challenges not only for current model training, but also for further distinguishing the direction of dissent (e.g., dovish vs. hawkish). With so few NO votes, further subdividing them into directional categories would leave too few observations per class for reliable prediction. Accordingly, our analysis is constrained to measuring the magnitude of dissent. Nevertheless, we show that our proposed measure of hidden dissent is a potent, and previously unmeasured, channel of information that provides statistically significant and economically meaningful insights.

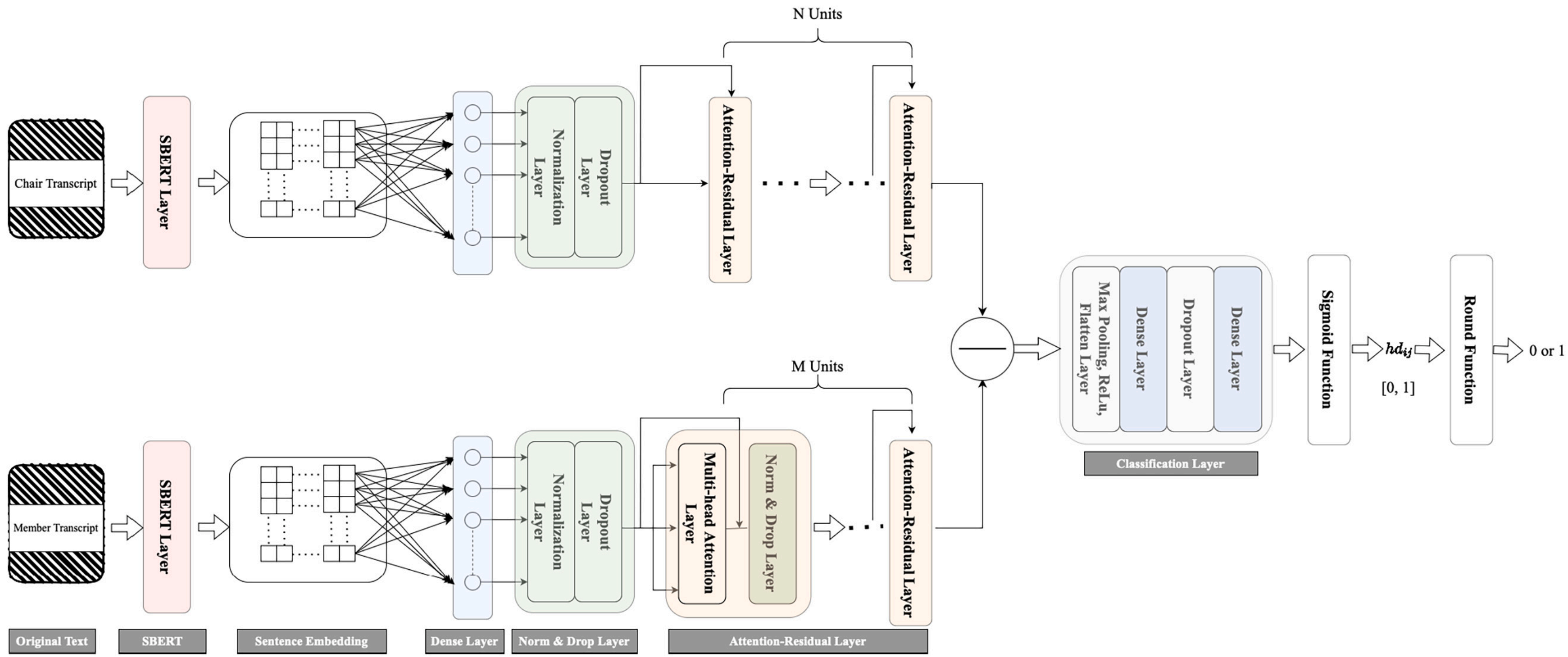

Fig. 3. FOMC Deep Learning Model. *Note:* This figure illustrates the Deep Learning model used in this paper. The SBERT layer transforms the original texts into sentence embeddings, high-dimensional arrays that can be processed by subsequent modules. Multiple multi-head self-attention modules, dense layers, and dropout layers are then applied to extract relevant features. For a detailed discussion, see subsection 3.1.

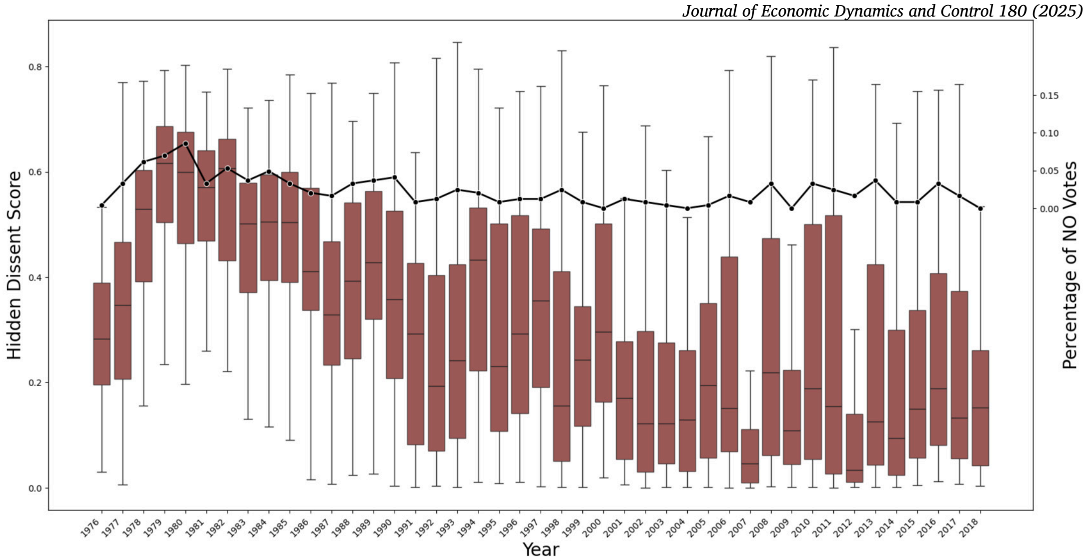

Fig. 4. Hidden Dissent Score Distribution. *Note:* This figure presents the boxplot of hidden dissent scores by year. The red box shows the interquartile range (Q1 to Q3), with the black line indicating the median (Q2), and whiskers extending up to 1.5 times the interquartile range (Q3-Q1). The black dotted line reflects the percentage of total NO votes cast in each year.

in members' positions that a simple binary vote. Furthermore, in section 4, we demonstrate that hd_{ij} provides unique information not captured by other FOMC communication channels.

3.2. Hidden dissent inside FOMC meeting transcripts

With the hidden dissent scores (hd_{ij}) from our customized model, we can now study what characteristics contribute to FOMC members' voting behaviors. Moreover, we are able to describe the hidden dissent that cannot be fully captured by voting records ($v_{ij} = 0$ or 1).

Fig. 4 shows the boxplot of hd_{ij} scores in each year. In the plot, the red box represents the interquartile range (Q1 to Q3), with the black line in the middle indicating the median (Q2). The whiskers extend to 1.5 times the interquartile range (Q3-Q1). Meanwhile, we compare the boxplot with the percentage of total NO votes, shown by the black dotted line, and they reveal a similar trend. For example, the high median score in 1980 corresponds with a significant proportion of total NO votes recorded in history, whereas lower median scores in recent years are associated with fewer NO votes.

Furthermore, Fig. 5 presents word clouds for different groups based on hidden dissent scores and FOMC meeting policy actions. The first two figures represent word clouds for members with hd_{ij} scores below and above 0.5, respectively. The subsequent rows further refine these word clouds based on FOMC meeting policy actions (i.e., maintaining, increasing, or decreasing the federal funds rate).

In the plots, both the gray shading and word sizes represent word frequency in meeting transcripts. One pattern is obvious: inflation has a high priority in every FOMC meeting. From the first row we can see that no matter the members have low (i.e., align with the meeting decision) or high hidden dissent scores (i.e., deviate from the meeting decision), inflation remains focus in both groups. While words like "economy" and "risk" show relatively high priority in the low-score group, the high-score group's emphasis stays on inflation. This pattern persists when groups are further refined based on policy actions. When FOMC opts not to reduce the policy rate, the low-score group prioritizes inflation, followed by economy, growth, and risk, etc. On the other hand, the high-score group mainly focuses on inflation alone, followed by economy, growth, unemployment, etc. However, a deviation from this pattern arises in the periods when FOMC seeks to decrease the rate. In those meetings, inflation drops to the third most frequent word for the low-score group. Meanwhile, inflation still has the highest priority in the high-score group, but other words like growth and economy also become more important. The observation may suggest that the decision to reduce the rate usually is reached when FOMC has to pivot its priority from inflation to other goals, like economic growth or market stability. For a robustness check, we also show word clouds for different groups based on members' voting records (see Figure B.1), and yield similar results.

3.3. Hidden dissent: hawkish or dovish?

Sentiment analysis that classifies policy preferences along a hawkish-dovish spectrum is a widely adopted and valuable method for studying the FOMC (Bordo and Istrefi, 2023; Malmendier et al., 2021; Istrefi, 2019). We propose our hidden dissent score as a complement to this approach, designed to capture a different aspect of policy deliberation. While sentiment indices effectively measure the directional leaning of preferences, we find that disagreements are often multi-dimensional and cannot be fully captured by a binary classification. Our measure therefore quantifies the intensity of these nuanced disagreements.

(a) Hidden Dissent Scores (< 0.5), Full Sample

(b) Hidden Dissent Scores (≥ 0.5), Full Sample

(c) Hidden Dissent Scores (< 0.5), Rate Unchanged

(d) Hidden Dissent Scores (≥ 0.5), Rate Unchanged

(e) Hidden Dissent Scores (< 0.5), Rate Increases

(f) Hidden Dissent Scores (≥ 0.5), Rate Increases

(g) Hidden Dissent Scores (< 0.5), Rate Decreases

(h) Hidden Dissent Scores (≥ 0.5), Rate Decreases

Fig. 5. The Word Cloud for Groups of Different Hidden Dissent Scores. *Note:* This figure displays word clouds for different groups categorized by hidden dissent scores and FOMC policy actions—rate increase, decrease, or no change. In each word cloud, both the gray shading and word size reflect their frequency in meeting transcripts.

The limitations of a simple hawk-dove classification can be illustrated by the voting record of President Jerry Jordan. In the October 6, 1992 meeting, President Jordan dissented in favor of a more accommodative policy, a seemingly "dovish" action. However, his reasoning was not a simple call for more loosening but a critique of the Fed's lack of credibility:

"I ask business people why they don't believe us when we say we're going to zero inflation...They just sort of shrug and say they don't believe it...I think the issue we have to attack is the credibility of our commitment; we as a Committee need to convey in the clearest way we possibly can that we are going toward zero inflation. That's what we should tell them about how to gauge our policy."

Less than two year later, in the March 22, 1994 meeting, President Jordan dissented again, this time in favor of a more aggressive tightening (a 50 basis point hike instead of the Committee's 25). This appears to be a classic "hawkish" dissent. His reasoning was again rooted in establishing a systematic policy to bolster credibility, arguing that the Committee was not moving decisively enough toward a neutral stance:

"And it's a useful idea to think that there is such a thing as a neutral policy stance. I feel very strongly that we are nowhere near a neutral stance and that we ought to be aggressive in moving toward it."

President Jordan was not simply a "dove" in 1992 and a "hawk" in 1994. Rather, he was a consistent advocate for a credible, systematic policy framework. He dissented when he believed the Committee's actions—whether by being too timid in tightening or too discretionary in easing—failed to achieve that primary objective. Our model captures this consistency, assigning high hidden dissent scores to President Jordan in both instances (0.82 in 1992 and 0.80 in 1994), reflecting his significant deviation from the Committee's discretionary approach, regardless of the policy direction.

Besides "No" votes that are more than hawkish or dovish, we also have "No" votes that do not have a directional leaning. According to the dataset compiled by Thornton and Wheelock (2014), out of a total of 503 dissenting votes have been recorded between March

19, 1936 and September 17, 2025, 269 are categorized as being for a tighter policy and 172 for an easier policy. The remaining 62 dissents—over 12% of the total—could not be classified in either category.[6] One example of such a dissent is that of President Charles Plosser in the September 17, 2014, meeting. He objected explicitly to the wording and communication strategy of the policy statement, not its immediate policy direction:

"At the last meeting I dissented over forward guidance language in alternative B...I have to renew my objection to the language, which continues, in my mind, to ignore the significant progress the economy has made toward our goals. It is not just the last number that matters. It is the accumulated progress we have made over the past year. And both the statement language and the forward guidance, in particular, fail to acknowledge that."

Ultimately, our hidden dissent score complements existing hawk-dove sentiment indices by capturing these nuanced, multi-dimensional disagreements. The analysis in subsection 4.3 will further show that this measure provides additional information not captured by traditional sentiment indices.

4. Results

Since the hidden dissent scores derived from transcripts are inferred at the individual level, a natural starting point is to examine the relationship between these scores and macroeconomic variables as well as personal characteristics. To test whether hidden dissent is related to the dual mandate (i.e., maximum employment and stable prices), we use the unemployment rate and core CPI as the target macroeconomic variables in this study.[7] And personal characteristics are discussed in subsection 2.1. Additionally, we average the scores at the committee level and assess whether the hidden dissent level can explain deviations of the FOMC from the optimal policy and whether financial markets respond to this information.

After obtaining the hidden dissent score hd_{ij} for FOMC member j in meeting i, we measure the hidden dissent level within each FOMC meeting by averaging the hidden dissent scores ($HD_i = \sum_{j=1}^{N} hd_{ij}$), which captures the hidden dissent intensity toward the chair. Similarly, for each meeting, we define the average of final voting results (0 or 1) as V_i.

4.1. What drives the hidden dissent inside FOMC meetings?

To examine how members' opinion divergence is related to macroeconomic variables and personal characteristics, we run the following regressions:

$$y_{ij} = \beta_0 + \boldsymbol{\beta_1} X_i^{Macro} + \boldsymbol{\beta_2} X_{ij}^{Char} + \varepsilon_{ij}, \tag{1}$$

where $y_{ij} = hd_{ij}, v_{ij}$. Considering the unbalanced nature of the panel data and the conditions where $hd_{ij} \in (0,1)$ and $v_{ij} \in \{0,1\}$, we employ mixed-effects beta panel regression for hd_{ij} and mixed-effects logistic panel regression for v_{ij}, respectively.[8] Both regressions are clustered at the individual level and the findings are presented in Table 6, showing that certain macroeconomic variables and personal characteristics can help explain the hidden dissent. In particular, as inflation is trending up, members on average have more reservations about the FOMC decision. This observation resonates with the conclusion from (Ball, 1992) that high inflation may raise inflation uncertainty since when inflation is high, the Federal Reserve is facing a dilemma: curbing inflation or a potential recession. Consistent with Bordo and Istrefi (2023), where the member went to school matters. Regarding other personal characteristics, the findings remain inconclusive, leading us to consider these factors as control variables. For a comprehensive presentation of the results, please refer to Appendix D. Furthermore, if we regress on voting results, v_{ij}, instead, while results for education mostly remain, macroeconomic variables do not matter anymore.

Our analysis thus far shows that, while hidden dissent is strongly related to the inflation mandate, its connection to unemployment is surprisingly modest. This is somewhat puzzling, given that unemployment is the other key mandate of the Federal Reserve. One potential explanation, advanced by Malmendier et al. (2021), is that members' personal experiences generate heterogeneity in their sensitivity to macroeconomic variables.[9] To test this hypothesis, we conduct another analysis with interaction terms between macroeconomic variables and members' formative-year experiences, estimated using a fixed-effects model:

$$y_{ij} = \beta_0 + \boldsymbol{\beta_1} X_i^{Macro} + \boldsymbol{\beta_2} X_i^{Macro} \cdot X_j^{Exp} + \tau_j + \varepsilon_{ij}, \tag{2}$$

where X_j^{Exp} represents one of three events experienced by FOMC members in their early ages: the Great Depression, World War II, or the Great Inflation. τ_j is the fixed effect for member j.

The results, presented in Table 7, strongly support this hypothesis. The modest aggregate effect of unemployment masks significant heterogeneity driven by members' early-age experiences. Specifically, during periods of high unemployment, members who, in their early age, lived through the Great Depression or WWII (two adjacent events) are significantly more likely to support the consensus accommodative policy. In contrast, members whose views were shaped by the Great Inflation exhibit significantly greater conservatism and are more likely to express dissent from policies of trading off unemployment for inflation.

[6] Restricting the data to our 1976–2018 sample period, 30 of the 281 recorded dissents are classified as neither "tighter" nor "easier."

[7] As mentioned in subsection 2.3, the core CPI data documented in the Tealbook (formerly Greenbook), is available starting from February 12, 1986. Therefore, the following regression analyses in this paper are exclusively based on data from this date forwards.

[8] For these and all the following regressions, using OLS yields similar results and does not change our conclusions.

[9] We thank an anonymous referee for the suggestion to explore this channel.

Table 6
Explaining Hidden Dissent and Revealed Dissent (Individual-level).

	hd_{ij} (*Mixed Effects Beta*)		v_{ij} (*Mixed Effects Probit*)	
	(1)	(2)	(3)	(4)
Macro Factors				
T_{unemp}	−0.2286*	−0.0136	0.0039	0.0584
	(0.1281)	(0.1289)	(0.1495)	(0.1515)
D_{unemp}	−0.0117	−0.1056**	0.2425*	0.1561
	(0.0443)	(0.0462)	(0.1299)	(0.1345)
T_{CPI}	1.0414***	1.0096***	0.1390	0.1433
	(0.1366)	(0.1436)	(0.1161)	(0.1200)
D_{CPI}	0.5246***	0.4524***	0.1773	0.2261
	(0.0797)	(0.1029)	(0.1723)	(0.2209)
Member Char.				
Econ Major		−0.0755		−0.0955
		(0.1580)		(0.6507)
School Northeast		−0.3826		−1.9152**
		(0.2335)		(0.9074)
School South		−0.7624***		−3.8795***
		(0.2374)		(1.0422)
School West		0.0669		−1.4407
		(0.3065)		(1.2051)
Control Var.	No	Yes	No	Yes
Log Likelihood	1622.9400	1642.1933	-413.5240	-393.9099
N	2,547	2,528	2,547	2,528

Note: This table examines variables potentially correlated with hidden dissent and dissent scores. Mixed-effects regressions are clustered at the FOMC member level, with member characteristics detailed in Table 1. The sample period spans from the February 1986 FOMC meeting, when Tealbook core CPI data first became available, to the December 2018 meeting. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

This finding not only provides further support for the mechanism in Malmendier et al. (2021) but also demonstrates the value of our hidden dissent measure. When we repeat the analysis using official votes (v_{ij}) as the dependent variable (see Table B.1), these nuanced effects disappear entirely, which demonstrates again that the official voting record is too coarse to detect these subtle yet economically important differences in policy preferences.

Next, we conduct a similar regression as equation (1) at the meeting level to examine the relationship between the hidden dissent level HD_i for meeting i, macroeconomic variables, and the composition of the FOMC committee's characteristics in meetings. The committee's characteristics at the meeting level are summarized as follows:

(i) Standard deviations of members' experience ($D_{experience}$), ages (D_{age}), and the endowment per student of the school where the member received her highest degree ($D_{SchoolWealth}$);

(ii) Percentage of female members (P_{gender}), members with highest degrees in econ-related field (P_{major}), and members who have lived through significant historical events (e.g., Great Depression, Great Inflation, WWII) (P_{event});

(iii) Entropy measures of diversity, including the regions of members' hometowns ($E_{hometown}$), regions of the schools where members earned their highest degrees (E_{school}), and the political party of the president (E_{POTUS}) who appointed the governor.[10]

Considering that $HD_i \in (0,1)$ and $V_i \in [0,1)$, we employ beta regression to model HD_i and fractional logistic regression for V_i, respectively. The results are reported in Table 8.[11] In column (1), the macroeconomic variables account for a significant portion of the variance in hidden dissent levels HD_i, with a pseudo R^2 of approximately 23%. Both lower unemployment and higher inflation are associated with increased hidden dissent. Meanwhile, column (2) shows that educational factors continue to play a crucial role at the meeting level. Beyond the locations of educations institutions, a higher proportion of FOMC members holding economics-related degrees is linked to lower level of hidden dissent. Furthermore, columns (3) and (4) reveal that the dissent measured by voting results exhibit an insignificant correlation with the macroeconomic variables after controlling personal characteristics. Our results are consistent with Thornton and Wheelock (2014) who report that the dissent in general is not correlated with either inflation or unemployment rate.

We also consider other variables that may be correlated with the hidden dissent measure. There is evidence that yield curve can predict recessions or output growth (see, among many examples, Ang et al. (2006)). In particular, an inverted yield curve (i.e., when the long rate is lower than the short) is often viewed as an ominous sign of an upcoming recession. FOMC members may take the yield curve into account when forming their view on the economy and monetary policy. In Table B.2, we include the yield curve either as the spread between 10-year and 2-year Treasury bonds or a dummy variable for an inverted yield curve (i.e., when the 2-year

[10] For chairs from regional Federal Reserve Banks, the state-level presidential election results are used as a proxy for the appointing party.

[11] Consistent with the individual-level analysis, the majority of these member characteristics are treated as control variables. A detailed report on these variables is available in Appendix D.

Table 7
Hidden Dissent and Personal Experience.

	hd_{ij} (*Beta Model*)		
	(1)	(2)	(3)
Macro Factors			
T_{unemp}	−0.0086	−0.9323***	0.1602
	(0.1404)	(0.2336)	(0.1573)
D_{unemp}	0.0081	−0.1530*	0.0037
	(0.0498)	(0.0882)	(0.0621)
T_{CPI}	0.7468***	1.1024***	0.5810**
	(0.1758)	(0.1863)	(0.2396)
D_{CPI}	0.5970***	0.4810***	0.5346***
	(0.1189)	(0.1034)	(0.1986)
Interaction with Personal Experience			
T_{unemp} × Great Depression	−1.1331***		
	(0.3156)		
D_{unemp} × Great Depression	−0.3728***		
	(0.1258)		
T_{CPI} × Great Depression	0.4688*		
	(0.2843)		
D_{CPI} × Great Depression	−0.1709		
	(0.1690)		
T_{unemp} × Great Inflation		1.0191***	
		(0.2775)	
D_{unemp} × Great Inflation		0.1453	
		(0.1040)	
T_{CPI} × Great Inflation		−0.3770	
		(0.2787)	
D_{CPI} × Great Inflation		0.0583	
		(0.1803)	
T_{unemp} × WWII			−1.0511***
			(0.2637)
D_{unemp} × WWII			−0.1838*
			(0.1035)
T_{CPI} × WWII			0.5648*
			(0.2969)
D_{CPI} × WWII			−0.0377
			(0.2200)
Fixed Effects	Yes	Yes	Yes
Log Likelihood	1786.0231	1779.7226	1784.1786
N	2,539	2,539	2,539

Note: This table examines how members' personal experience may interact with macroecomic situations and affect their hidden dissent. The sample period spans from the February 1986 FOMC meeting, when Tealbook core CPI data first became available, to the December 2018 meeting. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

yield is higher than the 10-year one). Both variables show an insignificant correlation with the hidden dissent level. However, when we regress the hidden dissent level solely on the yield curve variable, it becomes significant, suggesting that the macroeconomic variables already capture the relevant information in the yield curve.

Lastly, we examine whether the hidden dissent level is driven by uncertainty, as measured by either the CBOE Volatility (VIX) index or the Economic Policy Uncertainty (EPU) index. As shown in Table B.3, these indices have no explanatory power, which is consistent with the finding that aggregate uncertainty is driven by monetary policy and less so the other way round (Bekaert et al. (2013)).

The results in this section clearly confirm that the hidden dissent captured by our model is not merely noise. Compared to dissent revealed through voting outcomes in FOMC meetings, hidden dissent shows a stronger correlation with economic conditions and certain personal characteristics.

4.2. Is hidden dissent about what will be or what should be?

Having established that hidden dissent is closely tied to economic conditions, we now focus on unraveling the specific sources of this hidden dissent. Specifically, we explore whether disagreements stem more from differences in members' views on the expected trajectory of the economy or from divergences in opinions about what the appropriate monetary policy should be. To answer this, we use data from the Summary of Economic Projections (SEP) to understand how these two types of disagreements contribute to hidden dissent within the FOMC.

Table 8
Explaining Hidden Dissent and Revealed Dissent (Meeting-level).

	HD_i (*Beta*)		V_i (*Fractional Logistic*)	
	(1)	(2)	(3)	(4)
Macro Factors				
T_{unemp}	-0.5488^{**}	-0.5938^{***}	-0.0914	-0.0703
	(0.2213)	(0.2285)	(0.6175)	(0.6772)
D_{unemp}	0.0854	-0.1334	0.4631^{**}	-0.1468
	(0.0642)	(0.0842)	(0.1810)	(0.2812)
T_{CPI}	1.1071^{***}	0.6994^{***}	1.3953^{**}	1.2535
	(0.2333)	(0.2621)	(0.6480)	(0.8195)
D_{CPI}	0.6876^{***}	0.2525	0.5953^{***}	0.7648
	(0.0827)	(0.1746)	(0.2255)	(0.5876)
Member Char.				
P_{major}		-1.3761^{***}		-1.4270
		(0.3570)		(1.1393)
E_{school}		1.0154^{***}		1.5520
		(0.3134)		(1.0837)
Control Var.	No	Yes	No	Yes
Pseudo R^2	0.2275	0.3893	0.4547	0.4914
Log Likelihood	241.0162	274.6247	-14.4783	-13.5026
N	268	268	268	268

Note: This table analyzes factors that may correlate with hidden dissent levels and dissent. Hidden dissent, HD_i, is calculated as the average of hidden dissent scores, hd_{ij}, while dissent, V_i, is defined as the percentage of NO votes in a meeting. In the macro-variable section, T_x represents the trend of variable x, and D_x denotes its standard deviation, derived from past and forecast values in the Tealbooks. E_{school} captures education institutional diversity, and P_{major} represents the percentage of FOMC members with a highest degree in an economics-related field. The sample period spans from the February 1986 FOMC meeting, when Tealbook core CPI data first became available, to the December 2018 meeting. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

First, we use the data from the Summary of Economic Projections (SEP) to assess the divergence in members' view on the direction of the economy. Starting from 2007 (2012 for the federal funds rate), individual responses in the SEP are made available four times a year. The SEP contains FOMC members' anonymous assessments on future monetary policy and projections for unemployment rate, GDP growth, PCE inflation, and core PCE inflation.

In our analysis, we categorize SEP variables into two groups: projections of the federal funds rate, which represent what the member considers as the "appropriate monetary policy", and projections of other economic indicators, which indicate the members' expectations for the economic outlook. To quantify disagreement embedded within these projections, we calculate the average absolute deviation from the median projection for each category, following the approach used by Foerster and Martinez (2023). Due to the limited sample size and high correlations among the projections, we consolidate the SEP policy disagreement measures across different horizons (current year, next year, the following year, and long term) into up to two principal component, which explains 78.61% of the variations. For the economic outlook-related disagreement measures (same horizons, except no long run values for inflation measures), we use up to three principal components to capture 82.76% of the total variance.

We begin by regressing our hidden dissent measure on each category of SEP disagreement separately, with the results presented in Table 9. A clear pattern emerges: disagreement over the appropriate path of monetary policy is a strong and statistically significant predictor of hidden dissent, alone explaining over 12% of its variation (Column 1). In contrast, disagreement over the economic outlook is neither statistically nor economically significant, and its explanatory power is negligible in the longer sample (Column 3). This initial evidence suggests that our hidden dissent measure primarily captures heterogeneity in members' policy preferences rather than differing views of the economic outlooks.

A potential challenge to this interpretation, however, is that the two forms of disagreement are themselves moderately correlated. The correlation of Policy_{PC1} and Economy_{PC1} is -0.5640. A member's view on the appropriate policy path is naturally informed by their economic outlook. To isolate the independent contribution of each channel and test the robustness of our initial finding, we must therefore disentangle these effects.

To achieve this, we apply the Double Machine Learning (DML) method proposed by Chernozhukov et al. (2017). DML combines machine learning techniques with econometric models to control for confounding variables, and it aims to isolate the causal effect of a treatment variable (T) on the variable of interest (Y). The DML process involves two stages: first, machine learning algorithms are used to predict Y and T separately based on confounder variables X, and the algorithm helps us to capture the complex relationships between Y or T and X. Next, the residuals from these predictions are regressed against each other to estimate the causal effect. In

Table 9
Level of Hidden Dissent and Summary of Economic Projections.

	HD_i (*Beta*)				Residualized HD_i (*DML*)	
	(1)	(2)	(3)	(4)	(5)	(6)
Policy$_{PC1}$	0.1242**	0.1262**				
	(0.0607)	(0.0609)				
Policy$_{PC2}$		−0.0447				
		(0.0805)				
Economy$_{PC1}$			−0.0398	−0.0578*		
			(0.0256)	(0.0331)		
Economy$_{PC2}$			0.0058	−0.0032		
			(0.0637)	(0.0603)		
Economy$_{PC3}$			0.0210	−0.0436		
			(0.0731)	(0.0670)		
Residualized Policy$_{PC1}$					0.0242**	
					(0.0122)	
Residualized Economy$_{PC1}$						−0.0128
						(0.0109)
Pseudo R^2	0.1257	0.1349	0.0598	0.1057		
Log Likelihood	29.7784	29.9327	41.1820	29.4507		
N	29	29	40	29	29	29

Note: This table investigates the correlation between the level of hidden dissent observed in meeting transcripts and disagreement within the Summary of Economic Projections. Disagreement levels for each projection category are calculated as the absolute sum of deviations from the median projection, the same method employed by Foerster and Martinez (2023). These levels are subsequently categorized into two distinct groups: disagreement pertaining to current monetary policy, specifically Federal Funds Rate (FFR) projections, and disagreement related to the current state of the economy, encompassing other projection types. Principal component analysis is then applied to each group. Due to the availability of SEP data, the sample for the macroeconomic variables, which includes long-term projections, begins with the January 2009 meeting, whereas for the federal funds rate, it starts with the January 2012 meeting. Both samples conclude with the December 2018 meeting. In column (4), the sample of macroeconomic variables is maintained within the same period range as that of the federal funds rate sample. Column (5) and (6) show the second stage results from the Double Machine Learning model. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

our setting, each SEP disagreement takes the role of T or X alternately, with our transcript hidden dissent measure (HD_i) being Y.[12] The Lasso model is employed in the first stage, followed by linear regression in the second stage. Hyperparameter tuning is conducted to select the optimal model parameters. To mitigate overfitting and reduce estimation bias, cross-fitting is used in our model.

The second-stage results are reported in columns (5) and (6) of Table 9. The significant coefficient for Residualized Policy$_{PC1}$ implies that the disagreement on monetary policy significantly contributes to hidden dissent inside FOMC meetings, even after accounting for disagreement on the economy outlook. This suggests that policy disagreement encompasses additional factors related to our measure. One possibility is members having different loss functions, but it is also possible that members differ on variables not covered in the SEP. In contrast, Residualized Economy$_{PC1}$ is not statistically significant, suggesting that disagreement about the economic outlook does not have an independent influence on our measure.

Further evidence supporting this interpretation comes from the optimal policy perturbation (OPP) proposed by Barnichon and Mesters (2023).[13] Based on a loss function, the median projections, and impulse responses of inflation and unemployment rates to monetary policy shocks, OPP measures the deviation of monetary policy from its optimal level. A positive OPP means that monetary policy is looser than the optimal, while a negative OPP means it is too tight. Fig. 6 shows the correlation between the hidden dissent inside FOMC meetings and OPP measures across three different monetary policy definitions: the federal funds rate, the shadow rate, and the slope of the yield curve through quantitative easing.[14] Except the Financial Crisis period, during which the nominal interest rate approached the zero lower bound, significant deviations of the OPP measure from zero are frequently associated with higher level of hidden dissent.

To closely examine their relationship, in Table 10 we present regression results for these three different monetary policy definitions. We use the hidden dissent level calculated from the FOMC meeting immediately preceding the generation of the OPP measure as the independent variable. The results show that the absolute value of the OPP (federal funds rate) is strongly correlated with our hidden dissent measure. The results for the other two OPP measures appear different, primarily due to the large negative OPP values during the Financial Crisis. Once those observations are dropped, the relationship between hidden dissent and deviations from optimal policy becomes consistent across all OPP measures.

[12] SEP policy disagreement is characterized by four distinct measures, while SEP economic outlook disagreement encompasses fourteen measures. We treat the first principal component of one SEP disagreement as T, and utilize all measures from the other SEP disagreement as X.

[13] The OPP dataset spans from 1980 to 2022 and has varying frequencies due to data availability constraints. We matched the OPP data with the hidden dissent derived from the FOMC meetings held immediately before the date of the OPP data.

[14] To improve the readability, the hidden dissent level in Fig. 6 is smoothed with a rolling window size equals to twelve.

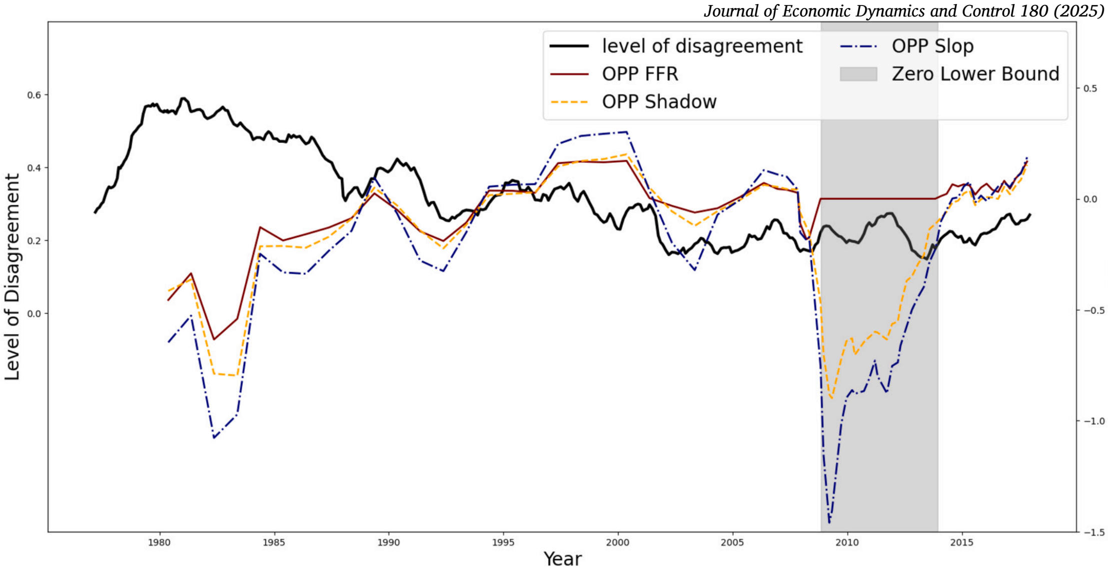

Fig. 6. Level of Hidden Dissent and Optimal Policy Perturbation. *Note:* This figure shows the trends of hidden dissent levels alongside various Optimal Policy Perturbation (OPP) measures introduced by Barnichon and Mesters (2023). The shaded gray area highlights the Financial Crisis period, during which the nominal interest rate reached 0%.

Table 10
Level of Hidden Dissent and Optimal Policy Perturbation (Barnichon and Mesters (2023)).

	OPP_{ffr}(Abs.)	OPP_{shadow}(Abs.)	OPP_{slop}(Abs.)
Full OPP Sample			
HD_i	0.4562***	0.0176	0.0340
	(0.1313)	(0.2412)	(0.3458)
V_i	0.2236	0.3404	0.2818
	(0.2332)	(0.4430)	(0.5630)
Adjusted R^2	0.3114	-0.0139	-0.0220
N	77	77	77
OPP Sample, Excludes Zero-Bound Period			
HD_i	0.4156***	0.5214***	0.8006***
	(0.1524)	(0.1800)	(0.2392)
V_i	0.2718	0.3715	0.3183
	(0.2396)	(0.4186)	(0.4989)
Adjusted R^2	0.3060	0.3189	0.3404
N	55	55	55

Note: This table examines the relationship between the level of hidden dissent inside the FOMC meeting and the deviation from the optimal policy after the meeting. Deviation is quantified by Optimal Policy Perturbation (OPP), as defined by Barnichon and Mesters (2023). OPP_{ffr} (OPP_{shadow}) denotes the deviation from the optimal Fed funds rate (shadow rate), and OPP_{slop} represents the deviation from the optimal slope of the yield curve. "Abs." means absolute value. The sample spans from 1980, when OPP data became available, to 2018, in line with the availability of transcript data. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Unlike the SEP data, the OPP does not allow us to distinguish between members' preferences and their projections. The OPP is derived from a reduced-form model and a loss function where the weights on inflation and unemployment gaps are equal, and we can at best conclude that both forms of heterogeneity contribute to hidden dissent. A more precise evaluation of their relative importance will require additional SEP data in the future.

4.3. Does hidden dissent move the market?

In the preceding subsections, we explored various methods to offer insights into the internal divergences of opinion among FOMC members and their relationships with economic indicators. Now, we shift our focus to understanding whether and how this hidden dissent influences financial markets.

Numerous studies have explored the impact of central bank communication on financial markets (Gürkaynak et al., 2005; Rosa, 2011; Schmeling and Wagner, 2016; Rosa, 2016; Alexopoulos et al., 2024; Gordon and Lunsford, 2024). However, due to the five-year embargo on FOMC meeting transcripts, the hidden dissent level within meetings cannot be promptly revealed to the public through transcripts, making it difficult to examine how financial markets react to the hidden dissent we measured above.

To address this issue, we consider two approaches. First, we can use public speech data from FOMC members as a proxy for hidden dissent. However, results show that public speeches by FOMC members can be informative only if we have knowledge of what the chair will say in the subsequent meeting. Without that reference point, information in the speeches becomes elusive (see Appendix C).

Our second approach involves FOMC minutes. Unlike transcripts, minutes are released just three weeks after the FOMC meeting, allowing the public to assess the hidden dissent in a more timely manner.[15] This shorter delay makes it possible to observe immediate financial market reactions to the hidden dissent detected from the minutes, whereas the five-year delay in the release of transcripts diminishes the likelihood of any market reaction. As such, meeting minutes, despite being less detailed than transcripts, serve as a crucial source for measuring hidden dissent within the meetings and its impact on financial markets. In this subsection, we propose using hidden dissent scores, HD_i, to predict the hidden dissent in minutes, HD_i^{min}. By utilizing scores derived on transcript data, we provide a consistent, data-driven approach for estimating hidden dissent within FOMC meetings and minimize the reliance on subjective domain expertise.

To accomplish this, we employ a MHSA-based deep learning model, a modified version of the model used earlier in this paper, to predict the hidden dissent from minutes. The model architecture, illustrated in Fig. 7, is designed to effectively handle the complex language in FOMC minutes, and accurately extract key features to predict the hidden dissent level revealed in corresponding transcript. The training set is constructed by extracting content related to committee members from the minutes and labeling it with HD_i, the hidden dissent level detected from transcript i. Following the training procedures in Section 3, the optimal model configuration includes six MHSA modules (each with four heads), a dropout rate of 0.46, and an initial learning rate of 4.57×10^{-5}. This setup achieves an average MAE of 5.835×10^{-2}, an R^2 of 0.704 on the training set, with 5.838×10^{-2} and 0.697 on the test set, respectively, based on five-fold cross-validation. We then apply the trained model to post-2018 minutes to extend the date to the present. As shown in Fig. 8 the hidden dissent level in transcripts and minutes align closely, with a correlation of 0.848. Meanwhile, HD_i^{min} shows a clear increase in hidden dissent during the second half of 2022, as the FOMC implemented four consecutive 75-basis-point rate hikes followed by a 50-basis-point hike, pushing its benchmark interest rate to the highest level in 15 years.[16]

While the overall sentiment (hawkish/dovish tone) of FOMC communications is known to influence markets, we propose in this section that the hidden dissent provides a separate, crucial information channel reflecting policy uncertainty.[17] To isolate its impact, we explicitly control for sentiment in our analysis, estimate the model following Swanson (2021) and Gorodnichenko et al. (2023).

$$Outcome_{t,t+h} = b_0^{(h)} + b_1^{(h)} HD_t^{min} + b_2^{(h)} S_t^{min} + error_t^{(h)} \tag{3}$$

where HD_t^{min} represents the level of hidden dissent measured from the minutes (i.e., $\hat{HD}_i$ in Fig. 7), and S_t^{min} denotes the sentiment in the minutes, captured by the intensity of dovish or hawkish language based on the minutes' content, following the methods of Kozlowski et al. (2019) and Jha et al. (2021). A higher value of S_t^{min} indicates a more dovish-leaning sentiment in the minutes. This specification allows us to separately examine the effects of hidden dissent and sentiment on financial markets.

Following Gorodnichenko et al. (2023), we define the outcome variables as the financial indicators (FI) change over different horizon, h. We select the horizon $h = [0, 15]$ where $h = 0$ represents the minute release date and estimate coefficients for each horizon separately to illustrate the dynamics of the response of these financial indicators. The list of indicators can be found in Table 11. Additionally, we employ the bias-corrected and accelerated (BCa) bootstrap method to correct potential biases and construct accurate confidence intervals.[18]

(1) Stock Market Reactions

We begin by examining the stock market's response to hidden dissent using daily total returns of the S&P 500 ETF (SPY). Returns are measured as the log of the close price at date $t + h$ minus the log of the open price at date t: $Outcome_{t,t+h}^{SPY} = \log(SPY_{t+h}^{close}) - \log(SPY_t^{open})$. Fig. 9 indicates that higher levels of hidden dissent predict a statistically significant decline in the SPY total return.

Furthermore, we employ the VIX index to evaluate how stock market volatility expectations react to hidden dissent. Plots in Fig. 10 shows that on the minute release date, higher hidden dissent detected in the minutes significantly increases market volatility in the ensuing few days. This observation suggests that the stock market responds to newly disclosed information about hidden dissent, which is not conveyed through other communication channels on the FOMC meeting day. In contrast, sentiment information embedded in the minutes does not significantly affect stock market. Meanwhile, as shown in subsection 4.1, VIX has no explanatory power over hidden dissent, our current findings clearly suggest a one-way influence, reinforcing the view that markets react to FOMC communications, not vice versa.

[15] Before December 2004, the minutes were released three days after the Committee's subsequent meeting.

[16] CNBC: Fed raises interest rates half a point to highest level in 15 years.

[17] A potential concern with using generated regressors in downstream tasks, as highlighted by Battaglia et al. (2024), is that measurement error can bias coefficient estimates. The authors show this bias is governed by the parameter $\kappa = \sqrt{n} \times \mathbb{E}[1/C_i]$, where a small κ indicates that the bias is likely to be minimal. In our application, the average text length (C_i) is large, leading to very small κ values: approximately 0.011 for our transcript-based model and 0.006 for our minutes-based model. These values are substantially smaller than the 0.44 benchmark in the CEO application re-analyzed by Battaglia et al. (2024), for which they find the bias to be negligible. We therefore conclude that this issue is unlikely to be a significant concern for our estimates. We thank our anonymous referee for pointing this out.

[18] We report results using the residual-based bootstrap method rather than the data-based bootstrap method. Swanson (2021) provides a detailed explanation of why the residual-based bootstrap method is preferred in the current setting. We also conduct the data-based BCa bootstrap, and the results are similar.

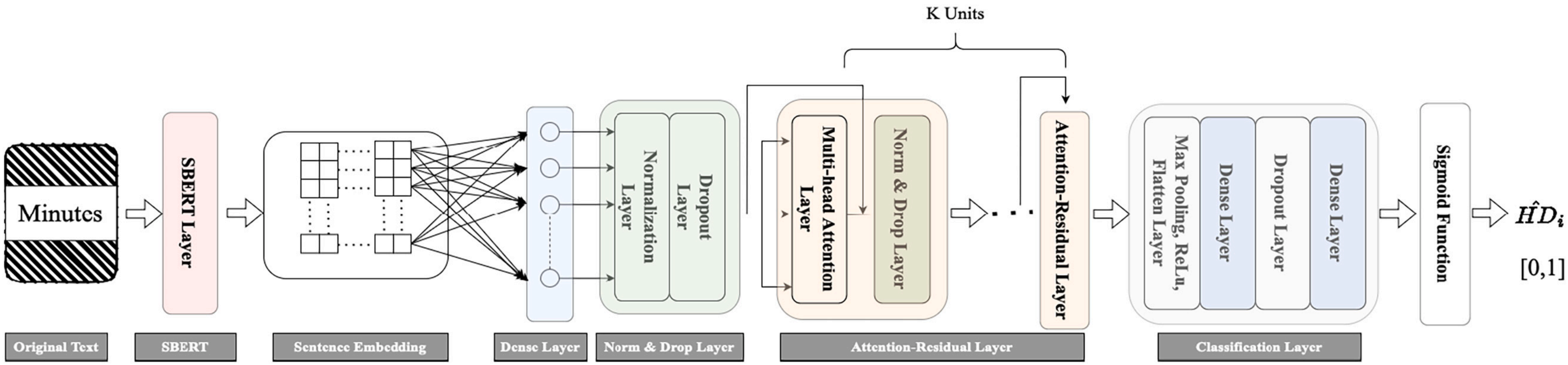

Fig. 7. Deep Learning Model For Minutes. *Note:* This figure illustrates the Deep Learning model used to predict hidden dissent levels in meeting minutes. This model is a simplified version of the Deep Learning model in Fig. 3.

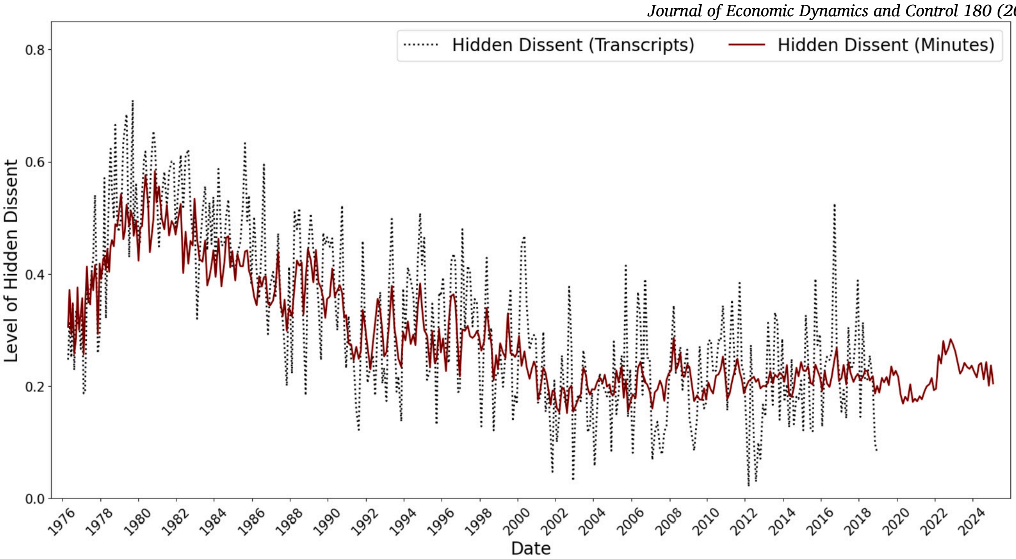

Fig. 8. Level of Hidden Dissent in transcripts and minutes. *Note:* This figure displays the trend of hidden dissent levels in transcripts and minutes, with transcript data ending in December 2018 and FOMC minutes data extending to December 2024.

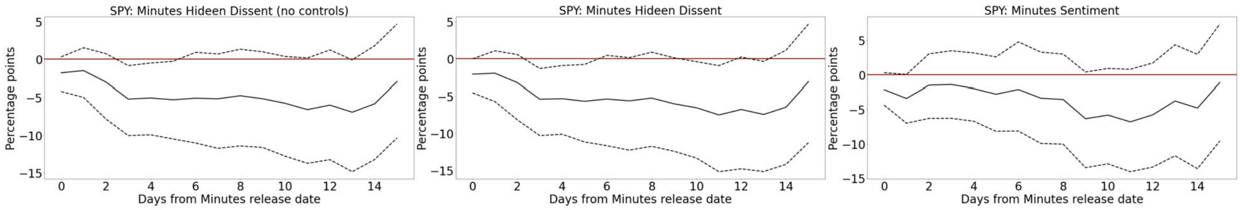

Fig. 9. Response of S&P 500 ETF to Hidden Dissent. *Note:* This figure shows the estimated 15-day dynamic impact of hidden dissent levels on SPDR S&P 500 ETF Trust (SPY). The dashed lines represent 90% bias-corrected and accelerated bootstrap confidence intervals. The sample covers 257 FOMC meetings from December 1992 to December 2024.

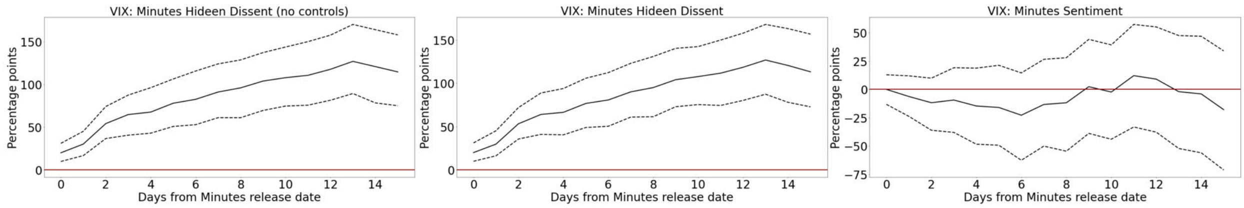

Fig. 10. Response of CBOE Volatility Index to Hidden Dissent. *Note:* This figure shows the estimated 15-day dynamic impact of hidden dissent levels on CBOE Volatility Index (VIX). The dashed lines represent 90% bias-corrected and accelerated bootstrap confidence intervals. The sample covers 280 FOMC meetings from December 1989 to December 2024.

Table 11
Financial Indicators.

Symbol	Financial Market Indicator	Data Period
SPY	SPDR S&P 500 ETF Trust	1993-01-29 to 2025-01-10
DGS10Y	10-Year Treasury Yield	1976-01-01 to 2025-01-10
VIX	CBOE Volatility Index	1990-01-02 to 2025-01-10
LQD	Investment Grade Corporate Bonds ETF	2014-06-17 to 2025-01-10
LQDH	Hedged Investment Grade Corporate Bonds ETF	2012-02-24 to 2025-01-10

Note: This table lists the financial indicators used to gauge the reactions of different financial markets to the hidden dissent in meetings. The corresponding data is sourced from Yahoo Finance. The sample period spans 408 FOMC meetings held between 1976 and 2024, subject to data availability for each specific indicator.

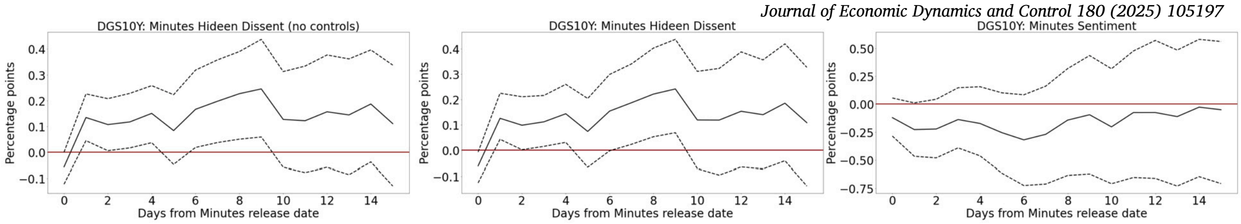

Fig. 11. Response of 10-Year Treasury Yield to Hidden Dissent. *Note:* This figure shows the estimated 15-day dynamic impact of hidden dissent levels on 10-Year Treasury Yield (DGS10Y). The dashed lines represent 90% bias-corrected and accelerated bootstrap confidence intervals. The sample covers 408 FOMC meetings from January 1976 to December 2024.

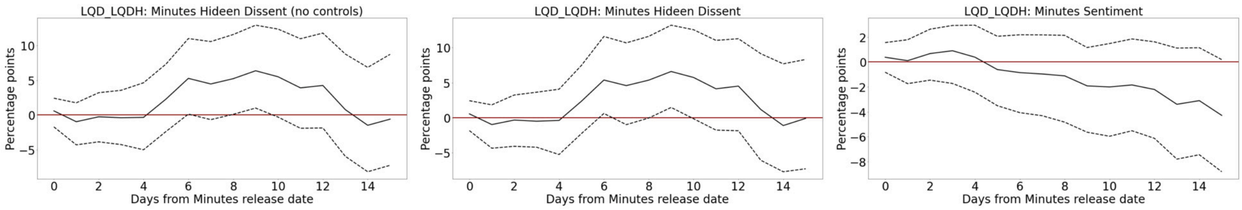

Fig. 12. Response of Interest Rate Risk to Hidden Dissent. *Note:* This figure shows the estimated 15-day dynamic impact of hidden dissent levels on Interest Rate Risk (LQD-LQDH), measured as the return spread between corporate bonds and hedged corporate bonds. The dashed lines represent 90% bias-corrected and accelerated bootstrap confidence intervals. The sample covers 85 FOMC meetings from June 2014 to December 2024.

(2) Bond Market Reactions

Next, we examine the reaction of U.S. Treasury yields to hidden dissent revealed in FOMC minutes. We analyze the cumulative change in yields over the 14 days following the minutes' release, using the 10-year bond yield (DGS10Y). Overall, the results presented in Fig. 11 indicate that higher hidden dissent drives up long-term bond yield changes. Meanwhile, we find that the impact of sentiment on Treasury bond is insignificant, suggesting that hidden dissent and sentiment transmit information through distinct channels.

Following Gorodnichenko et al. (2023), we further measure interest rate risk using the spread: $\log(\frac{P^{LQD}_{t+h,close}}{P^{LQD}_{t,open}}) - \log(\frac{P^{LQDH}_{t+h,close}}{P^{LQDH}_{t,open}})$, where an increase in this spread indicates higher perceived interest rate risk. Fig. 12 suggests that higher hidden dissent in FOMC meetings is associated with an increase in perceived interest rate risk. This suggests that greater hidden dissent may increase uncertainty about future monetary policy, economic growth, or market conditions, ultimately driving up interest rate risk.

The above analysis demonstrates that hidden dissent, as measured through the minutes, provides additional information not captured by other FOMC communication channels and has a measurable impact on various financial markets.

5. Conclusion

In this paper, we propose a deep learning model based on transfer learning and the self-attention mechanism to predict hidden dissent scores for FOMC meeting members using their transcripts. Leveraging these hidden dissent scores, we construct a measure to evaluate meeting-level hidden dissent and compare it with dissent observed in the actual voting records.

This paper has three main findings. First, hidden dissent is strongly correlated with macroeconomic variables and the education background of members, while other personal characteristics have little influence. Second, hidden dissent within FOMC meeting appears to stem from heterogeneity in both members' preferences and their projections. Third, and critically, we establish hidden dissent as a distinct information channel for financial markets, separate from overall policy sentiment. By analyzing market reactions to timely minutes releases while controlling for sentiment, we show that higher hidden dissent significantly impacts both major financial markets: in the stock market, it tends to increase volatility expectations and decrease share prices; in the bond market, it drives up yields and perceived interest rate risk. This confirms that how the committee reaches a decision, specifically the degree of underlying consensus or dissent, is valuable information for market participants beyond the stated policy or general tone.

One notable limitation of this study is that we do not differentiate the direction of hidden dissent (i.e., whether members advocate for looser or tighter policy). Hence, the underlying reasons for some members' hidden dissent remain ambiguous. More data, particularly additional NO votes, could help the deep learning model capture these subtle distinctions.

Another limitation comes from the change in monetary policy framework after 2008. The Federal Reserve no longer just focuses on the federal funds rate, and policy discussion touches on other tools like quantitative easing and forward guidance. FOMC members may disagree not only on the direction of monetary policy but also on the approach. With fewer than two decades of post-2008 data, addressing disagreements over not just the direction but also the approach to monetary policy remains challenging for the deep learning model.

Appendix. Supplementary material

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.jedc.2025.105197.

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