Quantifying standard-setting deliberations*

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Abstract

Official meetings of the International Accounting Standards Board (IASB) are crucial to shaping accounting standards globally. Researchers examining these meetings depend on voice recordings from the IASB website. This study processes all available audio recordings of board meetings, identifies speakers using voice printing technology, and applies natural language processing techniques for transcription. We intend to create a publicly available, fully indexed dataset organizing each participant's contributions by meeting and topic. Using textual analysis, we will connect these discussions to stakeholder comment letters and final accounting standard texts. Our granular data can provide new evidence on major unresolved issues in the political process of accounting standard-setting, such as how ideological standard-setting is and whether accounting standard-setters are captured by interest groups?

Keywords: Accounting standard-setting; IASB; Natural language processing; Text analysis; Speech recognition; Machine learning
JEL Codes: M41, M48, D72, C55

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1. Introduction

The standard-setting process in accounting largely unfolds during meetings of professional bodies tasked with promulgating rules. Organizations such as the Financial Accounting Standards Board, the International Sustainability Standards Board, and the International Accounting Standards Board conduct much of their work through open meetings, thereby enhancing public accountability. Despite the availability of extensive audio and video recordings of these meetings, researchers have not yet fully leveraged these resources. Prior studies have predominantly employed qualitative, interpretative approaches or focused on isolated events in the standard setting process, leaving a gap for systematic, large-scale quantitative examination of these proceedings.[1]

Recent advances in natural language processing algorithms, machine learning, and computing power now enable researchers to address the challenges associated with large volumes of unstructured data (Gipper et al., 2013). This registered report proposes developing a new dataset using computational linguistics methods to create a verbatim, sentence-by-sentence record of standard-setting board deliberations. Our approach documents who says what and when over an extended period, providing a detailed view of the standard-setting process. We integrate meeting transcripts with relevant documents including agenda papers, meeting summaries, official standards, comment letters, and board member biographical data. This comprehensive dataset addresses the limitations of current research methods by offering a granular, quantitative perspective on previously intangible aspects of standard-setting.

We demonstrate how granular-level data on discussions in standard-setting bodies enables researchers to construct refined measures that provide new evidence on major open issues in research on the political process of accounting rule-making. Summarizing the prior literature, Kothari et al. (2010) suggest two explanations for accounting standard-setter behavior:

> Under the *capture* theory, GAAP regulation is the result of accountants' and auditors' attempts to socialize the expected costs of producing standards, which include reputational loss and legal liability. The resulting standards are unlikely to yield efficient capital allocation. Regulated GAAP as a product of the *ideology* theory is the

[1] Examples include Klein and Fülbier (2019) and Großkopf et al. (2022) who use audio records for a qualitative study of standard setting.

> combined result of special interest lobbying and standard setters' ideologies about accounting principles, which is not necessarily optimal in facilitating efficient capital allocation.(emphasis added)(p. 251)

Motivated by these considerations, we introduce $VoicedPosition$, a new empirical measure that quantifies board members' expressed stance on accounting standards by measuring the sentiment in their spoken contributions. This measure enables direct comparisons across board members, meetings, and agenda items, making it possible to track positions over time and across different issues.[2] Because $VoicedPosition$ is cardinal, differences in scores have meaningful interpretations — higher scores reflect proportionally greater use of supportive or oppositional language. This measure is adaptable, allowing researchers to isolate sentiment on specific discussion aspects, track changes sentence by sentence, and pinpoint shifts in position within and across meetings.

We argue that the language standard-setters use during deliberations reveals their ideological stances and the influence of constituent groups on board discussions.[3] Ideology, defined as a stable belief system shaping individuals' $VoicedPosition$ across various issues (Poole, 2005), influences how standard-setters approach accounting topics during meetings (Allen and Ramanna, 2013; Kothari et al., 2010). Specifically, we consider the extent and intensity of language indicative of conservative versus liberal views on government intervention, arguing that such language uncovers board members' ideological leanings.

Concretely, we investigate whether ideology is directly associated with board members' positions expressed during deliberations, as well as how ideology indirectly affects these positions by interacting with pressures from interest groups. We also study whether ideology influences coalition-building among board members, using textual analysis to measure how frequently board members explicitly voice agreement with each other.

Ultimately, our goal is to understand how ideology affects the adoption of standards. We study textual similarities between final standards and the language used by various participants in the standard-setting process, including board members, stakeholders (e.g., users, preparers, auditors), and technical staff. We identify each constituent group's distinctive language patterns and compare

[2]No formal definition of "agenda item" is provided in IFRS literature, but IFRS Foundation sources use it to denote specific issues scheduled for discussion at IASB meetings. Agendas are structured into numbered items, each supported by documentation, addressing broad topics (e.g., an individual standard such as Leases) or narrower issues (e.g., specific amendments, subtopics, or IFRS implementation questions).

[3]Throughout the proposal, we use the terms "constituent group" and "interest group" interchangeably.

these patterns across comment letters, board contributions, and final standards. Extending earlier work (Monsen, 2022), we examine whether board members act as conduits for constituent policy ideas, and whether ideology facilitates or impedes these activities. shedding light on the timing and effectiveness of lobbying (van Lent, 1997).

Transparency initiatives in government and public accountability movements have led to increased availability of audio and video recordings from major decision-making bodies worldwide — ranging from the UK's National Health Service to the US Food and Drugs Administration, the Metropolitan Transportation Authority, and the United Nations Framework Convention on Climate Change. Our methodology provides a blueprint for leveraging these unstructured data to study key economic institutions.

Accounting standard-setting offers an especially instructive example because of its unusually high level of disclosure of internal deliberations — far more extensive than most regulatory agencies. For instance, while the US Securities and Exchange Commission (SEC) does release some documents and commissioners' statements, it does not consistently disclose transcripts or recordings of its proceedings. Central banks display similar variability: the Federal Reserve, European Central Bank, Bank of England, Bank of Korea, and Bank of Japan publish summary minutes or accounts of their meetings, but do not routinely release verbatim transcripts. Among these, only the Federal Reserve, Bank of England, and Bank of Japan eventually make transcripts public, and then only after lags of five, eight, and ten years, respectively.[4]

We make two primary contributions to the literature on accounting regulation and standard setting. First, we develop and share a new, large-scale dataset of International Accounting Standards Board (IASB) meeting recordings and accompanying materials processed with natural language and voice recognition technologies. In doing so, we introduce a methodological pipeline — from acquiring raw audio through diarization, speaker identification, and transcription — that can serve as a blueprint for researchers studying other domains where extensive but unstructured recorded proceedings exist (e.g., central bank meetings, legislative debates). This dataset, together with our transparent and replicable pipeline, stands to substantially lower barriers to future research on standard-setting deliberations and extend empirical studies into contexts where detailed transcripts or meeting discussions have been inaccessible.

[4]See Hansen et al. (2018) for a discussion on the disclosure rules of meeting transcripts of the Federal Reserve.

Second, we contribute to the study of ideology in accounting regulation by introducing a text-based measure of standard-setter ideology. Previous attempts to capture ideology in standard-setting have relied on proxies such as political donations, voting records, or professional backgrounds. In contrast, our text-based measure captures language that board members themselves use during deliberations, enabling us to identify ideological stances that might operate independently from constituent pressures. This new measure also allows us to examine how ideology shapes responses to lobbying attempts. Our findings may show that ideological leanings play an independent role in regulatory decisions while also shaping how standard setters respond to interest groups and form coalitions, providing new insight into how ideology influences policy outcomes.
{Comment for the editorial team: Here we insert a description of the main results and how they contribute to the literature}

2. Constructing a Dataset of IASB Deliberations

Transforming hundreds of hours of multi-speaker audio recordings into a structured dataset presents significant technical challenges. Standard speech recognition tools, designed primarily for clear single-speaker settings, struggle with the complex dynamics of board meetings where members speak in accented English, interrupt each other, and engage in dense technical discussions. This section details our methodological approach to constructing a comprehensive dataset of IASB deliberations. We present solutions for speaker identification in multi-party conversations, create robust speech-to-text processing pipelines for technical accounting terminology, and establish reproducible procedures for integrating audio data with regulatory documentation. The resulting dataset provides granular documentation of who says what and when during IASB meetings, enabling systematic analysis of standard-setting deliberations. We first describe our data collection strategy, then explain the development of our speaker identification system, detail our transcription approach, and conclude with extensive descriptive evidence on the dataset's coverage and quality.

2.1. Overview

Board meetings of the IASB provide an ideal setting for analyzing regulatory deliberations. The board consists of multinational professionals discussing complex technical issues in English, their

conversations are consistently recorded, and their decisions shape global accounting practice. Three features make these discussions particularly suitable for systematic analysis: First, meetings follow a clear agenda structure with well-documented topics and outcomes. Second, board membership changes predictably through term limits, allowing us to observe how different combinations of experts approach similar issues. Third, discussions involve both technical staff presentations and spontaneous debates, providing variation in speech patterns and interaction types.

Our dataset covers 898 audio recordings from 2013-2021, capturing discussions by 28 board members and technical staff. The construction of this dataset required four key innovations: automated processing of multi-speaker audio with varying quality levels, speaker identification in a setting with diverse English accents, accurate transcription of technical accounting terminology, and integration with regulatory materials including agenda papers, meeting summaries, and proposed and final standards. Beyond simple transcription, we identify individual speakers, track their contributions across meetings, and link these to the complete documentary record. The dataset enables researchers to analyze who speaks when, for how long, and in response to whom — revealing patterns in how expert committees develop regulatory policy through deliberations.

2.2. Data Collection and Preparation

The IASB makes audio recordings of board meetings publicly available on its official website. This practice began systematically in 2013, and we collect all available recordings from that year until 2021 when audio recordings were replaced by videos. Our initial sample comprises 898 recordings, totaling 878.3 hours of discussions, with an average duration of 58.68 minutes per recording. Each recording typically represents a complete discussion on a specific agenda item or a portion thereof.

Using an automated web scraper, we download both the MP3 files of the board meeting recordings and the PDF files of the corresponding agenda papers. Figure 1 shows the time series of total recording length by year during our sample period. The total time of board meeting discussions shows a declining trend, with notable lows in 2017 and 2020, possibly reflecting a relatively light agenda after completing several major standards projects, as well as COVID-19 disruptions. For each recording, we collect accompanying documentation including agenda papers and meeting summaries. The meeting summaries contain voting records on questions posed to the board in agenda papers, though often in condensed format. We standardize these records and incorporate them into

our dataset.

2.3. Speaker Identification and Transcription System

Building a reliable pipeline for converting IASB deliberations into analyzable text requires both speaker identification and accurate transcription. We begin by compiling a training dataset, selecting 50 audio recordings from our initial sample with even distribution across years. We partition these audio streams into segments by detecting speaker change points. This diarization is challenging because board meetings often feature dense discussions with members talking over each other and recordings have varying audio quality. Precise diarization is crucial to ensure that each segment contains only one speaker, avoiding false attribution later. In this process, we use scalable and automated software solutions, supplemented by extensive human checks to ensure data quality. Following diarization, we group diarized segments based on speaker voice characteristics.

The next step in constructing the training dataset is assigning each grouping to a specific board member from the 28 IASB members active between 2013 and 2021. We use two approaches for this task. For the period until December 2015, we rely on textual clues to identify speakers, such as the chairperson addressing members by name. When video recordings become available after December 2015, we align them with the audio to use visual cues for speaker identification. In total, we manually labeled more than 60 hours of audio.

Using this annotated dataset, we build a hybrid convolution neural network - recurrent neural network (CNN-RNN) deep learning model to recognize and differentiate voices. Our pre-processing extracts audio features that characterize individual voices: Mel-frequency cepstral coefficients capture essential sound qualities, chroma features capture harmonic content and tonal characteristics, spectral contrast measures differences between high and low energy in the sound spectrum, and zero-crossing rate provides insight into audio noisiness. Together, these features create detailed audio profiles for voice recognition.

The deep learning model uses CNN layers to extract features from audio signals and RNN layers to understand time-dependent patterns in speech. We perform comprehensive testing, including holdout sample testing, to evaluate and fine-tune the model. The model performs a classification task, assigning audio fragments to one of 28 possible classes representing each board member. We employ a confidence threshold system to ensure reliable speaker attribution, with segments

falling below our specified threshold being classified as technical staff contributions.[5] This speaker identification model — distinguishing individual board members — serve as critical inputs for the transcription process described next, allowing us to generate structured text data with aligned speaker identities.

We construct a transcription system to convert audio recordings into structured text data. We first use Deepgram, an AI-powered audio processing platform, to perform audio transcription and diarization. Once the audio is transcribed and diarized, our speaker identification model assigns speaker labels to each diarized segment. The final output is a comprehensive CSV file containing transcribed conversation fragments, speaker identities, timestamps, and classification confidence scores.

Processing this extensive collection of audio files requires considerable computing power. The tasks of speaker diarization, speaker identification, and speech-to-text transcription involve complex machine learning algorithms processing vast amounts of audio and text data. We utilize the Dutch National Supercomputer, Snellius, which provides the necessary resources through its advanced architecture combining high-speed processors, specialized GPUs, and vast internal network. In our implementation, we split our data by year and process each subset in parallel, with each using 1/8 of a node from Snellius's partition gpu mig, which allocates 9 CPU cores, 60 GB of RAM, and 1/2 of an NVIDIA A100 GPU, providing 20 GB of GPU memory per instance using Multi-Instance GPU (MIG) technology. Using this parallel structure, we estimate that processing our sample data from 2013 through 2021 takes about 20 hours on Snellius.

2.4. Dataset Structure and Features

Our dataset architecture links audio recordings with their associated documentation through unique meeting identifiers. This system connects transcribed speech segments with agenda papers, meeting summaries, and board member attendance records. We classify discussions by the primary agenda item under consideration and track project phases from the initial discussion of a standard through exposure drafts to final standards. The temporal structure allows us to link related discussions across multiple sessions and align them with relevant comment periods.

[5] We are in the process of identifying technical staff (and other non-board participants in IASB meeting) by name and exploring whether individual-level attribution of these segments will be feasible.

At its core, the dataset consists of individual speech segments, defined as uninterrupted speech by a single speaker. Each segment includes speaker identification, timestamp, and the spoken content, along with a confidence score from our identification system. This granular structure enables precise measurement of participation patterns and speaking dynamics.

We complement the meeting data with all comment letters submitted to the IASB during our sample period. Using the OpenAI API (current model: GPT-4o), we extract metadata from each letter, categorizing submissions into seven groups: regulators (e.g., national standard-setting boards, securities regulators), accounting professions (e.g., audit firms), preparers (individual firms or their representative bodies), users, public interest bodies (e.g., charities and NGOs), academics, and others. The API also identifies the geographical location of each comment letter writer.

The dataset's structure enables multiple analytical approaches. At the speaker level, we can examine individual participation patterns, speaking time distributions, and interaction characteristics. At the topic level, we can track the evolution of specific accounting issues from their initial deliberations to the final policy decisions. At the meeting level, we can analyze discussion flow, voting patterns, and the relationship between staff recommendations and board decisions. Figure 2 illustrates this organization through snapshots of our dataset structure, showing the layout of meeting transcripts (Panel A), comment letter integration (Panel B), meeting summaries (Panel C), and agenda papers (Panel D).

2.5. Descriptive Statistics

This section provides descriptive statistics on our dataset and demonstrates its potential to generate novel insights into the political economy of accounting rule-making. We focus on four pilot tests conducted using a subsample of IASB meeting transcripts on the agenda item *"Conceptual Framework"*, comprising 33 meetings held between 2013 and 2019. These tests illustrate how granular data on deliberations enable researchers to analyze speaker behavior, interaction dynamics, and linguistic patterns critical to understanding ideological and interest group influences.

2.5.1. Descriptive Evidence on the Dataset

The objective of this analysis is to characterize the composition and structure of IASB meeting discussions. We examine speaker participation, meeting duration, and deliberation intensity across meetings, aggregating statistics at the meeting, speaker, and speaker-meeting levels.

Our dataset comprises 7,564 diarized speech segments from 21 unique speakers (Table 1, Panel A). Prominent contributors include Hans Hoogervorst, the chair (1,249 segments), and Mary Tokar (1,033 segments) (Panel B). At the meeting level, discussions averaged 10.64 speakers and 229.21 speech segments. Total speaking time (i.e., deliberation length) ranged from 1.54 seconds (after excluding technical staff contributions) to 18,757.42 seconds (approximately 5.2 hours), with a median duration of 3,565.07 seconds (approximately 1 hour) (Panel C).[6] Speaker-level statistics reveal substantial heterogeneity: individuals averaged 360.19 speech segments, with speaking time per speaker ranging from 61.89 seconds to 25,277.09 seconds (Panel D).

At the meeting level, we report deliberation length by measuring the total speaking time of board members. Figure 3 Panel A illustrates over time variations in deliberation length, highlighting key spikes potentially linked to critical agenda milestones. At the speaker level, a ranked analysis of speaking-time allocation underscores the prominence of key board members, notably Mary Tokar and Hans Hoogervorst, who together accounted for approximately 30% of the total speaking time (Panel B). At the speaker-meeting level, Panel C presents a quantification of individual participation by showing speaking time proportions per speaker in each meeting.

2.5.2. Interruption Detection

Our dataset also allows us to quantify various aspects of the interaction between board members. For example, we plan to use the frequency of interruptions in debates as a measure of board deliberation quality. We employ a computer assisted keyword selection approach, combining an initial list of phrases (e.g., *interrupt*, *jump in*) with ChatGPT-generated suggestions (King et al., 2017; Sautner et al., 2023). After text cleaning (removing punctuation, converting to lowercase), segments are matched against 20 predefined phrases.

Results indicate measured interruptions occurred in 14 of 33 meetings, with 21 segments flagged (Table 2, Panel A). Frequently detected phrases include *interrupt* (5 instances), *sorry but* (3), and *agree with that but* (3) (Panel B). Notably, perhaps consistent with his role as chairperson, Hans Hoogervorst interrupted other members most frequently, challenging their arguments (e.g., *"And these are not just, if I may interrupt, Peter, these are not just, you know, retail investors with a*

[6] At the 24–25 January 2018 IASB meeting, the "Conceptual Framework" agenda item lasted just 109 seconds and served as an informational update with no board decisions. The technical staff provided a brief update, followed by closing remarks from the chair, Hans Hoogervorst: "Okay, thank you very much.". Our meeting-level statistics exclude technical staff, so the minimum recorded deliberation is 1.54 seconds.

very low level of sophistication, but also the quants at the investment banks with their computer programs often totally disregard OCI.") (Online Appendix Table 1).

Additional statistics on interruption references at the meeting, speaker, and speaker-meeting levels of analysis will be reported in the full version of the paper using the format in Panels C, D, and E of Table 2, respectively.

2.5.3. Private Meeting Detection

The dataset also provides us with the opportunity to quantify how often board members refer to meetings with non-board members, such as the general public or representatives of interest groups. We identify references to such informal discussions outside official meetings to explore possible interest group lobbying and coalition-building. Using keywords that refer to private interactions (e.g., *outreach*, *offline*, *conversation with*), we apply an NLP-augmented matching pipeline similar to the interruption detection methodology.

Of the 33 meetings, 17 contain references to private discussions, with 44 segments flagged (Table 3, Panel A). The phrase *outreach* dominates (34 instances), followed by *offline* (9) (Panel B). For example, Sue Lloyd cites private consultations with stakeholders (e.g., *"Um, when I was out doing some of the outreach on the conceptual framework ED, people raised with me quite a lot this issue of comparability."*) (Online Appendix Table 2). These references often coincide with agenda items requiring external feedback, suggesting private interactions facilitate information exchange.

Additional statistics on private discussion references at the meeting, speaker, and speaker-meeting levels of analysis will be reported in the full version of the paper following the format in Panels C, D, and E of Table 3, respectively.

Furthermore, for reference, Table 4 is presented as a template for reporting relevant statistics on our IASB meeting transcript dataset, to be completed once the full sample becomes available. Table 5 serves as a template for reporting statistics on comment letters submitted to the IASB during our sample period.

2.5.4. Voiced Position – Sentiment Analysis

Motivated by Loughran and McDonald (2011), who developed a sentiment lexicon tailored to financial text, we repurpose this lexicon-based sentiment analysis to understand the directional

(i.e., positive versus negative) voiced position of board members at the agenda item-meeting level.[7]

Following the approach used in recent work, we capture the textual sentiment as follows. For the speaker-meeting level:[8]

$$\text{VoicedPosition}_{b,a,m} = \frac{\text{SentimentWordCount}_{b,a,m}}{\text{TotalWordCount}_{b,a,m}}$$

Similarly, aggregated at the meeting level:

$$\text{VoicedPosition}_{a,m} = \frac{\text{SentimentWordCount}_{a,m}}{\text{TotalWordCount}_{a,m}}$$

Here, $\text{SentimentWordCount}_{b,a,m}$ denotes the total number of sentiment-related words spoken by board member b during discussions on agenda item a in meeting m, while $\text{TotalWordCount}_{b,a,m}$ indicates the overall number of words spoken by the same board member during these discussions. Analogously, $\text{SentimentWordCount}_{a,m}$ and $\text{TotalWordCount}_{a,m}$ represent these measures aggregated across all speakers participating in the discussion of agenda item a in meeting m.

Depending on our purpose, we flag positive tone words (e.g., "good," "strong," "great") and negative tone words (e.g., "loss," "decline," "difficult") separately to create $PosVoicedPosition$ and $NegVoicePosition$, respectively. Figure 4 demonstrates how $VoicedPosition_{a,m}$ can assess the directional sentiment over time.[9,10] At the speaker-meeting level, some members show notable shifts in sentiment across meetings.

3. Theoretical Framework

3.1. Ideology in Accounting Standard-Setting

Although accounting standard-setting is often portrayed as a neutral process driven by economic principles, research shows that political forces — such as lobbying by corporations and industry

[7] Aggregating sentiment scores to this level-of-analysis is likely to reduce the noise of within-meeting measures, but in principle, sentiment scores can be computed for shorter length speech, such as a speaker-segment.

[8] See, Hassan et al. (2024, 2019, 2023, 2024); Bae et al. (2023).

[9] It is possible that board members have adopted more optimistic or pessimistic vocabulary in meetings over time, resulting in a noticeable trend in sentiment. In most applications, this inflation of language can be easily controlled by including time fixed effects.

[10] Another potential concern is the use of negation, such as "not good" or "not terrible" (Loughran and McDonald, 2011). However, prior work has found this to have negligible effects once measures are aggregated to a sufficient level (Hassan et al., 2024).

groups, government interventions, and concerns over economic consequences — play a significant role in shaping regulatory outcomes (Gipper et al., 2013). While these external influences are well-documented, a more contentious issue is whether the personal ideological beliefs of regulators should influence their decision-making (Ball, 2008). In an influential essay, Kothari et al. (2010) emphasize the need for research on institutional mechanisms that could mitigate ideology's influence on standard-setting, implying concerns among scholars about its potential distortions.

Early interest group theories treated ideology as a secondary consideration — a convenient label to capture the preferences underlying lobbying coalitions (Stigler, 1971; Peltzman, 1976, 1984; Watts and Zimmerman, 1978; Holthausen and Leftwich, 1983). More recent work, however, has demonstrated that ideology functions as an independent force, shaping decisions even in the absence of overt lobbying (Witman, 1977; Alesina, 1988; Callander, 2008; Diermeier et al., 2005; Mian et al., 2010; Tahoun and van Lent, 2019).

In accounting, most prior work has viewed ideology as adherence to particular doctrines on measurement or recognition.[11] In contrast, we build on Kothari et al. (2010)'s argument that ideology extends beyond accounting views, a perspective reinforced by recent empirical findings showing that ideological positions often originate from broader political affinities rather than specific policy stances (Engelberg et al., 2023). Further support comes from political economy research demonstrating that differences in political ideology shape divergent beliefs and preferences across various domains (Feldman and Johnston, 2014; Ordabayeva and Fernandes, 2018).

Accordingly, we examine the extent to which accounting standard setting is fundamentally influenced by the stable ideological orientations of standard setters, defined as persistent belief systems and value-based preferences regarding market governance, the appropriate level of regulatory intervention, and the delineation between public and private interests (Allen and Ramanna, 2013; Engelberg et al., 2023). We position standard setters along a broader political spectrum, specifically examining their views on private-sector governance and government intervention in markets, which range from right-leaning to left-leaning.[12] These stable ideological preferences act as a filtering

[11]For instance, Jiang et al. (2015) describe FASB chairman Bob Herz's stance as that of a "mark-to-market valuation guy," when examining market reactions to his abrupt resignation. Meanwhile, Chakravarthy (2019) gauge standard setter ideology by comparing board votes to sponsoring organizations' positions in comment letters, and Allen and Ramanna (2013) find that standard setters' preferences for *relevance* versus *reliability* track with their political donations, suggesting ideological leanings.

[12]The characterization of ideology must account for the IASB's international context, where board members come from diverse national backgrounds.

mechanism throughout multiple critical stages of the standard-setting process, influencing board members' responsiveness to external policy inputs.

The political economy of standard-setting differs from broader legislative decision-making in ways that may amplify the role of ideology. Accounting regulation operates in what Ramanna (2015) terms a "thin political market," a setting characterized by limited public scrutiny and dominated by a small, professionally homogeneous group of experts (see also, Vogel, 2022). In such markets, standard setters often share common professional experiences and training, which foster alignment in their underlying worldviews. Rather than overt political lobbying or transactional exchanges, ideological influence emerges subtly through this professional affinity. Empirical evidence indicates that standard setters' votes often align closely with their professional experiences and previously established preferences, suggesting that underlying values — whether market-oriented or conservative — play a crucial role in shaping accounting standards, independent of direct lobbying efforts (Allen and Ramanna, 2013; Chakravarthy, 2019).

3.2. Ideology and Coalition Formation

Interest groups exert influence on the standard-setting process through formal inputs, primarily comment letters, which outline stakeholder preferences regarding proposed standards (Kothari et al., 2010; Monsen, 2022). A board member's ideological orientation represents a consistent and stable preference structure over fundamental tradeoffs inherent in the process of accounting standard setting. Such tradeoffs typically encompass the relevance versus reliability of financial information or deciding between rules-based and principles-based accounting standards. These ideological orientations serve as evaluative benchmarks for processing and assessing external input, particularly those articulated through constituent groups' formal comment letters. As these letters convey clearly articulated stakeholder positions, board members apply their ideological filters to integrate policy proposals that align with their pre-existing ideological predispositions, while disregarding or actively resisting proposals that conflict with their ideological views.

Central to understanding the role of ideology in this process is the concept of a "Voiced Position" — the explicit stance that each board member articulates during deliberations. This voiced position reflects a mix of factors: technical judgment, professional background, and reactions to the proposal under discussion. Some board members speak up because they believe the proposal is sound or

flawed accounting. But in many cases, voiced positions also reflect how external ideas are filtered through a member's ideological beliefs. When a comment or proposal fits with a board member's prior views, it is more likely to be repeated or supported. When it does not, it is more likely to be challenged or dismissed. The voiced position, then, gives us a way to observe how ideology shapes which arguments gain traction in the room.

Ideological similarity among standard setters encourages coalition formation within the board, leading to explicit expressions of mutual support that amplify and reinforce certain policy positions and constituent ideas (Chakravarthy, 2019). This process likely plays a crucial role in shaping which ideas and linguistic formulations gain prominence in board discussions and debates.

Ultimately, these coalition activities have a profound effect on the content and language of the finalized accounting standards. Ideological coalitions ensure that constituent proposals aligned with their shared values are more likely to be adopted into the final standards. Hence, the stable ideological preferences of board members are expected to actively shape outcomes throughout the entire standard-setting process — from initial reception and filtering of external policy proposals, through explicit position-taking in deliberations, to coalition formation and the finalization of accounting standards.

This theoretical framework clarifies how ideological preferences are expected to systematically shape not just the standard-setting outcomes, but also the intermediate processes through which constituent ideas propagate and gain formal acceptance.

4. Empirical Analysis Plan

This section details our empirical approach to testing the implications of the theoretical framework. We begin by quantifying standard setter ideology, defining it as a stable belief system that influences decision-making across different agenda items. We leverage large language models to classify ideological leanings based on board members' speech, focusing on their orientation toward regulatory intervention. Next, we assess the influence of constituent groups by analyzing comment letters, identifying distinctive linguistic patterns, and measuring the intensity of lobbying efforts. We then capture board members' $VoicedPosition$ — their expressed stance during deliberations — using sentiment analysis of speech transcripts. Building on these components, we examine how

ideology shapes responsiveness to lobbying by modeling the interaction between a board member's ideological stance and the intensity of interest group pressure. Additionally, we investigate coalition formation, testing whether ideological alignment between board members predicts explicit agreement during discussions. Next, we examine how policy ideas propagate by measuring textual similarity between constituent input, board member speech, and final standards, identifying potential channels of influence in the standard-setting process and assessing how these patterns relate to ideological alignment. Finally, we show evidence on whether ideology is associated with measures of the quality of board deliberations.

The results presented in this section are based on initial pilot analyses. It is important to flag that subsequent improvements to the machine learning algorithms, as well as the use of the full dataset, may lead to updates or changes in the findings.

4.1. Quantifying Standard Setter Ideology

First, we describe our approach to measuring standard setter ideology. Our approach assumes that while individual decisions (e.g., their *voiced positions*) may vary, ideological leanings represent a persistent underlying framework that guides decision-making.

Recent advances in computational text analysis provide an opportunity to systematically infer ideological positions from large bodies of text. In political science, LLMs have demonstrated the ability to reliably classify the conservative-liberal positions of political parties using zero-shot prompting, even in earlier model versions (Di Leo et al., 2025). More recent models (ChatGPT-4, LLaMA 3) achieve convincing results when benchmarked against expert classifications, crowdworker judgments, and traditional voting-record-based methods (Le Mens and Gallego, 2025). We extend this approach to accounting by applying LLMs to the speech records of board members, assessing their ideological orientation toward regulatory intervention.

For this task, we employ ChatGPT-4.5, chosen for its strong text classification performance in large-scale text analysis. We analyze the full body of each board member's speech during the sample period, assuming that ideology is a stable (i.e., fixed) trait that manifests across their statements. Consistent with Yoo (2024), we use chain-of-thought prompting to enhance the model's reasoning process, ensuring that classifications are based on a structured evaluation of text rather than relying on heuristics. A preliminary prompt subject to further testing is as follows:

> You will receive combined verbatim transcripts of an accounting standard setter's contributions to International Accounting Standards Board meetings, compiled from multiple sessions. Your task is to analyze step by step where this text stands on the conservative-to-liberal scale.
>
> Do not assume that certain accounting choices inherently signal ideological positions. Instead you should purely assess whether these statements signal a preference for private sector governance and a distaste for interventionist policies that increase regulatory burden (conservative ideology) or preferences for constraints on firms, investor protection and public accountability (liberal ideology).
>
> Provide your response as a score between -1 (extremely conservative) and +1 (extremely liberal), with 0 indicating neutrality. If the classification score is close to 0, explicitly state whether this is due to a genuine balance of perspectives or a lack of strong ideological signals. Also provide a confidence estimate in this response. Use the following format:
>
> `Explanation: [step-by-step analysis here]. Answer and Confidence (0-100): [numerical score], [confidence level].`

Initial pilot tests highlight the importance of explicitly instructing the LLM not to infer ideology from views on accounting principles. This precaution addresses the possibility that the model's training data includes extant accounting research linking technical accounting choices to ideological stances.

We demonstrate the viability of our method by estimating ideology scores for board members involved in the deliberations on the Conceptual Framework.[13] Table 6 presents these scores along with the LLM's confidence assessments. Online Appendix Table 3 illustrates the model's reported reasoning behind the classification of the most conservative and liberal board members.

Refining this approach may be necessary along two dimensions. First, analyzing the full corpus of each board member's speech may reveal additional needs for prompt adjustments.[14] Second,

[13] We anticipate estimates of ideology scores and relative rankings to change once discussions pertaining to specific standards are incorporated.

[14] For example, "Consider the overall ideological stance of the board member across all available contributions rather than isolating individual statements."

different LLM models may interpret the prompts differently. Since we intend to use the most advanced model available at the time of execution — balancing accuracy and computational efficiency — further prompt engineering may be required.[15] We will supplement our analysis by employing an alternative ideology measure based on a dictionary approach developed by Engelberg et al. (2023), offering both a benchmark and a contingency strategy to complement our LLM-derived measure of ideological orientation.[16]

4.2. Quantifying Constituent Group Pressure

We collect all comment letters submitted to the IASB during the sample period and categorize them by constituent group, as described in Section 2.4. To identify constituent influence, we use natural language processing techniques to identify linguistic patterns and specific bigrams reflecting distinctive stakeholder policy positions.[17]

We quantify the intensity of constituent group pressure by NLP analysis of comment letter attributes, including the total number of comment letters submitted, the total word count, and the mean and standard deviation of *net* sentiment across comment letters submitted by members of a given constituent group. *Net* sentiment is calculated by subtracting the number of negative words from the number of positive words — based on the dictionary in Loughran and McDonald (2011) — and scaling the result by the total word count of the comment letter.

We show proof of concept in Table 7, using descriptive statistics from comment letters submitted in response to the IASB's *Conceptual Framework* Exposure Draft, issued on 28 May 2015. We also plan to present preliminary evidence on how constituency groups coordinate their pressure by showing correlations in activity levels across groups.

[15] For example, one potential way to achieve such balance can be using random chunks of speech from the same board member for the most advanced models.

[16] Our dataset enables future researchers to adapt prompt instructions to construct measures along other ideological dimensions—for example, to assess the extent of a board member's home country bias, or their relative support for rule-based versus principles-based accounting standards.

[17] Traditionally, researchers have summarized these letters either supporting or opposing proposed standards. However, as Gipper et al. (2013) note, this reductive approach obscures the nuanced opinions and varied feedback expressed in these letters. Moreover, practical constraints of manual reading have often limited researchers to focusing on public companies and auditors, neglecting other important constituents such as academics and industry associations.

4.3. Measuring Voiced Position

We introduce a novel measure, *VoicedPosition*, which quantifies board members' expressed stance on accounting standards through sentiment analysis of transcribed speech segments. This approach provides a significant improvement over existing methods in the literature, offering greater flexibility and granularity in capturing individual positions during deliberations.

Unlike traditional approaches that infer board sentiment from exposure drafts, voting records, or dissenting statements, *VoicedPosition* directly measures the sentiment conveyed in spoken contributions across multiple agenda items and meetings. This provides three key advantages:

First, *VoicedPosition* allows for *cross-meeting* and *cross-agenda item* comparisons. Since it captures sentiment rather than discrete votes or document-level measures, it can be applied consistently across deliberations, enabling researchers to track board members' positions over time and across topics. Existing methods typically focus on final outcomes (e.g., dissenting votes) and thus overlook intra-deliberation shifts in stance.

Second, *VoicedPosition* enables *cardinal comparisons* across board members, agenda items, and meetings. Because it is based on word counts of positive and negative sentiment, it generates a cardinal measure that can be used to compare the relative strength of sentiment between board members or across issues (Hassan et al., 2024). In contrast, traditional measures, such as the presence of dissenting votes (e.g., Bradbury and Harrison, 2015; Chakravarthy, 2019), provide only binary or ordinal insights and do not account for the intensity of sentiment.

An alternative method to measure sentiment could be to rely on LLMs. However, LLM-based sentiment scores are less appropriate in the current context because they lack a clear benchmark, making direct comparisons across board members, agenda items, or meetings difficult.[18] In contrast, *VoicedPosition* provides a transparent and replicable method based on consistent word count principles.

Third, *VoicedPosition* is *highly adaptable* to specific research questions. Researchers can refine the measure by combining sentiment scores with keyword-based filters to isolate sentiment

[18]This limitation arises due to four key reasons: (1) LLM sentiment scores do not operate on a universal scale, making absolute comparisons unstable; (2) they are context-sensitive, meaning the same phrase may yield different sentiment scores based on surrounding text; (3) there is no standardized benchmark for cross-topic or cross-speaker calibration; and (4) different LLM models or prompt variations can produce inconsistent sentiment evaluations, complicating systematic analysis.

related to specific subtopics (e.g., scope, recognition criteria, measurement, or presentation) within a standard-setting discussion. This level of specificity is difficult to achieve with alternative methods, which often rely on broad document-level classifications or require manual coding of board discussions (Bae et al., 2023; Hassan et al., 2024).

These advantages set $VoicedPosition$ apart from existing approaches commonly used in the literature. Notably, some prior studies have attempted to infer board-level support or opposition through document similarity techniques (e.g., Monsen, 2022); however, these approaches are unable to capture shifts in sentiment within meetings or individual members' positions.

Overall, $VoicedPosition$ provides a scalable, systematic, and replicable method for analyzing board members' stances on proposed standards. By capturing sentiment at the level of individual speech contributions, this measure reveals patterns in standard-setting deliberations that are not accessible through existing methods, thereby providing a clearer view of how sentiment evolves over the course of a meeting.

4.4. Ideological Filtering and Responsiveness

We examine the role of ideology in standard setting by relating $VoicedPosition$ to board member ideology, the extent of interest group pressure, and the interaction between these two factors. This interaction term captures the idea that ideology may condition a standard setter's responsiveness to interest groups, particularly when those groups' positions align with their ideological priors.

To formalize this prediction, we estimate the following model:

$$\begin{aligned} VoicedPosition_{b,a,m} = \beta_0 + \beta_1 Ideology_b + \sum_{g=1}^{G} \beta_{2g} PressureIntensity_{g,a,m} \\ + \sum_{g=1}^{G} \beta_{3g} (Ideology_b \times PressureIntensity_{g,a,m}) \\ + \gamma X_{b,a,m} + \delta_a + \delta_m + \varepsilon_{b,a,m}. \end{aligned} \tag{1}$$

Here, $VoicedPosition_{b,a,m}$ captures the sentiment of board member b's contributions during the discussion of agenda item a in meeting m. The term $Ideology_b$ represents the board member's ideological stance, measured along a conservative-to-liberal spectrum. Interest group influence is

captured by $PressureIntensity_{g,a,m}$, which reflects the pressure exerted by group g on agenda item a prior to meeting m.[19] We quantify the intensity of each interest group's lobbying efforts using textual metrics — such as the total number of comment letters submitted, the total word count, and the mean and standard deviation of *net* sentiment across comment letters submitted by members of a given constituent group. The interaction term, $Ideology_b \times PressureIntensity_{g,a,m}$, allows us to assess whether ideology affects standard setters' responsiveness to interest groups.

Additionally, $X_{b,a,m}$ is a vector of control variables, while δ_a and δ_m represent agenda item and meeting fixed effects, respectively, to account for systematic differences across topics and over time (with "meeting fixed effects" referring specifically to meeting-date fixed effects, as used throughout the paper for simplicity).[20] The error term $\varepsilon_{b,a,m}$ captures unexplained variation. This specification allows us to assess both the direct effect of ideology on standard setters' expressed positions and how interest group pressure interacts with ideology in shaping their responsiveness.

To strengthen inferences regarding the interaction between ideology and interest group pressure, we also estimate an alternative specification of Equation 1 in which we exclude $Ideology_b$ and instead include board member fixed effects (α_b). This approach controls for all time-invariant characteristics of board members, ensuring that our estimates of interest group responsiveness are not confounded by unobserved heterogeneity at the individual level. In addition, we can leverage the granularity of our data to test whether the direct effect of ideology on $VoicedPosition$ differs by meeting or agenda item. This can be done by interacting $Ideology_b$ with the meeting fixed effects (δ_m) and the agenda item fixed effects (δ_a), respectively.

Next, we plan to extend our analysis to explicitly distinguish between ideological alignment and the intensity of pressure exerted by different interest groups. While ideological alignment captures how closely the political views of a board member match those of a given constituent group, pressure intensity reflects how vigorously or explicitly each group advocates for their preferred outcomes in

[19] We are aware that some agenda items (e.g., Disclosure Initiative) encompass discussions related to multiple accounting standards, some of which have separate comment letter collections. Accordingly, when constructing variables based on comment letters at the agenda item level — such as $PressureIntensity$ — we take care to manually classify and align comment letters with the relevant standards covered under each agenda item. This ensures consistency in linking input variables with the corresponding deliberation content. We plan to further refine this classification in subsequent iterations of the analysis and report the detailed classification procedure in the full version of the paper.

[20] It is possible that not all agenda items discussed on a given meeting date have associated comment letters, which are used to construct $PressureIntensity_{g,a,m}$. To address the potential issue that this variable is observable for only one agenda item per meeting date, we consider replacing meeting-date fixed effects with quarter or year fixed effects, if necessary.

their comment letters.

To operationalize ideological alignment, we use ideological scores for each board member and derive corresponding scores for each constituent group using our large language model-based classification approach described in 4.1. We then compute ideological proximity for each board member-constituent group pair as the absolute difference between their respective ideological scores.

With these constructs, we empirically test how ideological alignment moderates board members' responsiveness to lobbying pressure by estimating an augmented regression model of the form:

$$\begin{aligned} VoicedPosition_{b,a,m} = \beta_0 + \beta_1 Ideology_b + \sum_{g=1}^{6} \beta_{2g} PressureIntensity_{g,a,m} \\ + \sum_{g=1}^{6} \beta_{3g} (IdeologicalProximity_{b,g} \times PressureIntensity_{g,a,m}) \\ + \gamma X_{b,a,m} + \delta_a + \delta_m + \varepsilon_{b,a,m}, \end{aligned} \tag{2}$$

where $VoicedPosition_{b,a,m}$ captures the sentiment expressed by board member b during the discussion of agenda item a in meeting m, $Ideology_b$ is the ideological position of board member b, $PressureIntensity_{g,a,m}$ reflects the intensity of lobbying by group g, and $IdeologicalProximity_{b,g}$ measures the ideological closeness between board member b and interest group g. The vector $X_{b,a,m}$ contains relevant control variables, and δ_a and δ_m represent agenda item and meeting fixed effects, respectively.

The interaction terms specifically allow us to test whether board members are more responsive to intensive lobbying from groups whose ideological positions closely align with their own. To further strengthen identification, we will complement this analysis with an alternative specification of Equation 2 that includes board member fixed effects (α_b), removing the direct ideological term $Ideology_b$ and thus isolating the interactive effects while controlling for remaining unobserved individual-level heterogeneity.

Private Meetings: If ideology filters the policy ideas board members engage with, it should also affect how often and with whom they hold private meetings. The hypothesis is that board members are not merely passive recipients of publicly debated ideas; they actively cultivate, reinforce, and filter information through their informal interactions outside official deliberations. These private

discussions are often critical avenues through which board members align their perspectives, gauge political feasibility, and refine their positions before formal meetings.

To empirically examine this proposition, we adopt two approaches to proxy for the otherwise hard-to-observe private interactions of board members. First, we leverage publicly available data on the outreach activities of board members, which document formal external engagements, such as meetings with interest groups, preparers, and regulatory bodies. The frequency and composition of these interactions may serve as a proxy for broader engagement in private discussions. Specifically, we assess whether board members with distinct ideological leanings engage with systematically different constituencies and whether such engagements vary over time as key agenda items evolve.

Second, we use textual analysis of board deliberation transcripts to identify linguistic markers that indicate prior informal meetings or external consultations. Phrases such as "I had lunch with," "I spoke with," or "I heard from" may signal information exchanges outside formal settings. By systematically coding such references, we can infer patterns of informal interactions and their association with board members' ideological positions. This approach enables us to detect whether ideologically aligned board members rely more on private channels to reinforce shared perspectives or whether cross-ideological dialogues occur in private settings in ways that are not readily visible in public deliberations.

Taken together, these two complementary measures allow us to examine whether ideological sorting extends beyond formal meetings to informal networks, shaping how board members acquire and transmit policy ideas. If ideology systematically influences the structure of these private interactions, it provides further evidence that ideology serves as a gatekeeping mechanism in the standard-setting process, filtering which perspectives gain traction within deliberative bodies.

4.5. Ideology and Coalition Formation

To better understand coalition formation among board members, we examine two potential drivers of explicit agreement during deliberations: (1) ideological proximity between board members, and (2) the intensity of external interest groups pressure. Specifically, we measure coalition formation as explicit expressions of agreement between two board members b and b' during discussions of

agenda item a in meeting m, defined as follows:

$$Agreement_{b,b',a,m} = \frac{\text{Number of explicit agreement statements between } b \text{ and } b'}{\text{Total statements made by } b \text{ and } b' \text{ during agenda item } a \text{ in meeting } m}.$$

We measure ideological proximity as:

$$IdeologicalProximity_{b,b'} = 1 - |Ideology_b - Ideology_{b'}|,$$

where higher values indicate greater similarity between two board members' ideological positions.

Our goal is to examine whether ideological proximity explains coalition formation among board members while controlling for external interest group pressure. Since this pressure is identical across all board-member pairs within a given agenda item and meeting, we absorb it using agenda-item-by-meeting fixed effects. Thus, we estimate:

$$\begin{aligned} Agreement_{b,b',a,m} = \beta_0 + \beta_1 IdeologicalProximity_{b,b'} \\ + \gamma X_{b,b',a,m} + \delta_{a\times m} + \varepsilon_{b,b',a,m}, \end{aligned} \tag{3}$$

where $IdeologicalProximity_{b,b'}$ captures how similar two board members' ideological positions are. The fixed effects $\delta_{a\times m}$ absorb all agenda- and meeting-level factors, including interest group lobbying intensity, which does not vary within each agenda-meeting combination. This allows us to isolate the effect of ideological proximity on coalition formation. We also include pair-level control variables ($X_{b,b',a,m}$), such as similarity in professional backgrounds or tenure differences, to address other potential confounding factors.

4.6. Ideology and the Propagation of Policy Ideas

In this section, we outline our empirical approach to examining how ideology is associated with the propagation of policy ideas during standard-setting. We pilot the approach on the IASB Conceptual Framework deliberations. First, we assess the overall linguistic alignment between stakeholder comment letters and the final standard. Second, we isolate the distinctive language

contributions of each constituent group by estimating the likelihood that specific bigrams appear in the final standard. Third, we examine whether board members act as conduits for these policy ideas, and how their ideological orientations are associated with differences in the uptake of constituent language.

Overall Linguistic Similarity: We begin by measuring the aggregate linguistic similarity between each constituent group's comment letters and the final standard text. We follow Gad et al. (2024) and measure the *keyness* of bigrams (two-word combinations) in comment letters submitted by various constituent groups.

We identify *key* bigrams in each constituent group's comment letters (target corpus) by comparing their frequencies to those in the final standard text (reference corpus). We measure the statistical significance of each bigram's frequency difference between the target and reference corpora using a *keyness* statistic.[21] Specifically, in this pilot analysis, we compute the keyness statistic (G^2) for each comment letter by comparing the observed bigram frequencies in the comment letter (target corpus) with the expected frequencies derived from the final text of the revised Conceptual Framework (reference corpus). We then average these scores across all n_g comment letters in group g to obtain:

$$\bar{G^2}_g = \frac{1}{n_g} \sum_{i=1}^{n_g} G^2_{ig},$$

where G^2_{ig} denotes the keyness statistic for the ith letter in group g. A lower $\bar{G^2}_g$ indicates greater linguistic similarity between the group's comment letters and the final standard, whereas a higher score signals divergence. We also compute the standard deviation of keyness scores within each group. This statistic reflects the consistency of language across comment letters within each

[21] We use the log-likelihood ratio (G^2) (Dunning, 1993; Rayson and Garside, 2000) calculated as follows,

$$G^2 = 2 \sum_i O_i \times \ln \frac{O_i}{E_i},$$

where O refers to the observed frequencies and E refers to the expected frequencies in corpus i. The observed and expected frequencies are obtained by constructing a contingency table for each bigram, where the observed frequency is the actual occurrence of a given bigram and the expected occurrence is calculated as follows,

$$E_i = \frac{N_i \sum_i O_i}{\sum_i N_i},$$

where N is the number of all bigrams in corpus i and and O is the observed occurrence of a given bigram in corpus i. The G^2 statistic follows a chi-square distribution with one degree of freedom, allowing for significance testing of the keyness measure. Higher G^2 values indicate greater keyness, suggesting that the bigram is more characteristic of the target corpus compared to the reference corpus.

interest group category. Larger standard deviations suggest potential divisions within interest groups and, possibly, less coherent interest group pressure.

Figure 5 presents findings from the pilot analysis. Regulators and the Accounting Professions exhibit lower average keyness scores (4.42 and 5.35), indicating that, overall, the language in the final standard closely mirrors their comment letters. In contrast, Academics and respondents in the "Others" category display higher keyness scores (6.73 and 6.83), suggesting that their language deviates more significantly from that used in the final standard.

Unique Language Reuse: While the keyness statistics summarize overall similarity, they do not reveal the specific language elements driving that similarity. To address this limitation, we focus on bigrams unique to each constituent group to capture their distinctive language. Specifically, we construct a dataset consisting only of bigrams that appear exclusively within each group. We then define a binary variable, $\textit{Bigram in Final Standard}_{i,a}$, which equals 1 if bigram i appears in the final standard of agenda item a. Using this variable, we estimate the following logit model:

$$\ln\left(\frac{\Pr(\textit{Bigram in Final Standard}_{i,a})}{1-\Pr(\textit{Bigram in Final Standard}_{i,a})}\right) = \beta_0 + \sum_{g=1}^{6}\beta_g \textit{Group}_{i,g,a} + \delta_a + \varepsilon_{i,a}. \tag{4}$$

Here, $\textit{Group}_{i,g,a}$ is an indicator for whether bigram i originates from comment letters submitted by constituent group g for agenda item a. The constituent groups include Regulators, Accounting Professions, Preparers, Users, Public Interest Bodies, and "Others", with "Academics" serving as the reference category. This model allows us to examine whether bigrams uniquely associated with certain groups are more or less likely to be incorporated into the final standard, offering suggestive evidence on the relative influence of linguistic input across constituent groups.

As an illustration, in this pilot analysis we focus on the IASB deliberations on the Conceptual Framework. Online Appendix Table 4 presents a selection of bigrams uniquely associated with each group that appear in the final standard. Table 8 reports the estimation results of Equation 4. Using "Academics" as the reference group, we find significant differences in the odds of specific language being incorporated into the final standard across constituent groups. The Accounting Professions show significantly higher odds of language inclusion compared to Academics (coeff.= 0.43, p <0.01), implying 1.54 (=exp(0.43)) times higher odds, a 54 percent increase. Regulators show an even more pronounced effect (coeff.=0.79, p <0.01), with 2.20 times higher odds, a 120

percent increase.

This analysis not only reinforces the overall linguistic similarity observed in earlier results but also highlights which aspects of constituent group language are more likely to influence standard-setting outcomes.

Board Members as Policy idea Conduits: Building on the previous tests, we examine whether board members act as conduits for policy ideas and whether their ideological orientations are associated with differences in language uptake. First, we calculate board member–specific keyness scores to capture the similarity between each member's spoken contributions and the final standard. Figure 6 displays average keyness scores ($\bar{G^2}_b$) for each IASB board member b involved in the Conceptual Framework discussions. For comparison, we include the keyness score of the technical staff present at board meetings. The technical staff exhibit the closest alignment — that is, the lowest average keyness score — consistent with their role in drafting due process documents and presenting them at meetings. Other board members, including the IASB chair, Hans Hoogervorst, exhibit somewhat higher keyness scores. Notable differences emerge among board members, particularly from those with fewer contributions, starting from Wei-Guo Zhang (i.e., board members with $\bar{G^2} > 6.97$). This variation in language use across board members suggests differences in how their individual contributions align with the standard's final language.

Next, to provide evidence on whether board members are potential conduits through which comment letter language aligns with the final standard, we evaluate the text similarity between individual board members' speech and the comment letters from various constituent groups. We construct a corpus for each board member separately containing their complete speech during the Conceptual Framework discussions in March 2016, where they discussed comment letters received on the exposure draft. We define an indicator variable, $\textit{Bigram in Board Member Corpus}_{i,b,a}$, set to one if bigram i appears in the corpus of board member b during the discussion of agenda item a. We then modify Equation 4, replacing the dependent variable with this newly defined variable. This allows us to assess whether a specific constituent group's language is more likely to appear in a board member's speech. Figure 7 presents estimates of separate logit regressions for each board member involved in the Conceptual Framework discussions and for the technical staff. Recall that the omitted group for these logit regressions is Academics and, therefore, the estimated odds are relative to this group. Solid dots represent significant estimates at the ten percent level, circles

denote estimates with $p > 0.1$. Odds ratios on indicator variables can be compared across equations.

We reiterate that this analysis is intended as an illustration of the tests planned for the full version of the paper. Our focus on IASB deliberations on a single standard limits the available textual data, potentially leading to noisy estimates. A more comprehensive picture is expected to emerge with the full dataset.

Nevertheless, our preliminary findings reveal the following patterns. Some board members, including Chungwoo Suh, Darrel Scott, Ian Mackintosh, Patrick Finnegan, and Stephen Cooper, show no significant alignment between their language and that of any specific constituent group. In contrast, Wei-Guo Zhang's language aligns more closely with Academics (as all the other constituent groups have odds below one). The technical staff show similarities with the Accounting Professions, Regulators, and Users groups. Philippe Danjou is among the few whose language is closer to Users (relative to Academics).

In addition, to examine our main hypothesis regarding the association between board member ideology and language uptake, we plan to estimate the following logit model:

$$\begin{aligned} \ln\left(\frac{\Pr(\textit{Bigram in Board Member Corpus}_{i,b,a,m})}{1-\Pr(\textit{Bigram in Board Member Corpus}_{i,b,a,m})}\right) = \beta_0 + \beta_1 \textit{Ideology}_b + \sum_{g=1}^{6} \beta_{2g}\, \textit{Group}_{i,g,a,m} \\ + \sum_{g=1}^{6} \beta_{3g}\Big(\textit{Ideology}_b \times \textit{Group}_{i,g,a,m}\Big) \\ + \gamma X_{b,a,m} + \delta_a + \delta_m + \varepsilon_{i,b,a,m}. \end{aligned} \tag{5}$$

Here, $\textit{Bigram in Board Member Corpus}_{i,b,a,m}$ is an indicator for whether bigram i appears in the corpus of board member b during the discussion of agenda item a in meeting m. $\textit{Group}_{i,g,a,m}$ is an indicator for whether bigram i originates from comment letters submitted by constituent group g for agenda item a before meeting m. The key coefficients include β_{2g}, which captures the baseline log-odds that a bigram originating from group g appears in the speech of a board member with an ideology score of zero, and the interaction term β_{3g} measures how board member ideology moderates the likelihood of incorporating language from group g. Specifically, odds ratios ($e^{\beta_{3g}}$) greater than 1 indicate that higher (e.g., more liberal) ideology scores are associated with increased uptake of group g's language, while values below 1 suggest the opposite.

Integrating the Evidence: These three sets of analyses offer complementary insights. Step 1 provides a broad, aggregated measure of linguistic similarity, identifying which constituent groups, on average, are more closely aligned with or divergent from the language of the final standard. Step 2 refines this view by examining which unique language elements from each group are more frequently incorporated into the final standard. Step 3, through a logit regression framework, assesses whether variation in board members' ideological orientations is associated with differences in their uptake of constituent group language. In sum, while Step 1 reveals the overall landscape of language similarity, Step 2 isolates the specific linguistic features contributing to this similarity, and Step 3 connects these patterns to board member ideology.

4.7. Ideology and the Quality of Board Deliberations

An important open question is whether ideological diversity enhances or undermines the quality of board deliberations. Several observable characteristics can serve as proxies for deliberative quality, including meeting duration, the intensity of disagreement, and the time required to reach decision convergence. The board's composition naturally varies across meetings and agenda items—for instance, due to member turnover or absences—resulting in fluctuations in its ideological makeup.

We define a measure of board ideological composition, denoted as $IdeolComp_j$, where j refers to either meeting m or agenda item a. This measure may be associated with more substantive debates or, alternatively, with gridlock and inefficiency. Specifically, we examine whether greater ideological diversity within the board correlates with longer discussions and more intense disagreement, thereby shedding light on the relationship between ideological composition and deliberative quality.

To investigate this, we use meeting- and agenda item-level metrics — such as deliberation length, frequency of interruptions, and the number of explicit disagreement statements — as outcome variables.[22] We then regress these outcomes on the board's ideological composition at the time of each meeting or agenda item discussion.

Figure 8 presents a proof of concept for our measurement of board ideological composition, illustrating the trend in the IASB's average conservative–liberal ideology score during the deliberations on the Conceptual Framework.

[22] Alternative measures could include assessing the sentiment of comment letters during post-implementation reviews or evaluating the duration of discussions within the interpretations committee on specific standards.

5. Conclusions

To be written after completion of the project.

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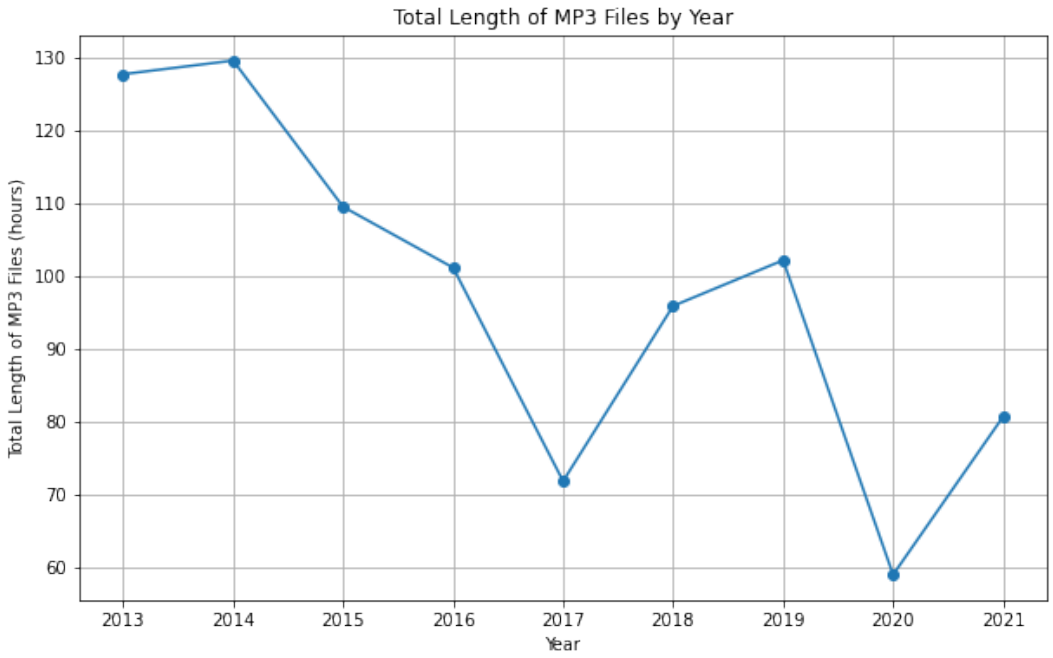
Figure 1. IASB Meeting Duration Over Time



Notes: This figure displays the annual total hours of IASB meeting recordings in our sample period. The dataset comprises 898 mp3 files, totaling 878.28 hours of audio, averaging 58.68 minutes per file. Each mp3 file typically captures the discussion of a single agenda item or a portion thereof.

Figure 2. Snapshot of Structured Dataset

Year	Date	Agenda Item	Audio Name	Sequence	Start Time(s)	End Time(s)	Diarized Segment	Speaker	Confidence Score
2016	15 - 16 March	Conceptual Framework	ap10-audio.mp3	168	3385.8901	3395.365	Just a point of clarification for the law. I think what the conceptual framework says is the primary users are those that can't demand that information themselves.	Technical staff	0.7192668
2016	15 - 16 March	Conceptual Framework	ap10-audio.mp3	169	3396.665	3412.1099	That is not the way it is understood. It is not the way. In Outreach activities, people do not understand that message this way. Would you clarify and explain that, of course, management is also using that information. By the way, they use a lot of extra information.	Philippe Danjou	0.99994993
2016	15 - 16 March	Conceptual Framework	ap10-audio.mp3	170	3412.97	3419.63	We can't get in a way we say, well, they don't give you that information.	Philippe Danjou	0.99348205
2016	15 - 16 March	Conceptual Framework	ap10-audio.mp3	171	3421.21	3434.86	Well, it's not yeah. And maybe maybe we can articulate it better, but I think we'd need to be careful not to inadvertently imply that as long as it's enough for management, it's enough for everybody else given they've got a whole extra source of information, which isn't what you're suggesting.	Sue Lloyd	0.99904424
2016	15 - 16 March	Conceptual Framework	ap10-audio.mp3	172	3435	3437.82	I agree. But the basic message is not very welcoming.	Technical staff	0.9128397
2016	15 - 16 March	Conceptual Framework	ap10-audio.mp3	173	3437.96	3442.84	It's hard to tinker at this stage though given that it's about to go. Next stage is final. So	Sue Lloyd	0.9999989
2016	15 - 16 March	Conceptual Framework	ap10-audio.mp3	174	3443.32	3450.645	But but the point we're trying to make isn't that these other groups aren't using the information. It's which needs are we designing the financial statements to meet? Yep.	Technical staff	0.95015806
2016	15 - 16 March	Conceptual Framework	ap10-audio.mp3	175	3450.645	3455.305	Yeah. Yeah. No. That's true. Martin?	Hans Hoogervorst	0.9980646
2016	15 - 16 March	Conceptual Framework	ap10-audio.mp3	176	3457.125	3468.3398	I think we we should not extend this primary user because I see it really linked to this materiality thing which we have also discussed and have our practice statement because and then if it's too broad,	Martin Edelmann	0.99911946
2016	15 - 16 March	Conceptual Framework	ap10-audio.mp3	177	3468.3398	3483.525	I think as a preparer, you cannot make really materiality decisions if you don't know, okay, who is the primary user? Is it the regulator? Is it the grandmother or whoever it is? Because then it is really difficult to make sense. So I think we should we should focus really on what we have.	Martin Edelmann	0.9997789

Panel A: Meeting Transcripts

Comment Letter ID	Response Period	Response to	Respondent Name	Constituent Group	Region of Origin	Corresponding IASB Meeting Year	Corresponding IASB Meeting Date	Corresponding IASB Meeting Agenda Item	Corresponding IASB Meeting Audio Name
50_5294_ATWhitfield	41	May - 26 Oct. 2015	Exposure Draft proposing	Australasian Council of Auditors-General	Accounting Professions	Australia	2016	15 - 16 March	Conceptual Framework	ap10-audio.mp3
50_5308_PeterWellsL	42	May - 26 Oct. 2015	Exposure Draft proposing	Peter Wells	Academics	Australia	2016	15 - 16 March	Conceptual Framework	ap10-audio.mp3
50_5312_JukkaRannil	43	May - 26 Oct. 2015	Exposure Draft proposing	Jukka S. Rannila	Others	Finland	2016	15 - 16 March	Conceptual Framework	ap10-audio.mp3
50_5313_BjoernSchn	44	May - 26 Oct. 2015	Exposure Draft proposing	The Linde Group	Preparers	Germany	2016	15 - 16 March	Conceptual Framework	ap10-audio.mp3
50_5363_RichardFMc	45	May - 26 Oct. 2015	Exposure Draft proposing	Edison Electric Institute	Preparers	United States	2016	15 - 16 March	Conceptual Framework	ap10-audio.mp3
50_5390_ChangqingL	46	May - 26 Oct. 2015	Exposure Draft proposing	Changqing Liu	Academics	China	2016	15 - 16 March	Conceptual Framework	ap10-audio.mp3
50_5396_ManuelOrte	47	May - 26 Oct. 2015	Exposure Draft proposing	Manuel Ortega	Others	Spain	2016	15 - 16 March	Conceptual Framework	ap10-audio.mp3
50_5398_AgnesMathi	48	May - 26 Oct. 2015	Exposure Draft proposing	Cooperatives Europe	Public Interest	Belgium	2016	15 - 16 March	Conceptual Framework	ap10-audio.mp3
50_5406_EckhardOtt	49	May - 26 Oct. 2015	Exposure Draft proposing	DGRV - German Cooperative and Raiffeis	Public Interest	Germany	2016	15 - 16 March	Conceptual Framework	ap10-audio.mp3
50_5408_CarienvanM	50	May - 26 Oct. 2015	Exposure Draft proposing	Carien van Mourik	Academics	UK	2016	15 - 16 March	Conceptual Framework	ap10-audio.mp3
50_5409_AngelaTanK	51	May - 26 Oct. 2015	Exposure Draft proposing	Angela Tan-Kantor	Academics	Australia	2016	15 - 16 March	Conceptual Framework	ap10-audio.mp3
50_5411_DavidPSmel	52	May - 26 Oct. 2015	Exposure Draft proposing	National Association of Water Companie	Preparers	United States	2016	15 - 16 March	Conceptual Framework	ap10-audio.mp3
50_5412_WilliamRFo	53	May - 26 Oct. 2015	Exposure Draft proposing	American Gas Association (AGA)	Preparers	United States	2016	15 - 16 March	Conceptual Framework	ap10-audio.mp3
50_5459_BoonSengTa	54	May - 26 Oct. 2015	Exposure Draft proposing	Tan Boon Seng (Dr)	Academics	N.A.	2016	15 - 16 March	Conceptual Framework	ap10-audio.mp3
50_5464_NevilleMitcl	55	May - 26 Oct. 2015	Exposure Draft proposing	The Group of 100 Incorporated	Preparers	Australia	2016	15 - 16 March	Conceptual Framework	ap10-audio.mp3
50_5471_FranciscoSa	56	May - 26 Oct. 2015	Exposure Draft proposing	European Banking Federation (EBF)	Preparers	Belgium	2016	15 - 16 March	Conceptual Framework	ap10-audio.mp3
50_5486_SofiaBildste	57	May - 26 Oct. 2015	Exposure Draft proposing	Confederation of Swedish Enterprise (So	Preparers	Sweden	2016	15 - 16 March	Conceptual Framework	ap10-audio.mp3
50_5488_QingmeiXue	58	May - 26 Oct. 2015	Exposure Draft proposing	Qingmei Xue	Academics	China	2016	15 - 16 March	Conceptual Framework	ap10-audio.mp3
50_5490_AndrewHigs	59	May - 26 Oct. 2015	Exposure Draft proposing	Dr. Andrew Higson	Academics	UK	2016	15 - 16 March	Conceptual Framework	ap10-audio.mp3
50_5494_LynessaDias	60	May - 26 Oct. 2015	Exposure Draft proposing	Lynessa Dias	Accounting Professions	N.A.	2016	15 - 16 March	Conceptual Framework	ap10-audio.mp3
50_5503_MaureenKe	61	May - 26 Oct. 2015	Exposure Draft proposing	The Institute of Certified Public Accounta	Accounting Professions	Ireland	2016	15 - 16 March	Conceptual Framework	ap10-audio.mp3
50_5512_HayatoKom	62	May - 26 Oct. 2015	Exposure Draft proposing	The Life Insurance Association of Japan (	Preparers	Japan	2016	15 - 16 March	Conceptual Framework	ap10-audio.mp3
50_5521_JorgeKatsun	63	May - 26 Oct. 2015	Exposure Draft proposing	Professor Doctor. Jorge Katsumi Niyama,	Academics	Brazil	2016	15 - 16 March	Conceptual Framework	ap10-audio.mp3
50_5581_SuatChengC	64	May - 26 Oct. 2015	Exposure Draft proposing	Singapore Accounting Standards Council	Regulators	Singapore	2016	15 - 16 March	Conceptual Framework	ap10-audio.mp3
50_5605_RamSubran	65	May - 26 Oct. 2015	Exposure Draft proposing	CPA Australia	Accounting Professions	Australia	2016	15 - 16 March	Conceptual Framework	ap10-audio.mp3
50_5624_JamesCraw	66	May - 26 Oct. 2015	Exposure Draft proposing	CFA Society of the UK (CFA UK)	Users	United Kingdom	2016	15 - 16 March	Conceptual Framework	ap10-audio.mp3
50_5625_RobertDohr	67	May - 26 Oct. 2015	Exposure Draft proposing	Robert Dohrer	Accounting Professions	United Kingdom	2016	15 - 16 March	Conceptual Framework	ap10-audio.mp3
50_5627_NiclasHellm	68	May - 26 Oct. 2015	Exposure Draft proposing	European Accounting Association (Niclas	Academics	Belgium	2016	15 - 16 March	Conceptual Framework	ap10-audio.mp3
50_5637_MariaGome	69	May - 26 Oct. 2015	Exposure Draft proposing	Quoted Companies Alliance	Preparers	N.A.	2016	15 - 16 March	Conceptual Framework	ap10-audio.mp3
50_5638_KevinSteven	70	May - 26 Oct. 2015	Exposure Draft proposing	Matt Pinnuck	Academics	Australia	2016	15 - 16 March	Conceptual Framework	ap10-audio.mp3
50_5646_GreggNelsoi	71	May - 26 Oct. 2015	Exposure Draft proposing	International Business Machines Corpora	Preparers	USA	2016	15 - 16 March	Conceptual Framework	ap10-audio.mp3
50_5655_HenryChan	72	May - 26 Oct. 2015	Exposure Draft proposing	The Hong Kong Association of Banks (HK/	Preparers	Hong Kong	2016	15 - 16 March	Conceptual Framework	ap10-audio.mp3
50_5657_StevenMaij	73	May - 26 Oct. 2015	Exposure Draft proposing	European Securities and Markets Author	Regulators	France	2016	15 - 16 March	Conceptual Framework	ap10-audio.mp3
50_5661_JohnIrvineB	74	May - 26 Oct. 2015	Exposure Draft proposing	John Irvine	Preparers	United Kingdom	2016	15 - 16 March	Conceptual Framework	ap10-audio.mp3
50_5663_MichaelFras	75	May - 26 Oct. 2015	Exposure Draft proposing	Chartered Accountants Australia and Nev	Accounting Professions	Australia	2016	15 - 16 March	Conceptual Framework	ap10-audio.mp3
50_5666_BrianSinglet	76	May - 26 Oct. 2015	Exposure Draft proposing	The Institute of Chartered Accountants in	Accounting Professions	UK	2016	15 - 16 March	Conceptual Framework	ap10-audio.mp3

Panel B: Comment Letters

Figure 2. Snapshot of Structured Dataset (C'd)

Year	Date	Agenda Item	Agenda Paper	Summary	Question Sequence	Vote	Next Steps
2013	19-21 March	IAS 41 Agricultu	ap10-due-proce	The IASB finalized	1	The IASB concluded that it had met the due process requirements	The IASB will
2013	19-21 March	IAS 41 Agricultu	ap10-due-proce	The IASB finalized	2	The IASB gave permission for the staff to begin the process of balloting the Exposure Draft.	The IASB will
2013	19-21 March	IAS 41 Agricultu	ap10-due-proce	The IASB finalized	3	The IASB decided that the Exposure Draft should be open for comment for 120 days. All IASB members agreed.	The IASB will
2013	19-21 March	IAS 41 Agricultu	ap10-due-proce	The IASB finalized	4	Two IASB members noted their tentative intentions to dissent from the publication of the Exposure Draft.	The IASB will
2013	19-21 March	Fair Value Mea	ap4-unit-of-acc	The IASB discusse	1	The IASB tentatively decided that the unit of account for investments in subsidiaries, joint ventures and associates is the investment as a whole. Nine IASB members agreed.	The IASB staff
2013	19-21 March	Fair Value Mea	ap4-unit-of-acc	The IASB discusse	2	The IASB tentatively decided that the fair value measurement of an investment composed of quoted financial instruments should be the product of the quoted price of the financial instrument (P) multiplied by the quantity (Q) of instruments held (ie P × Q) and that the fair value measurement of cash-generating units (CGUs) for impairment testing when those CGUs correspond to a quoted entity should also be the product of their quoted price (P) multiplied by the quantity (Q) of instruments held (ie P × Q), with eight IASB members agreeing and two members indicating their tentative intention to present an alternative view in the forthcoming Exposure Draft.	The IASB staff
...	...	...	...		...	...	...

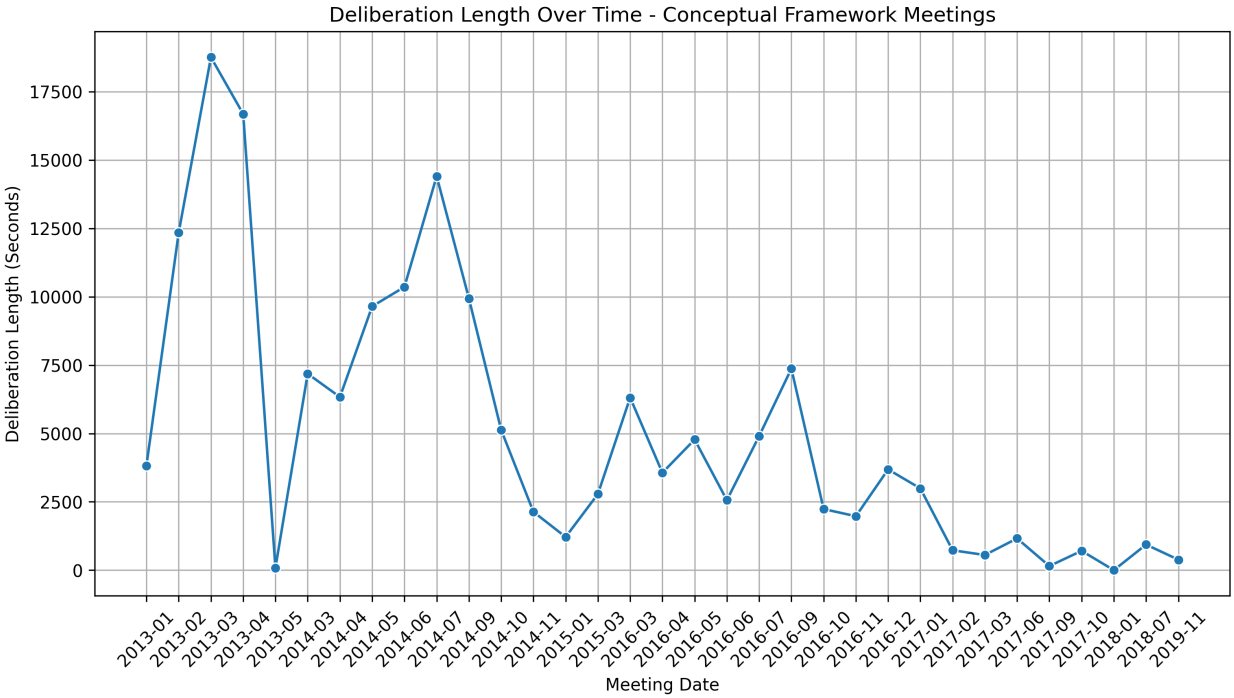
Panel C: Meeting Summaries

Year	Date	Agenda Item	Agenda Paper	Objective of the Meeting	Question Sequence	Question
2013	19-21 March	IAS 41 Agricultu	ap10-due-proce	The purpose of this meeting	1	Are there any further due process steps that the IASB think are necessary before beginning the balloting process?
2013	19-21 March	IAS 41 Agricultu	ap10-due-proce	The purpose of this meeting	2	Does the IASB grant the staff permission to begin the balloting process?
2013	19-21 March	IAS 41 Agricultu	ap10-due-proce	The purpose of this meeting	3	Do any IASB members intend to dissent from the proposal?
2013	19-21 March	IAS 41 Agricultu	ap10-due-proce	The purpose of this meeting	4	Does the IASB agree that the comment period should be 120 days?
2013	19-21 March	Fair Value Meas	ap4-unit-of-acc	This paper follows up the di	1	Does the IASB agree with the staff's conclusion that the unit of account in the Standards dealing with the accounting for subsidiaries, joint ventures and associates should be the investment as whole?
2013	19-21 March	Fair Value Meas	ap4-unit-of-acc	This paper follows up the di	2	On the basis of the staff's analysis, which of the options described above does the IASB consider to be the most appropriate for: (a) measuring investments in subsidiaries, joint ventures or associates at fair value whose underlying individual financial instruments have a Level 1 price (paragraphs 42-50): (i) Option 1 (unit of account is considered to be more important), or (ii) Option 2 (prioritisation of Level 1 inputs is considered to be more important)? (b) measuring fair value less costs of disposal for impairment testing purposes (paragraphs 51–56): (i) Option 1 (unit of account is considered to be more important), or (ii) Option 2 (prioritisation of Level 1 inputs is considered to be more important)?
...	...	...	...	...	...	...

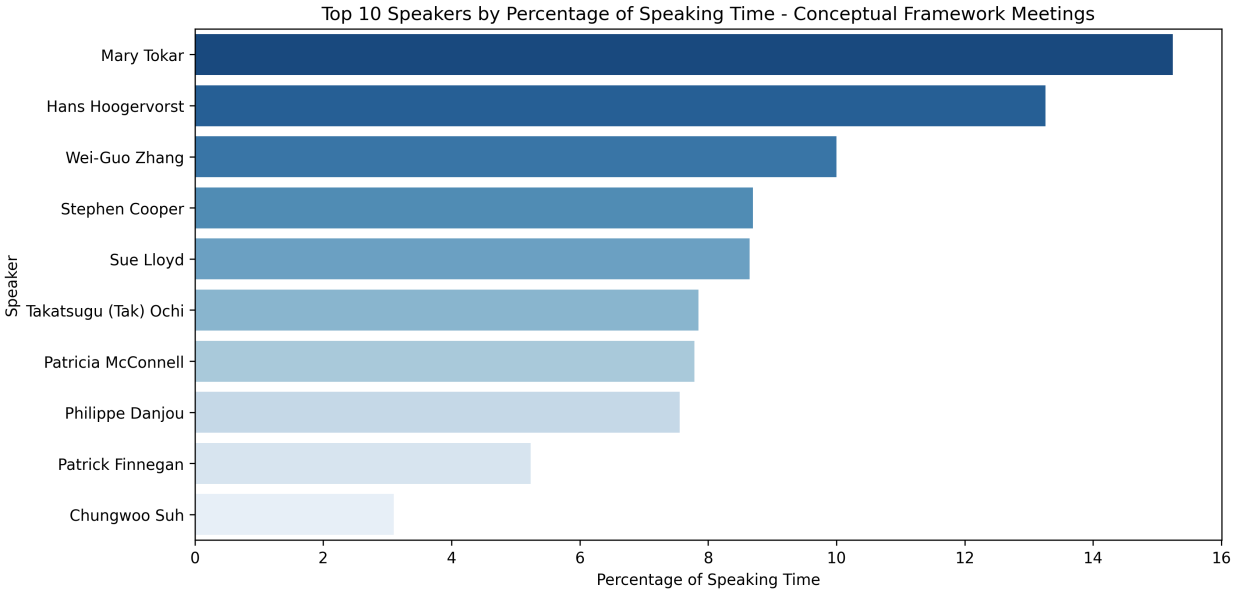
Panel D: Agenda Papers

Notes: This figure presents snapshots of our structured datasets. Panel A displays the layout of the meeting transcript dataset, Panel B illustrates the format of the comment letter dataset, Panel C shows the layout of the meeting summary dataset, and Panel D illustrates the format of the agenda paper dataset. The confidence score in the meeting transcript dataset is determined by selecting the highest probability value from the predicted class probabilities generated by the speaker identification model. This score reflects the model's confidence in its prediction. If the confidence score falls below a specified threshold (0.99 in our current model), the speaker is labeled as "Technical staff." It is important to acknowledge that refinements to the machine learning algorithms at various stages may lead to updates or modifications in the structure and composition of the table.

Figure 3. Descriptive Evidence on the Dataset

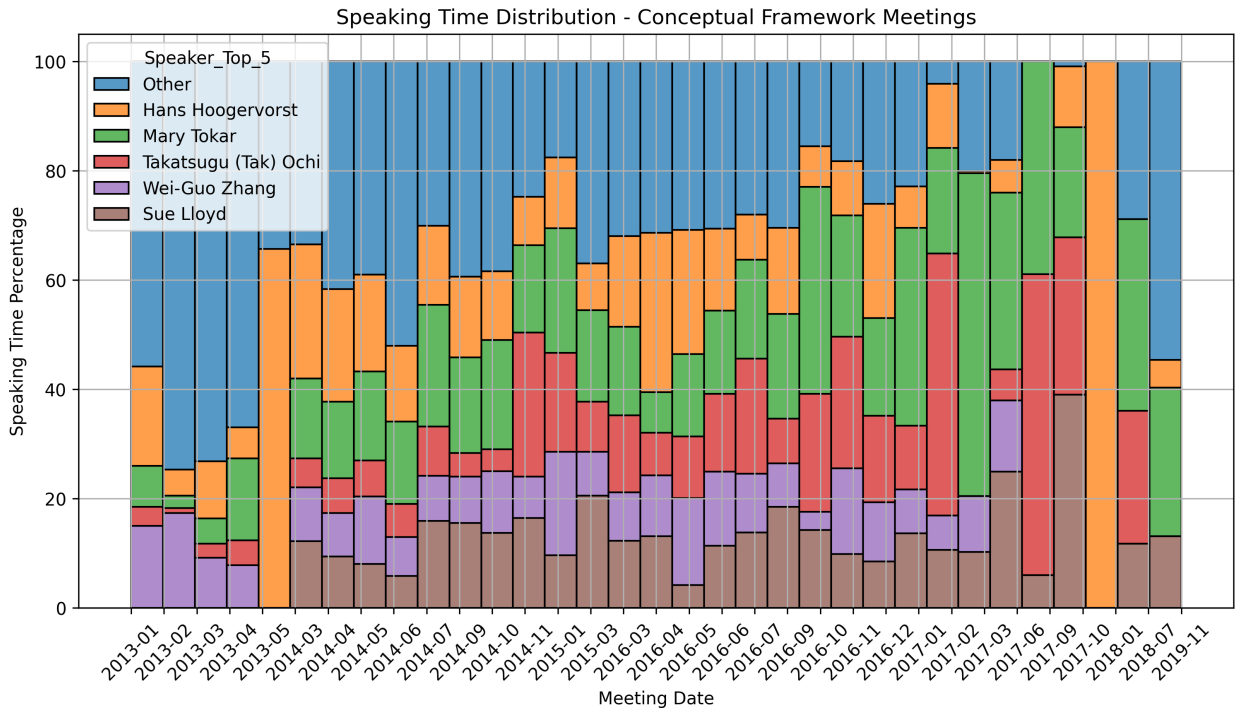


Panel A: Deliberation Length Over Time



Panel B: Top 10 Speakers by Percentage of Speaking Time

Figure 3. Descriptive Evidence on the Dataset (C'd)



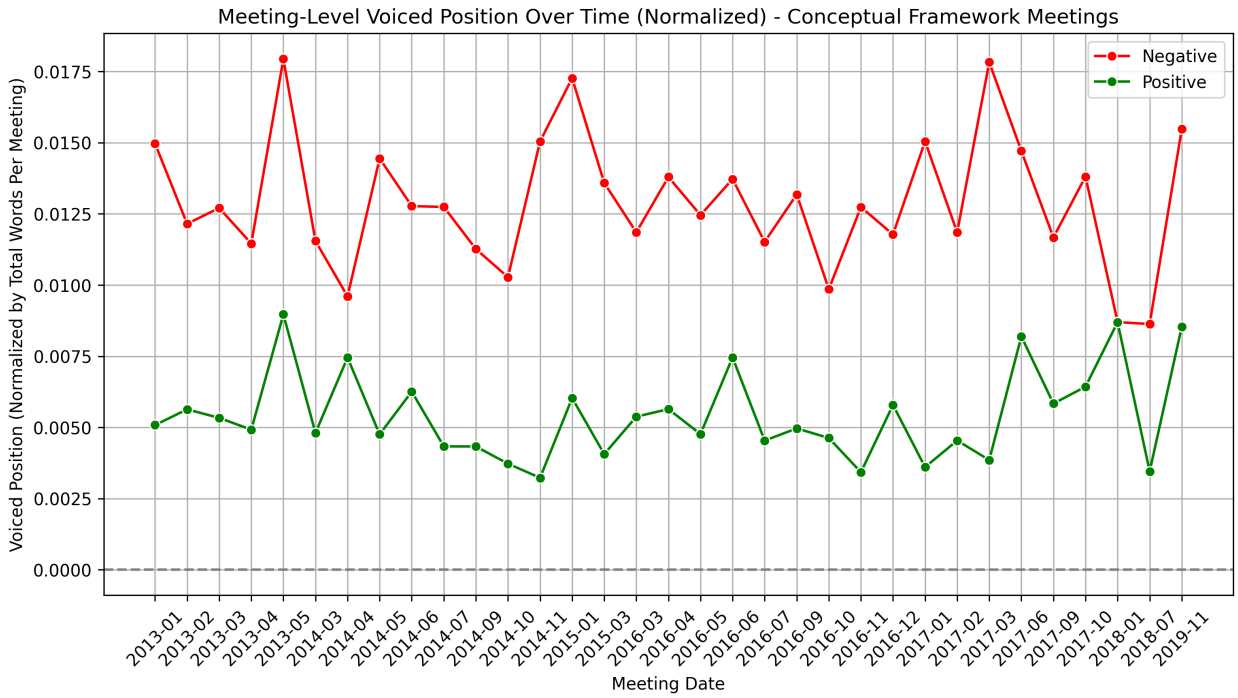
Panel C: Speaking Time Distribution

Notes: This figure presents descriptive evidence from our IASB meeting transcript dataset, using Conceptual Framework meetings as an illustration. Panel A shows the total speaking time of all board members in each meeting, representing the length of deliberations. Panel B depicts the percentage of total speaking time per speaker across all meetings, displaying only the top 10 speakers for clarity. Panel C presents the percentage of speaking time per speaker within each meeting. For clarity, only the top five speakers—determined based on the number of meetings attended—are shown individually, while the remaining participants are grouped under "Other." In all calculations, contributions from technical staff have been excluded. These results are based on an initial pilot analysis. It is important to acknowledge that refinements to the machine learning algorithms at various stages may lead to updates or modifications in the findings.

Figure 4. Voiced Position - Sentiment Analysis

Panel A: Speaker-Meeting Level Voiced Position Over Time (Normalized)

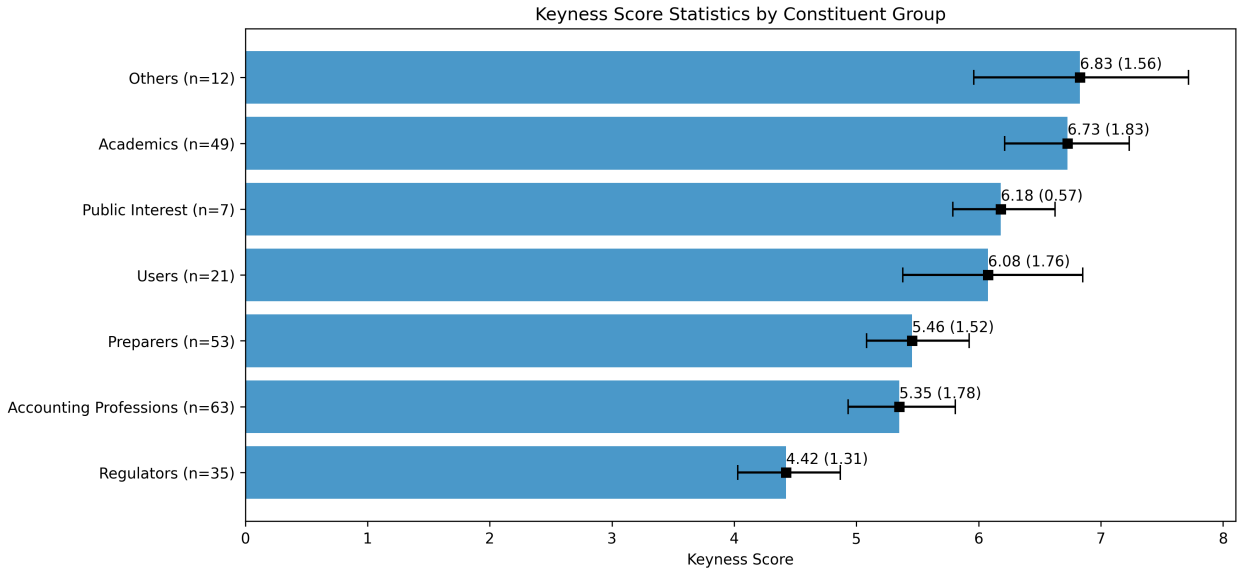
Figure 4. Voiced Position - Sentiment Analysis (C'd)



Panel B: Meeting Level Voiced Position Over Time (Normalized)

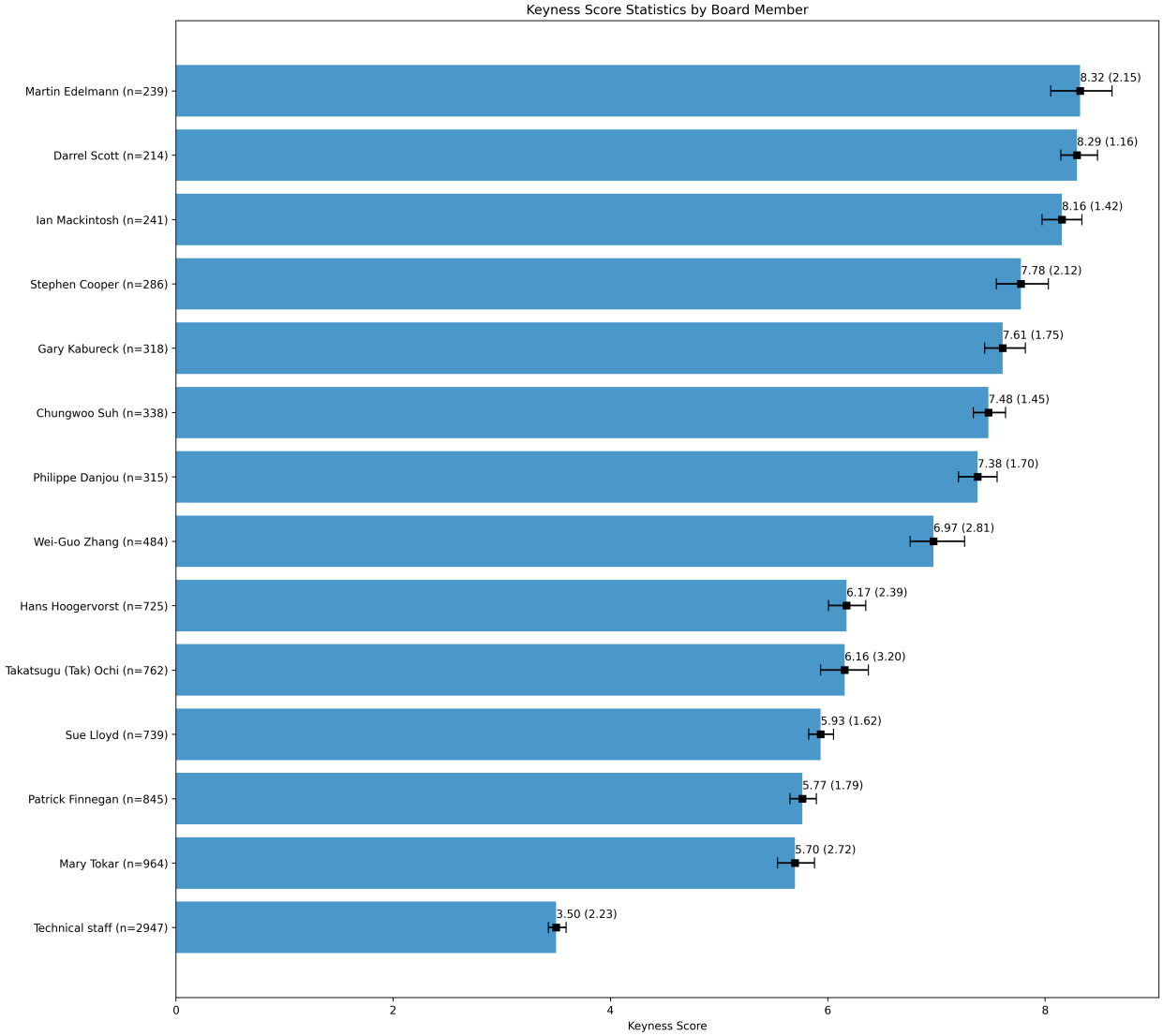
Notes: This figure presents the results of board members' voiced position (sentiment) analysis, using Conceptual Framework meetings as an illustration. Sentiment is measured using a lexicon-based approach, following Loughran and McDonald (2011). Panel A displays the speaker-meeting level trend in voiced positions. For clarity, the figure includes only the top five board members—determined based on the number of meetings attended, with technical staff included as a reference point. Panel B presents the meeting level trend in voiced positions. To control for differences in speech length, sentiment scores are normalized by dividing the keyword counts by the total number of words spoken. These results are based on an initial pilot analysis. It is important to acknowledge that refinements to the machine learning algorithms at various stages may lead to updates or modifications in the findings.

Figure 5. Keyness Score Statistics by Constituent Group



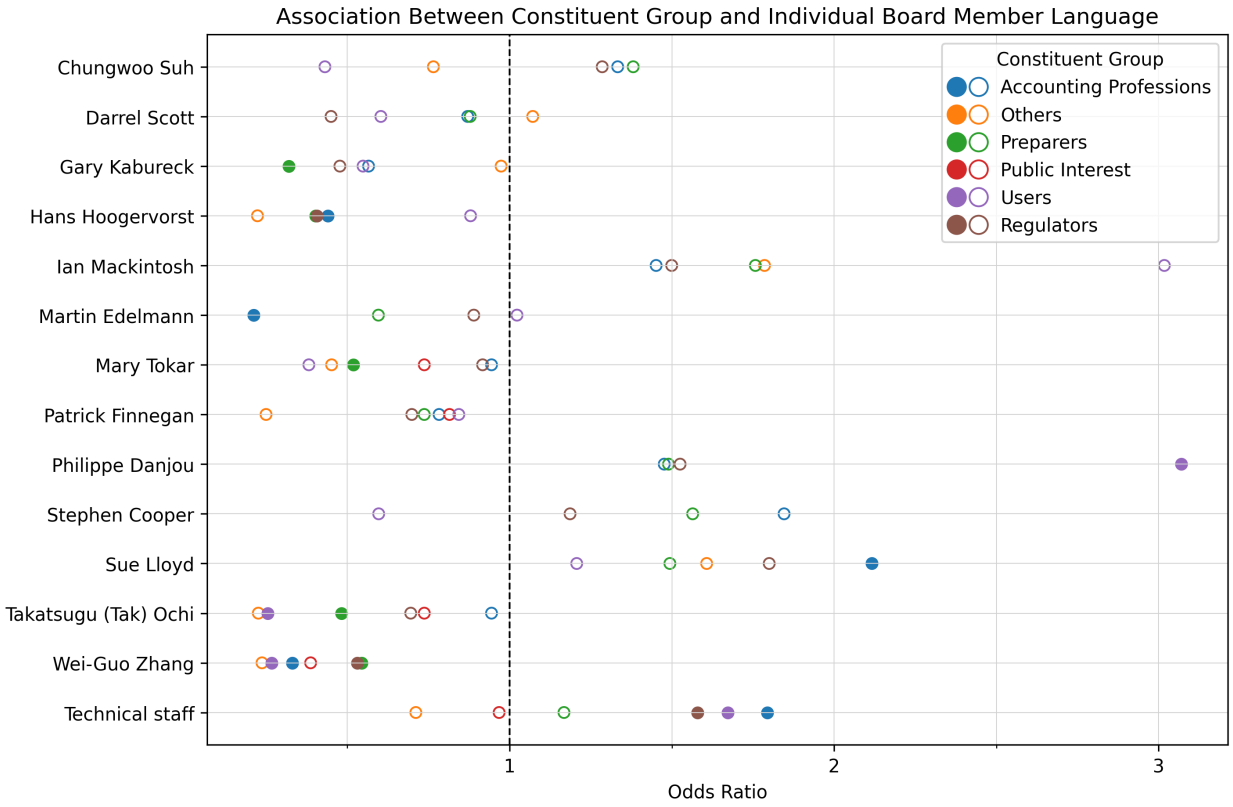
Notes: This figure presents the average keyness score for each constituent group, alongside the number of observations (comment letters) for each group. This pilot analysis uses comment letters submitted to the IASB in response to the *Conceptual Framework* Exposure Draft as an illustration. On 28 May 2015, the IASB published an Exposure Draft proposing a revised *Conceptual Framework for Financial Reporting*, which received 241 comment letters (one unsigned duplicate letter was excluded from the analysis). The G^2 statistic follows a χ^2 distribution. We derive the 95 percent confidence intervals from 1,000 bootstrap samples, each randomly drawn with replacement from the original data. We calculated the mean for each sample, and from these means, we identify the 2.5th and 97.5th percentiles to establish the 95 percent confidence intervals. Standard deviations are shown in parentheses, next to the keyness scores. These results are based on an initial pilot analysis. It is important to acknowledge that refinements to the machine learning algorithms at various stages may lead to updates or modifications in the findings.

Figure 6. Keyness Score Statistics by Board Member



Notes: This figure displays the average keyness scores for each board member, with technical staff included as a reference point. The number of bigrams associated with each individual is shown next to their name. This pilot analysis uses the Conceptual Framework meetings held in March 2016 as an illustration. On 15 March 2016, the IASB held public meetings to discuss the comment letters received on the *Conceptual Framework* Exposure Draft. Amaro Luiz de Oliveira Gomes has a high keyness score but made few contributions to this discussion, potentially skewing his keyness result. We omit this board member from the test as the corpus associated with his contributions is too small for reliable inferences. The G^2 statistic follows a χ^2 distribution. We derive the 95 percent confidence intervals from 1,000 bootstrap samples, each randomly drawn with replacement from the original data. We calculated the mean for each sample, and from these means, we identify the 2.5th and 97.5th percentiles to establish the 95 percent confidence intervals. Standard deviations are shown in parentheses, next to the keyness scores. These results are based on an initial pilot analysis. It is important to acknowledge that refinements to the machine learning algorithms at various stages may lead to updates or modifications in the findings.

Figure 7. Association Between Constituent Group and Individual Board Member Language

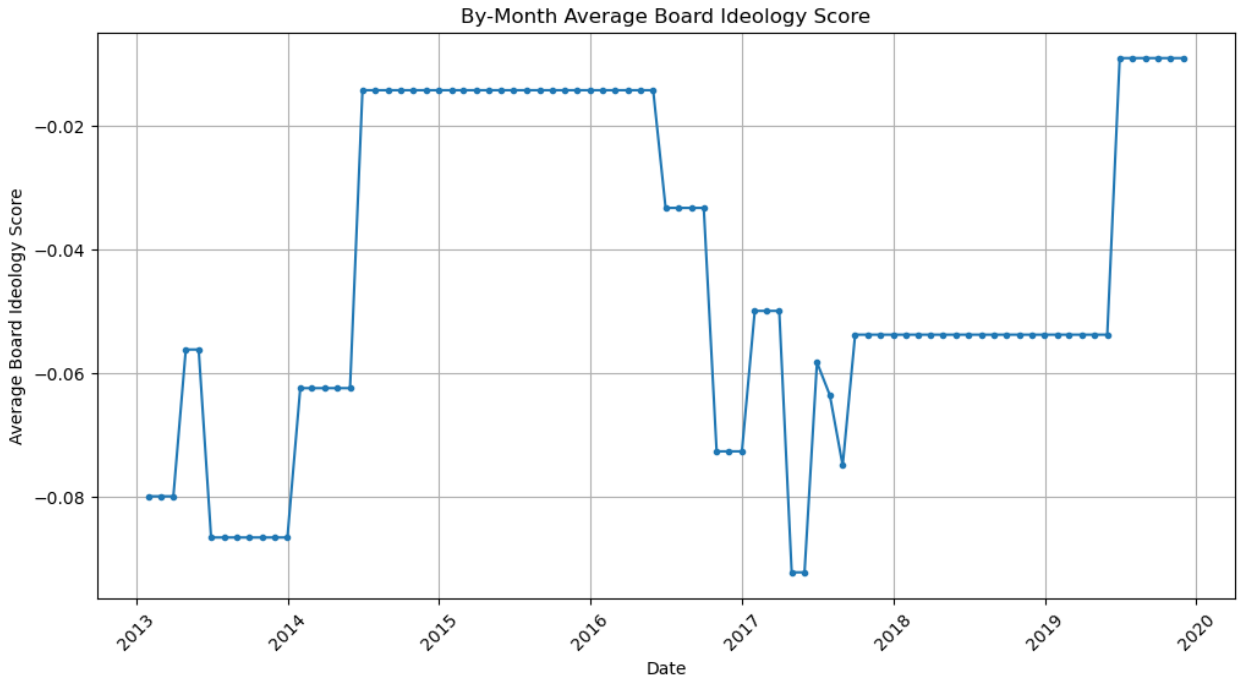


Notes: This figure presents the odds ratios showing the relationship between each constituent group's language in comment letters and the topics discussed during board meetings. This pilot analysis uses the Conceptual Framework meetings held in March 2016 as an illustration. On 15 March 2016, the IASB held public meetings to discuss the comment letters received on the *Conceptual Framework* Exposure Draft. These odds ratios are calculated from coefficients of individual logistic regression models, each predicting the specific language used by a single board member, with technical staff included as a reference point. We omit the board member, Amaro Luiz de Oliveira Gomes, from the test as the corpus associated with his contributions is too small for reliable inferences. The dependent variable ($Bigram\ in\ Board\ Member\ Corpus_{i,b,a}$) is an indicator equals to one if bigram i appears in the corpus of board member b during the discussion of agenda item a, and zero otherwise. The independent variables are indicators for each constituent group, with "Academics" as the reference category. Specifically:

$$Bigram\ in\ Board\ Member\ Corpus_{i,b,a} = \beta_0 + \sum_{g=1}^{6} \beta_g Group_{i,g,a} + \delta_a + \varepsilon_{i,b,a},$$

where $Group_{i,g,a}$ is an indicator for whether bigram i originates from comment letters submitted by constituent group g for agenda item a. The coefficients (β_g) represent the log odds that a bigram from group g appears in board member b's corpus, relative to bigrams from the academic group. A positive (negative) coefficient indicates a higher (lower) probability of appearance compared to the reference category. The vertical dashed line at x = 1 marks no association. Values above 1 represent positive associations, while values below 1 indicate negative associations. We omit constituent groups from the regression for perfect separation cases. Solid colored dots show statistically significant results ($p < 0.10$), while circles show insignificant results ($p \geq 0.10$). These results are based on an initial pilot analysis. It is important to acknowledge that refinements to the machine learning algorithms at various stages may lead to updates or modifications in the findings.

Figure 8. Average Board Conservative-Liberal Ideology Score



Notes: This figure depicts the trend in the mean conservative-liberal ideology score of the IASB during the deliberations on the Conceptual Framework (January 2013 to November 2019). An ideology score of +1 indicates an extreme liberal leaning, while –1 represents an extreme conservative leaning, with values in between capturing varying degrees of ideological orientation. The composition of the board during this period is presented in Table 1. Individual board members' ideology scores are derived using the LLM-based approach described in Section 4.1 and reported in Table 6. These results are based on an initial pilot analysis. It is important to acknowledge that refinements to the machine learning algorithms at various stages may lead to updates or modifications in the findings.

Table 1. Descriptive Evidence on the Dataset - Conceptual Framework Meetings

Panel A: Dataset Composition				
Agenda item	Conceptual Framework			
Total meetings	33			
Unique speakers	21			
Diarized segments count	7564			
Time range	2013 - 2019			
Panel B: Speaker Information				
Speaker	Role Start	Role End	Total Meetings Attend	Diarized Segments Count
Mary Tokar	Jan-13	Aug-22	31	1033
Hans Hoogervorst	Jul-11	Jun-21	31	1249
Takatsugu (Tak) Ochi	Jul-11	Jun-19	29	525
Wei-Guo Zhang	Jul-07	Jun-17	27	645
Sue Lloyd	Jan-14	Feb-22	27	566
Stephen Cooper	Aug-07	Jul-17	24	631
Chungwoo Suh	Jul-12	Jun-20	24	186
Gary Kabureck	Apr-13	Jun-20	21	168
Philippe Danjou	Nov-06	Oct-16	20	626
Darrel Scott	Oct-10	Sep-20	20	75
Ian Mackintosh	Jul-11	Jun-16	19	319
Amaro Luiz de Oliveira Gomes	Jul-09	Jun-19	18	116
Patrick Finnegan	Jul-09	Jun-16	17	375
Martin Edelmann	Jul-12	Jun-21	17	125
Patricia McConnell	Jul-09	Jun-14	8	502
Jan Engström	May-04	Jun-14	8	93
Prabhakar Kalavacherla	Jan-09	Jun-13	4	317
Françoise Flores	Jan-17	Jun-21	2	3
Nick Anderson	Sep-17	present	2	3
Jianqiao Lu	Aug-17	present	1	3
Tom Scott	Apr-17	Mar-22	1	4

Table 1. Descriptive Evidence on the Dataset - Conceptual Framework Meetings (C'd)

Panel C: Meeting-Level Statistics						
	Mean	Median	St.Dev.	Min	Max	*N*
Unique speakers	10.64	12.00	4.13	1.00	16.00	33
Diarized segments count	229.21	161.00	240.31	1.00	918.00	33
Deliberation length	5025.35	3565.07	4993.06	1.54	18757.42	33
Panel D: Speaker-Level Statistics						
	Mean	Median	St.Dev.	Min	Max	*N*
Diarized segments count	360.19	317.00	346.82	3.00	1249.00	21
Avg speaking time (s)	22.70	23.14	5.14	12.01	33.41	21
Total speaking time (s)	7896.97	4389.80	7628.36	61.89	25277.09	21
Speaking time percentage	4.76	2.65	4.60	0.04	15.24	21
Panel E: Speaker-Meeting-Level Statistics						
	Mean	Median	St.Dev.	Min	Max	*N*
Diarized segments count	21.55	12.00	27.61	1.00	168.00	351
Avg speaking time (s)	22.61	22.87	8.26	1.54	58.94	351
Total speaking time (s)	472.47	270.23	590.52	1.54	4557.93	351
Speaking time percentage	9.40	7.27	10.42	0.04	100.00	351

Notes: This table presents descriptive evidence from our IASB meeting transcript dataset, using Conceptual Framework meetings as an illustration. Panel A provides an overview of the dataset's composition and structure. Panel B presents information on individual board members who attended at least one Conceptual Framework meeting. Panels C, D, and E report relevant statistics on dataset composition at the meeting, speaker, and speaker-meeting levels of analysis, respectively. In all calculations, contributions from technical staff have been excluded. These results are based on an initial pilot analysis. It is important to acknowledge that refinements to the machine learning algorithms at various stages may lead to updates or modifications in the findings.

Table 2. Interruption

Panel A: Statistics - Conceptual Framework Meetings	*N*
Total meetings	33
Meetings with interruption references	14
Speakers with interruption references	10
Diarized segments with interruption references	21
Keywords/phrases tested	20
Keywords/phrases with matches	11
Panel B: Keyword/Phrase	
Category 1: Direct mentions of interruption	
interrupt	5
Category 2: Indirect interruption indicators	
can i clarify	0
just to clarify	1
if i may	1
sorry but	3
Category 3: References to interruption	
jump in	2
wait a second	0
wait a moment	0
you are right but	0
you're right but	1
that's right but	1
you can but	2
yes okay but	2
agree with that but	3
agree with you but	1
before you continue	0
just had one question	0
just have one question	0
should've asked earlier	0
should have asked earlier	0

Table 2. Interruption (C'd)

Panel C: Meeting-Level Statistics						
	Mean	Median	St.Dev.	Min	Max	*N*
Speakers_interrupting						
Speakers_interrupted						
Diarized segments count						
Diarized segments with interruption references						

Panel D: Speaker-Level Statistics						
	Mean	Median	St.Dev.	Min	Max	*N*
Diarized segments count						
Diarized segments with interruption references						

Panel E: Speaker-Meeting-Level Statistics						
	Mean	Median	St.Dev.	Min	Max	*N*
Diarized segments count						
Diarized segments with interruption references						

Notes: This table presents the results of the interruption detection analysis conducted on our IASB meeting transcript dataset, using Conceptual Framework meetings as an illustration. The objective of this analysis is to systematically identify references to interruptions within IASB meetings. This process seeks to generate structured insights into the occurrence and nature of interruptions using keyword-based detection techniques. Panel A provides an overview of the findings. Panel B presents the keywords and phrases used to identify references to interruptions. Panels C, D, and E provide a template for reporting relevant statistics on interruption references at the meeting, speaker, and speaker-meeting levels of analysis, respectively. The final data will be incorporated into the table in the full version of the paper. In all calculations, contributions from technical staff have been excluded. These results are based on an initial pilot analysis. It is important to acknowledge that refinements to the machine learning algorithms at various stages may lead to updates or modifications in the findings.

Table 3. Private Meeting

Panel A: Statistics - Conceptual Framework Meetings	*N*
Total meetings	33
Meetings with private discussion references	17
Speakers with private discussion references	13
Diarized segments with private discussion references	44
Keywords/phrases tested	31
Keywords/phrases with matches	8
Panel B: Keyword/Phrase	
Category 1: Direct mentions of private discussions	
private meeting	0
private discussion	0
privately	1
confidential discussion	0
in confidence	0
closed session	0
internal discussion	0
discussed internally	0
internal deliberation	0
Category 2: References to outreach and consultations	
outreach	34
conversation with	3
conversations with	1
conversations we have had	0
conversations we've had	0
Category 3: References to informal discussions	
i spoke with	1
i heard from	1
dinner with	1
lunch with	0
coffee with	0
offline	9
off the record	0
informal discussion	0
preparatory discussion	0
before this/our meeting	0
before this/our discussion	0
before this/our public discussion	0
before this/our official discussion	0

Table 3. Private Meeting (C'd)

Panel C: Meeting-Level Statistics						
	Mean	Median	St.Dev.	Min	Max	*N*
Speakers with private discussion references						
Diarized segments count						
Diarized segments with private discussion references						
Panel D: Speaker-Level Statistics						
	Mean	Median	St.Dev.	Min	Max	*N*
Diarized segments count						
Diarized segments with private discussion references						
Panel E: Speaker-Meeting-Level Statistics						
	Mean	Median	St.Dev.	Min	Max	*N*
Diarized segments count						
Diarized segments with private discussion references						

Notes: This table presents the results of the private meeting detection analysis conducted on our IASB meeting transcript dataset, using Conceptual Framework meetings as an illustration. The objective of this analysis is to systematically identify references to private discussions within IASB meetings. This process seeks to generate structured insights into the occurrence and nature of private discussions using keyword-based detection techniques. Panel A provides an overview of the findings. Panel B presents the keywords and phrases used to identify references to private discussions. Panels C, D, and E provide a template for reporting relevant statistics on private discussion references at the meeting, speaker, and speaker-meeting levels of analysis, respectively. The final data will be incorporated into the table in the full version of the paper. In all calculations, contributions from technical staff have been excluded. These results are based on an initial pilot analysis. It is important to acknowledge that refinements to the machine learning algorithms at various stages may lead to updates or modifications in the findings.

Table 4. IASB Meeting Transcript - Full Sample

Panel A: Descriptive Evidence on the Dataset - Agenda Item Level Statistics						
	Mean	Median	St.Dev.	Min	Max	*N*
Total meetings						
Unique speakers						
Deliberation length						
Diarized segments count						
Panel B: Interruption - Agenda Item Level Statistics						
	Mean	Median	St.Dev.	Min	Max	*N*
Speakers_interrupting						
Speakers_interrupted						
Diarized segments with interruption references						
Panel C: Private Meeting - Agenda Item Level Statistics						
	Mean	Median	St.Dev.	Min	Max	*N*
Speakers with private meeting references						
Diarized segments with private meeting references						

Notes: This table serves as a template for reporting relevant statistics on our IASB meeting transcript dataset at the agenda item level of analysis, to be completed when the full sample becomes available. Panel A provides a template for reporting descriptive evidence on dataset composition. Panel B outlines a template for reporting relevant statistics on interruption references. Panel C outlines a template for reporting relevant statistics on private discussion references. The final data will be incorporated into the table in the full version of the paper.

Table 5. Comment Letter - Full Sample

Panel A: Comment Letters Received at Different Stages of the Standard-setting Process

	Stages				
Standard	Agenda Consultation	Discussion Paper	Exposure Draft	Post-Implementation Review	Others
Conceptual Framework	120	254	241	N/A	40
⋮					

Panel B: Standard-Level Statistics

	Mean	Median	St.Dev.	Min	Max	*N*
Total comment letters						
Unique constituent groups						
Comment letters on agenda consultation						
Comment letters on discussion paper						
Comment letters on exposure draft						
Comment letters on post-implementation review						
Comment letters on other issues						
Comment letters from regulators						
Comment letters from accounting professions						
Comment letters from preparers						
Comment letters from users						
Comment letters from public interest bodies						
Comment letters from academics						
Comment letters from others						

Panel C: Year-Level Statistics

	Mean	Median	St.Dev.	Min	Max	*N*
(Same variables as in Panel B)						
⋮						

Notes: This table serves as a template for reporting statistics on comment letters submitted to the IASB during the sample period. Panel A presents the number of comment letters received at different stages of the standard-setting process for each IFRS accounting standard covered during the sample period. Data for the Conceptual Framework is shown as an example. For the "Others" category, on 28 May 2015, the IASB published a separate Exposure Draft — the *Updating References* Exposure Draft — in addition to the *Conceptual Framework* Exposure Draft, which received 40 comment letters. Panels B and C present statistics at the standard and year levels, respectively. The final data will be incorporated into the table in the full version of the paper.

Table 6. LLM-based Conservative-Liberal Ideology Leaning Measure

Liberal-Conservative Ideology Scores		
Name	Liberal-Conservative Ideology Scores	Confidence (%)
Patrick Finnegan	0.6	90
Prabhakar Kalavacherla	0.4	85
Martin Edelmann	0.4	85
Philippe Danjou	0.4	85
Stephen Lloyd	0.3	85
Gary Kabureck	0.3	85
Françoise Flores	0.2	75
Darrel Scott	0.2	75
Nick Anderson	0.2	80
Stephen Cooper	0.0	85
Jianqiao Lu	-0.2	75
Takatsugu (Tak) Ochi	-0.2	85
Chungwoo Suh	-0.2	75
Mary Tokar	-0.3	85
Technical staff and others	-0.3	70
Patricia McConnell	-0.4	75
Amaro Luiz de Oliveira Gomes	-0.4	85
Jan Engström	-0.4	85
Hans Hoogervorst	-0.4	85
Ian Mackintosh	-0.4	85
Wei-Guo Zhang	-0.5	80
Tom Scott	-0.6	85

Notes: This table presents the LLM-based conservative-liberal ideology scores of board members, derived from their speeches during Conceptual Framework meetings. Both the ideology scores and corresponding confidence levels are generated using ChatGPT 4.5. An ideology score of +1 indicates an extreme liberal leaning, while –1 represents an extreme conservative leaning, with values in between capturing varying degrees of ideological orientation. The methodology is detailed in Section 4.1. These results are based on an initial pilot analysis. It is important to acknowledge that refinements to the machine learning algorithms at various stages may lead to updates or modifications in the findings.

Table 7. Intensity of Constituent Group Pressure - Comment Letter Sentiment

Comment Letter-Level Net Sentiment Score by Constituent Groups							
	Mean	Median	St.Dev.	Min	Max	*N*	Total Words
Regulators	-0.012	-0.011	0.005	-0.020	-0.001	35	401,293
Accounting Professions	-0.011	-0.012	0.007	-0.024	0.016	63	437,602
Preparers	-0.012	-0.012	0.006	-0.028	0.005	53	279,680
Users	-0.012	-0.011	0.007	-0.033	-0.003	21	92,225
Public Interest	-0.005	-0.003	0.006	-0.018	0.000	7	22,674
Academics	-0.009	-0.009	0.009	-0.030	0.008	49	148,352
Others	-0.009	-0.009	0.010	-0.029	0.013	12	36,836

Notes: This table presents the results of the constituent group pressure intensity analysis, based on comment letter sentiment. This pilot analysis uses comment letters submitted to the IASB in response to the *Conceptual Framework* Exposure Draft as an illustration. On 28 May 2015, the IASB published an Exposure Draft proposing a revised *Conceptual Framework for Financial Reporting*, which received 241 comment letters (one unsigned duplicate letter was excluded from the analysis). Sentiment is measured using a lexicon-based approach, following Loughran and McDonald (2011). These results are based on an initial pilot analysis. It is important to acknowledge that refinements to the machine learning algorithms at various stages may lead to updates or modifications in the findings.

Table 8. Association Between Constituent Group and Final Standard

	Bigram in Final Standard	
Accounting Professions	0.432***	(0.092)
Others	-0.269	(0.212)
Preparers	0.005	(0.105)
Public Interest	-0.554*	(0.300)
Regulators	0.789***	(0.091)
Users	-0.209	(0.164)
Constant	-4.722***	(0.079)
McFadden's R-squared	0.012	
Observations	115,342	

Notes: The table reports logistic regression estimates of the likelihood that a bigram from constituent comment letters appears in the final standard text. This pilot analysis uses comment letters submitted to the IASB in response to the *Conceptual Framework* Exposure Draft as an illustration. On 28 May 2015, the IASB published an Exposure Draft proposing a revised *Conceptual Framework for Financial Reporting*, which received 241 comment letters (one unsigned duplicate letter was excluded from the analysis). The final standard refers to the final text of the revised Conceptual Framework. The dependent variable ($Bigram\ in\ Final\ Standard_{i,a}$) is an indicator equals to one if bigram i appears in the final standard of agenda item a, and zero otherwise. The independent variables are indicator variables for each constituent group, with "Academics" serving as the reference category. Specifically:

$$Bigram\ in\ Final\ Standard_{i,a} = \beta_0 + \sum_{g=1}^{6} \beta_g Group_{i,g,a} + \delta_a + \varepsilon_{i,a},$$

where $Group_{i,g,a}$ is an indicator for whether bigram i originates from comment letters submitted by constituent group g for agenda item a. The coefficients (β_g) represent the log odds that a bigram from group g appears in the final standard, relative to bigrams from the academic group. A positive (negative) coefficient indicates a higher (lower) probability of appearance compared to the reference category. Robust standard errors are in parentheses . ***, ** and * in this table represent the statistical significance of the regression coefficients at the 1%, 5% and 10% levels (two-tailed), respectively. These results are based on an initial pilot analysis. It is important to acknowledge that refinements to the machine learning algorithms at various stages may lead to updates or modifications in the findings.

Online Appendix

to

"Quantifying standard-setting deliberations"

Online Appendix Table 1. Interruption

Diarized Segments with References to Interruption					
Meeting Date	**Agenda Item**	**Keyword/Phrase**	**Speaker**	**Diarized Segment**	**False Positive**
29 - 31 Jan 2013	Conceptual_Framework	sorry but	Wei-Guo Zhang	I don't want to spend too much time on the **sorry. But** it seems, you know, we have similar problem.	1
18 - 22 Feb 2013	Conceptual_Framework	you can but	Hans Hoogervorst	**You can, but** then I think you need to be clear that you said it's cost at both times even though you used fair value as a deemed cost.	
18 - 22 Feb 2013	Conceptual_Framework	jump in	Wei-Guo Zhang	Peter, you prefer we **jump in** or by the end?	
19 - 21 Mar 2013	Conceptual_Framework	interrupt	Patricia McConnell	Sorry, Martin, to **interrupt**, but we have a recommendation on the unit of account.	
23 - 25 Apr 2013	Conceptual_Framework	you're right but	Patricia McConnell	Perfectly, **you're right. But** for the for the past maybe thirty years, the conceptual framework is a kind of a bible for all our stakeholders, not just ISP.	
23 - 25 Apr 2013	Conceptual_Framework	interrupt	Ian Mackintosh	Sean, would you just sorry to **interrupt**.	
23 - 25 Apr 2013	Conceptual_Framework	jump in	Prabhakar Kalavacherla	Can I just **jump in** for a second and say, for those people who are opposing it, when you are reading the revenue staff draft, please pay attention to para 15.	
23 - 25 Apr 2013	Conceptual_Framework	agree with that but	Stephen Cooper	I **agree with that. But** I don't think that's the same as cohesiveness.	
13 - 21 Mar 2014	Conceptual_Framework	interrupt	Takatsugu (Tak) Ochi	So my question is, uh, I think it's interesting because there is an **interruption** between the mezzanine approach and the strict liability approach.	1
13 - 21 Mar 2014	Conceptual_Framework	sorry but	Ian Mackintosh	I'm **sorry. But** what can you explain what you mean by this implicit capital maintenance objective?	

Online Appendix Table 1. Interruption (C'd)

Diarized Segments with References to Interruption (C'd)					
Meeting Date	**Agenda Item**	**Keyword/Phrase**	**Speaker**	**Diarized Segment**	**False Positive**
13 - 21 Mar 2014	Conceptual_Framework	interrupt, if i may	Hans Hoogervorst	And these are not just, **if I may interrupt**, Peter, these are not just, you know, retail investors with a very low level of sophistication, but also the quants at the investment banks with their computer programs often totally disregard OCI.	
20 - 22 May 2014	Conceptual_Framework	sorry but	Hans Hoogervorst	**Sorry, but** you were just mentioning liabilities.	
22 - 24 July 2014	Conceptual_Framework	you can but	Gary Kabureck	I don't think **you can. But** but there are there's every day.	
22 - 24 Oct 2014	Conceptual_Framework	just to clarify	Gary Kabureck	**Just to clarify** and process, this would be an exposure draft by its.	
19 - 20 Nov 2014	Conceptual_Framework	yes okay but	Patrick Finnegan	**Yes? Okay. But** but what standard permits that today is my my question.	
17 - 19 Mar 2015	Conceptual_Framework	that's right but	Ian Mackintosh	**That's right. But** we'll try and change our voices so you don't know who's speaking.	
19 - 21 Apr 2016	Conceptual_Framework	interrupt	Hans Hoogervorst	Sorry, Pat, to **interrupt**, but the decision is something is put in OCI or P and L is strictly disciplined by the standards.	
17 - 19 May 2016	Conceptual_Framework	agree with that but	Takatsugu (Tak) Ochi	I don't **disagree with that. But** the question is why?	
13 - 14 Dec 2016	Conceptual_Framework	agree with you but	Wei-Guo Zhang	I **agree with you. But** we cannot simply say the interest rate part should be purely market.	
13 - 14 Dec 2016	Conceptual_Framework	yes okay but	Gary Kabureck	**Yes. Okay. But** we can certainly take a look at the drafting.	

Online Appendix Table 1. Interruption (C'd)

Diarized Segments with References to Interruption (C'd)					
Meeting Date	**Agenda Item**	**Keyword/Phrase**	**Speaker**	**Diarized Segment**	**False Positive**
24 - 25 Oct 2017	Conceptual_Framework	agree with that but	Sue Lloyd	So I certainly **agree with that. But** I think maybe more is more in this case because there's been so many questions and so much confusion in groups I've been in at World Standard Setters and other sort of forums about just how far does this definition go.	

Notes: This table displays all diarized segments containing references to interruptions, along with a false positive indicator. A value of 1 in this indicator denotes that the detected segment does not genuinely reference an interruption. Contributions from technical staff have been excluded. These results are based on an initial pilot analysis. It is important to acknowledge that refinements to the machine learning algorithms at various stages may lead to updates or modifications in the findings.

Online Appendix Table 2. Private Meeting

Diarized Segments with References to Private Discussions					
Meeting Date	**Agenda Item**	**Keyword/Phrase**	**Speaker**	**Diarized Segment**	**False Positive**
18 - 22 February 2013	Conceptual_Framework	dinner with	Wei-Guo Zhang	Around last night, we had a regular **dinner with** AC ICAW, and, uh, you know, it is for coffee.	
19 - 21 March 2013	Conceptual_Framework	conversation with	Hans Hoogervorst	In my **conversation with** Leslie, she didn't I don't think she used the term parking lots, but she did basically mean it.	
19 - 21 March 2013	Conceptual_Framework	conversation with	Patrick Finnegan	Hans, you introduced it now, and you're referencing your **conversation with** Leslie.	
19 - 21 March 2013	Conceptual_Framework	outreach	Patricia McConnell	And in Maryella's paper, she did some **outreach** to users, and granted it was a small sample, but, Mariela, correct me if I'm wrong.	
23 - 25 April 2013	Conceptual_Framework	offline	Chungwoo Suh	I mean, maybe we can try and look at whether there are improvements we need to make to that drafting **offline**. And if people have suggestions, I'll pick them up off **offline**.	
23 - 25 April 2013	Conceptual_Framework	offline	Prabhakar Kalavacherla	Yeah. **Offline**, we can take it **offline**.	
23 - 25 April 2013	Conceptual_Framework	offline	Prabhakar Kalavacherla	I have a question on the example. B, we can talk **offline** and talk about it because I don't have issue on your conclusions on applying risk and rewards approach. And so we can take **offline**.	
13 - 21 March 2014	Conceptual_Framework	outreach	Philippe Danjou	Only one comment, uh, from the recent **outreach** I participated in.	
13 - 21 March 2014	Conceptual_Framework	outreach	Hans Hoogervorst	Mary, the my overall impression, both from the comment letters and the **outreach** meetings I went to, was that for the usual suspects, OCI measurement, liabilities, equity, we knew they were going to be difficult issues.	

Online Appendix Table 2. Private Meeting (C'd)

Diarized Segments with References to Private Discussions (C'd)					
Meeting Date	**Agenda Item**	**Keyword/Phrase**	**Speaker**	**Diarized Segment**	**False Positive**
13 - 21 March 2014	Conceptual_Framework	outreach	Hans Hoogervorst	That was one of the most common things that came up in the **outreach** I went to was what's what's the effect on existing standards.	
13 - 21 March 2014	Conceptual_Framework	outreach	Patrick Finnegan	I see two or three areas that are coming up consistently in the last, say, several board meetings and, uh, **outreach** discussions.	
13 - 21 March 2014	Conceptual_Framework	outreach	Hans Hoogervorst	Um, so when I was doing **outreach**, I specifically asked people about that quite a lot because I was a bit worried that they might find it difficult to understand.	
13 - 21 March 2014	Conceptual_Framework	outreach	Hans Hoogervorst	So with that, let me see if anybody has any comments or observations from your reading the comment as is all from your **outreach**.	
13 - 21 March 2014	Conceptual_Framework	outreach	Hans Hoogervorst	A common theme in the **outreach** meetings I went to was, um, is the board intending us to recognize more assets and liabilities or less assets and liabilities or the same?	
13 - 21 March 2014	Conceptual_Framework	outreach	Hans Hoogervorst	But what people tended to say, both in the comment letters and the **outreach**, was equity is a residual.	
13 - 21 March 2014	Conceptual_Framework	outreach	Mary Tokar	And that that's also consistent with one of the messages I had that something that wasn't formally **outreach** on our conceptual framework.	1
13 - 21 March 2014	Conceptual_Framework	outreach	Hans Hoogervorst	And just as a follow-on to that, one thing I found quite a lot during the **outreach** was that people objected to remeasuring derivatives on your own equity.	

Online Appendix Table 2. Private Meeting (C'd)

Diarized Segments with References to Private Discussions (C'd)					
Meeting Date	**Agenda Item**	**Keyword/Phrase**	**Speaker**	**Diarized Segment**	**False Positive**
13 - 21 March 2014	Conceptual_Framework	outreach	Ian Mackintosh	The **outreach** that I did, we really had to push people to comment on the statement of change in equity, and when they did, it appeared they either hadn't considered it much or they'd misunderstood it.	
13 - 21 March 2014	Conceptual_Framework	outreach	Sue Lloyd	What this whole discussion highlights and the main thing I got from this paper but also the bits I've heard from **Outreach** and **outreach** and the comment letters is I can't really tell when people are agreeing or disagreeing because everybody's coming to this discussion with their own idea of what the words mean.	
13 - 21 March 2014	Conceptual_Framework	outreach	Chungwoo Suh	Did anybody have any other comments on the user feedback or on any **outreach** you've done with users?	
22 - 25 April 2014	Conceptual_Framework	outreach, I spoke with	Patrick Finnegan	But then in the, uh, process of doing some **outreach** on the conceptual framework, Uh, **I spoke with** some investors, uh, in The US.	
22 - 25 April 2014	Conceptual_Framework	outreach	Sue Lloyd	We did further **outreach** with the global preparers forum and asking them how often preparers use the conceptual framework.	
20 - 22 May 2014	Conceptual_Framework	outreach	Hans Hoogervorst	Um, and somewhat to my surprise really, in the **outreach** and in the comment letters, most people seemed or at least claimed to understand it.	
20 - 22 May 2014	Conceptual_Framework	outreach	Gary Kabureck	I'm trying to think of, you know, some of the leasing **outreach** we did.	
17 - 19 June 2014	Conceptual_Framework	outreach	Amaro Luiz de Oliveira Gomes	I participate in a number of **outreach** activities and ASF and no one really ever brought an agreeable concept of performance.	

Online Appendix Table 2. Private Meeting (C'd)

Diarized Segments with References to Private Discussions (C'd)					
Meeting Date	**Agenda Item**	**Keyword/Phrase**	**Speaker**	**Diarized Segment**	**False Positive**
17 - 19 June 2014	Conceptual_Framework	outreach	Hans Hoogervorst	My reluctance to to include it, having seen the response really to the commenters and some of the reaction we had during the **outreach** is that I I think it becomes a distraction because everybody's got strong opinions about goodwill and people are on different sides of the fence.	
22 - 24 October 2014	Conceptual_Framework	outreach	Sue Lloyd	A longer comment period will allow interested parties to provide a more considerate response, and it will also allow us to conduct more **outreach** and proposals.	1
22 - 24 October 2014	Conceptual_Framework	outreach	Amaro Luiz de Oliveira Gomes	And also, there is another point is that if we do plan to do **outreach** as we did for the discussion paper, if we are in an exposure that is even more important in my view to do the **outreach**.	1
19 - 20 November 2014	Conceptual_Framework	offline	Hans Hoogervorst	Well, I suggest that, uh, we go takes this **offline** with this.	
15 - 16 March 2016	Conceptual_Framework	outreach	Philippe Danjou	In the various **outreach** activity that I participated in and in some commentators, I found an interesting discussion about the link between accountabilities to our ship, whatever we call it, and business activities, I. E.	
15 - 16 March 2016	Conceptual_Framework	outreach	Philippe Danjou	In **Outreach** activities, people do not understand that message this way.	
15 - 16 March 2016	Conceptual_Framework	outreach	Stephen Cooper	And in my experience from the **outreach** people have different views as to what neutrality is.	
15 - 16 March 2016	Conceptual_Framework	offline	Gary Kabureck	Yeah. The we can take it **offline**.	

Online Appendix Table 2. Private Meeting (C'd)

Diarized Segments with References to Private Discussions (C'd)					
Meeting Date	**Agenda Item**	**Keyword/Phrase**	**Speaker**	**Diarized Segment**	**False Positive**
15 - 16 March 2016	Conceptual_Framework	outreach	Mary Tokar	Um, I the the feedback here and also some of the discussions that are during that for, uh, exposure, so feedback and **outreach**, um, made made me think hard and ask the staff to come back kind of looking at projects and their their interactions area.	
15 - 16 March 2016	Conceptual_Framework	outreach	Sue Lloyd	I agree with Mary, um, both both in the comment letter analysis and in the **outreach** I did.	
19 - 21 April 2016	Conceptual_Framework	privately	Hans Hoogervorst	And I **privately** and I'll probably say to Andrew, try to go as far as you can and see whether it's perhaps too far and we might even necessitate.	
17 - 19 May 2016	Conceptual_Framework	outreach	Hans Hoogervorst	Um, when I was doing **outreach** on the discussion paper, this question of the trade off came up a lot, and it is one of people's big objections to the sort of loss of the old reliability... But it was a big point that came up in in the **outreach**.	
18 - 19 July 2016	Conceptual_Framework	conversation with	Sue Lloyd	I had a **conversation with** Mary at lunchtime, and I read this and came to the exact opposite position of of her because reading this thing about cash flows being collected directly made me think that prima facie, all financial assets were current value.	
18 - 19 October 2016	Conceptual_Framework	i heard from	Mary Tokar	And, you know, I think because what **I heard from** the world standard setters since he captured in this is that people were reading that as us pulling measurement considerations into the definitions about existence.	

Online Appendix Table 2. Private Meeting (C'd)

Diarized Segments with References to Private Discussions (C'd)					
Meeting Date	**Agenda Item**	**Keyword/Phrase**	**Speaker**	**Diarized Segment**	**False Positive**
14 - 16 November 2016	Conceptual_Framework	outreach	Mary Tokar	So I I I think you've tried to respond, and I can't think of a better way to try and respond to to the criticisms, concerns that we heard in in **outreach**.	
14 - 16 November 2016	Conceptual_Framework	outreach	Wei-Guo Zhang	And therefore, in the future snapshot and, uh, any, you know, your publications or **outreach** activity documents, we should emphasize.	1
13 - 14 December 2016	Conceptual_Framework	offline	Hans Hoogervorst	I just had a I'll give you my I've got some drafting points throughout, which I'll share with you **offline**.	
13 - 14 December 2016	Conceptual_Framework	outreach	Sue Lloyd	Um, when I was out doing some of the **outreach** on the conceptual framework ED, people raised with me quite a lot this issue of comparability.	
17 - 18 July 2018	Conceptual_Framework	conversations with	Sue Lloyd	When I was in **conversations with** people, they asked some questions about the interaction, which I think to me highlighted that now that we've got the new conceptual framework and we know that there are some known differences between some of the new words in there and some of the standards, it it seems likely that we will get more situations where people might need to at least think about whether they need to be going to the conceptual framework or not.	

Notes: This table displays all diarized segments containing references to private discussions, along with a false positive indicator. A value of 1 in this indicator denotes that the detected segment does not genuinely reference a private discussion. Contributions from technical staff have been excluded. These results are based on an initial pilot analysis. It is important to acknowledge that refinements to the machine learning algorithms at various stages may lead to updates or modifications in the findings.

Online Appendix Table 3. LLM-based Conservative-Liberal Ideology Leaning Measure

Liberal-Conservative Ideology Explanations	
Name	**Explanation**
Patrick Finnegan	The speaker demonstrates a consistent preference for clarity, simplicity, and reducing complexity, especially in disclosure. He explicitly expresses concerns about disclosure overload and disclosure complexity, arguing for simplicity and against "disclosure overload," indicating skepticism towards increasing regulatory burdens on private firms. **Preferences for Investor Protection and Public Accountability** The speaker emphasizes transparency, clarity, and understandability of financial statements, specifically to benefit investors, suggesting strong support for investor protection. Repeatedly expresses concerns that overly technical or opaque financial statements alienate typical investors (those without strong accounting backgrounds), suggesting a strong preference for accountability to the general investing public. Highlights stewardship responsibility, stating clearly that managers must transparently report the value of assets under their control to shareholders. Advocates for direct disclosure of financial condition to investors, such as clearly reporting values, maintenance expenditures, and capital expenditure clearly to avoid misleading investors. Explicitly points to the need to disclose fair value information to ensure that investors are not disadvantaged by management decisions that might obscure economic reality. **Attitude toward Complexity and Disclosure Burden** The speaker expresses concern over potential disclosure overload and complexity, which could hint at some conservatism in terms of limiting regulatory burden. However, this stance does not reflect an anti-regulatory sentiment but rather a practical concern about making disclosures meaningful and manageable for investor use, thus still leaning toward liberal transparency but seeking efficiency. **Use of OCI and Realization** The speaker supports OCI as a middle ground for managing uncertainty in measurement but argues for simplicity and clear criteria, prioritizing investor understanding rather than managerial flexibility, again suggesting a liberal tilt in prioritizing the user's needs over preparer discretion. **Concern about Management Incentives** Expresses clear discomfort with managerial manipulation or earnings management, particularly associated with measurement and reporting choices. Advocates disaggregation to improve transparency and reduce incentives for earnings management, aligning with investor protection and public accountability. **Attitude towards Measurement Consistency and Predictability** Argues strongly for consistency in application across standards to improve investor understanding and comparability of information, aligning with accountability and investor protection. **Importance of Relevance and Disclosure for Investor Decision-Making** Emphasizes repeatedly the importance of disclosure to aid investor decision-making, directly tying disclosure requirements to investor needs, signaling a liberal perspective on investor rights. **Overall Ideological Positioning** While the speaker does acknowledge the concern of complexity and disclosure overload, which could reflect mild conservatism, the repeated and explicit emphasis on transparency, accountability, investor protection, and accessibility strongly signals a liberal ideological orientation. The speaker prioritizes investor protection and clear communication of financial performance over minimizing regulatory intervention, reflecting more liberal tendencies. Given the weight of evidence emphasizing investor protection, public accountability, and transparent disclosures directly benefiting the typical investor rather than preparers or management, the statements clearly lean liberal. **Answer and Confidence** Score: +0.6 (Moderately Liberal) Confidence Level: 90%
Tom Scott	**Concerns About Absoluteness and Rigidity** The speaker expresses reservations about the rigidity ("written in a very absolute way") of the accounting standards. They specifically question the strict interpretation or inflexible application of rules, suggesting instead that judgments should allow flexibility ("similarity as a matter of degree and in the eye of the beholder"). Such criticism of rigid rules might reflect a preference for less regulatory burden, aligning more with a conservative viewpoint. **Advocating for Judgment and Flexibility** The speaker suggests the possibility of relaxing strict guidelines, allowing accountants more freedom to apply their judgment ("I don't think that should slam the door"). This stance implies a preference for private-sector decision-making autonomy and less prescriptive regulation, further indicating a conservative leaning. **Analogy to Academic Flexibility ("Normally")** The speaker humorously references academia's practice of inserting the word "normally" to maintain flexibility. This analogy underscores a desire to avoid overly restrictive or prescriptive regulations, reinforcing the conservative orientation (private sector autonomy and opposition to regulatory intervention). **Overall Ideological Positioning** The provided excerpt strongly signals a conservative stance on the conservative-liberal spectrum, favoring private sector governance and autonomy, and showing skepticism towards regulatory rigidity and constraints. **Answer and Confidence** Score: -0.6 (Moderately Conservative) Confidence Level: 85%

Notes: This table provides illustrative examples of the model's reported reasoning behind its classifications, using board members with the highest and lowest LLM-based Liberal–Conservative Ideology Scores as cases. These results are based on an initial pilot analysis. It is important to acknowledge that refinements to the machine learning algorithms at various stages may lead to updates or modifications in the findings.

Online Appendix Table 4. Constituent Language Reuse - Bigram Lists

Constituent Group	Bigrams in Final Standard
Regulators (n=35)	economics contract, price effect, reduce understandability, practical measurement, foundation mission, user neutral, reach consensus, account unit, release obligation, relevance materiality, information effective, value effect, disclosure related, current rate, liability market, satisfying fundamental, general cost, measurement inconsistency, creditor information, report useful, influence behaviour, asset depreciation, longer recoverable, jurisdiction entity, identify economic, costly complex, input validity, single economic, beyond economic, determine numerical, affect user, conclusion appropriate, treasury economic, expense principle
Accounting Professions (n=63)	particular subsidiary, transaction recognition, liability appropriate, standard description, constraint factor, report substance, sufficiently faithful, necessarily coincide, cost complex, related expense, impairment expense, reflect expense, benefit provided, contract term, liability treating, risk measurement, uncertainty different, position item, obligation issue, entity service, expense circumstance, equity provide, substance discernible, situation faithful, price available, inconsistency financial, transferred liability, claim liability, future salary, responsibility transfer, form contract, future employee, possible inflow, current estimate, satisfied criterion, unfaithful representation, timely information
Preparers (n=53)	recover cost, future sale, liability effect, cost extent, currently received, quantitative threshold, threshold materiality, market measurement, accounting language, cash dividend, risk value, equity component, overall assessment, complex economic, capital defined, subjective allocation, liability objective, information manner, entity principle, applied income, compensation penalty, current expectation, information timeliness, profit residual, information priority, decision intended, ability prevent, explanatory information, transaction asset, liability produce
Users (n=21)	individual investor, entity linked, time event, identify substance, particular basis, selected standard, estimate measure, measured nature, period amount, amount transferred, expense reflected, obligation third, individually measured, measured part, portfolio contract, liability pay, onerous asset, concern user, probability asset, materiality information, large volume, economy whole, liability measuring, entity acquired, benefit outweigh, long end, entity effect, relevant subject, cost factor, different individual, income equal
Public Interest (n=7)	global economy, entity difficult, legal regulatory, performance equity, regulatory requirement, information several, low see, power capital, give holder, conclusion entity, statement describe
Academics (n=49)	even measure, monetary term, risk preference, sufficiently visible, principle classification, usefulness limitation, conflicting information, entity flexibility, transparency accountability, uncertainty amount, accounting accrual, liability noted, difference recognition, relevance based, case verifiable, liability disposed, put option, current income
Others (n=12)	resulting cash, capital period, beginning period, agent entity, sell good, principal obligation, bring transparency, change trend, made order, opportunity risk, compensation entity, important cost, general economic, maintenance measured, similar information

Notes: This table reports a selection of unique bigrams that appear in the final standard for each constituent group. The number of observations (i.e., comment letters) for each group is shown in parentheses. This pilot analysis uses comment letters submitted to the IASB in response to the *Conceptual Framework* Exposure Draft as an illustration. On 28 May 2015, the IASB published an Exposure Draft proposing a revised *Conceptual Framework for Financial Reporting*, which received 241 comment letters (one unsigned duplicate letter was excluded from the analysis). The final standard refers to the final text of the revised Conceptual Framework. These results are based on an initial pilot analysis. It is important to acknowledge that refinements to the machine learning algorithms at various stages may lead to updates or modifications in the findings.