Government by Discussion: Deliberation, Media, and Policy-Making *

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Abstract

This paper examines whether oral, televised deliberation in Parliament is reflected in subsequent policy content. We study Question Hour in the Indian Parliament, where an institutional feature of the daily schedule quasi-randomly determines which members' questions receive oral discussion on the floor and which receive only a written reply, creating variation in televised deliberation that is plausibly unrelated to a question's content. We assemble a new fifteen-year dataset (2009–2024) that tracks every question and links it to subsequent bills, committee recommendations, parliamentary activity, and national newspaper coverage. Issues raised in questions debated on the floor are more closely reflected in the bills that are introduced, the recommendations made by committees, and the government's implementation of those recommendations than otherwise similar issues handled only in writing. Oral questions also attract greater public attention, and terrorist attacks abroad that crowd questions out of the news cycle provide suggestive evidence that press coverage helps carry these issues into law. Such coverage amplifies attention to a question's existing content, while the floor exchange, which exists only for oral questions, produces new statements and proposals; the traces of these exchanges in later bills suggest that the discussion supplies content and not only visibility.

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1 Introduction

A large literature in political economy studies the macroeconomics of policymaking, explaining how policies are chosen across institutional and economic contexts (Rodrik, 1998; Franzese Jr, 2002; Persson et al., 2007; Besley and Case, 2003; Bombardini and Trebbi, 2020). Policy choices, however, depend not only on macro-institutional settings, but also on the decision-making processes that operate within institutions. One such process, common across democratic legislatures, is deliberation. Legislatures across countries meet for an average of about 60–75 days per year, and much of this time is devoted to debating policy (Inter-Parliamentary Union and United Nations Development Programme, 2012). Yet deliberative institutions have weakened across the world. Varieties of Democracy data show that 57.63% of countries experienced declines in deliberative indicators between 2000 and 2025. This decline, even as policymakers continue to meet and debate, increasingly calls into question whether deliberative institutions matter for modern policymaking.

We bring this question to a deliberative setting in the Indian Parliament, Question Hour. Combining a new dataset with a novel identification strategy, we ask whether giving an issue oral discussion in Parliament affects subsequent policymaking. We assemble what is, to our knowledge, the most comprehensive dataset linking Indian parliamentary questions to downstream policy activity. Covering 2009 to 2024, the dataset links issues raised in Question Hour to outcomes, including laws and government policies. Our identification strategy exploits a computerised ballot that randomly assigns questions to positions in the Question Hour list, generating plausibly exogenous variation in whether they are reached for oral discussion or instead receive only a written government response. This allows us to estimate the effect of oral take-up on downstream policy outcomes and to examine the roles of deliberative exchange and public exposure.

Question Hour is a one-hour session held on each sitting day of the lower house of Parliament, during which Members of Parliament question the government about policy matters. On each day, up to twenty questions are selected to be answered during Question Hour. They are taken up in sequence until either all selected questions have been answered or the one-hour session ends. Questions taken up during the session receive oral replies in Parliament, while those not taken up receive written replies from the relevant ministry. An oral answer opens the floor to discussion: the member asks the question, the minister responds, and other members may ask follow-up questions on the same issue. These exchanges often involve policy justification, challenges to government claims, and consideration of alternative courses of action, expanding the question into a broader discussion of the underlying policy issue.

We refer to these exchanges as deliberation. Because Question Hour is broadcast live, oral discussion is also publicly observable. Written replies, by contrast, provide ministerial responses without televised floor discussion.

Our empirical strategy relies on the rule that determines the order in which questions are answered. A computerised lottery assigns each selected question a position in the Question Hour list. Questions are answered sequentially according to that order, but the session ends after one hour. As a result, not all listed questions are reached on most sitting days. Questions reached during the session constitute the treated group, while questions not reached constitute the control group. We compare oral and written questions from the same sitting day, using ballot rank as an instrument for oral take-up. Under the exclusion restriction, the IV estimates identify the effect of a question being reached for oral consideration within a fixed one-hour session. Oral take-up combines deliberative exchange with the additional public exposure generated by televised discussion; we provide separate evidence on the possible role of each channel.

We first assemble a Question Hour dataset that includes each question's text, ballot rank, whether it received an oral or written reply, and, for oral questions, the full floor exchange that followed. Covering the universe of Question Hour questions from 2009 to 2024, the dataset contains 17,421 questions and more than 40,700 floor speeches. We link these questions to a broad set of parliamentary records that capture multiple dimensions of policymaking. First, we use bill texts to assess whether issues raised during Question Hour appear in subsequent legislation. We compile textual summaries and legislative timelines for government bills and record their progression through Parliament, including the dates on which it is introduced, referred to committee, reviewed, debated, and enacted. Second, we use standing committee reports to measure committee scrutiny and policy recommendations. We collect the full set of reports submitted by department-related standing committees, record all recommendations made by the committees, and track whether the government subsequently implements them. Finally, we scrape more than 1.2 million articles from the *Times of India*, the most-read English-language daily newspaper in India, to measure media coverage of parliamentary activity.

We measure the extent to which issues raised in Question Hour are reflected in subsequent policy documents using textual alignment. For each question, we compare its text with the texts of bills introduced within 360 days, committee recommendations submitted within 360 days, and government responses to those recommendations. We construct two measures of alignment. The first captures lexical similarity using counts of shared bigrams and trigrams between each question–document pair. The second captures semantic similarity by embedding both texts with a pre-trained sentence transformer and

computing cosine similarity between the resulting vectors (Reimers and Gurevych, 2019). Larger values indicate greater textual correspondence between the issue raised in Question Hour and subsequent policy documents.

Our first result shows that oral take-up increases the extent to which the issues raised in questions are reflected in proposed laws. Relative to written questions asked on the same sitting day, orally answered questions are more closely aligned with bills introduced over the following year. Bills contain 9.4% more shared phrases with oral questions and are 0.78% more semantically similar to them. The same pattern appears in standing committees. Later committee recommendations are more closely aligned with issues raised orally, with 7.0% greater phrase overlap and 0.86% greater semantic similarity relative to written questions. These recommendations often concern concrete policy changes, including schemes, implementation rules, budgets, and service delivery. We also find that the effects extend to committee recommendations that the government subsequently implements. Instrumenting oral take-up with ballot rank yields point estimates of similar magnitude. Taken together, oral take-up increases the representation of raised issues across several forms of downstream policy activity: subsequent bill content, committee recommendations, and recommendations acted upon by the government. We find limited systematic heterogeneity across observable member and attendance characteristics.

Oral take-up differs from a written reply along two salient margins that we examine. The first is public exposure. Oral questions are publicly observable and receive more subsequent press attention. In the 28 days after Question Hour, *Times of India* articles are about 1% more semantically similar to oral questions than to written questions; phrase overlap points in the same direction, at around 2–3%, though it is less precisely estimated. Using severe terrorist attacks outside India on the following day as shocks to news attention, we find suggestive evidence that press coverage helps transmit orally raised issues into subsequent legislation. The second is the deliberative content generated during the floor exchange. A written reply fixes the relevant text at the submitted question and ministerial answer. An oral reply instead generates an exchange in which legislators and ministers can add facts, state constraints, challenge claims, and propose alternatives. We assess whether this additional material is related to later legislation by comparing subsequent bills with the submitted question and with statements from the full floor exchange. Phrase overlap with subsequent bills is higher when the exchange is included, and phrases introduced during the exchange subsequently appear in bill text. Semantic similarity adds a nuance: the exchange as a whole is less aligned with later bills than the question alone—much of what is said on the floor challenges or pushes beyond the policy eventually adopted—while the closest-matching statement in the exchange is more closely aligned. We interpret these comparisons as evidence that oral exchanges

contain material subsequently reflected in legislation.

We find little evidence for several alternative explanations. Oral questioning does not appear to induce observable forms of subsequent engagement by the questioning member that could drive the results (Kumar et al., 2024): we detect no effects on subsequent question submissions or attendance. Nor do the results appear to reflect narrow individual agenda-setting: the oral–written difference in overlap with subsequent questions is no larger when those questions are submitted by the same member, or by members from the same state or party, than when they are submitted by others. We also find no systematic evidence that the estimates vary with the identity or characteristics of the questioner. Finally, the estimates are similar in pre-election and other years, providing little indication that electoral cycles drive the findings (Akhmedov and Zhuravskaya, 2004).

Our empirical setting is the Indian Parliament, which we focus on for two reasons. First, as the world's largest democracy, and a highly heterogeneous one, effective policymaking in India requires aggregating and reconciling the interests of diverse social groups. Deliberation is a natural mechanism through which such aggregation and compromise can occur. At the same time, India illustrates a broader pattern of declining deliberation across democracies: its V-Dem deliberation index falls from 0.66 in 2000 to 0.29 in 2024 (Coppedge et al., 2024). In cross-country data, higher levels of deliberation are strongly correlated with better development outcomes, including economic growth, financial development, human capital, and state capacity (Figure B.1). If these correlations reflect, even in part, causal effects of deliberation on policy, micro-level evidence on whether and how deliberative exchange shapes policymaking can inform institutional design in settings experiencing deliberative decline. Second, random or quasi-random variation in deliberation across policy domains is rare in national legislatures. Question Hour in the Indian Parliament provides such leverage.

Related Literature. Our first contribution is to the literature on deliberation in legislatures and committees. In this literature, deliberation is defined as the process through which individuals share information about which alternative to choose before collective choice (Austen-Smith and Feddersen, 2005). Existing work treats deliberation as an outcome and studies how institutional rules affect deliberative quality, including when deliberation is informative under different voting rules (Austen-Smith and Feddersen, 2005; Gerardi and Yariv, 2007), how transparency shapes deliberative behaviour (Hansen et al., 2018; Meade and Stasavage, 2008; Gennaro and Ash, 2023), and how patience and preference heterogeneity matter (Chan et al., 2018; Jackson and Tan, 2013; Dietrich and Spiekermann, 2025). We study deliberation as an input to the policymaking process rather than as an outcome in itself.

Direct evidence on how deliberation affects outcomes is scarce. Structural studies of US appellate courts find fewer decision errors when judges deliberate, and counterfactual simulations suggest that curtailing FDA advisory committee discussion would reduce recommendation effectiveness (Iaryczower et al., 2018; Canen and Iaryczower, 2024). Field experiments with citizen deliberation report higher political knowledge, engagement, and lower clientelism (Fujiwara and Wantchekon, 2013; Parthasarathy et al., 2019; Bidwell et al., 2020). We differ from these studies in three respects: (i) we exploit random assignment of ballot rank to generate plausibly exogenous variation in oral discussion, rather than relying on structural assumptions to separate deliberation from preferences and agenda-setting; (ii) we trace the consequences of deliberation beyond immediate votes or recommendations to subsequent bill content and government action; and (iii) we examine deliberative exchange in a national legislature, where politicians face electoral accountability and party discipline, rather than in advisory committees or citizen forums with different institutional constraints.

The second literature we contribute to is on public exposure and long-run policy outcomes (Grossman, 2022). A large body of work studies how transparency affects political behaviour, corruption, and short-run budget allocations (Ferraz and Finan, 2008; Olken, 2007; Gavazza and Lizzeri, 2009; Snyder Jr and Strömberg, 2010; Besley and Burgess, 2001), providing important channels through which exposure could influence policy. However, there is relatively little direct evidence that transparency changes policy outputs themselves, with a few exceptions on local government expenditures (Gavazza et al., 2019; Ash and Galletta, 2023). These existing estimates are primarily local and short-run, whereas we document effects of news attention on national, long-run policies.

Finally, we contribute a novel dataset and identification strategy. We assemble a fifteen-year panel of Indian parliamentary activity combining Question Hour transcripts, review committee reports and government action reports, bill texts and timelines, and contemporaneous *Times of India* coverage, all linked at the policy-issue level. Randomly assigning opportunities for oral discussion is typically infeasible in legislatures; in our setting, a computerised ballot generates plausibly exogenous variation in whether they are reached for oral consideration. Although the resulting exchanges are brief, this is one of the few national legislative settings in which oral take-up varies quasi-randomly across issues, allowing us to estimate its causal effect on subsequent policymaking and investigate the roles of deliberative exchange and public exposure.

We provide background on the institutional setting in Section 2. Section 3 describes the data and Section 4 defines the outcomes. Section 5 explains the empirical strategy. Section 6 presents the main results. Section 7 examines mechanisms. Section 8 considers alternative explanations. Section 9 concludes.

2 Institutional Background

The Lok Sabha is the lower house of India's Parliament. It has 543 elected members, each representing a single-member constituency. The party or coalition with a majority in the House forms the government, and each Lok Sabha serves a five-year term. The House usually meets in three sessions each year: the Budget Session (February–May), the Monsoon Session (July–September), and the Winter Session (November–December). Our data cover 2009–2024 and span two successive governing coalitions: the Indian National Congress-led United Progressive Alliance (2009–2014) and the Bharatiya Janata Party-led National Democratic Alliance (2014–2024). Over this period, the Lok Sabha sat for about 62 days per year on average, and a typical sitting day lasted six hours. We first introduce Question Hour, the Lok Sabha session that forms our setting for studying deliberation. We then turn to the broader policymaking processes that generate the outcomes we study.[1]

2.1 Question Hour

Question Hour is the first hour of every Lok Sabha sitting, when Members of Parliament ask government ministers questions on various policy matters. Members may submit two types of questions for Question Hour: *Starred* and *Unstarred*. *Starred* questions are tabled for oral answer in the House. Ministers answer them on the floor, and members may ask follow-up questions, leading to a brief discussion of the issues raised. *Unstarred* questions receive written replies and are not taken up for oral discussion. Each sitting admits up to 20 *Starred* questions and 230 *Unstarred* questions. Our analysis focuses on *Starred* questions. We next describe how *Starred* questions are submitted, selected, and taken up during Question Hour. Figure I provides an overview of the process.

Submission of Questions. Each member of the Lok Sabha is allowed to submit at most one *Starred* question for a given parliamentary sitting. Submissions must be made at least fifteen days before the sitting. Ministries answer questions on fixed weekdays, so questions addressed to a ministry are listed for the day assigned to that ministry. A submission includes the question text, a subject line, the ministry addressed, and the date. Questions must concern a single subject and cannot exceed 150 words. Submitted questions are then examined by the Lok Sabha Secretariat for admissibility.[2] Questions are excluded if they fall outside the minister's portfolio, concern matters under judicial consideration, or

[1] The institutional background presented here is compiled from Kaul and Shakdher (2016). An archived copy of the cited volume is available in the GitHub repository at this link.

[2] The Lok Sabha Secretariat, which works under the Speaker, administers the business of the House, including the processing and scrutiny of parliamentary questions. For details, see: https://sansad.in/ls/secretariat/introduction.

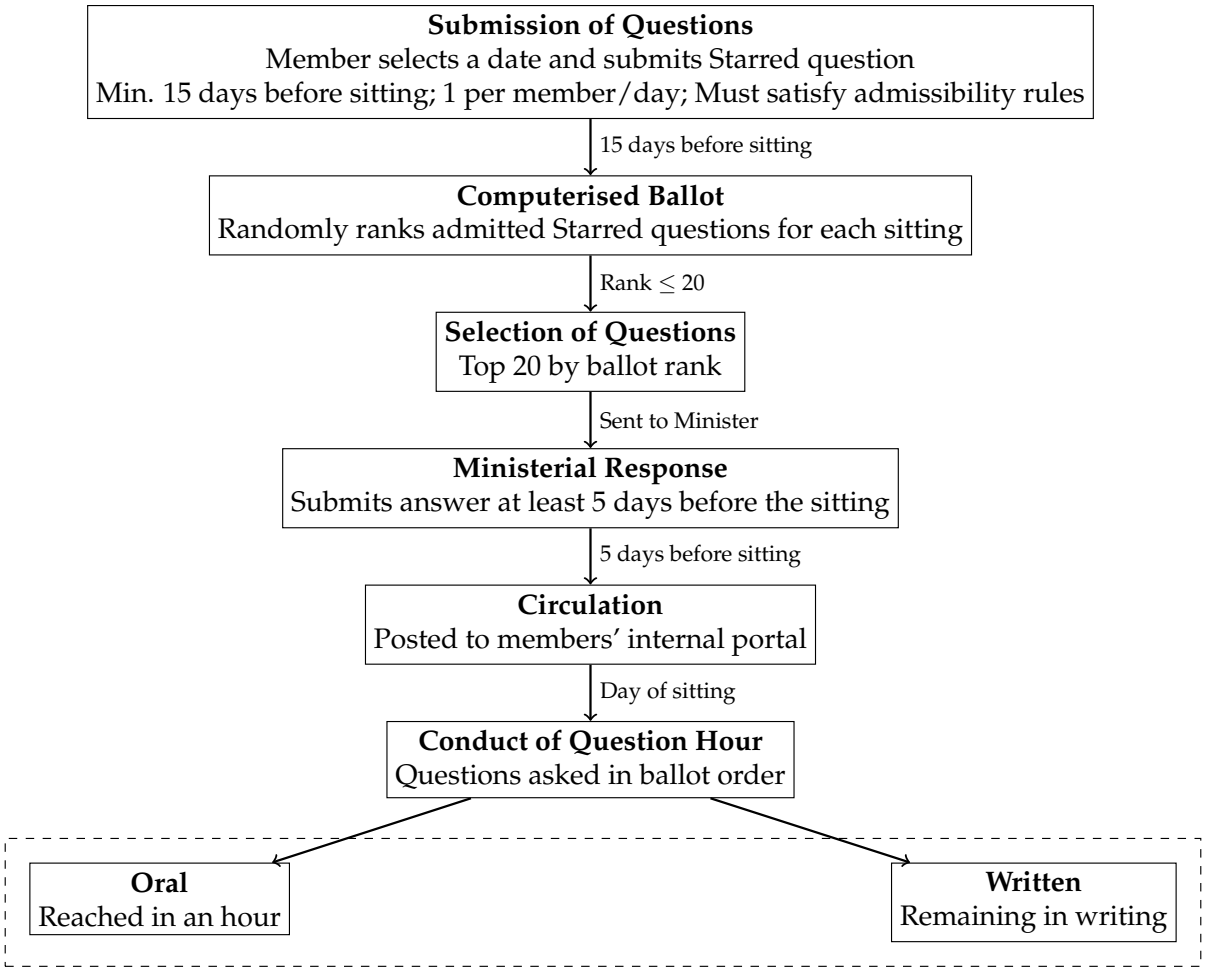


FIGURE I: *Question Hour Procedure in the Lok Sabha*

Notes: The figure shows the procedure for *Starred* questions in the Lok Sabha, from submission and admissibility review to balloting, ministerial replies, and consideration during Question Hour. Source: Lok Sabha Rules of Procedure and Conduct of Business, available at `sansad.in/ls/about/procedures`. An archived copy of the referenced material is available in the GitHub repository.

refer to committee proceedings that have not yet been reported. Questions that substantially repeat matters already answered, or matters on which an answer has been refused, are also not admitted. This prevents the same issue from being repeatedly raised through Question Hour. Where multiple members submit questions on the same or allied subject for a given sitting, the questions are clubbed and one is selected at random as the lead.

Selection of Questions. Each Question Hour session admits up to twenty *Starred* questions for oral answer. Since eligible submissions typically exceed this limit, a computerised ballot is conducted for each sitting. The ballot orders the submitted *Starred* questions, and the first twenty are listed for oral

answer. Questions below the cutoff are either transferred to the *Unstarred* list, subject to the daily limit on written-answer questions, or lapse. The ballot is held fifteen days before the sitting and is based on the questions submitted for that day.

Ministerial Response and Circulation. The *Starred* questions are then sent to the relevant ministries, which prepare and submit their replies at least five days before the sitting. The questions and replies are then circulated through the members' portal. Until the questions are answered in the House, neither members nor ministers are permitted to publicise them.

Conduct of Question Hour. *Starred* questions are answered in the order determined by the ballot. When a *Starred* question is reached, the member who submitted it asks the question and the minister answers orally. The member may then ask up to two follow-up questions, and other members may also ask follow-up questions. This creates discussion on the floor around the policy issue raised by the question, through follow-up questions from members and further explanation from the minister. In our data, each question involves about 5.7 members on average. This continues until Question Hour ends. Questions not reached before the end of Question Hour receive written replies only. These floor discussions are broadcast on Sansad TV, Parliament's television channel.[3]

2.2 Government Policymaking

We study three dimensions of policymaking: policy change through legislation, parliamentary committee recommendations, and the government's adoption of those recommendations. We describe each in turn.

Bills. Bills pass through several stages of scrutiny before they are enacted into law. For Government Bills, the ministry prepares the proposal, and the Cabinet of Ministers approves it for introduction in Parliament. The minister then introduces the bill in either House of Parliament.[4] The House of introduction then takes up the bill for consideration. Members debate the general principles of the bill and, where the House so decides, refer it to a committee for detailed examination. The committee reviews the bill's provisions and submits a report with recommendations. The House then considers the bill clause

[3] For illustration, see the Sansad TV telecast of 28 March 2022: here.

[4] We focus on Government Bills only. In India, ministers introduce Government Bills, while other members introduce Private Members' Bills. We exclude Private Members' Bills because no legislative proposal initiated by a private member has become law since the Fifth Lok Sabha, that is, since 1970, according to official parliamentary sources. We also exclude Money and Financial Bills, which follow special constitutional procedures and voting requirements. See https://sansad.in/ls/legislation/introduction.

by clause, takes up proposed amendments, and votes on the bill. After the first House passes the bill, it sends the bill to the other House, where members follow the same sequence of introduction, consideration, committee scrutiny where applicable, amendment, and voting. Once both Houses pass the bill, the President gives assent, and the bill becomes law.

Parliamentary Committees. Parliamentary committees are composed of members of Parliament and examine policy, administration, public expenditure, and legislation outside regular floor proceedings. We focus on the 24 department-related standing committees.[5] Each department-related standing committee is assigned to a ministry or a closely related group of ministries and departments. Members serve one-year terms, and ministers do not serve on these committees. The committees scrutinise budget proposals, review annual performance and future policy plans, examine policy subjects concerning the ministries under their charge, and consider bills referred to them by Parliament.

For each subject examined, the committee presents a report to Parliament setting out its recommendations. The relevant ministry then considers each recommendation and, normally within six months, submits a reply stating whether it has accepted the recommendation and what action it has taken or proposes to take. The committee reviews these replies in an Action-Taken Report, which records the recommendations accepted, the recommendations not pursued, the replies found unsatisfactory, and the final replies still pending.

3 Data

This section describes our data. We assemble four datasets: (i) *Starred* questions tabled for Question Hour, together with transcripts of the discussion that follows each question; (ii) bill-level data, including the summaries of the bill texts and information on their progression through Parliament; (iii) committee recommendations and the government's actions on them; and (iv) a daily corpus of articles from *The Times of India*. In addition, we use the Global Terrorism Database (START, 2022) to identify terrorist attacks outside India.

[5] Parliament also has financial committees, other standing committees, and ad hoc committees. We focus on the department-related standing committees because they are tied to specific ministries and departments, regularly scrutinise policy and expenditure, and generate comparable reports across topics. Many other standing committees instead deal with procedural or administrative matters, while ad hoc committees are constituted for specific purposes and limited durations.

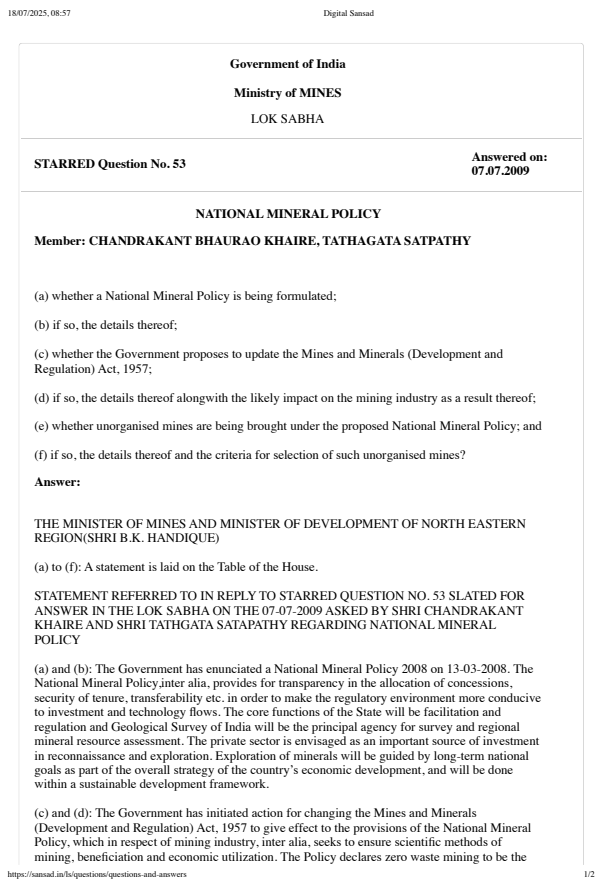
3.1 Question Hour Data

Our Question Hour sample consists of the twenty highest ballot-ranked *Starred* questions in each Lok Sabha sitting during the 15th (2009–2014), 16th (2014–2019), and 17th (2019–2024) Lok Sabhas.

Questions Metadata. We assemble question-level data from two sources. For the 15th and 16th Lok Sabhas, we use the TCPD Indian Parliament Dataset (Bhogale, 2019), which provides the question text, ministerial reply, subject, submitting member, ministry, and scheduled response date. On each day of Question Hour, every *Starred* question is assigned an official question number, which corresponds to its ballot position. TCPD neither reports official question numbers nor covers the 17th Lok Sabha, so we supplement it with data from the Sansad portal, the official digital repository of Lok Sabha records (https://sansad.in). From the Sansad portal, we recover official question numbers for the 15th and 16th Lok Sabhas and compile the full question-level metadata for the 17th Lok Sabha. We scrape the PDFs of *Starred* questions from the portal and extract their contents using Tesseract OCR. Figure IIa shows an example. For each question, we record the question text, ministerial reply, subject, submitting member, ministry addressed, scheduled response date, and official question number.

Oral Classification and Floor Transcripts. We classify each *Starred* question as oral or written using the *Lok Sabha Debates* from Sansad (https://sansad.in/ls/debates). Their contents pages list the *Starred* question numbers answered orally under "Oral Answers to Questions" and those answered in writing under "Written Answers to Questions." Figure IIb shows an example for 7 July 2009. We parse these lists and define $Oral_{qd} = 1$ if question q appears in the oral-answer list for sitting d, and 0 otherwise. This indicator is our main independent variable. For questions answered orally, we extract the corresponding floor exchange from the body of the same debates PDF. These transcripts record each speaker, the text of each intervention, and the sequence of exchanges.

Members' Data. We standardise the names of questioners, speakers, and ministers, and match them to the Indian Election Dataset (Asopa et al., 2023) and the Individual Incumbency Dataset (Agarwal et al., 2022). We do this by fuzzy string matching followed by manual verification. The matched data provide information on religion, caste group, gender, party affiliation, party type, state, constituency, and education. We also compile each member's electoral history, including vote shares, incumbency status, Lok Sabha terms served, and elections contested.



18/07/2025, 08:57 Digital Sansad

Government of India

Ministry of MINES

LOK SABHA

STARRED Question No. 53 **Answered on: 07.07.2009**

NATIONAL MINERAL POLICY

Member: CHANDRAKANT BHAURAO KHAIRE, TATHAGATA SATPATHY

(a) whether a National Mineral Policy is being formulated;

(b) if so, the details thereof;

(c) whether the Government proposes to update the Mines and Minerals (Development and Regulation) Act, 1957;

(d) if so, the details thereof alongwith the likely impact on the mining industry as a result thereof;

(e) whether unorganised mines are being brought under the proposed National Mineral Policy; and

(f) if so, the details thereof and the criteria for selection of such unorganised mines?

Answer:

THE MINISTER OF MINES AND MINISTER OF DEVELOPMENT OF NORTH EASTERN REGION(SHRI B.K. HANDIQUE)

(a) to (f): A statement is laid on the Table of the House.

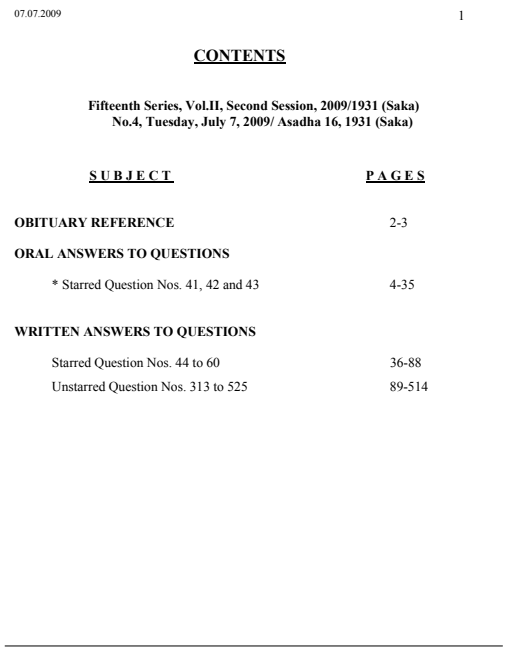
STATEMENT REFERRED TO IN REPLY TO STARRED QUESTION NO. 53 SLATED FOR ANSWER IN THE LOK SABHA ON THE 07-07-2009 ASKED BY SHRI CHANDRAKANT KHAIRE AND SHRI TATHGATA SATAPATHY REGARDING NATIONAL MINERAL POLICY

(a) and (b): The Government has enunciated a National Mineral Policy 2008 on 13-03-2008. The National Mineral Policy,inter alia, provides for transparency in the allocation of concessions, security of tenure, transferability etc. in order to make the regulatory environment more conducive to investment and technology flows. The core functions of the State will be facilitation and regulation and Geological Survey of India will be the principal agency for survey and regional mineral resource assessment. The private sector is envisaged as an important source of investment in reconnaissance and exploration. Exploration of minerals will be guided by long-term national goals as part of the overall strategy of the country's economic development, and will be done within a sustainable development framework.

(c) and (d): The Government has initiated action for changing the Mines and Minerals (Development and Regulation) Act, 1957 to give effect to the provisions of the National Mineral Policy, which in respect of mining industry, inter alia, seeks to ensure scientific methods of mining, beneficiation and economic utilization. The Policy declares zero waste mining to be the

https://sansad.in/ls/questions/questions-and-answers 1/2

(a) Question Record



07.07.2009 1

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* The sign + marked above the name of a Member indicates that the Question was actually asked on the floor of the House by that Member.

(b) Debate Contents Page

FIGURE II*: Official Records for Starred Questions*

Notes: The figure shows the official PDF records used to measure question-level characteristics and answer outcomes. Panel (a) shows the record for *Starred* Question No. 53, answered by the Ministry of Mines on 7 July 2009. The record reports the question number, member names, ministry, answer date, subject, and question text. Panel (b) shows the contents page of the Lok Sabha Debates for the same sitting, which lists the order of questions during Question Hour and indicates whether each *Starred* question received an oral or written answer. Source: Sansad portal, Questions and Answers section, `sansad.in/ls/questions/questions-and-answers`, and Text of Debates section, `sansad.in/ls/debates/text-of-debates`.

Data Description. The final dataset contains 17,421 *Starred* questions from 879 sittings (Table A.1). Of these, 3,030 are answered orally. Almost all oral questions, 2,891 out of 3,030, or 95.4%, generated follow-up discussion on the floor, so for this subset we observe both the minister's answer and the subsequent exchange. The average oral question involves 5.73 distinct speakers and 14.09 speaking turns. Table A.2 reports participation rates and average submissions by member characteristics. Participation is generally high across member characteristics, but several patterns stand out. Opposition members participate at higher rates than members of the ruling coalition in the 15th and 17th Lok Sabhas. Members from state-based parties participate at rates comparable to, and in some terms higher than, members from national

parties. Incumbents participate less consistently than non-incumbents, while members elected from close races show relatively high participation rates across terms. Average submissions decline over time for many groups, consistent with the lower number of *Starred* questions in the 17th Lok Sabha.

3.2 Bills Data

We construct a panel of government bills introduced in the Lok Sabha between 24 April 2000 and 1 April 2026. For each bill, we track its progress after introduction, including Lok Sabha discussion, referral to committee, submission of committee reports, passage, lapse, withdrawal, and other outcomes. We compile this panel by combining information from PRS Legislative Research (https://prsindia.org) and the Sansad portal (https://sansad.in/ls/legislation/bills). PRS provides the dates at which a bill moves from one legislative stage to the next, along with summaries of the bill text. Figure B.2 shows an example. Since PRS does not report the dates of Lok Sabha bill discussions, we recover those dates from the Sansad portal, together with the members who speak, the members present, and debate transcripts where available.

Data Description. The dataset contains 884 government bills across 53 ministries (Table A.3). On average, bills have 3.41 observed legislative stages; 63.01% are amendment bills and 40.84% are reviewed by committee. Final outcomes are concentrated in passage: 74.89% pass, 7.35% are rejected, and 14.82% remain ongoing. The mean time from introduction to passage is 226.79 days. Bills referenced in *Starred* questions account for 190 bills across 26 ministries. This subset closely resembles the full sample in amendment-bill share and number of stages, but has a higher passage rate, 80.53%, and a lower committee-review rate, 37.37%. These bills also pass somewhat faster, averaging 215.61 days from introduction to passage. Among committee-reviewed bills, those referenced in *Starred* questions spend longer under review, 262.73 days compared with 211.41 days, but move more quickly from committee report to final outcome, 355.79 days compared with 650.49 days.

3.3 Parliamentary Committees

We collect department-related standing committee reports for the 15th, 16th, and 17th Lok Sabhas from Sansad (sansad.in/ls/committee/subjects-reports). The dataset contains 2,916 committee reports: 1,546 initial *Overview* reports and 1,370 *Action-Taken Reports*. We download the report PDFs, extract their text using Tesseract OCR, and match each *Overview* report to the corresponding *Action-Taken Report* on the same subject. For each matched report, we extract the committee's recommendations and code whether

the government accepted each recommendation, using the classification reported in the *Action-Taken Report*. The average *Action-Taken Report* contains 20.61 recommendations, of which 10.37 are accepted by the government on average. This corresponds to an average acceptance rate of approximately 50.3%. Table A.4 reports the summary statistics.

3.4 Times of India

The Times of India (TOI) is India's leading English-language daily, with nationwide print and digital reach. The Indian Readership Survey 2019 identifies TOI as the most-read English daily, with a total readership of 17.3 million.[6] We construct a daily corpus from TOI's public archive covering 4 June 2009 to 8 March 2024.[7] The window begins 28 days before the first sitting in our sample and ends 28 days after the last. We restrict the corpus to the general-news sections *India*, *City*, *Business*, and *Home*, and exclude *Entertainment*, *Lifestyle*, and *Advertising*. The resulting corpus contains 1,278,701 articles over 5,392 days, averaging 237.15 articles per day, with a mean article length of 176.90 words.

3.5 Global Terrorism Database

We measure exogenous news shocks using the Global Terrorism Database, curated by START (START, 2022), which records terrorist incidents worldwide.[8] We focus on attacks outside India, to capture shocks that are likely to affect Indian news coverage while remaining plausibly exogenous to domestic events. The database covers incidents through June 2021, spanning 732 of the 879 Question Hour sitting days in our sample; between the first sitting in our sample and the end of this coverage, it records 113,116 incidents on 4,382 distinct days. Attacks are frequent enough that every covered sitting day coincides with at least one incident; the analysis therefore relies not on whether an attack occurred but on the severity of the day's attacks, as described in Section 7.

4 Measurement, Outcomes and Summary Statistics

This section introduces the policy outcomes used in the analysis. We measure how closely the content of a question is reflected in subsequent bills, committee recommendations, government actions, and

[6] See Media Research Users Council at https://mruc.net/latest-update.

[7] Archive: https://timesofindia.indiatimes.com/archive.

[8] The Global Terrorism Database classifies an incident as terrorism when a sub-national actor intentionally uses or threatens violence and the act (i) advances political, economic, religious, or social objectives; (ii) aims to intimidate beyond the immediate victims; and (iii) falls outside lawful warfare. START builds the dataset by monitoring major international agencies, leading national newspapers, official statements, and research organisations.

newspaper coverage, and we report summary statistics for the main variables.

Our main measure captures whether issues raised during Question Hour receive downstream policy attention in bills and committee recommendations using phrase overlap and semantic similarity. In addition, for the subset of questions that mention a specific bill, we track that bill's subsequent legislative trajectory.

Phrase Overlap. Our first set of outcomes captures exact overlap in short phrases between a submitted question and subsequent policy texts. Following Ash and Hansen (2023) and Gentzkow et al. (2019a), we preprocess all texts by lowercasing, removing punctuation and numbers, dropping English stopwords, and lemmatising tokens. We then extract all unique bigrams (consecutive two-word phrases) and trigrams (consecutive three-word phrases) from the cleaned text. We also remove phrases that appear in the top decile of the frequency distribution across question texts, since these common phrases contain little issue-specific information.[9] We then define overlap between question q and policy document d as:

$$\text{Phrase}_{q,d} = |\text{Tri}_q \cap \text{Tri}_d| + |(\text{Bi}_q \cap \text{Bi}_d) \setminus \text{Bi}(\text{Tri}_q \cap \text{Tri}_d)|,$$

where Tri_x represents the trigrams from text x, Bi_x represents the bigrams, and $\text{Bi}(S)$ denotes the bigrams contained within trigram set S. Thus, Phrase_{qd} counts shared unique trigrams and shared unique bigrams that are not part of any shared trigram. This avoids double-counting shorter phrases that are nested within longer matched phrases.

For each question, our main phrase-overlap outcome sums overlap across government bills introduced within 360 days:

$$\text{PhraseBill}_q = \sum_{b \in \mathcal{B}(q;360\text{d})} \text{Phrase}_{q,b},$$

where $\mathcal{B}(q;360\text{d})$ is the set of government bills introduced within 360 days of question q.

We also construct analogous outcomes for other downstream texts. For committee outputs, we define

$$\text{PhraseRC}_q = \sum_{r \in \mathcal{R}(q;360\text{d})} \text{Phrase}_{q,r},$$

$$\text{PhraseGovAcc}_q = \sum_{a \in \mathcal{A}(q;360\text{d})} \text{Phrase}_{q,a},$$

where $\mathcal{R}(q;360\text{d})$ is the set of recommendations in *Overview* reports presented to the Lok Sabha within

[9] For example, we exclude "central government" from the question texts, where it appears in 42% of texts.

360 days of question q, and $\mathcal{A}(q; 360\text{d})$ is the set of recommendations accepted by the government in *Action-Taken Reports* issued over the same window.

Table I reports summary statistics. The average question has a phrase-overlap score of 1.54 with subsequent bills, 65.83 with committee recommendations, and 40.88 with government-accepted recommendations. Phrase overlap is lowest for bills and substantially higher for committee-related policy texts.[10]

Phrase-based measures are transparent and widely used in empirical text analysis, including work on partisan language (Gentzkow and Shapiro, 2010; Gentzkow et al., 2019b), policy uncertainty (Baker et al., 2016; Caldara and Iacoviello, 2022; Hassan et al., 2019), and technological diffusion (Kalyani et al., 2025). Their main limitation is that they capture only exact lexical overlap and miss substantively similar texts expressed in different language or wording. We therefore complement them with a semantic similarity measure.

Semantic Similarity. We measure semantic similarity using embeddings from a pre-trained Sentence-BERT (SBERT) model (Reimers and Gurevych, 2019).[11] An embedding is a vector representation of a text in a high-dimensional space, where each dimension reflects a latent semantic feature learned by the SBERT model. Texts that are more similar in meaning receive more similar vector representations. We measure similarity between question embedding q and downstream-text embedding d using cosine similarity:

$$\text{sim}(q, d) = \frac{q \cdot d}{\|q\| \, \|d\|}.$$

$\text{sim}(q, d)$ ranges from -1 to 1. Higher values indicate greater semantic similarity, values near zero indicate little semantic relationship, and negative values indicate opposite semantic meaning. Appendix C provides further background on BERT and Sentence-BERT.

For each question, we define the semantic similarity outcome as the average cosine similarity across all downstream documents in the relevant window. For bills,

$$\text{SBERTBill}_q = \frac{1}{|\mathcal{B}(q; 360\text{d})|} \sum_{b \in \mathcal{B}(q; 360\text{d})} \text{sim}(q, b).$$

[10] For bills, we use PRS Legislative Research bill summaries rather than the full statutory text. Because these summaries are shorter and more condensed than the underlying bill text, this likely reduces measured phrase overlap with questions.

[11] Sentence-BERT is a transformer-based encoder designed to produce sentence-level embeddings for semantic similarity and retrieval tasks. It extends BERT using siamese or triplet-network training on sentence pairs, so that semantically similar texts are mapped to nearby vectors and dissimilar texts to more distant ones. We use the pre-trained `all-mpnet-base-v2` encoder, which produces 768-dimensional embeddings. See here.

TABLE I: *Summary Statistics*

Variable	Definition	Mean	S.D.	Min	Max	Obs.
(A) Outcome Variables						
PhraseBill	Phrase overlap with bills introduced within 360 days	1.54	2.37	0.00	16.00	16,964
SBERTBill	Average SBERT similarity to bills introduced within 360 days	0.30	0.05	0.08	0.41	16,964
PhraseRC	Phrase overlap with committee recommendations within 360 days	65.83	53.06	0.00	276.00	16,961
SBERTRC	Average SBERT similarity to committee recommendations within 360 days	0.36	0.04	0.12	0.46	16,961
PhraseGovAcc	Phrase overlap with government-accepted recommendations within 360 days	40.88	40.06	0.00	211.00	16,941
SBERTGovAcc	Average SBERT similarity to government-accepted recommendations within 360 days	0.36	0.04	0.15	0.46	16,941
PhraseNews	Phrase overlap with *Times of India* articles within 28 days	71.90	42.44	0.00	219.00	16,949
SBERTNews	Average SBERT similarity to *Times of India* articles within 28 days	0.26	0.04	0.09	0.33	16,949
BillProgress	Days from question to next legislative step on bill, right-winsorised at median	748.12	389.98	1.00	1,084.00	454
BillFinal	Days from question to final bill outcome, right-winsorised at median	843.59	407.81	3.00	1,180.50	403
FastOutcome	Indicator equal to one if bill reaches a final outcome within 30 days of introduction	0.26	0.44	0.00	1.00	454
(B) Control Variables						
Females	Total female MPs	0.16	0.39	0.00	2.00	17,455
Christian	Total Christian MPs	0.03	0.18	0.00	2.00	17,455
Muslim	Total Muslim MPs	0.04	0.21	0.00	2.00	17,455
Hindu	Total Hindu MPs	1.42	0.57	0.00	5.00	17,455
Sikh	Total Sikh MPs	0.02	0.14	0.00	2.00	17,455
General Caste	Total General Caste MPs	1.18	0.65	0.00	4.00	17,455
Scheduled Caste	Total Scheduled Caste MPs	0.21	0.43	0.00	2.00	17,455
Scheduled Tribe	Total Scheduled Tribe MPs	0.12	0.33	0.00	2.00	17,455
Ruling Coalition	Total MPs from the ruling coalition	0.73	0.71	0.00	4.00	17,455
Opposition Coalition	Total MPs from the opposition coalition	0.34	0.57	0.00	3.00	17,455
Other Coalition	Total MPs from neither the ruling nor opposition coalition	0.43	0.60	0.00	3.00	17,455

Notes: The table reports descriptive statistics for the main variables used in the analysis. Phrase variables measure phrase overlap between parliamentary questions and downstream policy or media texts within the specified time windows. SBERT variables report average cosine similarity between sentence-level embeddings of questions and the relevant downstream texts. News outcomes are based on articles from the *Times of India*. Bill trajectory outcomes are measured for question–bill pairs. Final bill outcomes include passage, withdrawal, lapse, negativing, replacement by an act, repromulgation, or an ordinance remaining in force. Bill timing outcomes are right-winsorised at the sample median where indicated. Control variables measure the number of submitting MPs with each demographic or political characteristic.

We construct analogous measures for committee recommendations.

The average SBERT similarity is 0.30 for bills, 0.36 for committee recommendations, and 0.36 for government-accepted recommendations. Phrase overlap and semantic similarity are positively correlated. A one-standard-deviation increase in phrase overlap is associated with a 0.19 standard-deviation increase in average SBERT similarity for bills, a 0.32 standard-deviation increase for committee recommendations, and a 0.29 standard-deviation increase for government-accepted recommendations.

Illustration of Textual Matches. Three examples illustrate the pairwise text measures underlying our outcomes. The first, shown in Figure B.3, compares a question on child labour to the *Atomic Energy Amendment Bill, 2015*, introduced within six months of the question. Both pairwise measures indicate little alignment: $\text{sim}(q, b) = 0.19$ and $\text{Phrase}_{q,b} = 0.95\%$ of the question's phrases. The second, shown in Figure B.4, compares the same question to the *Child Labour (Prohibition and Regulation) Amendment Bill, 2012*, which is directly related to the issue raised. Both measures indicate strong alignment: $\text{sim}(q, b) = 0.68$ and $\text{Phrase}_{q,b} = 9.52\%$. The third, shown in Figure B.5, compares a question on medical quackery to the *Indian Medical Council Amendment Act, 2012*. Although the amendment does not address quackery, both texts concern medical regulation. Phrase overlap is zero, but semantic similarity is 0.31.

Bill Trajectory Outcomes. As secondary outcomes, we track the legislative path of bills or laws raised during Question Hour. We identify bill-related questions as those containing legislative terms such as *bill*, *act*, *rule*, *regulation*, *ordinance*, *amendment*, *code*, *repeal*, *law*, and *sanhita*. For these questions, we extract the title of each specific law, bill, rule, or ordinance referenced in the text. We exclude references to laws enacted before 2000 and match the remaining references to PRS bill records.[12] If a question refers to an existing law, we also link it to amendment bills for that law that are introduced after the question date. The matched sample contains 1,054 question–bill pairs, covering 305 questions. Of these pairs, 454 have a subsequent recorded legislative event and enter the trajectory regressions.

We define three outcomes for bill trajectories. BillProgress_{qb} is the number of days from question q to the next recorded event for bill b. BillFinal_{qb} is the number of days from question q to the bill's final recorded outcome. Final outcomes include passage, withdrawal, lapse, negativing, replacement by an act, repromulgation, and ordinances remaining in force. FastOutcome_{qb} equals one if the bill reaches a final outcome within thirty days of introduction. We top-code BillProgressqb and BillFinalqb at the

[12] We match references to PRS bill titles using cleaned title overlap. We remove years, punctuation, stopwords, and generic legal terms such as *bill*, *act*, and *amendment* from both the question reference and the PRS title. We assign a match when at least half of the remaining content words in the question reference appear in the PRS title. We then validate all matches, remove false positives, and add correct links missed by the rule.

median of the matched question–bill sample, 1,084 and 1,180.5 days respectively.[13]

For the bill-trajectory outcomes in Figure B.4, $\text{BillProgress}_{qb} = 351$ because the bill next advanced when it passed the Lok Sabha 351 days after the question. $\text{BillFinal}_{qb} = 358$ because the bill reached its final outcome when it passed the Rajya Sabha 358 days after the question. Since the bill was not finalised within 30 days of introduction, $\text{FastOutcome}_{qb} = 0$.

5 Identification Strategy

Our baseline specification regresses policy outcomes on whether a question is orally answered. Identification requires two conditions. First, ballot rank in Question Hour is randomly assigned, so conditional on date fixed effects, rank is orthogonal to predetermined question characteristics. Second, conditional on rank, whether a question is reached within the one-hour window depends on idiosyncratic features of the sitting rather than on the question's content. The first condition follows from the institutional procedure; the second is the identifying assumption. To address potential violations of this assumption, we also estimate a two-stage least squares specification that instruments oral take-up with ballot rank. Section 5.1 presents the baseline specification and Section 5.2 discusses the rank instrument.

5.1 Baseline Estimation

We estimate the following linear specification as our baseline:

$$Y_{qd} = \phi_d + \lambda_m + \beta \, \text{Oral}_{qd} + \mathbf{X}'_{qd}\gamma + \varepsilon_{qd}. \tag{1}$$

Here, Y_{qd} denotes the outcome for question q scheduled on sitting-day d, including textual similarity to downstream policy documents and bill-trajectory outcomes. ϕ_d denotes day fixed effects, which absorb all factors common to questions listed on the same day, including the composition of that day's question pool. λ_m denotes ministry fixed effects, which absorb differences across ministries in question content, policy activity, and downstream document production. The indicator Oral_{qd} equals one if the question is reached and answered orally on the floor, and zero otherwise. The vector $\mathbf{X}_{qd}$ includes member-level controls for gender, coalition status (ruling, opposition, or other), caste (Scheduled Caste, Scheduled

[13] The timing outcomes are right-skewed because many questions refer to existing laws rather than bills already under consideration. In such cases, the next recorded event is often the introduction of a later amendment bill, which can occur years after the question. In the raw data, the median gap is 970.5 days for BillProgress_{qb} and 1,120 days for BillFinal_{qb}; the corresponding 99th percentiles are 4,302 and 3,943 days.

Tribe, or General Category), and religion (Hindu, Muslim, Christian, Sikh, or other). Standard errors are clustered at the day level. The coefficient of interest is β.

5.2 Instrumental Variables Estimates

We instrument oral take-up with ballot rank. Questions with lower ballot ranks are more likely to be reached during the one-hour Question Hour window, while rank itself is randomly assigned within each sitting. The first- and second-stage specifications are:

$$\text{Oral}_{qd} = \phi_d + \lambda_m + \pi \cdot \text{Rank}_{qd} + \mathbf{X}'_{qd}\delta + \nu_{qd}, \tag{2}$$

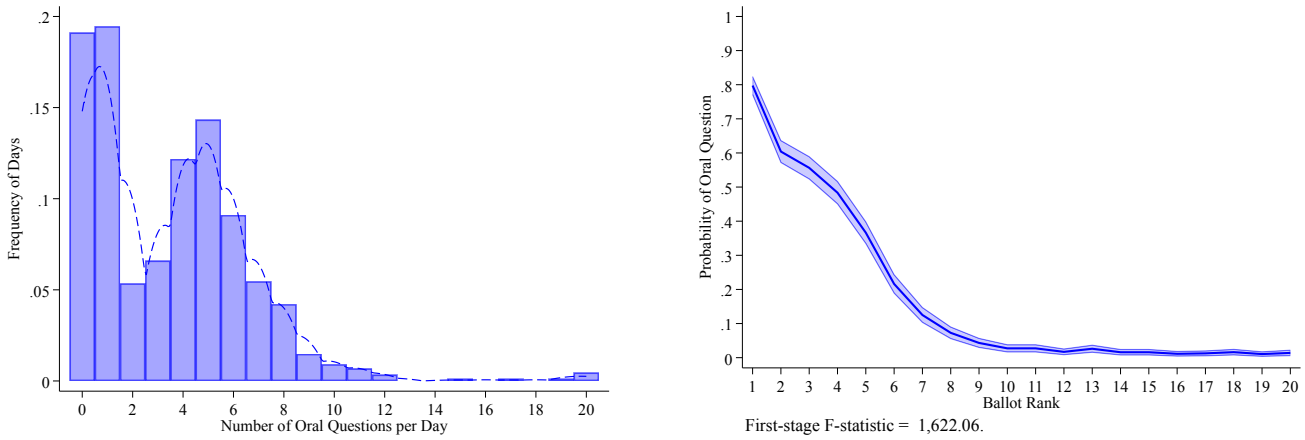
$$Y_{qd} = \phi_d + \lambda_m + \beta \cdot \widehat{\text{Oral}}_{qd} + \mathbf{X}'_{qd}\gamma + \varepsilon_{qd}, \tag{3}$$

where Rank_{qd} is the ballot rank of question q on day d, ϕ_d are date fixed effects, λ_m are ministry fixed effects, and $\mathbf{X}_{qd}$ is the vector of controls. Identification requires that the standard IV assumptions of independence, relevance, exclusion, and monotonicity hold.

The independence restriction requires Rank_{qd} to be unrelated to potential outcomes conditional on sitting-day fixed effects. This is supported by the random assignment of ballot rank within each sitting. Ballot rank is a strong predictor of oral take-up. Figure IIIa shows that the number of oral answers varies substantially across sittings, with an average of 3.46 oral questions per sitting day. This is because Question Hour almost always ends before all twenty questions are reached, making a question's ballot position consequential for whether it is answered orally. Figure IIIb shows a steep first stage: through rank 8, each additional ballot position reduces the probability of an oral answer by 10.2 percentage points. With sitting-day fixed effects, the first-stage F-statistic is 1,622.

The exclusion restriction requires ballot rank to affect outcomes only through oral take-up. Table A.5 tests for direct effects of rank by estimating rank–outcome relationships separately within the written and oral samples. In the written sample, all questions have $\text{Oral}_{qd} = 0$; in the oral sample, all have $\text{Oral}_{qd} = 1$. The estimated coefficients are small and statistically indistinguishable from zero in both samples, providing no evidence that rank affects outcomes conditional on oral status.

Monotonicity is implied by the ordering rule: questions are called sequentially by ballot rank, so moving a question later in the ballot cannot increase its probability of being reached. Oral take-up falls sharply across the ranks that are typically reached and is flat after rank 8.



(a) Oral Questions per Sitting

(b) Oral Take-Up by Ballot Rank

FIGURE III: *Distribution of Oral Questions and Oral Take-Up by Ballot Rank*

Notes: Panel (a) shows the distribution of the number of *Starred* questions answered orally per sitting day. Bars report the observed fraction of sitting days, and the dashed curve overlays an Epanechnikov kernel density estimate. Panel (b) plots the probability that a *Starred* question is answered orally by ballot rank. The solid line reports the mean oral take-up rate at each rank, and the shaded area shows 95 percent confidence intervals. The mean number of oral questions per sitting day is 3.46, and the median is 3. The first-stage F-statistic reported in Panel (b) comes from a regression of the oral-answer indicator on ballot rank with sitting-day fixed effects; standard errors are clustered by sitting day.

6 The Effects on Policymaking

This section reports the empirical results on how issues raised through oral questions and discussed on the floor shape policy. First, we examine changes to bills in Section 6.1. Second, we study committee recommendations and the government's acceptance of those recommendations in Section 6.2.

6.1 Bills

Table II reports OLS and 2SLS estimates of equations (1) and (3). The dependent variables measure the similarity between the submitted question and bills introduced within 360 days. Columns (1)–(2) use phrase overlap, PhraseBill_q, while Columns (3)–(4) use semantic similarity, SBERTBill_q. All outcomes are standardised, so coefficients are measured in standard-deviation units.

The estimates indicate that oral take-up is associated with subsequent legislative content moving towards the language and content of the submitted question. In the baseline OLS specifications, *Oral* questions increase phrase overlap with subsequently introduced bills by 0.0606 standard deviations and semantic similarity by 0.0517 standard deviations. Adding controls leaves these estimates largely unchanged, suggesting that the relationship is not driven by observable differences between *Oral* and *Writ-*

TABLE II: *Effect of Oral Questions on Bill Outcomes*

	PhraseBill		SBERTBill	
	(1)	(2)	(3)	(4)
Oral	0.0606***	0.0581***	0.0517**	0.0489**
	(0.0202)	(0.0201)	(0.0202)	(0.0201)
$\widehat{\text{Oral}}$	0.0593*	0.0547*	0.0558*	0.0494
	(0.0332)	(0.0330)	(0.0318)	(0.0317)
First stage: Rank	−0.0349***	−0.0349***	−0.0349***	−0.0349***
	(0.000868)	(0.000869)	(0.000868)	(0.000869)
First-stage *F*-statistic	1,606.8	1,603.5	1,606.8	1,603.5
Controls	No	Yes	No	Yes
Observations	16,964	16,964	16,964	16,964

Notes: The table reports OLS estimates from Equation 1 and 2SLS estimates from Equation 3. The outcomes measure similarity between the submitted question text and bills introduced within 360 days. PhraseBill is based on phrase matches with bill text, while SBERTBill is based on semantic similarity with bill text. Both outcomes are top-coded at the 99th percentile and standardised to have mean zero and standard deviation one over the full sample of starred question–bill pairs. The row labelled Oral reports OLS estimates. The row labelled $\widehat{\text{Oral}}$ reports 2SLS estimates, instrumenting oral take-up with ballot rank. The first-stage row reports the effect of ballot rank on oral take-up. Columns (1) and (3) include sitting-day and ministry fixed effects. Columns (2) and (4) additionally include controls for the submitting members' coalition status, religion, caste, and gender composition. Standard errors, clustered by sitting day, are reported in parentheses. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

ten questions. The 2SLS estimates are similar in magnitude to the OLS estimates. Using ballot position as an instrument for oral take-up, the estimated effects on phrase overlap are 0.0593 standard deviations without controls and 0.0547 standard deviations with controls. For semantic similarity, the corresponding estimates are 0.0558 and 0.0494 standard deviations. The first stage is strong: moving one position later in the ballot reduces the probability of oral take-up by 3.49 percentage points, and the first-stage *F*-statistics exceed 1,600 in all specifications. Although the Column (4) IV estimate for SBERTBill_q is not statistically significant at conventional levels, its point estimate is nearly the same as the controlled OLS estimate. The difference in statistical significance appears to reflect the larger standard error of the IV estimate, while the estimated magnitude remains essentially unchanged.

Table A.6 reports the same effects in raw units. For phrase overlap, the mean among written questions is 1.503 phrases. Oral take-up increases this measure by 0.141 phrases, or 9.4 percent relative to the written-question mean. For semantic similarity, oral take-up raises the measure by 0.78 percent relative to written questions. In angular terms, this corresponds to rotating the average bill embedding towards the question embedding by approximately 0.14°.[14] This angular change is small, but changes in cosine

[14]Cosine similarity equals the cosine of the angle between unit-normalised embeddings, $s = \cos\theta$, so $\theta = \arccos(s)$. At

similarity should be interpreted relative to the high-dimensional nature of the measure. A large increase would require the bill text to become substantially more aligned with the question across many features of the embedding. By contrast, even small increases can reflect movement along a sufficiently broad set of semantic dimensions. The estimates therefore point to a modest but systematic movement of subsequent bill language towards the issues, concepts, and framing raised in orally answered questions. Below, we show that changes of this magnitude can correspond to substantively meaningful differences in legislative content.

One interpretation of the results is that bills related to issues raised in both oral and written questions were already in the legislative pipeline, and that oral take-up mainly changes the timing of introduction by increasing the priority of bills related to orally answered questions. Under this interpretation, oral questioning affects which issues appear in bills within the 360-day window, but not necessarily the content of bills the government intended to introduce. A second interpretation is that oral questions affect legislative content more directly, either by inducing bills that were not previously under consideration or by shaping the language of bills still being drafted. Table A.7 helps distinguish between these interpretations by decomposing the 360-day effect into four 90-day windows after Question Hour. If the estimates were driven primarily by the re-timing of bills already in the pipeline, the effect should be concentrated immediately after Question Hour and then be offset in later windows as bills associated with written questions are introduced. In that case, the estimates should decline sharply or turn negative. Instead, the effects become more stable after the first 90 days, remain positive through days 181–270, and taper towards zero only in the final window. The absence of a large immediate effect or a subsequent reversal suggests that oral take-up is not simply reallocating bills across time, but is associated with subsequent legislative content moving towards the issues of the orally answered question.

We next examine whether oral questioning affects the trajectory of bills mentioned in questions. When a member raises a specific bill in Question Hour—for example, by asking about its passage, status, or implementation—oral take-up may affect that bill's subsequent progress. Table III restricts the sample to these questions and compares bill trajectories following oral and written answers. Across outcomes, the estimates with date fixed effects are statistically insignificant. The point estimates for BillProgress and BillFinal are negative, consistent with faster movement, but imprecisely estimated. Columns (7)–(9) similarly show no detectable effects on FastOutcome. Restricting the sample to questions that mention bills substantially reduces the number of observations, and date fixed effects absorb much of the remain-

the written-question baseline $s_0 = 0.297$, $\theta_0 = \arccos(0.297) = 72.72^\circ$. An increase of 0.00231 implies $s_1 = 0.29931$, so $\theta_1 = \arccos(0.29931) = 72.58^\circ$, a change of about 0.14°.

TABLE III: *Effect of Oral Questions on Bill Trajectories*

	BillProgress			BillFinal			FastOutcome		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Oral	−110.4	−142.8*	−62.23	−157.0	−172.4**	−135.5	0.0372	−0.0523	0.187
	(254.7)	(72.72)	(301.4)	(314.8)	(78.92)	(322.7)	(0.217)	(0.0443)	(0.190)
D.V. Mean	777.4	777.4	777.4	881.7	881.7	881.7	0.263	0.263	0.263
Controls	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Date fixed effects	Yes	No	Yes	Yes	No	Yes	Yes	No	Yes
Observations	454	454	454	403	403	403	454	454	454

Notes: The sample is restricted to questions that mention a bill. The table reports OLS estimates of the relationship between oral take-up and subsequent bill-trajectory outcomes. BillProgress_{qb} is the number of days from question q to the next recorded event for bill b. BillFinal_{qb} is the number of days from question q to the bill's final recorded outcome. Final outcomes include passage, withdrawal, lapse, negativing, replacement by an act, repromulgation, and ordinances remaining in force. FastOutcome_{qb} equals one if the bill reaches a final outcome within thirty days of introduction. BillProgress_{qb} and BillFinal_{qb} are top-coded at their sample medians before estimation. Columns (1), (4), and (7) include date fixed effects but no controls. Columns (2), (5), and (8) include controls but no date fixed effects. Columns (3), (6), and (9) include both controls and date fixed effects. Robust standard errors are reported in parentheses. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

ing variation. In specifications without date fixed effects but with the full set of controls, the estimated effects on bill timing are negative and statistically significant. Oral take-up is associated with a 142.8-day reduction in the time to the next recorded bill event, a decrease of 18.4 percent relative to written questions, and a 172.4-day reduction in the time to the bill's final recorded outcome, a decrease of 19.6 percent. With date fixed effects, however, identification comes only from the 49 days on which both oral and written bill-related questions are observed, limiting the precision of the estimates.

Robustness. Table A.8 examines whether the textual results are sensitive to sample composition, outliers, inference, or the construction of the outcome variables. The first panel excludes unusually high- and low-volume sitting days. This addresses the concern that the estimates are driven by days with unusually many oral questions, or by days with very little question activity. The coefficients remain positive and similar in magnitude for both bill and committee outcomes. For example, the bill estimates range from 0.0555 to 0.0579 for PhraseBill and from 0.0404 to 0.0485 for SBERTBill.

The second panel shows that the results are not driven by extreme realisations of the similarity measures. Dropping or winsorising the upper and lower tails of the outcome distributions leaves the estimates positive across all four textual outcomes. The magnitudes are somewhat smaller when upper outliers are dropped, especially for phrase overlap, but the estimates remain statistically significant. This suggests that the baseline effects are not mechanically generated by a small number of question–

bill or question–committee pairs with unusually high textual similarity. The third panel uses a more conservative clustering structure that allows errors to be correlated within date-by-ministry cells. The estimates remain positive and statistically significant, indicating that the inference is not sensitive to clustering only at the sitting-day level. The final panel considers alternative definitions of the textual outcomes. For phrase-based outcomes, the results remain positive under Poisson, negative-binomial, fractional, and logarithmic specifications. For semantic outcomes, using the maximum semantic similarity between the question and downstream text, rather than average similarity, also yields positive and significant estimates.

Illustrations. Figures B.6 and B.7 provide two examples that help interpret the magnitude of the estimated effects on SBERTBill_q.

Questions on Coal Mines. Figure B.6 compares two oral questions to the Ministry of Coal with the *Coal Mines (Conservation and Development) Amendment Bill, 2012*. The bill raises the coal excise from Rs 10 to Rs 50 per tonne and uses the additional revenue to finance work on mine fires, subsidence, and rehabilitation in the Jharia and Raniganj coalfields. Q10 asks about mine fires in Jharia and Raniganj, the rehabilitation of affected households, and the funds and schemes directed to these coalfields. Q257 asks about land acquisition for new coal projects and the policy for compensating and resettling those who lose land. The bill is closer in substance to Q10, and the similarity measures reflect that. For Q10, $sim(q, b) = 0.537$, compared with 0.527 for Q257, a difference of 0.010, or about 1.9 percent relative to Q257. In substantive terms, this difference corresponds to a shift within coal policy away from land acquisition for new projects and towards rehabilitation in existing coalfields. This is the kind of policy shift captured by our $sim(q, b)$ estimates.

Questions on Juvenile Justice. Figure B.7 compares two questions on juvenile justice with the *Juvenile Justice (Care and Protection of Children) Bill, 2014*. Q346 asks whether the government plans to lower the age at which juveniles can receive adult penalties and about the status of consultations and draft amendments. Q477 asks about recent trends in juvenile crime, including state-wise numbers and the reasons for any increase. The bill, which among other provisions allows 16–18 year olds to be tried as adults for certain serious offences, is substantively closer to Q346. $sim(q, b)$ equals 0.685 for Q346 and 0.677 for Q477, a difference of 0.008, or about 1.2 percent relative to Q477. Again, this difference reflects the kind of within-issue policy shift that our estimates suggest oral take-up can induce: from tracking patterns of juvenile crime to defining the penalties juveniles may face.

Heterogeneity of Effects. Tables A.9–A.11 examine whether the bill-content effects are concentrated in particular parliamentary terms, member types, or Question Hour attendance patterns.

Table A.9 first allows the effect of oral take-up to vary across Lok Sabha terms. For phrase overlap, the estimates are similar across terms. The omitted category is the 15th Lok Sabha, where the controlled estimate is 0.0739 standard deviations; the interactions for the 16th and 17th Lok Sabhas are negative but small and statistically insignificant. For semantic similarity, the controlled estimate for the 15th Lok Sabha is 0.0463 standard deviations, while the interaction with the 17th Lok Sabha is positive and statistically significant, implying a larger semantic effect in that term. This suggests that the strength of the semantic response may vary over time, although the broader evidence does not indicate that the main result is driven by a single term.

Table A.10 examines heterogeneity by member characteristics. Most interaction terms are statistically insignificant, including those for gender, caste, incumbency, education, close elections, vote share, and opposition status. The absence of strong demographic or electoral gradients suggests that the content effect is not concentrated among a narrow class of members. The significant interactions that do appear are concentrated mainly in the phrase-overlap outcome. Phrase overlap is larger for Muslim members and members of state parties, and smaller for Hindu members, national-party members, and members of the winning coalition. These patterns indicate some variation in the extent to which subsequent bills reuse the specific language of orally answered questions. By contrast, semantic similarity exhibits fewer significant interactions. The clearest exception is political experience: the interaction is positive for both elections contested and Lok Sabha terms served. This pattern suggests that more experienced members may be more effective at raising oral questions whose substance, rather than exact wording, is reflected in subsequent bill content.

Table A.11 asks whether the effect depends on the composition of Question Hour attendance. This exercise tests whether oral questions matter more when particular groups are present in the chamber. Interactions with total attendance, BJP attendance, INC attendance, and most demographic attendance measures are small and statistically insignificant.

6.2 Policymaking in Committees

Bills are our main policy outcome, but policymaking also occurs through other parliamentary channels. Review committees—the department-related standing committees described in Section 2.2—are one such channel: they examine issues within their ministries and make policy recommendations to the government. These recommendations can concern, for example, changes in government schemes, im-

plementation rules, budgets, or the delivery of public services. They are not merely advisory statements in the parliamentary record; the government is required to respond to them and report the action it has taken. Review committee recommendations therefore provide a second policy outcome, allowing us to study whether oral questions affect government policies beyond laws. This section asks whether issues raised in orally answered questions appear more often in subsequent review committee recommendations, and whether recommendations closer in content to oral questions are more likely to be acted on by the government.

Review Committee Recommendations. Columns (1)–(4) of Table IV show that oral take-up causes review committee recommendations issued after the question to focus more closely on the issue raised in the submitted question. For the phrase-based measure, the OLS estimates are 0.0906 standard deviations without controls and 0.0846 standard deviations with controls. The corresponding IV estimates are larger, at 0.128 and 0.116 standard deviations. For the semantic-similarity measure, the OLS estimates are 0.0722 and 0.0686 standard deviations, while the IV estimates are 0.0904 and 0.0833 standard deviations. All estimates are positive and statistically significant, indicating that when a question is taken up orally, review committees are more likely to subsequently make recommendations that address the same substantive issue.

Table A.12 reports the corresponding effects in raw units. Relative to the written-question mean, oral take-up increases phrase overlap between the question and subsequent review committee recommendations by 7.0 percent and semantic similarity by 0.86 percent in the controlled specification. The effects are also persistent across post-question windows. Table A.13 shows positive and statistically significant estimates within 90, 180, 270, and 360 days, indicating that orally raised issues continue to appear in review committee recommendations for up to a year after Question Hour.

Government Action on Committee Recommendations. Orally raised issues are not only more likely to appear in subsequent review committee recommendations; the government is also more likely to act on them. Table V shows that the government implements policies that are more closely aligned with the issues raised in oral questions. Columns (1)–(2) show effects of about 0.07 standard deviations for the phrase-based measure, with corresponding IV estimates of 0.08–0.09 standard deviations. Columns (3)–(4) show similar results for the semantic-similarity measure: the OLS estimates are about 0.06 standard deviations, while the IV estimates are around 0.08–0.09 standard deviations. These results indicate that issues raised orally are more likely to translate into subsequent government action.

TABLE IV: *Effect of Oral Questions on Review Committee Recommendations*

	PhraseRC		SBERTRC	
	(1)	(2)	(3)	(4)
Oral	0.0906***	0.0846***	0.0722***	0.0686***
	(0.0216)	(0.0216)	(0.0208)	(0.0207)
$\widehat{\text{Oral}}$	0.128***	0.116***	0.0904***	0.0833**
	(0.0338)	(0.0335)	(0.0326)	(0.0325)
First stage: Rank	−0.0349***	−0.0349***	−0.0349***	−0.0349***
	(0.000868)	(0.000869)	(0.000868)	(0.000869)
First-stage *F*-statistic	1,587.8	1,583.6	1,587.8	1,583.6
Controls	No	Yes	No	Yes
Observations	16,961	16,961	16,961	16,961

Notes: The table reports OLS estimates from Equation 1 and 2SLS estimates from Equation 3. The outcomes measure similarity between the submitted question text and review committee recommendations. PhraseRC is based on phrase matches with review committee recommendations, while SBERTRC is based on semantic similarity with review committee recommendations. The row labelled Oral reports OLS estimates. Both outcomes are top-coded at the 99th percentile and standardised to have mean zero and standard deviation one over the full sample of starred question–review committee recommendation pairs. The row labelled $\widehat{\text{Oral}}$ reports 2SLS estimates, instrumenting oral take-up with ballot rank. The first-stage row reports the effect of ballot rank on oral take-up. Columns (1) and (3) include sitting-day and ministry fixed effects. Columns (2) and (4) additionally include controls for the submitting members' coalition status, religion, caste, and gender composition. Standard errors, clustered by sitting day, are reported in parentheses. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

The *Action-Taken Reports* record whether the government accepted a recommendation and reported taking action, but they do not by themselves establish whether the action was implemented in practice. We therefore validate implementation for all recommendations that the reports classify as accepted and acted upon. For each case, we look for external evidence of a corresponding policy or administrative measure and code whether such evidence can be identified.[15] We find external evidence of a concrete implementing measure in 76.87% of accepted-and-acted-upon recommendations. This validation exercise indicates that the actions recorded in the reports generally correspond to observable policy changes, rather than merely rhetorical responses.

The effects in Table V may reflect two channels. First, as Table IV shows, oral questions shape the recommendations that committees subsequently make. If the government accepts a relatively stable

[15]For each recommendation in the *Action-Taken Reports* that is recorded as accepted by the government and accompanied by a stated action, we search for external corroborating evidence in: (i) government notifications, circulars, and budget documents; (ii) press releases and information on relevant ministry or agency websites; (iii) parliamentary questions and debates; and, where necessary, (iv) reports from major news outlets. We code a recommendation as implemented if we identify at least one specific administrative or policy measure that plausibly corresponds to the action recorded in the report, such as the launch of a scheme, the issuance of new guidelines, or a change in budgetary allocations. If no such measure can be identified, we code the case as having no external evidence of implementation. We use a standardised GPT-4o prompt to search for and summarise these sources.

TABLE V: *Effect of Oral Questions on Government Acceptance*

	PhraseGovAcc		SBERTGovAcc	
	(1)	(2)	(3)	(4)
Oral	0.0747***	0.0695***	0.0648***	0.0616***
	(0.0213)	(0.0213)	(0.0207)	(0.0206)
$\widehat{\text{Oral}}$	0.0904***	0.0808**	0.0901***	0.0835**
	(0.0333)	(0.0331)	(0.0332)	(0.0331)
First stage: Rank	−0.0349***	−0.0349***	−0.0349***	−0.0349***
	(0.000868)	(0.000869)	(0.000868)	(0.000869)
First-stage *F*-statistic	1,605.6	1,601.1	1,605.6	1,601.1
Controls	No	Yes	No	Yes
Observations	16,941	16,941	16,941	16,941

Notes: The table reports OLS estimates from Equation 1 and 2SLS estimates from Equation 3. The outcomes measure similarity between the submitted question text and government acceptance of review committee recommendations. PhraseGovAcc is based on phrase matches, while SBERTGovAcc is based on semantic similarity. Both outcomes are top-coded at the 99th percentile and standardised to have mean zero and standard deviation one over the full sample of starred question–government-accepted recommendation pairs. The row labelled Oral reports OLS estimates. The row labelled $\widehat{\text{Oral}}$ reports 2SLS estimates, instrumenting oral take-up with ballot rank. The first-stage row reports the effect of ballot rank on oral take-up. Columns (1) and (3) include sitting-day and ministry fixed effects. Columns (2) and (4) additionally include controls for the submitting members' coalition status, religion, caste, and gender composition. Standard errors, clustered by sitting day, are reported in parentheses. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

share of committee recommendations, government actions will then appear closer to oral questions because the recommendations themselves have moved closer to those questions. Second, oral questions may affect which recommendations the government chooses to implement, even holding fixed the set of recommendations available to it. To isolate this second channel, we re-estimate the question-level specification using only *Action-Taken Reports* that refer to recommendations issued before the question was asked. These cases account for 15.34 percent of the sample. Because these recommendations predate the question, they could not have been shaped by the question itself. Table A.14 shows that the coefficients remain positive and statistically significant. This indicates that the relationship between oral questions and government action is not driven solely by questions changing committee recommendations. Even among pre-existing recommendations, the government is more likely to implement policies that are closer to issues raised in oral questions. Question Hour therefore appears to shape both what committees recommend and which recommendations the government acts on.

Heterogeneity of Effects. Tables A.15–A.17 and Tables A.18–A.20 show limited systematic heterogeneity in the oral-question effect. For review committees, Table A.15 shows a positive and statistically sig-

nificant baseline effect in the 15th Lok Sabha for both PhraseRC and SBERTRC, with little evidence of consistent term-level variation, except for a weaker phrase-based effect in the 17th Lok Sabha. Table A.16 similarly shows that most interactions across MP characteristics are statistically indistinguishable from zero; the clearest exception is the negative interaction for female members. Table A.17 also provides little evidence that attendance composition systematically moderates the effect, with the few significant interactions appearing only for PhraseRC.

The government-accepted text results follow a similar pattern. Table A.18 shows a positive baseline effect in the 15th Lok Sabha, especially for PhraseGovAcc, but the Lok Sabha interactions are not statistically significant. Table A.19 indicates that most demographic, electoral, party, and coalition interactions are small and imprecisely estimated, again with a negative interaction for female members and some evidence that the effect declines with education. Table A.20 shows little systematic moderation by daily attendance composition; as with review committees, the significant attendance interaction is concentrated in PhraseGovAcc rather than SBERTGovAcc.

7 Mechanisms

The results above show that oral questions have greater downstream policy relevance than otherwise comparable written questions. Orally asked issues are more closely reflected in subsequent bills, in policy recommendations made by review committees, and in the government's implementation of those recommendations. In this section, we explore why.

Two features distinguish oral questions from written questions. First, because oral questions are asked on the floor and televised, they make the issue visible beyond the questioner and the relevant ministry, thereby increasing political accountability. Second, oral questioning permits follow-up questions, objections, justifications, and alternative proposals. This deliberative exchange generates additional information about the policy issue, including the government's reasoning, legislators' concerns, and potential policy alternatives. Together, these accountability and information channels may shape policy outcomes. Section 7.1 provides evidence that oral questions receive greater public exposure. Section 7.2 shows how deliberation adds information that subsequently informs policy outcomes.

7.1 Public Exposure

Public visibility raises the political cost of ignoring policy issues (Snyder Jr and Strömberg, 2010; Besley and Burgess, 2001; Ferraz and Finan, 2008; Strömberg, 2015); the greater exposure of oral questions may

therefore lead larger effects on policy. Oral questions are broadcast live with reporters in the gallery, enabling immediate coverage, whereas written questions are posted on the government website without a live exchange or video and with a one-day delay. We provide several pieces of evidence that oral questions receive greater public exposure than written questions.

YouTube Viewership. People engage with Question Hour broadcasts. While we do not observe Sansad TV viewership directly, YouTube uploads of these broadcasts receive substantial viewership. We scrape 97 Question Hour streams posted on the official Sansad TV YouTube channel from 29 November 2021 to 10 February 2024. These videos average 8,646 views, with view counts ranging from 465 to 90,946.[16] The average stream lasts 40.6 minutes, which translates to roughly 213 views per minute of content and about 5,800 viewer-hours per session on YouTube alone. Streams also average 103 likes and 14 comments.

Times of India Coverage. Questions may also gain public exposure through newspaper coverage. Although only oral questions are broadcast live, both oral and written questions can be covered when their content is newsworthy. We therefore examine follow-on coverage in the *Times of India* in Table VI. We estimate Equations 1 and 3 using PhraseNews and SBERTNews measures of *Times of India* coverage within 28 days of a question. The OLS estimates show that oral questions increase PhraseNews by 0.037–0.045 standard deviations and SBERTNews by 0.062–0.066 standard deviations. The 2SLS estimates are larger: oral questions increase PhraseNews by 0.066–0.083 standard deviations and SBERTNews by 0.083–0.092 standard deviations. The estimates are similar across specifications with and without controls, indicating that oral questions receive more subsequent newspaper coverage than comparable written questions. Table A.21 then decomposes the effect across post-question windows. For PhraseNews, the estimates are largest in the first two weeks and decline slightly as the window expands to 28 days. For SBERTNews, the estimates remain positive and stable across the 7-, 14-, 21-, and 28-day windows.

To interpret these magnitudes in levels, Table A.22 reports estimates using the raw outcomes. Mean coverage for written questions is positive: 71.07 for PhraseNews and 0.255 for SBERTNews. However, oral questions receive additional coverage relative to these baselines, increasing PhraseNews by about 2.9 percent, and SBERTNews by about 1 percent. These effects are not negligible relative to media responses in related work. In Madestam et al. (2013), rainfall reduces local newspaper coverage of Tea Party rallies by 20–25 percent of mean coverage; the oral-question effect on PhraseNews is about one-

[16]Since 29 November 2021, Parliament has posted Sansad TV live streams of Question Hour to its YouTube channel. We scrape all YouTube metrics from the Sansad TV channel's playlists page on 17 April 2025: https://www.youtube.com/@SansadTV/playlists.

TABLE VI: *Effect of Oral Questions on News Coverage*

	PhraseNews		SBERTNews	
	(1)	(2)	(3)	(4)
Oral	0.0454*	0.0370	0.0660***	0.0619***
	(0.0239)	(0.0236)	(0.0223)	(0.0222)
$\widehat{\text{Oral}}$	0.0825**	0.0659*	0.0924***	0.0831**
	(0.0353)	(0.0346)	(0.0339)	(0.0337)
First stage: Rank	−0.0349***	−0.0349***	−0.0349***	−0.0349***
	(0.000868)	(0.000869)	(0.000868)	(0.000869)
First-stage *F*-statistic	1,590.9	1,587.5	1,590.9	1,587.5
Controls	No	Yes	No	Yes
Observations	16,949	16,949	16,949	16,949

Notes: The table reports OLS estimates from Equation 1 and 2SLS estimates from Equation 3. The outcomes measure *Times of India* coverage linked to the submitted question within 28 days. PhraseNews is based on phrase matches, while SBERTNews is based on semantic similarity. The row labelled Oral reports OLS estimates. Both outcomes are top-coded at the 99th percentile and standardised to have mean zero and standard deviation one over the full sample of starred question–Times of India article pairs. The row labelled $\widehat{\text{Oral}}$ reports 2SLS estimates, instrumenting oral take-up with ballot rank. The first-stage row reports the effect of ballot rank on oral take-up. Columns (1) and (3) include sitting-day and ministry fixed effects; columns (2) and (4) additionally include controls for the submitting members' coalition status, religion, caste, and gender composition. Standard errors, clustered by sitting day, are reported in parentheses. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

eighth of that response. In Di Tella and Franceschelli (2011), a one-standard-deviation increase in government advertising reduces corruption coverage by 18 percent of a standard deviation; our standardised estimates are roughly one-fifth to one-third as large. Thus, oral questions receive more newspaper exposure than written questions by an amount that is meaningful relative to established media-response benchmarks.

Figure B.8 plots binned correlations between *Times of India* coverage and policy-text similarity, separately for oral and written questions, while Figure B.9 plots the corresponding relationships with the full set of controls from Equation 1. The relationship is positive in all panels: questions that receive more newspaper coverage are also more closely reflected in subsequent bills, review committee recommendations, and policies implemented by the government. The slopes are similar across formats, indicating that the news-to-policy gradient is not specific to oral questions. If anything, the fitted slopes are somewhat steeper for written questions in most specifications. This pattern is consistent with selection into coverage: because written questions are not broadcast and are less visible by design, those that attract newspaper attention are likely to concern issues that are especially policy-relevant.

Selection into coverage also makes the coverage–policy relationship for oral questions difficult to interpret causally: questions that attract attention may differ from others in ways that independently

affect policy. Using severe terrorist attacks outside India as shocks to news attention and media coverage allows us to separate the role of coverage from the newsworthiness of the question itself. An attack on the day after a question is asked arrives after the oral exchange has taken place but while the question is still in the news cycle, and can crowd the question out of subsequent coverage or otherwise reduce attention it. Because *Starred* questions are submitted, and the ballot is held, fifteen days before the sitting, question content and oral status are fixed before any attack occurs.

We define $\text{Shock}_d^S = 1$ if terrorist attacks outside India on day d collectively wound more than 50 people, the median of the daily total-wounded distribution across attack-days in the Global Terrorism Database (January 2009–June 2021); each question asked on day d is matched to Shock_{d+1}^S. Attacks occur on all but seventeen days in this window, so the relevant variation is the severity of the day's attacks rather than whether one occurred; 364 of the 732 sitting days within the database's coverage are followed by a shock day. Among orally answered questions, we then instrument a question's similarity to subsequent *Times of India* coverage with Shock_{d+1}^S and estimate its effect on the question's similarity to subsequent bills. The shock varies only across sitting days, so we replace day fixed effects with 15-day submission-window fixed effects and cluster standard errors by window. The estimation sample contains the 2,236 orally answered questions on sitting days within the database's coverage. Appendix Figure B.10 shows that the number of oral questions, their overlap with attack-related vocabulary, and bill introductions in the most exposed ministries do not change around severe attacks.

Among orally answered questions, an attack on the following day reduces a question's semantic similarity to subsequent *Times of India* coverage by 0.19 standard deviations (Table A.23). Using the shock as an instrument, the 2SLS estimate implies that a one-standard-deviation increase in news similarity raises subsequent bill similarity by 0.65 standard deviations; the weak-instrument-robust Anderson–Rubin test rejects a zero effect ($p = 0.02$). We regard this evidence as suggestive rather than conclusive. The effective first-stage F-statistic is only about ten, and the instrument has no power for the phrase-based measures. With those caveats, the pattern is consistent with press coverage helping, at least partly, to transmit orally raised issues into subsequent legislation.

7.2 Deliberation

Oral questions may affect policy differently because they expand the information available to policy-makers. Unlike written questions, oral questions generate exchanges between legislators and ministers in which participants can introduce facts, constraints, and alternative policy responses beyond those contained in the submitted question or answer. These exchanges enlarge the information set around an

TABLE VII: *Oral Questions, Deliberation Text, and Bill Outcomes*

	PhraseBill		SBERTBill		SBERTBill (Max)	
	(1)	(2)	(3)	(4)	(5)	(6)
Oral	1.873***	1.872***	−0.293***	−0.297***	0.179***	0.177***
	(0.0475)	(0.0475)	(0.0195)	(0.0195)	(0.0209)	(0.0210)
$\widehat{\text{Oral}}$	1.959***	1.956***	−0.279***	−0.286***	0.176***	0.172***
	(0.0487)	(0.0486)	(0.0333)	(0.0333)	(0.0333)	(0.0333)
First-stage F-statistic	1,529.5	1,526.8	1,529.5	1,526.8	1,529.5	1,526.8
Controls	No	Yes	No	Yes	No	Yes
Observations	16,743	16,743	16,743	16,743	16,743	16,743

Notes: The table reports OLS estimates from Equation 1 and 2SLS estimates from Equation 3. The outcomes measure overlap between parliamentary questions and subsequent bill text. For oral questions, the text is expanded to include the full floor exchange; written questions are measured using the submitted question and answer. PhraseBill is based on exact phrase matches. SBERTBill is based on average semantic similarity. SBERTBill (Max) records the closest semantic match between any statement in the exchange and any bill introduced within 360 days. The row labelled Oral reports OLS estimates. The underlying phrase- and SBERT-based measures are each top-coded at the 99th percentile before being combined into the outcomes above; the combined outcomes are then standardised to have mean zero and standard deviation one over the full sample of starred question–bill pairs. The row labelled $\widehat{\text{Oral}}$ reports 2SLS estimates, instrumenting oral take-up with ballot rank. Columns (1), (3), and (5) include sitting-day and ministry fixed effects; columns (2), (4), and (6) additionally include controls for the submitting members' coalition status, religion, caste, and gender composition. Standard errors, clustered by sitting day, are reported in parentheses. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

issue, increasing the likelihood that ideas or language from the discussion are reflected in subsequent policy.

We test this channel by asking whether issues discussed during oral exchanges are reflected in subsequent bills. In Table VII, we expand the text of oral questions to include the full floor exchange, while written questions continue to be measured using only the submitted question and answer. Columns (1)–(2) report phrase-overlap estimates. These estimates rise sharply: the OLS coefficients are 1.872–1.873 standard deviations, and the IV coefficients are 1.956–1.959 standard deviations. Part of this increase is mechanical, since longer text creates more opportunities for exact phrase matches. Nevertheless, the results show that phrases introduced during oral deliberation subsequently appear in bill text.

Columns (3)–(4) report mean semantic similarity. The estimates are negative for oral questions. The OLS coefficients range from -0.297 to -0.293 standard deviations, while the IV coefficients range from -0.286 to -0.279 standard deviations. This may reflect disagreement surfaced during oral exchanges, though it could also reflect the breadth of topics raised across a multi-speaker floor discussion relative to a single written question. For this reason, Columns (5)–(6) report a maximum SBERT measure. This measure replaces average similarity with the closest semantic match between the oral exchange and subsequent bill text. For each question, it records the highest similarity between any intervention made

during the exchange and any bill introduced within 360 days. The coefficients are positive. The OLS estimates range from 0.177 to 0.179 standard deviations, while the IV estimates range from 0.172 to 0.176 standard deviations. This reflects that the closest-matching statement in the exchange is more similar to subsequent legislative language than the exchange is on average, even though the exchange as a whole is less aligned with it.

8 Alternative Mechanisms

The interpretation of our results is that deliberation under public scrutiny affects subsequent legislative activity. Oral questions generate a quasi-random opportunity for real-time exchange on the floor, which receives public exposure and in turn shapes downstream policymaking. In this section we consider alternative mechanisms that could instead account for the estimated oral–written differences, and present evidence that they are unlikely to drive the results. In particular, we examine whether the effects are explained by the types of members who obtain oral questions, by strategic timing around elections, by persistent changes in members' own engagement following public exposure, or by outcomes that are narrowly concentrated on the original questioner.

Member Identity and Selection. A first concern is that our findings might reflect who participates in Question Hour rather than the effect of deliberation itself. While the ballot procedure implies that, conditional on submitting a *Starred* question, assignment to oral versus written answer is quasi-random, participation at this extensive margin is not random. If only a narrow set of especially prominent, connected, or effective members made use of *Starred* questions, the estimated effects could be driven by this selective group and would have limited external validity. Table A.2 addresses this concern by documenting which members submit *Starred* questions. Participation in Question Hour is widespread across observable characteristics: the share of members who ever submit a *Starred* question, their participation rates, and the average number of questions per participating member are broadly similar across gender, caste, religious groups and education levels. No category is systematically excluded from the pool of questioners.

Even if participation and assignment are not strongly selective, one might still worry that the oral advantage is concentrated among a particular subset of members, for example opposition members or those from very competitive constituencies, so that our estimates would not capture a general relationship between deliberation and lawmaking. Table A.10 examines this possibility by allowing the oral

effect on question–bill similarity to vary with member characteristics. We interact the oral indicator with gender, caste, religion, coalition status, party type, incumbency, vote share, electoral margin, and the number of elections contested. Across these dimensions, the interaction coefficients are small and imprecisely estimated, and joint tests do not reject the null hypothesis of homogeneous effects. The main oral coefficient remains positive and of similar magnitude to the baseline in all cases. Taken together, the participation patterns, and heterogeneity results indicate that our findings are not driven by a narrow set of members, but instead reflect a broadly shared effect of deliberative opportunity across different types of legislators.

Timing around Elections. A second potential mechanism is that the oral advantage reflects electoral incentives on the government side: if governments are more responsive to parliamentary scrutiny as elections approach, the oral effect should be larger closer to elections. In Table A.24, the baseline oral coefficients remain around 0.05–0.06 standard deviations for both similarity measures, while the interaction terms imply a slightly smaller oral–written gap as the next election nears and a larger gap further from elections, particularly for SBERT similarity. The magnitudes are modest, and the pattern points to a mild attenuation rather than an amplification of the oral effect in high-electoral-salience periods, suggesting that election-cycle shifts in government responsiveness are unlikely to be the primary mechanism.

Behavioural Responses. A third mechanism is that public exposure during Question Hour might change the behaviour of the members who obtain oral questions, independently of the deliberative content of the exchange. A televised appearance on the floor may raise a member's confidence, perceived influence, or reputation inside and outside Parliament (Kumar et al., 2024), increasing the expected return to further effort on that issue. In that case, the oral–written difference could arise because exposed members push their agenda more in subsequent stages of the process, for example by investing more time in follow-up questions, amendments, informal lobbying, or participation in debate, rather than because deliberation during Question Hour changes how the broader legislature treats the issue. To assess this channel, we examine whether oral exposure predicts a general increase in parliamentary activity by the questioning member. Table A.25 reports member-day level estimates of the effect of having a question answered orally on four outcomes: attendance in the chamber, the number of questions submitted, the number of days on which the member speaks in debate, and the number of speeches per sitting day. All specifications include the same set of controls as in the main regressions. Across all outcomes, the es-

timated coefficients are small and statistically indistinguishable from zero, and the confidence intervals rule out even modest increases in average participation.

Individual Agenda-Pushing. A fourth concern is that any apparent effect of deliberation could be confined to the questioning member alone, for example if a member who receives an oral answer simply raises the same issue again in their own subsequent questions, without the topic diffusing more broadly to other members, states, or parties. If so, the results would reflect individual agenda persistence rather than a genuine effect of public deliberation on the wider legislative process. Figure B.11 speaks to this concern using a related measure: phrase overlap between each question and future questions submitted within 30 days, comparing (i) the same MP to a different MP, (ii) the same state to a different state, and (iii) the same party to a different party. If the persistence we document reflected narrow, questioner-specific repetition, overlap should be systematically higher in each "same" category than in the corresponding "different" category. Instead, all six point estimates are small and statistically indistinguishable from zero, and none of the "same" categories exceeds its "different" counterpart. This pattern is inconsistent with a story in which subsequent legislative engagement is concentrated on the original questioner.

9 Conclusion

This paper asks whether deliberation under public scrutiny—the oral, televised exchange of Question Hour—is reflected in subsequent policymaking. We address this question using new data from the Indian Parliament that link the full universe of *Starred* parliamentary questions to subsequent bill texts, committee reports, floor debates, and contemporaneous newspaper coverage. The institutional design of Question Hour assigns questions quasi-randomly to oral answers on the floor or written answers off the floor, generating plausibly exogenous variation in opportunities for real-time, televised deliberation.

Our results show that questions that receive an oral answer are followed by legislation that more closely engages with the issues raised, as captured by both phrase-level overlap and SBERT-based semantic similarity between questions and later bills. The same pattern appears in committee recommendations and in the recommendations the government acts on. Oral questions receive greater public exposure: Question Hour broadcasts attract substantial viewership, and oral questions receive more subsequent newspaper coverage than comparable written questions. Terror shocks that arrive after the exchange has taken place and crowd questions out of the news cycle provide suggestive evidence that

coverage itself carries questions into subsequent legislation. The floor exchange also generates statements, objections, and alternatives that did not exist in the submitted question; patterns in the data are consistent with this material being reflected in later bills. Understanding how deliberative exchange produces its effects—which features of the exchange matter, and how much of the advantage each channel accounts for—is an important avenue for future work.

Taken together, the results suggest that deliberation matters for policy outcomes, and that public exposure is one of the channels through which it does so. The mechanisms we study are unlikely to be unique to India: parliamentary democracies more broadly institutionalise deliberation through question periods, floor debates, and committee hearings (Salmond, 2014; Gennaro and Ash, 2023; Hansen et al., 2018; Canen and Iaryczower, 2024). At the same time, these deliberative institutions appear to be weakening. According to V-Dem, 57.63% of countries have experienced declines in deliberative indicators between 2000 and 2025. If deliberation affects policy choices in the way our evidence suggests, the erosion of such practices is not only a change in parliamentary procedure, but a shift in the channels through which democratic societies aggregate information and enact policies.

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A Appendix Tables

TABLE *A.1: Summary Statistics for Starred Questions*

	LS 15	LS 16	LS 17	All
Sittings	324	321	234	879
Starred questions	6,430	6,354	4,637	17,421
Members submitting questions	431	455	457	1,057
Ministries receiving questions	50	53	54	58
Questions answered orally	647	1,177	1,206	3,030
Oral questions with floor exchanges	627	1,162	1,102	2,891
Speeches per oral question	20.16	13.69	11.06	14.09
Speakers per oral question	6.31	6.03	5.07	5.73

Notes: The table reports summary statistics for *Starred* questions admitted to Question Hour in the 15th, 16th, and 17th Lok Sabha. Oral questions are those answered on the floor; floor exchanges are the subset for which the corresponding debate transcript is available. Speeches and speakers per oral question are computed for this subset.

TABLE *A.2: Member Characteristics in Admitted Starred Questions*

	Share of MPs (%)			Participation Rate (%)			Average Questions		
	LS 15	LS 16	LS 17	LS 15	LS 16	LS 17	LS 15	LS 16	LS 17
Female	11.09	11.75	14.65	72.58	76.12	87.65	13.98	15.76	11.28
Religion: Christian	1.97	1.23	1.27	81.82	100.00	100.00	20.64	21.00	16.43
Religion: Hindu	92.31	92.98	93.13	76.55	77.36	81.75	19.21	16.27	11.58
Religion: Muslim	4.11	4.04	3.98	78.26	78.26	81.82	13.13	11.57	9.73
Religion: Sikh	1.61	1.93	1.63	100.00	100.00	100.00	16.44	11.00	7.11
Caste: General	74.78	71.93	60.04	77.03	79.51	82.23	19.79	17.59	11.97
Caste: Scheduled Caste	15.38	15.26	15.91	80.23	79.31	84.09	17.94	13.41	10.99
Caste: Scheduled Tribe	9.66	9.65	9.40	74.07	72.73	76.92	14.37	13.60	9.56
Education: Illiterate	0.18	0.18	0.18	0.00	100.00	0.00	0.00	30.00	0.00
Education: Primary	3.94	3.51	3.07	77.27	70.00	64.71	14.05	12.50	9.59
Education: Secondary	17.53	18.60	20.25	83.67	83.02	79.46	20.38	16.92	10.76
Education: Graduate	43.11	39.30	42.13	81.74	75.45	82.40	20.44	16.34	11.10
Education: Postgraduate	27.01	31.58	28.39	73.51	82.78	85.35	19.31	17.32	13.11
Coalition: Winning	47.76	61.40	60.76	64.42	77.14	79.46	13.80	15.64	10.71
Coalition: Opposition	25.22	11.93	17.36	91.49	79.41	92.71	23.81	19.88	13.57
Party: National	62.08	59.82	64.74	76.66	77.71	80.45	17.47	15.32	10.44
Party: State-Based	34.88	37.54	31.46	78.46	78.97	86.21	22.37	17.58	14.11
Party: Local	1.43	1.40	1.27	62.50	87.50	42.86	7.88	16.63	6.43
Party: Independent	1.61	0.53	0.72	77.78	66.67	100.00	11.56	11.67	13.00
Incumbent	30.77	29.30	40.87	66.86	74.25	74.78	19.48	18.14	12.00
Majority Winner	23.08	38.42	62.39	70.54	77.63	80.58	17.41	15.19	11.29
Close Race Winner (5%)	36.14	17.72	18.08	80.69	78.22	86.00	20.59	17.23	11.73

Notes: The table reports member-level summary statistics for admitted *Starred* questions in the 15th, 16th, and 17th Lok Sabha. We refer to a member as participating if the member has at least one admitted *Starred* question; the data do not observe all questions initially submitted or questions rejected at the admissibility stage. 'Share of MPs' gives the percentage of members in each group. 'Participation rate' gives the percentage of members in that group with at least one admitted *Starred* question. 'Average questions' is computed among participating members. Member groups are defined by demographics, education, party type, coalition status, incumbency, and electoral competitiveness.

TABLE *A.3: Summary Statistics: Bills*

	All Bills	Bills in Questions
Total bills	884	190
Total ministries	53	26
Amendment bills (%)	63.01	63.16
Stages per bill	3.41	3.49
Bills reviewed by committee (%)	40.84	37.37
Bills passed (%)	74.89	80.53
Bills rejected (%)	7.35	6.32
Bills ongoing (%)	14.82	11.58
Duration to passage	226.79	215.61
Duration to rejection	1545.19	611.64
Duration to passage, if reviewed	586.69	565.51
Duration to rejection, if reviewed	1665.49	796.88
Duration from introduction to review	23.89	19.87
Duration under review	211.41	262.73
Duration from report to final outcome	650.49	355.79

Notes: The table reports summary statistics for government bills in the Indian Parliament. The sample includes bills observed between 24 April 2000 and 1 April 2026, including bills already under consideration at the start of the period, bills introduced during the period, and bills still ongoing at the end of the period. The first column reports statistics for all bills in the dataset. The second column restricts the sample to bills referenced in *Starred* questions during Question Hour in the 15th, 16th, and 17th Lok Sabha. Duration measures are reported in days.

TABLE *A.4: Summary Statistics for Department-Related Standing Committee Reports*

	LS 15	LS 16	LS 17	All
Total reports	913	1,049	954	2,916
Overview reports	495	554	497	1,546
Action-Taken Reports	418	495	457	1,370
Recommendations per *Action-Taken Report*	23.80	19.41	18.98	20.61
Accepted recommendations per *Action-Taken Report*	10.85	9.82	10.51	10.37

Notes: The table reports summary statistics for department-related standing committee reports in the 15th, 16th, and 17th Lok Sabha. Total reports combines initial overview reports and *Action-Taken Reports*, including follow-up action-taken reports. Overview reports set out the committee's findings and recommendations on a subject. *Action-Taken Reports* record the government's replies to those recommendations and the committee's assessment of the action taken. The last two rows report averages across *Action-Taken Reports*. Accepted recommendations are coded from the committee's classification of recommendations accepted by the government.

TABLE *A.5: Exclusion Restriction Diagnostics by Oral Status*

	PhraseBill	SBERTBill	PhraseRC	SBERTRC
	(1)	(2)	(3)	(4)
(A) Oral Sample				
Rank	0.007	0.002	−0.003	−0.003
	(0.009)	(0.007)	(0.007)	(0.007)
Observations	2,966	2,966	2,946	2,946
(B) Written Sample				
Rank	−0.000	−0.000	−0.002	−0.001
	(0.002)	(0.002)	(0.002)	(0.002)
Observations	13,990	13,990	14,008	14,008
Controls	No	No	No	No

Notes: The table reports placebo tests for the effect of ballot rank on post-question policy outcomes. For each outcome, we estimate $Y_{qd} = \phi_d + \lambda_m + \beta\,\text{Rank}_{qd} + \varepsilon_{qd}$, separately in the oral and written samples, where ϕ_d denotes sitting-day fixed effects and λ_m denotes ministry fixed effects. Panel (A) reports estimates from the oral sample; Panel (B) reports estimates from the written sample. The coefficient reported is β. Standard errors are clustered by sitting day. Phrase outcomes measure textual overlap, while SBERT outcomes measure average semantic similarity. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

TABLE *A.6: Effect of Oral Questions on Raw Bill Outcomes*

	PhraseBill		SBERTBill	
	(1)	(2)	(3)	(4)
Oral	0.147***	0.141***	0.00244**	0.00231**
	(0.0491)	(0.0489)	(0.000953)	(0.000952)
Mean D.V.	1.503	1.503	0.297	0.297
Controls	No	Yes	No	Yes
Observations	16,964	16,964	16,964	16,964

Notes: The table reports OLS estimates of the effect of oral questions on non-standardised measures of similarity between question text and bills introduced within 360 days. PhraseBill is the number of phrase matches between the question and bill text. SBERTBill is the average semantic similarity between the question and bill text. Mean D.V. reports the mean of the dependent variable among written questions. Columns (1) and (3) include sitting-day and ministry fixed effects. Columns (2) and (4) additionally include controls for the submitting members' coalition status, religion, caste, and gender composition. Standard errors, clustered by sitting day, are reported in parentheses. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

TABLE *A.7: Effect of Oral Questions on Bill Content across Temporal Windows*

	PhraseBill				SBERTBill			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Oral	0.0223	0.0439**	0.0431*	0.0130	0.0418**	0.0368*	0.0377*	0.00725
	(0.0211)	(0.0210)	(0.0228)	(0.0208)	(0.0199)	(0.0203)	(0.0208)	(0.0219)
Mean D.V.	0.369	0.475	0.350	0.369	0.300	0.296	0.294	0.298
Time window	0–90	91–180	181–270	271–360	0–90	91–180	181–270	271–360
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	15,992	15,686	15,637	14,431	15,992	15,686	15,637	14,431

Notes: The table reports OLS estimates of the effect of oral questions on question–bill textual similarity across 90-day windows after Question Hour. Each column restricts the bill comparison to bills introduced in the listed window after the question. PhraseBill measures phrase-based textual overlap, and SBERTBill measures average semantic similarity. Outcomes are standardised. Mean D.V. reports the mean of the dependent variable among written questions. All specifications include sitting-day and ministry fixed effects, as well as controls for the submitting members' coalition status, religion, caste, and gender composition. Standard errors, clustered by sitting day, are reported in parentheses. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

TABLE *A.8: Robustness Checks for Bill and Committee Textual Outcomes*

Robustness Check	PhraseBill (1)	SBERTBill (2)	PhraseRC (3)	SBERTRC (4)
Volume Restrictions				
Exclude high-volume days	0.0555**	0.0404*	0.0873***	0.0627***
	(0.0220)	(0.0225)	(0.0241)	(0.0230)
Exclude low-volume days	0.0579***	0.0485**	0.0846***	0.0685***
	(0.0201)	(0.0202)	(0.0216)	(0.0207)
Outlier Treatment				
Drop upper outliers	0.0310**	0.0373**	0.0655***	0.0589***
	(0.0120)	(0.0189)	(0.0177)	(0.0199)
Drop lower outliers	0.0581***	0.0412**	0.0810***	0.0537***
	(0.0201)	(0.0184)	(0.0220)	(0.0180)
Winsorise upper tail	0.0473***	0.0454**	0.0782***	0.0666***
	(0.0148)	(0.0195)	(0.0194)	(0.0200)
Winsorise lower tail	0.0581***	0.0486**	0.0841***	0.0672***
	(0.0201)	(0.0190)	(0.0215)	(0.0195)
Alternative Clustering				
Date $\times$ Ministry	0.0581**	0.0489**	0.0846***	0.0686***
	(0.0231)	(0.0184)	(0.0311)	(0.0169)
Alternative Definitions				
Poisson	0.0876***	—	0.0665***	—
	(0.0291)		(0.0164)	
Negative Binomial	0.0997***	—	0.0714***	—
	(0.0298)		(0.0171)	
Fractional	0.0138***	—	0.0942***	—
	(0.00426)		(0.0320)	
Logarithmic transformation	0.0488***	—	0.0802***	—
	(0.0143)		(0.0207)	
Maximum SBERT	—	0.0603***	—	0.0981***
		(0.0208)		(0.0210)

Notes: The table reports robustness checks for the effect of oral questions on textual similarity to bills and committee recommendations. Phrase outcomes measure phrase overlap. The baseline SBERT outcomes measure average semantic similarity; the Maximum SBERT row instead uses the maximum cosine similarity between the question and the set of downstream texts within 360 days of the question. All specifications include sitting-day fixed effects and the control vector. Standard errors are clustered by sitting day unless otherwise indicated and are reported in parentheses. High- and low-volume restrictions exclude sitting days in the top and bottom 5 percent of the oral-question volume distribution, respectively. Upper- and lower-tail outlier checks drop or winsorise observations in the top and bottom 5 percent of the relevant outcome distribution, respectively. Alternative clustering uses date-by-ministry clusters. Alternative definitions apply count, fractional, logarithmic, and maximum-similarity transformations to the outcome measures. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

TABLE *A.9: Effects of Oral Questions on Bill Content by Lok Sabha Term*

	PhraseBill		SBERTBill	
	(1)	(2)	(3)	(4)
Oral	0.0771*	0.0739*	0.0493	0.0463
	(0.0398)	(0.0398)	(0.0447)	(0.0449)
Oral × LS 16	−0.0140	−0.0139	−0.0714	−0.0725
	(0.0485)	(0.0483)	(0.0549)	(0.0550)
Oral × LS 17	−0.0320	−0.0299	0.0978*	0.1000*
	(0.0563)	(0.0560)	(0.0535)	(0.0536)
Controls	No	Yes	No	Yes
Observations	16,964	16,964	16,964	16,964

Notes: The table reports OLS estimates of the effect of oral questions on standardised question–bill similarity by Lok Sabha term. The omitted category is the 15th Lok Sabha, so the coefficient on Oral gives the oral–written difference in the 15th Lok Sabha. The interaction terms report how the oral effect differs in the 16th and 17th Lok Sabhas relative to the 15th. The dependent variables are PhraseBill, a standardised phrase-overlap measure, and SBERTBill, a standardised average semantic-similarity measure. All specifications include sitting-day fixed effects. Columns (2) and (4) additionally include the control vector. Standard errors, clustered by sitting day, are reported in parentheses. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

TABLE *A.10: Heterogeneous Effect of Oral Questions on Textual Similarity to Bills*

Characteristic	Oral Coefficient		Interaction Coefficient	
	PhraseBill (1)	SBERTBill (2)	PhraseBill (3)	SBERTBill (4)
Female	0.0529**	0.0582**	−0.0192	−0.0687
	(0.0216)	(0.0236)	(0.0523)	(0.0487)
Caste: General	0.00562	0.0489	0.0575	0.00293
	(0.0392)	(0.0372)	(0.0390)	(0.0390)
Caste: Scheduled Caste	0.0584***	0.0518**	−0.0547	−0.00644
	(0.0221)	(0.0238)	(0.0469)	(0.0465)
Caste: Scheduled Tribe	0.0544**	0.0507**	−0.0486	0.00417
	(0.0222)	(0.0229)	(0.0608)	(0.0580)
Religion: Hindu	0.183**	0.0601	−0.141*	−0.00996
	(0.0793)	(0.0682)	(0.0781)	(0.0693)
Religion: Muslim	0.0427**	0.0504**	0.277**	0.0128
	(0.0214)	(0.0226)	(0.123)	(0.0947)
Religion: Sikh	0.0484**	0.0485**	0.182	0.181
	(0.0218)	(0.0227)	(0.164)	(0.146)
Religion: Christian	0.0526**	0.0530**	−0.0932	−0.110
	(0.0220)	(0.0227)	(0.111)	(0.111)
Incumbent	0.0437*	0.0448*	0.0225	0.0176
	(0.0239)	(0.0246)	(0.0341)	(0.0315)
Education	−0.0957	0.0263	0.0103	0.00185
	(0.0964)	(0.0950)	(0.00637)	(0.00617)
Close Election (5%)	0.0417*	0.0569**	0.0402	−0.0235
	(0.0233)	(0.0236)	(0.0328)	(0.0372)
Elections Contested	0.0239	0.0109	0.0121	0.0174**
	(0.0308)	(0.0292)	(0.00911)	(0.00871)
Lok Sabha Terms	0.0120	0.00862	0.0216	0.0230*
	(0.0331)	(0.0312)	(0.0135)	(0.0124)
Party Type: State	0.0240	0.0482*	0.0698**	0.00854
	(0.0249)	(0.0263)	(0.0327)	(0.0344)
Party Type: National	0.0927***	0.0548*	−0.0706**	−0.00538
	(0.0287)	(0.0304)	(0.0324)	(0.0345)
Party Type: Local	0.0501**	0.0523**	0.113	−0.0721
	(0.0217)	(0.0228)	(0.115)	(0.143)
Party Type: Independent	0.0518**	0.0515**	−0.0385	−0.000719
	(0.0218)	(0.0226)	(0.136)	(0.153)
Vote Share	0.0960	−0.0848	−0.000930	0.00285
	(0.0813)	(0.0948)	(0.00171)	(0.00194)
Coalition: Winning	0.115***	0.0550*	−0.0739**	−0.00598
	(0.0357)	(0.0315)	(0.0298)	(0.0278)
Coalition: Opposition	0.0323	0.0396	0.0542	0.0324
	(0.0245)	(0.0256)	(0.0408)	(0.0394)

Notes: The table reports OLS estimates of heterogeneity in the effect of oral questions on standardised question–bill similarity. The dependent variables are PhraseBill, a standardised phrase-overlap measure, and SBERTBill, a standardised average semantic-similarity measure. Columns (1) and (2) report the estimated oral effect for the omitted category or baseline value of the listed characteristic. Columns (3) and (4) report the interaction between Oral and the listed characteristic. Each row corresponds to a separate regression that includes Oral, the characteristic, and the interaction between the two. All specifications include sitting-day fixed effects. Standard errors, clustered by sitting day, are reported in parentheses. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

TABLE *A.11: Heterogeneous Effects by Question Hour Attendance*

Composition	Oral Coefficient		Interaction Coefficient	
	PhraseBill	SBERTBill	PhraseBill	SBERTBill
	(1)	(2)	(3)	(4)
Members Present	0.0798	0.0426	-5.17×10^{-5}	2.37×10^{-5}
	(0.198)	(0.185)	(0.000524)	(0.000485)
BJP	0.0724	0.0117	-6.99×10^{-5}	0.000227
	(0.0701)	(0.0722)	(0.000393)	(0.000382)
INC	0.0527	0.0518	0.000130	-4.42×10^{-6}
	(0.0356)	(0.0371)	(0.000507)	(0.000578)
Female	0.109	−0.0830	−0.00106	0.00289
	(0.118)	(0.103)	(0.00258)	(0.00211)
Religion: Muslim	−0.121	0.0429	0.0128*	0.000614
	(0.0971)	(0.106)	(0.00691)	(0.00735)
Religion: Christian	0.129*	0.0359	−0.0108	0.00247
	(0.0751)	(0.0835)	(0.0117)	(0.0128)
Religion: Sikh	0.102	0.179**	−0.00633	−0.0193*
	(0.0637)	(0.0771)	(0.00907)	(0.0113)
Religion: Hindu	0.0973	0.0137	−0.000106	0.000108
	(0.201)	(0.181)	(0.000575)	(0.000514)
Caste: Scheduled Caste	0.0330	0.298*	0.000433	−0.00393
	(0.174)	(0.173)	(0.00278)	(0.00276)
Caste: Scheduled Tribe	−0.0293	−0.0705	0.00249	0.00340
	(0.155)	(0.143)	(0.00433)	(0.00393)
Caste: General	0.0666	0.396***	-2.49×10^{-5}	−0.00133**
	(0.140)	(0.139)	(0.000524)	(0.000543)
Observations	16,451	16,451	16,451	16,451

Notes: The table reports OLS estimates of heterogeneity in the effect of oral questions by Question Hour attendance. The dependent variables are PhraseBill, a standardised phrase-overlap measure, and SBERTBill, a standardised average semantic-similarity measure. Attendance measures are constructed from the official Lok Sabha attendance register and count the number of MPs (or MPs from the listed subgroup) who signed in on the sitting day. Columns (1) and (2) report the oral–written difference when the attendance variable is zero. Columns (3) and (4) report the interaction between Oral and the listed attendance measure. Each row corresponds to a separate regression that includes Oral, the attendance measure, and their interaction. All specifications include sitting-day fixed effects and no additional controls. Standard errors, clustered by sitting day, are reported in parentheses. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

TABLE *A.12: Effect of Oral Questions on Review Committee Recommendations: Raw Units*

	PhraseRC		SBERTRC	
	(1)	(2)	(3)	(4)
Oral	4.861***	4.542***	0.00322***	0.00306***
	(1.159)	(1.160)	(0.000927)	(0.000925)
Mean D.V.	65.27	65.27	0.357	0.357
Controls	No	Yes	No	Yes
Observations	16,961	16,961	16,961	16,961

Notes: The table reports OLS estimates of the effect of oral questions on non-standardised measures of similarity between question text and review committee recommendations. PhraseRC is the number of phrase matches between the question text and review committee recommendations. SBERTRC is the average semantic similarity between the question text and review committee recommendations. Mean D.V. reports the mean of the dependent variable among written questions. Columns (1) and (3) include sitting-day and ministry fixed effects. Columns (2) and (4) additionally include controls for the submitting members' coalition status, religion, caste, and gender composition. Standard errors, clustered by sitting day, are reported in parentheses. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

TABLE *A.13: Effect of Oral Questions on Review Committee Recommendations across Temporal Windows*

	PhraseRC								SBERTRC							
	0–90		91–180		181–270		271–360		0–90		91–180		181–270		271–360	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Oral	0.0556***	0.0528***	0.0749***	0.0719***	0.0398**	0.0345*	0.0499***	0.0455**	0.0815***	0.0788***	0.0423**	0.0397**	0.0592***	0.0551**	0.0515**	0.0476**
	(0.0197)	(0.0196)	(0.0190)	(0.0191)	(0.0185)	(0.0185)	(0.0177)	(0.0177)	(0.0214)	(0.0212)	(0.0194)	(0.0194)	(0.0218)	(0.0217)	(0.0212)	(0.0212)
Controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Observations	15,061	15,061	16,002	16,002	15,051	15,051	14,458	14,458	15,061	15,061	16,002	16,002	15,051	15,051	14,458	14,458

Notes: The table reports OLS estimates of the effect of oral questions on standardised post-question similarity between question text and review committee recommendations, measured over different post-question windows. PhraseRC is the phrase-overlap measure, and SBERTRC is the average semantic-similarity measure. Each pair of columns corresponds to recommendations appearing within 90, 180, 270, or 360 days after the question. All specifications include sitting-day and ministry fixed effects. Even-numbered columns additionally include controls for the submitting members' coalition status, religion, caste, and gender composition. Standard errors, clustered by sitting day, are reported in parentheses. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

TABLE *A.14: Effect of Oral Questions on Government Acceptance of Pre-Question Recommendations*

	PhraseGovt		SBERTGovt	
	(1)	(2)	(3)	(4)
Oral	0.0670***	0.0621***	0.0729***	0.0697***
	(0.0212)	(0.0212)	(0.0210)	(0.0210)
D.V. Mean	28.56	28.56	0.362	0.362
Controls	No	Yes	No	Yes
Observations	16,340	16,340	16,340	16,340

Notes: The table reports OLS estimates of the effect of oral questions on government acceptance of review committee recommendations, restricting the sample to Action-Taken Reports that refer to recommendations issued before the question was asked. PhraseGovt is based on phrase matches, while SBERTGovt Mean is based on semantic similarity. Columns (1) and (3) include sitting-day and ministry fixed effects. Columns (2) and (4) additionally include controls for the submitting members' coalition status, religion, caste, and gender composition. Standard errors, clustered by sitting day, are reported in parentheses. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

TABLE *A.15: Effects of Oral Questions on Review Committee Content by Lok Sabha Term*

	PhraseRC		SBERTRC	
	(1)	(2)	(3)	(4)
Oral	0.107**	0.0977**	0.0918**	0.0864**
	(0.0420)	(0.0418)	(0.0421)	(0.0421)
Oral × LS 16	0.0467	0.0482	−0.0717	−0.0718
	(0.0557)	(0.0557)	(0.0535)	(0.0534)
Oral × LS 17	−0.105**	−0.0977*	0.0302	0.0355
	(0.0529)	(0.0525)	(0.0542)	(0.0540)
Controls	No	Yes	No	Yes
Observations	16,961	16,961	16,961	16,961

Notes: The table reports OLS estimates of the effect of oral questions on standardised question–review committee similarity by Lok Sabha term. The omitted category is the 15th Lok Sabha, so the coefficient on Oral gives the oral–written difference in the 15th Lok Sabha. The interaction terms report how the oral effect differs in the 16th and 17th Lok Sabhas relative to the 15th. The dependent variables are PhraseRC, a standardised phrase-overlap measure, and SBERTRC, a standardised average semantic-similarity measure. All specifications include sitting-day fixed effects. Columns (2) and (4) additionally include the control vector. Standard errors, clustered by sitting day, are reported in parentheses. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

TABLE *A.16: Heterogeneous Effect of Oral Questions on Textual Similarity to Review Committees*

Characteristic	Oral Coefficient		Interaction Coefficient	
	PhraseRC (1)	SBERTRC (2)	PhraseRC (3)	SBERTRC (4)
Female	0.0846***	0.0843***	−0.0822*	−0.104**
	(0.0233)	(0.0244)	(0.0491)	(0.0476)
Caste: General	0.0826**	0.0628*	−0.00859	0.0135
	(0.0377)	(0.0372)	(0.0390)	(0.0389)
Caste: Scheduled Caste	0.0765***	0.0753***	−0.00587	−0.0160
	(0.0236)	(0.0247)	(0.0441)	(0.0442)
Caste: Scheduled Tribe	0.0733***	0.0735***	0.0331	−0.00362
	(0.0230)	(0.0239)	(0.0604)	(0.0633)
Religion: Hindu	0.0769	0.103	−0.00140	−0.0322
	(0.0682)	(0.0728)	(0.0682)	(0.0748)
Religion: Muslim	0.0755***	0.0724***	−0.00158	0.0168
	(0.0228)	(0.0236)	(0.0932)	(0.0976)
Religion: Sikh	0.0758***	0.0701***	−0.00802	0.230
	(0.0227)	(0.0236)	(0.154)	(0.161)
Religion: Christian	0.0758***	0.0750***	−0.00749	−0.0917
	(0.0226)	(0.0236)	(0.102)	(0.114)
Incumbent	0.0749***	0.0821***	0.00156	−0.0228
	(0.0262)	(0.0259)	(0.0314)	(0.0329)
Education	0.203**	0.120	−0.00860	−0.00270
	(0.100)	(0.0992)	(0.00658)	(0.00633)
Close Election (5%)	0.0726***	0.0779***	0.0113	−0.0175
	(0.0246)	(0.0257)	(0.0360)	(0.0367)
Elections Contested	0.0767**	0.0553*	−0.000419	0.00806
	(0.0313)	(0.0304)	(0.00876)	(0.00835)
Lok Sabha Terms	0.0712**	0.0625*	0.00255	0.00622
	(0.0331)	(0.0327)	(0.0121)	(0.0124)
Party Type: State	0.0742***	0.0679**	0.00589	0.0162
	(0.0257)	(0.0283)	(0.0324)	(0.0357)
Party Type: National	0.0808***	0.0830***	−0.00733	−0.0149
	(0.0298)	(0.0302)	(0.0317)	(0.0352)
Party Type: Local	0.0762***	0.0743***	0.0282	−0.00721
	(0.0229)	(0.0236)	(0.146)	(0.148)
Party Type: Independent	0.0763***	0.0743***	0.0188	−0.0110
	(0.0227)	(0.0235)	(0.146)	(0.148)
Vote Share	0.227**	0.0588	−0.00319*	0.000312
	(0.0925)	(0.0919)	(0.00185)	(0.00193)
Coalition: Winning	0.0977***	0.0856***	−0.0280	−0.0162
	(0.0316)	(0.0307)	(0.0279)	(0.0293)
Coalition: Opposition	0.0760***	0.0579**	−0.000867	0.0446
	(0.0258)	(0.0270)	(0.0379)	(0.0411)

Notes: The table reports OLS estimates of heterogeneity in the effect of oral questions on standardised question–review committee similarity. The dependent variables are PhraseRC, a standardised phrase-overlap measure, and SBERTRC, a standardised average semantic-similarity measure. Columns (1) and (2) report the estimated oral effect for the omitted category or baseline value of the listed characteristic. Columns (3) and (4) report the interaction between Oral and the listed characteristic. Each row corresponds to a separate regression that includes Oral, the characteristic, and the interaction between the two. All specifications include sitting-day fixed effects. Standard errors, clustered by sitting day, are reported in parentheses. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

TABLE *A.17: Heterogeneous Effect of Oral Questions on Textual Similarity to Review Committees by Attendance*

Characteristic	Oral Coefficient		Interaction Coefficient	
	PhraseRC	SBERTRC	PhraseRC	SBERTRC
	(1)	(2)	(3)	(4)
Members Present	0.139	0.0433	−0.000124	0.0000735
	(0.215)	(0.190)	(0.000566)	(0.000502)
BJP Members Present	0.139**	0.0768	−0.000271	−0.0000319
	(0.0706)	(0.0694)	(0.000389)	(0.000379)
INC Members Present	0.0895**	0.0503	0.0000348	0.000361
	(0.0389)	(0.0378)	(0.000537)	(0.000547)
Female Members Present	0.288***	0.0103	−0.00422*	0.00131
	(0.111)	(0.104)	(0.00232)	(0.00221)
Muslim Members Present	0.220*	0.0587	−0.00906	0.000882
	(0.114)	(0.106)	(0.00780)	(0.00737)
Christian Members Present	0.109	0.0528	−0.00271	0.00290
	(0.0878)	(0.0845)	(0.0136)	(0.0130)
Sikh Members Present	0.0743	0.182**	0.00261	−0.0167
	(0.0771)	(0.0771)	(0.0114)	(0.0115)
Hindu Members Present	0.127	0.0224	−0.000100	0.000139
	(0.214)	(0.188)	(0.000612)	(0.000538)
SC Members Present	0.0918	0.265	−0.00000515	−0.00309
	(0.189)	(0.181)	(0.00302)	(0.00291)
ST Members Present	0.116	−0.0340	−0.000688	0.00293
	(0.163)	(0.143)	(0.00452)	(0.00397)
GC Members Present	−0.285*	0.220	0.00146**	−0.000575
	(0.159)	(0.150)	(0.000624)	(0.000586)
Observations	16,441	16,441	16,441	16,441

Notes: The table reports OLS estimates of heterogeneity in the effect of oral questions on standardised question–review committee similarity by attendance characteristics. Attendance measures are constructed from the official Lok Sabha attendance register and count the number of MPs (or MPs from the listed subgroup) who signed in on the sitting day. The dependent variables are PhraseRC, a standardised phrase-overlap measure, and SBERTRC, a standardised average semantic-similarity measure. Columns (1) and (2) report the estimated oral effect for the omitted category or baseline value of the listed attendance characteristic. Columns (3) and (4) report the interaction between Oral and the listed attendance characteristic. Each row corresponds to a separate regression that includes Oral, the attendance characteristic, and the interaction between the two. All specifications include sitting-day fixed effects. Standard errors, clustered by sitting day, are reported in parentheses. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

TABLE *A.18: Effects of Oral Questions on Government-Accepted Content by Lok Sabha Term*

	PhraseGovAccept		SBERTGovAccept	
	(1)	(2)	(3)	(4)
Oral	0.0876**	0.0789**	0.0699	0.0639
	(0.0384)	(0.0384)	(0.0438)	(0.0439)
Oral × LS 16	0.0367	0.0391	−0.0485	−0.0471
	(0.0512)	(0.0512)	(0.0542)	(0.0541)
Oral × LS 17	−0.0848	−0.0774	0.0459	0.0526
	(0.0537)	(0.0537)	(0.0554)	(0.0553)
Controls	No	Yes	No	Yes
Observations	16,941	16,941	16,941	16,941

Notes: The table reports OLS estimates of the effect of oral questions on standardised question–government-accepted content similarity by Lok Sabha term. The omitted category is the 15th Lok Sabha, so the coefficient on Oral gives the oral–written difference in the 15th Lok Sabha. The interaction terms report how the oral effect differs in the 16th and 17th Lok Sabhas relative to the 15th. The dependent variables are PhraseGovAcc, a standardised phrase-overlap measure, and SBERTGovAcc, a standardised average semantic-similarity measure. All specifications include sitting-day fixed effects. Columns (2) and (4) additionally include the control vector. Standard errors, clustered by sitting day, are reported in parentheses. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

TABLE *A.19: Heterogeneous Effect of Oral Questions on Textual Similarity to Government-Accepted Content*

	Oral Coefficient		Interaction Coefficient	
Characteristic	PhraseGovAccept	SBERTGovAccept	PhraseGovAccept	SBERTGovAccept
	(1)	(2)	(3)	(4)
Female	0.0759***	0.0798***	−0.0845*	−0.107**
	(0.0230)	(0.0245)	(0.0503)	(0.0476)
Caste: General	0.0632*	0.0651*	0.00476	0.00436
	(0.0382)	(0.0364)	(0.0374)	(0.0387)
Caste: Scheduled Caste	0.0653***	0.0682***	0.0113	0.000139
	(0.0227)	(0.0249)	(0.0441)	(0.0458)
Caste: Scheduled Tribe	0.0689***	0.0690***	−0.0273	−0.00844
	(0.0223)	(0.0242)	(0.0558)	(0.0596)
Religion: Hindu	0.0796	0.0907	−0.0136	−0.0240
	(0.0700)	(0.0714)	(0.0708)	(0.0727)
Religion: Muslim	0.0670***	0.0668***	−0.0103	0.0369
	(0.0223)	(0.0237)	(0.0880)	(0.0938)
Religion: Sikh	0.0660***	0.0671***	0.0664	0.0776
	(0.0223)	(0.0237)	(0.162)	(0.147)
Religion: Christian	0.0669***	0.0693***	−0.00395	−0.0618
	(0.0222)	(0.0237)	(0.108)	(0.120)
Incumbent	0.0766***	0.0724***	−0.0272	−0.0110
	(0.0251)	(0.0257)	(0.0298)	(0.0332)
Education	0.234**	0.122	−0.0113*	−0.00320
	(0.0976)	(0.101)	(0.00635)	(0.00645)
Close Election (5%)	0.0636***	0.0683***	0.0112	−0.00109
	(0.0244)	(0.0256)	(0.0379)	(0.0376)
Elections Contested	0.0771**	0.0525*	−0.00446	0.00690
	(0.0305)	(0.0306)	(0.00819)	(0.00843)
Lok Sabha Terms	0.0812**	0.0572*	−0.00767	0.00618
	(0.0317)	(0.0325)	(0.0111)	(0.0123)
Party Type: State	0.0747***	0.0512*	−0.0184	0.0443
	(0.0262)	(0.0282)	(0.0322)	(0.0356)
Party Type: National	0.0529*	0.0870***	0.0249	−0.0313
	(0.0283)	(0.0304)	(0.0316)	(0.0350)
Party Type: Local	0.0677***	0.0701***	−0.0238	−0.142
	(0.0224)	(0.0237)	(0.155)	(0.143)
Party Type: Independent	0.0689***	0.0703***	−0.122	−0.136
	(0.0224)	(0.0237)	(0.136)	(0.149)
Vote Share	0.112	0.0198	−0.000956	0.00102
	(0.0881)	(0.0904)	(0.00178)	(0.00189)
Coalition: Winning	0.0721**	0.0750**	−0.00837	−0.00980
	(0.0309)	(0.0313)	(0.0294)	(0.0294)
Coalition: Opposition	0.0726***	0.0586**	−0.0169	0.0282
	(0.0255)	(0.0258)	(0.0368)	(0.0391)

Notes: The table reports OLS estimates of heterogeneity in the effect of oral questions on standardised question–government-accepted content similarity. The dependent variables are PhraseGovAcc, a standardised phrase-overlap measure, and SBERT-GovAcc, a standardised average semantic-similarity measure. Attendance measures are constructed from the official Lok Sabha attendance register and count the number of MPs (or MPs from the listed subgroup) who signed in on the sitting day. Columns (1) and (2) report the estimated oral effect for the omitted category or baseline value of the listed characteristic. Columns (3) and (4) report the interaction between Oral and the listed characteristic. Each row corresponds to a separate regression that includes Oral, the characteristic, and the interaction between the two. All specifications include sitting-day fixed effects. Standard errors, clustered by sitting day, are reported in parentheses. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

TABLE *A.20: Heterogeneous Effect of Oral Questions on Textual Similarity to Government-Accepted Content by Attendance*

Characteristic	Oral Coefficient		Interaction Coefficient	
	PhraseGovAccept	SBERTGovAccept	PhraseGovAccept	SBERTGovAccept
	(1)	(2)	(3)	(4)
Members Present	0.0452	−0.0354	0.0000793	0.000262
	(0.208)	(0.181)	(0.000542)	(0.000477)
BJP Members Present	0.109*	0.0509	−0.000192	0.0000738
	(0.0642)	(0.0713)	(0.000359)	(0.000385)
INC Members Present	0.0692*	0.0518	0.000106	0.000211
	(0.0395)	(0.0371)	(0.000527)	(0.000549)
Female Members Present	0.216**	−0.0341	−0.00302	0.00211
	(0.0974)	(0.103)	(0.00205)	(0.00215)
Muslim Members Present	0.162	0.0471	−0.00608	0.00119
	(0.103)	(0.104)	(0.00699)	(0.00721)
Christian Members Present	0.0161	0.0311	0.00933	0.00517
	(0.0920)	(0.0809)	(0.0140)	(0.0125)
Sikh Members Present	0.0540	0.125	0.00323	−0.00919
	(0.0798)	(0.0772)	(0.0115)	(0.0114)
Hindu Members Present	0.0467	−0.0515	0.0000815	0.000329
	(0.205)	(0.180)	(0.000580)	(0.000512)
SC Members Present	0.134	0.157	−0.000943	−0.00149
	(0.190)	(0.170)	(0.00299)	(0.00272)
ST Members Present	0.0368	−0.0188	0.00107	0.00230
	(0.152)	(0.137)	(0.00418)	(0.00381)
GC Members Present	−0.279	0.172	0.00137**	−0.000419
	(0.174)	(0.148)	(0.000668)	(0.000574)
Observations	16,426	16,426	16,426	16,426

Notes: The table reports OLS estimates of heterogeneity in the effect of oral questions on standardised question–government-accepted content similarity by attendance characteristics. The dependent variables are PhraseGovAcc, a standardised phrase-overlap measure, and SBERTGovAcc, a standardised average semantic-similarity measure. Columns (1) and (2) report the estimated oral effect for the omitted category or baseline value of the listed attendance characteristic. Columns (3) and (4) report the interaction between Oral and the listed attendance characteristic. Each row corresponds to a separate regression that includes Oral, the attendance characteristic, and the interaction between the two. All specifications include sitting-day fixed effects. Standard errors, clustered by sitting day, are reported in parentheses. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

TABLE *A.21: Effect of Oral Questions on Times of India Coverage across Temporal Windows*

	PhraseNews								SBERTNews							
	0–7		8–14		15–21		22–28		0–7		8–14		15–21		22–28	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Oral	0.0478**	0.0397*	0.0483**	0.0405*	0.0418*	0.0340	0.0401*	0.0326	0.0672***	0.0631***	0.0619***	0.0579***	0.0688***	0.0648***	0.0650***	0.0611***
	(0.0238)	(0.0235)	(0.0237)	(0.0236)	(0.0233)	(0.0232)	(0.0234)	(0.0232)	(0.0223)	(0.0222)	(0.0221)	(0.0221)	(0.0219)	(0.0218)	(0.0220)	(0.0219)
Controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Observations	16,954	16,954	16,959	16,959	16,961	16,961	16,953	16,953	16,954	16,954	16,959	16,959	16,961	16,961	16,953	16,953

Notes: The table reports OLS estimates of the effect of oral questions on standardised post-question *Times of India* coverage, measured over different post-question windows. PhraseNews is the phrase-overlap measure, and SBERTNews is the semantic-similarity measure. Each pair of columns corresponds to coverage appearing within 7, 14, 21, or 28 days after the question. All specifications include sitting-day and ministry fixed effects. Even-numbered columns additionally include controls for the submitting members' coalition status, religion, caste, and gender composition. Standard errors, clustered by sitting day, are reported in parentheses. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

TABLE *A.22: Effect of Oral Questions on News Coverage: Raw Outcomes*

	PhraseNews		SBERTNews	
	(1)	(2)	(3)	(4)
Oral	2.920**	2.089*	0.00283***	0.00258***
	(1.363)	(1.221)	(0.000846)	(0.000767)
Mean D.V.	71.07	71.07	0.255	0.255
Controls	No	Yes	No	Yes
Observations	17,437	17,437	17,437	17,437

Notes: The table reports OLS estimates of the effect of oral questions on raw, non-standardised measures of subsequent *Times of India* coverage. The dependent variables are *PhraseNews* in columns (1)–(2) and *SBERTNews* in columns (3)–(4). All specifications include sitting-day and ministry fixed effects. Even-numbered columns additionally include controls for the submitting members' coalition status, religion, caste, and gender composition. Standard errors, clustered by sitting day, are reported in parentheses. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

TABLE *A.23: News Coverage and Bill Content: Terror-Shock Estimates*

	SBERTBill		PhraseBill	
	(1)	(2)	(3)	(4)
(A) Two-Stage Least Squares: Bill Similarity				
$\widehat{\text{News}}$	0.647***	0.641***	2.897	2.976
	(0.179)	(0.174)	(3.571)	(3.818)
(B) First Stage: News Similarity				
Shock^S	−0.189***	−0.192***	−0.050	−0.047
	(0.060)	(0.060)	(0.061)	(0.060)
(C) Reduced Form: Bill Similarity				
Shock^S	−0.122**	−0.123**	−0.144*	−0.138*
	(0.048)	(0.048)	(0.077)	(0.077)
Effective first-stage F	9.93	10.31	0.67	0.59
Anderson–Rubin p-value	0.020	0.020	0.086	0.098
Submission-window FE	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes
Observations	2,236	2,236	2,236	2,236

Notes: The table reports estimates of the relationship between newspaper coverage and subsequent bill content among orally answered questions, using terror shocks as an instrument for coverage. $Shock^S$ equals one if terrorist attacks outside India on the day after the question collectively wound more than 50 people, the median of the daily total-wounded distribution across attack-days. Columns (1)–(2) use semantic similarity and columns (3)–(4) phrase overlap; exposure and outcome measures are standardised. Panel (A) reports two-stage least squares estimates instrumenting news similarity with $Shock^S$; Panels (B) and (C) report the first stage and reduced form on the same sample. All specifications include 15-day submission-window fixed effects; controls are the member-level characteristics of the baseline specification. Standard errors, clustered by submission window, are in parentheses. The effective first-stage F-statistic follows Montiel Olea and Pflueger (2013), and the Anderson–Rubin test (Anderson and Rubin, 1949) is robust to weak instruments. The sample contains orally answered questions on sitting days within the coverage of the Global Terrorism Database. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

TABLE *A.24: Heterogeneous Effects by Electoral Cycle*

Electoral Timing	Oral Coefficient		Interaction Coefficient	
	PhraseBill	SBERTBill	PhraseBill	SBERTBill
	(1)	(2)	(3)	(4)
Days to Next Election	0.0555***	0.0565***	0.0230	−0.0219
	(0.0201)	(0.0206)	(0.0226)	(0.0208)
Days from Previous Election	0.0555***	0.0562***	−0.0228	0.0203
	(0.0201)	(0.0206)	(0.0228)	(0.0208)
Controls	No	No	No	No
Observations	16,964	16,964	16,964	16,964

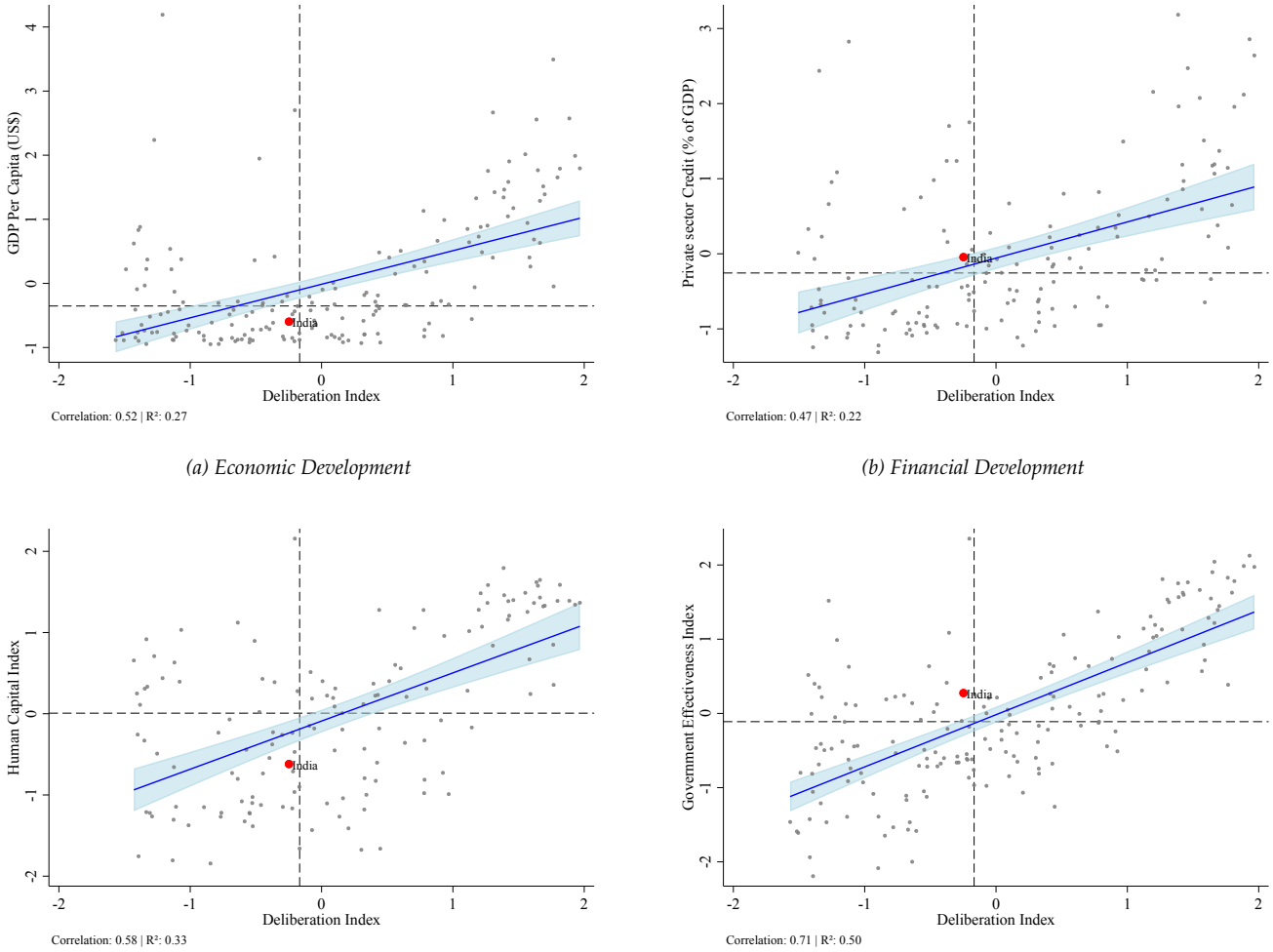
Notes: The table reports OLS estimates of heterogeneity in the effect of oral questions by electoral-cycle timing. The dependent variables are PhraseBill, a standardised phrase-overlap measure, and SBERTBill, a standardised average semantic-similarity measure. Columns (1) and (2) report the estimated oral effect at the baseline value of the timing variable. Columns (3) and (4) report the interaction between Oral and the listed timing measure. Each row corresponds to a separate regression that includes Oral, the timing measure, and their interaction. All specifications include sitting-day fixed effects and no additional controls. Standard errors, clustered by sitting day, are reported in parentheses. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

TABLE *A.25: Effect of Oral Exposure on Member Behaviour*

	Attendance	Questions Submitted	Debate Days	Speeches per Day
	(1)	(2)	(3)	(4)
Oral	0.00451	0.112	0.00122	0.0107
	(0.0131)	(0.115)	(0.0185)	(0.0166)
Controls	Yes	Yes	Yes	Yes
Observations	17,445	17,445	17,445	17,445

Notes: The table reports ordinary least squares (OLS) estimates of the association between oral question exposure and subsequent parliamentary activity at the member level. The dependent variables are measures of attendance in the chamber, Attendance; the number of questions submitted, Questions Submitted; the number of days on which the member speaks in debate, Debate Days; and the number of speeches per sitting day, Speeches per Day. Each coefficient corresponds to an indicator for a question answered orally. All specifications include the same set of controls as in the main regressions. Standard errors, reported in parentheses, are clustered at the member level. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

B Appendix Figures



(a) Economic Development

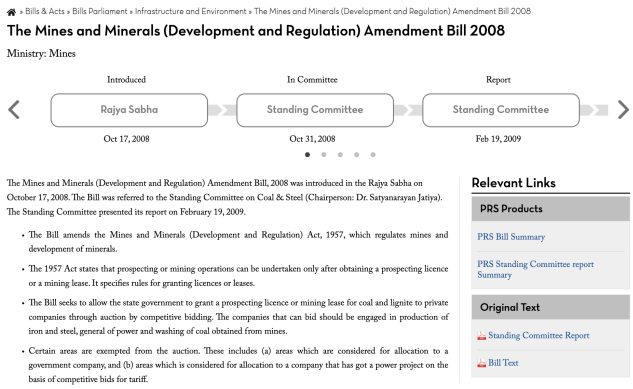
(b) Financial Development

(c) Human Capital Development

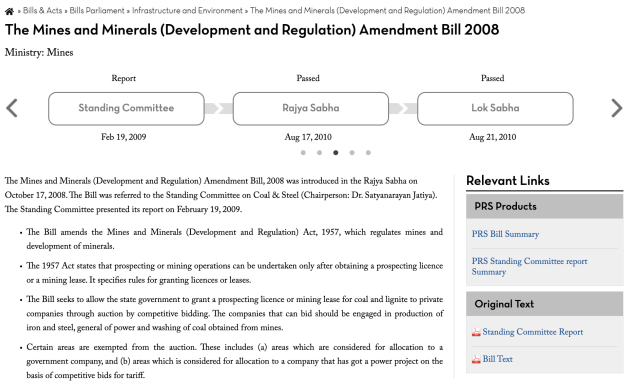
(d) Government Effectiveness

FIGURE *B.1: Deliberative Democracy and Development Indicators*

Notes: Each panel plots the deliberative democracy index against development indicators, averaged over 2012–2024. Panel (a) shows GDP per capita. Panel (b) shows domestic credit to private sector as a percentage of GDP. Panel (c) shows the Human Capital Index, which measures accumulated knowledge, skills, and health on a 0–1 scale. Panel (d) shows the Government Effectiveness Index, which measures public service quality and policy implementation. Each point represents a country-year observation. The Deliberative Democracy Index ranges from 0–1 and measures public reasoning in political decisions from V-Dem v15. GDP, HCI, and credit data are from World Bank WDI; Government Effectiveness is from World Bank WGI.



(a) Introduction and committee review



(b) Passage in both Houses

FIGURE *B.2: PRS Bill Tracker Timeline for a Government Bill*

Notes: The figure shows the legislative timeline reported by PRS Legislative Research for the Mines and Minerals (Development and Regulation) Amendment Bill, 2008. Panel (a) records the bill's introduction in the Rajya Sabha, its referral to the Standing Committee on Coal and Steel, and the submission of the committee report. Panel (b) records the bill's subsequent passage in the Rajya Sabha and Lok Sabha. The PRS page also provides the summary of the bill. Source: PRS Legislative Research, prsindia.org/billtrack/the-mines-and-minerals-development-and-regulation-amendment-bill-2008.

Q186 ranked 4th and asked orally on August 3, 2015.

- Whether despite enactment of various statutes, the menace of child labour still persists and if so, the reaction of the Government thereto;
- the details of vocations/sectors vulnerable to employ child labour;
- whether any surprise raids/checking have been conducted to unearth child labour and if so, the details thereof;
- the total number of cases registered under the Child Labour (Prohibition and Regulation) Act, 1986 during the last three years and the current year;
- whether any action has been taken against the guilty and also against the officials for not fulfilling their responsibility of checking child labour and if so, the details thereof, State-wise during the above period;
- $\text{sim}(q, b) = 0.19$, $\text{Phrase}_{q,b} = 0.95\%$

The Atomic Energy (Amendment) Bill, 2015

- The Bill proposes to amend the Atomic Energy Act, 1962. The Act empowers the central government to produce, develop, control, and use atomic energy.
- Under the Act, a government company is one in which at least 51% of the paid-up share capital is held by the central government. The Bill expands this definition to include companies where the whole of the paid-up share capital is held by one or more government company and whose articles of association empower the central government to constitute its Board of Directors.
- Under the Act, a licence is required for the acquisition, production, use, export, and import of any plant designed for the production and development of atomic energy or research. The Bill makes consequential amendments to state that such licences will only be granted to entities such as a government company or a department of the central government.

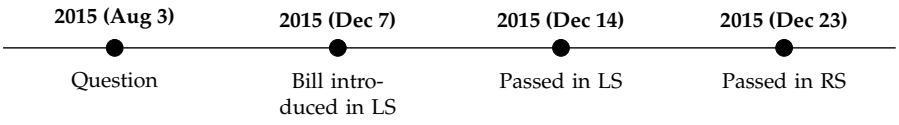


FIGURE *B.3: Q186 and The Atomic Energy (Amendment) Bill, 2015*

Notes: The figure presents parliamentary question Q186, ranked 4th and asked orally on August 3, 2015, on the issue of child labour. The left panel reports the text of the question and its outcome measures. The right panel summarises *The Atomic Energy (Amendment) Bill, 2015*, introduced within the subsequent outcome window, and lists its main provisions. The timeline below shows the bill's progression through Parliament, based on the PRS Legislative Research bill tracker. Because the bill concerns atomic energy rather than child labour, both textual measures indicate weak alignment between the question and the bill ($\text{sim}(q, b) = 0.19$ and $\text{Phrase}_{q,b} = 0.95\%$).

Q186 ranked 4th and asked orally on August 3, 2015.

- Whether despite enactment of various statutes, the menace of child labour still persists and if so, the reaction of the Government thereto;
- the details of vocations/sectors vulnerable to employ child labour;
- whether any surprise raids/checking have been conducted to unearth child labour and if so, the details thereof;
- the total number of cases registered under the Child Labour (Prohibition and Regulation) Act, 1986 during the last three years and the current year;
- whether any action has been taken against the guilty and also against the officials for not fulfilling their responsibility of checking child labour and if so, the details thereof, State-wise during the above period;
- $\text{sim}(q, b) = 0.68$, $\text{Phrase}_{q,b} = 9.52\%$

The Child Labour (Prohibition and Regulation) Amendment Bill, 2012

- The Bill seeks to amend the Child Labour (Prohibition and Regulation) Act, 1986, which prohibits the engagement of children in certain occupations and regulates the conditions of work of children in others.
- The Bill adds a new category of persons called "adolescent." An adolescent means a person between 14 and 18 years of age. The Bill prohibits employment of adolescents in hazardous occupations, including mines, inflammable substances, and hazardous processes.
- The penalty for employing a child is increased to imprisonment between 6 months and 2 years (from 3 months to 1 year) or a fine of Rs 20,000 to Rs 50,000 (from Rs 10,000 to Rs 20,000), or both.
- The Bill empowers the government to conduct periodic inspections of places in which the employment of children and adolescents is prohibited.

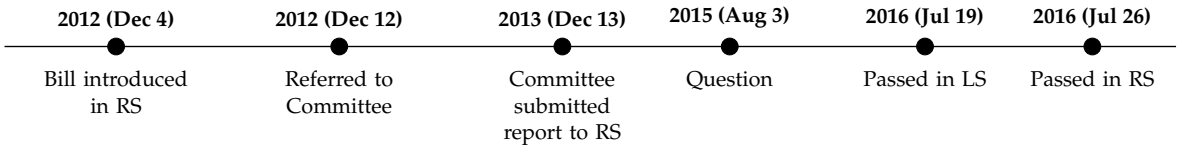


FIGURE *B.4: Q186 and The Child Labour (Prohibition and Regulation) Amendment Bill, 2012*

Notes: The figure presents parliamentary question Q186, ranked 4th and asked orally on August 3, 2015, on the issue of child labour. The left panel reports the text of the question and its outcome measures. The right panel summarises *The Child Labour (Prohibition and Regulation) Amendment Bill, 2012*, which addresses the same policy issue, and lists its main provisions. The timeline below shows the bill's progression through Parliament, based on the PRS Legislative Research bill tracker. Both textual measures indicate strong alignment between the question and the bill ($\text{sim}(q, b) = 0.68$ and $\text{Phrase}_{q,b} = 9.52\%$).

Q317 ranked 17th and asked in writing on April 16, 2010.

- Whether as per the latest estimates, two lakh fake doctors or quacks are operating in the Indian Medical System;
- if so, the details thereof and the corrective measures so far taken by the Government in this regard;
- whether health authorities have detected fake doctors in some hospitals in Delhi and other parts of the country;
- if so, the details thereof and the action taken against them;
- the number of cases registered against such fake doctors by the Medical Council of India (MCI) and the number out of them convicted during the last three years and the current year;
- whether the Government proposes to bring suitable amendments in the existing Indian Medical Council Act and also pass comprehensive anti-quackery legislation which is pending since 2003;
- if so, the details thereof and if not, the reasons therefor;
- $\text{sim}(q, b) = 0.31$, $\text{Phrase}_{q,b} = 0\%$

The Indian Medical Council Amendment Act, 2012

- In Section 3A of the Indian Medical Council Act, 1956, in sub-section (2), for the words "two years," the words "three years" shall be substituted.

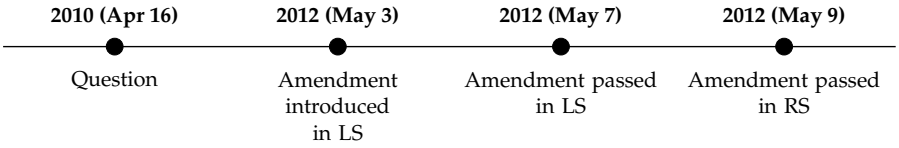


FIGURE *B.5: Q317 and The Indian Medical Council Amendment Act, 2012*

Notes: The figure presents parliamentary question Q317, ranked 17th and asked in writing on April 16, 2010, on the issue of fake doctors and quackery. The left panel reports the text of the question and its outcome measures. The right panel summarises *The Indian Medical Council Amendment Act, 2012*, which concerns medical regulation but does not directly address quackery. The timeline below shows the amendment's progression through Parliament, based on the PRS Legislative Research bill tracker. The example illustrates how the two textual measures capture different types of alignment: phrase overlap is zero, but semantic similarity remains positive because both texts concern the regulation of the medical profession ($\text{sim}(q, b) = 0.31$ and $\text{Phrase}_{q,b} = 0\%$).

Q10 asked on August 8, 2012.

- Whether the Government has taken note of the perennial problems arising out of mine fire in the Jharia and Raniganj Coalfield;
- if so, the details thereof;
- whether any master plan has been prepared to douse the fire and for rapid resettlement of the people affected by the fire;
- if so, the details thereof and the progress of work in this regard so far;
- the details of the funds sanctioned and utilized for rehabilitation of Jharia and Ranigunj Coalfields;
- whether any new township has been identified for rehabilitation and resettlement of the affected people; and
- if so, the details thereof;
- $\text{sim}(q, b) = 0.537$, $\text{Phrase}_{q,b} = 8.247\%$

Q257 asked on December 11, 2012.

- Whether the Government/Coal India Limited (CIL) has acquired/proposes to acquire land for their new projects in some of the coal-bearing States in the country;
- if so, the details thereof, State-wise and the steps being taken by the Government in this regard; and
- the details of the rehabilitation and resettlement policy being followed for the persons displaced due to acquisition of their land for projects;
- $\text{sim}(q, b) = 0.527$, $\text{Phrase}_{q,b} = 4.348\%$

The Coal Mines (Conservation and Development) Amendment Bill, 2012

- The Coal Mines (Conservation and Development) Amendment Bill, 2012 was introduced in the Lok Sabha on November 22, 2012 by the Minister of Coal, Sri Prakash Jaiswal. The Bill seeks to amend the Coal Mines (Conservation and Development) Act, 1974.
- The Act provides for the conservation of coal and development of mines. It also provides for the imposition of excise duty and customs duty.
- According to the Statement of Objects and Reasons, the Bill increases the maximum excise duty that can be levied on coal. Part of this duty funds the implementation of a master plan for dealing with fires, subsidence, and rehabilitation in the Jharia and Raniganj coalfields. The increase is intended to bridge the funding gap for this master plan.
- Under the Act, the central government may levy and collect excise duty on all coal raised and dispatched and on all coke manufactured and dispatched. The Act capped this duty at Rs 10 per tonne. The Bill raises the maximum duty to Rs 50 per tonne.

FIGURE *B.6: Q10, Q257 and The Coal Mines (Conservation and Development) Amendment Bill, 2012*

Notes: The figure compares two parliamentary questions to the Ministry of Coal with *The Coal Mines (Conservation and Development) Amendment Bill, 2012*. The top-left panel reports Q10, asked on August 8, 2012, which concerns mine fires, rehabilitation, and resettlement in the Jharia and Raniganj coalfields. The top-right panel reports Q257, asked on December 11, 2012, which concerns land acquisition and rehabilitation policy for coal projects. The bottom panel summarises the bill, which increases the maximum excise duty on coal partly to fund a master plan for fires, subsidence, and rehabilitation in the Jharia and Raniganj coalfields. The outcome measures report the textual alignment between each question and the bill.

Q346 asked on August 1, 2014.

- Whether suggestions have been received from various quarters to reduce the age of juvenile offenders, in the context of heinous crimes committed by them recently;
- if so, the reaction of the Government thereto along with other amendments proposed in the Juvenile Justice (Care and Protection of Children) Act, 2000;
- whether consultations with all the stakeholders, including States, have been underway or have been concluded and if so, the details thereof; and
- the time by which the legislation in this regard is likely to be introduced in Parliament;
- $\text{sim}(q, b) = 0.685$, $\text{Phrase}_{q,b} = 17.045\%$

Q477 asked on August 11, 2014.

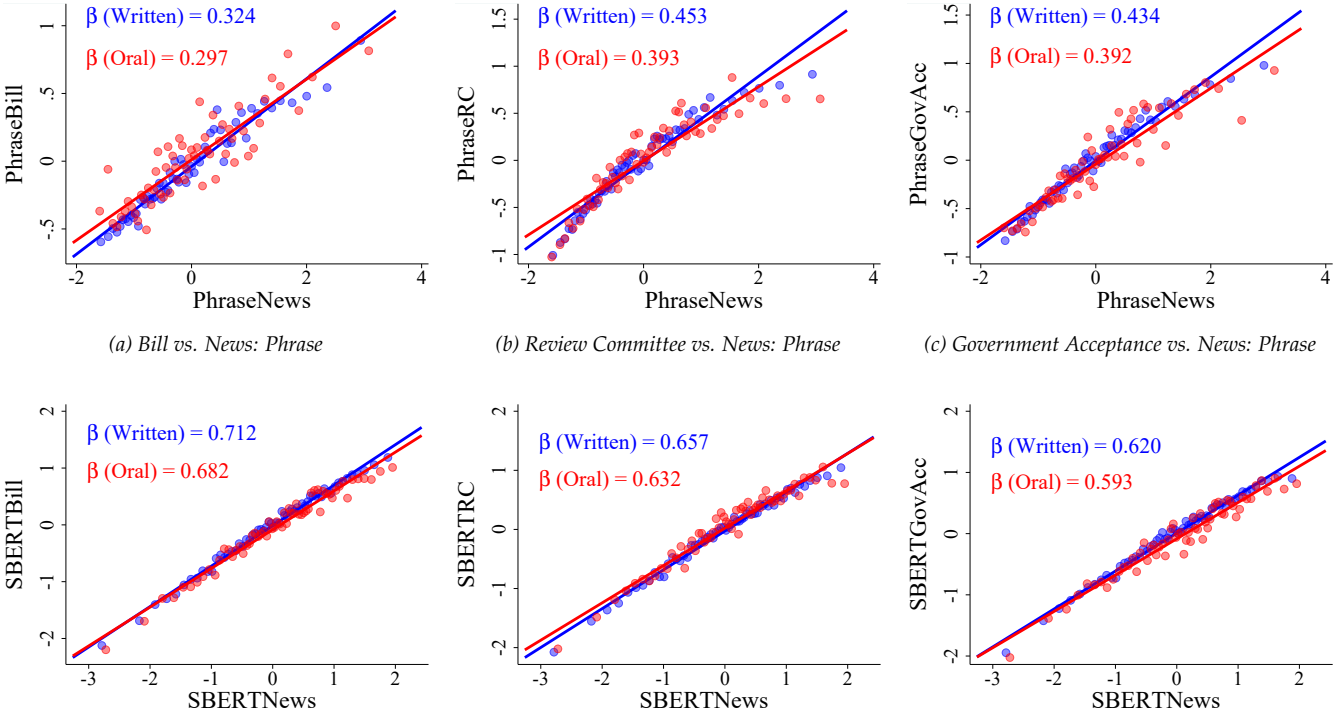
- The number of cases involving juvenile crimes registered and pending in the Supreme Court and High Courts during the last three years and the current year, State/UT-wise;
- whether there has been a rise in juvenile crimes in the recent past and if so, the details thereof and the reasons therefor; and
- whether the Government is considering having a separate provision in the Indian Penal Code and other acts dealing with serious and heinous criminal acts committed by minors and if so, the details thereof;
- $\text{sim}(q, b) = 0.677$, $\text{Phrase}_{q,b} = 3.614\%$

The Juvenile Justice (Care and Protection of Children) Bill, 2014

- The Bill replaces the Juvenile Justice (Care and Protection of Children) Act, 2000. It addresses children in conflict with law and children in need of care and protection.
- The Bill permits juveniles between the ages of 16–18 years to be tried as adults for heinous offences. Any 16–18 year old who commits a lesser serious offence may be tried as an adult only if apprehended after the age of 21 years.
- Juvenile Justice Boards and Child Welfare Committees will be constituted in each district. The Juvenile Justice Board will conduct a preliminary inquiry to determine whether a juvenile offender should be sent for rehabilitation or tried as an adult. The Child Welfare Committee will determine institutional care for children in need of care and protection.
- The Bill includes eligibility rules for adoptive parents and the procedure for adoption.
- The Bill prescribes penalties for cruelty against a child, offering a narcotic substance to a child, and abduction or sale of a child.

FIGURE *B.7: Q346, Q477 and The Juvenile Justice (Care and Protection of Children) Bill, 2014*

Notes: The figure compares two parliamentary questions with *The Juvenile Justice (Care and Protection of Children) Bill, 2014*. The top-left panel reports Q346, asked on August 1, 2014, which concerns reducing the age threshold for juvenile offenders in the context of heinous crimes. The top-right panel reports Q477, asked on August 11, 2014, which concerns juvenile crime and whether separate provisions should apply to serious offences committed by minors. The bottom panel summarises the bill, which permits juveniles aged 16–18 to be tried as adults for heinous offences and revises the institutional framework for juvenile justice. The outcome measures report the textual alignment between each question and the bill.

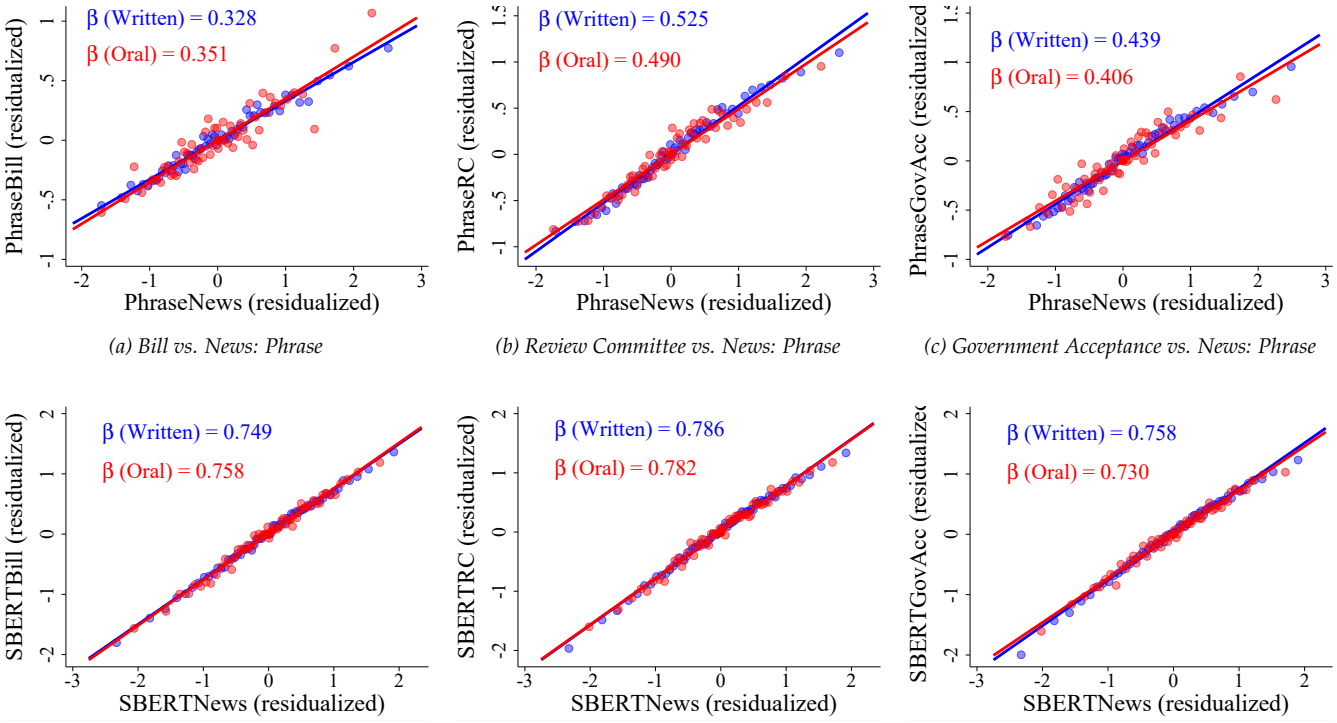


(a) Bill vs. News: Phrase *(b) Review Committee vs. News: Phrase* *(c) Government Acceptance vs. News: Phrase*

(d) Bill vs. News: SBERT *(e) Review Committee vs. News: SBERT* *(f) Government Acceptance vs. News: SBERT*

FIGURE *B.8: Correlations Between Newspaper Coverage and Policy Outcomes: No Controls*

Notes: Each panel relates a standardised measure of *Times of India* coverage to a standardised measure of subsequent policy-text similarity, without controls. Panels (a)–(c) use phrase-based measures, and panels (d)–(f) use SBERT-based measures. Points show quantile-bin means computed separately for oral and written questions. Solid lines plot group-specific OLS fits.



(a) Bill vs. News: Phrase *(b) Review Committee vs. News: Phrase* *(c) Government Acceptance vs. News: Phrase*

(d) Bill vs. News: SBERT *(e) Review Committee vs. News: SBERT* *(f) Government Acceptance vs. News: SBERT*

FIGURE *B.9: Correlations Between Newspaper Coverage and Policy Outcomes: With Controls*

Notes: Each panel relates a standardised measure of *Times of India* coverage to a standardised measure of subsequent policy-text similarity, after partialling out the full set of controls from Equation 1 (sitting-day and ministry fixed effects and the member-level control vector). Panels (a)–(c) use phrase-based measures, and panels (d)–(f) use SBERT-based measures. Points show quantile-bin means computed separately for oral and written questions. Solid lines plot group-specific OLS fits.

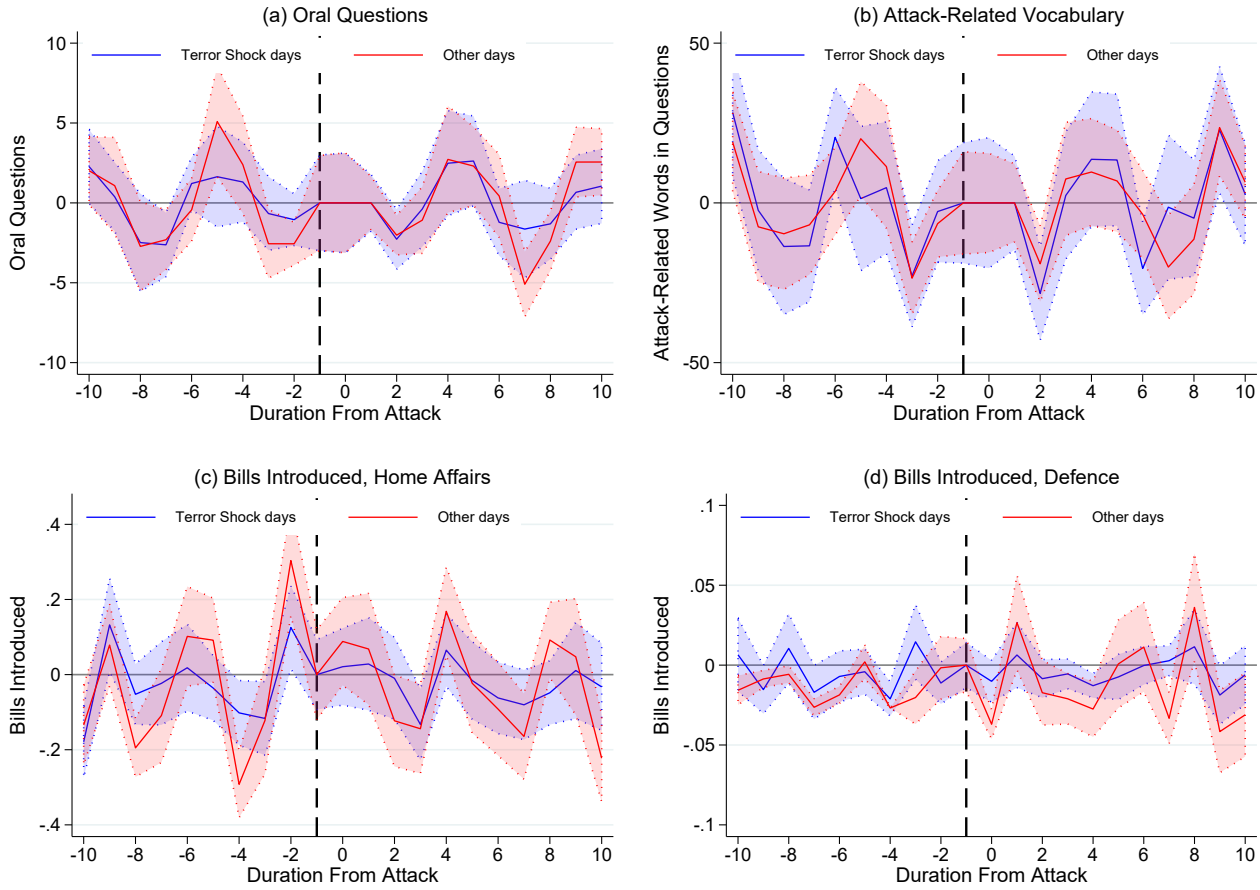


FIGURE *B.10: Parliamentary Activity Around Severe Terror Attacks*

Notes: Each panel compares Terror Shock days (blue) with other days (red) in event time. Terror Shock days are sitting days for which the following day is a severe attack day, as defined in Section 7; other days are the remaining sitting days within the coverage of the Global Terrorism Database. Bins are 30 days for question-side outcomes and 91 days for bill-side outcomes. Each series is residualised on calendar-year and calendar-month effects within group and normalised to the bin immediately preceding the attack, marked by the dashed vertical line. Shaded areas denote 95% confidence intervals based on bin-level means. Panel (a) plots the number of orally answered questions. Panel (b) plots the overlap between question text and vocabulary drawn from the shock-defining attacks, including their locations, attack types, and incident descriptions. Panels (c) and (d) plot the number of bills introduced by the Ministry of Home Affairs and the Ministry of Defence.

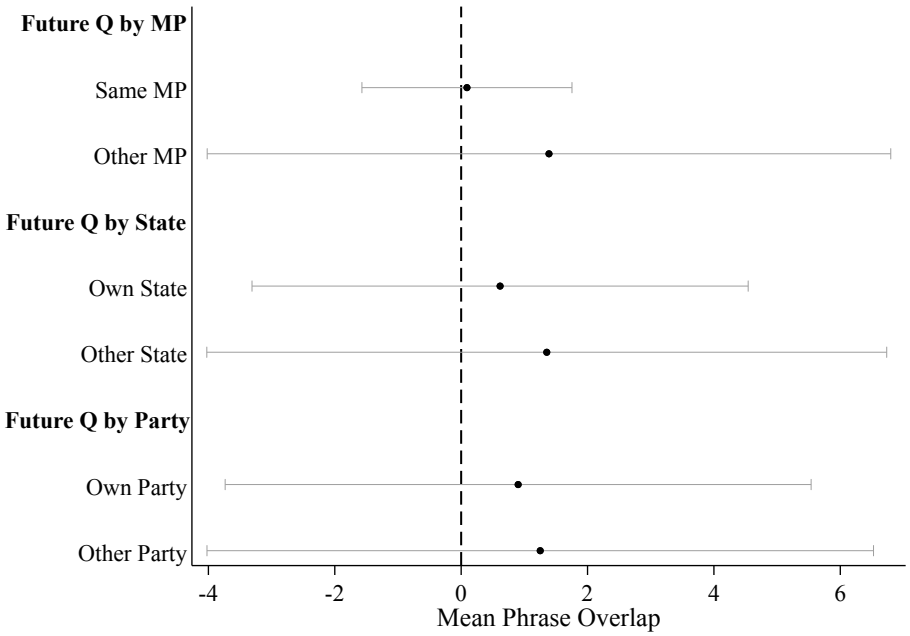


FIGURE *B.11: Phrase Overlap with Future Questions by Affiliation*

Notes: Figure displays the mean phrase overlap between each parliamentary question and future questions submitted to the same ministry within a 30-day window, beginning one day after the original question's date. For each question, six separate comparisons are made: the overlap is calculated with future questions submitted by (i) the same Member of Parliament (MP), (ii) a different MP, (iii) MPs from the same state, (iv) MPs from a different state, (v) MPs from the same political party, and (vi) MPs from a different political party. Phrase overlap is measured as the count of bigrams and trigrams shared between the original question and each relevant future question. Each bar in the plot represents the average number of overlapping phrases across all original questions, within the specified affiliation category. Vertical lines denote 95% confidence intervals based on one-sample *t*-tests of whether the average overlap differs from zero.

C Measuring Semantic Proximity with Sentence-BERT

We quantify the semantic alignment between each parliamentary question and downstream texts using Sentence-BERT (SBERT), which maps sentences to fixed-length vectors in a shared semantic space (Reimers and Gurevych, 2019). For each question–document pair we compute cosine similarity between their embeddings. Scores range from –1 to 1, with higher values indicating greater semantic proximity. We briefly review BERT's word-level representations, then show how Sentence-BERT yields sentence embeddings tailored to similarity, and finally describe our construction of question–document measures.

BERT Word Embeddings. BERT encodes texts as context-dependent vectors for each token (Devlin et al., 2019). It tokenises the text into subwords $\{w_1, \ldots, w_T\}$ and maps each token w_t to a 768-dimensional input vector

$$x_t = \text{token}(w_t) + \text{position}(t),$$

the sum of learned embeddings for lexical identity and absolute position in the sequence. Denote $h_t^{(0)} = x_t$. Across $L = 12$ transformer layers the model updates each token by aggregating information from all tokens in the sequence:

$$\tilde{h}_t^{(\ell)} = \sum_{t'=1}^{T} \alpha_{tt'}^{(\ell)} \, v_{t'}^{(\ell)}, \qquad h_t^{(\ell)} = \text{FFN}\big(\tilde{h}_t^{(\ell)} + h_t^{(\ell-1)}\big),$$

where $v_{t'}^{(\ell)} = \text{Proj}\big(h_{t'}^{(\ell-1)}\big)$ is a learned projection of the previous-layer state of token t', and the weights

$$\alpha_{tt'}^{(\ell)} = \text{softmax}_{t'}\left(\frac{\text{sim}\big(h_t^{(\ell-1)}, h_{t'}^{(\ell-1)}\big)}{\sqrt{d}}\right)$$

are nonnegative and sum to one over t'. Here $\text{sim}(\cdot,\cdot)$ is a scaled dot-product similarity and d is the attention dimension. After L layers the final token vectors $\{h_t^{(L)}\} \subset \mathbb{R}^{768}$ reflect meaning in context.

Intuition. Think of $v_{t'}^{(\ell)}$ as the *message* that token t' broadcasts at layer ℓ. The coefficient $\alpha_{tt'}^{(\ell)}$ is a *relevance weight* that says how much token t should listen to token t'. BERT computes $\alpha_{tt'}^{(\ell)}$ by comparing what t is seeking with what each t' offers (via a similarity score) and then normalising these scores so they form a probability distribution over t'. A larger $\alpha_{tt'}^{(\ell)}$ means a closer match, so more of the message $v_{t'}^{(\ell)}$ flows into the representation of t.[17]

BERT Pretraining: what it optimises. BERT learns the parameter vector $\theta \in \mathbb{R}^p$ that includes the token and position embedding tables; all attention parameters in each of the L transformer layers; and

[17] Consider how context affects attention weights: When processing "Banks typically lend money. The company borrowed from the bank yesterday," the attention weight $\alpha(\text{borrowed} \to \text{company})$ is moderate because "borrowed" identifies "company" as a standard borrowing entity. When the first sentence changes to "Banks typically refuse loans. The company borrowed from the bank yesterday," $\alpha(\text{borrowed} \to \text{company})$ increases because the verb "borrowed" now must attend more strongly to "company" to resolve the apparent contradiction—if banks refuse loans, how did this company successfully borrow? The company is no longer just a typical borrowing entity but must have distinctive characteristics that enabled it to overcome the general refusal pattern. The model increases attention to the subject to better process this unexpected semantic relationship. This demonstrates how contradictory context forces stronger attention weights as the model works harder to reconcile conflicting information.

the weights and biases of the position-wise feed-forward networks. Pretraining chooses $\boldsymbol{\theta}$ to minimise the sum of two cross-entropy losses. First, *Masked Language Modeling* hides a subset of tokens and asks the model to recover each hidden word from its final-layer position vector $h_t^{(L)}$. The loss is high when the predicted probability on the true word is low, so the model learns token representations that pull in exactly the contextual cues needed to "fill in the blank." Second, *Next Sentence Prediction* trains on a pair of sentences (A, B) to decide whether B naturally follows A. Misclassifying whether B follows A increases the loss, which pushes the model to encode cross-sentence structure—topic continuity, discourse cues, and whether one sentence entails the next. Across training steps, the attention patterns and feed-forward transformations shift so that masked words become easier to predict from context and sentence pairs become easier to judge as coherent, yielding final-layer vectors $h_t^{(L)}$ that are sensitive to meaning in context.

SBERT architecture and training. SBERT turns BERT into a Siamese encoder that produces one vector per sentence. Given token representations $\{h_1^{(L)}, \ldots, h_T^{(L)}\}$, it applies a pooling function $f(\cdot)$ to compress the sequence into a single sentence vector

$$s = f\left(h_1^{(L)}, \ldots, h_T^{(L)}\right) \in \mathbb{R}^{768}.$$

Typical choices for $f(\cdot)$ are mean pooling over tokens or taking the `[CLS]` embedding.[18] SBERT trains these vectors with a contrastive objective on sentence pairs. For a pair (s_1, s_2) labelled "similar," training increases their cosine similarity; for pairs labelled "dissimilar," it decreases it. The model learns coordinates where paraphrases and semantically related sentences cluster, and unrelated sentences separate. We use the pre-trained `all-mpnet-base-v2` model from the `sentence-transformers` library.[19]

Why SBERT rather than BERT cross-encoders? A BERT *cross-encoder* processes two texts jointly and uses cross-attention so that each token's representation is conditioned on the other text. This is effective for binary matching tasks, but it has two drawbacks for our setting: it yields no reusable sentence representation, and it makes the question's internal representation contingent on the specific comparison. That conflicts with our design goal: the question should have a single, stable embedding across all comparisons so that variation in similarity reflects differences in the downstream document rather than re-encodings of the question. By contrast, SBERT encodes each sentence independently into a fixed-length vector, and this helps in two ways:

- *Stability.* The question has one embedding that does not change across comparisons. Differences in similarity then reflect the content of the comparison text, not changes to the question's representation.
- *Scalability.* With Q questions and D policy documents, cross-encoders require QD joint forward passes. SBERT needs only $Q + D$ single-sentence encodings plus cheap QD dot products, enabling precomputation, caching, and efficient large-scale search.

[18] Mean pooling averages token vectors. Using `[CLS]` instead lets the network learn how to summarise the sequence through attention and non-linear layers. In practice both work; we follow the setting of `all-mpnet-base-v2`.

[19] Documentation available at https://www.sbert.net.