Evasive Answers in Financial Q&A: Earnings Calls vs. FOMC Press Conferences

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Abstract

Question–answer (Q&A) sessions in earnings calls and central bank press conferences provide high-stakes, unscripted insights into firms and the macroeconomy. Executives often respond evasively by avoiding, reframing, or obscuring answers, which limits transparency and biases downstream NLP tasks such as sentiment, risk, and event prediction. We introduce the task of *evasive answer detection* in financial Q&A and propose a three-level taxonomy grounded in pragmatics and psychology. Using annotated transcripts from earnings calls and FOMC press conferences, we show that lightweight features including hedges, verbosity, tense shifts, and semantic alignment capture robust signals of evasiveness. Our baselines demonstrate that evasiveness is linguistically and semantically distinct from sentiment and veracity, supporting its treatment as a standalone problem. This work establishes a foundation for benchmarks and models that incorporate evasiveness cues into financial NLP pipelines, market surveillance, and transparency assessment.

1 Introduction

Transparency, defined as the availability of firm-specific information to external stakeholders [Bushman et al., 2004], is essential for efficient markets. While much work has examined prepared disclosures, less attention has been paid to how executives and policymakers communicate in unscripted interactions such as question–answer (Q&A) segments in earnings calls or Federal Open Market Committee (FOMC) press conferences. These exchanges provide high-stakes, real-time insights, but also create opportunities for strategic communication.

Executives and central bankers often respond to difficult questions in ways that obscure, reframe, or avoid direct answers. Such evasiveness limits transparency and can bias downstream financial NLP tasks including sentiment analysis, risk assessment, and event forecasting. Unlike sentiment or veracity, which concern *what* is said, evasiveness concerns whether and how a question is answered, requiring discourse-level analysis of the alignment between questions and answers.

We introduce the task of **evasive answer detection** in financial Q&A. Our contributions are threefold: (i) a psychology- and pragmatics-informed taxonomy of evasive strategies spanning broad, mid-level, and fine-grained categories; (ii) annotated datasets of Q&A from both earnings calls and FOMC press conferences, enabling direct cross-domain analysis; and (iii) baseline models using lightweight, interpretable features—hedge counts, verbosity, tense usage, and semantic alignment—that capture systematic markers of evasiveness distinct from sentiment and factuality. By formalizing this task, we aim to support benchmarks and models that treat evasiveness as a standalone phenomenon, with applications to analyst tools, transparency assessment, and market surveillance.

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2 Related Work

Sentiment, veracity, and obfuscation. Most prior work in financial NLP has focused on sentiment and factuality. Domain-specific lexicons [Loughran and McDonald, 2011] and models such as FinBERT [Yang et al., 2020, Liu et al., 2020] capture tone in earnings calls and filings, while veracity detection emphasizes factual correctness [Leite et al., 2025, Irnawan et al., 2025]. These approaches assess *what* is said, not whether a question was answered. Communication research links evasive language to lower disclosure quality and worse outcomes: vague or overly positive language predicts restatements [Larcker and Zakolyukina, 2012], and about 11% of analyst questions receive "non-answers", more common under regulatory scrutiny or poor performance [Gow et al., 2021]. The management obfuscation hypothesis [Bushman and Smith, 2005, Khalmetski et al., 2017] similarly argues that executives obscure information strategically when fundamentals are weak.

Evasiveness and strategic communication. Recent computational work models evasiveness more directly. Chen et al. [2025] measure topic divergence between questions and answers, showing that evasiveness predicts negative market reactions. Their approach treats evasion as a scalar latent signal. In contrast, our work introduces an explicit, psychology-informed taxonomy, annotated datasets from both corporate and policy domains, and baselines grounded in interpretable features. The taxonomy adapts discourse pragmatics [Grice, 1975], psychological models of equivocation [Bavelas et al., 1990], and rhetorical strategies from political interviews [Bull, 1998, Rasiah, 2010] to financial Q&A, where evasion has direct market consequences.

3 Psychology-Informed Taxonomy of Evasiveness

Our taxonomy integrates three strands of theory: (i) Gricean maxims of discourse pragmatics [Grice, 1975], (ii) psychological models of equivocation [Bavelas et al., 1990], and (iii) fine-grained rhetorical strategies from political communication [Bull, 1998, Rasiah, 2010]. It is organized into three levels: **Level 1 (Rasiah)** distinguishes *Direct*, *Intermediate*, and *Fully Evasive* answers; **Level 2 (Bavelas)** groups evasions into *Omission*, *Vagueness*, *Non-Sequitur*, and *Restatement*; and **Level 3 (Bull)** specifies twelve rhetorical subtypes such as *Deflection*, *Agenda Shifting*, *Refusal to Answer*, and *Partial Answer*.

More information is provided in Appendix A, which includes the full label definitions, precedence rules, and additional examples. For illustration, Figure 2 shows the mid-level Bavelas categories, and Table 1 gives annotated (Q, A) examples across all three levels.

4 Datasets

4.1 Earnings Calls

We use quarterly earnings call transcripts of U.S. listed firms (2019–2022), scraped from The Motley Fool and available on Kaggle.[1] The corpus covers 18,755 calls from 2,876 companies. We focus on the **Q&A segments**, extracting $\sim$17,000 analyst–executive pairs (about 9 per call) with a hybrid pipeline of heuristics and LLM parsing. Each pair is annotated with our three-level taxonomy (Rasiah, Bavelas, Bull) and enriched with features such as length, hedges, tense, and embedding alignment. The processed data and annotations are released for replicability.[2]

4.2 FOMC Press Conferences

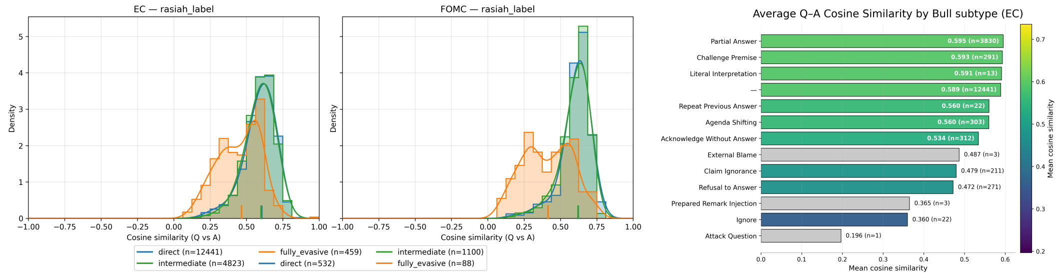
We also compile all 83 Federal Open Market Committee (FOMC) press conferences from 2011–2025,[3] spanning Chairs Bernanke, Yellen, and Powell. This corpus contains 1,728 journalist–Chair pairs (Figure 6). Pairs are annotated with the same scheme as above (evasion, sentiment, tense) using LLM prompts, validated on a stratified human subset. Data and prompts are also released.[4]

[1] https://www.kaggle.com/datasets/tpotterer/motley-fool-scraped-earnings-call-transcripts

[2] https://www.kaggle.com/datasets/gautiermarti/earnings-calls-qa-evasive-answers

[3] https://www.federalreserve.gov/monetarypolicy/fomccalendars.htm

[4] https://www.kaggle.com/datasets/gautiermarti/fomc-press-conferences-qa-evasive-answers



(a) Cosine similarity by Rasiah labels for EC and FOMC. (b) Mean similarity by Bull subtype (EC).

Figure 1: Semantic alignment between questions and answers.

5 Empirical Results with LLM-Assisted Annotations

5.1 Annotation Pipeline

We use a large language model (Claude 4 Sonnet) strictly as an *annotator*, assigning Rasiah (direct/intermediate/fully evasive), Bavelas (omission, vagueness, non-sequitur, restatement), and Bull subtypes to each Q–A pair. Prompts specify definitions and tie-breakers, and outputs are categorical. Annotations were produced at scale and validated on a stratified human subset. Details and examples are given in the appendix.

5.2 Prevalence and Typology

At the Rasiah level, earnings calls are dominated by direct answers (70%), with 27% intermediate and only 3% fully evasive. FOMC press conferences invert this balance: intermediate answers dominate (64%), with fewer direct (31%) and 5% fully evasive. At the Bavelas level, vagueness and non-sequiturs are most common in both domains, while omission and restatement are rare.

5.3 Linguistic Regularities

Domain comparisons reveal systematic contrasts:

- **Length.** FOMC questions and answers are consistently longer than earnings calls.
- **Vocabulary.** Earnings call answers are more lexically diverse, while FOMC Chairs rely on narrower phrasing.
- **Tense.** Corporate evasions often shift toward the future (hopeful projections), whereas FOMC evasions re-anchor in the present (restating mandate).
- **Sentiment.** In earnings calls, intermediate evasions and agenda shifting often carry a cautiously positive bias, while FOMC evasions are overwhelmingly neutral.
- **Semantics.** Embedding similarity cannot distinguish direct from intermediate answers (Figure 1a), but does capture fully evasive cases (lower alignment).

Appendix B provides additional descriptive evidence, including distributions of question and answer lengths, the number of questions per event, cross-domain comparisons, and summary statistics broken down by evasion category.

5.4 Market Reactions

We construct an event-level score Rasiah$_{i,t}$ by mapping labels to {direct = 1, intermediate = 0, evasive = -1} and averaging across all Q–A pairs in an event (earnings call or FOMC press conference). This score summarizes the overall transparency of a session.

We then regress event-day returns and volatility on this measure of evasiveness. For earnings calls, higher directness predicts significantly positive abnormal returns on the event day (Table 3; $t>3$). For FOMC press conferences, the coefficient is also positive but not statistically significant (Table 4), which is consistent with the smaller sample size (82 events versus ∼1,500 earnings calls) and the higher noise in index-level returns.

By contrast, volatility reacts more consistently across both domains. Direct answers are associated with significantly higher event-day volatility: for earnings calls the effect is extremely strong (Table 5, t=36, $R^2 \approx 45\%$), while for FOMC the coefficient remains positive and significant despite the smaller sample (Table 6, t=3.7, $R^2 \approx 15\%$). This pattern suggests that direct answers increase the amount of tradable information available, creating more scope for investor disagreement, while evasive answers dampen immediate reactions by withholding information.

Robustness checks using alternative return windows (3-day returns, ex-post monthly returns) and volatility measures (realized variance, ex-post 1-month volatility) yield results of similar magnitude and direction. Full regression outputs are reported in Appendix C.

In sum, linguistic analysis highlights clear domain-specific styles of evasion, while market regressions show that transparency is rewarded with higher returns and volatility across both corporate and policy contexts.

6 Limitations

This study is preliminary and several caveats remain. First, our LLM-based annotations are validated only on a stratified subset, and detailed inter-annotator agreement will require expansion. Second, broad categories such as *partial answer* may need refinement; in particular, partial disclosure strategies can be decomposed into narrower forms. Third, our reliance on large proprietary models (Claude 4 Sonnet) raises questions of reproducibility with open-source systems. Finally, both datasets focus on U.S. earnings calls and the FOMC; generalization to other geographies or institutions remains untested. These findings should be judged primarily by their utility in downstream tasks rather than as absolute ground truth.

7 Broader Impacts

Our datasets and methods enable more transparent financial NLP by detecting evasive communication, with applications in analyst tools, regulatory oversight, and academic research. At the same time, generative models could also be misused to engineer more sophisticated evasive answers, raising dual-use concerns. We release prompts and annotations to encourage scrutiny and responsible use of transparency-aware GenAI in finance.

8 Conclusion

We introduced the task of evasive answer detection in financial Q&A and released two annotated datasets covering earnings calls and FOMC press conferences, produced with LLM prompts and validated on human subsets. Our analysis highlights consistent markers of evasiveness, such as reduced Q–A alignment, brevity or verbosity, and tense shifts, while also revealing domain-specific differences: corporate executives tend to hedge through optimistic, forward-looking language, whereas central bankers rely more on neutral, present-tense framing. Lightweight linguistic and semantic features already capture robust signals, supporting the view that evasiveness should be treated as distinct from sentiment or veracity. Taken together, these resources establish a foundation for benchmark construction and model development in financial NLP, with direct implications for analyst tools, regulatory screening, and market surveillance. Future work will focus on refining the taxonomy, in particular by subdividing partial answers into finer-grained strategies, extending human validation, and exploring downstream applications ranging from investment signals to transparency assessment.

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A Evasiveness Taxonomy Definitions

Scope. We define an evasive answer as a response that fails to directly address the core informational intent of a question via omission, ambiguity, reframing, or selective disclosure. Labels are applied per (Q, A) pair. When multiple tactics are present, annotate the *dominant* tactic (see precedence below).

A.1 Level 1 — Response Type (Rasiah-style)

- **Direct** — Clear, relevant, and sufficiently specific answer to the focal question. It may include brief context but addresses the asked point (often includes numbers, dates, mechanisms, or decisions).
- **Intermediate** — Partially responsive: touches the topic but with hedging, selectivity, or missing specifics (answers *some* but not *all* of what was asked).
- **Fully Evasive** — Substantively non-responsive: avoids, deflects, or reframes such that the question's informational intent is not addressed.

A.2 Level 2 — Equivocation Form (Bavelas-style)

- **Omission** — Bypasses the request entirely (changes topic, declines to comment).
- **Vagueness** — Uses imprecise, generic, or abstract phrasing that withholds actionable detail (e.g., "we're optimistic," "various factors").
- **Non-Sequitur** — Provides content not relevant to the question's intent (answers a different question).
- **Restatement** — Paraphrases the question or prior material without adding new information.

A.3 Level 3 — Evasion Subtypes (Bull-style)

1. **Avoidance / Deflection** — Moves away from the focal point (e.g., "Let me step back..."), often to safer terrain.
2. **Acknowledging Without Answering** — Signals receipt/thanks or meta-discusses the question but withholds substance (e.g., "Great question; as you know...").
3. **Refusal to Answer** — Explicitly declines ("We don't guide on that", "Cannot comment").
4. **Agenda Shifting** — Redirects to a preferred topic or KPI not asked about.
5. **Claiming Ignorance** — Asserts lack of knowledge/readiness ("We don't have that number handy").
6. **Partial Answer / Selective Disclosure** — Answers only a subset (e.g., comments on revenue but not margin when asked for both).
7. **Literal Interpretation** — Overly narrow reading to dodge the broader intent (hair-splitting).
8. **Repetition of Prior Material** — Repeats earlier statement/guidance with no new content.
9. **Challenge Premise** — Disputes or reframes the question's assumptions rather than answering.
10. **Attack Question** — Labels the question as hypothetical, speculative, or unfair to avoid answering.
11. **Attack Questioner** — Undermines the analyst/questioner (rare in financial settings).
12. **External Blame** — Attributes inability to answer to external constraints (regulatory, legal, competitive).

A.4 Operational Guidance

Unit of annotation. Label per (Q, A) pair. If an answer contains multiple moves, choose the *dominant* form/tactic driving non-responsiveness.

Precedence (when multiple apply). *Refusal* > *Challenge Premise* > *Agenda Shifting* > *Partial Answer* > *Acknowledging w/o Answer* > *Literal Interpretation* > *Repetition* > *Claiming Ignorance* > *External Blame* > *Avoidance/Deflection*. Use **Omission/Non-Sequitur/Vagueness/Restatement** at Level 2 to summarize the psychological form of the chosen subtype.

Heuristic cues (non-exhaustive).

- *Directness* cues: concrete numbers, dates, time windows, named drivers/mechanisms, explicit decisions or guidance.
- *Vagueness* cues: hedges ("may", "could"), indeterminate quantifiers ("some", "various"), abstract nouns without instantiation.
- *Non-Sequitur/Agenda* cues: abrupt topic/KPI switch; high lexical divergence from Q; heavy promotional content.
- *Omission/Refusal* cues: "no comment", "we don't guide", legal/regulatory disclaimers.

- *Partial Answer* cues: answers only one conjunct of a multi-part Q; ignores requested dimensions (e.g., margin when asked revenue *and* margin).

A.5 Mapping Between Levels (typical alignments)

Level 2 (Form)	Common Level 3 Subtypes
Omission	Refusal; Avoidance/Deflection; External Blame; Claiming Ignorance
Vagueness	Acknowledging w/o Answer; Partial Answer; Literal Interpretation; Repetition
Non-Sequitur	Agenda Shifting; Challenge Premise; Attack Question/Questioner
Restatement	Repetition of Prior Material; Acknowledging w/o Answer

Examples (micro-templates).

- *Partial Answer* (**Vagueness**): *Q: "Revenue & margin outlook?" A: "Revenue should grow mid-single digits given APAC momentum."*
- *Agenda Shifting* (**Non-Sequitur**): *Q: "Regulatory impact on Q3 profits?" A: "What's important is our 10% revenue growth this quarter."*
- *Refusal* (**Omission**): *Q: "Will you cut headcount next quarter?" A: "We don't comment on future workforce actions."*
- *Acknowledging w/o Answer* (**Vagueness**): *"Great question. As we've said, we remain focused on long-term value."*

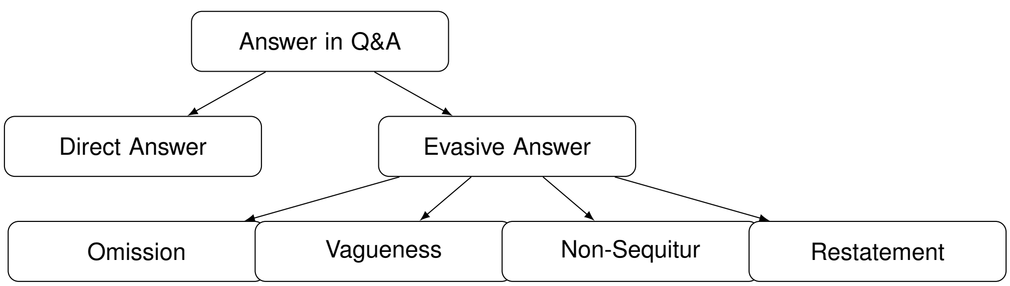
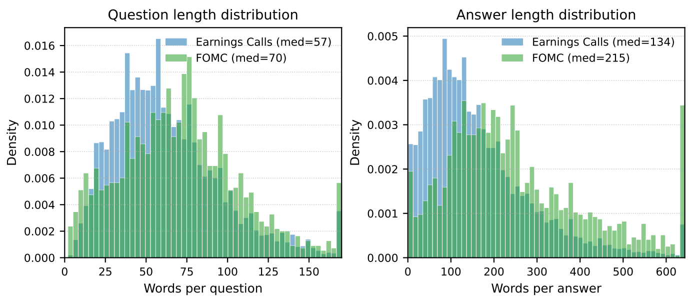


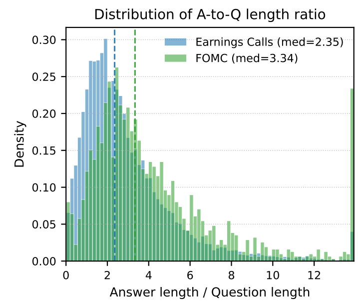
Figure 2: Mid-level taxonomy of evasive answers (Bavelas categories). Each category contains finer-grained rhetorical strategies.

Question	Answer	Rasiah	Bavelas	Subtype (Bull)
Will you revise earnings guidance for next quarter?	We remain focused on delivering long-term value to shareholders.	`fully_evasive`	Omission	Avoidance (Deflection)
What explains the decline in margins?	There are several interacting macroeconomic factors, including supply chain volatility and input costs.	`intermediate`	Vagueness	Obfuscation (Vague / Complex)
How will the new regulations affect your Q3 profits?	What's important to highlight is that our revenues have grown 10% this quarter.	`fully_evasive`	Non-Sequitur	Misdirection (Answering a Different Question)
Can you comment on both revenue and margin outlooks?	Revenue will increase 8% due to Asia-Pacific expansion.	`fully_evasive`	Omission	Partial Answer (Selective Disclosure)
Chair Powell, how confident are you that inflation will return to 2% without a significant rise in unemployment?	We continue to believe the labor market remains resilient and our tools are well positioned to achieve our mandate.	`intermediate`	Vagueness	Acknowledging Without Answer
Will the Committee rule out another rate hike this year?	It would be premature to speculate on future decisions; we will remain data dependent.	`fully_evasive`	Omission	Refusal to Answer
Has the banking sector stress influenced your baseline forecast?	No, our baseline outlook remains unchanged, though we are closely monitoring developments.	`direct`	—	—

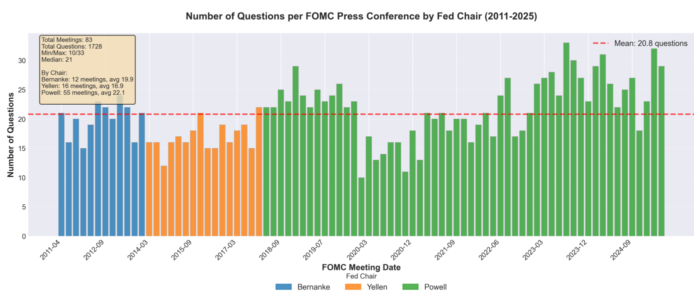
Table 1: Example annotations using our three-level taxonomy: Rasiah (response type), Bavelas (evasion form), and Bull (evasion subtype).



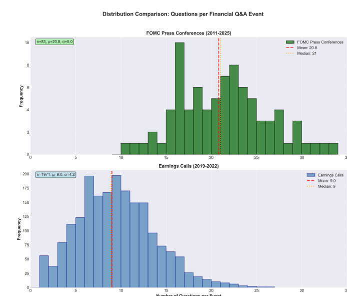
(a) Question and answer length distributions for Earnings Calls and FOMC (density histograms; legends show medians).



(b) Distribution of the answer-to-question length ratio.



(a) Number of questions per FOMC press conference over time, colored by Fed Chair. The dashed line shows the mean across meetings.



(b) Distribution comparison of the number of questions per event: FOMC press conferences (top) vs. earnings calls (bottom).

Figure 4: FOMC questions over time (left) and distributional comparison across event types (right).

B Datasets Summary Statistics

C Regression Results

	Question length		Answer length		Answer-to-Question ratio	
Rasiah label	EC	FOMC	EC	FOMC	EC	FOMC
Direct	54	66	124	194	2.24	3.03
Intermediate	63	73	168	248	2.59	3.69
Fully evasive	41	56	48	69	1.23	1.48

Table 2: Median question length, answer length, and answer-to-question ratio by Rasiah label for earnings calls (EC) and FOMC press conferences.

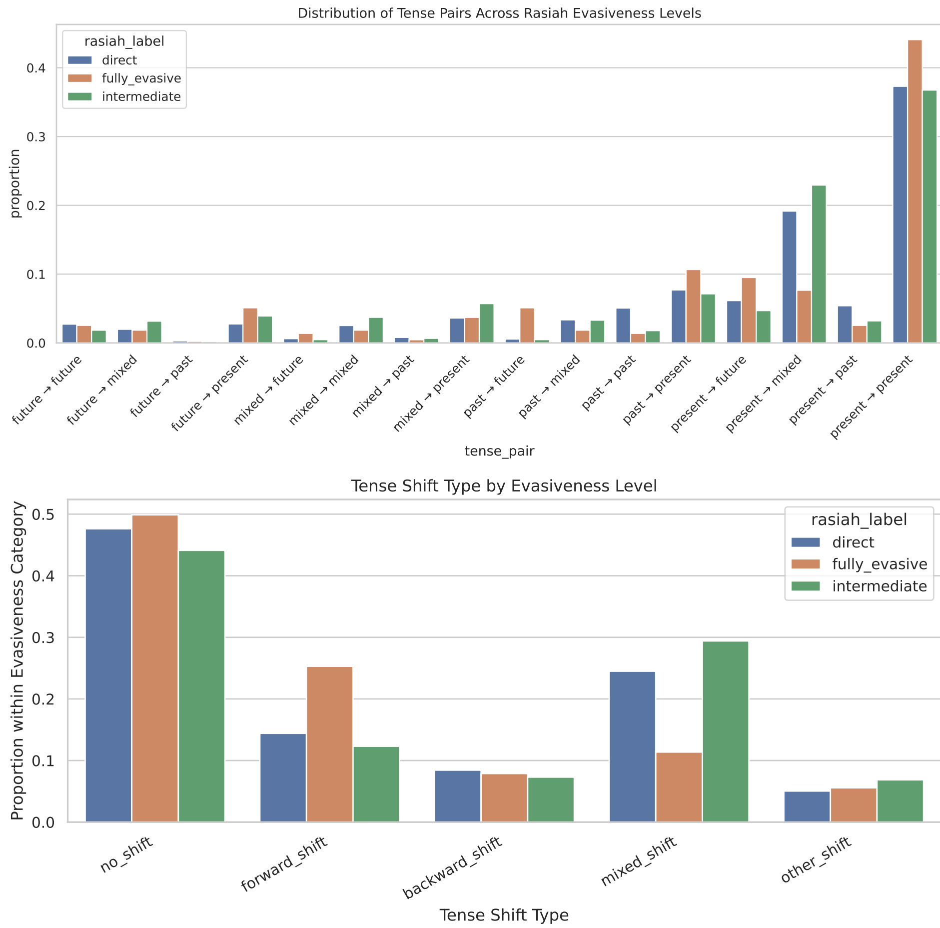
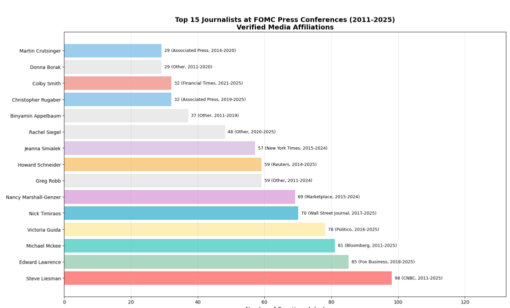
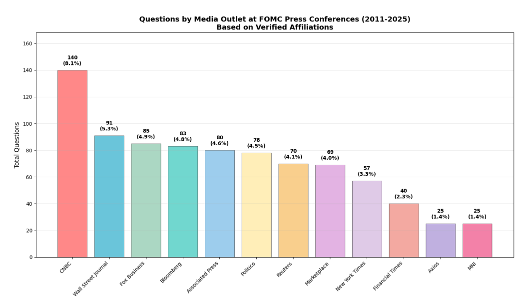


Figure 5: (Top) Distribution of question–answer tense pairs by Rasiah label. (Bottom) Distribution of tense shift types across Rasiah-style evasiveness levels.



(a) Top 15 journalists by number of questions at FOMC press conferences (2011–2025).



(b) Questions by media outlet (Top 10).

Figure 6: Distribution of questions in FOMC press conferences by (a) journalist and (b) media outlet.

Dep. Variable:	returns_0	**R-squared (uncentered):**	0.007
Model:	OLS	**Adj. R-squared (uncentered):**	0.006
Method:	Least Squares	**F-statistic:**	10.56
Date:	Fri, 29 Aug 2025	**Prob (F-statistic):**	0.00118
Time:	08:59:59	**Log-Likelihood:**	4897.2
No. Observations:	1576	**AIC:**	-9792.
Df Residuals:	1575	**BIC:**	-9787.
Df Model:	1		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P> |t|**	**[0.025**	**0.975]**
Rasiah_numeric_mean_per_doc	0.0013	0.000	3.249	0.001	0.000	0.002

Omnibus:	129.301	**Durbin-Watson:**	1.978
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	244.253
Skew:	-0.553	**Prob(JB):**	9.15e-54
Kurtosis:	4.579	**Cond. No.**	1.00

Table 3: OLS regression of company returns (on earning call day) against the Rasiah numerical value averaged at the earning call document level.

Notes:
[1] R^2 is computed without centering (uncentered) since the model does not contain a constant.
[2] Standard Errors assume that the covariance matrix of the errors is correctly specified.

Dep. Variable:	returns_0	**R-squared (uncentered):**	0.010
Model:	OLS	**Adj. R-squared (uncentered):**	-0.002
Method:	Least Squares	**F-statistic:**	0.8397
Date:	Fri, 29 Aug 2025	**Prob (F-statistic):**	0.362
Time:	09:14:30	**Log-Likelihood:**	245.72
No. Observations:	82	**AIC:**	-489.4
Df Residuals:	81	**BIC:**	-487.0
Df Model:	1		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P> |t|**	**[0.025**	**0.975]**
Rasiah_numeric_mean_per_doc	0.0125	0.014	0.916	0.362	-0.015	0.040

Omnibus:	2.856	**Durbin-Watson:**	2.130
Prob(Omnibus):	0.240	**Jarque-Bera (JB):**	2.234
Skew:	-0.387	**Prob(JB):**	0.327
Kurtosis:	3.234	**Cond. No.**	1.00

Table 4: OLS regression of S&P 500 returns (on the FOMC press conference day) against the evasion measure (Rasiah numeric score) averaged at the document level.

Notes:
[1] R^2 is computed without centering (uncentered) since the model does not contain a constant.
[2] Standard Errors assume that the covariance matrix of the errors is correctly specified.

Dep. Variable:	sq_returns_0	**R-squared (uncentered):**	0.452
Model:	OLS	**Adj. R-squared (uncentered):**	0.452
Method:	Least Squares	**F-statistic:**	1300.
Date:	Fri, 29 Aug 2025	**Prob (F-statistic):**	4.20e-208
Time:	09:21:01	**Log-Likelihood:**	5338.3
No. Observations:	1576	**AIC:**	-1.067e+04
Df Residuals:	1575	**BIC:**	-1.067e+04
Df Model:	1		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P> |t|**	**[0.025**	**0.975]**
Rasiah_numeric_mean_per_doc	0.0106	0.000	36.059	0.000	0.010	0.011

Omnibus:	341.697	**Durbin-Watson:**	1.957
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	629.543
Skew:	1.327	**Prob(JB):**	1.98e-137
Kurtosis:	4.594	**Cond. No.**	1.00

Table 5: OLS regression of volatility on the day of event onto our evasion measure for earnings calls.

Notes:
[1] R^2 is computed without centering (uncentered) since the model does not contain a constant.
[2] Standard Errors assume that the covariance matrix of the errors is correctly specified.

Dep. Variable:	sq_returns_0	**R-squared (uncentered):**	0.146
Model:	OLS	**Adj. R-squared (uncentered):**	0.136
Method:	Least Squares	**F-statistic:**	13.89
Date:	Fri, 29 Aug 2025	**Prob (F-statistic):**	0.000358
Time:	09:25:05	**Log-Likelihood:**	251.04
No. Observations:	82	**AIC:**	-500.1
Df Residuals:	81	**BIC:**	-497.7
Df Model:	1		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P> |t|**	**[0.025**	**0.975]**
Rasiah_numeric_mean_per_doc	0.0477	0.013	3.726	0.000	0.022	0.073

Omnibus:	3.134	**Durbin-Watson:**	0.897
Prob(Omnibus):	0.209	**Jarque-Bera (JB):**	3.094
Skew:	0.457	**Prob(JB):**	0.213
Kurtosis:	2.737	**Cond. No.**	1.00

Table 6: OLS regression of volatility of the S&P 500 on event day against our evasion measure for FOMC press conferences.

Notes:
[1] R^2 is computed without centering (uncentered) since the model does not contain a constant.
[2] Standard Errors assume that the covariance matrix of the errors is correctly specified.