FROM EARNINGS CALLS TO HEADLINES: INVESTIGATING THE ALIGNMENT BETWEEN CORPORATE TONE AND POST-CALL MEDIA SENTIMENT IN KUWAIT'S BANKING SECTOR

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The 2024 Second Place Research Paper Winner
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FROM EARNINGS CALLS TO HEADLINES: INVESTIGATING THE ALIGNMENT BETWEEN CORPORATE TONE AND POST-CALL MEDIA SENTIMENT IN KUWAIT'S BANKING SECTOR

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تـم اسـتخراج البيانـات باسـتخدام (Python)، حيـث تـم بنـاء خوارزميـات لجمـع وتنظيـم النصـوص بدقـة، وفصـل المقـالات المتعلقـة بـكل بنـك عـن غيرهـا لـضمان تحـليلات دقيقـة على مسـتوى المؤسسـة. بعـد ذلـك، اسـتخدمنا نمـوذج اللغـة الكـبير (LLM) المطـور لــ (ChatGPT) لقيـاس نبرة كل نـص سـواء كان مـن مؤتمـرات المسـتثمرين/المحللين أو مـن مقـال إخبـاري باللغـتين

العربيـة والإنجليزيـة. تتيـح هـذه التقنيـة الحديثـة تقييـم الـنبرة بشـكل موحـد عبر لغـات مختلفـة، مما يحـل واحـدة مـن أكبر تحديـات التحليـل الـنصي في السـياقات ثنائيـة اللغـة. وتـم بعـد ذلـك اسـتخدام نمـاذج انحـدار للبيانـات اللوحيـة (Panel Regression with Fixed Effects) لفحـص العلاقـة بين الـنبرة الأخبـار قبـل المؤتمـر، نبرة المؤتمـر نفسـها، ونبرة الأخبـار بعـد المؤتمـر، مـع التحكـم في الفروقـات الزمنيـة والمؤسسـية.

أهم النتائج:

تـشير نتائـج الدراسـة إلى أن نبرة التغطيـة الإعلاميـة (المقـالات إخباريـة) بعـد مؤتمـرات المسـتثمرين/المحللين تتأثـر بشـكل كـبير بالتفاعـل بين الـنبرة خلال المؤتمـر ونبرة التغطيـة الإعلاميـة السـابقة (المقـالات المنـتشرة قبـل المؤتمـر). عندما تكـون الـنبرة إيجابيـة في كلٍ مـن الأخبـار السـابقة والمؤتمـر، فـإن التغطيـة الإعلاميـة التاليـة تكـون أكثر إيجابيـة وبشـكل واضـح. ولكـن عندمـا تكـون نبرة المؤتمـر إيجابيـة وحدهـا، دون دعـم من نبرة سـابقة مماثلـة مـن التغطيـة الإعلاميـة، فـإن تأثيرهـا على التغطيـة الإعلاميـة يصبـح محـدوداً. هـذا يـشير إلى أن الاتسـاق في الرسـائل عبر الزمـن يلعـب دورًا حـاسمًا في تشـكيل السرد الإعلامـي.

كما أظهـرت النتائـج أن الاتسـاق في الـنبرة كان أقـوى عندمـا قـاد مؤتمـر المسـتثمرين/المحـللين مسـؤول تنفيـذي رفيع (مثـل الرئيس التنفيـذي أو المديـر المالي)، أو عندما كانت المكالمـة أطـول وأكثر تعقيـدًا مـن حيـث اللغـة. ويبـدو أن هـذه العوامـل تعـزز مصداقيـة الرسـالة وتسـهل تكرارهـا في الإعلام. إضافـة إلى ذلـك، تـبين أن البنوك الإسلاميـة والبنوك الكـبيرة كانـت أكثر قـدرة على نقـل رسـائلها بفعاليـة في الإعلام، خصوصًـا في المواضيـع ذات الأهميـة العامـة مثـل اللوائـح المصرفيـة والخدمـات الإسلاميـة.

الآثار والتوصيات:

تعكـس النتائـج أهميـة التناسـق في الرسـائل المؤسسـية وتـأثير البيئـة الإعلاميـة في الكويـت، حيـث تلعـب البنـوك دورًا مبـاشرًا في صياغـة الأخبـار المتعلقـة بهـا. وتـوصي الدراسـة الجهـات التنظيميـة وصنّـاع القـرار في الكويـت بضرورة تعزيـز اسـتقلالية الإعلام الاقتصـادي لـضمان تغطيـة أكثر توازنًـا وموضوعيـة، بعيـدًا عـن هيمنـة الخطـاب المـؤسسي. كما تُشـجّع البنـوك الكويتيـة على تحقيـق تـوازن فعّـال بين توجيـه الرسـائل الإعلاميـة والحفـاظ على الشـفافية، لما لذلـك مـن أثـر مبـاشر في تعزيـز ثقـة الجمهـور، ودعـم مصداقيـة المؤسسـات الماليـة، وتحـسين منـاخ الاسـتثمار في السـوق المـحلي. فـكلما ازدادت الشـفافية، زادت قـدرة المسـتثمرين والمسـتهلكين على اتخـاذ قـرارات

مـن مؤتمـرات الأربـاح إلى عناويـن الصحـف: دراسـة توافـق الـنبرة بين الخطـاب المـؤسسي والتغطيـة الإعلاميـة بعـد المؤتمـر في القطـاع المصرفي الكويتـي.

أهداف البحث:

تسلّط هـذه الرسالة الضـوء على كيفيـة انتقال نبرة الخطـاب مـن مؤتمـرات المسـتثمرين/المحلـلين التـي تعقدهـا البنـوك الكويتيـة إلى التغطيـة الإعلاميـة (المقـالات الإخباريـة) التـي تليهـا، وذلـك ضمـن سـياق إعلامـي يتميـز بخصوصيـة مؤسسـية. في الكويـت، غالبًا مـا تقـوم البنـوك بإعـداد المـواد الصحفيـة المتعلقـة بهـا وإرسـالها للـنشر في وسـائل الإعلام، مما يحـد مـن الـدور التحريـري التقليـدي للمؤسسـات الصحفيـة. هـذا الوضـع يوفـر للبنـوك قـدرة أكبر على تنسـيق رسـائلها العامـة، ويجعـل مـن المهـم دراسـة ديناميكيـات الاتصـال وتأثيرهـا على فهـم الجمهـور والمسـتثمرين للأداء المصرفي.

يهـدف البحـث إلى معرفـة مـا إذا كانـت نبرة الخطـاب في مؤتمـرات المسـتثمرين/المحللين تؤثـر على نبرة التغطيـة الإعلاميـة (المقـالات الإخباريـة) بعـد المكالمـة، ومـا إذا كان هـذا التـأثير يتـغير بنـاءً على نبرة الأخبـار المنشـورة قبـل المكالمـة. مـن خلال ذلـك، نسـعى لفهـم مـا إذا كانـت التغطيـة الإعلاميـة تعكـس تقيـيماً موضوعيًا للخطـاب المالي، أم أنهـا ببسـاطة تعيـد تكـرار مـا تقولـه البنـوك.

يرتبـط هـذا البحـث بشـكل مبـاشر بالمجـالات الاقتصاديـة والماليـة والمصرفيـة التي تسـهم في تطويـر عمـل القطـاع المصرفي الكويتـي. ففهـم كيفيـة تشـكيل الصـورة الإعلاميـة للبنـوك يسـاهم في تعزيـز الشـفافية، وتحـسين استراتيجيـات التواصـل المـؤسسي، وبالتـالي رفـع كفـاءة العلاقـة بين البنـوك والجمهـور. كما يسـاعد على وضـع حلـول علميـة للتحديـات المرتبطـة بثقـة المسـتثمرين، وفعاليـة الإعلام المالي، وهـو مـا يمثـل أحـد الاخـتلالات البنيويـة التـي تواجـه الاقتصـاد الكويتـي في بيئتـه الحاليـة.

بالإضافـة إلى ذلـك، يقـدم البحـث أداة تطبيقيـة حديثـة باسـتخدام الـذكاء الاصطناعـي وتحليـل اللغـة الطبيعـي، مما يفتـح المجـال أمـام اسـتخدام تقنيـات متطـورة لإعـادة تشـكيل طـرق تقييـم وتحليـل الخطـاب الاقتصـادي في الكويـت، وبمـا ينسـجم مـع التحـول نحـو نمـاذج اقتصاديـة أكثر تطـورً ا وشـفافية.

المنهجية العلمية:

يعتمـد هـذا البحـث على منهجيـة تحليـل نصي مدعومـة بتقنيـات الـذكاء الاصطناعـي. تـم تجميـع البيانـات مـن مصدريـن رئيسـيين: (1) نصـوص مؤتمـرات المسـتثمرين/المحللين التـي تعقدهـا البنـوك الكويتيـة المدرجـة في السـوق منـذ عـام 2018 الى عـام 2024 والتـي أصبحـت ملزمـة بالـنشر بموجـب لوائـح بورصـة الكويـت، و(2) مقـالات إخباريـة نُشرت في صحيفـة "الجريـدة"، وهـي واحـدة مـن الصحـف الاقتصاديـة المؤثـرة في الكويـت .

ABSTRACT

This paper examines whether corporate disclosure events affect the persistence of media narratives. The analysis is based on corporate communication and corresponding newspaper coverage of Kuwaiti banks over the period 2018 to 2025. First, we apply LLM-based sentiment analysis (ChatGPT) to measure the sentiment of Arabic and English newspapers and categorise the text of earnings calls transcripts. Second, a high-dimensional fixed effects panel data estimator is applied to estimate whether the earnings call tone affects the link between pre-call and post-call media sentiments. Our main results suggest that post-call media tone is most positive when the sentiment in earnings calls reinforces prior media sentiment. This effect is stronger for Islamic banks, larger institutions, and calls that are longer, more complex, or led by senior executives. Results remain robust using binary tone classification and alternative models.

Keywords: Banking; Corporate Disclosure; Sentiment Analysis; ChatGPT.

1. INTRODUCTION

In recent years, the business media has become a powerful channel for shaping how corporate events are communicated to the general public. Rather than simply reporting facts, media outlets actively interpret and reshape company narratives, making them more accessible and appealing to broad audiences. This process plays a key role in translating complex financial events into stories that are relevant for everyday readers, influencing how companies are perceived by investors, regulators, customers, and employees alike. One key example is earnings calls, which have evolved from straightforward reporting tools into carefully crafted performances. Executives use these events to highlight financial achievements, manage expectations, and control public messaging. These calls are frequently picked up by the media and disseminated widely. Yet, while many studies focus on how investors react to these messages, less is known about whether the calls themselves shape media perception. Hence, this work aims to explore whether the persistence of media coverage sentiment is affected by corporate events.

Several studies have shown that the way companies speak, in terms of their tone, can have a significant impact. When companies adopt a positive tone, investor sentiment often improves, and stock values tend to rise (Davis et al., 2012; Li, 2010; Huang et al., 2014). More recent research indicates that media coverage frequently mirrors the tone set by company executives (Ardia et al., 2021; Doey and de Jong, 2024). Other findings suggest that the media may either amplify or soften corporate messages depending on how newsworthy the subject is (Oliver et al., 2023). However, many of these studies assume that media outlets are independent and just react to what companies say. This might not be true in places where companies have more control over the media.

Our study contributes to the literature on business media by examining whether the tone used in earnings calls by banks translates directly into the tone of post-call media coverage. While prior research has explored tone transmission from firms to markets (e.g., Davis et al., 2012; Li, 2010; Huang et al., 2014), fewer studies have addressed whether tone travels in similar ways to the media, particularly in non-Western contexts where media independence is limited. We extend this literature by analysing tone alignment under conditions of direct corporate control over media output, providing new insights into how strategic communication unfolds in such environments. This helps clarify the communication link between corporate disclosure and media reporting, allowing us to understand better how tone can influence broader perceptions of corporate events.

To explore this further, the study examines several related questions. It considers whether post-call media tone becomes more positive when it aligns with both the tone of the earnings call and the sentiment expressed in earlier news coverage. It also looks at whether certain types of banks, such as Islamic banks or those with larger asset sizes, are more successful at maintaining this consistency. In addition, the analysis explores whether specific features of the earnings call, such as having a senior executive as the main speaker, using forward-looking language, expressing uncertainty, or using more complex speech, help strengthen the transmission of tone. Finally, it investigates whether the effect of tone alignment varies depending on the main topic discussed in the media, including regulation, customer service, or Islamic banking services.

We chose Kuwait as the setting for this study because it offers a special case. In Kuwait, many banks write their own press articles, which are then published in newspapers without much editing. This gives them an unusual level of control over their public image. Instead of acting like independent editors, journalists often just pass along what the banks provide. This creates a situation where banks can coordinate their message across both direct communications, like earnings calls, and indirect communications, like media articles. Because of this, Kuwait is a strong example of how tone might be deliberately managed across different channels.

Our findings show that the media's tone after an earnings call is shaped by both the tone of earlier news and the tone of the call. When both are positive, the media is more likely to continue using positive language. However, if the call is positive but earlier media coverage was negative, the later media tone does not improve. This suggests that having a consistent tone is important-just sounding positive in one setting is not enough. Especially in places like Kuwait, where the banks heavily influence media content, this consistency can be seen as a way to manage the message.

We also find that some features help banks keep their message consistent. For example, tone alignment is stronger when the call is led by a senior executive, when the call is longer, or when the language is more complex. This suggests that credibility, communication effort, and detailed speech help carry the tone across to the media. Islamic banks and larger banks are especially good at this, likely because they care more about their public image and have more influence in media. We also find stronger alignment when the topic is something the public cares about, such as regulations or Islamic banking services.

Besides the main findings, our study adds three other contributions. First, we focus on tone transmission in a unique institutional setting in Kuwait, where banks often influence or directly produce their own media coverage. Instead of assuming that tone naturally flows from earnings calls to the media, we ask whether this transfer happens in practice. We also examine cases where media coverage is absent entirely, revealing gaps between corporate messaging and public communication. This allows us to better understand how media framing functions even in environments with strong corporate control over content, building on findings by Gurun and Butler (2012), Engelberg and Parsons (2011), and Dyck and Zingales (2003).

Second, our paper contributes to the literature by examining whether the tone expressed in banks' earnings calls shapes the sentiment of subsequent media coverage. We extend prior research by focusing on the consistency of tone across communication platforms, considering the role of pre-call media sentiment and the institutional context in which banks operate (e.g., Doey and de Jong, 2024; Ardia et al., 2021; Oliver et al., 2023).

Third, our study contributes to the literature by applying OpenAI's large language model (ChatGPT) to both Arabic and English financial texts. Our study introduces a unified, cross-lingual sentiment analysis framework that overcomes the linguistic limitations of existing models. Unlike earlier tools such as FinBERT or AraBERT, which are limited to one language or trained on general content, OpenAI's model is trained on a wide range of languages and topics. This helps it understand context and tone more accurately. Using one model for both sources allow for better comparison between media and company announcements (e.g., Antoun et al., 2020; Fatouros et al., 2023; Kirtac and Germano, 2024).

The remainder of this paper is structured as follows. Section 2 provides background on the Kuwaiti banking sector. Section 3 reviews the related literature. Section 4 presents the empirical framework, including the data sources, sentiment analysis approach, and methodology. Section 5 discusses the results and key findings. Finally, Section 6 concludes.

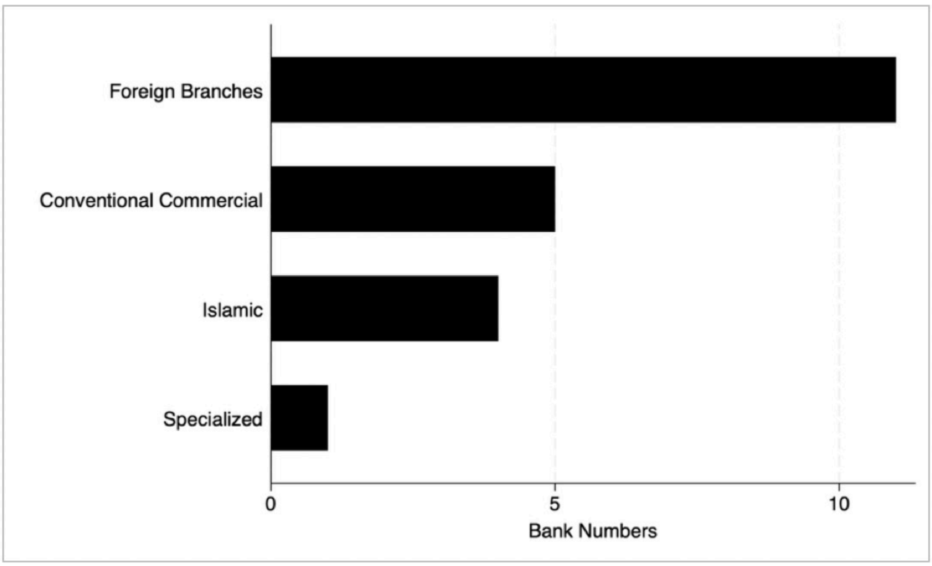
2. BACKGROUND: KUWAIT BANKING SECTOR

Kuwait's banking sector is one of the most established and stable in the Gulf region. As of 2024, there are 10 locally incorporated banks in the country. These include five conventional commercial banks, four Islamic banks, and one specialised institution known as the Industrial Bank of Kuwait. In addition, 11 foreign banks operate through branches. Although foreign institutions contribute to the market, domestic banks dominate, holding the vast majority of total banking assets. Islamic banks alone account for nearly 49% of all assets in the sector, reflecting the significant role of Sharia-compliant finance in Kuwait.

The foundation of Kuwait's banking sector was a market-driven initiative, beginning with the establishment of the National Bank of Kuwait (NBK) in 1952, the country's first indigenous bank. This was followed by the Commercial Bank of Kuwait in 1960 , with the Central Bank of Kuwait (CBK) being formally established in 1968 to provide a comprehensive regulatory and supervisory framework. The sector today is characterised by a dual system of strong conventional and Islamic banks. The National Bank of Kuwait is the largest traditional bank by assets, while Kuwait Finance House (KFH), a pioneer in Islamic finance established in 1977, holds the top position as the largest company in Kuwait by market capitalisation.

The Central Bank of Kuwait (CBK) regulates and supervises the entire banking system. Its role is crucial in maintaining financial stability, and it imposes rigorous standards consistent with international frameworks such as Basel III. For example, while the global minimum capital adequacy ratio (CAR) is 10.5%, Kuwaiti banks consistently maintain average CARs around 20%, far above the required threshold. This highlights the conservative and cautious approach of Kuwaiti regulators and banks alike.

Figure 1. Number of Banks Operating in Kuwait (2024)



Source: Helgi Library

Profitability in the sector has remained strong. According to KPMG (2025), the return on average assets for listed banks in Kuwait reached 1.4% in 2024, up from 1.3% in 2023. The return on equity rose to 11.45% from 11.11%, driven by higher interest income and lower impairment charges. The net interest margin improved to 3.22% in 2024, up from 2.98% the previous year.

In terms of asset quality, Kuwaiti banks continue to maintain a low non-performing loan (NPL) ratio, which stood at 1.4% in 2023. Provisions coverage improved further, reaching 312%, reflecting banks' prudent risk management. The capital adequacy ratio (CAR) for the sector also increased slightly from 19.2% to 19.9%, comfortably above regulatory requirements.

Table 1. Key Financial Indicators for Kuwaiti Banks

INDICATOR	2023	2024
RETURN ON ASSETS (ROA)	~1.3%	~1.4%
RETURN ON EQUITY (ROE)	~10.2%	~11.8%
NON-PERFORMING LOANS (NPL)	1.4%	1.4%
CAPITAL ADEQUACY RATIO	19.2%	19.9%
NET INTEREST MARGIN (NIM)	2.9%	3.1%
PROVISION COVERAGE RATIO	~250%	312%

Source: KPMG Kuwait Banking Results 2025

Financially, Kuwaiti banks remain robust, delivering strong profitability, solid asset quality, and high capital buffers. In 2024, listed banks achieved a return on assets of 1.4% and a return on equity of 11.45%, supported by an improved net interest margin of 3.22% and stable non-performing loan ratios at 1.4%. Provision coverage reached 312%, underscoring prudent risk management, while capital adequacy ratios averaged around 20%, significantly exceeding international requirements. Despite an average cost-to-income ratio of 47.26% and an 11.04% increase in loan provisions to KD 490.7 million, sector leaders such as NBK and KFH continued to deliver strong profitability, supported by digital transformation initiatives, regional expansion, and sustained investor confidence, positioning the industry for stable performance amid global uncertainties.

3. LITERATURE REVIEW

3.1 The Strategic Use of Tone in Managerial Communication

Recent research has increasingly focused on the way companies communicate with the public, especially during earnings calls. These meetings are not just platforms for reporting financial results, they are opportunities for management to shape investor expectations through language. Previous research has highlighted that how something is said can be as influential as what is said. In particular, the tone and structure of managerial speech during these calls can signal confidence, caution, or uncertainty, all of which play a role in shaping market reactions.

A large body of literature shows that the language used in earnings press releases carries incremental informational value beyond the numbers.

For instance, Davis et al., (2012) found that a more optimistic tone in narrative disclosures was positively associated with stock market reactions. Similarly, Huang et al., (2014) introduced the concept of "tone management," showing that managers strategically adjust the tone of earnings calls to shape investor sentiment and mitigate negative reactions to poor performance. Their findings suggest that tone is not merely a reflection of performance but a communicative tool that managers use to influence external perceptions. Li (2010) examined forward-looking statements in corporate filings using a Naive Bayesian approach. He found that narrative elements in these documents contain significant predictive information about stock returns and analyst behaviour, suggesting that textual content holds material value for financial forecasting. Mayew and Venkatachalam (2012) examined how vocal cues in earnings calls, such as pitch and emotional tone, reflect managerial confidence. They found that these vocal features are linked to future firm performance, suggesting that not only the content of what managers say but also the way they say it can influence how markets respond. Moreover, a recent by Cook et al., (2024) evaluates the performance of local large language models on bank earnings calls and finds that during the banking stress of early 2023, banks converged to similar topics and used a distinctly less positive tone. In a related study focusing on an emerging market, Kayed and Alta'any (2025) found that the tone in banks' annual reports was negatively associated with both current and future financial performance, which supports the impression management theory that tone can be used to mislead stakeholders rather than reflect the firm's financial health.

We build on this literature by exploring whether the tone used in earnings calls by banks translates directly into the tone of post-call media coverage. While much of the existing literature has examined the impact of tone on investor behaviour and firm valuation, our study focuses instead on the communication process, specifically the connection between corporate disclosures and subsequent media coverage.

3.2 The Role of the Media in Shaping Financial Narratives

Another stream of literature examines the media's role in amplifying, filtering, or reshaping the tone of corporate disclosures. This line of research highlights that media outlets can influence how corporate narratives are interpreted by investors and the public, depending on factors such as geography, ownership structure, and commercial incentives.

The work of Gurun and Butler (2012) investigated how local media slant influences coverage of nearby firms. They found that local newspapers tend to report more positively on firms headquartered in the same area, especially when advertising revenue is involved. This relationship, referred to as "hype bias," highlights how business incentives can influence journalistic tone. Dyck and Zingales (2003) discussed how ownership structures and competition levels in the media industry affect the objectivity of financial reporting. Their study suggested that media organizations with concentrated ownership or limited competition may be more susceptible to biased coverage. Engelberg and Parsons (2011) analysed how geography-based media exposure affects investor behaviour. Their findings demonstrated that when local news coverage of a firm increases, local trading activity rises as well, underscoring the influence of media tone on market behaviour. Tetlock (2007) found that media pessimism, as measured by negative word frequency in major newspapers, is significantly associated with downward pressure on stock prices. His results suggest that media tone can act as a predictor of near-term market performance. Peress (2014) studied the impact of newspaper strikes on market behaviour and discovered that the absence of media coverage led to reduced trading volume and slower information diffusion. This shows how vital media presence is for efficient market reactions.

Our study contributes to this literature by focusing on tone transmission in a unique institutional setting in Kuwait, where banks often influence or directly produce their own media coverage. Instead of assuming that tone naturally flows from earnings calls to the media, we ask whether this transfer happens in practice. We also examine cases where media coverage is absent entirely, revealing gaps between corporate messaging and public communication. This allows us to better understand how media framing functions even in environments with strong corporate control over content.

3.3 Connecting Executive Tone to Media Sentiment

Media outlets play a pivotal role in interpreting and disseminating the information conveyed during corporate earnings calls. The tone adopted by company executives during these calls can significantly influence subsequent media narratives, thereby affecting investor perceptions and market reactions.

A study by Ardia et al., (2021) conducted a tone-based event analysis to examine the dynamics of media tone around earnings announcements. Their findings suggest that media articles provide incremental information beyond what is contained in earnings press releases and calls, indicating that media tone can influence market reactions. Further, research by Doey and de Jong (2024) investigated the relationship between earnings call sentiment and subsequent media coverage sentiment. The paper found a significant positive correlation between negative sentiment in earnings calls and subsequent negative news sentiment. This indicates that media narratives often mirror the tone set by corporate disclosures. Moreover, Oliver et al. (2023) explored how newsworthiness shapes media volume and tone in the context of earnings announcements. Their research highlights that media coverage of earnings influences investor perceptions and can impact firm outcomes, emphasising the media's role in shaping financial narratives.

Our paper contributes to the literature by examining whether the tone expressed in banks' earnings calls shapes the sentiment of subsequent media coverage. We extend prior research by focusing on the consistency of tone across communication platforms, considering the role of pre-call media sentiment and the institutional context in which banks operate.

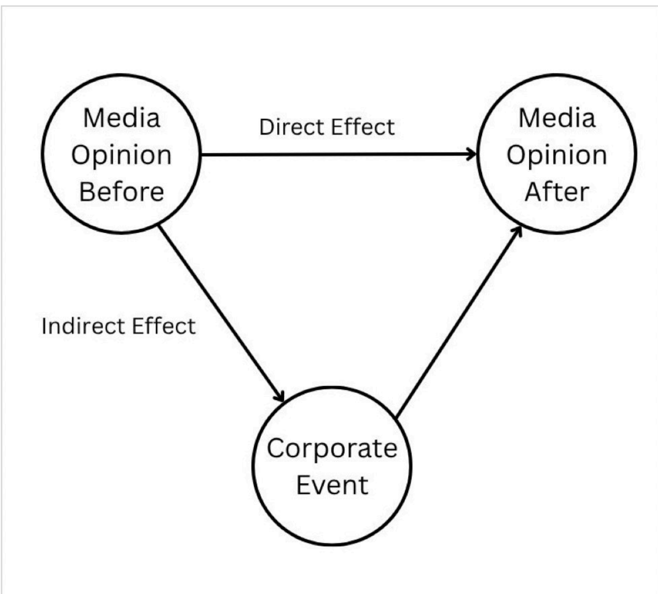
3.4 Challenges in Arabic Sentiment Analysis

Arabic is a challenging language for sentiment analysis because of its complex grammar, word structure, and many different dialects. These features make it difficult for standard sentiment models to work well, especially if they were not trained on Arabic texts. Aladeemy et al. (2024) highlight several limitations in Arabic sentiment analysis, including the lack of high-quality annotated datasets, limited handling of dialectal variation, and the reliance on general-purpose models that may overlook key linguistic cues, especially in financial contexts.

AraBERT, developed by Antoun et al. (2020) for Arabic natural language processing, represents a major step forward in adapting transformer-based models to the Arabic language. However, because it was trained on general-domain texts, it may not fully capture the tone and specialized terminology commonly used in financial communication, limiting its effectiveness in domain-specific sentiment analysis. Similarly, FinBERT, a BERT-based model fine-tuned on English-language financial texts, performs well in that domain (Araci, 2019). However, its monolingual design limits its ability to analyse sentiment in other languages, particularly Arabic, where cultural and linguistic differences are substantial. This reduces its value in multilingual financial settings that require consistent sentiment analysis across languages and formats. Our study contributes to the literature by applying OpenAI's large language model to both Arabic and English financial texts, our study introduces a unified, cross-lingual sentiment analysis framework that overcomes the linguistic limitations of existing models. Unlike earlier tools such as FinBERT or AraBERT, which are limited to one language or trained on general content, OpenAI's model is trained on a wide range of languages and topics. This helps it understand context and tone more accurately. Using one model for both sources allows for better comparison between media and company announcements.

The conceptual framework of the study is presented in Figure 2. It illustrates how media sentiment following an earnings call is shaped by both the tone of pre-call news coverage and the sentiment expressed during the call itself. Media tone may be influenced directly by prior news or indirectly through the way corporate events, such as earnings calls, reinforce or shift the narrative. This framework highlights the importance of tone alignment across communication stages and sets the foundation for the hypotheses tested in the following sections.

Figure 2. Conceptual Framework of Tone Transmission Across Corporate Communication Channels



Note: The diagram shows how pre-call news sentiment and earnings call tone influence post-call media sentiment through direct and indirect pathways.

3.5 Hypothesis Development

This study builds on earlier research that shows how companies use tone strategically and how the media helps shape the stories people hear about financial performance. We focus on how the tone of communication flows across three stages: before the earnings call, during the call itself, and in the media coverage that follows. Based on this idea, we test the following five hypotheses:

Hypothesis 1: Alignment Between Pre-Call News and Earnings Call Tone Predicts Post-Call Media Sentiment.

Post-call media coverage is most favourable when the tone of the earnings call reinforces the sentiment already set by earlier media. This tone alignment helps banks shape a consistent narrative and guide how the public interprets their performance. Prior studies have shown that when tone is consistent across communication channels, the message is more likely to be amplified in subsequent news (Doey and Jong 2025; Cahan et al., 2013).

Hypothesis 2: The Impact of Tone Alignment Depends on Bank Characteristics.

The strength of the tone alignment effect varies depending on the type and size of the bank. Islamic banks, for instance, tend to rely more heavily on clear and consistent messaging due to their governance structure and emphasis on transparency and trust. Bank size also experiences stronger effects, as they are generally harder to value and investors rely more on sentiment as a substitute for detailed financial information (Abdulrahman et al., 2024; Di et al., 2021; Cahan et al., 2013).

Hypothesis 3: Communication Features During the Call Shape the Effect of Alignment.

How earnings calls are delivered plays a key role in determining how effective tone alignment will be. Forward-looking statements, simpler language, and having senior executives like the CEO or CFO speak can all strengthen the transmission of tone. These features increase the credibility, clarity, and influence of the message, making it more likely to shape how the media covers the bank afterwards (Ning et al., 2024; Goldin et al., 2024).

4. EMPIRICAL STRATEGY

4.1 Data

A total of three sources of data were collected from 2018 to 2025 in order to conduct this study: (1) Information about bank earnings calls for each bank in Kuwait has been collected from Boursa Kuwait (the Kuwait Stock Exchange) in English. We included in our study all banks that are entering the premier market in Kuwait and that have already shared the transcripts of their earnings calls publicly on their websites or on the Boursa website[1]. (2) Media coverage data was collected from the website of Al-Jarida, an Arabic-language Kuwaiti newspaper. We chose Al-Jarida newspaper as our media reference for our study for two reasons. The first reason is the availability of data. There is a seven-year archive of news articles from the Al-Jarida newspaper available for the period 2018 to 2025 which can be accessed online. (3) However, all of the financial data (total assets) for each bank was collected from each bank financials report.

4.1.1 Newspaper (Al-Jarida)

Al-Jarida[2] is one of Kuwait's most influential Arabic-language newspapers, known for its comprehensive coverage of political, economic, and financial affairs. Established in 2007, it has become a key outlet for corporate communication, particularly in the banking sector. We used Python (BeautifulSoup4[3]) to collect news articles from the website of Al-Jarida. For each article, we extracted the full text as well as its publication date, title, and section (such as Economics, Politics, Sports, etc.). This allowed us to organize the news by topic and timeframe. After collecting the full set of articles, we searched for newspaper articles published within a 10-day window, covering the five days before and five days after the date of the earnings call. This time frame was chosen to capture how the media responded to the earnings call, both in the days leading up to the event and immediately after. It allowed enough time for news to be reported while remaining close enough to the event to reflect direct reactions.

In many cases, a single article might mention more than one bank or speak generally about the banking sector. To keep the analysis focused and accurate, we included only the articles that were mainly about a single bank. Specifically, we limited our sample to articles that were prepared or submitted by the bank itself, as is standard practice in Kuwait. This means the article clearly focused on one institution, rather than broadly discussing the industry or comparing several banks. By doing this, the sentiment and topics we analysed more directly reflect how the bank chose to present itself in the media, rather than general commentary about the financial sector.

1 https://www.boursakuwait.com.kw/en/

2 https://www.aljarida.com

3 A library called BeautifulSoup4 that helps to scrape information from the web.

We began by identifying 1005 articles that contained all banks that operated either before the earnings call or after it. Afterwards, we aggregated the data by bank, year, and quarter to arrive at 197 observations. Where we found that some banks didn't publish anything in the newspaper either before or after. The sentiment of each call is measured using OpenAI's large language model (ChatGPT) for the text of each article. We will provide additional details regarding the measurement of newspaper sentiment in the sentiment analysis section.

Figure 3 shows a word cloud that highlights the most common topics mentioned in newspaper articles after bank earnings calls. Larger phrases appear more often in the media coverage, showing which themes received the most attention. Before creating the word cloud, we used OpenAI language model (gpt-3.5-turbo) to analyse each article, classify its sentiment, and identify key content. Common topics such as banking regulation, financial performance, and market expansion suggest that the media often focuses on rules, profits, and growth plans. Other terms like CSR (corporate social responsibility) and customer services show that newspapers also mention social efforts and how banks serve customers. This figure gives us an overall view of the topics that appeared most frequently in the news articles published both before and after the earnings calls.

Figure 3. Word Cloud of Main Topics in Newspaper Articles.

Note: This word cloud shows the most frequent main topics discussed in newspaper coverage of Kuwaiti banks between 2018 and 2024. Topics were classified into predefined categories using OpenAI (ChatGPT). Larger words indicate topics that appeared more frequently across all articles.

4.1.2 Earnings call:

Due to the fact that the study will be conducted in Kuwait, the banks that will be included in our analysis will be divided into two categories: commercial banks and Islamic banks. There are five commercial banks in Kuwait: National Bank of Kuwait (NBK), Gulf Bank, Al Ahli Bank of Kuwait (ABK), Commercial Bank of Kuwait (CBK) / Al-Tijari and Burgan Bank. For Islamic banks, we have Kuwait Finance House (KFH), Boubyan Bank, Kuwait International Bank (KIB), and Warba Bank. In Kuwait, there is only one specialized bank, the Industrial Bank of Kuwait (IBK). The bank earnings calls are listed based on four quarters a year from 2018 to 2024. However, only ABK bank has been collected from 2023-2024 due to ABK's listing on the premier market in 2024, and the bank started publishing transcripts of its earnings calls from 2023 onwards. Despite this, Altijari Bank was excluded from the study since it does not publish recordings of its earnings calls but only publishes data and reports on the bank's financial performance. Furthermore, the IBK was excluded since it is a specialised bank not listed on the premier market, so it does not have earnings calls.

We collected earnings call transcripts starting from 2018, aligning with the period when several Kuwaiti banks began publicly sharing their analyst conference calls. In 2019, Boursa Kuwait introduced Rulebook[4] version 4V.2, which mandated listed companies, particularly those on the premier market, to publish full bilingual transcripts of their investor calls within three business days after the event. This regulation aimed to enhance transparency and ensure equal access to information for all investors. Notably, all banks missed the first quarter of 2020 due to disruptions caused by the COVID-19 pandemic. Additionally, ABK has only eight earnings call transcripts available for 2023–2024, as the bank joined the market recently, as mentioned at the beginning of this section. In total, our final sample includes 197 observations across banks, years, and quarters.

For our analysis, it is necessary to identify each call's main speaker. In order to identify who was the main speaker in each earnings call, we automated the process using OpenAI's large language model (ChatGPT). Due to the fact that we have text to process, all the code is done in Python. First, we extracted the text from each PDF transcript using a tool called pdfplumber[5]. If the file was scanned or saved as an image and the text couldn’t be read directly, we applied Optical Character Recognition (OCR), which converts images of text into actual readable text. This was done using pytesseract[6] and pdf2image[7]. Once the full transcript was ready, we sent it to OpenAI language model (gpt-3.5-turbo) with a prompt asking the model to identify the person who spoke the most. The model provided the speaker’s name, their role (such as CEO or CFO), how many words they spoke, and what percentage of the total transcript that represents.

4 Boursa Kuwait Rulebook.

5 A Python tool that extracts text from PDF files, as long as the text is not part of an image.

6 A Python wrapper for Google’s Tesseract OCR engine. It reads text from images or scanned documents and turns it into editable text.

7 A Python library that converts pages from a PDF into image files, which can then be used for OCR when direct text extraction isn’t possible.

The prompt specifically instructed the model to "identify the person who spoke the most, along with their role and word count." This allowed us to consistently identify the individual who led the discussion and delivered the majority of the call's content. Table 2 provides examples of how OpenAI's language model was used to identify speakers and quantify their contributions to earnings calls based on word count and role.

Table 2. Speaker-Level Data from Earnings Calls.

BANK	YEAR	QUARTER	SPEAKER	ROLE	WORD COUNT	CONTRIBUTION (%)
NBK	2019	QUARTER3	JIM MURPHY	GROUP CFO	1546	44%
WARBA	2022	QUARTER2	MOHAMED SALEH	EXECUTIVE MANAGER - FINANCIAL PLANNING AND ANALYSIS	2398	46.59%

Note: This table presents examples of speaker-level data from earnings calls. "Word Count" refers to the number of words spoken by the individual, and "Contribution (%)" indicates their share of total words spoken during the call. Speaker identification and contribution were estimated using OpenAI's large language model applied to full transcript data.

Summary statistics for the key variables used in the analysis are presented in Table 3, with additional details available in Appendix Table A1. The average sentiment score for news articles published after the earnings call is 0.531, slightly higher than the average pre-call news sentiment of 0.522. The earnings call sentiment, based on the full transcript, shows a higher average of 0.703, suggesting that banks generally adopt a positive tone in their communications. The interaction term between pre-call news sentiment and call sentiment has a mean of 0.413, capturing how media tone aligns with the bank's messaging. The speaker position variable, which identifies the rank of the main speaker (e.g., CEO, CFO), has a mean value of 1.782, indicating that senior executives frequently lead these calls. The average log of total assets, used as a proxy for bank size, is 15.91. Lastly, the log-transformed total word count of the call averages 8.135, with a range suggesting substantial variation in the length and depth of discussions across earnings calls.

Table 3. Summary Statistics.

BANK	# OBS	MEAN	ST DEV	MIN	MAX
POST CALL NEWS SENTIMENT	197	0.531	0.413	-0.900	0.950
PRE-CALL NEWS SENTIMENT	197	0.522	0.399	-0.750	0.917
EARNINGS CALL SENTIMENT	197	0.703	0.544	-0.900	1.000
PRE-CALL NEWS SENTIMENT × EARNINGS CALL SENTIMENT	197	0.413	0.511	-0.900	0.917
SPEAKER POSITION	197	1.782	1.155	1.000	8.000
BANK SIZE	197	15.910	0.851	14.420	17.510
TOTAL CALL WORD COUNT	197	8.135	0.474	6.944	9.432

Note: This table presents summary statistics for key continuous variables. Post-Call News Sentiment is defined as the sentiment score of news articles published within 5 days following the earnings call and is measured on a scale from -1 (very negative) to +1 (very positive). Pre-Call News Sentiment refers to the sentiment score of news articles published within 5 days before the earnings call, also ranging from -1 to +1. Earnings Call Sentiment represents the sentiment score of the entire earnings call transcript, capturing the overall tone of the call, and is similarly scaled between -1 and +1. Pre-Call News Sentiment × Earnings Call Sentiment is the interaction term between earnings call tone and pre-call news sentiment, used to test alignment effects, and is constructed from the same scaled variables. Speaker Position indicates the role of the main speaker during the earnings call (e.g., CEO, CFO, Other). Bank Size is the natural logarithm of the bank's total assets. Total Call Word Count is the total number of words spoken during the earnings call.

4.2 Sentiment Analysis

To examine how tone is communicated across sources, we applied the same OpenAI language model to both earnings call transcripts and newspaper articles. Despite differences in style and structure between spoken and written formats, using a unified model ensured consistency in how sentiment was measured across texts. Recent research supports the effectiveness of large language models in financial applications. Fatouros et al., (2023) demonstrate that ChatGPT outperforms traditional tools such as FinBERT in detecting tone in financial disclosures, while Kirtac and Germano (2024) highlight its strength in capturing context that drives market reactions.

4.2.1 Earning call sentiment analysis

To understand the tone of each bank's earnings call, we used OpenAI's language model (gpt-3.5-turbo) to classify the overall sentiment. Each transcript was analysed as one full document and labelled as either positive or negative. We also asked the model to give a sentiment score between -1 and 1 to show how strong the tone was. A score closer to 1 means very positive and confident, while a score closer to -1 means more negative or cautious.

The model was given a clear instruction to read the whole text carefully, understand the tone, and avoid being neutral. Part of the instruction we used was:
"You are a critical sentiment analysis assistant specialized in financial and media text. Your job is to evaluate the overall sentiment of the given text and classify it as either Positive or Negative. You must also assign a sentiment score between -1 and 1, where the absolute value reflects the intensity of sentiment. If the text tries to sound balanced or hides bad news, uncover the real sentiment."

This prompt helped the model go beyond simple keywords and focus on the full message, tone, and wording used by the speakers. In financial communication, companies often avoid showing strong emotions.
Even when the news is negative, they tend to use careful or polished language to sound more balanced or positive. Previous research show that managers often choose optimistic or vague words to make performance seem better than it really is. For example, Loughran and McDonald (2016) explain that financial documents often use positive words even during weak performance. Other studies also show that managers may hide bad news by using complex or unclear language, especially when results are disappointing (Huang et al. 2014; Muslu et al. 2015). By using our approach, we were able to capture both the clear and hidden tone in these calls, not just from the words themselves but from how results were described and framed.

We also asked the model to give a short explanation showing why it chose that label. These results were saved in a table that included the bank name, year, quarter, sentiment, score, and the model's explanation. A few examples are shown in table 4.

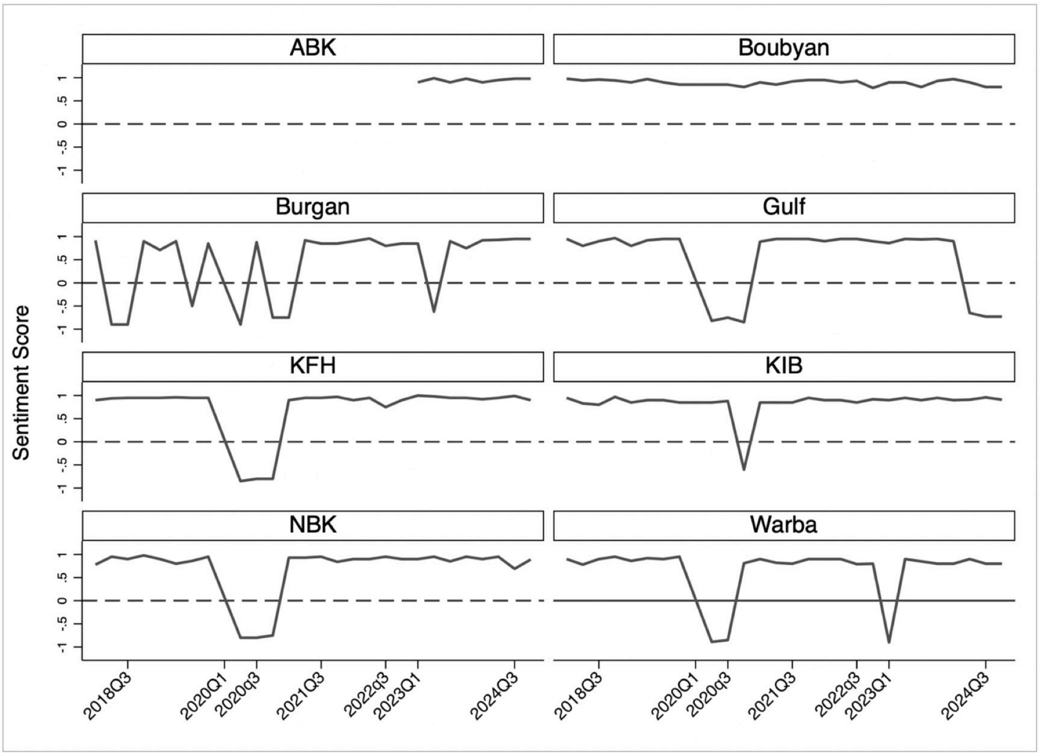
Table 4. Example of Sentiment Scores and Explanations from Earnings Calls.

BANK	YEAR	QUARTER	SENTIMENT	SCORE	EXPLANATION
NBK	2021	Q2	POSITIVE	0.84	STRONG CONFIDENCE IN PROFIT GROWTH AND FUTURE PLANS.
KFH	2020	Q4	NEGATIVE	-0.42	FOCUS ON RISKS AND PROVISIONS DUE TO ECONOMIC CHALLENGES.
BOUBYAN	2019	Q3	POSITIVE	0.35	POSITIVE TONE LINKED TO CUSTOMER GROWTH AND NEW SERVICES.

Note: This table presents examples of sentiment scores assigned to earnings call transcripts. The sentiment score ranges from -1 (very negative) to +1 (very positive). Explanations reflect the key themes and tone identified in each call. Sentiment classification and scoring were conducted using OpenAI's large language model.

Figure 4 shows the sentiment scores from earnings calls for eight Kuwaiti banks between 2018Q1 and 2024Q4. Each panel represents one bank, with sentiment measured from -1 to +1. Most banks display consistently positive sentiment, suggesting generally optimistic communication from management. However, several banks exhibit a marked decline in sentiment around early 2020, likely reflecting the uncertainty and economic disruption brought on by the COVID-19 pandemic. Notably, Burgan and NBK show clear downward shifts during this period. The figure illustrates how sentiment varies both across banks and over time, particularly in response to external shocks.

Figure 4. Media Sentiment Scores by Bank Over Time.



Note: This figure plots quarterly sentiment scores extracted from the earnings call transcripts of eight Kuwaiti banks between 2018Q1 and 2024Q4. Sentiment is measured on a scale from 1 (negative tone) to 1 (positive tone) based on language used by management during the call.

4.2.2 Newspapers sentiment analysis

To measure sentiment, we used OpenAI's model to evaluate the tone of Al-Jarida newspaper articles published before and after each bank's earnings call. Each article was analysed using a structured prompt that instructed the model to act as a financial analysis assistant and classify the content as either positive or negative. The model also provided a sentiment score between –1 and +1, reflecting the strength and direction of tone. By applying the same instruction to both earnings call transcripts and news articles, we ensured consistency in sentiment evaluation across sources, allowing for a direct and meaningful comparison between bank disclosures and media coverage. We chose OpenAI's language model because it can handle both English and Arabic text with contextual understanding, making it suitable for analysing mixed-format financial content. Unlike traditional financial sentiment models, which are often language-specific or rule-based, OpenAI allows for a more flexible and consistent classification across sources.

4.3 Methodology

We examine whether the sentiment of media coverage after bank earnings calls is shaped by the interaction between the tone of the call itself and the tone of news articles published beforehand. To do this we employ a panel data regression model with fixed effects that accounts for unobserved heterogeneity across banks, time periods, and reporting cycles.

$$\begin{aligned}
&Post_Call_News_Sentiment_{i,t,q} = \beta_0 + \beta_1 Pre_Call_News_Sentiment_{i,t,q} + \\
&\beta_2 Pre_Call_News_Sentiment_{i,t,q} \times Earnings_call_Sentiment_{i,t,q} + \\
&\beta_3 Earnings_call_Sentiment_{i,t,q} + X_{i,t,q} + \alpha_i + \gamma_t + \gamma_q + \varepsilon_{i,t,q} \qquad (1)
\end{aligned}$$

Where $_{i,t,}$ and q denote the bank name, the year of the earnings call, and the quarter. The dependent variable is news sentiment following the earnings call Post_Call_News_Sentiment$_{i,t,q}$. This measures the positive or negative sentiment expressed in the news articles published after the bank announces its financial results on its earnings call. The sentiment scores for each article are generated using OpenAI (Fatouros et al., 2023). The scores range from -1 to +1, where values closer to -1 indicate more negative language and values closer +1 indicate more positive language.

For the main explanatory variable, we include two key variables and their interactions. The Earnings_call_Sentiment$_{i,t,q}$ variable measures the tone of the language used during the earnings call. The second variable is Pre_Call_News_Sentiment$_{i,t,q}$ variable captures the tone of news articles published prior to the earnings call, also scored by OpenAI. Both variables are generated using OpenAI's language model, which provides a sentiment score ranging from –1 (negative) to 1 (positive). To capture how the effect of the call's tone may depend on the prior media tone, we include Pre_Call_News_Sentiment$_{i,t,q}$ × Earnings_call_Sentiment$_{i,t,q}$, calculated as the product of the two sentiment scores (interaction).
To account for other factors that may influence media sentiment, the model includes several control variables. First, we control for the role of the main speaker (Speaker Position$_{itq}$), such as CEO or CFO, since different positions of the earnings main speaker may carry varying levels of authority and credibility in investor communications (Mayew & Venkatachalam, 2012). We also include bank size (Bank Size$_{itq}$), measured by the natural log of total assets, as larger banks tend to attract more media attention and may communicate differently (Engelberg et al., 2012). Additionally, we control for the length of the call, using the total word count of the full transcript (Total Call Word Count$_{itq}$), as longer calls may signal greater complexity, transparency, or uncertainty (Huang et al., 2014). Including these controls helps isolate the effect of sentiment from differences in communication style, content volume, or institutional size. We include bank, year, and quarter fixed effects to control for unobserved differences that could affect media sentiment. Bank fixed effects account

for characteristics that do not change over time, such as reputation or communication style. Year fixed effects capture broader events like economic changes or policy shifts, while quarter fixed effects control for seasonal patterns in reporting. These fixed effects help ensure that the results reflect differences in sentiment, not differences between banks or time periods. Finally, $\varepsilon_{i,t,q}$ represents the error term.

While media sentiment data offers rich insights into tone and narrative framing, it is not immune to systematic bias and measurement error. Bias in media sentiment can have implications depending on the role of the variable. If mismeasurement affects the dependent variable (e.g. Post-Call News Sentiment), the model will suffer from classical noise, reducing the precision of estimates without biasing coefficients. However, if sentiment is mismeasured as a regressor (i.e., right-hand-side variable), the resulting attenuation bias will likely dampen the estimated effect. This suggests that the results we observe may be conservative, and the true relationship could be even stronger.

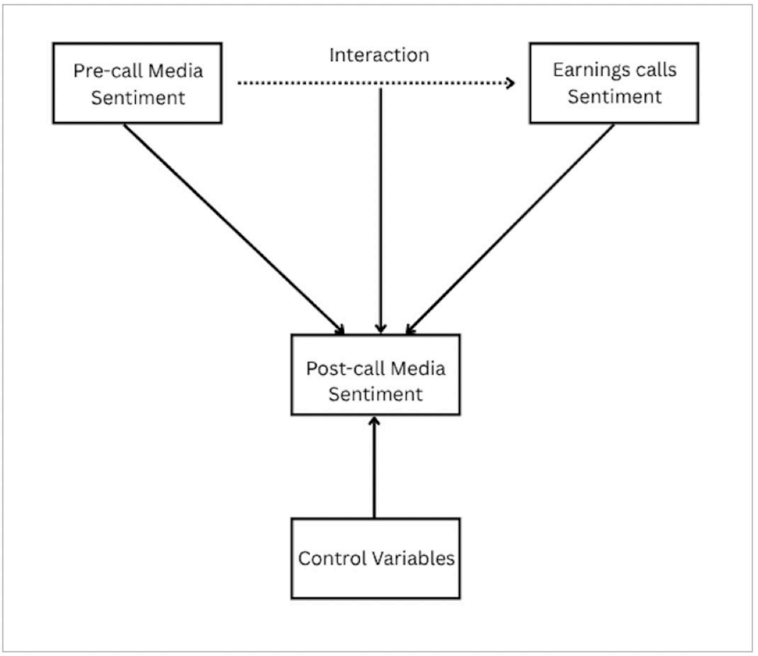
Several studies highlight the sources and risks of such bias. Groeling (2013) distinguishes between selection bias, where media outlets choose to report certain events over others, and presentation bias, where the same event is framed differently depending on editorial stance. This framing can influence how financial news is perceived by investors. Morstatter and Liu (2017) emphasise that data collected from social and digital platforms often suffers from sampling bias, resulting from algorithmic filtering, API limitations, or the non-random availability of posts. Even in curated environments, Seifert et al. (2019) show that document collection bias can arise due to metadata structures, search algorithms, and human classification systems used in assembling corpora. These findings underscore the importance of interpreting media-based sentiment measures with caution. Whether sourced from online platforms or archival datasets, media sentiment may reflect underlying biases that influence both tone and visibility, potentially affecting empirical results.

5. RESULTS DISCUSSION

In this section, we first estimate how the interaction between pre-call news sentiment and earnings call tone shapes post-call media sentiment. We then test whether this effect varies by topic type, bank characteristics, and call features, followed by robustness checks to confirm our findings.

The study's conceptual framework is illustrated in Figure 5, outlining how pre-call media sentiment, earnings call sentiment, and their interaction influence post-call media sentiment. Control variables are included to account for bank-specific and structural differences.

Figure 5. Tone Transmission Across Media and Earnings Calls



Note: Pre-call media sentiment, earnings call sentiment, and their interaction shape post-call media sentiment, controlling for bank and call characteristics.

5.1 Main Results:

We begin by examining how the tone in pre-call and in-call communication affects how banks are presented in the media after earnings calls. In Column (1) of Table 5, we include only pre-call news sentiment as the main variable, along with year, quarter, and bank fixed effects. These fixed effects help account for broader time trends and differences across banks that do not change over time. The results show that pre-call sentiment is strongly related to post-call media tone. A one-point increase in pre-call sentiment is associated with a 0.81-point increase in post-call sentiment. This suggests that once a positive tone is established before the earnings call, it is likely to continue afterward. In the context of Kuwait, where banks often contribute directly to the content of the media by preparing or influencing how news is written, this finding reflects how tone continuity may be managed internally rather than shaped by independent journalistic reactions. It aligns with the idea that narrative control is easier when both the message and the media are closely connected (Gurun and Butler, 2012; Dyck and Zingales, 2003).

In Column (2), we add the tone of the earnings call itself and an interaction between pre-call sentiment and earnings call sentiment. This allows us to examine whether the effect of pre-call media tone changes depending on how positive or negative the bank sounds during the call. The interaction term is positive and statistically significant. This means that when the earnings call is more positive, it strengthens the impact of earlier sentiment. For example, if the bank's pre-call media already carried a positive message, and the call continues that tone, the follow-up media will likely maintain or even amplify that positivity. On the other hand, the main effect of earnings call sentiment is negative, suggesting that a positive call alone may not shift the tone of post-call media if the earlier sentiment was negative. This supports the idea that controlling the tone across all stages of communication—before, during, and after the call—requires consistency. A positive message during the call is more effective when it follows an already supportive narrative (Davis et al., 2012; Huang et al., 2014).

In Column (3), we add control variables to check whether these effects might be driven by other features of the communication. These controls include whether the main speaker was a senior executive such as a chief executive officer, the total word count of the call transcript, and the size of the bank. These factors could influence how the communication is received. For instance, a chief executive-led call might be more impactful, or a longer call might provide more clarity. However, none of these controls are statistically significant, and the key results remain consistent. This suggests that it is tone, rather than structural details of the call or bank, that most influences how the message is repeated in the media, which is consistent with findings in the literature that highlight the role of linguistic cues over content volume or formality (Li, 2010; Loughran and McDonald, 2011).

Table 5. Effect of Pre-Call and Earnings Call Sentiment on Post-Call Media Tone.

	(1)	(2)	(3)
	BASELINE	INTERACTION MODEL	FULL MODEL
PRE-CALL NEWS SENTIMENT	0.811*** (0.051)	0.656*** (0.071)	0.649*** (0.071)
PRE-CALL NEWS SENTIMENT × EARNINGS CALL SENTIMENT		0.236*** (0.077)	0.242*** (0.077)
EARNINGS CALL SENTIMENT		-0.142** (0.059)	-0.144** (0.060)
SPEAKER POSITION			0.014 (0.018)
TOTAL CALL WORD COUNT			-0.081 (0.052)
BANK SIZE			-0.039 (0.166)
R-SQUARED	0.634	0.653	0.658
OBSERVATIONS	197	197	197

Note: This table reports results from regressions estimating the effect of pre-call news sentiment and earnings call sentiment on post-call media sentiment. Column (1) presents the baseline model with pre-call news sentiment only. Column (2) adds earnings call sentiment and an interaction term to test whether tone alignment across stages affects post-call coverage. Column (3) includes control variables: Speaker Position (role of the main speaker, e.g., CEO, CFO, or Other), Total Call Word Count (total number of words spoken), and Bank Size (log of total assets). All sentiment variables are scaled from -1 (very negative) to +1 (very positive). Bank, year, and quarter fixed effects are included in all models. Robust standard errors are shown in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

5.2 Channels

To better understand how tone is transmitted from earnings calls to post-call media coverage, we next examine several potential channels that may strengthen or weaken this relationship. Specifically, we explore whether tone alignment varies depending on the topics discussed in the news, characteristics of the bank itself, and structural features of the earnings call. These analyses help identify the conditions under which consistent messaging is most effectively carried across platforms.

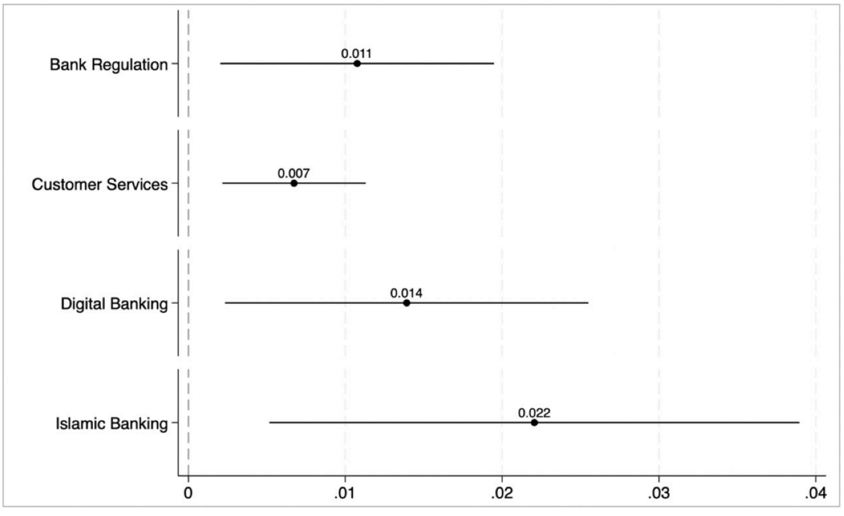
5.2.1 Tone Consistency Across Media by Topic

Table A2 and figure 6 show how the connection between earnings call tone and media tone changes depending on the topic covered in the news. The results show that banks are more likely to keep a consistent tone when the media focuses on topics such as banking regulation, customer services, digital banking, or Islamic banking. These topics are often more visible to the public, linked to rules and regulations, or important for the bank's image. Because of this, banks seem more careful to make sure the tone used during the call also appears in the articles that follow.

This pattern is especially strong for Islamic banking services. In Kuwait, Islamic banking services is not limited to fully Islamic banks. Many conventional banks also offer Islamic banking services that follow religious principles. Since these services are tied to trust and ethical values, banks may work harder to control how they are presented in the media.

In contrast, when the topic is something like corporate social responsibility or market expansion, the connection is weaker. In those cases, the tone in the media does not closely match the tone used in the call. This suggests that banks do not always repeat their tone across platforms but instead focus on doing so when the topic has a bigger impact on how they are seen by the public.

Figure 6. Bank Characteristics as Moderators of Tone Transmission.



Note: This figure shows the estimated effect of tone alignment on post-call media sentiment across different news topics. The impact is strongest for Islamic Banking, followed by Digital Banking and Banking Regulation. Lines represent 95% confidence intervals.

5.2.2 Bank Characteristics as Moderators of Tone Transmission

In Table A3 and figure 7, we look at whether some banks are better at making sure the story they tell during their earnings call ends up being the story that shows up in the media. What we find is Islamic banks show a strong and significant interaction between pre-call media sentiment and earnings call tone. That means when the tone is consistent, before and during the call, Islamic banks are better at making sure that same tone appears in the news afterward.

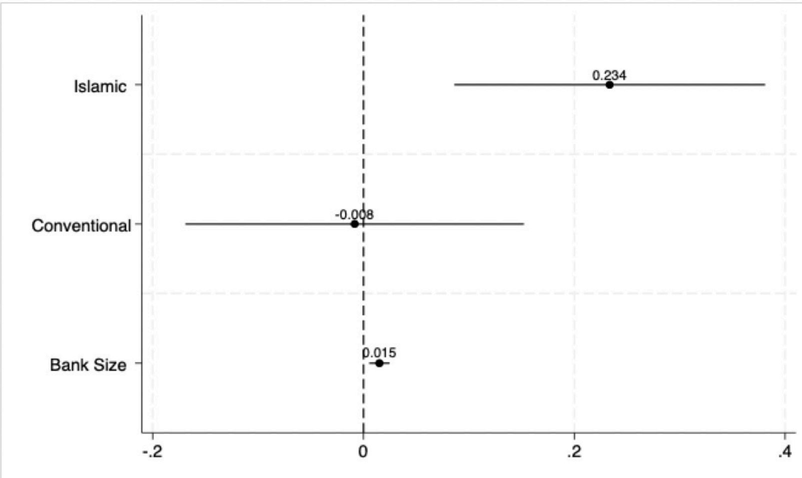
This is not just about influence. It is about control. In Kuwait, banks often write or directly shape their own media coverage. They maintain full-year relationships with business editors and frequently provide the language, structure, and even tone of post-call articles. For Islamic banks, this control might be even stronger. These institutions tend to emphasize ethical consistency and stakeholder trust (Beck et al. 2013; Farook et al. 2011), so they are more likely to ensure their internal messaging is mirrored in the headlines.

Conventional banks, by comparison, do not show the same effect. The interaction term is small and insignificant, which may suggest a looser grip on the media narrative or less emphasis on consistent tone across platforms.

Interestingly, larger banks also show a significant interaction. This is not surprising. Big banks typically have full PR teams, stronger ties with media outlets, and more power to shape how they are talked about. When they set a tone, it travels.

These results reveal a key insight: in markets like Kuwait, where media independence is limited, tone transmission reflects not just persuasion but authorship. Banks are not merely subjects of coverage; they are often the source of it.

Figure 7. Bank Characteristics as Moderators of Tone Transmission.



Note: This figure shows that tone alignment has a stronger effect for Islamic banks, while the effect is weaker and not significant for conventional banks and bank size. Bars represent 95% confidence intervals.

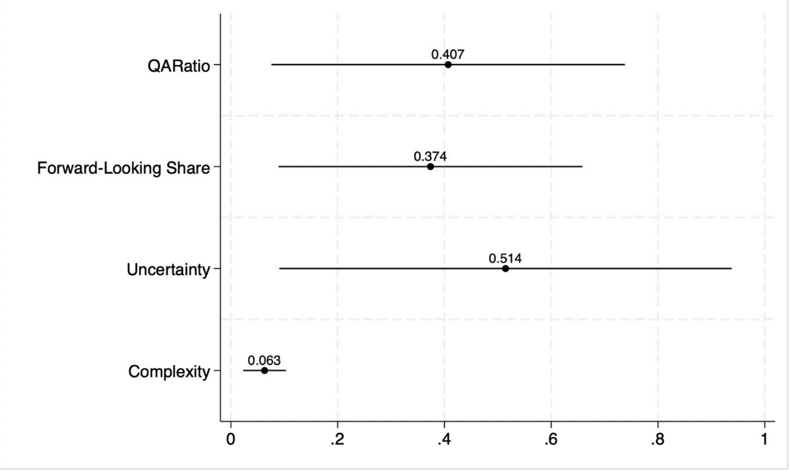
5.2.3 Earnings Call Features as Channels of Tone Transmission

This section examines whether certain characteristics of earnings calls influence how effectively tone is transmitted from pre-call media coverage and the earnings call itself into the tone of post-call news articles. The idea is that some calls may create a stronger "channel" for tone transmission, depending not only on what is said, but also on how it is communicated. We focus on four key features: the share of unscripted Q&A (proportion of the call dedicated to analyst), the degree of forward-looking content, the presence of uncertainty, and the overall linguistic complexity of the call.

To measure these characteristics, we use a prompt-based method with OpenAI's (ChatGPT) large language model. The model was instructed to act as a financial language analyst, reading the full transcript of each call and estimating standardized indicators for each feature. Specifically, it rated how complex the language is on a scale from 0 to 100, identified the share of the transcript devoted to analyst Q&A, estimated the proportion focused on future expectations, and captured the extent to which hedging or uncertainty terms (such as "may," "could," or "depends") appear in the text. These automated, language-aware scores allow us to consistently quantify subtle yet important elements of communication across all transcripts.

Our results in Table A4 and figure 8 show that tone alignment between pre-call media sentiment and the earnings call tone is more strongly reflected in the post-call media tone when any of these four features are present to a greater degree. Specifically, when earnings calls include more spontaneous discussion, greater emphasis on future performance, higher levels of uncertainty, or more complex language, the tone communicated by the bank is more likely to be maintained in the media coverage. These features appear to strengthen the bank's control over its messaging—making the communication more intentional, content-rich, and likely to be reproduced consistently in the media narrative that the bank itself produces.

Figure 8. Earnings Call Features as Channels of Tone Transmission.



Note: This figure shows that tone alignment is stronger when earnings calls include more Q&A, forward-looking statements, uncertainty, or complex language. Bars represent 95% confidence intervals.

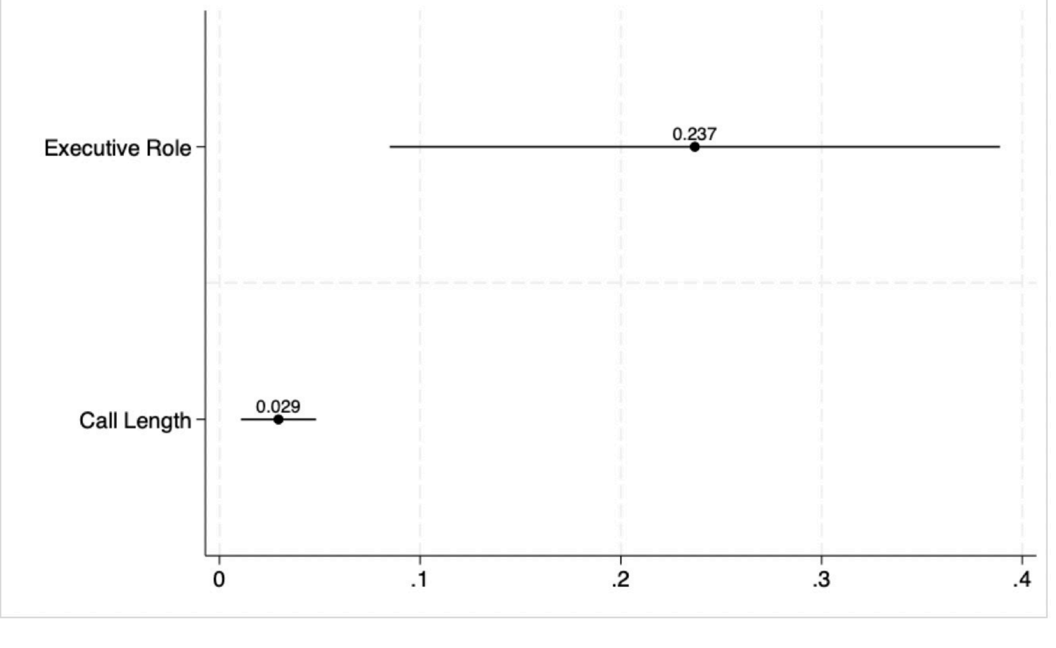
5.2.4 Role of Call Structure and Delivery

In Table A6 and figure 9, we examine whether specific characteristics of the earnings call shape how pre-call and in-call tone are carried into post-call media coverage. The results point to three important channels: who speaks, how long they speak, and how complex the message is.

In Column (1), the triple interaction between Pre-Call News Sentiment, Earnings Call Sentiment, and Executive Role is positive and highly significant. This suggests that when a senior executive such as a CEO or CFO leads the call, the alignment in tone between the call and the media becomes stronger. Executives bring authority and credibility, and prior research shows that markets and media respond more seriously to their words compared to lower-level spokespersons (Huang et al. 2014). In a media environment like Kuwait's, where banks help craft their own narrative, having an executive deliver the message may reinforce control and perceived importance.

In Column (2), longer calls also strengthen the link between aligned tone and media sentiment. The interaction term is positive and significant, indicating that when managers speak at length, the message is more likely to carry through. Longer calls may reflect greater effort to shape expectations or address uncertainty. This supports findings from Loughran and McDonald (2016), who show that narrative length often signals strategic communication.

Figure 9. Role of Call Structure and Delivery.



Note: This figure shows that tone alignment is stronger when the earnings call is led by a senior executive or when the call is longer. Bars represent 95% confidence intervals.

5.3 Robustness

As a further check, we simplify how we measure tone by turning the sentiment scores into dummy variables that indicate whether the tone is positive or negative. This allows us to see whether our results still hold when we don't rely on the exact score, but just on whether the tone is generally good or bad. We re-run our main regressions using these dummies instead of continuous sentiment values.

The results in table 6 are consistent and reassuring. The interaction between pre-call media tone and earnings call tone remains positive and statistically significant. In fact, the strength of the interaction effect stays similar to the original models, even though we now use a much simpler tone measure. This shows that the relationship we're capturing — how consistent tone before and during the call leads to more aligned media coverage after the call — is not just a result of using fine-grained sentiment scores. It also appears clearly when tone is classified more broadly.

To further test the robustness of our findings, we re-estimate the main model using an alternative method to measure sentiment in earnings call transcripts. Specifically, we replace the OpenAI-based sentiment scores with those generated by FinBERT, a financial-domain BERT model that is trained specifically on financial texts. FinBERT is widely used in finance research because it is tailored to understand the tone and vocabulary used in financial disclosures. By comparing results across models, we can assess whether our findings are sensitive to the tool used to evaluate tone.

As shown in Table 7, the results using FinBERT are consistent with our main analysis. The interaction between pre-call news sentiment and FinBERT-based earnings call sentiment is positive and statistically significant (Column 2 and Column 3). The size of the interaction coefficient is even larger than in our baseline models, suggesting that the effect of tone alignment may be even more pronounced when financial-specific sentiment is used. In Column 3, the effect remains strong after controlling for speaker role, bank size, and word count.

Table 6. Robustness Check Using Binary Sentiment Classification.

	(1) BASELINE	(2) INTERACTION MODEL	(3) FULL MODEL
PRE-CALL NEWS SENTIMENT	0.806*** (0.050)	0.656*** (0.064)	0.648*** (0.064)
EARNINGS CALL SENTIMENT (FINBERT)		-0.188*** (0.067)	(0.068)
PRE-CALL NEWS SENTIMENT × EARNINGS CALL SENTIMENT		0.220*** (0.061)	0.224*** (0.061)
SPEAKER POSITION			0.019 (0.020)
TOTAL CALL WORD COUNT			-0.024 (0.191)
BANK SIZE			-0.086 (0.060)
R-SQUARED	0.639	0.665	0.670
OBSERVATIONS	197	197	197

Note: This table presents results from a robustness check in which all sentiment variables are converted into binary indicators. Sentiment is coded as +1 for positive tone and –1 for negative tone. Column (1) shows the baseline model with only pre-call news sentiment. Column (2) adds earnings call sentiment and the interaction term to test for tone alignment effects. Column (3) includes additional control variables: Speaker Position (main speaker's role), Total Call Word Count, and Bank Size (log of total assets). All models include fixed effects for bank, year, and quarter. Robust standard errors are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 7. Robustness Check Using FinBERT for Earnings Call Sentiment.

	(1) BASELINE	(2) INTERACTION MODEL	(3) FULL MODEL
PRE-CALL NEWS SENTIMENT	0.811*** (0.051)	0.304** (0.134)	0.305** (0.135)
EARNINGS CALL SENTIMENT (FINBERT)		-0.410*** (0.139)	-0.431*** (0.143)
PRE-CALL NEWS SENTIMENT × EARNINGS CALL SENTIMENT		0.696*** (0.173)	0.702*** (0.174)
SPEAKER POSITION			0.010 (0.017)
TOTAL CALL WORD COUNT			-0.053 (0.168)
BANK SIZE			0.008 (0.038)
R-SQUARED	0.634	0.666	0.667
OBSERVATIONS	197	197	197

Note: This table presents results from a robustness check in which earnings call sentiment is measured using FinBERT, a language model specifically trained on financial texts. Pre-call and post-call media sentiment are measured using OpenAI's sentiment model. Column (1) includes only pre-call news sentiment. Column (2) introduces FinBERT-based earnings call sentiment and the interaction term. Column (3) adds control variables: Speaker Position (role of the main speaker), Bank Size (log of total assets), and Total Call Word Count. All models include fixed effects for bank, year, and quarter. Robust standard errors are shown in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

6. Conclusion

This study shows that the tone of media coverage following bank earnings calls is not solely a reflection of independent reporting but is shaped by the alignment between pre-call media sentiment and the tone of the earnings call itself. In Kuwait's media environment, where banks routinely prepare or directly influence news articles about themselves, tone transmission reflects a deliberate communication strategy rather than spontaneous editorial judgment. Our results demonstrate that tone consistency is most effective when reinforced across all stages of communication, particularly by larger banks, Islamic institutions, and calls led by senior executives.

We further find that specific call features, such as forward-looking language, uncertainty, and linguistic complexity, amplify the strength of tone alignment, suggesting that message control is enhanced not only by what is said but how it is said. While we rely on sentiment analysis models to detect tone, robustness checks using both simplified tone classifications and alternative models such as FinBERT confirm the stability of our findings.

Overall, our study contributes to a deeper understanding of how tone is strategically managed in financial communication, especially in institutional contexts with limited media independence. Future research could explore similar dynamics in other regulatory environments or examine whether these strategies influence investor decisions or market pricing more directly. In environments where banks are both the source and the shaper of the message, the distinction between disclosure and distribution becomes increasingly blurred.
These findings suggest that regulators and market observers should consider not only the content of corporate disclosures but also the structure of the media environment in which they are delivered. In contexts where banks have substantial control over media narratives, additional transparency requirements such as third-party oversight of media reporting or disclosure of article authorship could help ensure that financial communication remains credible, balanced, and useful to all stakeholders.

6.1 Limitations and future research

Although the sample is limited to a handful of Kuwaiti banks, this narrow focus provides a rare window into tone management in a market where banks directly shape media narratives; as more banks release transcripts, future research can build on this foundation. Similarly, analysing only one newspaper limits media diversity, but it ensures consistent coverage and reveals the direct link between corporate communications and subsequent reporting in a controlled setting. As additional news outlets make archives accessible, future work can expand this approach to multiple papers. Finally, the unique Kuwaiti context may constrain external validity, yet this exclusivity underscores the novelty of the study. It is the first to systematically examine tone alignment between pre-call news, earnings calls and post-call media sentiment in the region, highlighting a method that can later be tested in other markets. Recognising that sampling bias can limit generalizability. These limitations point to clear opportunities: as more data become available, researchers can broaden the sample of banks, incorporate diverse media sources and assess whether similar patterns hold beyond Kuwait.

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APPENDIX

A1. Variables Definitions.

INDICATOR	DEFINITION
POST CALL NEWS SENTIMENT	SENTIMENT SCORE OF NEWS ARTICLES PUBLISHED WITHIN 5 DAYS AFTER THE EARNINGS CALL.
PRE-CALL NEWS SENTIMENT	SENTIMENT SCORE OF NEWS ARTICLES PUBLISHED WITHIN 5 DAYS BEFORE THE EARNINGS CALL.
EARNINGS CALL SENTIMENT	SENTIMENT SCORE OF THE ENTIRE EARNINGS CALL TRANSCRIPT, REFLECTING THE OVERALL TONE OF THE CALL.
PRE-CALL NEWS SENTIMENT × EARNINGS CALL SENTIMENT	INTERACTION TERM BETWEEN EARNINGS CALL TONE AND PRE-CALL NEWS SENTIMENT, USED TO TEST ALIGNMENT EFFECTS.
SPEAKER POSITION	ROLE OF THE MAIN SPEAKER DURING THE EARNINGS CALL (E.G., CEO, CFO, OTHER).
BANK SIZE	NATURAL LOGARITHM OF THE BANK'S TOTAL ASSETS.
TOTAL CALL WORD COUNT	TOTAL NUMBER OF WORDS SPOKEN DURING THE ENTIRE EARNINGS CALL.

Table A2. Bank Characteristics as Moderators of Tone Transmission

	(1)	(4)	(5)	(8)
	BANKING REGULATION	CUSTOMER SERVICES	DIGITAL BANKING	ISLAMIC BANKING
PRE-CALL NEWS SENTIMENT × EARNINGS CALL SENTIMENT × NEWS MAIN TOPIC	0.011** (0.004)	0.007*** (0.002)	0.014** (0.006)	0.022** (0.009)
PRE-CALL NEWS SENTIMENT	0.005 (0.004)	0.009*** (0.002)	0.008 (0.005)	0.003 (0.006)
EARNINGS CALL SENTIMENT	-0.008*** (0.002)	-0.005*** (0.002)	-0.011** (0.005)	-0.010** (0.005)
SPEAKER POSITION	-0.002 (0.026)	0.006 (0.024)	-0.011 (0.027)	-0.017 (0.026)
BANK SIZE	-0.055 (0.248)	-0.002 (0.223)	-0.000 (0.259)	-0.042 (0.253)
TOTAL CALL WORD COUNT	-0.168** (0.077)	-0.114 (0.069)	-0.161** (0.080)	-0.183** (0.078)
R-SQUARED	0.246	0.388	0.183	0.219
OBSERVATIONS	197	197	197	197

Note: This table reports results from regressions examining whether the effect of tone alignment between pre-call news sentiment and earnings call sentiment on post-call media sentiment varies by the main topic discussed in the news article. Each column represents a different topic category: Banking Regulation, Customer Services, Digital Banking, and Islamic Banking. The key variable of interest is the three-way interaction term (Pre-Call News Sentiment × Earnings Call Sentiment × News Main Topic), which captures whether tone consistency has a stronger effect within specific thematic contexts. All sentiment variables are scaled from -1 (very negative) to +1 (very positive). Control variables include Speaker Position (role of the main speaker), Bank Size (log of total assets), and Total Call Word Count. All models include bank, year, and quarter fixed effects. Robust standard errors are shown in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table A3. Bank Characteristics as Moderators of Tone Transmission

	(1) ISLAMIC BANKS	(2) CONVENTIONAL BANKS	(3) BANK SIZE
PRE-CALL NEWS SENTIMENT × EARNINGS CALL SENTIMENT ×ISLAMIC	0.234*** (0.075)		
PRE-CALL NEWS SENTIMENT × EARNINGS CALL SENTIMENT ×CONVENTIONAL		-0.008 (0.081)	
PRE-CALL NEWS SENTIMENT ×EARNINGS CALL SENTIMENT ×TOTAL ASSETS			0.0151*** (0.005)
PRE-CALL NEWS SENTIMENT	0.711*** (0.058)	0.806*** (0.056)	0.647*** (0.071)
EARNINGS CALL SENTIMENT	-0.057 (0.047)	-0.021 (0.055)	-0.143** (0.060)
SPEAKER POSITION	0.010 (0.018)	0.010 (0.018)	0.014 (0.018)
BANK SIZE	-0.008 (0.167)	-0.028 (0.172)	-0.051 (0.167)
TOTAL CALL WORD COUNT	-0.077 (0.052)	-0.076 (0.053)	-0.081 (0.052)
R-SQUARED	0.658	0.639	0.658
OBSERVATIONS	197	197	197

Note: This table examines how bank characteristics moderate the relationship between tone alignment (Pre-Call News Sentiment × Earnings Call Sentiment) and post-call media sentiment. Column (1) reports the interaction effect for Islamic banks, Column (2) for conventional banks, and Column (3) includes a continuous interaction with bank size (log of total assets). The key three-way interaction terms capture whether tone consistency has a stronger influence on media sentiment for specific bank types or sizes. All sentiment variables are scaled from -1 (very negative) to +1 (very positive). Control variables include Speaker Position (role of the main speaker), Bank Size, and Total Call Word Count. All models include fixed effects for bank, year, and quarter. Robust standard errors are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table A4. Earnings Call Features as Channels of Tone Transmission.

	(1)	(2)	(3)	(4)
	QARATIO	FORWARD-LOOKING SHARE	UNCERTAINTY	COMPLEXITY
PRE-CALL NEWS SENTIMENT ×EARNINGS CALL SENTIMENT ×QARATIO	0.407** (0.168)			
PRE-CALL NEWS SENTIMENT ×EARNINGS CALL SENTIMENT ×FORWARD-LOOKING SHARE		0.374** (0.144)		
PRE-CALL NEWS SENTIMENT ×EARNINGS CALL SENTIMENT ×UNCERTAINTY			0.514** (0.215)	
PRE-CALL NEWS SENTIMENT ×EARNINGS CALL SENTIMENT ×COMPLEXITY				0.063*** (0.020)
PRE-CALL NEWS SENTIMENT	0.717*** (0.062)	0.682*** (0.069)	0.712*** (0.064)	0.648*** (0.071)
EARNINGS CALL SENTIMENT	-0.101* (0.056)	-0.105* (0.056)	-0.103* (0.057)	-0.145** (0.060)
SPEAKER POSITION	0.013 (0.018)	0.016 (0.018)	0.013 (0.018)	0.013 (0.018)
BANK SIZE	0.004 (0.169)	0.000 (0.168)	-0.017 (0.169)	-0.035 (0.167)
TOTAL CALL WORD COUNT	-0.079 (0.052)	-0.092* (0.053)	-0.081 (0.053)	-0.080 (0.052)
R-SQUARED	0.651	0.652	0.651	0.658
OBSERVATIONS	197	197	197	197

Note: This table reports results from regressions examining whether specific characteristics of earnings calls moderate the relationship between tone alignment (Pre-Call News Sentiment × Earnings Call Sentiment) and post-call media sentiment. Each column presents a separate model including a three-way interaction term between tone alignment and one of four call features: (1) QARatio – the proportion of the call devoted to analyst Q&A; (2) Forward-Looking Share – the proportion of forward-looking statements; (3) Uncertainty – the share of uncertain or hedging language; and (4) Complexity – a linguistic complexity score based on readability. All sentiment variables are scaled from -1 (very negative) to +1 (very positive). Control variables include Speaker Position (role of the main speaker), Bank Size (log of total assets), and Total Call Word Count. All models include fixed effects for bank, year, and quarter. Robust standard errors are in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

A5. Descriptive Statistics for Call-Level Language Features

	# OBS	MEAN	ST DEV	MIN	MAX
QARATIO	197	0.351	0.153	0.050	0.800
FORWARD-LOOKING SHARE	197	0.468	0.127	0.200	0.700
UNCERTAINTY	197	0.294	0.0826	0.120	0.600
COMPLEXITY	197	3.765	0.253	2.708	4.248

Table A6. Role of Call Structure and Delivery.

	(1) EXECUTIVE ROLE	(2) CALL LENGTH	(3) ALL
PRE-CALL NEWS SENTIMENT ×EARNINGS CALL SENTIMENT ×EXECUTIVE ROLE	0.237*** (0.077)		
PRE-CALL NEWS SENTIMENT ×EARNINGS CALL SENTIMENT ×CALL LENGTH		0.029*** (0.009)	
PRE-CALL NEWS SENTIMENT ×EARNINGS CALL SENTIMENT			0.242*** (0.077)
PRE-CALL NEWS SENTIMENT	0.652*** (0.070)	0.649*** (0.071)	0.646*** (0.071)
EARNINGS CALL SENTIMENT	-0.137** (0.059)	-0.143** (0.060)	-0.144** (0.060)
SPEAKER POSITION	0.021 (0.018)	0.014 (0.018)	0.014 (0.018)
BANK SIZE	-0.015 (0.167)	-0.039 (0.167)	-0.035 (0.167)
TOTAL CALL WORD COUNT	-0.087* (0.052)	-0.090* (0.052)	-0.081 (0.052)
R-SQUARED	0.658	0.658	0.658
OBSERVATIONS	197	197	197

Note: This table presents results from regressions examining whether features of earnings call delivery moderate the relationship between tone alignment (Pre-Call News Sentiment × Earnings Call Sentiment) and post-call media sentiment. Column (1) includes a three-way interaction with Executive Role, capturing whether the effect is stronger when a senior executive (e.g., CEO or CFO) leads the call. Column (2) includes Call Length as a moderator, measured by the total word count. Column (3) includes control variables: Speaker Position (role of the main speaker, e.g., CEO, CFO, or Other), Total Call Word Count (total number of words spoken), and Bank Size (log of total assets). All sentiment scores range from -1 (very negative) to +1 (very positive). Control variables include Speaker Position, Bank Size (log of total assets), and Total Call Word Count. All models include fixed effects for bank, year, and quarter. Robust standard errors are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

A7. Displays the prompt used to classify each news article by sentiment and topic using OpenAI's GPT-3.5-turbo, assigning a sentiment score, a main topic from a predefined list, and a brief summary label.

```
def analyze_article_with_openai(article, model="gpt-3.5-turbo"):  1 usage
    try:
        print("Analyzing article sentiment, topic, and main topic...")

        allowed_main_topics = [
            "Financial Performance",
            "Corporate Strategy",
            "Innovation",
            "Technology",
            "Market Expansion",
            "Banking Regulation",
            "Digital Banking",
            "Customer Services",
            "CSR",
            "Islamic Banking"
        ]

        main_topic_list = "\n".join([f"- {topic}" for topic in allowed_main_topics])

        response = client.chat_completion(
            model=model,
            messages=[
                {
                    "role": "system",
                    "content": (
                        "You are a financial analysis assistant. Be strict and consistent.\n"
                        "Classify sentiment as either Positive or Negative (never Neutral).\n"
                        "Provide a sentiment score between -1 and 1, where:\n"
                        "- Negative = -1.00 to -0.01\n"
                        "- Positive = 0.01 to 1.00\n"
                        "Summarize the topic in 1-2 words.\n"
                        "Select ONE main topic from this list:\n"
                        f"{main_topic_list}"
                    )
```

A8. Python function used to scrape article headlines and types from the Al Jarida newspaper archive, enabling structured extraction of Arabic financial news by date and page.

```python
import requests
from bs4 import BeautifulSoup
import csv
import os
from datetime import datetime, timedelta
import time

# Function to fetch news types and headlines from a given page with retries
def fetch_articles(date, page_number, retries=3):
    url = f"https://www.aljarida.com/archive/{date}?pgno={page_number}"
    attempt = 0
    while attempt < retries:
        try:
            response = requests.get(url)
            if response.status_code == 200:
                soup = BeautifulSoup(response.content, 'html.parser')
                articles = []

                table = soup.find('table')
                if not table:
                    print(f"No table found on page {page_number} for {date}")
                    return []

                rows = table.find_all('tr')
                for row in rows:
                    columns = row.find_all('td')
                    if len(columns) >= 2:
                        news_type = columns[0].get_text(strip=True)
                        headline = columns[1].get_text(strip=True)
                        articles.append((news_type, headline, date))

                return articles
```

A9. An example of the prompt used to extract call-level characteristics—such as complexity, Q&A share, forward-looking content, and uncertainty.

```python
def analyze_call_characteristics(text, transcript_name, model="gpt-4-turbo"):
    prompt = (
        "You are a financial language analyst. I will give you a full earnings call transcript. "
        "Analyze and return the following metrics:\n\n"
        "1. Call Complexity Score (0-100): Rate how complex the language is. Use a Flesch Reading Ease-style scale.\n"
        "2. Q&A Ratio (0-1): Estimate the portion of the call that is unscripted Q&A.\n"
        "3. Forward-Looking Content Share (0-1): Estimate the portion of the call discussing future expectations.\n"
        "4. Uncertainty Score (0-1): Estimate how much uncertainty or hedging language appears (e.g., may, could, depends).\n\n"
        "Format:\n"
        "Call Complexity Score: <number>\n"
        "Q&A Ratio: <decimal>\n"
        "Forward-Looking Content Share: <decimal>\n"
        "Uncertainty Score: <decimal>"
    )
```

الوطني
NBK

بيت التمويل الكويتي
KFH

بنك الخليج
GULF BANK

بنك برقان
BURGAN BANK
driven by you

التجاري
Al-Tijari

بوبيان
Boubyan

الأهلي
ABK

KIB

بنك وربة
WARBA BANK

الصناعي
IBK