Initial Evidence on Earnings Conference Call Mention Contracts for Investor Relations Officers

William J. Mayew*
william.mayew@duke.edu
Duke University

Boyan Zhu
boyan.zhu@duke.edu
Duke University

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SYNOPSIS: Prediction markets now offer contracts on whether managers will mention specific words during earnings conference calls. While prior research shows that prediction market prices can identify outcomes, it is unclear whether these prices incrementally predict outcomes relative to investor relations (IR) disclosure work products like prior conference calls and press releases. Using 1,437 earnings conference call mention contracts from the Kalshi platform during the first nine months of existence, we find that prices are strong predictors of contract outcomes, with an area under the receiver operating characteristic curve (AUC) equal to 0.893. This value is well above chance levels but only slightly greater than the AUC of 0.891 resulting from disclosures alone. Prices are incrementally predictive of contract outcomes when considered jointly with disclosures, but the model improvement relative to disclosures alone is economically modest. The prediction market price association with contract outcomes is more pronounced in the presentation versus the Q&A portion of the call, consistent with managers responding to prices as a signal of information demand. These findings are inconsistent with prices simply capturing gambling-driven noise but also suggest there is little novel information in prediction market contract prices for IROs beyond disclosures that IR departments already provide.

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I. SYNOPSIS AND CONTRIBUTION TO PRACTICE

Prediction markets have exploded in popularity with contract prices commonly interpreted as market-implied probabilities of future events. A growing literature shows that these prices can be informative about realized outcomes. However, whether prediction market prices are meaningful for corporate decision makers is less clear. A central question for investor relations officers (IROs) is whether they can learn anything novel about stakeholder information demand from earnings call mention contract prices to inform firm disclosures. Mention contracts ask whether a specific word will be spoken by firm representatives during a firm's earnings conference call. Incorporating price signals into disclosure decisions is only appropriate if prices reflect stakeholder demand for information that managers are unaware of. If prices instead primarily reflect gambling activity (Rabinovitz and Packin 2025), monitoring such prices and altering disclosures would represent a costly use of scarce managerial resources.

Whether the "information in price" view or "gambling" view dominates is unclear. On the one hand, retail investors comprise a large proportion of the prediction market. Given retail investors have been shown to uncover novel insights in some settings (Lee and Zhong 2022; Markov and Yezegel 2024), prediction market prices may contain useful incremental information for investor relations officers (IROs) who seek to meet stakeholder information demand through disclosure. On the other hand, features of the earnings call mention market setting, including substantial analyst following, limited liquidity, and high trading costs limit the incentives for retail investors to uncover and trade on novel information. These features may result in most trades simply capturing gambling as a leisure activity, generating little information in price for

managers to learn from. Whether, and to what extent, earnings mention prices are useful signals for IROs is therefore an empirical question.

We address this question by comparing prediction market prices to traditional IR activities in identifying conference call content. Using a sample of 1,437 earnings conference call mention contracts from the Kalshi exchange, we assess whether prices capture information about whether a contracted word is ultimately mentioned during the call. We find that prediction market prices and IR disclosures exhibit similar standalone predictive ability. However, when considered jointly, prices provide incremental information beyond firm disclosures. However, the improvement in model fit from joint consideration, while statistically significant, is economically modest. For example, the area under the receiver operating characteristic curve (AUC) increases slightly from 0.891 to 0.917 when moving from a model considering disclosures to a model including both disclosures and prices. Mean squared errors, captured by Brier scores, decrease slightly from 0.132 to 0.114. In terms of marginal effects in the joint model, we find that a standard deviation change in prediction market prices increases the probability of word mention by 18.7 percentage points, while a standard deviation change in word mentions in prior call presentation (press releases) increase the probability of word mention by 10.1 percentage points (6.1 percentage points).

Additional analyses indicate that the association between prices and word mentions is stronger in the presentation portion of conference calls, where managers proactively communicate with investors, rather than in the Q&A portion, where disclosure is more reactive to analyst questions. Taken together, the findings are inconsistent with prices solely reflecting gambling activity. Rather, the results are more consistent with the managers responding to

prediction market prices as if they contain an additional, albeit economically small, signal of stakeholder information demand.

We acknowledge that we cannot directly observe management actions. As a result, the associations we document are ultimately joint tests that prices contain signals useful for management and that management acts on such signals. This limitation prevents us from completely ruling out the possibility that the associations we document represent tipping whereby managers do not learn from price but rather share material nonpublic information with some market participants. Another limitation pertains to external validity. Our results are based upon an initial sample of earnings mention contracts on Kalshi. The contracts we study pertain to some of the largest firms in the economy and so whether our findings generalize to smaller firms is unclear. Additionally, earnings call mention contracts are now available on the Polymarket platform. Whether our findings generalize to Polymarket is also an important issue for future research.

With these limitations in mind, we believe our study contributes to the academic literature, regulators and practice. With respect to the academic literature, we add to the emerging literature on prediction markets by considering the earnings call mention contract market. A stream of this literature assesses whether prediction market prices identify outcomes better than other predictors. We extend this literature by benchmarking prediction market prices against a comprehensive set of IR work products, including prior conference calls, press releases, regulatory filings, and peer disclosures. Our findings are therefore distinct from, but complementary to, a concurrent study in this market by Glaze et al. (2026), who investigate whether unexpected word mentions during earnings calls impact equity market prices, rather than the informational role of prices for corporate decision makers.

For regulators, our evidence should be informative to the CFTC, who has recently sought public comment on the cost-benefit considerations of prediction markets and regulations that apply to prediction markets (CFTC 2026). Our study describes current market conditions and highlights cost-benefit considerations for IROs. Additionally, our evidence on which firm representatives generate contract resolutions, and which part of the call generates resolutions, can inform regulators regarding the parties who both potentially have contract outcome information and can influence the contract outcome.

For practitioners, our findings provide IROs with empirical evidence consistent with managers viewing prediction market prices as more signal than noise. Because market prices aggregate beliefs of market participants that are primarily retail investors, our results have implications for how firms strategize with respect to retail investor engagement. Historically, firms have prioritized interactions with institutional investors during conference calls, as direct engagement with retail investors was viewed as a costly use of management time. More recently, some firms have adopted platforms such as Say Technologies to aggregate retail investor questions, thereby lowering the cost of direct interaction. However, Say Technologies adoption remains limited to date, suggesting the platform costs outweigh the benefits. Prediction market prices offer an alternative approach. Because they are publicly observable and continuously updated, prices offer an appealing low-cost tool for gauging investor demand. However, acting on such price signals introduces several practical considerations.

First, prediction market contracts ultimately settle after the conference call with one winner and one loser. In a setting dominated by retail participation, managerial response to prices may be perceived as management picking winners and losers and in turn alienating a proportion of the retail investor base. Second, contract resolution may not always be fully under

managerial control. Direct analyst questions containing the word in the Q&A may necessitate word use by management in the response despite managers avoiding the term in the presentation. We also find two instances where contracts resolve to Yes based on statements made by conference call operators, despite operators generally not being employees of the firm. Third, firm insiders privately interact with analysts and call operators and as a result potential insider trading can occur through multiple channels. Firms may wish to update their quiet period policies regarding prediction markets to minimize the potential for claims of insider trading.

Taken together, these considerations highlight a trade-off for IROs. While prediction market prices may provide a low-cost signal of investor demand, the costs associated with acting on potentially noisy signals, managing investor perceptions, and addressing regulatory concerns may outweigh the benefits. For firms where the costs outweigh the benefit, IROs may consider policies that purposefully limit prediction market costs. For example, a policy whereby the firm pre-commits to state contracted words during the conference call would collapse the market given the outcome is a certainty.

II. BACKGROUND AND HYPOTHESIS DEVELOPMENT

Prediction Markets

Prediction markets are operated on exchange-based platforms that allow participants to trade contracts tied to the realization of future events. In a standard binary prediction market, each contract corresponds to a Yes/No question and pays $1 if the specified event occurs and $0 otherwise. For example, consider a contract that asks, “Will it rain in New York tomorrow?” If the contract trades at $0.70, a trader who believes it will rain can buy a Yes contract for 70 cents and receive $1 if it rains (earning 30 cents), or $0 if it does not (losing 70 cents). Conversely, a trader who believes it will not rain can buy a No contract for 30 cents, which pays $1 if it does not rain (earning 70 cents) and $0 otherwise (losing 30 cents). As a result, contract prices, which

range between \$0 and \$1, can be interpreted as the market-implied probability of the event. Because a Yes contract priced at p and a No contract priced at $1 - p$ provide complementary payoffs, the two positions are economically equivalent ways of taking opposing views on the same underlying event. An early body of research, primarily based on small-scale and experimental prediction markets, demonstrates that prediction market prices effectively aggregate dispersed information across traders and often produce accurate forecasts of future outcomes (Wolfers and Zitzewitz 2004; Berg, Nelson, and Rietz 2008). Using data from the Iowa Electronic Markets, Berg, Nelson, and Rietz (2008) show that market-generated election forecasts outperform traditional polls in 74% of over 900 comparisons across five U.S. presidential election cycles.

The growth of regulated prediction markets in the United States has been supported by the Commodity Futures Trading Commission (CFTC). In November 2020, Kalshi was granted approval as a Designated Contract Market (DCM), making it the first federally regulated prediction market exchange in the country (CFTC 2020). Unlike earlier platforms such as PredictIt or the Iowa Electronic Markets, which operated under no-action letters and imposed strict limits on position sizes and participation, Kalshi operates within a formal regulatory framework that permits broader participation and higher position limits.[1]

The composition of participants on Kalshi differs meaningfully from earlier prediction market platforms. While the Iowa Electronic Markets were populated almost exclusively by small-scale academic participants subject to a \$500 investment cap per trader (Berg, Nelson, and Rietz 2008), Kalshi attracts a broader and more heterogeneous participant base. According to Kalshi's own description, participants fall into three primary categories: directional traders who

[1] Polymarket is a competing prediction market to Kalshi; its primary platform operates outside US regulation, although a limited US regulated version launched in late 2025.

take positions based on their assessment of event probabilities, hedgers who use event contracts to insure against external risks such as inflation or interest rate fluctuations, and market makers who provide liquidity by posting limit orders and earning the bid-ask spread. Kalshi reports that most participants fall into the first two categories and that the majority of traders on the platform are retail rather than institutional. Diercks, Katz, and Wright (2026) note that Kalshi's retail-heavy participant base provides a distinctive investor perspective relative to traditional financial derivatives markets, where participation is concentrated among professional investors.

Kalshi operates as a centralized exchange rather than as a market maker. Trades occur between participants through a limit order book. Traders can submit limit orders that rest on the order book (makers) or execute immediately against existing orders (takers). Makers choose a side (Yes or No), a price, and a quantity, while takers accept prevailing market prices. A trade occurs when orders are matched, resulting in one trader holding a Yes contract and the counterparty holding the complementary No contract. After a contract is formed, traders can realize profits either by (1) selling the contract before settlement at a new market price or (2) holding it to maturity and receiving the outcome-based payout. Bürgi, Deng, and Whelan (2026) provide the first detailed characterization of this quote-driven microstructure. They show that Kalshi's data uniquely identify which side of each trade was initiated by the maker and which by the taker, allowing researchers to study market microstructure without relying on trade-initiator classification algorithms such as Lee and Ready (1991).

Since the platform itself does not take directional positions in these contracts, Kalshi generates revenue through transaction fees charged to both makers and takers. Fees are assessed at the time a trade is executed and depend on the number of contracts traded and the contract price. Makers, who provide liquidity by posting limit orders to the order book, pay lower fees, while takers, who execute immediately against existing orders, pay higher fees. Specifically,

maker fees are given by $0.0175 \times c \times p(1-p)$, while taker fees are $0.07 \times c \times p(1-p)$, where c is the number of contracts and p is the contract price. This fee structure implies that fees are highest when prices are near 0.5 and lower when prices approach 0 or 1.

A rapidly growing body of research studies modern prediction markets. This literature can be broadly organized along three dimensions: (1) the accuracy and properties of prediction market prices, (2) the role of prediction market prices in capturing expectations and factors that change market expectations, and (3) assessment of how well prices perform relative to established forecasting benchmarks in predicting outcomes.

Regarding the first dimension, Bürgi, Deng, and Whelan (2026) use transaction-level data from Kalshi to show that contract prices are broadly informative and become more accurate as resolution approaches. At the same time, they document a persistent favorite–longshot bias, whereby low-priced contracts underperform relative to their implied probabilities after accounting for fees, while high-priced contracts tend to outperform and generate modest positive returns. Extending this line of work, Ng, Peng, Tao, and Zhou (2026) study price discovery across major prediction market platforms and show that more liquid markets play a leading role in incorporating information into prices. They document meaningful differences across platforms, with Polymarket tending to lead Kalshi in price discovery, particularly during periods of high trading activity and liquidity. In the earnings mention prediction market we study, Glaze et al. (2026) show that mention contract prices are informative about contract outcomes by documenting a positive association between contract prices and whether the contracted word is mentioned by management during the conference call.

Regarding the second dimension, Swanson, Wu, and Wang (2025) use prediction market prices to proxy for market expectations to study the effects of monetary policy announcements on macroeconomic expectations. Li and Xie (2025) derive trade policy surprises

by comparing trade announcements against market expectations from prediction market prices to assess how U.S. Treasury convenience yields change. Diercks, Katz, and Wright (2026) show CPI surprises are associated with federal funds rate changes. In the earnings call mention contract setting, which is our focus, Glaze et al. (2026) examine equity market responses to unexpected firm disclosure, where expectations are derived from prediction market prices.

Third, a growing body of research compares prediction market forecasts to more existing benchmarks across a range of domains. In economic and financial forecasting settings, Diercks, Katz, and Wright (2026) show that Kalshi's macroeconomic forecasts are broadly comparable in accuracy to survey-based measures of the macroeconomy. Gómez-Cram, Guo, Jensen, and Kung (2026) and Feng (2026) find that prediction market prices of earnings outcome contracts are superior predictors of reported earnings relative to analyst forecasts, in part due to some analyst forecasts being stale and also due to standard analyst forecast bias. In the context of elections, prediction markets have been shown to perform at least as well as, and in some cases better than, polling data, particularly at longer horizons. For example, Berg, Nelson, and Rietz (2008) find that prediction markets outperform polls in forecasting election outcomes well in advance of Election Day. Other studies, however, find more mixed results. Graefe (2015) finds that simple expectation-based surveys outperform both polls and prediction markets in predicting election outcomes. Similarly, Erikson and Wlezien (2012) show that prediction markets add little incremental information beyond polls in modern elections. In sports forecasting, prediction markets and betting odds exhibit comparable predictive accuracy and both outperform expert tipsters (Spann and Skiera 2009).

Earnings Conference Call Mention Contracts and Hypothesis Development

We seek to extend the third branch of this literature with a focus on earnings conference call mention contracts. Mention contracts ask whether a particular word or phrase will be

mentioned during a firm's earnings conference call. For example, a contract might ask, “Will Apple say ‘tariff’ during their next earnings call?” Traders can buy Yes or No contracts depending on their beliefs about whether the keyword will be spoken, and contracts settle based on the realized content of the call. A contract pays $1 if the keyword (in singular or plural form) is spoken by a company representative or the call operator at any point during a firm’s earnings conference call (either in the prepared remarks or the Q&A) and $0 otherwise.

In our sample, Appendix B reveals the top 90 mention contract word frequencies. The words represent business topics ranging from macroeconomic issues (“tariff” and “recession”) to firm strategy (“acquisition” and “partnership”) to accounting numbers (“operating margin” and “revenue”) to returning capital to shareholders (“dividend” and “buyback”). In our sample the most frequently contracted words were “tariff,” “China,” “shutdown,” “supply chain,” “autonomous,” and “regulator/regulatory/regulation.”

The central question for investor relations officers (IROs) is whether they can learn anything novel about stakeholder demand for information from earnings call mention contract prices. The primary function of IROs and their departments is to communicate with the investment community to meet their information demands, lower their processing costs, and shape the company narrative (Brown et al. 2019). Given selective disclosure prohibitions under Regulation FD that limit what can be stated privately to the investment community, IROs primarily meet information demands through public disclosures such as during earnings conference calls and in press releases. One way to ascertain whether novel information exists in mention contract prices is to take these firm disclosures as the benchmark and assess whether mention contract prices are better able to identify the contract outcome. Whether, and to what extent, earnings contract prices enhance outcome prediction is unclear.

On the one hand, equity prices have been shown to be important signals to inform

investment decisions of managers of public companies (Chen et al. 2007). Prices aggregate information, including the private information of investors, which can enable managers to learn from price. Applying this concept to the mention contract setting, suppose investors engage in costly information search and uncover that tariffs may have an important impact on a firm's fundamentals.[2] Trading on this information would result in tariff mention contract prices increasing. If managers were unaware of the importance of the tariff issue, they may not have otherwise discussed tariffs. If a sufficient proportion of traders invest in information search to uncover topics related to the fundamentals of the firm, contract prices may provide a signal to inform managers' communication decisions, in turn generating the mention of the contracted word during the conference call. We label this possibility the *information in price hypothesis*.

The information in price hypothesis assumes that managers observe prices and believe the prices potentially contain valuable insights that were not already known to them and communicated to the market. Four features of the mention contract setting may limit the amount of novel information that could be contained in price to inform management. The first is that firms for which earnings call mention contracts exist are some of the largest in the economy, with the median firm being followed by 22 analysts. Managers serve this constituency with conference calls each quarter, making it potentially difficult for retail investors to find a topic that is important to discuss that has not already been publicly voiced by the firm in their regular public dialog with these analysts.

The second is that sample firms generally fall in the large-cap and mega-cap categories, with the average firm size (measured by total assets) being $50.8 Billion. NIRI survey evidence

[2] Costly information search can include uncovering unique sources of information that the investor processes to engage in trading to impact price or observing a public disclosure and incurring the processing costs to underpin a trade (Blankespoor, deHaan, and Marinovic 2020).

reveals that the majority of these types of firms have either formal or informal earnings quiet periods, with the quiet periods beginning at the end of the calendar quarter or earlier (NIRI 2023). During quiet periods firms voluntarily restrict private communication with firm outsiders, in turn increasing the costs of generating private information (Choy 2024). The median mention contract in our sample opens 28 days prior to the conference call, falling squarely within the quiet period of most firms. If investors may find the cost of information search and processing to be too excessive to be profitable due to quiet periods, it may limit the novel information contained in price.

The third feature pertains to low mention contract market liquidity. In our sample, zero trading is observed for 32.6% of days in which the mention contract is open. The dollar trading volume over the life of the average contract is $9,369, which is roughly three times smaller than the $27,197 average dollar volume of contracts based on the outcome of firm earnings (Gómez-Cram et al. 2026). Without sufficient ability to enter and exit positions, traders in expectation may find it too costly to engage in information search and processing.

The fourth issue pertains to platform fees. Recent evidence on prediction market trading profitability suggests that prices are generally well-calibrated and that expected returns are approximately zero before costs, becoming negative once trading fees are taken into account (Akey, Grégoire, Harvie, and Martineau 2026). As a result, participation in these markets is unlikely to be systematically profitable for the average trader. If investors understand this, then the value must come from the utility of gambling *per se* rather than an expected positive payoff from investments in information search. Consistent with this idea, some researchers suggest prediction markets simply repackage traditional betting as a financial activity (Rabinovitz and Packin 2025). If a sufficient majority of trades reflect gambling as a leisure activity, there will be limited information in price. We label this the *gambling as a leisure activity hypothesis*.

To gather practitioner perspectives on whether the *information in price* versus the *gambling as a leisure activity* hypothesis is likely to hold in the earnings conference call mention contract market, one author asked National Investor Relations Institute (NIRI) members how, if at all, they would adjust their conference call disclosures based on Kalshi earning call mention contract prices. One NIRI member suggested the information should be actively avoided because Kalshi traders are not interested in fundamental value. As such, it would be a costly diversion of scarce IR resources to consider prices that reflect bets on conference call word usage. This view suggests the *gambling as a leisure activity hypothesis* dominates. Another NIRI member noted there was a real danger of focusing on "gamblers and speculators rather than the investors you want to attract," but also suggested the possibility that under certain conditions Kalshi prices could serve as useful tip-and-cue market surveillance. Such conditions were that there is sufficiently high volume (so the implied probability is sufficiently precise) and the topic implied by the word was sufficiently relevant. This view suggests both hypotheses have merit. A final NIRI member stated that we now live in the prediction markets era. Unlike the early 2000s when IROs catered to the buy-side and sell-side, a large amount of money is moving into prediction markets, and this makes prices matter rather than simply reflecting noise. This view is most consistent with the *information in price hypothesis*.

Given the competing hypotheses on a conceptual and practitioner level, it is an empirical question as to whether mention contract prices contain novel information regarding stakeholder information demand. We therefore state our hypothesis in null form as follows:

H_0: Earnings conference call mention contract price is not an additional signal of information demand for IR departments.

III. RESEARCH DESIGN

Empirical Model

For price to be an additional signal to IR departments, it must provide insights beyond the efforts they already undertake to identify and meet stakeholder information demands. We test H_0 through two complementary analyses. The first examines whether mention contract prices are better standalone predictors than efforts IR departments already undertake to meet and understand stakeholder demand. The second is whether mention contract prices incrementally predict conference call outcomes conditional on IR department efforts.

We undertake the first analysis by estimating the following logistic regressions where the dependent variable is the binary outcome of mention contracts (MENTION), which equals one if management mentions the contracted keyword during the earnings conference call and zero otherwise.

$Pr(\text{MENTION}) = f(\text{mention contract price})$ (1a)
$Pr(\text{MENTION}) = f(\text{firm disclosures, other IR efforts to understand information demand})$ (1b)

In equation (1a), we utilize the last mention contract price immediately prior to the conference call, which is the most comprehensive signal available to managers prior to the conference call. In equation (1b), firm disclosures pertain to conference calls, press releases, 10-K/10-Q financial filings and 8-Ks. These disclosures have been identified as those for which IR departments exert influence (Brown et al. 2019). We count word mentions during prior earnings conference calls going back four quarters.[3] We then count word mentions in all press releases, 10-K/10-Q filings, and non-press release 8-K filings issued between the four-quarters-ago conference call and the target conference call. These disclosures reflect an observable outcome of efforts by IR departments to understand and meet stakeholder information demand. We acknowledge that other efforts to understand information demand include monitoring peer firm discussions with

[3] In the rare case the firm does not have four prior earnings conference calls, we utilize all available earnings conference calls.

analysts, which we operationalize by counting word mentions in peer disclosures. IR departments also exert costly effort to understand information demand through private communication with analysts and investors (Brown et al. 2019; Soltes 2014). As we have no means to directly observe and measure private interactions between managers and outsiders, we include firm fixed effects to capture unobservable but stable disclosure policies that would govern such interactions. Because analyst demand can vary over time with macroeconomic events, we also include conference call month fixed effects.

Estimation of (1a) and (1b) allows for the calculation of the area under the receiver operating characteristic curve (AUC). A receiver operating characteristic curve illustrates the likelihood of correctly identifying a true signal relative to incorrectly identifying a false one. Constructing this curve involves estimating the true positive rate (sensitivity) and the false positive rate (1 − specificity) across a range of cutoff values, denoted as c, applied to predicted probabilities obtained from a logistic regression model. By design, fitted probabilities from logistic regression models, such as those described in equations (1a) and (1b), fall within the interval from 0 to 1. For instance, if $c = 0.80$, any observation with a predicted value at or above this threshold is classified as a case where the word is mentioned during the conference call, while those below it indicate the word is not mentioned. At this cutoff, a 2×2 contingency table can be created comparing predicted outcomes (word mentioned vs. word not mentioned) with actual conference call outcomes. This allows for the calculation of sensitivity and specificity at $c = 0.80$. Repeating this procedure for all cutoff values between 0 and 1 and plotting sensitivity against 1 − specificity produces the receiver operating characteristic curve, with the area under the curve (AUC) summarizing overall predictive ability.

An AUC of 0.50 indicates a predictor can identify the outcome at no better than chance levels, whereas an AUC of 1.00 indicates perfect predictive ability. Values in between are

typically interpreted as follows: 0.50-0.60 suggests poor performance, 0.60-0.70 is moderate performance, 0.70-0.80 suggests acceptable performance, 0.80–0.90 indicates excellent performance, and values above 0.90 are considered outstanding (Hosmer and Lemeshow 2000). In medical research, the AUC is frequently used to compare the effectiveness of different types of diagnostic tests in distinguishing between diseased and non-diseased individuals (Zou et al. 2007). Within the social sciences, the AUC has been used to assess issues ranging from how well different financial indicators detect fraud in equity markets (Hobson et al. 2012) to how well different player rating systems can identify tennis match outcomes (Kiely et al. 2025).

Our goal is to compare IR disclosure work products and efforts to understand information demand with mention contract prices to ascertain which is better at identifying mention contract outcomes. Given the extant literature shows that prediction market prices are able to identify outcomes at better than chance levels in a wide variety of settings (Wolfers and Zitzewitz 2004; Berg, Nelson, and Rietz 2008; Diercks, Katz, and Wright 2026; Gómez-Cram, Guo, Jensen, and Kung 2026), including specifically in the context of earnings call mention contracts (Glaze et al. 2026), we expect AUC_{1a} will exceed chance levels of 0.50. Additionally, it is well established that firm conference calls and press releases contain information (e.g. Matsumoto, Pronk and Roelofsen 2011; Kothari, Li and Short 2009). Given Kalshi prices aggregate information we also expect AUC_{1b} to exceed chance levels.[4] Our interest is in the AUC differences. If mention contract prices can help discriminate between the mention of a word during a conference call and the absence of such a word better than IR output and effort, then we would observe $AUC_{1a} > AUC_{1b}$ and this would provide evidence consistent with H_0 in favor of the information in price

[4] Kim et al. (2026) study how to improve prediction accuracy in the earnings mention market setting by combining prediction market prices with other public information. As part of this exercise, they show that the immediate prior conference call and all public news about the firm generates a Brier score of 0.1991.

hypothesis.

As a second test, we combine the determinants of equation (1a) and (1b) into the same specification:

$$Pr(\text{MENTION}) = f(\text{mention contract price, firm disclosures, other IR efforts to understand information demand}) \quad (1c)$$

Equation (1b) is nested within equation (1c), which enables us to test whether mention contract price is incrementally predictive of contract outcomes over IR disclosure work products and other efforts to understand information demand. A statistically significant likelihood ratio would reject H_0 as it indicates the model fit improves with the inclusion of mention contract price (equation 1c) relative to a model without mention contract price (equation 1b). Estimation of (1c) also allows for the assessment of marginal effects of mention contract prices determinants, which can be descriptively informative to IR departments.

Data and Sample Selection

We begin with the universe of markets listed on the Kalshi exchange as of December 22, 2025, obtained via Kalshi's REST API using the Get Markets endpoint.[5] We restrict this universe to earnings mention markets, defined as markets whose ticker or event ticker contains the string "earningsmention." For each earnings-mention market, we retain market identifiers, event identifiers, creation and close times, trading volume, contract status, and resolution outcomes, as well as the specific word or phrase referenced in each market. The event ticker embeds the firm ticker and an inferred earnings conference call date, which we extract and use in subsequent merges with firm-level and transcript data.

We obtain historical price data for each earnings-mention contract directly from the

[5] We study mention contracts on the Kalshi platform instead of Polymarket for two reasons. First, earnings call mention contracts appear on Kalshi before Polymarket, which facilitates the study of a larger sample. Second, Polymarket restricts orders placed from some geographic locations (including the United States)due to regulatory requirements.

Kalshi platform. For each contract, we collect the time series of daily prices along with their associated timestamps over the contract's duration. These prices reflect the market-implied probability that the specified word or phrase is mentioned during the earnings call. The timestamped price history allows us to precisely identify the last observed price prior to the conference call, which will be the focus of our analysis.

We obtain firm-level data from Compustat and conference call transcripts from Capital IQ. We match each contract to Compustat quarterly observations based on firm ticker and require the inferred conference call date to fall within ±15 days of the earnings announcement date. We then link contracts to conference call transcripts using firm identifiers and call dates, requiring the transcript date to fall within ±10 days of the inferred conference call date. With these criteria, we are able to match each earnings call mention contract with a unique firm-quarter and its related conference call transcript which contains the words upon which the contract outcome will be determined. From Capital IQ we also obtain historical conference call data for the firm as well as competitors.

We obtain the text of firm press releases, non-press release 8-Ks, 10-Q filings and 10-K filings from the SEC Analytics Suite on WRDS. Press releases are identified via 8-K filings containing Exhibit 99 attachments. For foreign private issuers in our focal firm sample, we map 20-F filings to 10-Ks and 6-K filings to 8-Ks; press release 6-Ks are identified analogously by the presence of an Exhibit 99 attachment. We then count the contracted word mentions in each disclosure. We set 10-Q filing mentions to zero for foreign filers because they are exempt from quarterly reporting. We obtain analyst-related information from IBES, including analyst following, forecast dispersion, and earnings announcement dates and times, which we use to characterize the firm's information environment. Capital IQ provides detailed information on the date and time of earnings conference calls, which we use to align prediction market prices with

the call and identify the last observed price prior to the event.

Table 1 Panel A summarizes the sample selection process. As of December 22, 2025, Kalshi listed 1,540 earnings-mention contracts covering 110 conference calls from 76 firms. The first contract in our sample was created on March 12, 2025. We exclude 16 contracts that were still open (i.e., had not yet resolved) as of the data collection date, 10 contracts pertaining to one firm that does not report in US dollars, 15 contracts pertaining to one unique conference call that resolved to zero because the conference call was not held, and 62 contracts that were not traded and therefore lack price information. The final sample contains 1,437 earnings-mention contracts, corresponding to 105 conference calls across 72 firms.

Table 1 Panel B reports the distribution of firms across Fama–French 48 industries for 72 sample firms. As of the sample cutoff date, only 18 of the 48 industries are represented among firms with earnings mention contracts on Kalshi. The highest concentrations are in Business Services, Electronic Equipment, and Retail sectors. The distribution of conference call start times is displayed in Panel C of Table 1. The majority of calls (67.6%) occur after market hours, with an additional 27.6% taking place pre-market and only 4.8% during regular trading hours. Because Kalshi offers round-the-clock trading, mention contract prices taken immediately prior to the conference call start time offer market expectations without the restriction of equity security trading hours that can limit samples in other conference call related research (Mayew, Sethuraman and Venkatachalam 2020; Rennekamp, Sethuraman and Steenhoven 2022). As shown in Panel C of Table 1, the median time between the last observed price and the conference call is approximately 16 minutes, while the median time between the earnings press release and the call is approximately 1 hour. In untabulated analysis, we find that in 100 out of 105 sample conference calls, the last trade prior to the conference call occurs after the press release is issued.

IV. EMPIRICAL RESULTS

Descriptive Statistics and Correlations

Table 2 reports descriptive statistics for the sample at the firm, call, and contract levels. Panel A presents firm-level characteristics for the Kalshi sample alongside the broader IBES universe. Firms associated with mention contracts are substantially larger and are followed by a greater number of analysts, indicating that earnings mention contracts are concentrated among firms with high investor attention. Mention contract firms have lower book to market ratios, suggesting they are more growth as opposed to value relative to the IBES universe, although no meaningful differences in sales growth rates are observable. Analyst forecast dispersion is slightly higher for mention contract firms, although a statistically significant difference only exists at the median. Taken together, these patterns suggest that earnings mention contracts are more likely to be written on large, widely followed firms that are familiar to retail traders, for which there is a slightly elevated level of disagreement among analysts. While we do not know the precise determinants that drive Kalshi to open a market on a given firm's conference call, we do know Kalshi receives fees on a contract-by-contract basis. Focusing on large popular firms where there is some disagreement would conceptually help maximize trader interaction with the platform and, in turn, trading revenue.

Panel B reveals that the average call has 13.7 mention contracts written on it. Total trading volume across these contracts exceeds $128,000 on average. From the contract level descriptive statistics in Panel C we observe that the average contract duration (DURATION) is approximately 28 days, with some contracts created as early (late) as 92 (2) days prior to the contracted earnings call. The average price (AVE_PRICE) while the contract is open is 0.619, implying the probability that the word is mentioned is 61.9%, slightly above the realized mention rate (MENTION) of 56.6%. Of this overall mention rate, the first word mention occurs in the presentation portion of the call (MENTION_PRES) 46.8% of the time and the Q&A

(MENTION_QA) 9.9% of the time. In terms of how routinely the firm mentions the contracted word, we find the contracted word is mentioned at least once in over half of the firm's prior conference calls (FIRM_ROUTINE = 0.580). In terms of word mention magnitudes, we find the contracted word is mentioned 4.311 times per call during prior earnings conference calls (PRIOR_CC_MENTION) with mentions roughly equally distributed across the presentation (PRIOR_CC_MENTION_PRES = 2.202) and Q&A (PRIOR_CC_MENTION_QA = 2.108). The keyword magnitude is higher for press releases filed on form 8-K (FIRM_PR_MENTION = 2.945) than non-press release 8-Ks (FIRM_NONPR_MENTION = 0.762) and higher in 10-Ks (FIRM_10K_MENTION = 45.677) relative to 10-Qs (FIRM_10Q_MENTION = 23.992). Except for non-press release 8-Ks, peer mentions of the word occur at lower levels than the focal firm across all disclosure types. Given the disclosure word counts exhibit some skewness due to some large values, in our empirical analysis we make a natural logarithm transformation for all word count variables. This serves two purposes. First, it captures the economic notion that there is likely diminishing marginal returns to an additional word being provided in a disclosure with respect to the likelihood the word is stated on the contracted conference call. Second, it helps lessen the likelihood that outlier observations are responsible for any associations we document.

Panel C also reveals that word mentions can occur in different parts of the conference call. For example, 814 of our sample 1,437 contracts resolve to "yes" (MENTION = 814/1,437 = 56.6%). Of these resolutions, 672 occur in the presentation (MENTION_PRES = 672/1,437 = 46.8%), with the remaining 142 occurring in the Q&A portion of the call (MENTION_QA = 142/1,437=9.9%). We decompose these resolutions by which company representative spoke the word in Panel D. There we find that the CEO triggers the contract resolution in 506/814 = 62.1% of cases, followed by the CFO (other named executive) stating the word in 215/814 = 26.4% (89/814 = 10.9%) of cases. We even observe that the operator triggers the contract

resolution two times. In Panel D, we also decompose Q&A resolutions based upon the degree of analyst inquiry. Of the 142 Q&A resolutions, 13 occur as a result of the manager saying the word in direct response to the analyst saying the word in the question. In 4 instances, the firm executive says the word following the word being stated by an analyst, although not in an immediate response to the analyst question. Finally, in 125 instances, the executive says the word in the Q&A without any previous mention of the word by any analyst.

We provide Pearson correlations in the lower triangle of Table 3 and denote statistical significance using the 5% level.[6] We find positive and statistically significant correlations between contract outcomes (MENTION) and both the opening contract price (FIRST_PRICE, ρ=0.641) and the price immediately prior to the start of the conference call (LAST_PRICE, ρ=0.678). This implies that as prices increase, the likelihood the contracted word is mentioned increases, consistent with Glaze et al. (2026). We also find positive and statistically significant correlations between contract outcomes (MENTION) and the mentions of the contract word in prior conference calls (LN_PRIOR_CC_MENTION, ρ=0.566), in firm press releases (LN_FIRM_PR_MENTION, ρ=0.388), in non-press release 8-Ks (LN_FIRM_NONPR_MENTION, ρ=0.090), in 10-Ks (LN_FIRM_10K_MENTION, ρ=0.263), and in 10-Qs (LN_FIRM_10Q_MENTION, ρ=0.250). Contract outcomes are also positively associated with peer mentions of the contracted words for all disclosure types. Whether the disclosures firms make or the disclosures of peers IR department monitor better identify contract outcomes versus contract prices alone cannot be ascertained from these correlations. We turn to estimation of equations (1a), (1b) and (1c) to formally make such comparisons.

[6] We also provide Spearman rank correlations and find the magnitude and statistical significance closely matches the Pearson correlations and so we do not discuss them further.

Main Analysis Results

When estimating the logistic regressions, we z-score each continuous variable to have a mean of zero and a standard deviation of one in order to ease interpretation and facilitate comparison of marginal effects. We begin by estimating equation (1a) separately for the contract price at contract inception (Z_FIRST_PRICE) as well as last contract price before the earnings call (Z_LAST_PRICE) in order to confirm the result in the extant literature that prices become more predictive of outcomes as the event date approaches (Diercks, Katz, and Wright 2026; Gómez-Cram et al. 2026). In Table 4 Panel A, we find in column (1) that the first price results in an AUC of 0.870, which is statistically greater than chance levels ($p<0.01$). In column (3), we find the last price before the conference call increases to an AUC of 0.893, which is also statistically greater than chance ($p<0.01$). Recall that AUC values between 0.80 and 0.90 are considered to indicate excellent ability to identify contract outcomes (Hosmer and Lemeshow 2000). However, the 0.023 AUC magnitude increase over the average 28-day period mention contracts are open suggests little new information arrives to enhance the predictive ability of mention contract prices.

The predictive ability of Z_LAST_PRICE that we observe is consistent with Glaze et al. (2026).[7] In column (3) we find the Z_LAST_PRICE odds ratio equals 6.768, implying that a one standard deviation increase in Z_LAST_PRICE increases the odds of the word being mentioned by a factor of 6.768. The marginal effect probability of 0.252 is reported in column (4), implying that a one standard deviation increase in implied probability increases the

[7] Glaze et al. (2026) use Brier scores to assess predictive ability instead of AUC values in the earnings call mention market. A Brier score is the mean squared error applied to binary outcome defined as $\sum_{m=1}^{N}(P_m - X_m)^2/N$, where *m* is the contract, *P* is the predicted probability derived from the logistic regression, *X* is the actual contract outcome, and *N* is the number of observations. Brier scores equal to 0.00 represents perfect classification accuracy and Brier scores equal to 0.25 represents chance levels. Glaze et al. (2026) report a Brier score of 0.135, nearly identical to the 0.134 we report in Panel A of Table 4.

likelihood of word mention by 25.2 percentage points on average.

In columns (5-6) we assess IR department disclosure work products only, followed by disclosures and all efforts in columns (7-8). We estimate these separately to provide descriptive evidence on how important firm disclosures are *per se*. In column (6) we find positive and statistically significant marginal effects for a one standard deviation change in the fraction of prior conference calls where the contracted word was spoken at least once (Z_FIRM_ROUTINE = 0.074, $p<0.01$), the number of word mentions in prior conference call presentations (Z_LN_PRIOR_CC_MENTION_PRES = 0.164, $p<0.01$), Q&A sessions (Z_LN_PRIOR_CC_MENTION_QA = 0.080, $p<0.01$), and press releases (Z_LN_FIRM_PR_MENTION = 0.107, $p<0.01$). Word mentions in non-press release 8-Ks, 10-Qs and 10-Ks are not incrementally associated with contract outcomes. These findings suggest that mentions in past conference calls and press releases, which are the two disclosures that are most impacted by IROs (Brown et al. 2019) matter for contract outcomes. These findings remain in columns (7-8) where we add other IR efforts beyond disclosures. The AUC in column (7) which includes all IR disclosure work products as well as proxies for efforts to understand investor demand reaches 0.891, which is not distinguishable statistically from the Z_LAST_PRICE AUC of 0.893 ($p=0.782$). This evidence fails to reject H_0 in terms of standalone prediction.

The results in columns (9-10) replicate columns (7-8) but also include the last mention contract price (Z_LAST_PRICE). The log-likelihood tends toward zero from -583.717 to -516.175, and the LR test rejects zero suggesting the inclusion of event contract prices improves the model's overall fit. This result rejects H_0 and suggests there is some novel information in event contract prices, consistent with the information in price hypothesis. In terms of marginal effect sizes, the marginal effect probability of prediction market price decreases to 0.187 in

column (10) from the standalone probability of 0.252 in column (4). Additionally, the marginal effect pertaining to prior conference call mentions in the presentation (press release) decreases from 0.185 (0.090) in the standalone model in column (8) to 0.101 (0.061) once the prediction market price is included in the specification. Additionally, the frequency of mentions over the past four calls and the count of Q&A mentions in prior calls are no longer statistically significant predictors of contract outcomes.

The statistical improvement in model fit suggested by the LR test is also observable in other model statistics, although the results suggest the economic significance is small. The AUC in column (9) improves slightly to 0.917 from the 0.891 AUC from the model in column (7) that includes only firm disclosure and IR efforts ($p<0.01$). In terms of the mean squared errors, the Brier Score decreases by 0.018 from 0.132 to 0.114, consistent with an accuracy improvement when both prediction market prices and IR disclosures and efforts are considered. These findings overall are consistent with prediction market prices serving as an indicator of market demand for information and responding to it by mentioning the word during the conference call. However, there is little novel information in prediction market prices beyond what IROs already provide to meet information demand through disclosures.

V. ADDITIONAL ANALYSIS AND SENSITIVITY TESTS

Presentation versus Q&A

Our current interpretation is that managers are responding to prices as if they are an additional signal of information demand. An alternative interpretation is that analysts publicly observe mention contract prices and managers ignore them under the presumption that there is no novel information in price. Rather, analysts ask about the topic reflected in the mention contracts to confirm managers have no interest in the topic. Under this scenario, the observed association between mention contract prices and word mention outcomes is not due to managers

learning from price but rather from analyst inquiry. This possibility exists given that 142 of 814 contracts that resolve to Yes do so during the Q&A portion of the call (Table 2 Panel D).

To distinguish between interpretations, we re-estimate Panel A of Table 4 by separating the dependent variable based on whether the contract resolved to Yes during the presentation (Z_MENTION_PRES) or the Q&A (Z_MENTION_QA). The results for contracts resolving due to presentation mentions in Panel B are virtually identical to Panel A. The only exception is that in column (10) press release mention word counts are no longer statistically significant and the only firm disclosure that remains incrementally associated with mention is prior conference call presentation word counts. Mention contract event prices, although not better standalone predictors, incrementally improve model fit over IR work products and other efforts, with similar economic magnitudes as observed for the entire call.

We find different results in Panel C when considering contracts that resolve to Yes in the Q&A. The first difference is that event contract prices alone are far worse standalone predictors of contract outcomes than IR work products. In column (3) the AUC for the model that solely considers LAST_PRICE is 0.545. While this value is statistically, but not economically, different from chance, it is far below the 0.881 observed in the presentation. More importantly, it is statistically less than the AUC of 0.809 observed for IR work products and other efforts in column (7). Despite the poor standalone predictive ability, when prediction market price is added as an incremental predictor in column (9), the model fit nonetheless improves (LR test p-value <0.05). The marginal effect probability of price is 0.045 in the Q&A which is far less than the 0.195 observed in the presentation.

Column (9) also reveals two findings not observed in the contracts that resolve in the presentation. First, the marginal effect on Z_LN_PRIOR_CC_MENTION_PRES is negative in

Panel C but positive in Panel B. Second, the marginal effect of Z_LN_PEER_CC_MENTION_QA is positive in Panel C but insignificant in Panel B. What these two findings suggest is that when the firm does not mention a word in prior call presentations and when the word is mentioned by peer firms in discussions with analysts, interaction with analysts for the focal firm drives contract resolutions to Yes.

We conclude from this evidence that the overall effect of prediction market prices in Panel A of Table 4 is driven more so by the presentation than the Q&A. Stronger effects in the presentation are consistent with contract prices containing novel information that managers act upon because the presentation is where managers proactively attempt to meet known information demands. For example, Chapman and Green (2018) document that when analysts ask about items during a conference call that were not provided in the presentation, such items are more likely to be provided by management in future conference call presentations. In the Chapman and Green (2018) setting, managers learn from prior interactions with analysts. In this setting, managers learn from mention contract prices.

Tipping

Another explanation for the positive association between word mentions and prediction market prices is tipping. Under the tipping explanation, managers are not learning from price but instead insiders of the firm are providing material nonpublic information about pending conference call word usage. Tipping would imply stronger effects in the presentation portion of the call versus the Q&A as we have observed. Ruling out tipping completely is difficult because we cannot observe private communications between the firm and prediction market participants. However, we can empirically measure whether the firm is in a quiet period. Under the assumption that during earnings quiet periods tipping is less likely, the marginal effect of price

should attenuate for firms who have explicit quiet periods relative to those who do not.

To empirically assess this possibility, in Panels B and C of Table 4, in columns (11-12) we include the interaction term between firms with quiet periods and prediction market prices (Z_LAST_PRICE x QUIET_PERIOD). Firms publicly disclose quiet periods for 61% of our sample observations per Table 2 Panel C. There is no main effect for QUIET_PERIOD because it is subsumed by firm fixed effects. The interaction term is statistically insignificant in both Panel B and Panel C, suggesting quiet periods do not moderate the association between prices and contract outcomes. This insignificant result, therefore, cannot rule tipping in or out as an explanation. The lack of an observable differential price effect may be due to noise in our quiet period proxy. Indeed, firms who do not publicly disclose quiet periods can nonetheless engage in quiet period activity informally (NIRI 2023).

Confounding external signals

Another alternative interpretation of the positive and statistically significant marginal effects of prediction market price on mention contract outcomes is that both managers and prediction markets are responding to a common external signal rather than managers responding to the prediction market price. Such a situation would also result in prediction market price effects being concentrated in the presentation portion. We view this interpretation as unlikely given the evidence in Table 4 Panel A and Panel B. Peer disclosures represent a signal that both managers and prediction markets would respond to. If prediction market prices were capturing these external signals, we would observe a positive association between those signals and word mentions in the absence of prediction market prices, which then attenuate when prediction market prices are added as an additional covariate. This is not the case when one compares column (7) with column (9) of Table 4 Panel A and Table 4 Panel B. In column (7), no peer disclosure exhibits a statistically significant association with firm word mentions prior to

considering prediction market price. While we cannot completely rule out that some other public signal unobservable to us drives both word mentions and prediction market prices, it is unclear what such a signal would be.

VI. CONCLUSION

Prediction markets have recently expanded to settings where contracts are written on whether firm representatives will mention specific words during earnings conference calls. While prior research shows that prediction market prices can identify outcomes in a variety of settings, whether these prices provide meaningful information to corporate decision makers remains unclear. From the perspective of investor relations officers (IROs), monitoring such prices is only valuable if they reflect stakeholder demand for information that is not already known and acted upon through existing disclosures.

In this study, we examine this issue using earnings conference call mention contracts traded on the Kalshi platform. We compare the ability of prediction market prices and IR disclosure work products to identify whether contracted words are ultimately mentioned during earnings calls. We find that prediction market prices exhibit strong standalone predictive ability. However, IR disclosure work products generate comparable performance. Although prices provide incremental predictive ability when combined with IR disclosures, the magnitude of this improvement is modest. Additional analyses indicate that prediction market prices perform similarly to IR disclosures in the presentation portion of conference calls but perform substantially worse in the question-and-answer portion.

Taken together, our findings suggest that, in this setting, prediction market prices contain limited incremental information beyond what IROs already provide through existing disclosure activities. These results contribute to the emerging literature on prediction markets by providing initial evidence from a novel setting in which contracts are written on firm disclosures. Our

findings also have implications for practice and regulation. For IROs, prediction market prices represent a low-cost, forward-looking signal derived largely from retail investor activity. However, the limited incremental information contained in these prices suggests that the benefits of incorporating them into disclosure decisions may be small. Moreover, acting on such signals introduces potential costs, including the perception of favoring certain investors, limited control over contract outcomes, and concerns related to insider trading and information leakage. For regulators, our evidence provides insight into how these markets function in a disclosure setting and may inform ongoing discussions regarding the costs and benefits of prediction market activity.

This study is subject to several limitations. Our sample is drawn from the early stages of earnings conference call mention contracts on a single platform and focuses on large, widely followed firms. As these markets evolve and expand to other firms and platforms, the extent to which our findings generalize remains an open question. Future research may also examine whether prediction market prices influence other dimensions of corporate disclosure or whether different market structures generate more informative price signals.

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Table 1: EARNINGS MENTIONS SAMPLE

Panel A: Sample Selection (first contract existed 03/12/2025)

	# of contracts	# of unique calls	# of unique firms
Kalshi earnings mention markets (as of 12/22/2025)	1,540	110	76
Less: contracts still open	– 16	– 1	– 1
Less: contracts from firm not USD denominated	– 10	– 1	– 1
Less: contracts where conference call was cancelled	– 15	– 1	– 1
Less: untraded contracts prior to call (missing price)	– 62	– 2	– 1
Equals: final earnings mention markets	1,437	105	72

Panel B: Sample Firm Industry Composition

Fama-French 48	Industry Label	Firm Count	% of Total
3	Candy & Soda	2	2.78%
4	Beer & Liquor	1	1.39%
7	Entertainment	3	4.17%
9	Consumer Goods	1	1.39%
10	Apparel	1	1.39%
13	Pharmaceutical Products	1	1.39%
21	Machinery	1	1.39%
23	Automobiles and Trucks	4	5.56%
26	Defense	1	1.39%
32	Communication	2	2.78%
34	Business Services	16	22.22%
35	Computers	2	2.78%
36	Electronic Equipment	8	11.11%
40	Transportation	6	8.33%
42	Retail	10	13.89%
43	Restaurants, Hotels, Motels	6	8.33%
44	Banking	3	4.17%
47	Trading	4	5.56%
	Total	**72**	**100.00%**

Panel C: Conference Call Timing Distribution

			Time between last price and call (hours)			Time between earnings press release and call (hours)		
Session	**N**	**%**	**Mean**	**Median**	**Std Dev**	**Mean**	**Median**	**Std Dev**
Pre-Market Before 9:30 AM (ET)	29	27.6%	5.310	0.510	14.330	2.090	1.540	2.820
During Hours 9:30 AM - 4:00 PM (ET)	5	4.8%	0.420	0.230	0.550	5.970	3.480	7.060
After-Hours 4:00 PM or later	71	67.6%	2.940	0.220	7.560	1.030	0.920	1.150
Total	**105**	**100%**	**3.470**	**0.270**	**9.760**	**1.550**	**0.970**	**2.480**

TABLE 2: Descriptive Statistics

Panel A: Firm Level Summary Statistics (N=72)

	Kalshi Sample (N=72)					IBES Universe (N=3462)		Difference Tests	
	Mean	**Median**	**SD**	**P25**	**P75**	**Mean**	**Median**	**t-stat (mean)**	**z-stat (median)**
SIZE	10.836	11.140	1.756	9.217	11.896	7.849	7.907	14.240***	10.610***
BTM	0.185	0.118	0.303	0.058	0.315	0.584	0.469	-10.753***	-7.306***
SALES_GROWTH	0.042	0.032	0.096	0.002	0.072	0.064	0.023	-1.838*	0.690
ANALYSTS	22.618	21.833	10.074	16.000	29.250	7.798	5.750	12.438***	11.689***
DISPERSION	0.135	0.070	0.249	0.034	0.120	0.108	0.048	0.926	2.240**

SIZE represents the natural logarithm of total assets. BTM represents the book-to-market ratio, defined as book equity divided by market equity. SALES_GROWTH represents the quarterly growth rate in firm sales. ANALYSTS represents the number of analysts issuing quarterly earnings forecasts for the firm. DISPERSION represents the standard deviation of analysts' quarterly earnings forecasts. All firm characteristics are measured at the conference call level and are averaged across a firm's conference calls when multiple calls are available. The variables in the IBES Universe are winsorized at the 1% and 99% levels.

Panel B: Call Level Summary Statistics (N=105)

	Mean	Std. Dev.	Min	25%	Median	75%	Max
CALL_DOLLAR_VOLUME	128,224.886	147,568.447	8,952.000	48,629.000	80,860.000	136,780.000	1,028,373.000
NUM_CONTRACTS	13.686	3.089	7.000	12.000	14.000	15.000	21.000

CALL_DOLLAR_VOLUME represents the cumulative dollar value of trading volume summed across all contracts associated with the call. NUM_CONTRACTS represents the total number of earnings mention contracts written on a call.

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TABLE 2: Descriptive Statistics – continued

Panel C: Contract Level Summary Statistics (N=1,437)

Variable	Mean	Std. Dev.	Min	25%	Median	75%	Max
DURATION	28.351	21.268	2.000	9.000	24.000	43.000	92.000
PCT_ZERO_TRADE	32.561	23.626	0.000	12.500	27.600	48.800	98.100
DOLLAR_VOLUME	9369.251	22169.492	1.000	2039.000	4457.000	9459.000	628715.000
AVE_PRICE	0.619	0.289	0.013	0.358	0.693	0.885	0.990
FIRST_PRICE	0.607	0.294	0.010	0.340	0.684	0.880	0.990
LAST_PRICE	0.624	0.299	0.020	0.350	0.700	0.900	0.990
MENTION	0.566	0.496	0.000	0.000	1.000	1.000	1.000
MENTION_PRES	0.468	0.499	0.000	0.000	0.000	1.000	1.000
MENTION_QA	0.099	0.299	0.000	0.000	0.000	0.000	1.000
FIRM_ROUTINE	0.580	0.390	0.000	0.250	0.750	1.000	1.000
PRIOR_CC_MENTION	4.311	9.040	0.000	0.250	1.500	4.500	179.500
PRIOR_CC_MENTION_PRES	2.202	6.609	0.000	0.000	0.500	2.000	169.750
PRIOR_CC_MENTION_QA	2.108	3.771	0.000	0.000	0.750	2.250	30.500
FIRM_PR_MENTION	2.945	8.575	0.000	0.000	0.379	2.100	148.909
FIRM_NONPR_MENTION	0.762	4.456	0.000	0.000	0.000	0.000	96.500
FIRM_10K_MENTION	45.677	126.184	0.000	0.000	6.000	32.000	1526.000
FIRM_10Q_MENTION	23.992	95.146	0.000	0.000	1.333	14.333	2236.667
PEER_ROUTINE	0.234	0.277	0.000	0.007	0.094	0.417	1.000
PEER_CC_MENTION	1.346	3.081	0.000	0.000	0.196	1.333	43.000
PEER_CC_MENTION_PRES	0.642	1.514	0.000	0.000	0.075	0.646	20.667
PEER_CC_MENTION_QA	0.705	1.672	0.000	0.000	0.083	0.650	22.333
PEER_PR_MENTION	1.126	3.118	0.000	0.000	0.084	0.772	39.596
PEER_NONPR_MENTION	0.943	3.354	0.000	0.000	0.000	0.132	33.033
PEER_10K_MENTION	24.658	75.218	0.000	0.000	1.127	13.182	718.800
PEER_10Q_MENTION	10.482	38.206	0.000	0.000	0.301	4.618	439.792
QUIET_PERIOD	0.610	0.488	0.000	0.000	1.000	1.000	1.000

DURATION represents the number of days between market creation and the target conference call for a given contract. PCT_ZERO_TRADE represents the fraction of days during a contract's duration on which no trading price is observed. DOLLAR_VOLUME represents the cumulative dollar value of trading volume over the life of the contract. AVE_PRICE represents the average daily market price over the duration of a given contract. FIRST_PRICE represents the first observed Kalshi contract price after market creation and following the firm's most recent prior earnings conference call. LAST_PRICE represents the final observed Kalshi contract price immediately prior to the earnings conference call. MENTION represents an indicator equal to 1 if the Kalshi contract resolves "Yes", and 0 if the Kalshi contract resolves "No". MENTION_PRES represents an indicator equal to 1 if the keyword first appears in the prepared remarks portion of the earnings call transcript, and 0 otherwise. MENTION_QA represents an indicator equal to 1 if the keyword first appears during the Q&A portion of the earnings call transcript, and 0 otherwise. PRIOR_CC_MENTION represents the total number of keyword mentions across the firm's up to four most recent earnings conference calls, divided by the number of such calls. PRIOR_CC_MENTION_PRES represents the total number of keyword mentions in the prepared section across the firm's up to four most recent earnings conference calls, divided by the number of such calls. PRIOR_CC_MENTION_QA represents the total number of keyword mentions in the Q&A section across the firm's up to four most recent earnings conference calls, divided by the number of such calls. FIRM_ROUTINE represents the fraction of the firm's up to four most recent earnings conference calls in which the keyword was mentioned at least once. PEER_CC_MENTION represents the total number of keyword mentions across peer firms' earnings conference calls occurring between the focal firm's most recent prior call and its target call, divided by the total number of peer firms, where peers are defined as domestic firms in the same FF48 industry and size quartile. PEER_CC_MENTION_PRES represents the total number of keyword mentions in the prepared section across peer firms' earnings conference calls occurring between the focal firm's most recent prior call and its target call, divided by the total number of peer firms, where peers are defined as domestic firms in the same FF48 industry and size quartile. PEER_CC_MENTION_QA represents the total number of keyword mentions in the Q&A section across peer firms' earnings conference calls occurring between the focal firm's most recent prior call and its target call, divided by the total number of peer firms, where peers are defined as domestic firms in the same FF48 industry and size quartile. PEER_ROUTINE represents the fraction of the peer firm's up to four most recent earnings conference calls in which the keyword was mentioned at least once. FIRM_PR_MENTION represents the total number of keyword mentions across the firm's 8-K press release filings (or 6-K for foreign private issuers) issued between the firm's up to four most recent earnings conference calls and its target call, divided by the total number of such filings issued over that period. FIRM_NONPR_MENTION represents the total number of keyword mentions across the firm's 8-K non-press release filings (or 6-K for foreign private issuers) issued between the firm's up to four most recent earnings conference calls and its target call, divided by the total number of such filings issued over that period. FIRM_10K_MENTION represents the total number of keyword mentions across the firm's 10-K filings (or 20-F for foreign private issuers) issued between the firm's up to four most recent earnings conference calls and its target call, divided by the total number of such filings issued over that period. FIRM_10Q_MENTION represents the total number of keyword mentions across the firm's 10-Q filings issued between the firm's up to four most recent earnings conference calls and its target call, divided by the total number of 10-Q filings issued over that period. PEER_PR_MENTION, PEER_NONPR_MENTION, PEER_10K_MENTION, PEER_10Q_MENTION are defined analogously but using filings from peer firms. QUIET_PERIOD represents an indicator variable equal to 1 if the firm has adopted a quiet period policy that restricts communications in advance of its quarterly earnings release, and 0 otherwise.

TABLE 2: Descriptive Statistics – continued

Panel D: Individuals Responsible for Contract Resolutions to Yes (N=814 of 1,437)

Firm Representative	Presentation	QA: Direct Pull	QA: Indirect Pull	QA: Not Pulled	Total
CEO	427	9	3	67	506
CFO	179	2	1	33	215
OTHER NAMED EXECUTIVE	64	2	0	23	89
UNIDENTIFIED	0	0	0	2	2
OPERATOR	2	0	0	0	2
Total	672	13	4	125	814

TABLE 3: Correlation Matrix

The upper (lower) right triangle of the matrix shows Spearman (Pearson) correlations. Bolded coefficients indicate statistical significance at the 5% level or better. The LN_ prefix indicates the variable is natural logarithm transformed as ln(1+x). Detailed variable definitions are provided in Appendix A.

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)
(1) MENTION		**0.820**	**0.290**	**0.637**	**0.677**	**0.578**	**0.598**	**0.560**	**0.488**	**0.452**	**0.123**	**0.267**	**0.256**	**0.228**	**0.235**	**0.240**	**0.233**	**0.188**	**0.125**	**0.168**	**0.176**	0.043
(2) MENTION_PRES	**0.820**		**-0.310**	**0.607**	**0.644**	**0.541**	**0.563**	**0.624**	**0.405**	**0.403**	**0.088**	**0.247**	**0.236**	**0.165**	**0.173**	**0.187**	**0.164**	**0.146**	**0.086**	**0.123**	**0.135**	0.010
(3) MENTION_QA	**0.290**	**-0.310**		0.045	0.047	**0.056**	0.052	**-0.113**	**0.134**	**0.077**	**0.056**	0.031	0.032	**0.104**	**0.102**	**0.087**	**0.113**	**0.070**	**0.064**	**0.073**	**0.067**	**0.055**
(4) FIRST_PRICE	**0.641**	**0.597**	**0.067**		**0.917**	**0.841**	**0.832**	**0.767**	**0.692**	**0.551**	**0.157**	**0.422**	**0.386**	**0.297**	**0.300**	**0.306**	**0.295**	**0.248**	**0.175**	**0.233**	**0.227**	**0.084**
(5) LAST_PRICE	**0.678**	**0.631**	**0.072**	**0.922**		**0.829**	**0.848**	**0.788**	**0.701**	**0.573**	**0.151**	**0.418**	**0.395**	**0.294**	**0.309**	**0.315**	**0.302**	**0.247**	**0.166**	**0.229**	**0.227**	**0.077**
(6) FIRM_ROUTINE	**0.577**	**0.535**	**0.063**	**0.842**	**0.828**		**0.891**	**0.788**	**0.743**	**0.528**	**0.145**	**0.439**	**0.387**	**0.321**	**0.298**	**0.297**	**0.298**	**0.255**	**0.183**	**0.238**	**0.239**	0.035
(7) LN_PRIOR_CC_MENTION	**0.566**	**0.552**	0.017	**0.763**	**0.774**	**0.810**		**0.841**	**0.884**	**0.575**	**0.169**	**0.456**	**0.434**	**0.321**	**0.330**	**0.322**	**0.333**	**0.258**	**0.192**	**0.239**	**0.246**	**0.066**
(8) LN_PRIOR_CC_MENTION_PRES	**0.511**	**0.580**	**-0.121**	**0.667**	**0.679**	**0.683**	**0.881**		**0.560**	**0.509**	**0.138**	**0.386**	**0.374**	**0.191**	**0.197**	**0.209**	**0.193**	**0.155**	**0.100**	**0.138**	**0.148**	**0.058**
(9) LN_PRIOR_CC_MENTION_QA	**0.466**	**0.407**	**0.094**	**0.633**	**0.641**	**0.671**	**0.900**	**0.632**		**0.466**	**0.145**	**0.405**	**0.369**	**0.333**	**0.343**	**0.322**	**0.353**	**0.253**	**0.187**	**0.249**	**0.250**	**0.055**
(10) LN_FIRM_PR_MENTION	**0.388**	**0.341**	**0.074**	**0.460**	**0.473**	**0.458**	**0.562**	**0.521**	**0.467**		**0.368**	**0.640**	**0.617**	**0.340**	**0.330**	**0.331**	**0.304**	**0.375**	**0.370**	**0.391**	**0.381**	**0.113**
(11) LN_FIRM_NONPR_MENTION	**0.090**	**0.072**	0.029	**0.119**	**0.119**	**0.121**	**0.162**	**0.138**	**0.135**	**0.380**		**0.412**	**0.401**	**0.295**	**0.264**	**0.257**	**0.259**	**0.384**	**0.461**	**0.403**	**0.389**	0.000
(12) LN_FIRM_10K_MENTION	**0.263**	**0.244**	0.029	**0.386**	**0.381**	**0.422**	**0.461**	**0.403**	**0.404**	**0.677**	**0.424**		**0.834**	**0.468**	**0.430**	**0.429**	**0.404**	**0.528**	**0.536**	**0.614**	**0.592**	**0.077**
(13) LN_FIRM_10Q_MENTION	**0.250**	**0.227**	0.037	**0.353**	**0.357**	**0.371**	**0.444**	**0.399**	**0.374**	**0.693**	**0.453**	**0.857**		**0.423**	**0.393**	**0.389**	**0.369**	**0.488**	**0.490**	**0.546**	**0.544**	**0.104**
(14) PEER_ROUTINE	**0.249**	**0.182**	**0.108**	**0.316**	**0.314**	**0.336**	**0.309**	**0.185**	**0.328**	**0.329**	**0.236**	**0.459**	**0.408**		**0.927**	**0.904**	**0.880**	**0.851**	**0.658**	**0.821**	**0.821**	0.037
(15) LN_PEER_CC_MENTION	**0.263**	**0.193**	**0.115**	**0.310**	**0.320**	**0.300**	**0.353**	**0.232**	**0.378**	**0.307**	**0.177**	**0.396**	**0.365**	**0.885**		**0.963**	**0.959**	**0.817**	**0.609**	**0.777**	**0.788**	**0.065**
(16) LN_PEER_CC_MENTION_PRES	**0.259**	**0.197**	**0.101**	**0.305**	**0.314**	**0.287**	**0.347**	**0.244**	**0.358**	**0.328**	**0.173**	**0.392**	**0.366**	**0.857**	**0.968**		**0.879**	**0.817**	**0.608**	**0.762**	**0.778**	**0.064**
(17) LN_PEER_CC_MENTION_QA	**0.249**	**0.179**	**0.115**	**0.286**	**0.299**	**0.280**	**0.346**	**0.222**	**0.382**	**0.252**	**0.147**	**0.343**	**0.319**	**0.818**	**0.970**	**0.900**		**0.773**	**0.588**	**0.744**	**0.756**	0.051
(18) LN_PEER_PR_MENTION	**0.178**	**0.126**	**0.085**	**0.215**	**0.208**	**0.212**	**0.214**	**0.129**	**0.214**	**0.460**	**0.495**	**0.566**	**0.543**	**0.725**	**0.658**	**0.681**	**0.568**		**0.788**	**0.904**	**0.918**	0.015
(19) LN_PEER_NONPR_MENTION	**0.108**	**0.072**	**0.059**	**0.116**	**0.115**	**0.128**	**0.118**	**0.060**	**0.116**	**0.394**	**0.640**	**0.505**	**0.492**	**0.439**	**0.319**	**0.318**	**0.263**	**0.778**		**0.800**	**0.799**	-0.008
(20) LN_PEER_10K_MENTION	**0.167**	**0.112**	**0.090**	**0.223**	**0.215**	**0.229**	**0.220**	**0.126**	**0.233**	**0.429**	**0.433**	**0.655**	**0.593**	**0.762**	**0.679**	**0.657**	**0.604**	**0.865**	**0.700**		**0.949**	0.023
(21) LN_PEER_10Q_MENTION	**0.172**	**0.129**	**0.070**	**0.216**	**0.216**	**0.228**	**0.223**	**0.133**	**0.232**	**0.432**	**0.436**	**0.634**	**0.600**	**0.747**	**0.679**	**0.667**	**0.606**	**0.902**	**0.725**	**0.959**		0.026
(22) QUIET_PERIOD	0.043	0.010	**0.055**	**0.070**	**0.061**	0.035	**0.085**	**0.085**	**0.071**	**0.131**	-0.006	**0.079**	**0.102**	0.048	**0.072**	**0.080**	**0.057**	0.035	-0.011	0.037	0.023	

TABLE 4: Determinants of Conference Call Mention Contract Outcomes

This table reports logistic regression estimations. The Z_ prefix indicates the variable is standardized to have mean zero and unit variance based on the full sample. The LN_ prefix indicates the variable is transformed as ln(1+x). Detailed variable definitions are provided in Appendix A. Robust standard errors clustered at the call level are reported below the coefficient estimates. Column header ODDS (dY/dX) indicates the coefficient is the odds ratio (marginal effect probability). *, **, *** represents statistical significance at the 10%, 5% and 1% levels in a two tailed test. The number of observations in each panel do not equal the full sample due to singletons resulting from fixed effects in column (7).

Panel A: Mention Occurs Anywhere in Conference Call

DEPENDENT VARIABLE = MENTION	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	ODDS	dY/dX	ODDS	dY/dX	ODDS	dY/dX	ODDS	dY/dX	ODDS	dY/dX
Intercept	1.384***		1.355***		2.017***		0.465**		0.564	
	(0.110)		(0.106)		(0.210)		(0.144)		(0.200)	
Z_FIRST_PRICE	5.447***	0.245***								
	(0.458)	(0.003)								
Z_LAST_PRICE			6.768***	0.252***					5.121***	0.187***
			(0.618)	(0.003)					(0.938)	(0.017)
Z_FIRM_ROUTINE					1.641***	0.074***	1.629***	0.065***	0.773	-0.029
					(0.200)	(0.017)	(0.257)	(0.020)	(0.147)	(0.022)
Z_LN_PRIOR_CC_MENTION_PRES					3.002***	0.164***	4.032***	0.185***	2.419***	0.101***
					(0.558)	(0.026)	(0.889)	(0.027)	(0.529)	(0.024)
Z_LN_PRIOR_CC_MENTION_QA					1.710***	0.080***	1.465**	0.051**	1.169	0.018
					(0.207)	(0.018)	(0.241)	(0.022)	(0.197)	(0.019)
Z_LN_FIRM_PR_MENTION					2.046***	0.107***	1.967***	0.090***	1.707***	0.061***
					(0.320)	(0.023)	(0.388)	(0.025)	(0.341)	(0.022)
Z_LN_FIRM_NONPR_MENTION					0.965	-0.005	0.901	-0.014	0.892	-0.013
					(0.094)	(0.014)	(0.127)	(0.019)	(0.122)	(0.016)
Z_LN_FIRM_10K_MENTION					0.807*	-0.032*	0.783	-0.032	0.814	-0.024
					(0.101)	(0.019)	(0.169)	(0.029)	(0.166)	(0.023)
Z_LN_FIRM_10Q_MENTION					0.836	-0.027	0.892	-0.015	0.896	-0.012
					(0.118)	(0.021)	(0.197)	(0.029)	(0.184)	(0.023)
Z_PEER_ROUTINE							1.041	0.005	1.127	0.014
							(0.212)	(0.027)	(0.224)	(0.023)
Z_LN_PEER_CC_MENTION_PRES							1.222	0.027	1.015	0.002
							(0.356)	(0.038)	(0.310)	(0.035)
Z_LN_PEER_CC_MENTION_QA							1.301	0.035	1.311	0.031
							(0.291)	(0.030)	(0.312)	(0.027)
Z_LN_PEER_PR_MENTION							0.983	-0.002	1.041	0.005
							(0.308)	(0.042)	(0.348)	(0.038)
Z_LN_PEER_NONPR_MENTION							1.176	0.021	1.154	0.016
							(0.281)	(0.032)	(0.318)	(0.031)
Z_LN_PEER_10K_MENTION							1.023	0.003	1.025	0.003
							(0.354)	(0.046)	(0.380)	(0.042)
Z_LN_PEER_10Q_MENTION							0.845	-0.022	0.865	-0.017
							(0.348)	(0.055)	(0.355)	(0.047)
Model Type	Logit		Logit		Logit		Logit		Logit	
Firm FE	No		No		No		Yes		Yes	
Month FE	No		No		No		Yes		Yes	
Pseudo R-Squared	0.336		0.385		0.337		0.402		0.471	
# of Observations	1,425		1,425		1,425		1,425		1,425	
Brier Score	0.147		0.134		0.149		0.132		0.114	
Log-Likelihood	-648.638		-600.260		-647.818		-583.717		-516.175	
AUC	0.870		0.893		0.864		0.891		0.917	
Z-stat for Test AUC = 0.500	18.733		18.734		18.732		18.734		18.735	
p-Value for Test AUC = 0.500	0.000		0.000		0.000		0.000		0.000	

Model Fit Comparisons

Comparison (A vs B)	**AUC**			**Log-Likelihood**		
	(A)	**(B)**	**Difference**	**(A)**	**(B)**	**Difference**
(3) vs (7)	0.893	0.891	0.002			
(7) vs (9)	0.891	0.917	-0.026***	-583.717	-516.175	67.543***

Panel B: Mention Occurs in Presentation Portion of Conference Call

DEPENDENT VARIABLE = MENTION_PRES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	ODDS	dY/dX	ODDS	dY/dX	ODDS	dY/dX	ODDS	dY/dX	ODDS	dY/dX	ODDS	dY/dX
Intercept	0.820**		0.760***		1.088		0.284***		0.329***		0.358**	
	(0.070)		(0.068)		(0.101)		(0.111)		(0.139)		(0.158)	
Z_FIRST_PRICE	5.297***	0.255***										
	(0.457)	(0.004)										
Z_LAST_PRICE			6.655***	0.269***					5.254***	0.195***	4.504***	0.177***
			(0.615)	(0.004)					(1.046)	(0.019)	(1.103)	(0.026)
Z_LAST_PRICE x QUIET_PERIOD											1.336	0.034
											(0.321)	(0.028)
Z_FIRM_ROUTINE					1.606***	0.072***	1.742***	0.075***	0.816	-0.024	0.819	-0.023
					(0.195)	(0.018)	(0.258)	(0.019)	(0.149)	(0.021)	(0.150)	(0.021)
Z_LN_PRIOR_CC_MENTION_PRES					3.915***	0.207***	4.283***	0.195***	2.752***	0.119***	2.730***	0.118***
					(0.690)	(0.024)	(0.836)	(0.024)	(0.583)	(0.024)	(0.577)	(0.024)
Z_LN_PRIOR_CC_MENTION_QA					1.141	0.020	1.113	0.014	0.913	-0.011	0.900	-0.012
					(0.121)	(0.016)	(0.169)	(0.020)	(0.135)	(0.017)	(0.136)	(0.018)
Z_LN_FIRM_PR_MENTION					1.527***	0.064***	1.469**	0.052**	1.269	0.028	1.255	0.027
					(0.229)	(0.023)	(0.270)	(0.025)	(0.227)	(0.021)	(0.226)	(0.021)
Z_LN_FIRM_NONPR_MENTION					0.954	-0.007	0.858	-0.021	0.848	-0.019	0.850	-0.019
					(0.069)	(0.011)	(0.115)	(0.018)	(0.100)	(0.014)	(0.101)	(0.014)
Z_LN_FIRM_10K_MENTION					0.899	-0.016	0.805	-0.029	0.847	-0.019	0.853	-0.019
					(0.113)	(0.019)	(0.168)	(0.028)	(0.166)	(0.023)	(0.167)	(0.023)
Z_LN_FIRM_10Q_MENTION					0.796*	-0.035*	0.881	-0.017	0.869	-0.017	0.873	-0.016
					(0.103)	(0.020)	(0.180)	(0.027)	(0.167)	(0.022)	(0.166)	(0.022)
Z_PEER_ROUTINE							1.041	0.005	1.114	0.013	1.126	0.014
							(0.188)	(0.024)	(0.209)	(0.022)	(0.215)	(0.022)
Z_LN_PEER_CC_MENTION_PRES							1.290	0.034	1.082	0.009	1.075	0.008
							(0.357)	(0.037)	(0.308)	(0.033)	(0.306)	(0.033)
Z_LN_PEER_CC_MENTION_QA							0.966	-0.005	0.947	-0.006	0.946	-0.006
							(0.202)	(0.028)	(0.200)	(0.025)	(0.202)	(0.025)
Z_LN_PEER_PR_MENTION							1.057	0.007	1.169	0.018	1.174	0.019
							(0.305)	(0.039)	(0.358)	(0.036)	(0.362)	(0.036)
Z_LN_PEER_NONPR_MENTION							1.261	0.031	1.216	0.023	1.215	0.023
							(0.238)	(0.025)	(0.254)	(0.025)	(0.253)	(0.024)
Z_LN_PEER_10K_MENTION							0.627	-0.063	0.608	-0.058	0.603	-0.059
							(0.209)	(0.044)	(0.210)	(0.040)	(0.212)	(0.041)
Z_LN_PEER_10Q_MENTION							1.411	0.046	1.460	0.044	1.460	0.044
							(0.575)	(0.054)	(0.579)	(0.046)	(0.583)	(0.047)
Model Type	Logit		Logit		Logit		Logit		Logit		Logit	
Firm FE	No		No		No		Yes		Yes		Yes	
Month FE	No		No		No		Yes		Yes		Yes	
Pseudo R-Squared	0.316		0.361		0.327		0.396		0.462		0.462	
# of Observations	1,377		1,377		1,377		1,377		1,377		1,377	
Brier Score	0.154		0.142		0.152		0.133		0.117		0.116	
Log-Likelihood	-652.916		-609.686		-642.315		-576.085		-513.686		-512.863	
AUC	0.860		0.881		0.859		0.889		0.914		0.914	
Z-stat for Test AUC = 0.500	18.556		18.557		18.556		18.558		18.559		18.559	
p-Value for Test AUC = 0.500	0.000		0.000		0.000		0.000		0.000		0.000	

Model Fit Comparisons

Comparison (A vs B)	**AUC**			**Log-Likelihood**		
	(A)	**(B)**	**Difference**	**(A)**	**(B)**	**Difference**
(3) vs (7)	0.881	0.889	-0.008			
(7) vs (9)	0.889	0.914	-0.025***	-576.085	-513.686	62.399***

Panel C: Mention Occurs in Question and Answer Portion of Conference Call

DEPENDENT VARIABLE = MENTION_QA	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	ODDS	dY/dX	ODDS	dY/dX	ODDS	dY/dX	ODDS	dY/dX	ODDS	dY/dX	ODDS	dY/dX
Intercept	0.154***		0.153***		0.108***		0.035***		0.038***		0.038***	
	(0.021)		(0.021)		(0.013)		(0.022)		(0.024)		(0.024)	
Z_FIRST_PRICE	1.278***	0.029**										
	(0.116)	(0.012)										
Z_LAST_PRICE			1.296***	0.030**					1.651**	0.045**	1.496	0.036
			(0.125)	(0.013)					(0.390)	(0.021)	(0.483)	(0.029)
Z_LAST_PRICE x QUIET_PERIOD											1.193	0.016
											(0.383)	(0.029)
Z_FIRM_ROUTINE					1.708***	0.056***	1.506*	0.037*	1.127	0.011	1.133	0.011
					(0.289)	(0.018)	(0.321)	(0.019)	(0.275)	(0.022)	(0.277)	(0.022)
Z_LN_PRIOR_CC_MENTION_PRES					0.247***	-0.146***	0.355***	-0.094***	0.317***	-0.103***	0.316***	-0.103***
					(0.052)	(0.023)	(0.080)	(0.020)	(0.074)	(0.020)	(0.074)	(0.020)
Z_LN_PRIOR_CC_MENTION_QA					1.590***	0.048***	1.387	0.030	1.309	0.024	1.280	0.022
					(0.247)	(0.016)	(0.297)	(0.019)	(0.285)	(0.020)	(0.284)	(0.020)
Z_LN_FIRM_PR_MENTION					1.377**	0.033**	1.337	0.026	1.286	0.023	1.280	0.022
					(0.222)	(0.017)	(0.292)	(0.020)	(0.286)	(0.020)	(0.290)	(0.020)
Z_LN_FIRM_NONPR_MENTION					0.964	-0.004	1.101	0.009	1.092	0.008	1.091	0.008
					(0.098)	(0.011)	(0.105)	(0.009)	(0.106)	(0.009)	(0.107)	(0.009)
Z_LN_FIRM_10K_MENTION					0.811	-0.022	0.966	-0.003	1.009	0.001	1.018	0.002
					(0.154)	(0.020)	(0.258)	(0.024)	(0.267)	(0.024)	(0.270)	(0.024)
Z_LN_FIRM_10Q_MENTION					1.114	0.011	1.019	0.002	1.007	0.001	1.002	0.000
					(0.235)	(0.022)	(0.297)	(0.026)	(0.294)	(0.026)	(0.291)	(0.026)
Z_PEER_ROUTINE							0.935	-0.006	0.991	-0.001	0.996	0.000
							(0.224)	(0.022)	(0.231)	(0.021)	(0.234)	(0.021)
Z_LN_PEER_CC_MENTION_PRES							0.986	-0.001	0.903	-0.009	0.897	-0.010
							(0.293)	(0.027)	(0.266)	(0.026)	(0.264)	(0.026)
Z_LN_PEER_CC_MENTION_QA							1.760**	0.051**	1.757**	0.051**	1.761**	0.051**
							(0.407)	(0.021)	(0.403)	(0.020)	(0.404)	(0.020)
Z_LN_PEER_PR_MENTION							0.953	-0.004	0.965	-0.003	0.968	-0.003
							(0.263)	(0.025)	(0.267)	(0.025)	(0.268)	(0.025)
Z_LN_PEER_NONPR_MENTION							0.953	-0.004	0.943	-0.005	0.939	-0.006
							(0.149)	(0.014)	(0.147)	(0.014)	(0.146)	(0.014)
Z_LN_PEER_10K_MENTION							2.017*	0.064*	1.912	0.058	1.884	0.057
							(0.841)	(0.037)	(0.797)	(0.037)	(0.789)	(0.037)
Z_LN_PEER_10Q_MENTION							0.403**	-0.082**	0.431*	-0.076*	0.437*	-0.074*
							(0.175)	(0.038)	(0.190)	(0.039)	(0.193)	(0.039)
Model Type	Logit		Logit		Logit		Logit		Logit		Logit	
Firm FE	No		No		No		Yes		Yes		Yes	
Month FE	No		No		No		Yes		Yes		Yes	
Pseudo R-Squared	0.008		0.009		0.117		0.232		0.239		0.240	
# of Observations	1,044		1,044		1,044		1,044		1,044		1,044	
Brier Score	0.117		0.117		0.104		0.090		0.089		0.089	
Log-Likelihood	-411.750		-411.402		-366.496		-318.880		-315.928		-315.705	
AUC	0.545		0.545		0.735		0.809		0.812		0.811	
Z-stat for Test AUC = 0.500	10.499		10.497		11.068		11.078		11.079		11.079	
p-Value for Test AUC = 0.500	0.000		0.000		0.000		0.000		0.000		0.000	

Model Fit Comparisons

Comparison (A vs B)	**AUC**			**Log-Likelihood**		
	(A)	**(B)**	**Difference**	**(A)**	**(B)**	**Difference**
(3) vs (7)	0.545	0.809	-0.264***			
(7) vs (9)	0.809	0.812	-0.003	-318.880	-315.928	2.952**

APPENDIX A: Variable Definitions

Variable	Definition	Source
MENTION	Indicator equal to 1 if the Kalshi contract resolves "Yes", which occurs when the contracted word (in singular or plural form) is spoken by a company representative or the call operator at any point during the earnings conference call, and 0 otherwise.	Kalshi
MENTION_PRES	Indicator equal to 1 if the keyword first appears in the presentation portion of the earnings call transcript, and 0 otherwise.	Capital IQ
MENTION_QA	Indicator equal to 1 if the keyword first appears during the Q&A portion of the earnings call transcript, and 0 otherwise.	Capital IQ
FIRST_PRICE	The first observed Kalshi contract price after market creation and following the firm's most recent prior earnings conference call.	Kalshi
LAST_PRICE	The final observed Kalshi contract price immediately prior to the earnings conference call.	Kalshi
FIRM_ROUTINE	The fraction of the firm's up to four most recent earnings conference calls in which the keyword was mentioned at least once.	Capital IQ
PRIOR_CC_MENTION	The total number of keyword mentions across the firm's up to four most recent earnings conference calls, divided by the number of such calls.	Capital IQ
PRIOR_CC_MENTION_PRES	The total number of keyword mentions in the prepared section across the firm's up to four most recent earnings conference calls, divided by the number of such calls.	Capital IQ
PRIOR_CC_MENTION_QA	The total number of keyword mentions in the Q&A section across the firm's up to four most recent earnings conference calls, divided by the number of such calls.	Capital IQ
FIRM_PR_MENTION	The total number of keyword mentions across the firm's 8-K press release filings (or 6-K for foreign private issuers) issued between the firm's up to four most recent earnings conference calls and its target call, divided by the total number of such filings issued over that period, where press release filings are defined as 8-K (or 6-K) filings containing Exhibit 99 attachments.	SEC Analytics Suite
FIRM_NONPR_MENTION	The total number of keyword mentions across the firm's 8-K non-press release filings (or 6-K for foreign private issuers) issued between the firm's up to four most recent earnings conference calls and its target call, divided by the total number of such filings issued over that period, where non-press release filings are defined as 8-K (or 6-K) filings not containing Exhibit 99 attachments.	SEC Analytics Suite
FIRM_10K_MENTION	The total number of keyword mentions across the firm's 10-K filings (or 20-F for foreign private issuers) issued between the firm's up to four most recent earnings conference calls and its target call, divided by the total number of such filings issued over that period.	SEC Analytics Suite
FIRM_10Q_MENTION	The total number of keyword mentions across the firm's 10-Q filings issued between the firm's up to four most recent earnings conference calls and its target call, divided by the total number of 10-Q filings issued over that period. Foreign private issuers do not file 10-Qs and are set to zero for this variable.	SEC Analytics Suite
PEER_ROUTINE	The fraction of the peer firm's up to four most recent earnings conference calls in which the keyword was mentioned at least once.	Capital IQ
PEER_CC_MENTION	The total number of keyword mentions across peer firms' earnings conference calls occurring between the focal firm's most recent prior call and its target call, divided by the total number of peer firms, where peers are defined as all firms in the same FF48 industry and size quartile.	Capital IQ
PEER_CC_MENTION_PRES	The total number of keyword mentions in the presentation portion across peer firms' earnings conference calls occurring between the focal firm's most recent prior call and its target call, divided by the total number of peer firms, where peers are defined as all firms in the same FF48 industry and size quartile.	Capital IQ

PEER_CC_MENTION_QA	The total number of keyword mentions in the Q&A portion across peer firms' earnings conference calls occurring between the focal firm's most recent prior call and its target call, divided by the total number of peer firms, where peers are defined as all firms in the same FF48 industry and size quartile.	Capital IQ
PEER_PR_MENTION	The total number of keyword mentions across peer firms' 8-K press release filings issued between the firm's up to four most recent earnings conference calls and its target call, divided by the total number of 8-K press release filings issued over that period, where 8-K press release filings are defined as 8-K filings containing Exhibit 99 attachments. Peers are defined as domestic firms in the same FF48 industry and size quartile.	SEC Analytics Suite
PEER_NONPR_MENTION	The total number of keyword mentions across peer firms' 8-K non-press release filings issued between the firm's up to four most recent earnings conference calls and its target call, divided by the total number of non-8-K press release filings issued over that period, where 8-K non-press release filings are defined as 8-K filings not containing Exhibit 99 attachments. Peers are defined as domestic firms in the same FF48 industry and size quartile.	SEC Analytics Suite
PEER_10K_MENTION	The total number of keyword mentions across peer firms' 10-K filings issued between the focal firm's up to four most recent earnings conference calls and its target call, divided by the total number of 10-K filings issued over that period. Peers are defined as domestic firms in the same FF48 industry and size quartile.	SEC Analytics Suite
PEER_10Q_MENTION	The total number of keyword mentions across peer firms' 10-Q filings issued between the focal firm's up to four most recent earnings conference calls and its target call, divided by the total number of 10-Q filings issued over that period. Peers are defined as domestic firms in the same FF48 industry and size quartile.	SEC Analytics Suite
QUIET_PERIOD	Indicator variable equal to 1 if the firm has adopted a quiet period policy that restricts communications in advance of its quarterly earnings release, and 0 otherwise. We hand-code this variable based on a structured search of (i) firm investor relations webpages, (ii) earnings conference call and investor conference transcripts retrieved from LSEG/Refinitiv Workspace, (iii) sell-side analyst reports retrieved from LSEG/Refinitiv Workspace, and (iv) news articles and press releases retrieved from Factiva. A firm is classified as having a quiet period if at least one of these sources contains a direct, firm-specific reference to a pre-earnings quiet period.	Manually Collected
SIZE	The natural logarithm of total assets.	Compustat
BTM	Book-to-market ratio, defined as book equity divided by market equity as of the fiscal quarter end to which the conference call relates.	Compustat
SALES_GROWTH	Quarter-over-quarter growth rate in firm sales, measured as the change in quarterly sales from the immediately preceding fiscal quarter to the fiscal quarter to which the conference call relates.	Compustat
ANALYSTS	The number of analysts issuing quarterly earnings forecasts for the firm, measured from the last available IBES consensus for the fiscal quarter end to which the conference call relates.	IBES
DISPERSION	The standard deviation of analysts' quarterly earnings forecasts.	IBES
DURATION	The number of days between market creation and the target conference call.	Kalshi & Capital IQ
DOLLAR_VOLUME	The cumulative dollar value of trading volume over the life of the contract, measured as the sum across trades of transaction price multiplied by the number of contracts traded.	Kalshi
CALL_DOLLAR_VOLUME	The sum of DOLLAR_VOLUME for all contracts of a given conference call	Kalshi
AVE_PRICE	Average daily market price over the duration of a given contract.	Kalshi
NUM_CONTRACTS	The total number of earnings mention contracts written on a call.	Kalshi
PCT_ZERO_TRADE	The fraction of days during a contract's duration on which no trading price is observed.	Kalshi

APPENDIX B: Top 90 Word Frequencies from N=1,437 Kalshi Conference Call Mention Contracts

WORD	Contracts	WORD	Contracts	WORD	Contracts
tariff	43	sustainability	6	regulator / regulation / regulatory	4
shutdown / shut down	28	blockchain	6	azure	4
china	22	labor	6	stargate	4
supply chain	13	openai	6	traffic	4
dividend	13	loyalty	5	manufacturing	3
acquisition	13	innovation	5	healthcare	3
automation	12	automotive	5	hpc	3
competition	12	data center	5	prime day	3
holiday	11	inference	5	robotics	3
regulator / regulatory / regulation	10	advertising	5	stablecoin	3
inflation	10	operating margin	5	trading	3
nvidia	10	subscription	5	trading volume	3
autonomous	10	regulation	5	membership	3
international	9	guidance	5	espn	3
cloud	9	europe	5	layoff	3
gaming	9	microsoft	5	canada	3
inventory	9	market share	5	engagement	3
expansion	8	black friday	5	e-commerce / ecommerce	3
revenue	8	weather	4	deepmind / deep mind	3
partnership	7	digital	4	pixel	3
delivery	7	efficiency	4	m&a	3
margin	7	recession	4	fintech	3
quantum	7	amazon	4	hiring	3
waymo	7	bitcoin	4	arizona	3
hyperscaler	7	union	4	threads	3
streaming	6	subscriber	4	whatsapp	3
trump	6	retention	4	tiktok	3
ai / artificial intelligence	6	freight	4	vr / virtual reality	3
debt	6	antitrust	4	copilot	3
buyback	6	privacy	4	cybersecurity	3