Beyond Earnings: Sales Calls

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Beyond Earnings: Sales Calls

Abstract

Despite their importance and relevance, sales receive relatively less attention than earnings. This study provides an overview of an unexplored form of voluntary disclosure in the existing literature—sales calls—and examines their determinants and consequences. Companies with more pre-existing sales-related announcements, losses, or heightened uncertainties are more likely to conduct sales calls, consistent with the information-based and impression-management motivation of voluntary disclosure. Notably, uncertainty and loss are significant drivers for firms conducting sales calls in addition to earnings calls. Following sales calls, financial analysts' sales and earnings forecasts are more accurate and less dispersed. Moreover, compared to firms that only hold earnings calls, companies with both types of calls experience an improvement in sales forecast accuracy, but with a weak increase in EPS forecast errors. The distinct nature of sales calls is further supported through the comparison of the content between sales calls and earnings calls: (1) sales calls prioritize addressing questions in Q&A sessions, while earnings calls focus on scripted presentations; and (2) sales calls exhibit a more negative tone and contain more uncertainty words than earnings calls. Overall, this paper emphasizes the importance of sales-specific disclosures during challenging times and offers practical implications for firms to leverage them in improving their information environment.

Keywords: Conference calls; Earnings; Financial analysts; Sales; Value relevance

1. Introduction

Sales are essential for a company's survival and offer distinct insights for investors and stakeholders across the economy. First, sales are a fundamental driver of firm value. They play a pivotal role in a company's daily operations, such as operating budgeting, production planning, and setting revenue-growth strategies (e.g., Walker and Bain, 1989; and Ghosh et al., 2005). In addition, managers provide sales forecasts to cater to external stakeholders' information needs (e.g., Kasznik and Lev, 1995; Lansford et al., 2013; and Acito et al., 2021). Sales also serve as a tool through which managers conduct real earnings management (e.g., Ahearne et al., 2016), as a benchmark in executive compensation contracts (e.g., Liu et al., 2023), and as an indicator of accounting conservatism (e.g., Byzalov and Basu, 2016; and Banker et al., 2017).

Second, in certain settings, sales numbers convey unique information for investors and information intermediaries. For investors, sales are a key variable of fundamental analysis (e.g., Olsen and Dietrich, 1985; Swaminathan and Weintrop, 1991; Ertimur et al., 2003; Froot et al., 2017; Agarwal et al., 2021; and Dichev and Qian, 2022).[1] It is particularly useful at valuing loss-incurred firms, as reflected by a low return-earnings association for this category of firms (e.g., Hayn, 1995; Collins et al., 1999; Davis, 2002; Joos and Plesko, 2005; Darrough and Ye, 2007; Callen et al., 2008; Barth et al., 2023; and Srivastava, 2023).[2] Moreover, anecdotal evidence suggests that investors might exhibit even more pronounced reactions to sales performance than

[1] For instance, detailed information on sales has the predictive power of revenue or earnings surprises (Froot et al., 2017; and Dichev and Qian, 2022) and stock returns (Agarwal et al., 2021). In addition, customer' monthly sales announcements are associated with their supplier firms' security prices given that the sales performance of a customer firm can be indicative of their suppliers' sales levels (Olsen and Dietrich, 1985).
[2] Current loss is uninformative of firm value, as (1) the firm may adopt the abandonment option or (2) the future potential of loss firms is not captured in the present accounting framework (e.g., Joos and Plesko 2005; and Darrough and Ye, 2007). Therefore, sales are more relevant for firms operating at a loss. This is evident from the substantial market reaction to revenue surprises (e.g., Davis, 2002).

to earnings results (Rees and Sivaramakrishnan, 2007).[3] Information intermediaries, such as media outlets and financial analysts, frequently delve into sales-related discussions within their analyses (e.g., Cheng et al., 2020). In particular, a sales estimate is the starting point for estimating any other financial statement items such as earnings, and financial analysts increasingly provide sales forecasts along with earnings forecasts (e.g., Keung, 2010; Curtis et al., 2013; and He and Lu, 2018).

Third, sales information concerns a broader set of stakeholders, such as lenders, suppliers, and peers, who may adjust their business activities or strategies according to the focal firm's sales conditions. Specifically, suppliers may plan their inventory and production levels based on customers' sales performance, and their product prices based on customers' cost strategies. The sales of a focal firm may also be useful for peer firms' price and production decisions. Lenders may infer the repayment ability of a firm from its sales performance, which is the source of its cash flow. Overall, sales are a crucial component of the economy.

Despite the relevance and importance of sales, earnings have dominated the focus of researchers, practitioners, and investors (e.g., Graham et al., 2005; and Srivastava, 2023).[4] This paper unveils an unexplored type of voluntary corporate disclosure primarily dedicated to the topic of sales, namely sales/trading statement calls (hereafter, sales calls). Specifically, I provide an overview of this practice, examine the determinants of conducting these calls (in addition to earnings calls), and analyze the informativeness of such calls through the lens of financial analysts.

[3] Investors reacted negatively to Apple's 2005 Q4 earnings announcement. Its earnings exceeded the consensus estimate but its revenue figure did not (Rees and Sivaramakrishnan, 2007).

[4] According to a survey paper (Graham et al., 2005), chief finance officers and financial analysts consider earnings to be the single most important output of financial statements. From the perspective of investors, earnings are one of the most quoted numbers and are considered as the most fundamental factor in equity valuation (source: https://www.usbank.com/investing/financial-perspectives/market-news/focus-on-corporate-earnings.html).

The initial sample starts with 6,655 records of sales calls conducted by 924 publicly traded firms between 2005 and 2022. Of these calls, 63% were executed by public firms headquartered in member nations of the European Economic Area (EEA), the United Kingdom, and Switzerland.[5] Remarkably, within this 63%, a significant proportion (79%) originated from the United Kingdom and France. The United States contributed 29% of the sales calls. Intriguingly, while there has been a steady rise in sales calls across Europe, the number of sales calls has declined in the United States since 2009. The content analysis reveals that sales calls feature keywords, such as "market," "share," "growth," "business," and "product." The presentation parts of these calls center on discussions related to "sales operation", alongside other topics, such as personnel management and business strategies.

To mitigate heterogeneity in corporate disclosure practices among different institutions, I focus on public firms headquartered and listed in the same country within the EEA, the United Kingdom, or Switzerland. I document that loss-making firms conduct sales calls 1.3 times more often than profit-making firms, consistent with prior findings showing that sales are particularly relevant for firms operating at a loss (e.g., Joos and Plesko, 2005; and Barth et al., 2023) and that firms with lower profitability are less inclined to withhold sales information due to competition concerns (Dedman and Lennox, 2009). I also find that higher uncertainty (proxied by beta, intangible assets, and sales volatility) drives decisions to hold sales calls, which indicates the role of sales calls in alleviating information asymmetry between company insiders and external stakeholders. As an example, a one standard deviation increase in sales volatility corresponds to a 16.4% rise in the likelihood of conducting sales calls. In addition, the likelihood of conducting

[5] The EEA countries include Austria, Belgium, Bulgaria, Croatia, Republic of Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Italy, Latvia, Liechtenstein, Lithuania, Luxembourg, Malta, Netherlands, Norway, Poland, Portugal, Romania, Slovakia, Slovenia, Spain and Sweden.

sales calls rises with more geographic segments and preceding sales-related announcements, suggesting that sales calls serve as a channel for disseminating sales-related information. Moreover, firms with larger total assets, higher market-to-book (MTB) ratio, and greater institutional ownership are more likely to engage in sales calls, supporting the idea that sales calls are resource-intensive and driven by investors' information demand. Furthermore, a comparative analysis demonstrates that factors related to uncertainty and losses are significantly correlated with a firm's probability of conducting both sales calls and earnings calls, as opposed to exclusively having earnings calls. This highlights the incremental relevance of sales calls during uncertain times.

In addition, I investigate whether sales calls are informative from the perspective of financial analysts. Predicting sales is challenging since a wide range of factors play a role in shaping sales (e.g., Curtis et al., 2013; Brüggen et al., 2021; and Hoffmann et al., 2021). Hence, I expect that financial analysts can enhance their forecasting accuracy by incorporating insights gained from sales calls. Following sales calls, there is a reduction in both the error and dispersion of sales and EPS forecasts. This outcome remains robust across different time frames for constructing analyst forecast measures, with a within-firm analysis design, and using an entropy-balanced sample. Moreover, firms conducting both sales and earnings calls experience a reduction in sales forecast dispersion and errors compared with firms only holding earnings calls. However, the association is opposite for EPS forecast errors. Overall, these findings confirm the informativeness of sales calls and suggest that sales calls provide greater insights for forecasting sales than earnings, particularly when both types of calls coexist.

Lastly, the comparative analysis of sales calls and earnings calls throughout the paper yields three findings. First, loss-making firms favor sales calls for two reasons: (1) firms experiencing losses are more likely to conduct sales calls in addition to earnings calls; and (2) the presentation segments of sales calls contain both more positive and negative expressions, yet the overall tone remains less positive compared to earnings calls. Second, uncertainty is an influential driver of sales calls, as substantiated by two observations: (1) uncertainty-related determinants like sales volatility, intangible assets, and Beta motivate firms to conduct both sales and earnings calls; and (2) the presentation sections of sales calls contain a higher proportion of uncertainty words than the presentation sections of earnings calls. Third, sales calls exhibit an inquiry-driven nature as earnings calls allocate more time to presentations, while sales calls predominantly focus on responses. The presentation section of earnings calls contains about 2.5 times more words than that of sales calls.

This paper makes several contributions to the existing literature and managerial practice. First, it adds to the literature on the incremental usefulness of sales compared with earnings by showing the importance of sales calls that provide information not contained in expenses or earnings, such as market shares and growth, especially during uncertain periods and for firms with negative earnings. While prior literature has documented the relevance of sales for investors and even the superior information content of sales over earnings in the context of loss-making firms or firms missing or largely exceeding earnings estimates (e.g., Lu and Skinner, 2020; Gu et al., 2023; Huang and Hairston; 2023; and Srivastava, 2023), this paper explores an overlooked channel through which companies disclose comprehensive sales-related information and the conditions under which financial analysts benefit from such disclosures. Moreover, the comparative analysis between sales calls and earnings calls reinforces the need for disclosures specifically tailored to sales. Notably, this study, to the best of my knowledge, is the first paper to investigate sales calls.

Second, this study carries managerial implications that firms, particularly those facing losses or operating in uncertain environments, would benefit from adopting the practice of sales calls to enhance their information environments. Despite the fundamental nature of sales information, sales calls are not as prevalent as earnings calls, especially in the United States. Embracing sales calls can enhance financial analysts' forecast performance, reduce information asymmetry, and potentially manage external stakeholders' impression for such companies.

Third, it adds to the discussion on revenue disclosure by exploring an alternative approach to providing disaggregated revenue information—namely, sales calls. There is a long standing and ongoing discussion around revenue disclosure disaggregation in academia and regulatory communities. Two major accounting standard setters, FASB and IASB, have undertaken the development of standards mandating enhanced revenue disclosure in financial statements, such as ASC 606 and IFRS 15. While existing research highlights the impact of such regulations, this study distinguishes itself by delving into an alternative avenue of supplying sales information.[6] By examining the determinants and benefits of conducting sales calls, this paper offers an alternative disclosure strategy for companies and regulatory bodies.

Finally, it also contributes to the literature on company conference calls that serve a single primary purpose. In contrast to the well-established literature on multi-purpose calls (such as earnings calls (e.g., Bushee et al., 2003; and Kimbrough, 2005) and analyst/investor days (e.g., Kirk and Markov, 2016; and Park, 2022), the literature on specific types of calls has yet to be developed. Previous work has examined M&A calls (Kimbrough and Louis, 2011), special conference calls (Hu, 2020), and fixed income calls (De Franco et al., 2023). This paper introduces an under-investigated type of specific call, namely one focused on sales.

[6] In the first quarter of 2018, FASB adopted a new revenue standard that requires companies to disclose more detail about revenues (i.e., ASC 606). With the new revenue disaggregation regulation, companies provide additional information that is mostly about the sales distributions among geographic regions or product lines. Existing studies document that the adoption of the new regulation is associated with improved accuracy of analysts' sales forecasts (Hinson et al., 2022), enhanced financial reporting quality (Ahn et al., 2021; and Choi et al., 2023), shortened revenue cycles (Ali and Tseng, 2023), and augmented labor costs due to increased demand for accounting personnel (Enache et al., 2022).

2. Institutional background

In general, there are two categories of sales-related corporate disclosures: (1) comprehensive disclosures that incorporate sales information within a broader context (e.g., "comparable store sales" in annual reports (e.g., Curtis et al., 2013; and Hong et al., 2019) and earnings conference calls (e.g., Huang et al., 2018)), (2) disclosures with an explicit focus on sales, such as sales press releases (Hao et al., 2014) and sales calls. Sales calls are a type of conference call that discusses sales, trading, or results other than earnings.[7] A sales call typically includes an operator, company executives, financial analysts, the media, and investors. The structure of sales calls closely resembles that of earnings calls, beginning with uninterrupted executive presentations and followed by a question and answer (Q&A) session. In certain instances, particularly prerecorded calls, the Q&A sessions may be omitted.

Sales calls predominantly revolve around sales-related subjects, such as sales strategies, inventory levels, product development, and market shares. For instance, during L'Oréal's October 29th, 2019 sales call, Françoise Lauvin, head of investor relations, addressed various sales topics during the presentation, including the number of net sales, factors contributing to sales growth, the performance and future potential of certain business and geographic segments, sales channels, and sales guidance. In the subsequent Q&A session, analysts asked questions related to topics such as e-commerce, strategies for expanding sales through geographic exposure, weak sales of and an M&A deal within the fragrance business, and customer engagement. For additional examples, Appendix B provides excerpts from two sales call transcripts.

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[7] The definition of sales calls is taken from the article 000036662 entitled "Definitions for Key Development Categories and Types in Screening on CIQ" from S&P Global.

Sales calls have characteristics that distinguish them from various corporate disclosures. First, they center around a singular theme, specifically sales; by contrast, multipurpose disclosures, such as earnings calls and annual reports, include sales information within a broader context. Second, sales calls can be held as frequently as monthly, thereby exceeding the quarterly or annual release pattern of most corporate disclosures. Third, sales calls attract a broader audience: Beyond conventional investors, stakeholders throughout the supply chain—such as upstream suppliers or downstream consumers—are likely to be interested in sales calls. Other types of disclosures tend to have a narrower audience; for instance, equity investors are the main consumers of earnings calls (Heinrichs et al., 2019) and analyst/investor days (Kirk and Markov, 2016), and fixed income calls are followed by debt holders (De Franco et al., 2023). Overall, sales calls provide more timely and in-depth information, which receives attention from financial media outlets such as Seeking Alpha and the Street.[8] Despite the importance and uniqueness of sales calls, they have not been investigated by academia.

3. Data

I gather sales call records from Capital IQ, a database that collects key development events from more than various news sources (such as corporate websites, regulatory filings, and business news outlets) spanning both public and private companies on a global scale.[9] I download all historical records of sales calls from the "Key Development Screening" section within the Capital

[8] For instance, an example of a sales call from Unilever can be found at https://seekingalpha.com/article/304965-unilever-plc-q3-2011-sales-trading-statement-call-nov-03-2011, and an example of Ford's monthly sales calls can be found at https://www.thestreet.com/investing/stocks/ford-motor-co-sales-trading-statement-call-11515714

[9] The official description of Capital IQ's Key Developments dataset can be found at https://www.marketplace.spglobal.com/en/datasets/key-developments-(15). This dataset has been widely used as a source for corporate events and news in previous research across accounting (e.g., Livnat and Zhang, 2012; Aobdia, 2018), finance (e.g., Edmans et al., 2018; Grennan and Michaely, 2021), and management (e.g., Shi et al., 2018; Chen et al., 2021) domains.

IQ web interface, which yields 6,765 calls conducted by both public and private entities worldwide between 2005 and 2022.[10] For each sales call event, I collect its company identifier, event date, event time, event headline, and supplementary company-level information, including primary industries, headquarters location, and stock exchange listings. Given that sales calls conducted by private entities comprise a mere 1.6% (i.e., 110 calls) of the total, and recognizing the heterogeneity in disclosure practices between private and public firms, this section focuses on the dataset of 6,655 sales calls hosted by public firms around the globe.

3.1. Descriptive statistics

The descriptive analysis starts with 6,655 records of sales calls conducted by 924 public firms from 2005 to 2022. The geographical distribution of these calls is presented in Panel A of Table 1. Notably, the majority of sales calls, amounting to 63% (equivalent to 4,194 calls), are conducted by public firms headquartered in EEA countries, the United Kingdom, and Switzerland. Within this subset, a significant portion—79% (i.e., 4,194 calls)—is derived from 631 firms headquartered in the United Kingdom and France. The United States contributes 29% of the overall sales calls, corresponding to 1,899 calls. This distribution indicates a greater prevalence of sales calls among European firms. An untabulated analysis reveals that among the 3,128 distinct firm-year observations, 44.8% feature a single call per firm-year, 39.3% involve two calls per firm-year, 6.6% encompass three calls per firm-year, and 2.1% exhibit a higher frequency of exactly 12 calls per firm-year.

Panel B of Table 1 depicts the industry distribution of firms engaged in sales calls, categorized by their two digit SIC codes.[11] Among these, the primary industry divisions are retail

[10] The first year for which there are a considerable number of sales calls records is 2005. In 2004, there is only one sale call, whereas the number of sales calls is 35 in 2005.
[11] More details about the SIC are available at https://siccode.com/sic-code-lookup-directory.

trade, manufacturing, and services. Specifically, the sales calls from the retail trade and wholesale trade industries collectively account for 36.8% (2,450 instances) of the total sample. This observation aligns with the fact that wholesalers and retailers are the two primary actors within the supply chain, where discussions related to sales hold particular relevance.

[Insert Table 1 here]

3.2. Time trend of sales calls

Figure 1 illustrates the annual sales call volumes from 2005 to 2022. On a global scale, call volumes increased from 2005 to 2011 and then from 2014 onward, with a decline between 2011 and 2014. In individual regions, a notable trend emerges: Europe (i.e., the EEA, United Kingdom, and Switzerland line) sees a rise in sales calls, while the United States has experienced a decline since 2009. Within Europe, a substantial portion of calls originates from the United Kingdom and French firms. Additionally, the United Kingdom witnesses two spikes in the number of sales calls: first, between 2008 and 2011, and then from 2014 to 2015. In contrast, France sustains a steady growth in call volume since 2005, plateauing in 2018.

In summary, two key observations stand out: (1) sales calls appear to surge during periods of uncertainty, such as the 2008 financial crisis and the United Kingdom's 2015 commitment to an in-out referendum on European Union membership; and (2) the practice of sales calls initially gained popularity in the United States, but has declined since 2009, even as their European counterparts have increasingly adopted it.

[Insert Figure 1 here]

3.3. Topical content of sales calls

In this section, I delve into the topics discussed in sales calls using transcripts available through Capital IQ. As topics may vary in different institutional settings, I focus on 3,691 sales calls that are conducted by publicly listed firms headquartered in the EEA, United Kingdom, or Switzerland to reduce heterogeneity across firms. Within this dataset, 64.1% of the calls (2,366) have transcripts accessible via Capital IQ, whose transcript coverage for most call types begins in 2011.[12] Since the content of Q&A sections during sales calls is influenced in part by the topic interests of attendees, I exclusively conduct topic modeling on the presentation sections. This approach allows for a more focused and clearer understanding of the information companies intend to deliver to their audience. Consequently, the sample size for the topical analysis is 2,362, excluding four transcripts that lack a presentation part.

I employ Latent Dirichlet allocation (LDA), a Bayesian probabilistic model introduced by Blei et al. (2003) in the field of machine learning, to extract and analyze topics from sales call transcripts. It has been widely applied to various domains, including accounting, finance, and management. For instance, in the field of accounting, researchers have applied LDA to analyze SEC filings, earnings calls, and analyst reports.[13] LDA assumes that each document is a mixture of topics, and each topic is a mixture of words. Consequently, the output of LDA includes a topic vector for each document, showing the proportion of each topic present in that document, and a word vector for each topic, indicating the percentage of words associated with that particular topic. Appendix C contains more detailed information about the fundamental mechanism of LDA and implementation procedures.

Before applying LDA, I generate a word cloud to offer an overview of the principal words used in sales calls. Figure 2 is a word cloud that presents the most frequently used terms within

[12] More information about Capital IQ's transcript coverage can be found in the S&P Global's article titled "History of Transcripts Data" (article number 000027265).

[13] For instance, Huang et al. (2018) employ LDA to conduct a comparative analysis of topics derived from conference call transcripts and analyst reports while Bellstam et al. (2021) develop an innovative metric for evaluating firm innovation based on LDA analysis of analyst reports. Likewise, Dyer et al. (2017) and Brown et al. (2020) use LDA to model topics within 10-K reports. In addition, Allee et al. (2022) apply LDA to identify business-related topics, and Wang and Xing (2020) extract COVID-related disclosures from earnings calls.

the presentation sections of sales calls. The top prominent words include business, market, growth, product, increase, expect, and result. These words signify that sales calls predominantly focus on core issues related to sales.

[Insert Figure 2 here]

LDA requires a pre-defined number of topics. I explore a range of two to 100 topics and use a coherence score measure to assess the interpretability of LDA models. In this case, the optimal number of topics is eight. Table 1 Panel C records the percentage of tokens that each topic makes up in all sales calls, the top 30 frequent words related to each topic, and the respective topic labels. Notably, topic labeling is a subjective process, as there is no universally accepted formula available for this task. To enhance the credibility of these topic labels, I validate them by cross-referencing with labels identified in relevant studies, including those focused on earnings calls and annual reports. Topic 1 ("Healthcare and R&D") and Topic 7 ("Real estate and financing") are more industry-specific, while Topic 4 ("Sales operations") is the most prevalent and general topic across all documents. There are also topics related to human resources, namely Topic 3 ("Personnel management and compliance") and Topic 6 ("Personnel recruitment and efficiency"). Additionally, Topic 2 revolves around "Product management and development," while the last group of topics addresses general business operations and development, including Topic 5 ("Operational efficiency and compliance") and Topic 8 ("Sales growth and business development").

Panel D of Table 1 provides additional statistics of the distribution of these eight topics among all 2,362 sales calls. On average, Topic 4 accounts for 82% of tokens, aligning with the primary purpose of sales calls to provide comprehensive insights into sales operations. Following closely is Topic 8, with an average proportion of 3.5%, indicating the release of forward-looking information during sales calls. Collectively, "sales operations" emerges as the central theme among the pre-selected topics that managers discuss during these calls, complemented by other topics, such as personnel, product, and broader business management and development.

4. Determinant analysis of sales calls

4.1. Research design

I explore the determinants of conducting sales calls using the following model:

$$\begin{aligned} SalesCall_{i,t+1} = {} & \beta_0 + \beta_1 SalesGuid_{i,t} + \beta_2 SalesRelease_{i,t} + \beta_3 ClientProduct_{i,t} \\ & + \beta_4 BusSeg_{i,t} + \beta_5 GeoSeg_{i,t} + \beta_6 SalesGrowth_{i,t} + \beta_7 GrossMargin_{i,t} \\ & + \beta_8 SalesVolatility_{i,t} + \beta_9 Loss_{\ i,t} + \beta_{10} InsOwn_{i,t} + \beta_{11} Size_{\ i,t} + \beta_{12} MTB_{i,t} \\ & + \beta_{13} Intangible_{i,t} + \beta_{14} Beta_{i,t} + \beta_{15} HHI_{i,t} + Country\ FE + Industry\ FE \\ & + Year\ FE + \varepsilon \qquad (1) \end{aligned}$$

The dependent variable, denoted as *SalesCall*, is a binary indicator that takes the value 1 if a firm conducts at least one sales call in the subsequent year (t+1) following the end of fiscal year t, and 0 otherwise. Regarding the determinant side, I first investigate a firm's willingness to provide voluntary disclosure concerning sales. This is measured by whether the company provides sales guidance (*SalesGuid*) or issues sales releases (*SalesRelease*) in year t. Since these alternative forms of sales-related disclosures either demonstrate a willingness to supply sales-related information voluntarily or act as substitutes for sales calls, I do not make specific predictions regarding the signs of *SalesGuid* and *SalesRelease*. Given that the content of sales calls is closely tied to production, customers, and suppliers, I expect that customer and product announcements can signal a company's willingness to disclose sales-related information. The empirical measure is an indicator variable *ClientProduct* that captures whether there is any client-, product-, business expansion-, or strategic-alliance-related announcements in year t.

Next, I look into a set of sales-related variables: the number of business segments (*BusSeg*), the number of geographic segments (*GeoSeg*), sales growth (*SalesGrowth*), gross margin

(*GrossMargin*), sales volatility (*SalesVolatility*), and loss (*Loss*) (e.g., Crawford et al., 2020). Since the content of sales calls is centered around sales-related topics, I anticipate a correlation between the propensity for conducting sales calls and these sales-related variables. Specifically, the number of business or geographic segments—reflecting business complexity—is likely to be positively correlated with the likelihood of holding sales calls. This is because firms with complex business models encounter greater information asymmetry and benefit from providing public disclosures to all stakeholders rather than relying on private communication with selective investors (e.g., Bushee et al., 2003). Regarding profitability and sales performance, companies may either choose to withhold negative news and avoid sales calls during periods of poor sales performance or find value in conducting such calls to highlight positive developments and offer explanations. Therefore, I do not have a directional prediction on the coefficients of *SalesGrowth*, *GrossMargin*, and *Loss*. Sales volatility reflects uncertainty in a company's sales performance, which may complicate firm evaluation and increase the demand for information from external stakeholders. This heightened need for information could boost the likelihood of firms making voluntary disclosures. Thus, I anticipate positive coefficients for *SalesVolatility* in the determinant model.

Lastly, drawing upon the existing body of literature examining determinants of voluntary disclosure more broadly, such as earnings calls (e.g., Bushee et al., 2003), analyst/investor days (e.g., Kirk and Markov, 2016), and management sales guidance (e.g., Crawford et al., 2020), I incorporate additional groups of general determinants: (1) the percentage of institutional ownership (*InsOwn*), which gauges the information demands of institutional investors; (2) firm size (*Size*) and market-to-book ratio (*MTB*), which reflect the financial status and resources available to a company for conducting conference calls; (3) intangible assets (*Intangible*) and Beta

(*Beta*), which are associated with valuation uncertainty and stock price volatility; and (4) industry competition (*HHI*), which captures proprietary costs associated with public disclosure.

To reduce potential sensitivity in regression outcomes to model specifications, I perform the determinant analysis using three different regression models: Logit, Probit, and OLS. In each regression, I include fixed effects for country, industry, and year to control for factors that remain constant across countries, industries, and time, and which could affect corporate disclosure choices. To account for within-firm correlations of the residuals, I cluster the standard errors at the firm level.

4.2. Sample construction

The initial sample includes 87,619 European public firm-year observations from 2005 to 2022. To ensure consistency in institutional attributes and disclosure practices, I narrow the focus to public firms headquartered and listed within the EEA countries, the United Kingdom, or Switzerland for the determinant analysis.

Subsequently, I gather financial data and stock market data from both the Capital IQ and Compustat Global databases. After removing observations with missing values for explanatory variables in the determinant model and those excluded due to fixed effects, the final count of firm-year observations for the determinant analysis is 31,455, corresponding to a pool of 3,186 unique firms. All continuous variables are winsorized at the 1st and 99th percentiles. Panel A of Table 2 provides a detailed breakdown of the sample selection and filtering process.

[Insert Table 2 here]

4.3. Interpretation of the results

Panel B of Table 2 provides descriptive statistics for the sample used in the determinant analysis. There are several notable observations. The mean of *SalesCall* is 0.044, meaning that 4.4%

of the sample constitutes the treatment group (i.e., firm-years with at least one sales call). The issuance of management sales guidance (*SalesGuid*) is not a common practice, with only 6.2% of observations indicating its use. Approximately 20% of the sample has sales announcements (*SalesRelease*) in the year preceding sales calls. In terms of sales performance, the average year-over-year sales growth rate is 13.1%, and gross profitability averages around 41%. The proportion of loss-making firm-year observations accounts for 20.2%. Lastly, firm size, proxied by total assets, spans from 88.3 million euros (p25) to 2,255.2 million (p75) euros, indicating a diverse range of small and large companies within the sample.

In Panel C of Table 2, the results of Logit, Probit, and OLS regressions reveal four distinct patterns. First, the likelihood of conducting sales calls increases with the occurrence of preceding sales-related announcements (i.e., *SalesRelease* and *ClientProduct*) and the number of geographic segments (*NumGeoSeg*). For example, firms with prior sales announcements are 11 times more likely to conduct sales calls than those without, suggesting that sales calls serve as a platform for communicating recent sales events and business information to external stakeholders. Second, I observe a positive correlation between elevated uncertainty, measured by *SalesVolatility*, *Intangible*, and *Beta*, and the occurrence of sales calls. For instance, a one standard deviation increase in sales volatility corresponds to roughly a 16.4% higher probability of conducting sales calls under the Logit model specification. This highlights the role of sales calls in providing supplementary information and reducing information asymmetry between internal stakeholders and external investors during uncertain periods. Third, loss-making firms (*Loss*) are about 1.25 times more likely to conduct sales calls, in line with prior research indicating the importance of sales discussions for firms operating at a loss (e.g., Joos and Plesko, 2005; and Barth et al., 2022) and showing that firms with lower profitability are less concerned about competition pressures in the context of public disclosure (e.g., Dedman and Lennox, 2009). Lastly, larger firms (*Size*), those with greater institutional ownership (*InsOwn*), and those with higher market-to-book ratios (*MTB*) are more inclined to engage in sales calls, which supports the notion that sales calls require significant resources and are driven by the demand for information from investors.

4.4. Comparative analysis: sales calls in addition to earnings calls

In light of the conceptual parallels between sales and earnings, as well as the resemblances in the formats of their respective calls, I investigate the conditions of selecting sales calls in addition to earnings calls to gain a deeper understanding of the uniqueness of sales calls. Earnings call data is collected from Capital IQ, the same source for sales call records. I use the following model, which is similar to model (1).

$$\begin{aligned} BothCall_{i,t+1} = {} & \beta_0 + \beta_1 SalesGuid_{i,t} + \beta_2 SalesRelease_{i,t} + \beta_3 ClientProduct_{i,t} \\ & + \beta_4 BusSeg_{i,t} + \beta_5 GeoSeg_{i,t} + \beta_6 SalesGrowth_{i,t} + \beta_7 GrossMargin_{i,t} \\ & + \beta_8 SalesVolatility_{i,t} + \beta_9 Loss_{\ i,t} + \beta_{10} InsOwn_{i,t} + \beta_{11} Size_{\ i,t} + \beta_{12} MTB_{i,t} \\ & + \beta_{13} Intangible_{i,t} + \beta_{14} Beta_{i,t} + \beta_{15} HHI_{i,t} + Country\ FE + Industry\ FE \\ & + Year\ FE + \varepsilon \qquad (2) \end{aligned}$$

The dependent variable, denoted as *BothCall*, is a binary indicator that takes the value 1 if a firm conducts at least one sales call and at least one earnings call in the subsequent year (t+1) following the end of fiscal year t. It takes the value of 0 if a firm conducts only earnings calls in year t+1. The definitions of other variables are the same as those in Section 4.1. Table 3 displays the descriptive statistics and regression results of this comparative analysis.

There are approximately 7.3% observations with both sales calls and earnings calls among firm-years with only earnings calls, underscoring the relatively lower prevalence of sales calls compared to earnings calls. Regarding the determinants that drive firms to conduct sales calls in addition to earnings calls, most of the findings align with factors driving the decision to hold sales calls. For example, variables related to valuation uncertainty, like sales volatility, and intangibles, display significantly positive coefficients, indicating the demand for sales calls alongside earnings calls during periods of high uncertainty. Moreover, loss-making firms are more inclined to hold sales calls in addition to earnings calls, implying that companies facing weaker performance may opt for this combination. *SalesRelease* is significantly positively related to the likelihood of holding both sales calls and earnings calls, aligning with a bundling effect of sales releases and sales calls. Lastly, firm size and institutional ownership play a significant role in deciding sales calls with earnings calls, indicating that holding extra calls requires resources and is driven by higher information demands from investors.

Overall, this comparative analysis reveals circumstances where sales calls are necessary alongside sales calls, indicating that sales calls provide unique or incremental value in addition to earnings calls, even though sales and earnings are closely related topics.

[Insert Table 3 here]

5. Consequence: sales calls and analysts' forecast performance

5.1. Research design

In this section, I explore the informativeness of sales calls, specifically from the perspective of financial analysts. Financial analysts, as information intermediaries, represent a key audience for sales calls. Given that they interpret public data and generate new insights for investors, their work output potentially reflects the informativeness of sales calls (e.g., Hollander et al., 2010; and Huang et al., 2018). According to the analytical framework developed by Barron et al. (1998), analyst forecast properties are a function of the volume or precision of public information and individual analysts' possession of private information. Enhanced public information or its precision can directly reduce uncertainties about future prospects and help analysts generate more precise private information. This, in turn, enhances analysts' forecast performance, reflected as a decrease in forecast errors and dispersion (e.g., Bowen et al., 2002).[14]

Previous research has shown that financial analysts' earnings forecast performance improves after earnings calls (e.g., Mayew, 2008; Matsumoto et al., 2011; Huang et al., 2018; and Call et al., 2023). If sales calls enhance the amount and/or precision of public information, I anticipate a more significant reduction in analyst forecast errors and dispersion during periods with sales calls. I assess both sales and earnings per share (EPS) forecasts, with a stronger expectation of improved sales forecast performance due to the focus of sales calls on sales-related information, which helps them refine sales forecasts.

To assess the informativeness of sales calls, I employ the following Ordinary Least Squares (OLS) model to regress changes in analyst forecast error and forecast dispersion surrounding sales calls:

$$\begin{aligned}\Delta Forecast_{i,t} &= \beta_0 + \beta_1 SalesCall_{i,t} + \beta_2 PreLevel_{i,t} + \beta_3 \Delta Age_{i,t} + \beta_4 PreNumAna_{i,t} \\ &\quad + \beta_5 Size_{i,t} + \beta_6 SURP_{i,t} + Country\ FE + Industry\ FE + Year\ FE + \varepsilon \qquad (3)\end{aligned}$$

Following earlier research examining earnings call informativeness (e.g., Bowen et al., 2002; and Bassemir et al., 2013), I focus on changes in forecast errors and dispersion to isolate the impact of sales calls and control for cross-sectional differences in information environments. If forecast error or dispersion decreases after sales calls, the post-call values will be lower than the pre-call values. Consequently, I expect negative coefficients for *SalesCall* in equations (2). As demonstrated in the determinant analysis in Section 4, firms that conduct sales calls differ from those that do not. To enhance comparability between samples with and without sales calls, each

[14] The relationship between forecast errors and the precision of public information is contingent upon the relative precision of public and private information. This hinges on the underlying assumption that public information is more precise than private information. This assumption is justified by the fact that public information sources, such as annual filings or press releases, undergo processes like auditing, regulatory oversight, and public scrutiny, ensuring a higher degree of accuracy (e.g., Bowen et al., 2002).

sales call observation is matched with a no-sales call counterpart in the same industry (based on two-digit SIC codes), the same year, and the closest firm size (measured by market value). The control group consists exclusively of firms that never conduct sales calls throughout the sample period.

Forecast errors are measured as the absolute difference between the consensus annual analyst estimates and the actual figures, with forecast dispersion represented as the standard deviation of analyst estimates. For each sales call observation, I identify the closest consensus mean and dispersion in annual sales and EPS forecasts for fiscal year t, both before and after the sales call. Similarly, for instances without sales calls, I establish the base date using the matched treatment observation's sales call date and employ the same method to determine pre- and post-forecast mean and dispersion. The pre- and post- forecast data are limited to the time window [-30, +10], with date 0 corresponding to the (falsification) sales call date. This window duration minimizes the impact of concurrent events or information on forecast errors or dispersion. Alternatively, I use a window [-60, +60] to expand the sample size and increase testing power.[15] Thus, the dependent variable, Δ*Forecast*, is the post-call forecast errors (dispersion) minus pre-call forecast errors (dispersion), deflated by the stock price at the beginning of year t.

The independent variable of interest, denoted as *SalesCall,* takes a value of 1 if there is a sales call for year t and 0 otherwise. I require sales call dates to occur after the end of fiscal year t and before the end of year t+1. In addition, I control for four variables associated with changes in forecast errors and dispersion: (1) *PreLevel,* measured as the pre-call forecast errors or dispersion deflated by the stock price at the beginning of year t. The initial levels of forecast errors or dispersion may reflect the pre-call information environment and the potential for further

[15] In untabulated test results, the finding is robust to alternative windows, such as [-30, +30] and [-30, 60].

improvement. Thus, the initial levels may be correlated with both the changes in forecast measures and the likelihood of holding a call (e.g., Bowen et al., 2002; and Bassemir et al., 2013); (2) ΔAge, representing the change in analysts' forecast age, calculated as the post-call forecast's age minus the pre-call forecast's age. Forecast age, which is crucial for forecast performance, may impact forecast errors and dispersion levels and capture analysts' tendency to revise forecasts following sales calls (e.g., Brown, 2001; Bowen et al., 2002; and Bassemir et al., 2013); (3) *PreNumAna*, capturing the number of analysts contributing to consensus forecasts, calculated as the pre-call number of estimates. The number of analysts issuing forecasts affects consensus forecast errors or dispersion and reflects investor information demand, thereby correlating with sales call instances; and (4) SURP, the percentage of estimation surprise calculated as the actual yearly revenue (EPS) minus the last consensus mean estimates of revenue (EPS) before the actual release dates, divided by the consensus mean. It captures the difficulty of estimating sales (EPS). In all regression analyses, I include country fixed effects to account for factors that remain constant across countries. To address the impact of within-firm correlation on residuals, standard errors are clustered at the firm level. Although I match the control sample with the sales call sample based on industry, year, and firm size, I conduct regressions controlling for firm size and including industry and year fixed effects as a precaution.

5.2. Sample construction and interpretation of the results

I collect analyst sales and EPS forecasts from the IBES summary file and merge forecast data with the sales call and other financial data from Compustat and Capital IQ. Given the limited availability of sales or EPS forecasts within a specified time window around sales calls, the largest sample size for the analysis is 804, significantly smaller than the determinant analysis sample. I winsorize all continuous variables at the 1% and 99% percentile.

Table 4 presents the regression test results for changes in forecast errors and dispersion following sales call occurrence. Panel A displays summary statistics of variables used in the regressions. Notably, the average changes in forecast dispersions and errors are negative, indicating improved forecast performance. Panel B and C present the empirical results of the regression analysis. Panel B takes the window of [-30, +10] for forecast data selection, and the window is [-60, +60] for the results in Panel C. The coefficients of *SalesCall* consistently exhibit negative significance across various model specifications for sales and EPS forecast dispersion and errors. This suggests a significant decrease in forecast dispersion and errors during firm years with sales calls. The negative and significant coefficient of *PreLevel* for dispersion aligns with the concept of greater potential for reducing forecast dispersion when the initial dispersion is higher. The negative association between the number of analysts (*PreNumAna*) and changes in forecast dispersion indicates that more analysts following a firm correlates with improved forecast performance. However, when compared with sales forecasts, EPS forecasts show a weaker effect, with the economic magnitude of the *SalesCall* coefficient smaller for EPS forecasts. To illustrate, firm years with sales calls see a significant 21.3 standard deviation reduction in sales forecast dispersion and a 0.9 standard deviation decrease in sales forecast errors, but a minor 0.1% standard deviation decline in EPS forecast dispersion. Overall, the findings confirm the informativeness of sales calls. Furthermore, the comparison between the influence on sales and EPS forecast errors or dispersion suggests that sales calls contain more informative sales-related content, consistent with their focused theme.

[Insert Table 4 here]

5.3. Cross-sectional variation analyses

In this section, I further investigate whether the relationship between sales calls and analysts' forecast performance varies among different types of firms. These analyses aim to shed light on the circumstances under which sales calls are more informative for financial analysts.

5.3.1. Information asymmetry—total intangible assets

Information asymmetry between managers and investors complicates analysts' forecasting tasks, leading to less accurate forecasts (e.g., Duru and Reeb, 2002). One way to address this issue is to have managers provide more information to analysts (e.g., Healy and Palepu, 2001; and Muslu et al., 2019). Therefore, I expect that sales calls will be especially beneficial in improving analyst forecast performance for firms with higher information asymmetry. I measure information asymmetry using the total amount of intangible assets, as the presence of intangible assets inherently increases uncertainty about firm value (e.g., Barth et al., 2001).

To investigate this hypothesis, I divide the sample into two groups based on information asymmetry: "High" and "Low." The "High" ("Low") group includes observations with total intangible assets exceeding (falling below) the median industry-year level. Employing a Fisher's permutation test, I compare the impact of *SalesCall* on Δ*Forecast* between these two groups. In Panel A of Table 5, I present the results of this comparison. The "Difference" row shows the coefficients of *SalesCall* in the "High" group minus those in the "Low" group. A negative difference suggests a more pronounced reduction in forecast dispersion or errors for firms with higher information asymmetry (i.e., the "High" group). With the exception of EPS forecast dispersion, I observe a significant negative difference for sales forecast measures and EPS forecast errors, supporting the notion that sales calls are more effective in improving analysts' forecast performance for firms with higher information asymmetry.

[Insert Table 5 here]

5.3.2. Firm size—total assets

Larger firms possess greater resources, such as financial capacity and personnel, that enable them to conduct more comprehensive sales calls. These resources facilitate extensive presentations, the use of specialized investor relations teams, and the adoption of advanced technology for effective information dissemination (e.g., Ettredge et al., 2011). Moreover, larger firms inherently operate in a richer information environment, as they attract more analysts and adopt more transparent disclosure practices (e.g., Lang et al., 2003). As a result, larger firms are better equipped to derive benefits from sales calls, and I expect a more significant improvement in analyst forecast performance for these firms.

To investigate this, I segment the sample into two asset groups: “High” and “Low”, based on total assets, with the “High” (“Low”) group comprising observations with assets above (below) the median industry-year level. The results of the Fisher’s permutation test, presented in Table 5, Panel B, validate this expectation. Particularly in the case of sales forecast dispersion and EPS errors, these results underscore the stronger impact of sales calls on analyst forecasts for larger firms.

Overall, these analyses reveal that sales calls are most valuable for firms characterized by high information asymmetry, and for larger companies. These insights further support the role of sales calls in enhancing analyst forecast performance.

5.4. Additional tests on sales call content and analyst forecast dispersion and errors

In this section, I narrow my focus to observations with available sales call transcripts to explore the relationship between sales call textual content and forecast dispersion and errors. The objective is to identify specific aspects of sales call content that contribute to the enhancement of analyst forecast performance. Drawing on the topics identified within all sales call transcripts, I investigate which topics contribute to or impair improvement in forecast performance. Since each topic represents an objective description of the content, I do not make a specific directional prediction for the sign of the association. To empirically examine this, I regress changes in forecast measures on the percentage of each topic within each sales call, as reflected in model (4).

$$\begin{aligned}\Delta Forecast_{i,t} = \beta_0 &+ \beta_1 Topic1_{i,t} + \beta_2 Topic2_{i,t} + \beta_3 Topic3_{i,t} + \beta_4 Topic5_{i,t} + \beta_5 Topic6_{i,t} \\ &+ \beta_6 Topic7_{i,t} + \beta_7 Topic8_{i,t} + \beta_8 PreLevel_{i,t} + \beta_9 \Delta Age_{i,t} + \beta_{10} PreNumAna_{i,t} \\ &+ \beta_{11} SURP_{i,t} + Country\ FE + Industry\ FE + Year\ FE + \varepsilon \qquad (4)\end{aligned}$$

Since the percentage of topic 4 is highly correlated with other topics (e.g., the correlation between topic 4 and topics 3/6/7 is around 0.5.) and *Size* is highly correlated with *PreNumAna*, I do not include these two variables in model (4). Table 6 presents the regression results. The findings indicate that the decrease in sales forecast dispersion and EPS forecast errors is more pronounced for sales calls containing personnel related topics (i.e., topic 3—Personnel management and compliance, and topic 6—Personnel recruitment and efficiency). This suggests that discussions related to workforce management and efficiency are associated with improved forecast accuracy. More discussions about topic 7 (Real estate and financing) are also weakly related to a larger reduction in EPS forecast errors. However, a higher percentage of content related to topic 8 (Sales growth and business development) is associated with a smaller reduction in sales forecast dispersion. This implies that the presentation on sales growth and business development in sales calls may lead to more confusion among analysts. Overall, the topics covered in sales calls have varying effects on forecast errors and dispersion, with some industry or domain-specific topics significantly improving forecast performance.

[Insert Table 6 here]

5.5. Comparative analysis: the association between sales calls in addition to earnings calls and analysts' forecast performance

Considering overlapping information that may be released in sales and earnings calls, I conduct a comparative analysis on these two calls to explore the incremental informativeness of sales calls. Specifically, I analyze analysts' forecast performance for firms with only earnings calls and firms with both sales calls and earnings calls. If adhering to a research design akin to that of model (4), data availability becomes a constraint. Consequently, I shift the focus to the most recent annual sales or EPS forecast dispersion and errors, rather than examining changes in these forecast metrics. Specifically, I adopt the following model:

$$\begin{aligned} Forecast_{i,t} = {} & \beta_0 + \beta_1 BothCall_{i,t} + \beta_2 BusSeg_{i,t} + \beta_3 GeoSeg_{i,t} + \beta_4 SalesGrowth_{i,t} \\ & + \beta_5 GrossMargin_{i,t} + \beta_6 SalesVolatility_{i,t} + \beta_7 Loss_{\ i,t} + \beta_8 InsOwn_{i,t} \\ & + \beta_9 Size_{\ i,t} + \beta_{10} MTB_{i,t} + \beta_{11} Intangible_{i,t} + \beta_{12} Beta_{i,t} + \beta_{13} HHI_{i,t} \\ & + Country\ FE + Industry\ FE + Year\ FE + \varepsilon \qquad (5) \end{aligned}$$

The dependent variable, denoted as *Forecast*, is either the absolute value of sales or EPS forecast errors or forecast dispersion. These values are adjusted by dividing them by the actual sales or EPS figures. I take the latest consensus annual forecast for the fiscal year t. The focal independent variable, *BothCall*, is a binary indicator that equals 1 if a firm conducts at least one sales call and at least one earnings call in the year t. It equals 0 if the firm conducts only earnings calls in year t. I require the dates of sales calls or earnings calls must fall within the interval [-360, 0] days relative to the forecast announcement dates and after the beginning of fiscal year t. Regarding control variables, I consider a set of variables that are determinants of sales calls in model (1) and are also linked to forecast performance. For instance, I consider variables such as the number of business or geographic segments, which reflects the complexity of a firm's operations and is thus expected to have a positive correlation with forecast errors or dispersion. Additionally, prior studies show lower-quality forecasting when firms are incurring losses.

Furthermore, I include variables such as sales volatility, intangible assets, and Beta, all of which are associated with valuation uncertainty and stock price volatility. These factors are expected to exhibit a negative association with analyst forecast accuracy, as they contribute to increased complexity and uncertainty in the valuation process. To account for the demand for information from market participants, I incorporate variables such as firm size (Size) and market-to-book ratio (MTB) into the analysis. Moreover, the presence of a high product market threat tends to result in analysts producing less precise forecasts due to increased competitive pressures and heightened uncertainty about future cash flows (Ali et al., 2014).

Given the potential inherent differences between firms conducting both sales and earnings calls and those exclusively holding earnings calls, I employ the entropy balancing technique to match treatment and control observations, thus enhancing the comparability between these two groups. Specifically, I ensure that the covariate distributions of all control variables adhere to three moment conditions (i.e., means, variances, and skewness). In each regression conducted with the reweighted sample, I incorporate fixed effects for country, industry, and year to account for factors that remain constant across countries, industries, and time. Additionally, I cluster the standard errors at the firm level to control for within-firm correlations of the residuals.

Table 7 presents the empirical results through the estimation of model (5). The coefficient of *BothCall* is significantly negative for sales forecast dispersion and errors, suggesting that additional sales calls help analysts with sales forecasting. Nevertheless, EPS forecast errors increase in firm years with both sales calls and earnings calls, in comparison to observations exclusively featuring earnings calls. This opposite effect may be attributed to factors such as analysts' limited focus, and potential information redundancy. In summary, these results imply that sales calls provide valuable insights primarily concerning sales, but not necessarily contribute to improved EPS forecasting accuracy.

[Insert Table 7 here]

6. Other comparisons between sales calls and earnings calls

6.1. Comparison of the content

In this section, I contrast the content of sales calls and earnings calls to identify the unique disclosure formats or content in sales calls. To ensure the comparability of sales call transcripts and earnings call transcripts, I start with all the 2,366 sales call transcripts from public firms headquartered and traded in the same EEA/United Kingdom/Switzerland countries (i.e., all sales call transcripts analyzed in Section 4) and identify earnings calls involving the same companies, conducted within a year of the respective sales calls. Among the 2,366 sales calls with transcripts, 566 of them can be linked to at least one earnings call conducted within the one-year timeframe. This process yields a total of 1,387 matched earnings calls corresponding to the 566 sales calls.

Employing natural language processing tools in Python, I segment each call into three components: the management team's initial presentation (termed "Pre"), participants' questions raised during a Q&A session (labeled "Q"), and the subsequent responses by corporate executives (designated "A"). I also extract the job titles of corporate executives from the transcripts. To analyze the linguistic attributes of sales calls, I use the Loughran-McDonald sentiment word lists, which include categories such as positive, negative, uncertainty, constraint, strong modal, and weak modal, and other measures from prior literature. [16] The details on the construction of each linguistic attribute can be found in Appendix D.

[16] The sentiment lists are downloaded from https://sraf.nd.edu/loughranmcdonald-master-dictionary/.

Table 8 presents a comparison of the content in both sales calls and earnings calls. I compare the length, number of participants, executive titles, tone, and several linguistic attributes. Notably, earnings calls tend to be lengthier, with the presentation section of earnings calls containing approximately 2.5 times more words than that of sales calls. This divergence in call duration underscores that earnings calls cover more topics and devote more time to presentations, while sales calls predominantly allocate their time to responses, suggesting a more inquiry-driven focus. In terms of participants, due to the wider range of topics addressed in and a greater attention attracted by earnings calls, they typically involve a larger number of analysts. Additionally, chief financial officers (CFOs) and investor relations officers (IROs) are more likely to participate in sales calls than in earnings calls.

Turning to the tone, the presentation sections of sales calls contain higher percentages of both positive and negative words in comparison to earnings calls. However, the overall net tone of sales call presentations is less positive than that of earnings calls. This discrepancy suggests that sales calls are frequently conducted during challenging periods, necessitating discussions of adverse events, yet an effort is made to incorporate more positive language. Furthermore, the comparison of linguistic attributes reveal that sales calls tend to be more specific, as is particularly evident in the presentation and response segments. Sales call presentations display a higher usage of uncertainty and weak modal words, consistent with other content analysis results.

[Insert Table 8 here]

6.2. Comparison of the timing

In this section, I conduct a comparison of the timing of firms holding sales calls versus earnings calls. To begin, I examine a dataset comprising 2,942 sales calls from public firms headquartered and traded in the same EEA/United Kingdom/Switzerland countries. Out of the

2,942 sales calls, 774 of them (equivalent to 26.3%) can be linked to at least one earnings call conducted within a one-year timeframe. This matching process results in a total of 1,387 paired earnings calls corresponding to the 774 sales calls.

Figure 5 visually presents the relative timing between the sales calls and their corresponding earnings calls. The x-axis represents the absolute difference in days between the date of a sales call and the date of an earnings call. The chart illustrates that most earnings calls are spaced either three or eight months apart from their associated sales calls. This observation suggests that there is no consistent bundling pattern between the two types of calls.

[Insert Figure 5 here]

7. Robustness checks

7.1. Within-firm analysis of sales calls and analyst forecast performance

In Section 5, I conduct a panel regression analysis to compare changes in forecast dispersion and errors between firms that hold sales calls during the sample period and those that do not. In this section, I employ a within-firm analysis to control for firm-specific factors that remain constant over time. Specifically, I compare changes in forecast performance during firm years with sales calls to those in the year immediately preceding the sales call year for the same firms, which do not involve sales calls. Consistent with prior findings from Section 5, I expect that firm years with sales calls will demonstrate a more significant reduction in forecast dispersion and forecast errors. To empirically test this hypothesis, I conduct t-tests to compare the mean changes in forecast errors and dispersion between these two groups. Given the limited sample availability, this test takes a time window of [-60, +60] for the forecast data selection. Table 9 presents the results of this comparison. In column (5), a negative value indicates a greater reduction in forecast dispersion or errors for firm years with sales calls. Except for EPS forecast errors, all three measures of forecast performance support the idea that sales calls are informative for analyst forecasting activities.

[Insert Table 9 here]

7.2. The analysis of sales calls, analyst forecast dispersion and errors using matched sample

The decision to conduct sales calls is voluntary and may introduce self-selection bias. I address this issue by using the entropy balancing method to balance the distribution of determinants between the treatment and control groups. This matching approach comes with two advantages: (1) it assigns continuous weights to each observation in the control group, minimizing the loss of observations compared to other matching methods, like propensity score matching; and (2) it eliminates the need for researchers to make discretionary judgments regarding which observations to retain (McMullin and Schonberger, 2020). To enhance the similarity between the control and treatment groups, I require that the covariate distributions of all control variables included in the reweighted sample meet two or three moment conditions (i.e., means, variances, and skewness), depending on the convergence possibility. Subsequently, I re-estimate models (3) using the reweighted sample. The results, presented in Table 10, are qualitatively similar to those in Table 4, reinforcing the robustness of the findings about the informativeness of sales calls.

[Insert Table 10 here]

7.3. Determinant analysis of sales calls—Pre- and post- COVID-19 periods

According to the determinant analysis of sales calls in Section 4, loss and uncertainty play significant roles in the decision to conduct sales calls. Thus, a potential concern is that these results might be influenced by the unique time period of the COVID pandemic. To address this concern, I re-run model (1) while segmenting the sample into two subperiods: the fiscal years of firms before 2020 (Pre-COVID periods) and those after 2020 (Post-COVID periods). The Logit regression results from two subsamples and the full sample are presented in Table 11. Intriguingly, proxies associated with uncertainty (such as sales volatility, intangible assets, and Beta) exhibit a more pronounced correlation with the likelihood of holding sales calls. This aligns with the findings from previous sections, indicating that sales calls are particularly in need during uncertain times. Additionally, firms with higher sales growth are more inclined to conduct sales calls, suggesting that during unfavorable economic conditions, firms are more willing to communicate positive sales figures to the public, possibly as a strategic response to challenging environments.

[Insert Table 11 here]

7.4. Determinant analysis of sales calls—Matched sample

Given the potential inherent differences between firms with and without sales calls, I construct a matched non-sales call sample to increase the comparability of the treatment and control groups. Specifically, for each individual sales call observation. I identify a corresponding non-sales call observation that matches with the sales call observation in terms of industry (i.e., within the same two-digit SIC industry), year (i.e., within the same fiscal year), and size (i.e., having the closest total assets). Table 12 presents the regression results derived from this refined sample, which supports the robustness of the main determinant analysis.

[Insert Table 12 here]

8. Conclusion

This study explores a novel type of sales-specific voluntary disclosure, namely sales/trading statement calls. The investigation of the determinants and outcomes of these calls uncovers significant insights. The determinant analysis highlights that sales calls are driven by diverse factors such as loss, uncertainty, sales-related events, and resource allocation. In terms of outcomes, these calls prove beneficial to financial analysts, as evidenced by the enhanced accuracy of sales and EPS forecasts following sales calls, particularly for firms with higher information asymmetry and among larger firms. Moreover, a comparative analysis with earnings calls underscores the distinct determinants of sales calls, emphasizing their question-driven nature. As compared to earnings calls, they tend to be shorter in duration, involve fewer participants, and prioritize answering questions. Overall, the exploration of sales calls contributes to our understanding of specific types of conference calls beyond earnings calls. This study's insights could guide firms in enhancing their communication strategies, especially in challenging circumstances, and in providing more disaggregated disclosure.

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Appendix A. Variable definitions

Variable	Definition	Source
The determinant analysis		
Beta	1 year Beta, the slope of the 52-week regression line of the percentage price change of the stock relative to the percentage price change of its benchmark	Capital IQ
BothCall	An indicator variable that equals 1 if the firm holds at least one sales/trading statement call and at least one earnings call during the next fiscal year, and equals 0 if the firm only holds at least one earnings call during the next fiscal year	Capital IQ
BusSeg	The number of business segments, measured as the natural logarithm of one plus the number of business segments in the fiscal year. Assumed to be 1 if missing	Capital IQ
ClientProduct	An indicator variable that equals 1 if the firm issues at least one customer or product related announcement (including four types of events from Capital IQ, i.e., “client announcements,” “product-related announcements,” “business expansions,” and “strategic alliances”) during a fiscal year	Capital IQ
GeoSeg	The number of geographic segments, measured as the natural logarithm of one plus the number of geographic segments in the fiscal year. Assumed to be 1 if missing	Capital IQ
GrossMargin	Gross profit (sales minus costs of sales) divided by sales	Capital IQ, Compustat
HHI	Herfindahl-Hirschman Index, measured as the sum of squared market shares of all firms in the same two-digit SIC industry for the same year	Capital IQ, Compustat
InsOwn	The percentage of institutional ownership	Capital IQ
Intangible	Intangible assets, measured as total intangible assets divided by total assets	Capital IQ, Compustat
Loss	Net loss, an indicator variable equal to one if a firm reported a negative net income in a year and zero otherwise	Capital IQ, Compustat

(Continued)

Appendix A (continued)

SalesCall	An indicator variable that equals 1 if the firm holds at least one sales/trading statement call during the next fiscal year	Capital IQ
SalesGuid	An indicator variable that equals 1 if the firm issues at least one sales guidance during a fiscal year	Capital IQ
SalesRelease	An indicator variable that equals 1 if the firm issues at least one sales release (including two types of events from Capital IQ, i.e., "announcements of sales/trading statement" and "sales/trading statement release date") during a fiscal year	Capital IQ
MTB	Market-to-book ratio, calculated as the market value of equity divided by the book value of equity at the end of the fiscal year	Capital IQ, Compustat
SalesGrowth	One-year sales growth, dividing the current year's sales by the sales from the previous year, subtracting 1	Capital IQ, Compustat
SalesVolatility	The standard deviation of annual sales divided by average total assets in the current year and previous year over the prior seven years	Capital IQ, Compustat
Size	Firm size, calculated as the natural logarithm of total assets, measured in millions of euros and converted to euros if the reporting currency is not EUR	Capital IQ
The association with analyst forecast errors and dispersion		
ΔForecast	Post-call forecast error (dispersion) minus pre-call forecast error (dispersion), deflated by the stock price at the beginning of year t. The forecast is selected within the time window [-30, +10] or [-60, +60] before and after a sales call date	IBES
Forecast	The absolute value of the difference between the latest mean consensus annual forecast and its actual value, divided by the absolute value of the actual value. It may also refer to the latest consensus standard deviation of analyst forecasts, adjusted by the absolute value of the actual values	IBES

(Continued)

Appendix A (continued)

ΔAge	The post-call forecast's age minus the pre-call forecast's age, divided by 100	IBES
PreNumAna	The number of estimates that analysts contribute to the pre-call forecast, divided by 10	IBES
PreLevel	The pre-call forecast error (dispersion) deflated by the stock price at the beginning of year t	IBES
SURP	The percentage of estimation surprise calculated as the actual yearly revenue (EPS) minus the last consensus mean estimates of revenue (EPS) before the actual release dates, divided by the consensus mean	Capital IQ

Appendix B. Two sales call transcript examples

#1 L'Oréal S.A. (ENXTPA: OR) Sales/Trading Statement Call

Time: Tuesday, October 29, 2019 12:00 AM GMT

Source: Capital IQ

Call Participants

Executives

Christophe Babule (*Former General Chief Executive of Administration & Finance, CFO*)
Françoise Lauvin (*Head of Investor Relations*)
Jean-Paul Agon (*Chairman & CEO*)
Mark Prestwich (*Group General Manager of Financial Communications and Strategic Prospective*)

Analysts

Celine A.H. Pannuti (*JP Morgan Chase & Co, Research Division*)
David Hayes (*Societe Generale Cross AssetResearch*)
Fulvio Cazzol (*Joh. Berenberg, Gossler & Co. KG, Research Division*)
Guillaume Gerard Vincent Delmas (*BofA Merrill Lynch, Research Division*)
Jeremy David Fialko (*HSBC, Research Division*)
Marion Cohet Boucheron (*MainFirst Bank AG, Research Division*)
Mark Stiefel Astrachan (*Stifel, Nicolaus & Company, Incorporated, Research Division*)
Robert Edward Ottenstein (*Evercore ISI Institutional Equities, Research Division*)

Presentation

(Note: The operator and other executives' welcoming messages are omitted here for brevity.)

Françoise Lauvin (*Head of Investor Relations*)

Hopefully, you had the chance to look at our press release, which was sent out earlier. Let me briefly give you the highlights of this release before we move to the Q&A.

At the end of September, sales increased 10.7% to EUR 21,994 million. There was a positive 1 percentage point impact from changes in the scope of consolidation, mainly linked with the first time consolidation of acquisitions that is Pulp Riot since last May; the German organic beauty company, Logocos, last July; the Korean lifestyle makeup brand, Stylenanda, last October; and this year, Valentino.

After taking account a positive 2.2% impact from currencies, stemming mainly from a stronger U.S. dollar and Japanese yen as well as a more stable sterling against the euro, like-for-like growth came to a very dynamic 7.5%.

In the third quarter, sales rose a strong 11% to EUR 7,182 million. Currency impact was positive by 2.2% and scope of consolidation also positive by 1%. Like-for-like sales growth maintained a very strong rhythm of plus 7.8%, even slightly accelerating from the first half.

Q3 showed the best quarterly growth in more than a decade.

Growth momentum remains strong and the performance by division continues to be contrasted. L'Oréal Luxe maintains its high strong momentum at plus 13.4% at the end of

September on a like-for-like basis. So does the Active Cosmetics Division with plus 13.8% increase. Growth at the Consumer Products Division is steady at plus 3% and the Professional Products Division recorded 3% growth, with a nice acceleration in the third quarter at plus 3.9%.

Across the regions, growth in the new markets continued at a very consistent plus 16.7%, led by Asia Pacific, up 23.7%; and Eastern Europe, up 9.2%. Latin America rose plus 2.4%, while Africa and Middle East was at minus 4%. Western Europe showed a 1.7% increase after a robust third quarter, while North America recorded minus 0.4%.

By channel, our 2 powerful growth engines continued to drive the overall performance. E-commerce sales jumped 47.5% to 13.5% of total sales and Travel Retail maintained a dynamic 20.8% pace to above 9% of sales.

As usual, a few remarks to help you with your full year forecast. Extrapolating from the end of September currency rates against the euro, that is EUR 1 at around USD 1.09 until year-end, would have a positive currency impact of about 2.2% on full year sales and the net impact of changes in the scope of consolidation can be estimated at 0.8% over full year.

To conclude, the overall environment remains volatile, uncertain and contrasted, but L'Oréal's strong performance over the first 9 months reinforce our confidence to outperform a dynamic beauty market in 2019 and to achieve another year of increase in both sales and profits.

I thank you for your attention. We are now ready to take your questions.

Question and Answer

(Note: To demonstrate, only one relatively shorter question-answer pair is shown here.)

Marion Cohet Boucheron *(MainFirst Bank AG, Research Division)*

It was the e-commerce, how would you describe it.

Jean-Paul Agon *(Chairman & CEO)*

Yes. E-commerce is a completely different story. So e-commerce, e-commerce -- the great thing with e-commerce is that it's a very broad-based growth. I think that the full loyal company has understood. All loyal teams in all divisions, all brands, all regions, they have understood that e-commerce now is not the icing on the cake, but it's the cake, as I explained to them 2 years ago, and they are all going for e-commerce first, and this is really paying off. So it's pretty impressive to see that the growth that we have on e-commerce is across division. I can give you some numbers, even if I should not.

For example, we are growing at 50% in Luxury, but also 48% in mass; 47% for dermocosmetics; 38% for Professionals. So it's really across base. Françoise will not like me to tell you all these numbers, but she will forgive me.

And it's true also for regions. Of course, Asia and China are very strong. But it's true also, for example, in Eastern Europe, we are plus 45. So -- and paradoxically, the only region where we are a bit slow in terms of growth is North America, but it's also linked to the -- to what we said before. And we are also hopeful to be able to accelerate again there. So it's really -- I think it's an important information. I think your question is very right.

E-commerce at L'Oréal is not the story of one single country or one single division, it's totally broad-based. Of course, the base is not the same. Some countries are already at 30% e-commerce and some others are only at 3%. But every country, region, division is considering e-commerce as priority #1, and that explains the fact that we are able to grow at twice the speed of the market, which is pretty extraordinary. It's even--I will be honest with you, it's even stronger than what we expected.

#2 Pearson plc (LSE: PSON) Sales/Trading Statement Call

Time: Thursday, September 26, 2019 8:00 AM GMT

Source: Capital IQ

Call Participants

Executives

Coram Williams (*CFO & Executive Director*)
John Joseph Fallon (*CEO & Executive Director*)

Analysts

Giasone Ulisse Salati (*Macquarie Research*)
Ian Richard Whittaker (*Liberum Capital Limited, Research Division*)
Katherine Tait (*Goldman Sachs Group Inc., Research Division*)
Matthew John Walker (*Crédit Suisse AG, Research Division*)
Nicholas Michael Edward Dempsey *(Barclays Bank PLC, Research Division*)
Patrick Thomas Wellington (*Morgan Stanley, Research Division*)
Sarah Simon (*Joh. Berenberg, Gossler & Co. KG, Research Division*)

Presentation

(Note: To demonstrate, only one relatively shorter executive's opening speech is presented here.)

John Joseph Fallon (*CEO & Executive Director*)

Good morning, everybody, John Fallon here with our CFO, Coram Williams. Thank you for joining us at short notice. As you all have seen, back-to-school sales in U.S. Higher Education Courseware, which accounts for around 25% of group sales have been worse than we expected, prompting us to bring forward our 9-month trading update for today. For reasons that Coram will explain in a moment. We now expect sales in our U.S. Higher Education Courseware business to be down around 10% at the end of September, and to be down in the 8% to 12% range for the full year. The rest of the company is performing well, which means that we still expect to stabilize group revenues this year, that's because sales from the other 75% of Pearson in aggregate are expected to be up around 3% at the end of September, meaning the overall group revenues are broadly flat on last year. We are also on track to deliver the planned GBP 330 million in annualized cost savings by the end of the year. And this means that with the help of some additional cost savings, we still expect to make our guidance range for operating profits of GBP 590 million to GBP 640 million for the full year. Although, it is likely to be towards the lower end of that range.

Today's news on Higher Education Courseware is difficult, particularly, after 10 quarters in which the market performed in line with our guidance. Yet, this does provide an opportunity to make this a more sustainable and truly digital-first business more quickly. But before I say more about that, let's have Coram talk you through in more detail, what's happened in Higher Education Courseware, where we expect sales to be for the 9 months through to September 30, and the outlook for the rest of the year. Coram?

Question and Answer

(Note: To demonstrate, only one relatively shorter question-answer pair is shown here.)

Patrick Thomas Wellington *(Morgan Stanley, Research Division)*

But just to confirm, there's no direct incremental revenue effect with the introduction of Revel products on the global, digital platform?

Because they're going to be substitution of...

John Joseph Fallon *(CEO & Executive Director)*

I think what -- I think as I said at the half year in July, I think through the second half of next year and more into 2021, we will start to see top line benefits from the new digital products coming through. There's lots of new features and enhancements that we're able to provide on Revel on the new platform. AIDA, which is our new AI-inspired, direct-to-consumer product launches in the next few weeks, where we've -- as we've talked about a number of times before, our competitive pressure on the digital front has really been in developmental math, where there's a competitive product that does work, some customers would perceive as having some advantages in more of an emporium model, which is where that market has been going We will launch Rio commercially later next year. So you can take another 6 to 12 months to come through, but you will start to see the top line benefits of that coming through over the next 12 to 18 months.

Appendix C. Topic modeling and LDA

Topic modeling is an unsupervised machine learning method used to identify prevalent topics within a collection of documents. This approach shares conceptual similarities with the process of crafting articles, where key topics guide the narrative. When addressing a particular theme, the selection of relevant words is crucial. To illustrate, in discussions related to "finance", terminologies like "mortgage," "lending," and "creditor" are commonly used. In the context of "medicine", terms such as "dose," "pharmacy," and "diagnose" hold more relevance. Essentially, topic modeling views a document as a composite representation of these topics, with each topic regarded as a collection of specific words. This analytical approach employs mathematical principles to detect thematic patterns across documents by analyzing word and topic distributions.

Latent Dirichlet Allocation (LDA), developed by Blei et al. (2003), is one type of topic modeling approach. LDA excels at extracting semantically meaningful themes, approaching the accuracy of human coders (e.g., Chang et al., 2009; Anaya, 2011). It has been widely applied to various domains, including accounting, finance, and management, as evidenced in academic works such as Dyer et al. (2017), Huang et al. (2018), Brown et al. (2020), and Bellstam et al. (2021). LDA assumes that each document is a mix of topics, and each topic is a collection of various words. The fundamental framework of LDA unfolds as follows. Starting with a collection of words (a corpus), LDA generates documents from those words by assigning a random distribution over a pre-defined number of topics (denoted as "k") and randomly selecting words from the vocabulary distribution associated with each topic. LDA iteratively refines these assignments by adjusting the association of topics to words in documents during each iteration to arrive at more accurate estimates of the probability of a word (denoted as "w") belonging to a specific topic (denoted as "t"). This probability, denoted as "P(t|w)," is derived from two factors: P(t|d), the proportion of words in a given document (denoted as "d") that are assigned to topic "t," and P(w|t), the proportion of assignments to topic "t" across all documents that originate from word "w." For a document "d," the proportion of topic "t" is calculated as the sum of P(wi)*P(t|wi) based on the law of total probability. In this equation, "wi" represents each word within the document, and P(wi) is the proportion of word "wi" occurring in the document. The final product of LDA comprises two vectors: a topic distribution vector for each document (e.g., a document is 30% about t1, 20% about t2, and 50% about t3), and a word vector for each topic (e.g., a topic is composed of 30% "sports," 20% "outdoor," and 50% "nature"). Importantly, the sum of all components in each vector equals 1.

Following common practice in textual analysis, the initial step of conducting topic modeling is preprocessing the texts, which involves the removal of punctuation, numbers, URLs, emojis, and common stop words from the texts. Next, frequent phrases that represent specific terms are standardized by either adding hyphens or using abbreviations, preserving their intended meanings. Subsequently, I apply stemming and lemmatization techniques to reduce words to their base forms. After obtaining the cleaned texts, I set a filter to eliminate terms that account for the top 10% of word frequency and those occurring in fewer than 15 documents to remove both overly common and extremely infrequent words.

Before applying LDA, I generate a word cloud to offer an overview of the principal words used in sales calls. The word cloud visually highlights words with higher frequency by displaying them in larger fonts. Specifically, I construct this word cloud through the "wordcloud" package in

Python, incorporating all cleaned, lemmatized and stemmed lexicons from the presentation sections of 2,362 sales call transcripts.[17] Figure 2 presents this word cloud.

The final LDA outputs include two key components: a list of words associated with each topic and the topic distributions within each sales call. To offer visual representations of topic relationships and word compositions, I employ the pyLDAvis python library developed by Sievert and Shirley (2014) to generate an interactive web page, a snapshot of which is shown in Figure 3. It facilitates the exploration of word distributions within each topic and the topic similarity. To the left, eight bubbles symbolize the identified topics. The proximity between bubbles suggests the similarity between topics. The size of each bubble indicates the prevalence of the corresponding topic within all sales calls. To the right, it displays the top 30 most frequent terms across all sales calls. For simplicity, I present the most common terms for each individual topic through word clouds as depicted in Figure 4.

[17] Out of 2,366 sales call transcripts available from Capital IQ, there are four transcripts without the presentation part.

Appendix D. Definitions of linguistic attributes

To analyze the tone of each segment of sales and earnings calls, I employ the LM sentiment word lists to calculate the percentage of positive or negative words, scaled by the total word count in the corresponding section, and calculate the net tone for each segment. For each part, the net tone is calculated as (the number of positive words – the number of negative words)/(the number of positive words + the number of negative words). The larger the measure is, the more positive it is. Notably, the presentation sections of sales calls contain higher percentages of both positive and negative words in comparison to earnings calls. However, the overall net tone of sales call presentations is less positive than that of earnings calls. This discrepancy suggests that sales calls are frequently conducted during challenging periods, necessitating discussions of adverse events, yet an effort is made to incorporate more positive language.

Next, I analyze the usage of uncertainty, modal, constraint, and litigation words within sales calls. Uncertainty words, such as approximate, almost, and contingency, refer to words indicating imprecision (Loughran and McDonald, 2011). Modal verbs refer to words that reflect the level of confidence, including both weak modal words (e.g., could and almost) expressing weak possibility and strong modal words (e.g., always and must) expressing strong necessities (Loughran and McDonald, 2011). Constraining words, as identified by Bodnaruk et al. (2015), pertain to vocabulary indicative of financial constraints (e.g., constraint, commit, obligation, and prevent). Litigious words, such as contract, litigation and claims, capture litigation risk. For each linguistic category and segment, I calculate a percentage of words from each linguistic category, divided by the total number of words in each corresponding segment and then multiplied by 100.

In addition, I delve into the specificity and quantitative density of sales call content. Prior studies show that more specific disclosures are associated with a greater capital market reaction and better analyst performance (Hope et al., 2016). Moreover, Dyer et al. (2017) document that high risk firms provide more specific and more numerical information. Drawing from Hope et al. (2016), I use specificity to refer to how frequently the text references specific entities like people, places, organizations, times, or numerical values. For this, I employ a Python-based named entity recognition (NER) tool to quantify the number of specific entity names. I measure the specificity of each segment (e.g., Specificity_Pre) as the number of specific entity names mentioned in that segment divided by the number of total words within that segment and then multiplied by 100. Following Blankespoor (2019), I measure the relative amount of numerical information (e.g., HardInfo_Pre) as the percentage of the number of informative numbers (i.e., excluding dates and section numbers) in each segment and then multiplied by 100.

Figure 1. Trend of sales calls around the world

This figure illustrates the annual count of sales calls from 2005 to 2022, encompassing 6,655 calls conducted by 924 publicly traded firms around the world. The lines on the graph represent the cumulative number of sales calls across distinct geographic regions, including the global sample, major European economic countries (EEA members, the United Kingdom, and Switzerland), the United Kingdom (UK), France, and the United States (US).

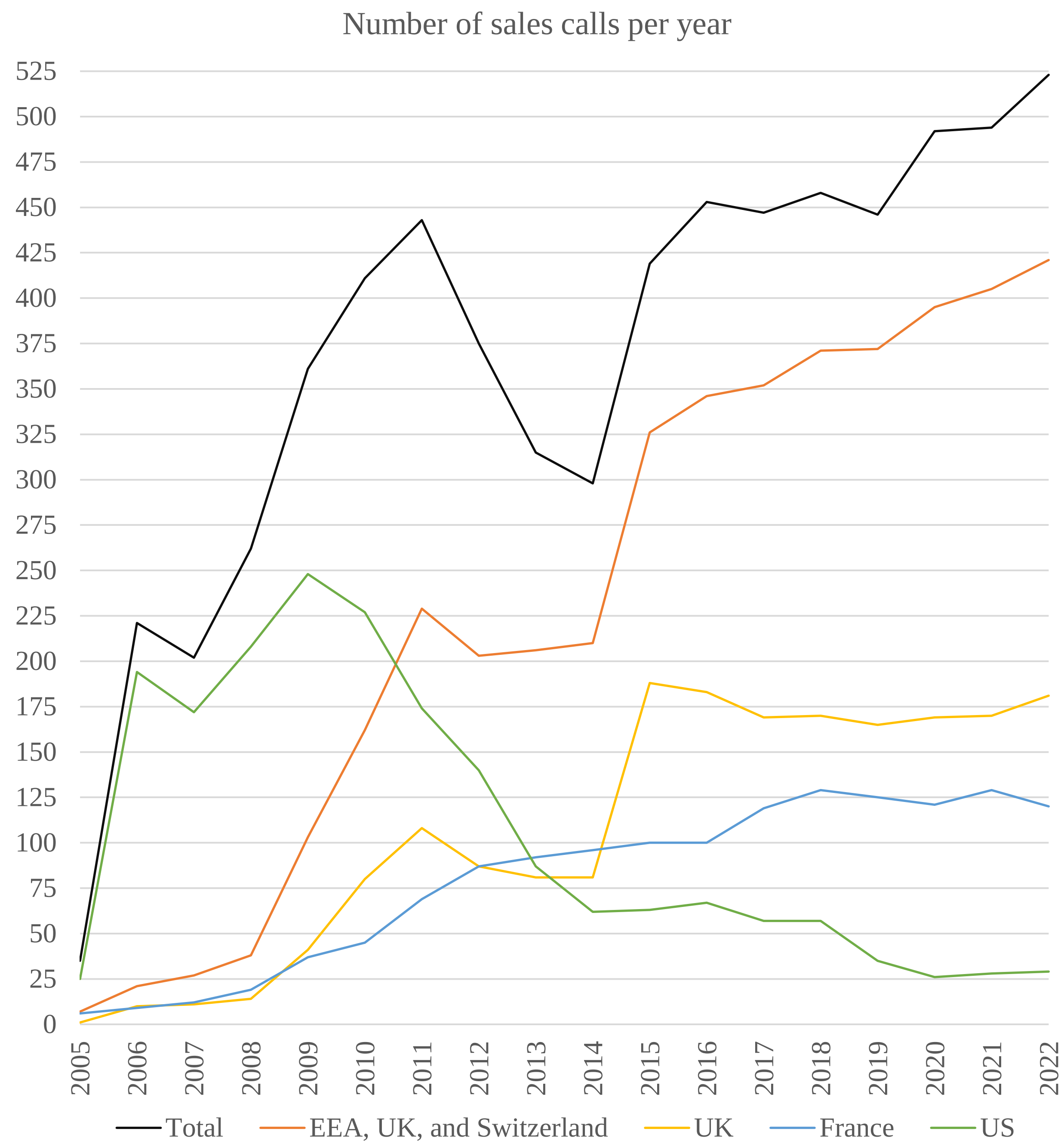

Figure 2. A word cloud of sales call transcripts

This figure presents the word cloud generated using the presentation parts from 2,362 sales call transcripts from public firms headquartered and traded in the same EEA countries, the United Kingdom, or Switzerland. In the word cloud, words that occur more frequently appear larger and more prominently. The words are in their lemmatized and stemmed forms.

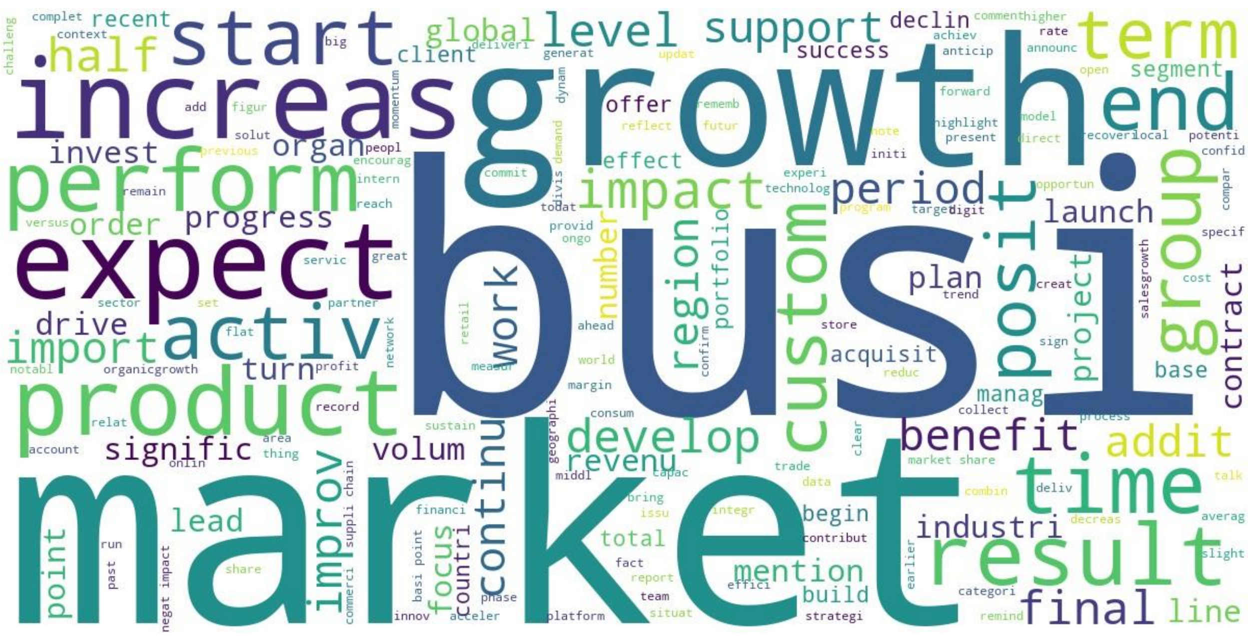

Figure 3. Visualization of eight topics in sales calls from LDA

This figure is a screenshot from an interactive html file generated from pyLDAvis after running LDA, which provides a visual representation of eight topics identified within the presentation sections of 2,362 sales call transcripts. The visualization illustrates the relationships between these topics and their respective word distributions. On the left side, the proximity of circles on the Intertopic Distance Map reflects the similarity between topics. On the right side, the figure displays the top 30 most frequent words across all transcripts.

Figure 4. Word clouds for eight topics identified in sales calls

This figure displays individual word clouds for each topic generated using LDA. The sample consists of presentation sections extracted from 2,362 sales call transcripts from public firms headquartered and traded in the same EEA countries, the United Kingdom, or Switzerland. In these word clouds, more frequent words appear larger. All words are in their lemmatized and stemmed forms.

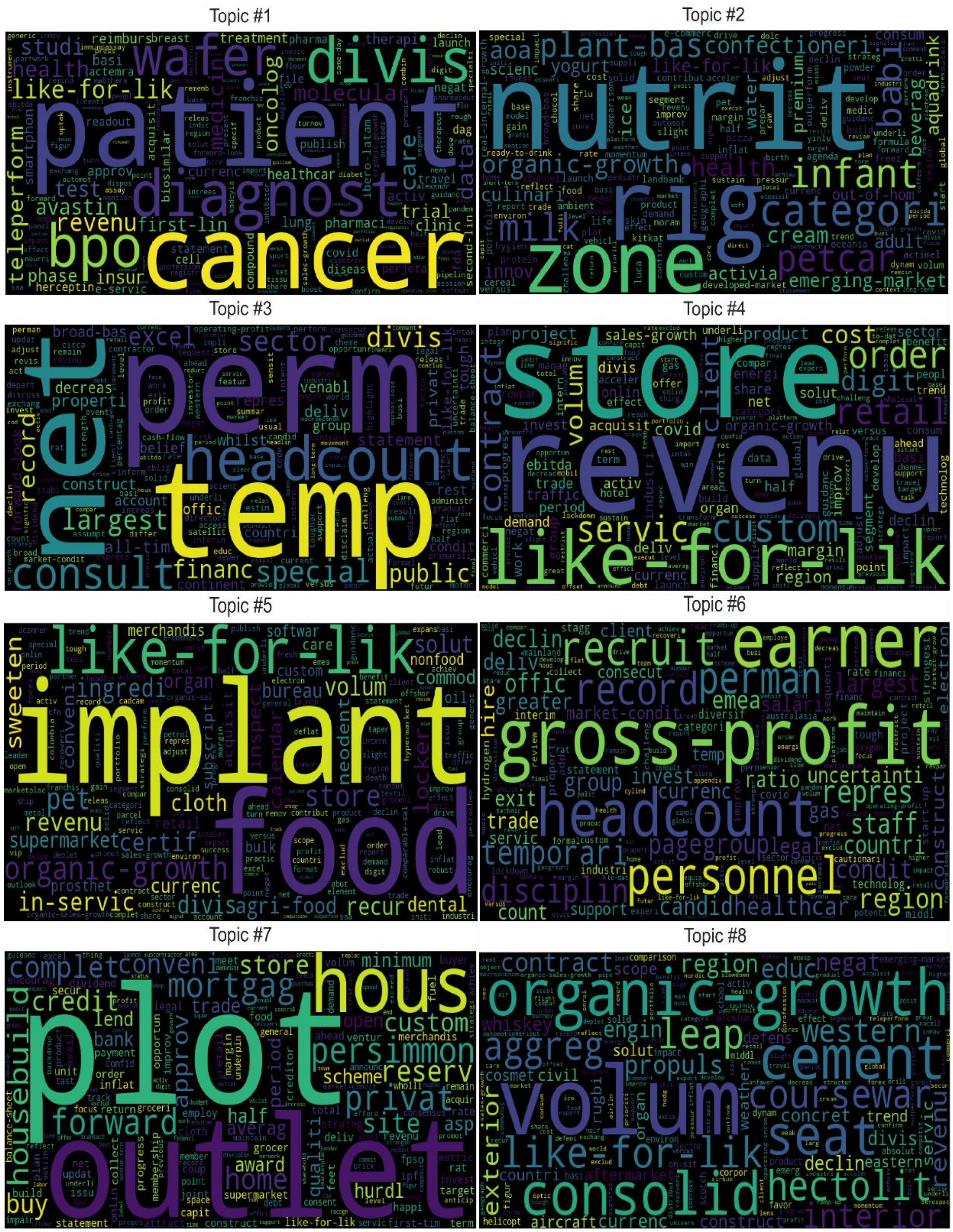

Figure 5. Relative timing between sales calls and earnings calls

This figure displays the relative timing between sales calls and their matched earnings calls conducted by the same companies from public firms headquartered and traded in the same EEA countries, the United Kingdom, or Switzerland. The x-axis represents the absolute difference in days between the date of a sales call and the date of an earnings call.

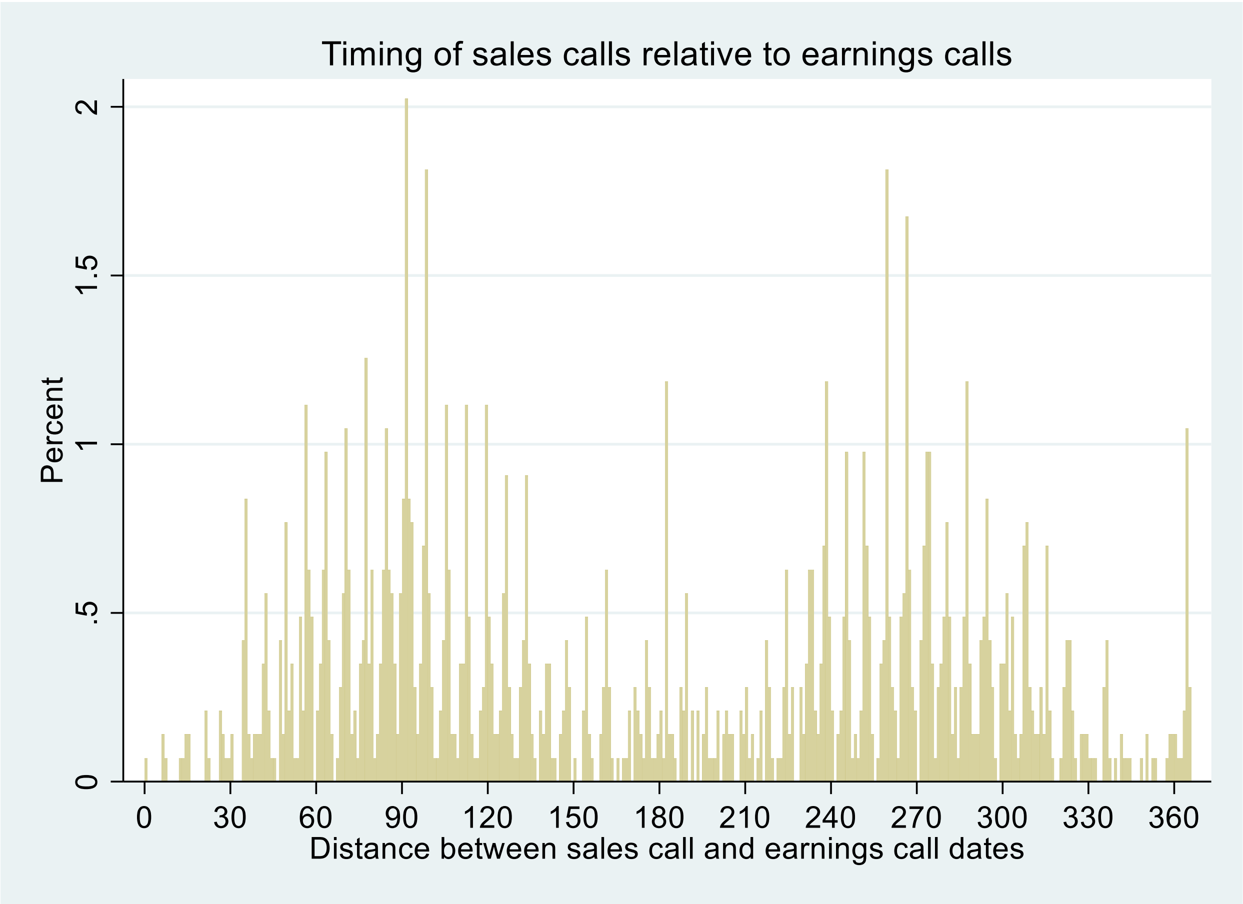

Table 1. Overall description of sales calls

Panel A and B of this table present the geographical and industry distribution of 6,655 sales calls conducted by 924 public firms around the world from 2005 to 2022. Panel C and D display the topical content of the presentation sections of 2,362 sales call transcripts from public firms headquartered and traded in the same EEA countries, the United Kingdom, or Switzerland. Specifically, Panel C presents the labels and word components for each topic identified within the sales calls. Panel D displays descriptive statistics of the topic distribution.

Panel A: Region and country of headquarters	Number of sales calls	Number of unique firms	Number of unique firm-years
EEA, UK and Switzerland	4,194	631	2,429
Country			
United Kingdom	*1,909*	*318*	*1,126*
France	*1,415*	*138*	*774*
Switzerland	*229*	*30*	*138*
Netherlands	*177*	*29*	*107*
Ireland	*97*	*11*	*56*
Italy	*90*	*17*	*48*
Belguim	*58*	*14*	*38*
Denmark	*51*	*14*	*32*
Luxembourg	*44*	*9*	*24*
Norway	*32*	*13*	*20*
Others	*92*	*38*	*66*
North America	1,912	129	346
Country			
United States	*1,899*	*117*	*334*
Canada	*13*	*12*	*12*
Other countries	549	164	353
Total	6,655	924	3,128

Panel B: Industry classification (two-digit SIC codes)			
Retail Trade	2,223	135	626
Manufacturing	2,048	327	1,083
Services	1,028	182	590
Finance, Insurance, and Real Estate	419	127	292
Transportation, Communications, Electric, Gas, and Sanitary Services	285	59	186
Wholesale Trade	227	25	101
Mining	225	44	136
Construction	180	19	104
Agriculture, Forestry, and Fishing	11	3	4
Public Administration	9	3	6
Total	6,655	924	3,128

(Continued)

Table 1 (continued)

Panel C: Topical content of sales calls

Topic number	% of tokens	Label	Top 30 frequent words
1	3.0%	Healthcare and R&D	Patient, cancer, diagnost, divis, bpo, wafer, like-for-lik, revenue, data, care, health, teleperform, studi, molecular, oncolog, test, avastin, medicin, first-lin, trial, insur, phase, pharmacy, lung, healthcar, reimburs, treatment, active, basi, therapi
2	1.9%	Product management and development	Nutrit, rig, zone, categori, infant, milk, petcar, babi, plant-bas, organic-growth, aoa, health, confectioneri, cream, emerging-market, ice, culinari, adult, like-for-lik, innov, beverag, yogurt, aquadrink, activia, premium, water, out-of-hom, consum, scienc, developed-market
3	2.0%	personnel management and compliance	Perm, temp, net, headcount, consult, special, sector, divis, largest, excel, financ, public, record, properti, all-tim, statement, deliv, privat, construct, repres, whilst, broad-bas, tough, venabl, decreas, rest, condit, forward-look, account, like-for-lik
4	83.4%	Sales operations	Revenu, store, like-for-lik, custom, order, retail, servic, contract, digit, client, volum, cost, project, margin, product, region, covid, organic-growth, currenc, period, trade, sales-growth, acquisit, half, energi, net, divis, ebitda, invest, demand
5	2.2%	Operational efficiency and compliance	Implant, food, like-for-lik, organic-growth, store, pet, sweeten, in-servic, revenu, ingredi, certif, volum, divis, locker, recur, solut, agri-food, cloth, supermarket, calendar, inspect, commod, organ, dental, conveni, bureau, neodent, currenc, prosthet, bulk
6	1.8%	Personnel recruitment and efficiency	Gross-profit, earner, headcount, personnel, recruit, record, perman, disciplin, temporari, repres, religion, staff, pagegroup, condit, healthcar, candid, offic, largest, emea, group, countri, declin, deliv, ratio, greater, uncertainti, currenc, gas, invest, construct
7	2.4%	Real estate and financing	Plot, outlet, hous, persimmon, mortgag, forward, privat, housebuild, complet, home, reserv, site, conveni, credit, store, custom, buy, approv, minimum, bank, hurdl, qualiti, lend, half, scheme, averag, asp, trade, open, award
8	3.4%	Sales growth and business development	Volum, organic-growth, cement, consolid, seat, like-fo-lik, leap, hectolit, coursewar, aggreg, interior, western, propuls, educ, exterior, revenu, contract, region, negat, engin, whiskey, divis, declin, concret, currenc, construct, servic, countri, scope, aircraft

Panel D: Summary statistics of topic distributions

Topic	Obs	Mean	SD	Min	P25	Median	P75	Max
1	2,362	0.028	0.095	0.000	0.010	0.012	0.014	0.877
2	2,362	0.017	0.055	0.000	0.010	0.012	0.014	0.886
3	2,362	0.019	0.085	0.000	0.010	0.012	0.014	0.919
4	2,362	0.820	0.217	0.011	0.865	0.911	0.928	0.957
5	2,362	0.022	0.071	0.000	0.010	0.012	0.014	0.880
6	2,362	0.018	0.066	0.000	0.010	0.012	0.014	0.891
7	2,362	0.026	0.102	0.000	0.010	0.012	0.014	0.916
8	2,362	0.035	0.120	0.000	0.010	0.012	0.014	0.926

Table 2. Determinant analysis of sales calls

This table presents the sample selection process, descriptive statistics of variables used in the determinant analysis, and empirical results of estimating regression model (1). Variable definitions are outlined in Appendix A. All continuous variables are winsorized at their 1st and 99th percentiles. Robust standard errors are presented in parentheses below the coefficients. ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively.

Panel A: Sample selection of the determinant analysis	
Total number of public European firm-year observations from 2005 to 2022	87,619
Less	
Not headquartered in EEA, United Kingdom, or Switzerland	(4,234)
Not listed on EEA, United Kingdom, or Switzerland stock exchanges	(3,091)
Headquartered and listed in different countries	(3,041)
Missing values of explanatory variables	(38,997)
Observations dropped due to fixed effects	(6,801)
Final number of firm-year observations	31,455 (3,186 firms)

Panel B: Summary statistics

	Obs	Mean	SD	P25	Median	P75
SalesCall	31,455	0.044	0.206	0.000	0.000	0.000
SalesGuid	31,455	0.062	0.241	0.000	0.000	0.000
SalesRelease	31,455	0.200	0.400	0.000	0.000	0.000
ClientProduct	31,455	0.453	0.498	0.000	0.000	1.000
BusSeg	31,455	2.098	0.797	1.609	2.197	2.708
GeoSeg	31,455	2.137	0.775	1.609	2.197	2.708
SalesGrowth	31,455	0.131	0.434	-0.029	0.063	0.182
GrossMargin	31,455	0.410	0.264	0.240	0.392	0.571
SalesVolatility	31,455	0.166	0.167	0.063	0.115	0.204
Loss	31,455	0.202	0.401	0.000	0.000	0.000
InsOwn	31,455	0.149	0.134	0.037	0.114	0.225
Size	31,455	6.189	2.291	4.481	5.962	7.721
MTB	31,455	1.179	0.587	0.753	1.078	1.495
Intangible	31,455	0.197	0.197	0.028	0.133	0.318
Beta	31,455	0.672	0.544	0.309	0.630	0.991
HHI	31,455	0.096	0.102	0.039	0.059	0.111

(Continued)

Table 2 (continued)

Panel C: Multivariate analysis

	Dependent variable—SalesCall		
	Logit	Probit	OLS
SalesGuid	0.087	0.048	-0.001
	(0.251)	(0.124)	(0.011)
SalesRelease	2.406***	1.167***	0.122***
	(0.144)	(0.064)	(0.009)
ClientProduct	0.379***	0.197***	0.009**
	(0.120)	(0.060)	(0.004)
BusSeg	-0.121	-0.058	-0.003
	(0.120)	(0.059)	(0.004)
GeoSeg	0.318**	0.157**	0.004
	(0.129)	(0.062)	(0.003)
SalesGrowth	0.148	0.104*	0.001
	(0.130)	(0.062)	(0.002)
GrossMargin	-0.132	-0.077	-0.005
	(0.324)	(0.156)	(0.007)
SalesVolatility	0.909**	0.490**	0.020**
	(0.432)	(0.202)	(0.008)
Loss	0.227*	0.127*	0.007**
	(0.137)	(0.068)	(0.003)
InsOwn	2.140***	1.070***	0.068***
	(0.599)	(0.290)	(0.019)
Size	0.505***	0.247***	0.014***
	(0.056)	(0.027)	(0.002)
MTB	0.414***	0.212***	0.010***
	(0.138)	(0.067)	(0.004)
Intangible	1.073**	0.611***	0.046***
	(0.457)	(0.213)	(0.014)
Beta	0.306***	0.174***	0.005*
	(0.099)	(0.050)	(0.003)
HHI	0.972	0.532	0.011
	(1.601)	(0.809)	(0.037)
Country, Industry, and Year FE	Y	Y	Y
Cluster	Firm	Firm	Firm
N	31,455	31,455	38,256
Pseudo R^2	0.494	0.485	
Adj. R^2			0.185

Table 3. Determinant analysis of sales calls in addition to earnings calls

This table provides a comparative analysis of factors linked to the choice to hold both sales calls and earnings calls versus holding only earnings calls. Panel A presents summary statistics for variables used in this analysis, and Panel B displays the empirical results of estimating model (2). Variable definitions are outlined in Appendix A. All continuous variables are winsorized at their 1st and 99th percentiles. Robust standard errors are presented in parentheses below the coefficients. ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively.

Panel A: Summary statistics

	Obs	Mean	SD	P25	Median	P75
BothCall	18,267	0.073	0.260	0.000	0.000	0.000
SalesGuid	18,267	0.080	0.271	0.000	0.000	0.000
SalesRelease	18,267	0.244	0.430	0.000	0.000	0.000
ClientProduct	18,267	0.569	0.495	0.000	1.000	1.000
BusSeg	18,267	2.243	0.783	1.792	2.398	2.773
GeoSeg	18,267	2.305	0.742	1.946	2.398	2.833
SalesGrowth	18,267	0.121	0.395	-0.021	0.062	0.170
GrossMargin	18,267	0.415	0.257	0.241	0.392	0.573
SalesVolatility	18,267	0.151	0.152	0.057	0.106	0.183
Loss	18,267	0.163	0.369	0.000	0.000	0.000
InsOwn	18,267	0.195	0.136	0.088	0.173	0.280
Size	18,267	7.095	2.199	5.445	7.070	8.616
MTB	18,267	1.228	0.573	0.804	1.135	1.542
Intangible	18,267	0.217	0.203	0.040	0.161	0.350
Beta	18,267	0.773	0.525	0.424	0.733	1.081
HHI	18,267	0.095	0.098	0.039	0.059	0.110

(Continued)

Table 3 (continued)

Panel B: Multivariate analysis

	Dependent variable—BothCall		
	Logit	Probit	OLS
SalesGuid	-0.008	0.009	-0.005
	(0.270)	(0.136)	(0.013)
SalesRelease	2.356***	1.194***	0.164***
	(0.148)	(0.068)	(0.013)
ClientProduct	0.226*	0.121*	0.015**
	(0.124)	(0.063)	(0.006)
BusSeg	-0.046	-0.019	-0.000
	(0.126)	(0.065)	(0.007)
GeoSeg	0.254*	0.126*	0.007
	(0.132)	(0.067)	(0.006)
SalesGrowth	0.166	0.104	0.005
	(0.139)	(0.068)	(0.004)
GrossMargin	-0.050	-0.054	-0.006
	(0.343)	(0.173)	(0.014)
SalesVolatility	0.851*	0.497**	0.034*
	(0.470)	(0.231)	(0.019)
Loss	0.298**	0.174**	0.017***
	(0.151)	(0.077)	(0.006)
InsOwn	1.621**	0.845***	0.080***
	(0.632)	(0.315)	(0.030)
Size	0.421***	0.205***	0.018***
	(0.059)	(0.029)	(0.003)
MTB	0.429***	0.228***	0.017**
	(0.143)	(0.072)	(0.007)
Intangible	1.101**	0.643***	0.066***
	(0.471)	(0.228)	(0.022)
Beta	0.284***	0.168***	0.007
	(0.106)	(0.056)	(0.005)
HHI	2.534	1.565	0.091
	(2.205)	(1.182)	(0.111)
Country, Industry, and Year FE	Y	Y	Y
Cluster	Firm	Firm	Firm
N	18,267	18,267	18,267
Pseudo R^2	0.475	0.467	
Adj. R^2			0.254

Table 4. Sales calls and analyst forecast dispersion and errors

This table reports the regression results that investigate the association between sales calls and analysts' forecast dispersion and errors for sales and EPS, as per model (3). Panel A shows summary statistics for the variables used in the regressions. For brevity, statistics are tabulated for one sample. Panel B and C present the regression results for changes in sales and EPS forecast dispersion and error, using the time windows of [-30, +10] and [-60, +60], respectively. A negative coefficient of *SalesCall* indicates a greater reduction in forecast dispersion or errors for firm years with sales calls. Variable definitions are outlined in Appendix A. All continuous variables are winsorized at their 1st and 99th percentiles. Robust standard errors are presented in parentheses below the coefficients. ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively.

Panel A. Summary statistics

	Obs	Mean	SD	P25	Median	P75
Sales dispersion						
ΔForecast	463	0.024	9.868	-0.280	0.000	0.072
SalesCall	463	0.296	0.457	0.000	0.000	1.000
PreLevel	463	21.321	54.047	0.742	3.951	14.804
ΔAge	463	-0.217	0.051	-0.260	-0.230	-0.190
PreNumAna	463	1.001	0.610	0.500	0.900	1.400
Size	463	7.114	1.193	6.241	7.243	7.831
SURP	463	0.004	0.034	-0.007	0.001	0.013
Sales errors						
ΔForecast	487	-0.100	1.964	-0.050	0.000	0.001
SalesCall	487	0.285	0.452	0.000	0.000	1.000
PreLevel	487	-0.095	13.205	-0.235	0.007	0.357
ΔAge	487	-0.218	0.051	-0.260	-0.230	-0.190
PreNumAna	487	0.957	0.626	0.400	0.800	1.400
Size	487	6.996	1.319	6.067	7.160	7.757
SURP	487	0.003	0.037	-0.007	0.001	0.013
EPS dispersion						
ΔForecast	417	-0.002	0.047	-0.001	0.000	0.000
SalesCall	417	0.314	0.465	0.000	0.000	1.000
PreLevel	417	0.132	0.220	0.005	0.025	0.154
ΔAge	417	-0.218	0.050	-0.260	-0.230	-0.190
PreNumAna	417	1.074	0.668	0.500	0.900	1.500
Size	417	7.247	1.122	6.400	7.312	7.887
SURP	417	0.006	0.175	-0.035	0.000	0.057
EPS errors						
ΔForecast	426	-0.000	0.002	-0.000	0.000	0.000
SalesCall	426	0.310	0.463	0.000	0.000	1.000
PreLevel	426	0.003	0.014	-0.001	0.001	0.004
ΔAge	426	-0.218	0.050	-0.260	-0.230	-0.190
PreNumAna	426	1.052	0.677	0.500	0.900	1.500
Size	426	7.194	1.146	6.374	7.281	7.862
SURP	426	0.008	0.179	-0.036	0.000	0.057

(Continued)

Table 4 (continued)

Panel B. OLS regressions during the window [-30, +10]

	Sales		EPS	
	(1)	(2)	(3)	(4)
Δ*Forecast*	Dispersion	Errors	Dispersion	Errors
SalesCall	-2.155*	-0.465**	-0.024**	-0.001**
	(1.186)	(0.208)	(0.010)	(0.0003)
PreLevel	-0.033*	0.032	-0.038	-0.022
	(0.019)	(0.028)	(0.043)	(0.020)
ΔAge	-7.931	0.976	0.035	-0.0004
	(7.340)	(2.175)	(0.059)	(0.002)
PreNumAna	-1.358	-0.164	-0.006	0.0002
	(1.201)	(0.165)	(0.005)	(0.0003)
Size	1.081	0.010	0.003	-0.0001
	(0.662)	(0.086)	(0.004)	(0.0002)
SURP	-7.752	-3.193	0.002	0.002**
	(20.006)	(2.673)	(0.013)	(0.001)
Country, Industry, Year FE	Y	Y	Y	Y
Cluster	Firm	Firm	Firm	Firm
N	463	487	417	426
Adj. R2	0.107	0.017	0.018	0.086

Panel C. OLS regressions during the window [-60, +60]

	Sales		EPS	
	(1)	(2)	(3)	(4)
Δ*Forecast*	Dispersion	Errors	Dispersion	Errors
SalesCall	-0.933**	-0.692***	-0.014*	-0.001*
	(0.449)	(0.197)	(0.008)	(0.0003)
PreLevel	-0.047***	0.056**	-0.082**	0.000
	(0.012)	(0.023)	(0.033)	(0.032)
ΔAge	-1.814	0.525	0.020	-0.002
	(2.256)	(0.792)	(0.028)	(0.001)
PreNumAna	-0.149	-0.083	-0.009**	-0.0001
	(0.500)	(0.153)	(0.004)	(0.0003)
Size	0.099	0.042	0.002	0.0002
	(0.236)	(0.075)	(0.004)	(0.0002)
SURP	8.354	-3.133	-0.011	0.003*
	(8.399)	(2.252)	(0.009)	(0.002)
Country, Industry, Year FE	Y	Y	Y	Y
Cluster	Firm	Firm	Firm	Firm
N	762	804	695	714
Adj. R2	0.119	0.136	0.056	0.111

Table 5. Cross-sectional variations in the association between sales calls and analyst forecast performance across different types of firms

This table presents the cross-sectional variations in the association between sales calls and analyst forecast dispersion and errors across various types of firms. Panel A and B display cross-sectional test results from regressions using total intangible assets and total assets as partitioning variables, respectively. "High" ("Low") refers to the subsamples where the values of corresponding partitioning variables are higher (lower) than the median levels. The "Difference" rows show the differences in coefficients on *SalesCall* between subsamples and the significance of these differences. Variable definitions are outlined in Appendix A. All continuous variables are winsorized at their 1st and 99th percentiles. Robust standard errors are presented in parentheses below the coefficients. ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively.

Panel A. Information asymmetry—total intangible assets

	Sales				EPS			
Δ*Forecast*	Dispersion		Errors		Dispersion		Errors	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	High	Low	High	Low	High	Low	High	Low
SalesCall	-6.016**	0.998	-0.637	0.299	-0.002	-0.039**	-0.001*	-0.00004
	(2.815)	(2.393)	(0.395)	(0.312)	(0.009)	(0.016)	(0.00046)	(0.00039)
Difference	-7.014***		-0.936***		0.037***		-0.001*	
Controls	Y	Y	Y	Y	Y	Y	Y	Y
Country, Industry, Year FE	Y	Y	Y	Y	Y	Y	Y	Y
N	225	222	235	236	205	201	210	203
Cluster	Firm	Firm	Firm	Firm	Firm	Firm	Firm	Firm
Adj. R2	-0.035	0.237	0.130	0.046	-0.066	0.072	0.074	0.207

Panel B. Firm size—total assets

	Sales				EPS			
Δ*Forecast*	Dispersion		Errors		Dispersion		Errors	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	High	Low	High	Low	High	Low	High	Low
SalesCall	-4.435**	-0.121	-0.508	-0.294	-0.035***	-0.024	-0.001*	0.0002
	(2.179)	(1.567)	(0.313)	(0.333)	(0.012)	(0.019)	(0.001)	(0.0004)
Difference	-4.314***		-0.214		-0.011		-0.001***	
Controls	Y	Y	Y	Y	Y	Y	Y	Y
Country, Industry, Year FE	Y	Y	Y	Y	Y	Y	Y	Y
N	213	240	226	253	193	216	199	220
Cluster	Firm	Firm	Firm	Firm	Firm	Firm	Firm	Firm
Adj. R2	0.019	0.202	0.163	-0.103	0.030	-0.023	0.147	0.043

Table 6. Sales call content and analyst forecast dispersion and errors

This table presents the associations between sales calls' topical content and analyst forecast performance for observations with sales call transcripts available. The independent variables related to topics represent the percentage of corresponding topics in sales calls. A negative coefficient indicates a greater improvement in forecast performance for observations with higher values of these independent variables of interest. Variable definitions are outlined in Appendix A. All continuous variables are winsorized at their 1st and 99th percentiles. Robust standard errors are presented in parentheses below the coefficients. ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively.

	Sales		EPS	
	(1)	(2)	(3)	(4)
Δ*Forecast*	Dispersion	Errors	Dispersion	Errors
Topic1	1.544	0.905	0.176	0.005
	(3.330)	(1.148)	(0.160)	(0.003)
Topic2	-129.390	-36.209	-1.458	0.140
	(145.818)	(43.334)	(3.198)	(0.092)
Topic3	-12.519**	-0.580	-0.029	-0.0001
	(5.563)	(0.683)	(0.055)	(0.001)
Topic5	-11.320	-1.158	0.005	0.003
	(7.501)	(2.322)	(0.256)	(0.004)
Topic6	5.191	0.127	-0.046	-0.002**
	(3.675)	(0.676)	(0.048)	(0.001)
Topic7	2.736	0.134	-0.034	-0.001*
	(2.563)	(0.405)	(0.051)	(0.001)
Topic8	100.823**	-0.727	0.804	-0.016
	(44.660)	(10.717)	(0.767)	(0.017)
Country, Industry, and Year FE	Y	Y	Y	Y
Cluster	Firm	Firm	Firm	Firm
N	162	162	159	159
Adj. R2	0.105	0.570	0.787	0.294

Table 7. Sales calls in addition to earnings calls and analyst forecast dispersion and errors

This table reports the results of a comparative analysis that examines the association between sales calls in addition to earnings calls and analysts' forecast dispersion and errors for sales and EPS, using model (5). A negative coefficient of *BothCall* indicates a decrease in forecast dispersion or errors for firm years with sales calls in addition to earnings calls. Variable definitions are outlined in Appendix A. All continuous variables are winsorized at their 1st and 99th percentiles. Robust standard errors are presented in parentheses below the coefficients. ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively.

	Sales		EPS	
	(1)	(2)	(3)	(4)
Forecast	Dispersion	Errors	Dispersion	Errors
BothCall	-0.004*	-0.006***	0.068	0.057*
	(0.003)	(0.002)	(0.198)	(0.029)
BusSeg	0.000	0.003**	-0.144	0.011
	(0.002)	(0.001)	(0.116)	(0.017)
GeoSeg	-0.001	-0.002	-0.265	-0.011
	(0.003)	(0.003)	(0.189)	(0.021)
SalesGrowth	0.012	0.020*	-0.451	-0.016
	(0.008)	(0.012)	(0.566)	(0.068)
GrossMargin	-0.000	-0.004	-0.159	-0.051
	(0.008)	(0.005)	(0.540)	(0.064)
SalesVolatility	0.064***	0.036***	2.248*	0.001
	(0.022)	(0.011)	(1.213)	(0.122)
Loss	0.024***	0.024***	2.493***	0.475***
	(0.005)	(0.006)	(0.503)	(0.064)
InsOwn	-0.010	-0.010	-0.681	-0.253*
	(0.012)	(0.010)	(1.224)	(0.137)
Size	0.003**	0.000	-0.058	-0.025***
	(0.001)	(0.001)	(0.073)	(0.009)
MTB	0.001	-0.005**	-0.406	-0.114***
	(0.003)	(0.002)	(0.251)	(0.021)
Intangible	-0.039***	-0.023***	-1.138*	-0.113*
	(0.009)	(0.007)	(0.665)	(0.067)
Beta	0.009**	-0.002	0.661***	0.031
	(0.003)	(0.003)	(0.228)	(0.035)
HHI	-0.007	0.040	2.325	-0.396
	(0.032)	(0.025)	(2.597)	(0.526)
Country, Industry, and Year FE	Y	Y	Y	Y
Cluster	Firm	Firm	Firm	Firm
N	13,552	17,178	13,427	16,913
Adj. R2	0.421	0.134	0.369	0.151

Table 8. Comparison in the content of sales calls and earnings calls

This table presents the descriptive statistics of the content of 566 sales calls and 1,387 matched earnings calls from the same companies. Column (5) is the t-test for testing whether the mean in (2) is significantly different from the mean in column (4). Variable definitions are specified in Appendix D.

	Sales calls		Earnings calls		T-test of Mean-Diff	
	(1) Obs	(2) Mean	(3) Obs	(4) Mean	(5) (2)-(4)	(6) T-statistic
Length						
NumWord_Pre	566	1,847	1,387	4,656	-2,808***	-27.978
NumWord_Q	566	1,062	1,387	1,088	-26	-0.911
NumWord_A	566	3,002	1,387	3,251	-249***	-2.940
NumWord_Total	566	6,048	1,387	9,081	-3,033***	-19.125
Number of participants						
NumAnalyst	566	6.443	1,387	6.253	0.190	1.134
NumExecutive	566	2.410	1,387	2.981	-0.571***	-9.134
NumMedia	566	0.023	1,387	0.012	0.011	1.509
NumTotal	566	8.880	1,387	9.249	-0.369**	-1.985
Title of executives						
CEO	566	0.744	1,387	0.748	-0.004	-0.177
CFO	566	0.922	1,387	0.770	0.152***	7.970
IRO	566	0.265	1,387	0.192	0.073***	3.596
Tone						
PosWord_Pre	565	2.367	1,386	2.130	0.237***	5.849
PosWord_Q	557	0.967	1,330	0.928	0.039*	1.677
PosWord_A	557	1.412	1,335	1.366	0.045*	1.722
NegWord_Pre	565	0.960	1,386	0.823	0.137***	5.900
NegWord_Q	557	1.796	1,330	1.705	0.090**	2.476
NegWord_A	557	1.003	1,335	0.997	0.005	0.263
NetTone_Pre	564	0.894	1,386	0.950	-0.057***	-4.581
NetTone_Q	554	0.119	1,329	0.135	-0.016	-0.914
NetTone_A	557	0.713	1,333	0.720	-0.007	-0.327

(Continued)

Table 8 (continued)

	Sales calls		Earnings calls		T-test of Mean-Diff	
	(1) Obs	(2) Mean	(3) Obs	(4) Mean	(5) (2)-(4)	(6) T-statistic
Content						
Specificity_Pre	565	5.875	1,386	5.290	0.585***	7.934
Specificity_Q	557	4.381	1,330	4.439	-0.059	-0.946
Specificity_A	557	3.643	1,335	3.326	0.316***	6.249
HardInfo_Pre	565	2.423	1,386	2.488	-0.066	-1.227
HardInfo_Q	557	1.299	1,330	1.423	-0.125***	-3.598
HardInfo_A	557	1.201	1,335	1.208	-0.006	-0.232
UncerWord_Pre	565	0.480	1,386	0.455	0.025**	2.011
UncerWord_Q	557	1.585	1,330	1.538	0.047	1.539
UncerWord_A	557	0.765	1,335	0.783	-0.017	-1.097
StromodalWord_Pre	565	0.577	1,386	0.594	-0.016	-1.201
StromodalWord_Q	557	0.317	1,330	0.366	-0.049***	-3.078
StromodalWord_A	557	0.824	1,335	0.815	0.008	0.459
WkmodalWord_Pre	565	0.197	1,386	0.182	0.015**	2.220
WkmodalWord_Q	557	1.160	1,330	1.092	0.068**	2.526
WkmodalWord_A	557	0.350	1,335	0.368	-0.017*	-1.838
ConstrainWord_Pre	565	0.113	1,386	0.130	-0.017***	-2.782
ConstrainWord_Q	557	0.075	1,330	0.085	-0.010	-1.303
ConstrainWord_A	557	0.117	1,335	0.127	-0.010*	-1.822
LitiWord_Pre	565	0.141	1386	0.149	-0.008	-0.907
LitiWord_Q	557	0.133	1,330	0.132	0.001	0.023
LitiWord_A	557	0.152	1,335	0.158	-0.006	-0.708

Table 9. Within-firm analysis of sales calls and analyst forecast dispersion and errors

This table presents the result of a within-firm analysis comparing analyst forecast performance for firm-years with and without sales calls within the same set of firms. Column (5) displays the difference in analyst sales or EPS forecast dispersion and errors between firm-years with and without sales calls. Variable definitions are outlined in Appendix A. All continuous variables are winsorized at their 1st and 99th percentiles. ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively.

With sales calls?	Yes		No		T-test of Mean-Diff	
	(1) Obs	(2) Mean	(3) Obs	(4) Mean	(5) (2)-(4)	(6) T-statistic
Sales						
ΔDispersion	284	-1.704	308	-0.589	-1.115**	2.286
ΔErrors	304	-0.860	323	-0.347	-0.513***	2.798
EPS						
ΔDispersion	284	-0.051	309	0.009	-0.059*	1.913
ΔErrors	303	-0.004	319	-0.004	0.000	0.278

Table 10. Sales calls and analyst forecast dispersion and errors—Entropy-balanced sample

This table presents the results of examining the association between sales calls and analyst forecast performance using the entropy-balanced sample. Variable definitions are outlined in Appendix A. All continuous variables are winsorized at their 1st and 99th percentiles. Robust standard errors are presented in parentheses below the coefficients. ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively.

Panel A. OLS regressions during the window [-30, +10]

	Sales		EPS	
	(1)	(2)	(3)	(4)
Δ*Forecast*	Dispersion	Errors	Dispersion	Errors
SalesCall	-2.717*	-0.514*	-0.031**	-0.000
	(1.628)	(0.267)	(0.012)	(0.000)
PreLevel	-0.022	0.005	-0.011	-0.038
	(0.023)	(0.049)	(0.053)	(0.029)
ΔAge	-5.106	0.623	0.130	-0.002
	(10.458)	(2.163)	(0.091)	(0.003)
PreNumAna	-2.531	-0.309	-0.006	0.000
	(1.884)	(0.233)	(0.010)	(0.000)
Size	1.522*	0.009	0.005	-0.000
	(0.856)	(0.127)	(0.010)	(0.000)
SURP	-14.978	0.408	0.051*	0.001
	(30.249)	(3.284)	(0.030)	(0.001)
Country, Industry, Year FE	Y	Y	Y	Y
Cluster	Firm	Firm	Firm	Firm
N	463	487	417	426
Adj. R2	0.112	0.110	0.105	0.137

Panel B. OLS regressions during the window [-60, +60]

	Sales		EPS	
	(1)	(2)	(3)	(4)
Δ*Forecast*	Dispersion	Errors	Dispersion	Errors
SalesCall	-0.954*	-0.519*	-0.014*	-0.000
	(0.533)	(0.312)	(0.009)	(0.000)
PreLevel	-0.047***	0.086**	-0.096**	-0.016
	(0.012)	(0.034)	(0.037)	(0.037)
ΔAge	-1.638	0.953	0.043	-0.001
	(2.022)	(0.863)	(0.030)	(0.001)
PreNumAna	-0.069	-0.189	-0.011*	-0.001*
	(0.651)	(0.187)	(0.006)	(0.000)
Size	0.104	0.115	0.003	0.001*
	(0.292)	(0.094)	(0.005)	(0.000)
SURP	5.801	-4.288	-0.016	0.003*
	(10.946)	(3.104)	(0.010)	(0.002)
Country, Industry, Year FE	Y	Y	Y	Y
Cluster	Firm	Firm	Firm	Firm
N	762	804	695	714
Adj. R2	0.118	0.238	0.209	0.162

Table 11. Determinant analysis of sales calls—Pre- and post-COVID-19 pandemic periods

This table presents the findings of a re-examination of the determinants of conducting sales calls with the sample period ending after and before the COVID-19 pandemic. All continuous variables are winsorized at their 1st and 99th percentiles. Robust standard errors are presented in parentheses below the coefficients. ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively.

Dependent variable—SalesCall	Sample period		
	>=2020	<2020	Full
SalesGuid	-0.239	0.174	0.086
	(0.293)	(0.278)	(0.251)
SalesRelease	2.799***	2.361***	2.408***
	(0.257)	(0.163)	(0.144)
ClientProduct	0.484***	0.360***	0.379***
	(0.183)	(0.134)	(0.120)
BusSeg	-0.031	-0.145	-0.123
	(0.116)	(0.136)	(0.120)
GeoSeg	0.232	0.346**	0.319**
	(0.150)	(0.142)	(0.129)
SalesGrowth	0.512***	-0.079	0.146
	(0.158)	(0.196)	(0.127)
GrossMargin	-0.490	-0.047	-0.120
	(0.330)	(0.362)	(0.312)
SalesVolatility	1.576**	0.787	0.954**
	(0.768)	(0.497)	(0.444)
Loss	0.334	0.190	0.226*
	(0.229)	(0.168)	(0.137)
InsOwn	1.569**	2.497***	2.132***
	(0.754)	(0.681)	(0.598)
Size	0.446***	0.536***	0.507***
	(0.063)	(0.063)	(0.056)
MTB	0.267*	0.524***	0.411***
	(0.160)	(0.156)	(0.137)
Intangible	1.805***	0.864	1.072**
	(0.491)	(0.531)	(0.455)
Beta	0.379**	0.302***	0.304***
	(0.180)	(0.116)	(0.098)
HHI	-5.569	0.983	1.808
	(6.258)	(2.407)	(1.933)
Country FE, Industry and Year FE	Y	Y	Y
Cluster	Firm	Firm	Firm
N	6,193	24,043	31,455
Pseudo R^2	0.505	0.498	0.494

Table 12. Determinant analysis of sales calls—Matched sample

This table presents results from reinvestigating the determinants of conducting sales calls in a sample where treatment and control groups are matched based on firm size, year, and industry. Column (1) displays the Logit regression results without controlling the matching variables, while Column (2) includes these controls. Variable definitions are in Appendix A. Continuous variables are winsorized at their 1st and 99th percentiles. Robust standard errors are in parentheses below the coefficients. ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively.

Dependent variable—SalesCall	(1)	(2)
SalesGuid	0.011	-0.151
	(0.425)	(0.424)
SalesRelease	2.425***	2.824***
	(0.183)	(0.212)
ClientProduct	0.374*	0.549***
	(0.199)	(0.197)
BusSeg	0.018	0.016
	(0.146)	(0.167)
GeoSeg	0.297*	0.679***
	(0.168)	(0.224)
SalesGrowth	0.456	0.360
	(0.293)	(0.349)
GrossMargin	-0.409	-0.776
	(0.602)	(0.634)
SalesVolatility	1.623**	2.139**
	(0.810)	(0.900)
Loss	0.522**	0.436*
	(0.242)	(0.250)
InsOwn	3.194***	3.827***
	(0.929)	(1.085)
Size		-0.201**
		(0.083)
MTB	0.061	0.241
	(0.228)	(0.238)
Intangible	0.660	2.432***
	(0.596)	(0.685)
Beta	0.314*	0.334**
	(0.162)	(0.164)
HHI	-0.386	-4.360**
	(0.901)	(1.984)
Country FE	Y	Y
Industry and Year FE	N	Y
Cluster	Firm	Firm
N	2,462	2,462
Pseudo R^2	0.438	0.491