A NEW TECHNIQUE FOR MEASURING A FIRM'S MARKETING EMPHASIS

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ABSTRACT

A firm's marketing emphasis is reflected in its market orientation, marketing capabilities, and marketing excellence. We propose a new large language model (LLM)-based technique that uses a firm's managers' words in earnings calls to measure its marketing emphasis and lower-order components. We demonstrate the value of our technique by measuring marketing emphasis for 254,522 firm-quarter observations and testing the measures' internal and external validity. Additionally, we show that including our marketing-emphasis scores improves machine-learning models' predictions of advertising, R&D, trade credit, sales revenue, profit, and market value. We offer three deliverables: (1) data files containing the quarterly marketing emphasis measures for 9,916 U.S. public firms observed from 2003q1 to 2023q1, (2) Python code files, and (3) a website that measures marketing emphasis in any input text or file. These deliverables enable academics, corporate managers, and policymakers to easily assess the impact of a firm's marketing emphasis on marketing theory and practice.

Keywords: market orientation, marketing capabilities, marketing excellence, marketing emphasis, earnings call transcripts, large language models, advertising, R&D, sales revenue, profit, market value, total q.

INTRODUCTION

Marketing emphasis refers to the firm's overall "philosophy of business management, based upon a company-wide acceptance of the need for customer orientation, profit orientation, and recognition of the important role of marketing in communicating the needs of the market to all major corporate departments" (McNamara, 1972, p. 51). Prior research has argued that marketing emphasis is reflected in the firm's (1) market orientation[1] (Deshpandé and Farley 1998; Kohli and Jaworski 1990; Narver and Slater 1990), (2) marketing capabilities[2] (Day 1994; Vorhies and Morgan 2005), and (3) marketing excellence[3] (Homburg, Theel, and Hohenberg 2020; Moorman and Day 2016).

Early research on this topic (Brower and Nath 2018; Kohli, Jaworski, and Kumar 1993; Narver and Slater 1990) surveyed managers to measure the three constructs. Later, the availability of firm- or CEO-generated text allowed academics to measure these constructs by the frequency of dictionary terms in the text directed at capital-market participants. For instance, Zachary et al. (2011) created five dictionaries representing Narver and Slater's (1990) five components of market orientation. Numerous studies have since used Zachary et al.'s (2011) dictionary to measure a firm's market orientation from the firm's annual reports (Bhattacharya, Misra, and Sardashti 2019; Feng, Patel, and Xiang 2020; Srivastava, Kashmiri, and Mahajan 2023) or letters to shareholders (Bhandari et al. 2020; Noble, Sinha, and Kumar 2002). The ease of use of this technique has proliferated its adoption.

This widely adopted technique for measuring a firm's marketing emphasis has two limitations. First, the mere tallying of terms in dictionaries overlooks the broader range of related

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[1] A firm's market orientation is "the organization-wide generation of market intelligence pertaining to current and future customer needs, dissemination of the intelligence across departments, and organization-wide responsiveness to it" (Kohli and Jaworski 1990, p. 6)

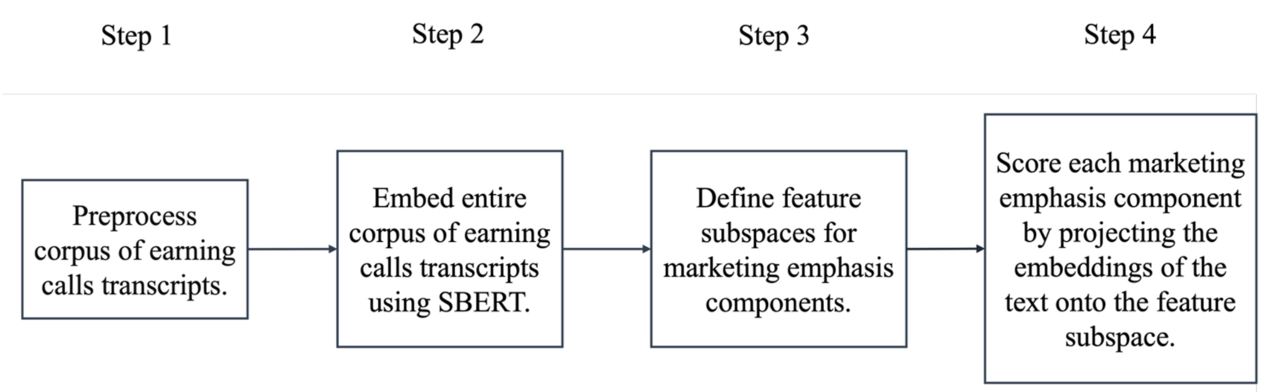
[2] "Marketing capabilities are the processes by which firms select intended value propositions for target customers and deploy resources to deliver these value offerings in pursuit of desired goals" (Morgan, Katsikeas, and Vorhies 2012, p. 273)

[3] A firm's marketing excellence as its "superior ability to perform essential customer-facing activities that improve customer, financial, stock market, and societal outcomes" (Moorman and Day 2016, p. 6)

words and phrases commonly found in the corpus, thereby neglecting the complexity and context in which these terms appear (Li, Mai, et al. 2021). Second, annual reports and letters to shareholders are often "scripted" and thus not the best source for inferring the managers' cognitions (Desjardine and Shi 2021; Martin and Kushwaha 2024; Pollock, Ragozzino, and Blevins 2024).

We propose an alternative technique that overcomes these limitations. We reason that managers' words in an earnings conference call are a more appropriate source for inferring managers' true cognitions (Crilly, Hansen, and Zollo 2016). Research on cognitive linguistics (Langacker 2001) has shown that managers' use of words—particularly when the use is subliminal, like in a real-time earnings call—is a powerful indicator of their thoughts (Crilly, Hansen, and Zollo 2016). Further, we suggest relying on semantic projection instead of tallying dictionary terms. Semantic projection leverages the power of pre-trained large language models (LLMs) to capture the meaning of the text in a dense, continuous semantic space (Grand et al. 2022; Reimers and Gurevych 2019). Our proposed technique for measuring a firm's marketing emphasis consists of four main steps (see Figure 1).

Figure 1: Our Proposed Technique



We measure the 19 lower-order components[4] of the marketing emphasis for 254,522 firm-quarter observations, spanning 9,916 distinct U.S. public firms from the first quarter of 2003 to the first quarter of 2023. Next, we check the reliability, convergent validity, and nomological validity of the obtained measures for the 19 lower-order components and the three higher-order constructs of the marketing emphasis. Lastly, we build base and augmented versions of seven machine-learning models. The augmented models include our marketing-emphasis scores. The models predict (1) advertising, (2) R&D, (3) trade credit, (4) sales revenue, (5) profit, and (6) market value. Overall, we find that including the marketing emphasis scores improves the predictive accuracy of the models, which shows our scores' managerial value.

Our deliverables aim to facilitate the use of our technique and boost our contribution to research and practice. First, we create an open-source and interactive website (https://marketing-measures.streamlit.app). Our website takes as input any textual entry—entered as a single text or a comma-separated values (CSV) file with multiple rows of text—and outputs the scores of the 19 marketing emphasis components. Second, we provide our Python code as packages that researchers can edit to measure other constructs, such as selling orientation (Kindermann et al. 2021; McKenny et al. 2018; Noble, Sinha, and Kumar 2002; Short et al. 2010). Third, we deliver two CSV data files with firm-quarter values of the marketing emphasis components and firm identifiers that allow academics to easily merge these files with external data sources. The first file contains the measured values of the 19 marketing emphasis components, calculated using managers' presentations and answers to analyst questions (i.e., our proposed measure of marketing emphasis). In the interest of completeness, we provide a second data file that contains data for *analysts'* customer orientation measured using the questions they ask. We hope these

[4] 8 components for market orientation, 8 components for marketing capabilities, and 3 components for marketing excellence.

files facilitate research that links a firm's marketing emphasis to managers' characteristics and decisions, as well as the subsequent firm performance outcomes. The Python packages and data files are available at https://marketing-measures.github.io/.

OUR PROPOSED TECHNIQUE

We propose measuring a firm's marketing emphasis in four steps: (1) parsing the earnings calls transcripts, (2) embedding the transcripts with a pre-trained LLM, (3) defining feature subspaces for the marketing emphasis constructs, and lastly, (4) scoring a firm on the 19 marketing emphasis components (see Web Appendix B).

Parsing the Transcript XML Files

The XML transcripts of quarterly earnings calls of U.S. public firms (available from Thomson Reuters, Bloomberg, SeekingAlpha.com, Factiva, and company websites) contain metadata fields and the transcripts of the earnings calls. We start by parsing the XML files to separate the metadata from the main body of the transcripts.

Embedding Earnings Call Transcripts

Our proposed technique leverages the power of language embedding and semantic projection to capture text semantics in a dense, multidimensional space. We suggest using a state-of-the-art transformer LLM, SBERT (Sentence-BERT; Reimers and Gurevych 2019). SBERT is a modification of the popular BERT (Bidirectional Encoder Representations from Transformers; Devlin et al. 2019) architecture that has been fine-tuned to derive semantically meaningful sentence embeddings.

The SBERT model overcomes BERT's limitation in the semantic textual similarity (STS) tasks, as its pre-trained transformer LLM is fine-tuned on STS tasks using supervised data. The training data consists of pairs of sentences that are labeled to be semantically relevant to each other. Once encoded, the model's weight is calibrated so that two similar texts have high cosine similarity. We use an SBERT model that is pre-trained and fine-tuned to embed each paragraph of the earnings call transcript.[5]

Defining Feature Subspaces for Marketing Emphasis Constructs

One can define a set of feature subspaces within the embedding space generated by the SBERT model to reflect the core constructs of market orientation, marketing capabilities, and marketing excellence. Each feature subspace corresponds to one of the 19 lower-order marketing emphasis components. We use the existing dictionaries in the literature to define the relevant subspaces. For example, the subspace for "customer orientation" is defined by anchor terms such as "market segment," "end user," and "clientele." Similarly, the subspace for "marketing communication capabilities" includes dictionary terms like "advertising," "promotion," and "public relations."

Once the anchor terms for each component are identified, we use SBERT to generate embedding vectors for each term. Then, the centroid of these term vectors is used as a single, representative vector for each component subspace. This centroid vector effectively captures the component's central tendency or "prototype" in the embedding space. This way, a set of theoretically grounded reference points is created, against which the embeddings of individual earnings call sentences and paragraphs can be compared. This sets the stage for measuring a firm's marketing emphasis.

Scoring a Firm on 19 Marketing Emphasis Components

With the marketing emphasis component subspaces defined, each component can be measured by the extent to which a firm's earnings call discourse aligns with the component's

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[5] Available at https://www.sbert.net/. We use the *all-mpnet-base-v2* model that has the top performance score.

subspace. This can be done by projecting the embedding vector of each sentence or paragraph onto each of the 19 component subspaces and computing the cosine similarity between the projected vector and the component centroid.

Using cosine similarity as a measure of alignment is grounded in the distributional hypothesis of word meaning (Harris 1954), which posits that words occurring in similar contexts have similar meanings. By extension, texts semantically like the words and expressions defining a subspace, are likely to reflect the corresponding marketing emphasis to a greater degree.

Computing the alignment score for each sentence-component pair provides a fine-grained, multidimensional profile of how a firm's marketing emphasis discourse maps onto the key elements of marketing emphasis sophistication. Next, the average of the alignment scores across all paragraphs in the earnings call transcript can be used to measure a firm's alignment with each component in each quarter. This approach provides a principled way to link the continuous, high-dimensional representations learned by LLMs to the discrete, categorical structures that underlie human conceptual knowledge (Grand et al. 2022; Reimers and Gurevych 2019). Thus, the approach leverages semantic projection's representational power to derive theoretically grounded, contextually sensitive measures of a firm's marketing emphasis from its public communications.

MEASURING MARKETING EMPHASIS FOR A SAMPLE OF U.S. PUBLIC FIRMS

We use firm-quarter-specific earnings call transcript data and follow the four-step procedure to apply our semantic projection approach. First, we obtain the XML transcripts of U.S. public firms' quarterly earnings calls from the FactSet Document Distributor (database) product.[6] These calls were held between January 2001, and April 2023. We write Python code to

[6] https://insight.factset.com/resources/at-a-glance-document-distributor-xml-company-events-transcript-datafeed

parse the XML files, separate the metadata from the main body, and split the Q&A section into analysts' questions and managers' answers. Second, we use the SBERT model to convert each paragraph in the corpus to a dense, 768-dimensional vector that captures the semantic meaning of the text. Third, we use the SBERT model to generate embeddings for the terms in the 19 dictionaries extracted from the literature (one dictionary per each lower-order component of the marketing emphasis). These embeddings represent the semantic subspaces corresponding to each of the 19 components. Next, we calculate the centroid of these term vectors to obtain one representative vector for each component subspace. Fourth, we calculate each marketing emphasis component as the average cosine similarity score between the embeddings of the managers' presentations, their answers to analyst questions, and the centroid of the component's subspace. These similarity scores represent the measured values of the 19 marketing emphasis components for each firm in each year-quarter. These scores comprise our proposed measure of the marketing emphasis as reflected in its 19 lower-order components.

Semantic embeddings often suffer from the anisotropic problem,[7] where vectors are unevenly distributed and tend to cluster in a narrow cone of the embedding space. This leads to high correlations between conceptually distinct components, which is particularly problematic when measuring constructs with overlapping components. To address this, we apply ZCA transformation[8] to the component-level embeddings for each of the three higher-order constructs, which de-correlates the components and mitigates redundancy.

The CSV file that contains the calculated raw and ZCA-transformed values of the 19 components for the 254,522 firm-year-quarter observations is the first deliverable of our

[7] https://arxiv.org/abs/2401.12143

[8] ZCA (Zero-phase Component Analysis) transformation is a whitening technique that decorrelates input features while preserving their original spatial structure as much as possible. It adjusts the data so that the resulting variables have unit variance and zero covariance, helping to reduce redundancy and overlap between dimensions, while preserving the components' variance and orientation, so the measures are still aligned with their original direction in embedding space.

research. Though we focus on the managers' presentations and their answers to analysts' questions, in the interest of completeness, we use *analysts' questions* in each firm-year-quarterly transcript to compute the analysts' customer orientation. We also deliver the CSV files that contain the firm-year-quarter level values of analysts' customer orientation to the users of our research. The data files and Python code packages are available at https://marketing-measures.github.io.

Reliability

Reliability is the degree to which a measure is error-free and yields consistent results (Peter 1979). In practice, reliability is often tested via Cronbach's Alpha coefficient, which examines the extent of internal consistency among construct components (Nunnally 1967; Peter 1979). Column V of Table 1 presents the results of computing Alpha for each of the three higher-order dimensions of the marketing emphasis. In short, our proposed measures show a high level of internal consistency, with Alpha values higher than the conservative .9 benchmark proposed in the literature (Greco et al. 2018; Nunnally 1978).

Convergent Validity

Convergent validity refers to the extent to which a new measure correlates strongly with existing measures of the same construct obtained from other methods (Churchill 1979). Following existing studies (Chung et al. 2022; McAlister et al. 2016), we check the convergent validity of our measures via their correlation with alternate measures of the same constructs.

We obtain alternate measures of market orientation, marketing capabilities, and marketing excellence by counting the words in (1) the earnings call transcripts and (2) each of the 19 component dictionaries extracted from the literature. For instance, a firm's customer orientation in a quarter is measured as the count of words in Zachary et al.'s (2011) customer orientation dictionary *and* the focal firm's earnings call transcript in the focal quarter. We stay consistent with our proposed technique by counting the dictionary words in the managers' (1) presentation and (2) answers to analyst questions. Extant research has extensively used this measurement method, and the measure is thus an appropriate benchmark.

Next, we check the pairwise correlations of our market orientation, capabilities, and excellence measures with their corresponding alternative (count-based) measures. Table 1's Column VI reports the correlation coefficients. We note that all three higher-order constructs have positive and significant correlations with their corresponding alternative measures, providing evidence for the convergent validity of our measures.

Table 1: Reliability and Convergent Validity Scores

Construct	List of Components	Number of Components	Average Interitem Covariance	Reliability Coefficient (Alpha)	Correlation with Alternative Measure
	II	III	IV	V	VI
Market orientation	Customer orientation Competitor orientation, Interfunctional coordination Longterm focus Profit focus Intelligence generation Intelligence dissemination Responsiveness	8	.0007	.95	.17**
Marketing capabilities	Marketing information management Marketing planning Marketing implementation Pricing Product development Channel management Marketing communication Selling	8	.0014	.98	.21**
Marketing excellence	Marketing ecosystem priority End user priority Marketing agility priority	3	.0090	.97	.21**

N = 254,522
** indicates Bonferroni-adjusted significance at 5%

Nomological Validity

Next, we examine whether a firm's marketing emphasis helps predict its *advertising intensity* in the following period. We choose advertising intensity because it is the quintessential marketing spending. We proceed in two steps.

First, we average firm-quarter-specific scores of each of the 19 components of the marketing emphasis to generate firm-year-specific values. This step leaves us with a data set of 78,876 firm-year observations, which contains 9,916 unique firms from 2003 to 2023. Next, we download data on firm-year-specific financial variables from Compustat. Merging the two data sets leaves us with 35,891 firm-year observations, spanning 3,942 firms from 2003 to 2022.

Next, we build *base* machine learning (ML) models that predict a firm's advertising intensity in the following year using the "base" features suggested by the literature. For instance, prior studies have shown that a firm's size, R&D intensity, and return on assets predict its advertising intensity (Chakravarty and Grewal 2016; Currim, Lim, and Kim 2012; Park, Chintagunta, and Suk 2019; Varma, Bommaraju, and Singh 2023). Table 2 lists the base features for predicting advertising intensity and their formulas (see Table D1 for the summary statistics and correlation coefficients).

Table 2: Variables

Note: Subscripts *i* and *t* represent firm and year, respectively

Variable	Role	Measure (Formula)	References
Advertising ($Advertising_{i,t}$)	Outcome variable	Advertising expenses divided by total revenue ($XAD_{i,t} \div REVT_{i,t}$)	Currim, Lim, and Kim (2012); Varma, Bommaraju, and Singh (2023)
R&D ($R\&D_{i,t-1}$)	Base feature	R&D expenses divided by total revenue ($XRD_{i,t-1} \div REVT_{i,t-1}$)	Currim, Lim, and Kim (2012); Varma, Bommaraju, and Singh (2023)
Firm size ($Size_{i,t-1}$)	Base feature	Logarithm of firm assets ($\ln(AT_{i,t-1})$)	Jindal (2020); Jindal and Slotegraaf (2024); Mani, Astvansh, and Antia (2023)
Profit ($ROA_{i,t-1}$)	Base feature	Net income divided by total assets ($NI_{i,t-1} \div AT_{i,t-1}$)	Han, Mittal, and Zhang (2016); Varma, Bommaraju, and Singh (2023)
Book leverage ($Leverage_{i,t-1}$)	Base feature	Long-term debt divided by total assets ($DLTT_{i,t-1} \div AT_{i,t-1}$)	Varma, Bommaraju, and Singh (2023)
Financial slack ($Slack_{i,t-1}$)	Base feature	Net cash flow divided by total assets ($OANCF_{i,t-1} \div AT_{i,t-1}$)	Varma, Bommaraju, and Singh (2023
Relative performance ($RP_{i,t-1}$)	Base feature	Difference between firm's return on investment and average industry return on investment in the focal year ($ROA_{i,t-1} - ROA_{j,t-1}$)	Han, Mittal, and Zhang (2016); Varma, Bommaraju, and Singh (2023)

We build seven ML models: (1) Ridge, (2) Lasso, (3) Elastic Net, (4) K-nearest Neighbors, (5) Decision Trees, (6) Random Forests, and (7) Gradient Boosting Regressor. We estimate each model twice: once with the variables listed in Table 2 (base model) and once with the variables in the base models plus our measures of the 19 components of the firm's marketing emphasis (augmented model). Table 3's Columns II and III report the 5-fold cross-validated mean squared error (MSE) of the base and augmented models, respectively. Column IV reports the *p* values of the paired *t*-tests that determine whether the difference in the MSE of each model's base and augmented versions is statistically significant. All seven models have a significantly lower MSE after including the 19 components of the firm's marketing emphasis.

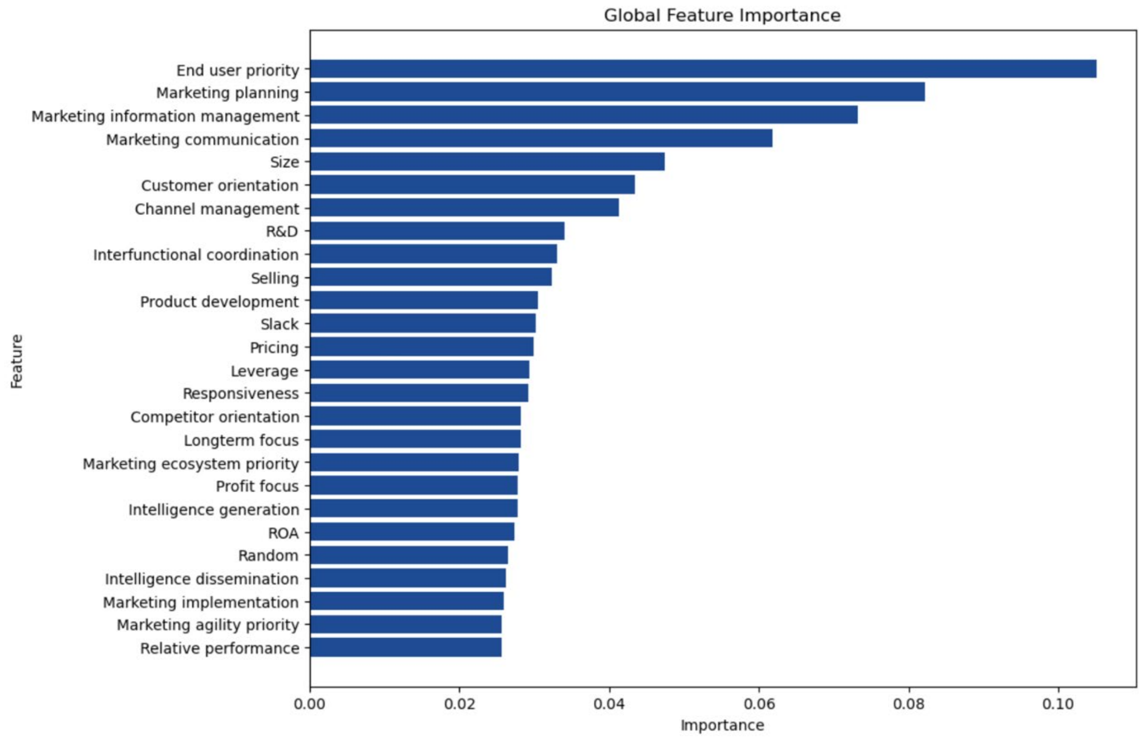
Table 3: Predictive accuracy of ML models

Outcome variable: Advertising$_{i,t}$	**Base Model MSE**	**Augmented Model MSE**	***p*-value**
	II	**III**	**IV**
Ridge	33×10^{-5}	25×10^{-5}	.015
Lasso	33×10^{-5}	27×10^{-5}	.017
Elastic Net	33×10^{-5}	26×10^{-5}	.012
K-nearest Neighbor	38×10^{-5}	28×10^{-5}	.019
Decision Trees	33×10^{-5}	27×10^{-5}	.031
Random Forests	34×10^{-5}	24×10^{-5}	.014
Gradient Boosting Regressor	32×10^{-5}	24×10^{-5}	.020
N = 35,891			

Of the seven models, we use Random Forests (the augmented ML model with the lowest cross-validated MSE) to examine the relative importance of the features. Figure 2 depicts the importance of the 25 features in descending order (19 components of the marketing emphasis plus 6 "base" features). It also shows the importance of a randomly generated feature (*Random*) that acts as a benchmark. Comparing the importance of real features with the *Random* feature shows whether the real feature's importance could be due to chance. Of the market emphasis' 19 components, four are more important than any of the existing (base) features extracted from the literature. Importantly, only four of the 19 components have an importance lower than the *Random* feature.

In summary, we find that (1) our measure of the 19 components of the marketing emphasis significantly increases the predictive accuracy of ML models built to predict advertising intensity, and (2) of the 19 components, 15 provide real (i.e., not due to chance) predictive power. Thus, we find evidence for our measures' nomological and external validity.

Figure 2: Feature Importance



We repeat this procedure for five additional outcome variables: (1) $R\&D_{i,t}$ (Compustat: $XRD_{i,t} \div REVT_{i,t}$), (2) Trade $credit_{i,t}$ (Compustat: $RECTR_{i,t} \div REVT_{i,t}$), (3) Sales $revenue_{i,t}$ (Compustat: natural logarithm of $SALE_{i,t}$), (4) $Profit_{i,t}$, and (5) Total $q_{i,t}$ (Peters and Taylor 2017). Thus, we consider all three marketing expense variables: advertising, R&D, and trade credit. Plus, we consider three quintessential firm-performance outcome variables: (1) the marketing outcome of sales revenue, (2) accounting return (i.e., profit), and (3) the financial outcome of market value (i.e., total q). Web Appendix D's Tables D2–D6 report the five-fold cross-validated accuracy results for these outcome variables. Across these five variables, the augmented models generally achieve lower MSE compared to the base models, indicating improved predictive performance after including the 19 components of marketing emphasis. This improvement is statistically significant for most models when predicting trade credit and sales revenue, with *p*-values consistently below .05. For R&D, profit, and Total q, the MSE reductions are directionally consistent but reach statistical significance in fewer models. These results suggest that the added marketing components enhance predictive accuracy, particularly for customer-facing product-market variables. Notably, the augmented random forests model achieves the lowest MSE for the majority (four out of five) of these variables.

WEBSITE

We provide an open-access interactive website (https://marketing-measures.streamlit.app). The website is developed and hosted using Streamlit.[9] The website outputs the input text's scores on each of the 19 marketing components. The input text can be provided as a single text entry (e.g., a sentence or a paragraph) or a CSV file that contains multiple rows of text. Web Appendix E describes each page.

DISCUSSION

Implications for Marketing Theory

First, a firm's marketing emphasis and its 19 lower-order components can act as mechanism variables that shed light on how events in a firm's internal and external environments shape managers' cognitions and sensemaking (Weick 1969), which in turn determine their actions. For instance, researchers can study how a firm's market orientation changes following an unfavorable incident, such as Russia's invasion of Ukraine, a takeover bid, a failed acquisition bid, a supply chain crisis, a data breach, or competitive attacks. Such events may affect a firm's marketing emphasis and its lower-order components (e.g., interfunctional coordination) and subsequently impact decisions such as myopic marketing spending or prioritizing shareholders over stakeholders.

Second, by definition, financial analysts are oriented toward capital markets. However,

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[9] https://streamlit.io/

the interlinkage between product and financial markets suggests that analysts would also be oriented toward customers, and their customer orientation may vary by firm and period. Researchers can rely on our financial analysts' customer orientation measure to explore this interfirm and intertemporal variation and empirically assess its determinants and performance consequences.

Third, marketing academics can view marketing emphasis as a CEO-specific characteristic and thus relate the heterogeneity in marketing emphasis to the characteristics of the CEO. For instance, researchers can study whether a CEO's marketing emphasis increases with their tenure with a firm or whether a higher equity component in a CEO's compensation suppresses their marketing emphasis. Further, academics have thus far not examined (to our knowledge) the conversational dynamics between the firm's officers and the analysts on an earnings call. These dynamics unfold in the Q&A section of an earnings call. Future research can rely on our deliverables to measure the match/mismatch between the marketing emphasis of an analyst's question and the manager's answer.

Fourth, market orientation is one of a firm's many strategic orientations (Noble, Sinha, and Kumar 2002). Other orientations include production orientation (Noble, Sinha, and Kumar 2002), selling orientation (Noble, Sinha, and Kumar 2002), digital orientation (Kindermann et al. 2021), and entrepreneurial orientation (McKenny et al. 2018; Short et al. 2010). Relatedly, while we provide data on managers' external focus, one could use our method to measure managers' internal focus (Yadav, Prabhu, and Chandy 2007). Future research may consider using our approach to measure these orientations/foci.

Implications for Marketing Practice

Our interactive website allows managers to measure a firm's marketing emphasis or an analyst's customer orientation via our proposed technique. Moreover, our Python codes enable researchers and more tech-savvy managers to tweak the code and calculate other firm-level measures, such as selling orientation and digital orientation (Kindermann et al. 2021; McKenny et al. 2018; Noble, Sinha, and Kumar 2002; Short et al. 2010). Last, our data files inform chief officers of the nearly 10,000 U.S. public firms how their impromptu use of words suggests their firm's market orientation, marketing capabilities, and marketing excellence.

A firm's business customers, employees, and suppliers can use our data files to measure its current market orientation, capabilities, and excellence. Low values on these constructs—particularly when measured over time and relative to industry peers—signal a lack of motivation and ability to serve customers (Martin and Kushwaha 2024). Such signals can alarm business customers, employees, and suppliers. Low marketing emphasis scores may indicate a lack of financial well-being in the longer term. Conversely, using words that suggest market orientation, superior marketing capabilities, and excellence, a firm's chief officers assure stakeholders that the firm is focused on its product market.

A firm's financial stakeholders—such as financial analysts, stock investors, and credit providers—would also value quantitative and arguably unbiased measures of a firm's marketing emphasis (Martin and Kushwaha 2024). Our proposed technique and deliverables would help these stakeholders decide which firms to bet on and predict/estimate the probability of a firm's success/failure.

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A NEW TECHNIQUE FOR MEASURING A FIRM'S MARKETING EMPHASIS

WEB APPENDICES

WEB APPENDIX A: THE LITERATURE ON MARKETING EMPHASIS

This manuscript originated from our review of the literature on how to measure a firm's marketing emphasis. This literature received a watershed moment in 1990 with Kohli and Jaworski (1990) and Narver and Slater (1990) conceptualized market orientation's components and provided scales for measuring the components.

Market orientation is a subset of the broader term strategic orientation (Noble, Sinha, and Kumar 2002). Strategic management discipline differentiates between shareholder orientation and stakeholder10 orientation, thus suggesting that a firm may focus on its shareholders or non-shareholding stakeholders, which include customers, competitors, employees, suppliers, the government, the community, and the natural environment (Bettinazzi and Zollo 2017). Consequently, literature has developed on a firm's orientation toward its product market (Kohli and Jaworski 1990; Narver and Slater 1990), supply chain (Hult et al. 2008), social responsibility (Liu, Luo, and Shi 2002), and environmental orientation (Yang and Jiang 2023).

Three scales exist to measure a firm's market orientation. Kohli and Jaworski (1990) and Narver and Slater (1990) proposed that market orientation should comprise five and three components, respectively. More specifically, Narver and Slater (1990) created 21 items to measure their five components—the three behavioral variables of customer orientation, competitor orientation, and interfunctional coordination and the two decision criteria of long-term focus and profit objective. Kohli, Jaworski, and Kumar (1993) provided 32 items to measure their three components—intelligence generation (10 items), intelligence dissemination (8 items), and responsiveness (14

[10] A firm's stakeholders are "individuals and constituencies that contribute, either voluntarily or involuntarily, to its wealth creating capacity and activities" (Post et al., 2002).

items) (see page #476 in the authors' article). Deshpandé and Farley (1998) listed 10 items to measure a firm's market orientation (see page #224).

Follow-up empirical research used all three scales while surveying key managers to self-report their ratings on each item. Specifically, Kohli, Jaworski, and Kumar's (1993) scale has been used the most often (Deshpandé, Farley, and Webster 1993; Grewal and Tansuhaj 2001; Jayachandran, Hewett, and Kaufman 2004; Kumar et al. 2011; Özturan, Özsomer, and Pieters 2014), by Narver and Slater's (1990) scale (Rindfleisch and Moorman 2003; Theoharakis and Hooley 2008).

As data on a firm's annual reports (e.g., Form 10-K in the United States) became readily available, academics replaced self-reported managerial survey data with annual reports, which are arguably a less biased source of data (Noble, Sinha, and Kumar 2002). Typically, these academics hired undergraduate students as research assistants and trained them on coding each sentence in the annual report on whether it met a specific orientation (e.g., customer orientation) (Noble, Sinha, and Kumar 2002).

This literature experienced an innovation when academics (Saboo and Grewal 2013; Yadav, Prabhu, and Chandy 2007; Zachary et al. 2011) provided dictionaries for the five components of Narver and Slater's (1990) market orientation. Follow-up research (Bhandari et al. 2020; Bhattacharya, Misra, and Sardashti 2019; Feng, Patel, and Xiang 2020; Srivastava, Kashmiri, and Mahajan 2023) has applied these dictionaries to a firm's annual report to measure its market orientation.

Parallel to the literature on market orientation grew a stream of research on marketing capabilities (Day 1994; Moorman and Slotegraaf 1999; Vorhies and Morgan 2005), and its eight components—(1) marketing information management, (2) marketing planning, (3) marketing implementation, (4) pricing, (5) product development, (6) channel management, (7) marketing communication, and (8) selling. Just like market orientation is a subset of stakeholder orientation, marketing capabilities are a subset of firm capabilities (Leonard-Barton 1992). The most recent extension to the literature came when Moorman and Day (2016) introduced the notion of marketing excellence.

The literature on marketing emphasis grew further when Homburg, Theel, & Hohenberg (2020) extended Moorman and Day’s (2016) conception of marketing excellence and differentiated it from market orientation and marketing capabilities. Homburg, Theel, and Hohenberg (2020) reasoned that a firm’s marketing capabilities and excellence can be measured through the firm’s—or its C-level officer’s—use of specific words. Consistent with this reasoning, the authors provided dictionaries of eight components of marketing capabilities and three components of marketing excellence: (1) marketing-ecosystem priority, (2) end-user priority, and (3) marketing-agility priority.

Although a dictionary of all components of market orientation became available in 2011 (Zachary et al. 2011), marketing capabilities and excellence dictionaries were introduced as recently as 2020. Specifically, Homburg, Theel, and Hohenberg (2020) contributed the dictionary of the eight components of marketing capabilities (see the table in the authors’ Web Appendix W9 on p. 20) and the three components of marketing excellence (see the article’s Table 2 on p. 14). As such, marketing capabilities and excellence measurement has lagged market orientation’s.

WEB APPENDIX B: EARNINGS CALLS

WHAT ARE EARNINGS CALLS?

What Are Earnings Calls Substantively?

A firm communicates with its stakeholders—e.g., investors, employees, customers, suppliers, and the community—through, for example, advertising, philanthropy/donation, press releases, CEO interviews with the news media, social media messages, annual reports, and earnings calls. Consistent with research in accounting (Larcker and Zakolyukina 2012), finance (Barth, Mansouri, and Woebbeking 2023), management (Desjardine and Shi 2021), and marketing (Martin and Kushwaha 2024), we reason that among these channels, an earnings call is the least scripted and thus least susceptible to the firm's management of its impressions on its stakeholders (Pollock, Ragozzino, and Blevins 2024).

An earnings call is a conference (mostly audio and typically lasting one hour) call held typically within a day of the firm's public announcement of its quarterly earnings. The call is voluntary (e.g., Berkshire Hathaway famously does not have earnings calls) but institutionally expected by the firm's shareholders. Since the U.S. SEC's enactment of Regulation Fair Disclosure in August 2000, the conference calls have been open to virtually anyone wishing to listen. A third party often manages the calls (e.g., InterCall). In practice, the conference includes the firm's "call team" at one end and participants at the other end. The call team includes the firm's CEO, CFO, two or three other C-level officers, head of investor relations, and legal counsel. In most calls, only the CEO and the CFO speak as the firm's representatives. The participants are usually sell-side financial analysts and, occasionally, institutional investors (Cohen, Lou, and Malloy 2020). Also involved is a call operator, who determines who speaks when and thus provides conversational turns.

The call comprises two sections: the 15- to 20-minute management presentation section,11 and the 30- to 45-minute question-and-answer (Q&A) section. In most calls, the presentation section is an uninterrupted monologue delivered by the CEO (and sometimes includes the CFO). The CEO presents the firm's performance in the most recently completed fiscal quarter and provides an outlook for the currently ongoing quarter (Desjardine and Bansal 2019; Desjardine and Shi 2021). The Q&A section follows the presentation section. The call team sees the names and affiliations of all participants. Whenever multiple participants raise their hands to ask a question, the software platform used for the conference call (e.g., Leader-View) shows a flag next to the participants' names. The call operator invites a participant to ask their question. The CEO (or CFO) answers the question in real-time (Brochet, Kolev, and Lerman 2018; Chen, Demers, and Lev 2018).

Finance, accounting, management, and marketing academics have sourced earnings call transcripts from Factiva's CQ FD Disclosure database (Davis et al. 2015; Desjardine and Bansal 2019), Refinitiv's Company Events Coverage (formerly Thomson Reuters' StreetEvents) database (Desjardine and Bansal 2019), Bloomberg (Desjardine and Bansal 2019), firm websites (Desjardine and Bansal 2019), and SeekingAlpha.com12 (Martin and Kushwaha 2024; Pollock, Ragozzino, and Blevins 2024).

What Are Earnings Calls Theoretically?

Two theoretical perspectives—spearheaded by finance and accounting academics and the other espoused predominantly by management academics—have determined the theoretical meaning of earnings calls.

Finance and accounting academics have framed a firm's earnings calls as voluntary

[11] Some academics (e.g., DesJardine & Bansal, 2019)refer to the section as Management Discussion & Analysis (MD&A). Others (Matsumoto et al., 2011)use the term "management presentation." We use the latter for two reasons. First, MD&A is the label of Item #7 in Form 10-K, and we prefer to avoid confusing our readers. Second, the first section of an earnings call is merely an uninterrupted presentation from the firm's managers. We thus view the terms "discussion" and "analysis" as potentially misleading.
[12] https://seekingalpha.com/earnings/earnings-call-transcripts

disclosure of information about (1) the most recent quarter's financial results and (2) project expectations about the next quarter (Brown, Hillegeist, and Lo 2004; Kimbrough and Louis 2011). This view builds on the U.S. Securities and Exchange Commission's (SEC) enactment of the Regulation for Fair Disclosure (Regulation FD) on August 24, 2000. "The regulation provides that when an issuer, or person acting on its behalf, discloses material nonpublic information to certain enumerated persons (in general, securities market professionals and holders of the issuer's securities who may well trade based on the information), it must make public disclosure of that information" (U.S. SEC., 2000). Consistent with this framing, accounting academics have documented that each section of an earnings call provides useful, incremental information over the accompanying earnings press release (Brochet, Kolev, and Lerman 2018; Matsumoto, Pronk, and Roelofsen 2011). This information improves the accuracy of analysts' forecasts (Bowen, Davis, and Matsumoto 2002), and lowers shareholders' information asymmetry (Brochet, Kolev, and Lerman 2018).

While earnings calls are conduits of "hard" information, they also provide the firm's stakeholders with "soft" information. Indeed, academics have viewed conference calls as verbal accounts or impression management opportunities for the firm's managers to influence external stakeholders' perceptions of past events. Earnings calls allow managers to (1) shift responsibility or reframe events positively, (2) provide justifications and explanations, and/or (3) provide a broader, strategic perspective on past events (Elsbach 2003; Washburn and Bromiley 2014). Interestingly, earnings calls can also cause managers to reveal new information (Brochet, Kolev, and Lerman 2018; Brown, Hillegeist, and Lo 2004).

This revelation mainly occurs when analysts ask managers to clarify statements that the managers made in the preceding presentation section and/or address issues that they may have avoided in the presentation. This personal responsibility and lack of managerial control make an earnings call riskier than other firm-generated content, such as press releases (Washburn and Bromiley 2014).

Table B1: Research that has Used Earnings Calls Transcripts to Measure Linguistic Features

Note: We use the term "managers" for a firm's C-level officers (CEO and often, CFO, and occasionally others) who speak in the call. Similarly, we use the term "analysts" for financial analysts, investors, and other stakeholders who attend the conference call. DV = Dependent variable. EV = Explanatory variable. LIWC = Linguistic Inquiry and Word Count, version 2022 (LIWC-22). I use italics to denote names of variables used in software programs, such as LIWC and Diction Software.

Citation and Journal's Discipline	Source of Raw Text	Linguistic Measure? Role of Linguistic Measure?	Measurement Method	Key Findings
Allee et al. (2021) Accounting	Managers' presentation + managers' answers	Net positivity DV	LIWC emo_pos and emo_neg {(The number of positive words – the number of negative words) ÷ total number words} × 100 Loughran and McDonald's (2011) Uncertainty The number of uncertain words ÷ total number words) × 100	The higher a firm's product-market competition, the lower the net positivity and the higher the uncertainty in managers' presentations and answers to analysts' questions.
Barth et al. (2023) Finance	Managers' answers	Nonanswers or blathering EV	Gao, Larcker, and Zakolyukina's (2021) dictionary of nonanswers + Barth, Mansouri, Woebbeking, and Zörgiebel's (2021) dictionary of blathering	A CEO's "nonanswer" answers lower their firm's stock return and raise the option's implied volatility.
Benton et al. (2022) Management	Managers' presentation	Disclosure of COVID-19 risk DV	Numerator = Number of mentions of COVID-19 or its synonyms and presence (within 10 words) of risk or uncertainty or their synonyms Denominator = Number of words in the presentation	A firm's partisanship (higher values indicate liberal ideology) raises the extent to which the firm discloses its risk due to COVID-19.
Bushee and Huang (2024) Accounting	Managers' presentation + analysts' questions + managers' answers	Obfuscation, information content EV	Information component of Gunning Fog index Obfuscation component of Gunning Fog index	Obfuscation (in MD&A and answers and both) lowers whereas information content raises (1) growth in operating income and (3) favorable revision from analysts. Neither EV impacts the inefficiency of analysts' forecasts. Obfuscation lowers CAR.

Chen et al. (2018) Accounting	Managers' presentation + analysts' questions + managers' answers	Net negativity DV	Loughran and McDonald's (2011) Negative and Positive The number of negative words − the number of positive words	As the day progresses, managers and analysts use more negative words.
Davis et al. (2015) Accounting	Managers' presentation	Positive tone and uncertainty DVs	Dictionaries from (1) Diction, (2) Loughran and McDonald (2011), and (3) Henry (2006, 2008) (The number of positive words − the number of negative words) ÷ total number of words	Meeting or beating market expectations causes the manager to use more positive words.
De Amicis et al. (2021) Finance	Managers' presentation + managers' answers + analysts' questions	Net positivity and vagueness (or uncertainty) DV	(The number of positive words – the number of negative words) ÷ total number of words The number of uncertain words ÷ total number of words Loughran and McDonald's (2011) Negative, Positive, Uncertainty	Female managers use more positive and less vague words than their male counterparts. Financial analysts use less positive and more vague words when asking female (vs. male) managers.
Desjardine and Bansal (2019) Management	Managers' presentation + analysts' questions + managers' answers	Long time-horizon DV	The number of long time-horizon words ÷ (the number of long time-horizon words + the number of short time-horizon words) Authors' dictionary	Analysts' upgrades (downgrades) raise (lowers) managers' long-term horizon.
DesJardine and Shi (2021) Management	Managers' presentation + answers	Time horizon (focus on past, present, and future) EVs	LIWC's focuspast, focuspresent, and focusfuture	Managers' time horizon moderates the effect of their current wealth on their prospective wealth.
DesJardine and Shi (2023) Management	Managers' presentation	Agency EV	Pietraszkiewicz et al.'s (2019) dictionary of agency The number of agency words ÷ total number of words	Managers' agentic value (or agency) increases the odds of the firm becoming target of a shareholder activist.
Graf-Vlachy et al. (2020) Management	Managers' answers	Cognitive complexity = differentiation + nuance + comparison DV	LIWC's differentiation dictionary. LIWC tentative dictionary + Loughran and McDonald's (2011) Weak_Modal Own dictionary for comparison	The higher a CEO's tenure with a firm, the greater their cognitive complexity.

Guo et al. (2020) Management	Unreported	Complexity and vagueness Moderator	Fog index for complexity Hiller's (2011) Communication Vagueness Dictionary	Negative surprise in a rival's earnings induces the focal firm's to raise the intensity of its competitive actions. Complexity and vagueness in the rival's earnings calls amplify these positive effects.
Guo et al. (2021) Management	Managers' answers	Newness, simplicity (obverse of complexity), and unscriptedness EV	Content words for newness Reverse coded Fog index for simplicity Function words for unscriptedness	Newness, simplicity, and unscriptedness in managers' answers are positively associated with convergence in investors' opinions of the firm.
König et al. (2018) Management	Managers' answers	Metaphorical communication = metaphor + simile + analog + metonym EV	Number of words belonging to subject, predicate, and object ÷ total number of words Manual coding	A CEO's use of metaphorical communication elicits favorable reports from journalists but unfavorable evaluations from analysts.
Larcker and Zakolyukina (2012) Accounting	Managers' answers	Deception EV	Machine learning classification based on reports from Glass, Lewis & Co.	Deception lowers annual stock return.
Lee (2016) Accounting	Managers' presentations + answers	Lack of spontaneity EV	LIWC's dictionaries of function words	Lack of spontaneity in managers' presentation and answers lowers CAR.
Lee et al. (2015) Management	CEO's presentation	Negative (overconfidence) DV	The number of negative words ÷ the number of all words, using Loughran and McDonald's (2011) Negative and Positive	Founder (vs. professional) CEO are less negative and thus more overconfident.
Li, Liu, et al. (2021) Accounting	COVID-19-related paragraphs in managers' presentation	Risk exposures, risk responses DV and mechanism	Dictionary of COVID-19 terms + Word2vec	The authors discover six types of risks that COVID-19 exposed a firm to. Each of these six types of risk lowered the firm's stock return. The primary finding is that corporate culture weakens these six negative effects. The authors propose four mechanisms, and their empirical evidence supports three: community engagement, digital transformation, and new-product development.

Li, Mai, et al. (2021) Finance	Managers' presentation	Corporate culture of innovation, integrity, quality, respect, and teamwork EV	Dictionaries of each of five dimensions of culture + Word2vec	Corporate culture of innovation raises (1) the number of patents, (2) R&D intensity, and (3) KLD score on innovation strength. Culture of integrity lowers odds of (1) restatement and (2) backdating. Culture of quality (1) raises KLD score on strengths in product quality, (2) lowers KLD score on concerns in product safety, and (3) raises odds of the firm appearing in Brand Finance's list of top 500 brands. Culture of respect raises (1) KLD's number of diversity strengths minus KLD's number of diversity concerns, and (2) the odds of the firm featuring in Fortune's list of 100 Best Company to Work for in America. Culture of teamwork raises the (1) odds of the KLD scores the firm to have strength in employee involvement and (2) the number of joint ventures and strategic alliances.
Majzoubi and Zhao (2023) Management	Analysts' questions	Heterogeneity in the topics underlying analysts' questions EV	Machine learning	Heterogeneity in analysts' questions increases the favorability of analysts' ratings.
Malhotra et al. (2018) Management	Managers' answers	Extraversion EV	Mariesse et al.'s (2007) "The Personality Recognizer," which combines machine learning on 88 dictionaries from LIWC and 14 dictionaries from the MRC Psycholinguistic database (Coltheart, 1981)	The more extraverted a firm's CEO, the higher the firm's odds of completing an M&A deal and the higher the average transaction value of a deal.
Mannor et al. (2015) Management	CEO's words in presentation + answers	Job anxiety EV	Unreported	Job anxiety lowers risk taking, manifest in R&D spending, capital expenditures, and debt.

Martin and Kushwaha (2024) Marketing	CEO's words in presentation + answers	Earnings emphasis and marketing emphasis EVs.	Three dictionaries: marketing Orientation (Zachary et al. 2011; Saboo and Grewal 2013), Marketing Capabilities (Homburg, Theel, and Hohenberg 2020) and Marketing Excellence (Homburg, Theel, and Hohenberg 2020).	The more the CEO/CFO use words that emphasize earnings in a quarter, the more myopic the firm's marketing spending in the following quarter.
Mohr and Schumacher (2019) Management	Managers' presentation	Patriotic rhetoric and unpatriotic rhetori EVs	Authors' own dictionaries of patriotic rhetoric and unpatriotic rhetoric The number of patriotic rhetoric words ÷ (the number of patriotic rhetoric words + the number unpatriotic rhetoric words)	Patriotic rhetoric boosts ROA when the nationalist sentiment is high and impedes ROA when the firm's overseas involvement (in terms of sales and assets) is high.
Nadkarni et al. (2016) Management	Managers' presentation + answers	Past temporal depth, future temporal depth EV	Manual coding	Past (future) time horizon lowers (raises) competitive aggressiveness.
Pan et al. (2018) Management	Managers' presentation	Concreteness EV	Normalized scores of LIWC's (verb, number, and focuspast) − normalized scores of each of (adj, quantity, and focusfuture)	Concreteness in managers' presentation boosts CAR.
Park and Westphal (2013) Management	Unreported	Impression management EV	Unreported	A CEO's impression management in an earnings call that discusses lower than expected earnings has a positive effect on an observer CEO's internal attribution of the underperforming firm.
Pollock et al. (2024) Management	Managers' answers	Positivity, concreteness, certainty, and self-regard DV	Loughran and McDonald's (2011) Negative and Positive; LIWC's concrete; Loughran and McDonald's (2011) Uncertainty, and authors' own dictionary of self-focused and other-focused	A-list celebrity CEO is more likely to use words that suggest positivity, concreteness, and self-regard. No effect on certainty.
Ridge and Ingram (2017) Management	Managers' presentation	Modesty EV	Diction 6's praise and self-reference	Modesty in managers' presentation of a firm's earnings is positively associated with the firm's CAR[0,1] and ROA.

Shi and DesJardine (2022) Management	CEO's answers	CEO's implicit motives: achievement, power, and affiliation EV	LIWC's affiliation, achieve, and power	The authors' study the response of a firm targeted by activist short sellers. They report that after becoming the target of an activist short seller, the firm raises its tactical competitive actions. However, the CEO's implicit motives of achievement and power weaken the competitive intensity following targeting by an activist short seller. Affiliation does not matter.
Shi et al. (2023) Management	CEO's presentation + answers	Internal attribution Moderator	LIWC's I and we for internal attribution. Authors' own dictionary for external attribution. The number of internal attribution words ÷ (the number of internal attribution words + the number of external attribution words)	A firm's underperformance increases its number of downsizing actions. The CEO's internal attributions amplify this positive effect.
Shi et al. (2019) Management	CEO's and CFO's answers	Function words (nine types) EV	LIWC's function	The higher the match between CFO's use of function words and the CEO's similar use, the higher the CFO's salary and odds of being nominated to the board of directors.
Suslava (2021) Accounting	CEO's answers + analysts' questions	Euphemism EV	"The words classified as business or commerce euphemisms in (1) the Dictionary of Euphemisms and Other Doubletalk and (2) the Oxford Dictionary of Euphemisms" (p. 7188)	Managers' use of euphemism in their answers suppresses stock return. Analysts' use of euphemism does not impact return.
Um et al. (2022) Management	CFO's words in presentation	Function-based language incongruity EV	LIWC's emo_pos, risk, futurefocus. Gamache et al.'s (2015) promotion	A bank's CFO's use of role-incongruent language increases the number of covenants the bank includes in its debt contracts.
Vadakkepatt et al. (2022) Marketing	Unreported	Customer focus Mechanism	Yadav, Prabhu, and Chandy's [2007] customer focus dictionary	A firm's lobbying intensity lowers customer focus, which suppresses the firm's customer satisfaction score. Thus, customer focus mediates the lobbying-customer satisfaction link.

Yi et al. (2020) Management	CEO's presentation	Ingratiation = public praise of predecessor + commitment to strategic continuity Self-promotion = self-centered expression + expression of confidence EVs	Diction's activity variable for commitment to strategy continuity Diction's self-reference for self-centered expression Loughran and MacDonald's (2011) strong modal variable for expression of confidence	A new CEO's ingratiation of the former CEO and self-promotion weakens the positive effects of (1) retention of predecessor CEO as chair and (2) negative stock market reaction to the announcement of the focal CEO's appointment on the focal CEO's early dismissal.
Zyung and Shi (2022) Management	CEO's answers	Overconfidence DV	LIWC's clout variable	The more overpaid a CEO has been in their past, the more overconfident they would be in the present.

WEB APPENDIX C: TECHNICAL DETAILS OF OUR PROPOSED METHOD

WHY SBERT?

An LLM such as BERT turns a passage of text i with N tokens: $s_i = [w_1, w_2, \ldots, w_N]$, to $[\overrightarrow{[CLS]}_i, \overrightarrow{w_{i1}}, \overrightarrow{w_{i2}}, \ldots, \overrightarrow{w_{iN}}]$, where each $\overrightarrow{w_{in}}$ is a k dimensional contextual word embedding vector and $\overrightarrow{[CLS]}_i$ is the embedding vector for a token that marks the beginning of the sentence i. BERT was trained in an unsupervised way using a general corpus. As such, the model excels at many language tasks such as parsing, translation, and classification. However, an important limitation of BERT is that it does not perform well at the semantic textual similarity task (STS). That is, the model is limited in automatically measuring the meaning similarity of a pair of texts. When using the special $\overrightarrow{[CLS]}$ vector or averaging the contextual word embeddings, a BERT sentence embedding is often worse than averaging non-contextual word embeddings such as GloVe or word2vec (Reimers and Gurevych 2019).

SBERT overcomes this limitation, as its training data consists of pairs of sentences labeled semantically relevant to each other. Pairs of text passages $[s_i, s_j]$ enter a siamese network structure (i.e., two transformer language models with parameter weights constrained to be identical). The output of the siamese networks, $[\overrightarrow{[CLS]}_i, \overrightarrow{w_{i1}}, \overrightarrow{w_{i2}}, \ldots, \overrightarrow{w_{iN}}]$ and $[\overrightarrow{[CLS]}_j, \overrightarrow{w_{j1}}, \overrightarrow{w_{j2}}, \ldots, \overrightarrow{w_{jN}}]$, are averaged individually, resulting in a pair of embedding vectors $\overrightarrow{s_i}, \overrightarrow{s_j}$. Then the pair of vectors enters a softmax layer that predicts if the original passages i and j are labeled to be similar.

Dictionaries used in our Technique

We use (1) Zachary et al.'s (2011) dictionaries of Narver and Slater's (1990) five components of market orientation, (2) Homburg, Theel, and Hohenberg's (2020) dictionaries of Kohli and Jaworski's (1990) three components of market orientation, (3) Homburg, Theel, and

Hohenberg's (2020) dictionaries of Vorhies and Morgan's (2005) eight components of marketing capabilities, and (4) Homburg, Theel, and Hohenberg's (2020) dictionaries of three components of marketing excellence.

Cosine Similarity Calculation

Mathematically, let $\vec{s_i}$ denote the embedding vector for the ith paragraph in an earnings call transcript, and let $\vec{c_j}$ denote the centroid vector for the jth marketing emphasis component subspace. The alignment score between sentence i and component j can be calculated as:

$$a_{ij} = \cos(\vec{s_i}, \vec{c_j}) = \frac{\vec{s_i} \cdot \vec{c_j}}{\|\vec{s_i}\| \, \|\vec{c_j}\|}$$

Where · denotes the dot product and ‖·‖ denotes the Euclidean norm. This alignment score ranges from −1 to 1, with higher values indicating greater semantic similarity between the sentence and the component.

WEB APPENDIX D

Table D1: Summary Statistics and Pairwise Correlation Coefficients

	Mean	SD	(1)	(2)	(3)	(4)	(5)	(6)
(1) Advertising	.01	.02						
(2) R&D	.09	.21	-.03*					
(3) Size	7.25	1.99	-.01*	-.36*				
(4) ROA	.00	.15	.02*	-.61*	.42*			
(5) Leverage	.21	.18	-.04*	-.18*	.33*	.01*		
(6) Slack	.06	.12	.04*	-.63*	.41*	.80*	.05*	
(7) RP	.04	.14	.01	-.02*	.12*	.49*	-.09*	.33*
N = 35,891								

Table D2: Predictive accuracy of ML models (outcome: $R\&D_{i,t}$)

Outcome variable: $R\&D_{i,t}$	Base Model MSE	Augmented Model MSE	p-value
	II	III	IV
Ridge	13×10^{-3}	9×10^{-3}	.095
Lasso	13×10^{-3}	10×10^{-3}	.111
Elastic Net	13×10^{-3}	9×10^{-3}	.105
K-nearest Neighbor	12×10^{-3}	9×10^{-3}	.076
Decision Trees	11×10^{-3}	9×10^{-3}	.117
Random Forests	10×10^{-3}	7×10^{-3}	.074
Gradient Boosting Regressor	10×10^{-3}	7×10^{-3}	.084
N = 35,891			

Table D3: Predictive accuracy of ML models (outcome: Trade $credit_{i,t}$)

Outcome variable: Trade $credit_{i,t}$	Base Model MSE	Augmented Model MSE	p-value
	II	III	IV
Ridge	11×10^{-3}	10×10^{-3}	.035
Lasso	11×10^{-3}	10×10^{-3}	.038
Elastic Net	11×10^{-3}	10×10^{-3}	.039
K-nearest Neighbor	13×10^{-3}	11×10^{-3}	.042
Decision Trees	10×10^{-3}	9.9×10^{-3}	.102
Random Forests	11×10^{-3}	9×10^{-3}	.023
Gradient Boosting Regressor	10×10^{-3}	9×10^{-3}	.026
N = 35,891			

Table D4: Predictive accuracy of ML models (outcome: Sales revenue$_{i,t}$)

Outcome variable: Sales revenue$_{i,t}$	**Base Model MSE**	**Augmented Model MSE**	**p-value**
	II	III	IV
Ridge	46×10^{-2}	38×10^{-2}	.031
Lasso	46×10^{-2}	38×10^{-2}	.031
Elastic Net	46×10^{-2}	38×10^{-2}	.031
K-nearest Neighbor	50×10^{-2}	51×10^{-2}	.346
Decision Trees	49×10^{-2}	50×10^{-2}	.227
Random Forests	43×10^{-2}	33×10^{-2}	.021
Gradient Boosting Regressor	42×10^{-2}	37×10^{-2}	.030
N = 35,891			

Table D5: Predictive accuracy of ML models (outcome: Profit$_{i,t}$)

Outcome variable: Profit$_{i,t}$	**Base Model MSE**	**Augmented Model MSE**	**p-value**
	II	III	IV
Ridge	93×10^{-4}	90×10^{-4}	.059
Lasso	94×10^{-4}	92×10^{-4}	.054
Elastic Net	93×10^{-4}	91×10^{-4}	.056
K-nearest Neighbor	11×10^{-3}	15×10^{-3}	.058
Decision Trees	95×10^{-4}	96×10^{-4}	.141
Random Forests	93×10^{-4}	89×10^{-4}	.062
Gradient Boosting Regressor	89×10^{-4}	88×10^{-4}	.067
N = 35,891			

Table D6: Predictive accuracy of ML models (outcome: Total q$_{i,t}$)

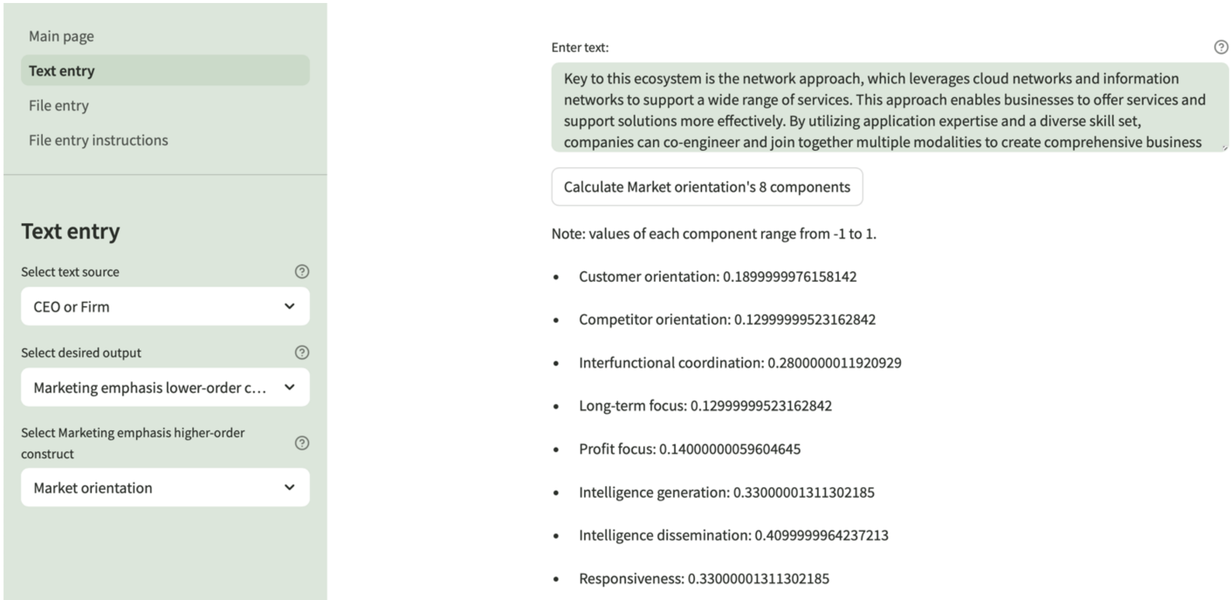
Outcome variable: Total q$_{i,t}$	**Base Model MSE**	**Augmented Model MSE**	**p-value**
	II	III	IV
Ridge	5.62	5.16	.067
Lasso	5.62	5.17	.069
Elastic Net	5.64	5.17	.071
K-nearest Neighbor	6.07	6.31	.184
Decision Trees	5.15	5.03	.102
Random Forests	5.23	4.68	.019
Gradient Boosting Regressor	4.99	4.73	.033
N = 35,891			

WEB APPENDIX E: THE WEBSITE

When a user clicks on the URL of our website, they land on the website's Main page. This page informs the user on (1) how we score the input text on the 19 marketing components and (2) the functionality of the other three pages.

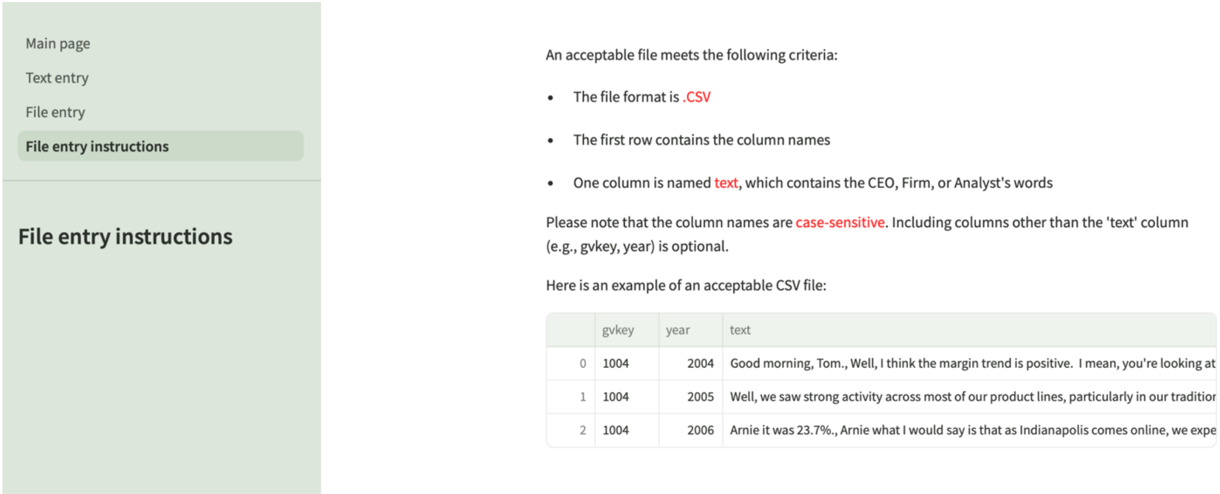
The Text entry page asks the user to input text. The page shows a sample paragraph as a default if the user inputs no text. The user can hover over the question mark next to the text input box and read the default paragraph. Next, the user specifies whether their input text is generated by a (1) CEO or Firm, or (2) Financial analyst. The user can hover over the question mark next to this selection box (or any other selection box on the website) and read about the meaning of each option. Users that choose the CEO or firm are given a further option to select their desired output: (1) Marketing emphasis or (2) Marketing emphasis lower order components. On the one hand, if the user chooses "Marketing emphasis" as the desired output, they receive the scores of the three higher-order constructs of market orientation, marketing capabilities, and marketing excellence. The scores of the three higher-order constructs are the average of their corresponding lower-order components (8 for market orientation, 8 for marketing capabilities, and 3 for marketing excellence). On the other hand, if the user chooses "Marketing emphasis' lower order components" as the desired output, they can choose one of the three higher-order constructs. For instance, a user that chooses "Marketing emphasis' lower order components" as the desired output and "Marketing capabilities" as the higher-order construct will receive the values of the eight lower-order components of market orientation (see Figure 3). Lastly, if the user chooses "Financial analyst" as the source, they will receive the analysts' customer orientation value.

Figure E1: Using the Website to Calculate the Eight Lower-Order Components of the Market Orientation Construct



The File entry page prompts the user to upload a CSV file. The user can visit the File entry instructions page to read about the acceptable format for the input file (see Figure 4). If the user does not input a file, they can still run the program with a default input CSV file, which uses sample text for three firm-year observations. The user can download the output CSV file after the program runs on the test CSV file. The user can read this information by hovering over the question mark next to the file entry button. For example, the text entry page allows the user to choose one of the following two sources for the text: (1) CEO or firm, or (2) Financial analyst. Depending on the choice of the source for the text, the user will either receive a CSV output file that contains the values of the firm's 19 lower-order components per each row of the input file or a CSV output file that contains the value of the analysts' customer orientation per each row.

Figure E2: File Entry Instructions Page



Our website targets researchers and managers who wish to use the CEO's answers in earnings calls and score the CEO/firm on one or more of the 19 marketing components. More broadly, however, managers and researchers can input the text generated by the firm or CEO in any setting other than earnings calls. In addition, users can input text from a financial analyst and measure the analyst's customer orientation.

Figure E3: Using the Website to Calculate the 19 Lower-Order Components of Marketing Emphasis for Multiple Text Entries