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ABSTRACT

We demonstrate how a novel synthesis of three methods—(1) unsupervised topic modeling of text data to generate new measures of textual variance, (2) sentiment analysis of text data, and (3) supervised ML coding of facial images with a cutting-edge convolutional neural network algorithm—can shed light on questions related to CEO oral communication. With videos and corresponding transcripts of interviews with emerging market CEOs, we employ this synthesis of methods to discover five distinct *communication styles* that incorporate both verbal and nonverbal aspects of communication. Our data are comprised of interviews that represent *unedited* expressions and content, making them especially suitable as data sources for the measurement of an individual's communication style. We then perform a proof-of-concept analysis, correlating CEO communication styles to M&A outcomes, highlighting the value of combining text and videographic data to define styles. We also discuss the benefits of using our methods versus current research methods.

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1. INTRODUCTION

With the advent of empirical techniques based on machine learning (ML), research in social sciences is arguably at an inflection point (Athey, forthcoming). Recent papers in economics—such as Mullainathan and Spiess (2017) and Kleinberg et al. (2017)—have demonstrated the usefulness of empirical predictive techniques that build on machine learning concepts. Machine learning techniques have been shown to be particularly helpful in analyzing new sources of "big data" that previously have been underutilized for research, such as large textual archives (Antweiler and Frank, 2004) and repositories of images (Glaeser et al., 2018). More broadly, research across several fields within management has started to embrace big data and text/image mining tools (e.g., Kaplan and Vakili, 2015; Arts, Cassiman, and Gomez, 2018; Riedl et al., 2016; Menon, Tabakovic, and Lee, 2018). In this paper, we detail a novel synthesis of ML methods for coding textual data and facial expressions to shine light on CEO oral communication. In doing so, we attempt to advance the study of CEO oral communication by: (1) synthesizing multiple methods and data related to both verbal and nonverbal aspects of communication to generate measures for a CEO's *communication style*; and (2) demonstrating the benefit of using state-of-the-art methods (e.g., a convolutional neural network method to code facial images) vis-à-vis methods currently being used in the literature (e.g., videometrics driven by human coding).

We study CEO oral communication in response to the call made by Helfat and Peteraf (2015) to study verbal language and nonverbal communication, which they highlight as important components of managerial cognitive capabilities. Communicating well is one of the most important skills in the CEO toolkit. As Bandiera et al. (2018) argue, CEOs need to create organizational alignment, and this requires significant investment in communication across a broad variety of constituencies, including persuasion of internal and external stakeholders to embrace cognitively distant opportunities (Gavetti, 2012). In prior research on CEO communication, the focus has been on content analysis of text from written communication by the CEO, using data such as CEO letters to stakeholders (Watzlawick, Bavelas, and Jackson, 1967; Salancik and Meindl, 1984; Barr, 1998; Kaplan, 2008; Gamache and McNamara, forthcoming); there is also a recent literature that analyzes transcripts of earnings conference call presentations (Pan et al., 2018). To code text-based communication, the current approach in CEO communication research is to use dictionary-based methods, such as the Linguistic Inquiry and Word Count (LIWC) software (Pan et al., 2018; Gamache and McNamara, forthcoming).

Helfat and Peteraf (2015) make a persuasive argument for why strategy scholars should study "oral language" (such as CEO oral communication) in addition to studying "language production" (such as CEO written communication). Both verbal and nonverbal aspects of CEO oral communication are related to "managerial cognitive capabilities" and appear to rely less on controlled mental processing, compared to written communication. There is also nascent empirical scholarship in the strategy and accounting literatures in analyzing CEO oral communication, that is, the analysis of what CEOs say (i.e., verbal oral communication), and their facial gestures (i.e., nonverbal oral communication) by studying videographic data (Petrenko, Aime, Ridge, and Hill, 2016; Blankespoor, Hendricks, and Miller, 2017; Hill, Petrenko, Ridge, and Aime, forthcoming). Here, the methodological tool of choice has been the "videometric" method, wherein third-party human raters are trained to code CEO expressions using psychometrically validated instruments. We instead employ a state-of-the-art convolutional neural network method to code facial expressions and use two methods to code CEO communication text: topic modeling based on unsupervised ML (the latent Dirichlet allocation or LDA model) and dictionary-based sentiment analysis.

Our first text-based method estimates unsupervised topic models through latent Dirichlet allocation (Blei, Ng, and Jordan, 2003). Topic modeling offers a systematic way of measuring the distribution of topics that describe the content of a set of documents in the form of sets of keywords (Kaplan and Vakili, 2015). Our second method of textual analysis relies on a more standard dictionary-based approach to conduct sentiment analysis. The sentiment measures in this paper are calculated using the *Syuzhet* R package (Jockers, 2017), which employs crowdsourced lexicons developed by Saif Mohammad at the National Resource Council Canada (NRC). Topic modeling and sentiment analysis enable us to analyze the content and valence of CEO oral communication. From these text-based methods, we calculate two novel measures: one indicating the *variance of sentiment* over the scope of the interview and another, *topic entropy,* indicating the diversity of semantic topics covered in the interview.

The third method employed in the paper uses supervised ML to code expressions of facial images. The underlying algorithm (to be explained in detail later) uses convolutional neural networks (Yu and Zhang, 2015) to code facial emotions. At a very high level, the image recognition process involves taking an image as an input (e.g., static frame of a CEO's face) and transforming the image into a field of weighted pixels to code eight facial emotions (*Anger*, *Contempt*, *Disgust*, *Fear*, *Happiness*, *Neutral*, *Sadness*, and *Surprise*) that have long been established as universal across cultures (Ekman and

Friesen 1971). The weights are generated by minimizing a loss/error function that compares the input image to images from a prior training set that has been coded for facial emotions.

To illustrate our methodology, we use an archive of video interviews with CEOs and founders conducted as part of Harvard Business School's "Creating Emerging Markets" project (publicly available for academic use in teaching and research). The archive consists of a collection of oral history transcripts—as well as their corresponding video recordings—of interviews with the CEOs of 69 unique organizations; the interviews were conducted from 2008 to 2018. CEOs came from a diverse set of countries, representing Asia, Africa, the Middle East, and Latin America. We used each of the CEO interview transcripts to code the variance of sentiment and topic entropy measures. We also coded the corresponding videographic material to generate facial expression scores for the eight emotions outlined earlier. Through a factor analysis, we then used our interview text sentiment scores (measures derived from the topic model of the interview texts) and our video-based facial expression sentiment variables to construct five distinct communication styles, which we label *Excitable*, *Stern*, *Dramatic, Rambling,* and *Melancholy*. Even within our highly selected sample of "star" emerging market CEOs, we find meaningful variation in CEO communication styles. We find that these five factors describe 87% of the variance among our video- and text-based variables.

For the purposes of illustration, we then engage in a proof-of-concept analysis to demonstrate the value of using our methods to synthesize text sentiments and facial expressions into CEO communication styles. The analysis employs a deductive approach in which we evaluate the suggestion from Helfat and Peteraf (2015) that firm leaders' language and oral communication are correlated with firm-level dynamic capabilities related to reconfiguration. Specifically, we collect data on acquisitions made by the CEOs' firms, a likely signal of asset reconfiguration. We conduct our analysis with both our full sample of CEOs and a subsample of 46 "active" CEOs, that is, those in our sample who were still performing the role of CEO at the time of their interviews. Our results reveal that CEOs who exhibit dramatic styles in their speech are less likely to oversee acquisitions. Our analysis also reveals the value of synthesizing textual sentiment and facial expressions into CEO communication styles, as opposed to analyzing firm-level outcomes using text and video data separately.

Finally, we compare our method to the prior methods of analyzing videographic data, and we outline the advantages of using our approach. As an example, we replicated the "videometric" method from prior work (Hill et al., forthcoming) by performing analyses using 100 human coders, and our analyses revealed a strong correlation between facial expressions coded by human coders and the state-of-the-art ML algorithm; however, as we argue later, the ML-based method has significant advantages in reducing research costs and time.

Our paper contributes to the literatures on managerial cognitive capabilities and CEO communication. By explicating our methods, we describe a new approach to operationalizing *communication styles* which, as yet, has been only suggested in the theory literature. We also demonstrate empirically the value of synthesizing multiple methods to generate CEO oral communication styles (that capture both verbal and nonverbal aspects of communication, as outlined by Helfat and Peteraf, 2015); and we compare our methods, which represent the state-of-the-art facial emotion recognition methods, to prior research methods. Most importantly, our methodological exposition opens up the possibility of strategy researchers embracing these methods and working with large repositories of textual, image, and video data across a variety of settings. Thus, the findings from our analysis are meant to illustrate the promise of our approach with ample room for future investigations.

2. CEO COMMUNICATION: PRIOR THEORY AND METHODS

The CEO arguably occupies the most central and important leadership role at any firm, as he/she is principally charged with setting firm strategy (Hambrick and Mason, 1984). One of the most important ways that a CEO might influence firm strategy is by communicating his/her ideas to internal and external stakeholders (D'Aveni and MacMillan, 1990; Lefebvre, Mason, and Lefebvre, 1997; Yadav, Prabhu, and Chandy, 2007). In fact, Bandiera et al. (2013, 2018) measure how CEOs spend their time and show that a disproportionate percentage (85%) of CEO time is spent on activities that might involve communication (e.g., activities such as meetings, public speeches, phone calls, and conference calls).

From a theoretical standpoint in the strategy literature, CEO communication has been viewed as a core managerial cognitive capability that underpins the firm-level dynamic capability of reconfiguring. In the dynamic capabilities literature, reconfiguring is instrumental in achieving strategic asset alignment and overcoming resistance to change. As Helfat et al. (2007) argue, in the face of a change in the external environment, "reconfiguring" involves the acquisition of new assets, as well as the enhancement and/or reconfiguring of existing assets through innovation. Helfat and Peteraf (2015) establish a link between CEO communication and reconfiguring, outlining several characteristics of oral communication by CEOs and their effects on individual workers and firm strategy. "The communication style of top managers in general, and the way in which they communicate a vision for the organization in particular, can inspire workers, encourage initiative, and drive entrepreneurial growth (Baum, Locke, and Kirkpatrick, 1998; Westley and Mintzberg, 1989). Managerial skill in using language, such as through impromptu talks, flow of words, and articulation in conversation, may affect worker response to change initiatives" (Helfat and Peteraf, 2015, p. 843).

The authors also distinguish between "oral language" (i.e., what the CEOs say) and "nonverbal" communication (i.e., how they say it). In fact, Helfat and Peteraf (2015) argue that nonverbal behavior such as facial expressions and gestures can convey a range of information, including a person's opinions, values, cognitive states (such as comprehension or confusion), physical states (such as fatigue), and emotions. As the authors state, CEOs can use oral language and nonverbal communication "to facilitate strategic change within organizations and drive alignment by orienting members toward common goals (Hill and Levenhagen, 1995)", (Helfat and Peteraf, 2015, p.843). Together, these verbal and nonverbal forms of expression, in addition to written communication, constitute a CEO's *communication style*.

The empirical literature in strategy has long studied the effect of CEO communication on firm-level outcomes; however, the focus has been almost entirely on the content of written communication, rather than nonverbal and/or verbal forms of expression. Yadav et al. (2007) coded CEO communication using letters to shareholders that were featured in firms' annual reports. Using these data, the authors show that certain features of CEO communication—specifically having greater internal and external focus—can have a "positive and long-term impact on how firms detect, develop, and deploy new technologies over time" (Yadav et al., 2007, p. 84). Similarly, D'Aveni and MacMillan (1990) compared senior managers' letters to shareholders during demand-decline crises for 57 bankrupt firms and 57 matched survivors. The authors found that under environmental uncertainty, not only do surviving firm CEOs pay disproportionate attention to the output environment of the firm, but their communication to shareholders also more strongly reflects these structural differences in their attention. CEO communication also has been studied in the strategy literature on cognitive frames (the lenses that are shaped by their past experiences and through which CEOs interpret external stimuli). Kaplan (2008) uses CEO letters to shareholders and content analysis to measure managerial cognition.

In fact, in our review of strategy research on CEO communication, the workhorse methodological tool has been content analysis of CEO written communication, such as the analysis of CEO letters to stakeholders (Watzlawick et al., 1967; Salancik and Meindl, 1984). A recent literature looks at the text of earnings conference call presentations (Pan et al., 2018). The method of choice in the recent literature has been the linguistic inquiry and word count (LIWC) method. As Gamache and McNamara (forthcoming) explain, LIWC contains predesigned and pre-validated dictionaries of words measuring the positive and negative emotions within the text. LIWC is one of the several other text analysis tools used in the literature, having been increasingly adopted in strategic management research (Kanze et al., 2018, Lungeanu et al., 2018, Pan et al., 2017, Crilly 2017). Using this method, the authors find that negative media reactions to the announcement of a major acquisition is correlated with the degree to which the CEO and the firm engage in subsequent acquisition activity. The authors also find that the CEOs' "temporal focus," that is, the degree to which CEO attention is directed toward the past (coded using CEO letters to shareholders and employing the LIWC method) influences how sensitive CEOs are to media coverage. In another recent paper, Pan et al. (2018) use the LIWC method to code the level of "concreteness" in the top managers' language in earnings conference call presentations; they find that the use of concrete language by CEOs is correlated with positive investor reactions.

Only very recently have strategy scholars started paying attention to coding and studying CEO oral communication using videographic data.[2] Petrenko et al. (2016) developed a "videometric" method where third-party coders viewed snippets of CEO videos of varying lengths and rated each focal CEO on narcissism using a seven-point Likert scale. Using this videometric measure, the authors report a positive correlation between narcissism and measures of corporate social responsibility (CSR). More broadly, in a working paper, Hill et al. (forthcoming, p. 2) define videometrics as a method that "uses third-party ratings of video samples to assess individuals' characteristics with psychometrically validated instruments of the measures of interest." In the accounting literature, scholars have used similar methods to code how CEOs' visual characteristics correlate to firm outcomes. Blankespoor et al. (2017) use 30-second content-filtered video clips of initial public offering (IPO) roadshow presentations to develop a measure of "investor perception" of a CEO and find that this measure is positively related to pricing at all stages of the IPO. The authors employ 900 workers on Amazon's Mechanical Turk (MTurk) to code 224 thin slices of

[2] Arguably, an important reason why researchers have neglected CEO oral communication has been the absence of methodologies hitherto that can perform "unsupervised" analysis using large datasets of CEO oral communication. In fact, Kaplan (2008) acknowledges this constraint and justifies the use of CEO written communication in her analyses by saying, "other kinds of statements by CEOs, such as those obtained through interviews or surveys, might initially appear to be attractive (data) sources, but they are impractical for larger samples of firms over long periods" (Kaplan, 2008, p. 679).

videos created from the roadshow presentations and ask MTurk workers to use a seven-point Likert scale to provide their perceptions about a CEO's competence, trustworthiness, and attractiveness after watching the CEO's roadshow presentation.[3]

Despite the burgeoning interest in utilizing videographic data, the approaches reviewed above have been limited to analyzing snippets of videos, given the constraints of human coding. Furthermore, the content of what is being communicated has been overlooked in the stand-alone videometric analysis. However, recent advances in ML techniques now present strategy scholars with a chance to push the methodological boundaries to study CEO oral communication further. In fact, given that these ML algorithms could be applied to both text and facial image data, we now have an opportunity to begin to deliver on what Helfat and Peteraf (2015) have argued for: the systematic study of both verbal and nonverbal CEO oral communication. We now outline our methods, dataset, and results.

3. A NEW APPROACH TO MEASURING COMMUNICATION STYLES

3.1. Overview

We develop an approach that synthesizes methods for coding unstructured text data from oral communication and video data from the corresponding speakers to measure communication styles. We do so in the spirit of Helfat and Peteraf (2015, p. 837), who identify verbal and nonverbal "oral language" as one of the chief inputs to a manager's cognitive capabilities; it can have a profound influence on strategic decision making. Communication styles have been analyzed in a variety of settings, from physician-to-patient interactions (Buller and Buller, 1987) to political speeches (Perloff, 2008). Although a variety of definitions exist, Norton's (1978, p. 99) is arguably the most generalizable across contexts: "The way one *verbally* and *paraverbally* interacts to signal how literal meaning should be taken, interpreted, filtered, or understood" (emphasis added).

We illustrate a general approach for coding CEO communication style, with two major aims for strategy researchers. First, because our method brings together verbal text data and nonverbal facial

[3] In the broader management field, there is a related literature of coding still images of CEO faces and linking the coded measures to firm and individual performance. Graham, Harvey, and Puri (2016) study the facial traits of CEOs using nearly 2,000 subjects and link facial characteristics to both CEO compensation and performance. In one experiment, the authors use pairs of photographs and find that subjects rate CEO faces as appearing more "competent" than non-CEO faces. Halford and Hsu (2014) employ a sample of photographs for S&P 500 CEOs and find that facial attractiveness of the CEOs, coded from the still photographs, is positively correlated with firm returns. ten Brinke and Adams (2015) code facial expressions of CEOs from still photographs and find that when the face of the CEO exhibits happiness while he/she is tendering an apology following some firm transgression, the negative returns of the firm are heightened.

expression data, we demonstrate how researchers can better understand how these two dimensions of communication interact to capture the unedited expressions of organizational leaders. Strategy researchers have begun to draw on ML methods to analyze and categorize large corpora of text data (e.g., Menon et al., 2018). However, in the context of CEO communication, text data are codified and written, representing the *edited* thoughts and views of their authors. Intent, attitudes, and views are often conveyed in nonverbal expression which, in some cases, can bring nuance to our understanding of content that is spoken and, in other cases, can contribute to surfacing a speaker's "authentic" perspective on a given matter. Therefore, our approach allows researchers to gain insight into *unedited* attitudes and feelings directly from the speaker.

Second, we *synthesize* our methods in a way that we hope can be generalized across different sources of text and video data. Specifically, we bring attention to the widespread availability of video data. Although the video data for our sample of CEOs comes from a curated online archive of video interviews, we remind researchers that large online platforms (such as YouTube) and more focused news outlets (such as TechCrunch or CNN) contain searchable video archives of CEO speeches, interviews, and other forms of communication. Given that we increasingly consume information through online videos, researchers of CEO communication should be sensitive to online video platforms as an as yet untapped data source of managerial communication. Automated transcription software and facial expression coding algorithms constitute a set of freely available tools for the analysis of such widely available data. We describe how we take advantage of these types of tools in a way that can be generalized to other sources of video and communication data.

Figure 1 reports a general roadmap summary of our methodological approach.

INSERT FIGURE 1 ABOUT HERE

The first three tracks in the flowchart represent the independent variables, or the measures we introduce to analyze the text and video: the topic model measures, which model the content of the interview text (Track A in Figure 1); the text sentiment measures (Track B in Figure 1), which represent the positive and negative sentiment reflected in the text; and the facial emotions gleaned from the video (Track C in Figure 1). Once these measures have been calculated, we use factor analysis to identify five clusters of CEO communication styles based on the text and video measures (E in Figure 1). As an illustrative example, we then examine how these inductive styles relate to the incidence of M&A transactions, represented in Track D. We describe each of these steps in detail, along with examples from our data, in the next section.

3.2. Data and Sample Description

Our input text and video data come from an archive of video interviews with organizational leaders and founders conducted as part of Harvard Business School's "Creating Emerging Markets" project. The archive consists of a collection of oral history transcripts and video recordings of interviews with the leaders of 69 unique organizations; the interviews were conducted from 2013 to 2018 by researchers at the Harvard Business School. The individuals interviewed are typically entrepreneur founders, descendants of founders, or leaders. They may not be formally designated as "CEO," but are regarded as the leaders of companies or organizations regarded as iconic in their respective countries. The dataset, when we last accessed it (on 10.15.2018) had 115 interview transcripts but only 69 of these interviews had an accompanying video given that the video making process started in 2012. Given that our analysis requires the synthesis of text and facial image data, we based our analysis on the 69 interviews starting 2012, where we had both text and video data.

Given the unstructured nature of the interview format, the discussions give unique insight into each leader's unedited thoughts and attitudes but may not be reflective of CEO communication to other key stakeholders such as Board Members, stockholders, the media, etc. The interviews ranged from 1.5 to 2 hours in length and were transcribed and approved by the leaders prior to public distribution through the archive website. The dataset also has a key limitation: because our data come from interviews with "star CEOs from emerging markets", our sample is not representative of all organizational leaders. We position therefore our analysis as a proof-of-concept study that could be generalized to other CEO populations in future research. Also, the typical participant was over the age of 60. This arguably helped reduce informant bias, given that older informants could be more frank, as their words no longer affected their career prospects (Gao et al., 2017).

Examples of the organizations that the interviewed CEOs represented are the Tata Group from India, Aramex from the Middle East, and BTG Pactual from Brazil. We included 40 organizations from Asia, 12 from Latin America, nine from the Middle East, and eight from Africa. The average interviewee was 68 years old at the time of the interview, and all video-recorded interviews occurred from 2012 to 2018.

3.3. Coding Interview Text Content: A Machine Learning Approach

3.3.1. Cleaning the Text Data

To code the verbal sentiment of CEO communication, we first obtained transcripts of the interviews with each of the 69 CEOs in our data. The interviews were, on average, 8,234 words in length, with a standard deviation of 3,458 words. A number of preprocessing steps were necessary prior to calculating our measures. In particular, we used only text that was spoken by the interviewee so that we did not simultaneously model the thoughts and opinions of the interviewer. Also, because several of the CEOs were interviewed in a language other than English (specifically, Spanish, Portuguese, or Turkish), we used the English translations of the interview transcripts as our input data. We acknowledge that this might stand as a limitation of our approach, as our model might be accounting for a translator's own interpretations of a CEO's words rather than capturing the CEO's native tongue expressions.

The question-and-answer design of an oral interview provides a natural structure by which to segment each document. Specifically, after removing the interviewer questions, we treated each response as a separate "segment" for the LDA model (described below). We also calculated the average word length of segments for each CEO (*Average Answer Length*), considering that the tendency to respond to questions with brief, to-the-point answers or rather more long-winded replies may be a defining element in communication style. We also again acknowledge a key limitation of the dataset: our data relies on CEO oral communication during semi-structured interviews with academics to conduct a proof-of-concept analysis; it is conceivable that the CEO might engage in different styles of communication with other key stakeholders.

3.3.2. Content Coding with the LDA Topic Model

Our next step was to use an unsupervised topic modeling approach to code the content of the CEOs' verbal responses. By unsupervised, we mean that the only input provided by the researchers in the topic model estimation is the overall number of topics. This approach allows the text to "speak for itself" in that the topics that emerge from the model are not influenced by what semantic subject matter the researchers might expect to find.[4] Given that the Latent Dirichlet Allocation method has been described in detail in prior strategy research (e.g., Kaplan and Vakili, 2015), we briefly summarize how the LDA algorithm generates topics from a set of documents.

The LDA model treats each document as a bag of words, meaning that the word order is not considered, and assumes an underlying random generative process in the creation of the "corpus"—

[4] This feature of the LDA method is in sharp contrast to one of the limitations of dictionary-based methods. As an example, Loughran and McDonald (2011) show that word lists developed for other disciplines "misclassify" common words in financial text.

or the set of documents being analyzed. It assumes that the collection of documents was generated by an imaginary probabilistic process, word by word, by first sampling a topic from a given document's distribution of topics and then sampling a word from that topic's word distribution. The sampling algorithm takes in the cleaned documents and then works backward, returning the most probable set of topics to have produced the given set of documents, if they had indeed been created in this imaginary way. A researcher can then infer the meaningful subjects represented by these topics and calculate the proportions of each document estimated to belong to each topic. We estimate the model on our sample of interview transcripts using the *topicmodels* package in R (Grün and Hornik, 2011).

Our final topic model for the set of transcripts contains 100 topics. This topic number was selected by triangulating across several different measures of model fit using the *ldatuning* package (please see our Online Supplement for a description of how we settled on 100 topics). The top 10 terms for each of the 100 topics can be viewed in Figure A3 in the Online Supplement. The resulting model gives an intuitive summary of the semantic subjects discussed in the body of interviews. Some of the topics appear to be industry specific, while others are more general. Topic 75, for example, clearly seems to refer to marketing and branding ("brand," "brands," "market," "consumer," "strong") while Topic 22 seems related to retail ("stores," "store," "retail," "sell," "concept"). The more general topics appear to span both work-related subjects (Topic 38, which seems to pertain to corporate boards, for example: "board," "members," "executive," "directors," "holding"), as well as personal subjects (Topic 55, seemingly about family history: "father," "brother," "grandfather," "died," "brothers"). This breadth reflects the variety of subjects encountered in the freewheeling interview format and the manner in which it provides a unique view into the thoughts of each CEO.

To generate document-level covariates from the topic model, we calculate the proportion of words belonging to each topic in each segment. As our corpus structure consists of long documents split into segments, we collapse each topic proportion back to the original document—that is, the interview transcript—by weighting by the length of each segment. The resulting covariates each have a value between zero and one, and the proportions of the 100 topics will sum to one for each interview.

3.3.3. Constructing Measures from the Topic Model: *Topic Entropy*

A central component of communication style is the tendency to stay on subject versus a penchant for bouncing between different semantic topics (Cech et al. 2015, Wang and Liu 2017). We use the LDA topic proportions to capture this tendency by calculating a Shannon entropy measure for each CEO. The measure—calculated as $-\Sigma(p_i*\log_2 p_i)$ in which each p_i represents the proportion allocated to each topic—captures the extent to which a given CEO's interview reflects attention to many different topics or is concentrated around just a few. Specifically, low values of entropy (those closer to 0) represent concentrated attention to few topics and high values represent attention to a diversity of topics. In short, entropy measures the range of information content in a body of text. We are careful not to assign a strict interpretation to what it means to exhibit high topic entropy as it could reflect an individual's tendency to bounce around different topics or a capacity to forge connections among diverse topics. Therefore, as a baseline, we suggest that higher values of entropy for an interview transcript signals a wider range of ideas and opinions, which communicates whether a CEO takes a more specialized or generalist approach to reflecting on personal and professional matters.

3.4. Coding Interview Text Sentiment: A Dictionary Approach

Sentiment analysis is an umbrella term referring to methods that measure the emotional valence of a document – i.e., the extent to which a text expresses positive or negative sentiment. These methods are usually dictionary based. The sentiment measures in this paper are calculated using the *Syuzhet* R package (Jockers, 2017), which employs crowdsourced lexicons (Mohammad & Turney, 2013). The NRC lexicons used here correspond to two sentiment categories, positive and negative.[5] The salience of 'sentiment' in organizational communication has been long theorized in the strategy and organizations literature; Neilsen and Rao (1987) view the dominant coalition in the organization (comprising the CEO) as 'producers of meaning' and other organizational members as 'consumers of meaning' with their own attributions regarding the organization, the motives of the elite, and their own needs, and sentiments. Recent literature has used measurements of sentiment to analyze how positive and negative coverage of firm behaviors affect managerial decisions (Shipilov et al., 2019, Pan et al., 2017) or to inform measures of CEO personality, which has implications for firm performance and strategic change (Harrison et al., 2019).

For each sentiment, the terms in the lexicon have binary values for association. For example, the word "abandon" is assigned negative sentiment value, while the word "ability" is given positive sentiment. This approach is somewhat crude, as it does not consider the context or word order of a phrase; but on balance, it typically performs nearly as well as more complex approaches

[5] In future work, it may be useful to develop custom dictionaries specific to the purposes of strategy researchers.

(Mohammad et al., 2013). We sum the terms associated with each of the sentiments at the sentence level and then calculate the proportion of each document dedicated to each sentiment so that the values sum to one. This suggests that the measures of negative and positive text sentiment for a document are perfectly collinear. Therefore, in our generation of communication styles, we use only the measure of *Negative Text Sentiment*.

As an example of how this process works, consider the following passage from Anu Aga's (then Chairperson of Thermax, one of India's largest energy companies) transcript:

> I don't think joining HR was difficult, but what was difficult was getting back to work after a gap of many years. I wondered how I could be away the whole day and come home late, leaving the children without me. I kept thinking, what if my children or my mother-in-law got sick and needed me? I was a bit anxious about how the other professionals in HR who had studied HR would accept me. But I must say, we had a wonderful team.

This segment would be scored with five negative words ("difficult," "gap," "late," "sick," "anxious") and two positive words ("mother," "wonderful"). If this short section was the entire interview, these sentiment values would then be converted to proportions, with a value of 0.71 for *negative* and 0.29 for *positive* (the sentiment values will always sum to one). The higher negative value reflects that the segment dwells mainly on negative sentiment (concern and anxiety about returning to work) punctuated with some positive sentiment (warm thoughts about the team).[6] Across the entire interview, the sentiment values provide a picture of the extent to which the CEO prefers to reflect on negative emotions or adopts a more positive tone—a key component of style.

Beyond the average sentiment valence reflected in these measures, an additional style component might be the tendency to vary between positive and negative verbal sentiment over the course of a conversation, an aspect of emotional expressivity (Kring et al. 1994) which may affect perceptions of leadership (Van Kleef et al. 2009, Slepian and Carr 2019). To capture this, we calculated the *Text Sentiment Variance* across the different segments for each interview. This is measured by calculating the negative text sentiment for each question response and then taking the standard deviation of these values. Higher values of text sentiment variance will reflect an inclination to swing more widely between positive and negative language over the course of the interview.

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[6] We acknowledge, however, that whether a CEO exhibits positive or negative sentiment in their interviews might also be related to variation in the settings in which they are interviewed. Our models capture and control for the time frames during which CEOs are interviewed, but not necessarily other elements of the interview setting. We also note that based on comumunication with the originators of the data collection, the settings in which the interviews took place do not vary meaningfully that we should expect there to be a major effect of the interview environment on what each interviewee says.

3.5. Coding Videographic Facial Expressions: A Machine Learning Approach

The third analytical tool employed in this paper uses supervised ML technology that takes a static facial image as input and generates as output, weights along eight facial expressions: *Anger*, *Contempt*, *Disgust*, *Fear*, *Happiness*, *Neutral*, *Sadness,* and *Surprise.* Ekman and Friesen (1971) first proposed that the human face could express seven basic emotions that persisted across world cultures—anger, disgust, fear, happiness, sadness, surprise, and contempt. An eighth category—neutral—is frequently evoked to describe the absence of emotional facial expression in the automated coding of facial expressions. The tool we use—the Microsoft Azure Computer Vision REST API—was developed by Microsoft and builds on research by Yu and Zhang (2015) and for static frame, generates weights on these eight facial expressions as part of the standard output.[7] We first describe the algorithm underlying this tool and then explain the use of the technology in detail.

3.5.1. The Convolutional Neural Network Algorithm

The Microsoft Application Program Interface (API) utilizes a version of a class of algorithms known as convolutional neural networks (Yu and Zhang, 2015). Arguably, this method is state-of-the-art and an area of active research in computer science (e.g., multimodal analysis in Chen et al., 2017). The technical details of the algorithm are vital for researchers of artificial intelligence, but for strategy researchers, we simply summarize the conceptual ideas.

A supervised neural network algorithm is implemented in three steps. In the first step, researchers employ a "training set" (frame-by-frame snapshots of a video, in our case) that is labeled according to the speaker's facial emotions. In the second step, the actual input image is transformed into a field of "weighted pixels" by using a neural network. These pixel weights are used to generate values for parameters such as "openness of the mouth," "curvature of lips," "dimples on the cheek," etc. These parameters are then used to generate "output values" for facial expressions of the input image. In the third step, the weights (on the pixels) are optimized based on minimizing a loss function/error function, where the error is coded based on the difference of the "output values" of facial expressions coded in the prior step and the "target value" of the same facial expressions. The target values of facial expressions are generated based on the same parameters used to generate the output values; however, unlike the "output values," the "target values" are based on data from the training set.

[7] Available at https://azure.microsoft.com/en-us/services/cognitive-services/emotion/.

To explain how the neural network algorithm works, we build on the rich literature in the field of computer science of employing neural net (NN) methods. As Duffner (2008) says, NN algorithms are inspired by the human brain and its capacity to perform complex tasks by means of interconnected neurons, each performing a relatively simple operation. Similar to the human brain, an NN is a trainable structure consisting of a set of interconnected "neurons," each implementing a very simple function. Collectively, the NN performs a complex classification function or approximation task.

In the case of facial image recognition algorithms, each "neuron" corresponds to a pixel in the image data. The task of the algorithm is to "read" the input image file and generate a set of "weights" to be assigned to pixels to code the parameters of interest, such as "skin color" or "openness of the mouth." As an example, skin color might indicate the existence of eyes or hair (versus rest of the face). An open mouth with dimples on the cheeks might indicate the facial expression of "happiness."

In a simple, brute-force approach, the NN algorithm could consider each pixel of the input image data and assign weights to every pixel to compute the parameters of interest and minimize the loss function (as described earlier). However, this would be a case of "over-specification" and would be computationally intractable for most image datasets (Dietterich, 1995; Mullainathan and Spiess, 2017). Instead, the NN algorithm conducts localized optimization, where pixels in a "neighborhood" are assigned weights to successively generate higher level weights. A convolutional NN algorithm builds on this principle by converting an input image into a multilayer hierarchical structure where the first layer relates to the input image, the next few layers relate to "shallow" collections of pixels, pixels are grouped based on their neighborhood (e.g., neighborhoods comprising the edges of the image, part of the nose, part of the eye, etc.), and the subsequent layers relate to "deep" explorations of distant neighborhoods covering the entire face. To summarize, the weights are iteratively chosen to minimize the loss function described earlier. Once the final weights are assigned, the algorithm generates scores for the facial expression emotions.

3.5.2. Capturing and Coding Static Frames from Videos

We use the Microsoft API, which outputs facial expression scores for a set of images with the NN algorithm described above. Before using the Microsoft tool, researchers must prepare the facial image data; if the facial image data is available as part of a video file (as in our case), this entails capturing individual static image frames from the video file. This task can be achieved by using media player applications. We use a cross-platform, open-source "VLC media player," which allows for the capture and export of static image frames from video data by using its "scene video filter" option. Settings within the VLC filter preferences can be used to adjust the number of frames extracted and their associated filenames and file types. We captured one static image frame per second of video footage and, most importantly, used only the static image frames that related to the face of the CEO. In other words, we dropped from the sample all static image frames related to the face of the interviewer and static image frames without any facial images (e.g., title frame).

It is important to note, however, that the algorithm implemented by the Microsoft API is also able to "recognize" a face amid other objects in a static image. Although seemingly an obvious innovation, this capability represents a major breakthrough in artificial intelligence image recognition technology, which makes the use of facial expression tools much more accessible across scientific fields. In effect, the ability to recognize faces removes the major barrier of having to manually crop images so that the faces contained therein are made apparent.

Once the static images are ready for use, researchers can employ the Microsoft tool to generate facial image recognition scores. To do so, they must first apply for an API key from Microsoft Cognitive Services for permission to use the Face API. A free trial and set of API keys for the Face API is available to researchers through the Microsoft Cognitive Services website.[8] Signing up for the Face API grants a single user a key that permits processing up to 30,000 static images at a rate of 20 images per minute. The API returns emotion scores for the eight facial emotions, where each emotion receives a score between zero and one, according to the algorithm developed by Microsoft. That data is reported back in a JSON file. We used SAS to collate the facial emotion scores and the frame number from the collection of JSON files.

3.5.3. Facial Expression Data Output

The data returned from the Face API assigns scores between 0 and 1 for each of eight different emotions—*Anger, Contempt, Disgust, Fear, Happiness, Neutral, Sadness,* and *Surprise*—for each image. The sum of the eight scores (for the eight emotions) for a given image is equal to 2. Therefore, a score for a given emotion can be interpreted as an indicator of the intensity of the emotion expressed relative to the other emotions that could be expressed. Because a set of images for a given interviewee represents one-second snapshots of the interviewee's video, taking the average score of *Fear*, for example, for the entire video gives a summary of the extent to which the individual on camera expressed fear. Figure 2 displays examples of static frames with the emotions recognized by

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[8] https://azure.microsoft.com/en-us/services/cognitive-services/face/.

the algorithm as having the highest scores. To assess the validity of the algorithm, in our Online Supplement, we summarize an analysis in which we compared the Face API-coded expressions to human-coded expressions for a selected set of facial images from our video data. The evidence shows that although the human coders in our sample do not align perfectly with the Face API's classification of facial expressions, there is considerable overlap. As a result, we take these results to indicate that we can treat the facial expressions coded by the Microsoft Face API with reasonable validity.

INSERT FIGURE 2 ABOUT HERE

3.6. Synthesizing Interview Content, Interview Sentiment, and Facial Expressions

3.6.1. Discovering Communication Styles through Factor Analysis

In the next step, we use the facial expression and text sentiment scores along with measures from our topic model to discover communication styles among the CEOs in our sample (Section E of Figure 1). The reasoning behind this step is that facial cues and spoken content are likely to reveal some information about the speaker's preferred mode of communicating. Much in the same way we might expect that bystanders could watch a CEO conduct a meeting and come to general agreement about whether that CEO is serious and buttoned-up, loose and informal, or expressive and excitable, we are assuming in this analysis that the sentiments expressed in the speaker's words and facial expressions will help approximate these "styles" in a way that the content of the interview cannot. We use factor analysis to discover the styles in our sample although any form of dimensionality reduction could serve a similar purpose.

3.6.2. Factor Analysis Results

In our factor analysis, we include 12 variables: the net negative text sentiment measure (*Negative Text Sentiment*), the text sentiment variance measure (*Text Sentiment Variance*), the average word length of each response (*Average Answer Length*), the topic entropy measure (*Topic Entropy*), and the eight facial emotion measures (*Anger*, *Contempt*, *Disgust*, *Fear*, *Happiness*, *Neutral*, *Sadness*, and *Surprise*). Employing the Kaiser-Guttman rule (retaining factors with an eigenvalue greater than 1), we obtain five factors constituting five different "styles."[9] We termed these five styles *Excitable*, *Stern*, *Dramatic, Rambling,* and *Melancholy* after examining the factor loadings, which are displayed in Table 1.

The first factor, *Excitable,* is defined by consistently positive language (negative loadings on both negative text sentiment and text sentiment variance), as well as an association with fearful, surprised, and happy facial expressions. Those strong in this factor display significantly fewer neutral facial expressions, which is notable, as neutral is the most dominant facial emotion overall. The second factor, which we call *Stern*, is characterized by more angry, contemptuous, and disgusted facial expressions and less facial happiness; however, this factor is also associated with more neutral faces, leading us to interpret it as a stern, no-nonsense style.

INSERT TABLE 1 ABOUT HERE

We term the third factor *Dramatic,* as its strongest associations are with such disparate facial expressions as anger, disgust, happiness, sadness, and a lack of neutral expressions. We name the fourth factor *Rambling*, as it is most strongly characterized by long answer responses with high topic entropy. This style is also associated with facial contempt and happiness. Finally, we name the fifth factor *Melancholy.* This style loads heavily on facial sadness and contempt and negatively on facial happiness and anger.

In checking the stability of the style factors, we tested whether the same or different factors are revealed when only the text-based measures—or conversely, only the video-based measures—were used. On their own, the video-based measures produce two factors that appear similar to the ultimate *Excitable* and *Melancholy* styles. The text-based measures, when used alone in the factor analysis, produce only one factor that loads heavily on the *Average Answer Length* and *Topic Entropy* measures and negatively on the *Text Sentiment Variance* measure. This factor corresponds most closely to our *Rambling* style, though this style was also characterized strongly by facial contempt and happiness, features that are not evident from the text-based factor analysis alone. In general, the observed styles do not seem to emerge fully without the inclusion of both text- and video-based measures, supporting the idea that both verbal and paraverbal communication are crucial to establishing a communication style.

[9] For an implementation of a parallel analysis and a longer discussion of the number of factors retained, please see Appendix Figure A4 in the online supplement.

4. CEO COMMUNICATION STYLES AND FIRM OUTCOMES: A PROOF-OF-CONCEPT ANALYSIS

4.1. M&A Activity and CEO Communication

To illustrate the value of synthesizing multiple methods and measures to generate CEO communication styles, we perform proof-of-concept analyses and correlate the styles to a firm-level outcome. Our choice of the firm-level outcome is driven by prior literature. Helfat and Peteraf (2015) state that managers' cognitive capabilities for language and communication are likely related to dynamic managerial capabilities for reconfiguration. In turn, as Helfat et al. (2007) argue, reconfiguration often involves "asset orchestration," that is, the selection, modification, configuration, and alignment of tangible and intangible assets. In fact, prior literature suggests that reconfiguration and asset orchestration might involve mergers and acquisitions (Capron, Dussauge, and Mitchell, 1998; Helfat and Peteraf, 2003; Teece, 2007). Given this, we choose acquisitions as the firm-level outcome variable for our analyses.

4.1.1. Firm Outcome Measures

Acquisition data was compiled using the SDC Platinum database from Thomson Reuters. Restricting our data to all U.S. and non-U.S. targets within the date range 1980 to present, we accessed every M&A transaction in which the companies run by the interviewees acted as the acquiring company, during the tenure of the CEO.[10] Once that list of transactions had been compiled, we restricted our data to the time window surrounding the interview, calculating the number of completed acquisitions in the one-, three-, and five-year windows before and after the interview date. In our subsequent analysis, we restricted our data to the set of interviewees who were acting CEOs at the time of the interview. The number of completed acquisitions ranges from zero to six, with mean values of 0.22, 0.39, and 0.59 transactions within each of the respective time periods.

4.1.2. Relationships between Styles and Completed Acquisitions

Table 2 examines the relationships between the CEOs' scores on the style factors and the number of completed acquisitions within one, three, and five years of the interview (Columns 1-3, respectively). The models estimate OLS regressions following the specification:

$$Acquisitions_i = \beta_0 + \beta_1 Excitable_i + \beta_2 Stern_i + \beta_3 Dramatic_i + \beta_4 Rambling_i + \beta_5 Melancholy_i + \beta \boldsymbol{X}_i + \varepsilon_i$$

[10] Systematic data on divestitures, which also constitute asset reconfiguration, were not readily available.

The covariate vector X_i includes gender and region indicators for Asia, Africa, and Latin America (the omitted region being the Middle East), as well as fixed effects for each year in the sample (2012-2018).

INSERT TABLE 2 ABOUT HERE

The coefficients on the styles can be interpreted as the number of additional (or fewer) completed acquisitions associated with a one standard deviation increase in that style factor score. We observe, for example, that a one standard deviation increase in the *Dramatic* score is associated with 0.26 fewer acquisitions within one year of the interview (Column 1, p = 0.14). This effect increases to 0.39 fewer acquisitions within three years (p = 0.04) and 0.56 fewer acquisitions within five years (p = 0.06). The manner in which the effect size increases with time might point to a cumulative "CEO effect;" while a one-year time frame might be subject to some noise, as the time window increases, the impact of the CEO could rise (similarly, the effect size associated with female CEOs grows over time).

Why might there be a relation between CEOs exhibiting a "dramatic" style and CEOs pursuing fewer M&A transactions? Are they less growth oriented or perhaps more likely to pursue different growth strategies? Questions such as these might be tested with larger, more robust samples (where researchers can control for fixed firm effects, endogeneity of the choice of CEO, etc.), and we employ this correlational analysis as an illustrative example of how these methods may be used in inductive theory building. While this analysis is correlational in nature and intended primarily as a proof-of-concept, we encourage readers to use it as a springboard for related work on CEO communication and strategic decision making.

4.1.3. Illustrating the Value of Synthesis

Why use the styles gleaned from the factor analysis, as opposed to the individual measures produced by the sentiment and facial analyses? Table 3 explores how the component measures perform relative to the synthesized styles. Using OLS regressions with the number of completed transactions as a dependent variable, we compare the explanatory power of the text sentiment measures (Column 1), the answer length and topic entropy measures (Column 2), the facial expression scores (Column 3), all component measures together (Column 4), and the synthesized style scores (Column 5), in turn.

INSERT TABLE 3 ABOUT HERE

The text sentiment measure has very little explanatory power on its own, with an adjusted R^2 of -0.01. The segment length and topic entropy measures perform only slightly better, with an adjusted R^2 of 0.04. The video measures explain the most variance on their own, but are difficult to interpret, with only one measure showing a meaningful relationship with the outcome (*Fear*, p = 0.06).[11] Comparing Columns 4 and 5 demonstrates why the clustered styles are useful: while the R^2 drops slightly, the adjusted R^2 rises from 0.00 to 0.09. Furthermore, the negative relationship between the firm acquisition activity and the *Dramatic* style emerges in a way that would not necessarily have been apparent from the component measures. The synthesized styles, therefore, provide us with a more intuitive and interpretable result than the component measures, with little loss of information.

5. COMPARISON TO EXTANT TEXT-BASED AND VIDEOMETRIC METHODS

In our analysis of the interview transcripts, we employ both unsupervised topic modeling and more traditional dictionary-based methods to code sentiment. We create two measures to reflect both the variance in sentiment expressed and the diversity of topics discussed, both of which we view to be relevant features of a communication style. Our approach is meant to illustrate the potential value of synthesizing these different elements of communication as a way of quantifying a leader's communication style. Combining these features allows for greater flexibility than more standard approaches to textual analysis, such as LIWC, which rely on prevalidated dictionary measures. Most notably, LDA inductively models the content of a body of texts in a way that is not influenced by a researcher's priors and is difficult to achieve through set dictionaries (unless those dictionaries have been specifically designed for an empirical context). The LDA model estimated in this paper, for example, reveals topics about constructs of interest to strategy scholars (such as investment and corporate social responsibility), as well as topics highly specific to our data (such as Topic 64, which is about the tea industry). In addition, our new *topic entropy* measure provides a standardized method for estimating topic concentration that may be used across a variety of contexts, without being reliant on an established list of terms. This is not to say that dictionary-based methods are not

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[11] Given that "fear" and "sadness" load together on the "Dramatic" style with the lowest p-values, it is possible that their simultaneous inclusion is redundant. It is also possible that "fear" and "sadness" are largely what explain most of the variance in our facial expression measures. To assess this possibility, we conducted our analysis by creating factors without measures of "fear" and "sadness" to test whether such factors would also contribute to explaining acquisitions. We find that without "fear" and "sadness", the factors that emerge from the other emotions still contribute considerably to predicting acquisitions, demonstrating the value of synthesizing facial expression and textual data to measure communication style. These additional analyses are available from the authors upon request.

valuable; we employ the crowdsourced *Syuzhet* lexicons in our sentiment analysis precisely because this remains a reliable and efficient way to measure sentiment. However, in our approach of combining both supervised and unsupervised methods, we aim to provide a model for a more flexible way of characterizing text-based communication that is less beholden to context.

Our approach also contributes to growing interest in the use of videometric methods to code visual expressions from videographic data that is now widely accessible (Blankespoor et al., 2017; Cade et al., 2018; Hill et al., forthcoming). Nevertheless, there are several challenges associated with implementing the videometric methods deployed in existing work. As such, we describe how our approach improves upon existing methods in *efficiency*, *replicability*, and *adaptability*. As a baseline, we compare our method to the approach pioneered by Hill et al. (forthcoming), but we raise similar examples from other recent work, as well.

Specifically, Hill et al. (forthcoming) describe the procedures involved in training a set of "raters" for a videometric coding task for a set of recorded interviews with CEOs (as described earlier). Although, Hill et al. (forthcoming) do not report the total length of time required to code their CEO videos from the start of rater recruitment to the final robustness checks, we can speculate that the task itself required a minimum of several days and could take as long as several weeks.

Our approach in using the Microsoft REST API for accomplishing the same videometric coding task eliminates the need to train human coders, given that it is a software tool accessible to any researcher with an internet connection. In addition, the processing time is dramatically shorter. Whereas it would be almost inconceivable to ask human coders to code every second of a video that is even an hour long, the REST API takes still frames (which are less than a second long) of a video as input data that can then be processed in mere seconds, even for a video that is hours in length. Finally, because human coders are not required, researchers do not face the administrative cost of securing a physical environment for the coding task. Together, these efficiency advantages make videometric coding via an automated API like ours far more preferable because they lower the barriers to measurement for video data.

In addition, because our approach relies on software, researchers can follow our methods and reproduce the exact same measures with the same data. This is vital for efforts to replicate studies that use videometric data. Specifically, if one attempted to replicate a study that relied on human coding of video recorded facial expressions, it would be difficult to rule out that any unexpected differences in results might simply be a function of using different coders, for example. Our method facilitates the process of replication, making it easier for future researchers to confidently extend the results obtained using the Face API platform as well as verify the reproducibility of the analysis.

Finally, although by default, the Face API outputs ratings for a fixed set of eight different emotions, the algorithm also yields precise measurements of an individual's physical facial attributes. For example, the algorithm measures the physical coordinates of one's eyes, nose, ears, and mouth, the presence of eye and lip makeup, the angle of one's head tilt, and the precise shape of one's head. These precise measurements serve as variables that researchers could potentially use to train new machine learning algorithms for identifying other expressions that might not be captured by the set of emotions we exploit in our analysis.

6. DISCUSSION AND CONCLUSION

6.1. Summary

In this paper, we outline a novel synthesis of three methodologies—topic modeling (using unsupervised ML), sentiment analysis of text, and a cutting-edge facial image expression recognition (using supervised ML)—with an application to CEO oral communication. Exposition of these methodologies allows us to respond to the call made by Helfat and Peteraf (2015) to study verbal language and nonverbal communication, important inputs to managerial cognitive capabilities. Specifically, we collected and processed verbal and nonverbal data from a set of video-recorded interviews with CEOs and founders from emerging markets to show that both components are informative when identifying different communication styles.

6.2. Contributions

Our analysis offers a glimpse of a potentially important predictor—CEO communication style—of firm behavior. Because our video data come from recorded sessions of unstructured interviews in which CEOs engage in free association with minimal prompting from an interviewer, our setting provides a unique perspective on how CEOs view what is important to them. Researchers have recently taken an interest in measuring how CEOs allocate their attention as a key input into understanding how they make decisions about firm strategy. In particular, researchers gather data by collecting information on how CEOs spend their days through detailed diaries (Bandiera et al., forthcoming). Our approach sheds light on several promising ways to further the literature on CEO oral communication by: (1) introducing how the synthesis of text- and video-based measures can generate CEO communication styles, (2) introducing a new measure of communication entropy

(Shannon entropy) using the analysis of topics embedded in CEO communication text, and (3) revealing how communication style might be related to firm-level outcomes.

In the context of research on CEO communication, the set of methodologies developed in this paper could be used in the literature of cognitive frames (Kaplan, 2008), interpretation (Barr, 1998), and how CEOs spend their time (Bandiera et al., 2013, 2018). More broadly, these new methods for coding verbal and nonverbal communication could be particularly instrumental in research that uses analyses of language. As Suddaby and Greenwood (2005) outline, drawing from Burke's (1966) notion of language as "symbolic action," several streams of research related to strategy employ the analysis of language. Important subfields of related research include semiotics (Barley, 1983), hermeneutics (Phillips and Brown, 1993), discursive analysis (Kilduff, 1993), narrative analysis (Boje, 1995), and rhetorical analysis (Freedman and Medway, 1994). Scholars in each of these subfields could benefit from using the methodologies outlined in this paper.

Related, we argue that the use of videographic data is necessary to measure the CEO's *communication style*. A communication style includes how one *verbally* – i.e., *what* we say – and *paraverbally* – i.e., *how* we say it – interacts to signal how what one says should be interpreted. By developing insight into what constitutes a CEO's communication style, we build directly on Helfat and Peteraf's (2015, p. 843) observation that "managerial skill in using language" can "inspire workers, encourage initiative, and drive entrepreneurial growth." We argue that this "skill" can be captured and measured by synthesizing measures of verbal and nonverbal communication that are uniquely available through videographic data.

Our methodological exposition is relevant for the literature that uses language to assess how personality traits of CEOs relates to strategic change in the companies they manage (Chatterjee & Hambrick, 2007; Nadkarni & Chen, 2014). In a recent paper in this literature, Harrison et al. (2019) created personality measures using R's machine-learning capabilities in three stages: (a) text vectorization, (b) training and model selection, and (c) trait prediction. In the first stage, they used Word2Vec to extract language features from the larger text corpus of 3,573 CEOs. Our methods and exposition of coding CEO communication style could be helpful in further advancing this stream of research.

More broadly for strategy research in the age of Twitter, Instagram, and YouTube, these tools could be used by strategy scholars to code text, static images, and video data in a wide variety of settings. Arguably, a new set of methodologies to work with qualitative data such as text, static images, and video images provides an empirical breakthrough. In fact, as a recent *SMJ* editorial persuasively argues, studies using qualitative empirical methods have been instrumental in advancing the field of strategic management (Bettis et al., 2015). The article outlines several qualitative methods that have been used in strategy research, including qualitative comparative analysis (Ragin, 2014), first- and second-order analysis (Gioia, 2014), the case study method (Eisenhardt and Graebner, 2007), and rhetorical analysis (Suddaby, 2014).

The exposition of our novel set of methodologies to utilize oral history data adds to the relatively thin literature on the use of historical data in strategy research. In particular, Jones and Khanna (2006) outline two dimensions of historical data that make it difficult for use in broad strategy research—such data is often "qualitative" and "small sample." The authors then suggest methods that strategy scholars could use to analyze historical data and list methods related to Boolean algebra (Ragin, 2014), string analyses (Abbott, 2001), and computational models (O'Rourke and Williamson, 1999). Oral history data—especially that accompanied by images or video—is arguably an underutilized data source for strategy research, and it often shares the qualitative and small sample properties outlined by Jones and Khanna (2006); our novel set of methodologies provides strategy scholars yet another empirical tool to use to further historical analysis in strategy research. In effect, we show how, even with a small sample of interviews (n = 69), our approach (through segmenting each interview transcript) allows for a meaningful and replicable quantitative analysis through topic modeling, sentiment analysis, and facial image recognition analysis.[12]

6.3. Limitations

Our study has several limitations. Because our data are limited to interviews with CEOs of firms in emerging markets, we cannot generalize our results about CEOs' emotions and topical attention to those in other settings, such as developed markets. We encourage researchers to adopt our methods to future projects that might examine such a comparison. As stated earlier, our proof-of-concept analysis relies on CEO communication with academics via semi-structured interviews. It is plausible that CEO communication is different with other internal and external stakeholders. Also, our correlational analysis relating CEO communication styles to M&A outcomes is meant to be expositional and not intended to generate inductive insights. Ultimately, we hope researchers will

[12] In the Appendix, we list selected oral history archives (mostly housed in university libraries) that contain a diverse array of interviews with business leaders, covering a wide range of industries, regions, and topics. One notable resource is Columbia University's Oral History Archive, which has been widely acknowledged as the largest searchable database of oral history records in the world, giving access not only to audio and video records of interviews with business executives, but also their accompanying transcripts.

find our method generative as means to develop new ways to incorporate diverse data sources into the study of strategic decision-making and leadership.

In addition, in terms of data limitations, as Kaplan (2008) states, the study of oral interview data suffers from the risk of retrospective bias, as managers would likely adapt their memories of their views in prior years to subsequent outcomes. Oral history data might suffer from biases attributed to data generated from situational interviews, as identified in the psychology literature (Latham and Saari, 1984). Additionally, oral history data might be relevant in establishing links to firm outcomes only if the leader being interviewed is in an "active" managerial role during the time of the interview; this prompted us to utilize only the subsample of "active CEO" data in our baseline analysis. Also, we note that our analysis is constrained by the lack of repeated observations of the CEOs over time; our analysis would be improved with longitudinal videographic data.

As for other technical limitations, we can account for differences only in the region-of-origin for our CEO interviewees and the firms they represent. In other words, because our CEOs represent emerging markets, we caution readers that the results of our analysis of how communication styles are related to firm outcomes might not generalize to samples of CEOs from other regions. However, as a feature of the interview data collection, the CEOs' regions are also associated with whether the interviews were conducted in English. For instance, most CEOs from South American countries were interviewed in their native Spanish, which means our analysis could incorporate only the English translations of their interview transcripts.

Finally, although the format of the textual data we used in our analysis was especially well suited for generating topic models, text from other videographic data, such as lengthy addresses or speeches, might not be. In our data, we split each interview transcript into text segments, each of which represents an answer to a question posed by an interviewer. Therefore, each interview text segment is relatively cohesive in terms of meaning and consistent in terms of length. However, in other videographic data, the text associated with an individual's speech might not be segmented as conveniently. In such instances, the researcher must define the segmentation as part of a preprocessing step. How text is segmented might then affect the ultimate results of a topic model, which has implications for the set of communication styles that might be discovered.

6.4. Future Directions and Applications

While the current study represents our efforts to advance our understanding of how ML methods could be used gainfully in strategy research focused on CEO oral communication, future efforts could augment our current study in several ways. Future research could explore whether we learn more from studying oral communication – or learn something different – than from studying written statements of CEOs. While we focus coding on text and facial expressions of oral communication, it would be possible to additionally use voice intonation and code yet one more dimension of oral communication. Also, it would be interesting to investigate the sensitivity of topic model results to translation effects. Additionally, although our approach utilized unsupervised LDA to estimate topic models, it is possible that a supervised approach could produce additional insights on topic estimates (Ramage et al., 2009). A supervised approach would require researchers to read through a sample of transcripts and to associate certain words with predetermined topics, giving the topic model a fixed prior method for structuring the relationship between estimated topics. A supervised approach is encouraged when the language used in a corpus of documents has excessive jargon, such that relevant experts would be able to identify which specific and salient words should cohere as a topic. The language in our interviews does not necessarily reflect the excessive use of jargon, but it is possible that other oral business histories would exhibit higher proportions of industry-specific terminology. Additionally, while we use "bag of words" methods to construct the topics, it might also be interesting to study how the order of words correlates with sentiments expressed. Finally, future research might augment our textual sentiment analysis by creating and using a lexicon of words curated from papers published in the field of strategy to code sentiments expressed in the words spoken or written by CEOs.

Our approach can also be extended to other sources of videographic data that are becoming widely available. Media organizations and firms alike frequently post videos to open access video platforms such as YouTube, many of which contain recordings of executives speaking and interacting. These videos can reveal a great deal about a CEO's leadership approach through verbal and nonverbal patterns that have been unexplored as yet. Therefore, an opportunity exists to collect a data archive of CEO videos, which might then be categorized along a number of dimensions—such as recordings of leaders speaking in formal versus informal situations. Future researchers might adapt our approach to generate stylistic profiles of each CEO. Possible questions that could be explored include how CEOs' communication styles affect perceptions of them as leaders. In addition, researchers might use videographic data to predict executives' ascension into CEO positions. The tools we present in our analysis would facilitate research into these new questions.

In conclusion, from the perspective of strategy research on CEO oral communication, we document three replicable methodologies based on topic modeling of text, sentiment analysis of text, and a state-of-the-art facial image emotion recognition algorithm; and we demonstrate a novel synthesis of the three methods to generate CEO oral communication styles that incorporate both verbal and nonverbal aspects of communication. We exploit an underutilized type of data for strategy research, that is, oral history text and video data, and describe in detail three replicable methods. We also develop a proof-of-concept of using our methodology and provide evidence suggestive of how communication style correlates with the firm-level outcomes, such as completed acquisitions. This result speaks to the importance of studying *both* verbal and nonverbal language in relation to cognitive capabilities related to reconfiguration, highlighted by Helfat and Peteraf (2015). Most important, our set of methodologies—and the exposition of synthesizing these methods—opens the door for strategy scholars to use easily available yet underutilized text, image, and video data in a wide variety of settings.

References

Abbott, A. (2001). Time matters: On theory and method. University of Chicago Press.

Antweiler, W., & Frank, M. Z. (2004). Is all that talk just noise? The information content of internet stock message boards. *Journal of Finance, 59*(3), 1259-1294.

Arts, S., Cassiman, B., & Gomez, J. C. (2018). Text matching to measure patent similarity. *Strategic Management Journal, 39*(1), 62-84.

Athey, S. The impact of machine learning on economics. In A. K. Agrawal, J. Gans, & A. Goldfarb (Eds.), *The Economics of Artificial Intelligence: An Agenda* (in press). Chicago, IL: University of Chicago Press.

Bandiera, O., Guiso, L., Prat, A., & Sadun, R. (2018). What do CEOs do? *Review of Financial Studies*, Forthcoming.

Bandiera, O., Lemos, R., Prat, A., & Sadun, R. (2013). Managing the family firm: Evidence from CEOs at work. NBER Working Paper No. 19722.

Barley, S. R. (1983). Semiotics and the study of occupational and organizational cultures. *Administrative Science Quarterly, 28*(3), 393-413.

Barr, P. S. (1998). Adapting to unfamiliar environmental events: A look at the evolution of interpretation and its role in strategic change. *Organization Science, 9*(6), 644-669.

Baum, J. R., Locke, E. A., & Kirkpatrick, S. A. (1998). A longitudinal study of the relation of vision and vision communication to venture growth in entrepreneurial firms. *Journal of Applied Psychology, 83*(1), 43.

Bettis, R. A., Gambardella, A., Helfat, C., & Mitchell, W. (2015). Qualitative empirical research in strategic management. *Strategic Management Journal, 36*(5), 637-639.

Blankespoor, E., Hendricks, B. E., & Miller, G. S. (2017). Perceptions and price: Evidence from CEO presentations at IPO roadshows. *Journal of Accounting Research, 55*(2), 275-327.

Blei, D. M., Ng, A. Y., & Jordan, M. I. (2003). Latent Dirichlet allocation. *Journal of Machine Learning Research, 3*, 993-1022.

Boje, D. M. (1995). Stories of the storytelling organization: A postmodern analysis of Disney as "Tamara-Land". Academy of Management journal, 38(4), 997-1035.

Buller, M. K., & Buller, D. B. (1987). Physicians' communication style and patient satisfaction. Journal of health and social behavior, 375-388.

Burke, K. (1966). Language as symbolic action: Essays on life, literature, and method. Univ of California Press.

Cade, N., Koonce, L., & Mendoza, Kim (2018), Using video to disclose forward-looking information: The effect of non-verbal cues on investors' judgments. Working Paper.

Capron, L., Dussauge, P., & Mitchell, W. (1998). Resource redeployment following horizontal mergers and acquisitions in Europe and North America, 1988-1992. *Strategic Management Journal, 19*(7), 631-661.

Čech, R., Garabík, R., & Altmann, G. (2015). Testing the thematic concentration of text. *Journal of Quantitative Linguistics*, *22*(3), 215-232.

Chang, J., Gerrish, S., Wang, C., Boyd-Graber, J. L., & Blei, D. M. (2009). Reading tea leaves: How humans interpret topic models. Available at: https://papers.nips.cc/paper/3700-reading-tea-leaves-how-humans-interpret-topic-models.pdf

Chatterjee, A., & Hambrick, D. C. (2007). It's all about me: Narcissistic chief executive officers and their effects on company strategy and performance. *Administrative Science Quarterly*, 52(3), 351-386.

Chen, M., Wang, S., Liang, P. P., Baltrušaitis, T., Zadeh, A., & Morency, L.-P. (2017). Multimodal sentiment analysis with word-level fusion and reinforcement learning. *Proceedings of the 19th ACM International Conference on Multimodal Interaction*, 162-171.

Crilly, D., 2017. Time and space in strategy discourse: Implications for intertemporal choice. *Strategic Management Journal*, 38(12), 2370-2389.

D'Aveni, R. A., & MacMillan, I. C. (1990). Crisis and the content of managerial communications: A study of the focus of attention of top managers in surviving and failing firms. *Administrative Science Quarterly, 35*(4), 634-657.

Dietterich, T. (1995). Overfitting and undercomputing in machine learning. *ACM computing surveys*, *27*(3), 326-327.

Duffner, S. (2008). *Face image analysis with convolutional neural networks* (Doctoral dissertation). University of Freiburg, Freiburg, Germany.

Eisenhardt, K. M., & Graebner, M. E. (2007). Theory building from cases: Opportunities and challenges. *Academy of Management Journal, 50*(1), 25-32.

Freedman, A., & Medway, P. (1994). Locating genre studies: Antecedents and Prospects. In A. Freedman, & P. Medway (Eds.), *Genre and the New Rhetoric* (pp. 1-20). London, England: Taylor & Francis.

Gamache, D. L., & McNamara, G. Responding to bad press: How CEO temporal focus influences the sensitivity to negative media coverage of acquisitions. *Academy of Management Journal*, Forthcoming.

Gao, C., Zuzul, T., Jones, G., & Khanna, T. (2017). Overcoming institutional voids: A reputation-based view of long-run survival. *Strategic Management Journal, 38*(11), 2147-2167.

Gavetti, G. 2012. PERSPECTIVE—Toward a behavioral theory of strategy. *Organization Science*, *23*(1), 267-285.

Gioia, D. (2014). A 1st-order/2nd-order qualitative approach to understanding strategic management. In *Primer: Qualitative Research in Strategic Management*, *Strategic Management Journal*. Available at: https://www.strategicmanagement.net/smj/overview/submission/editorials-and-primers

Glaeser, E. L., Kominers, S. D., Luca, M., & Naik, N. (2018). Big data and big cities: The promises and limitations of improved measures of urban life. *Economic Inquiry, 56*(1), 114-137.

Griffiths, T. L., & Steyvers, M. (2004). Finding scientific topics. *Proceedings of the National Academy of Sciences of the United States of America, 101*(Suppl 1), 5228-5235.

Graham, J. R., Harvey, C. R., & Puri, M. (2016). A corporate beauty contest. Management Science, 63(9), 3044-3056.

Grun, B., & Hornik, K. (2011). Topicmodels: An R package for fitting topic models. *Journal of Statistical Software, 40*(13), 1-30.

Halford, J. T., & Hsu, S. H. (2014). Beauty is wealth: CEO appearance and shareholder value.

Hambrick, D. C., & Mason, P. A. (1984). Upper echelons: The organization as a reflection of its top managers. *Academy of Management Review, 9*(2), 193-206.

Harrison, J.S., Thurgood, G.R., Boivie, S., & Pfarrer, M.D. 2019. Measuring CEO personality: Developing, validating, and testing a linguistic tool. *Strategic Management Journal.* Forthcoming.

Helfat, C. E., Finkelstein, S., Mitchell, W., Peteraf, M. A., Singh, H., Teece, D. J., Winter, S. G. (2007). *Dynamic Capabilities: Understanding Strategic Change in Organizations*. Malden, MA: Blackwell Publishing.

Helfat, C. E., & Peteraf, M. A. (2003). The dynamic resource-based view: capability lifecycles. *Strategic Management Journal*, *24*(S1), 997-1010.

Helfat, C. E., & Peteraf, M. A. (2015). Managerial cognitive capabilities and the microfoundations of dynamic capabilities. *Strategic Management Journal, 36*(6), 831-850.

Hill, A., Petrenko, O., Ridge, J., & Aime, F. Videometric measurement of individual characteristics in difficult to access subject pools: Demonstrating with CEOs. In D. J. Ketchen, Jr., & D. D. Bergh (Eds.), *Research Methodology in Strategy and Management* (in press). Bingley, England: Emerald Publishing.

Hill, R. C., & Levenhagen, M. (1995). Metaphors and mental models: Sensemaking and sensegiving in innovative and entrepreneurial activities. *Journal of Management, 21*(6), 1057-1074.

Jockers, M. (2017). Package 'Syuzhet.' Available at: https://cran.r-project.org/web/packages/syuzhet

Jones, G., & Khanna, T. (2006). Bringing history (back) into international business. *Journal of International Business Studies, 37*(4), 453-468.

Kanze, D., Huang, L., Conley, M.A., & Higgins, E.T. (2018). We ask men to win and women not to lose: Closing the gender gap in startup funding. *Academy of Management Journal*, 61(2), 586-614.

Kaplan, S. (2008). Framing contests: Strategy making under uncertainty. *Organization Science, 19*(5), 729-752.

Kaplan, S., & Vakili, K. (2015). The double-edged sword of recombination in breakthrough innovation. *Strategic Management Journal, 36*(10), 1435-1457.

Kilduff, M. (1993). Deconstructing organizations. *Academy of Management Review, 18*(1), 13-31.

Kleinberg, J., Lakkaraju, H., Leskovec, J., Ludwig, J., & Mullainathan, S. (2017). Human decisions and machine predictions. *Quarterly Journal of Economics, 133*(1), 237-293.

Kring, A. M., Smith, D. A., & Neale, J. M. (1994). Individual differences in dispositional expressiveness: development and validation of the Emotional Expressivity Scale. *Journal of Personality and Social Psychology*, *66*(5), 934.

Latham, G. P., & Saari, L. M. (1984). Do people do what they say? Further studies on the situational interview. *Journal of Applied Psychology, 69*(4), 569-573.

Lefebvre, L. A., Mason, R., & Lefebvre, E. (1997). The influence prism in SMEs: The power of CEOs' perceptions on technology policy and its organizational impacts. *Management Science, 43*(6), 856-878.

Loughran, T., & McDonald, B. (2011). When is a liability not a liability? Textual analysis, dictionaries, and 10-Ks. *Journal of Finance, 66*(1), 35-65.

Loughran, T., & McDonald, B. (2016). Textual analysis in accounting and finance: A survey. *Journal of Accounting Research, 54*(4), 1187-1230.

Lungeanu, R., Paruchuri, S., & Tsai, W. (2018). Stepping across for social approval: Ties to independent foundations' boards after financial restatement. *Strategic Management Journal*, *39*(4), 1163-1187.

Menon, A., Tabakovic, H., & Lee, C. (2018). Using machine learning to predict high-impact general technologies (Working Paper). Philadelphia, PA: Wharton School.

Mohammad, S. M., & Turney, P. D. (2013). Crowdsourcing a word–emotion association lexicon. Computational Intelligence, 29(3), 436-465.

Mohammad, S. M., Kiritchenko, S., & Zhu, X. (2013). NRC-Canada: Building the state-of-the-art in sentiment analysis of tweets. *arXiv:1308.6242*.

Mullainathan, S., & Spiess, J. (2017). Machine learning: An applied econometric approach. *Journal of Economic Perspectives, 31*(2), 87-106.

Nadkarni, S., & Chen, J. (2014). Bridging yesterday, today, and tomorrow: CEO temporal focus, environmental dynamism, and rate of new product introduction. *Academy of Management Journal*, 57(6), 1810-1833.

Neilsen, E. H., & Rao, M. H. (1987). The strategy-legitimacy nexus: A thick description. *Academy of Management Review*, 12(3), 523-533.

Norton, R. W. (1978). Foundation of a communicator style construct. *Human Communication Research*, *4*(2), 99-112.

O'rourke, K. H., & Williamson, J. G. (1999). Globalization and history: the evolution of a nineteenth-century Atlantic economy. MIT Press.

Pan, L., McNamara, G., Lee, J. J., Haleblian, J., & Devers, C. E. (2018). Give it to us straight (most of the time): Top managers' use of concrete language and its effect on investor reactions. *Strategic Management Journal, 39*(8), 2204-2225.

Perloff, R. M. (2008). *Political Communication: Politics, Press, and Public in America*. Boca Raton, FL: Routledge.

Petrenko, O. V., Aime, F., Ridge, J., & Hill, A. (2016). Corporate social responsibility or CEO narcissism? CSR motivations and organizational performance. *Strategic Management Journal, 37*(2), 262-279.

Phillips, N., & Brown, J. L. (1993). Analyzing communication in and around organizations: A critical hermeneutic approach. *Academy of Management Journal, 36*(6), 1547-1576.

Ragin, C. C. (2014). *The Comparative Method: Moving Beyond Qualitative and Quantitative Strategies*. Oakland, CA: University of California Press.

Ramage, D., Hall, D., Nallapati, R., & Manning, C. D. (2009). Labeled LDA: A supervised topic model for credit attribution in multi-labeled corpora. *Proceedings of the 2009 Conference on Empirical Methods in Natural Language Processing*, 248-256.

Riedl, C., Zanibbi, R., Hearst, M. A., Zhu, S., Menietti, M., Crusan, J., Metelsky, I., & Lakhani, K. R. (2016). Detecting figures and part labels in patents: competition-based development of graphics recognition algorithms. *International Journal on Document Analysis and Recognition, 19*(2), 155-172.

Salancik, G. R., & Meindl, J. R. (1984). Corporate attributions as strategic illusions of management control. *Administrative Science Quarterly, 29*(2), 238-254.

Shipilov, A.V., Greve, H.R., & Rowley, T.J. 2019 Is all publicity good publicity? the impact of direct and indirect media pressure on the adoption of governance practices. *Strategic Management Journal*. Forthcoming.

Slepian, M. L., & Carr, E. W. (2019). Facial expressions of authenticity: Emotion variability increases judgments of trustworthiness and leadership. *Cognition*, *183*, 82-98.

Suddaby, R., & Greenwood, R. (2005). Rhetorical strategies of legitimacy. *Administrative Science Quarterly, 50*(1), 35-67.

Suddaby, R. (2014). Editor's comments: Why theory?

Teece, D. J. (2007). Explicating dynamic capabilities: the nature and microfoundations of (sustainable) enterprise performance. *Strategic Management Journal 28*(13), 1319-1350.

ten Brinke, L., & Adams, G. S. (2015). Saving face? When emotion displays during public apologies mitigate damage to organizational performance. Organizational Behavior and Human Decision Processes, 130, 1-12.

Van Kleef, G. A., Homan, A. C., Beersma, B., Van Knippenberg, D., Van Knippenberg, B., & Damen, F. (2009). Searing sentiment or cold calculation? The effects of leader emotional displays on team performance depend on follower epistemic motivation. *Academy of Management Journal*, *52*(3), 562-580.

Wang, Y., & Liu, H. (2018). Is Trump always rambling like a fourth-grade student? An analysis of stylistic features of Donald Trump's political discourse during the 2016 election. *Discourse & Society*, *29*(3), 299-323.

Watzlawick, P., Bavelas, J. B., & Jackson, D. D. (1967). *Pragmatics of Human Communication: A Study of Interactional Patterns, Pathologies, and Paradoxes*. New York, NY: W. W. Norton & Co.

Watson, D., Clark, L. A., and Tellegen, A. (1988). Development and validation of brief measures of positive and negative affect: the PANAS scales. Journal of Personality and Social Psychology, 54, 1063–1070.

Westley, F., & Mintzberg, H. (1989). Visionary leadership and strategic management. *Strategic Management Journal, 10*(S1), 17-32.

Yadav, M. S., Prabhu, J. C., & Chandy, R. K. (2007). Managing the future: CEO attention and innovation outcomes. *Journal of Marketing, 71*(4), 84-101.

Yu, Z., & Zhang, C. (2015). Image based static facial expression recognition with multiple deep network learning. *Proceedings of the 2015 ACM on International Conference on Multimodal Interaction*, 435-442.

TABLES AND FIGURES

Table 1. Factor Loadings

	Factors, Labeled by Authors				
	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5
Variable	Excitable	Stern	Dramatic	Rambling	Melancholy
Negative Text Sentiment	-0.165	-0.078	-0.004	0.021	0.062
Text Sentiment Variance	-0.257	-0.169	0.055	-0.186	0.086
Average Answer Length	-0.001	0.174	-0.227	0.406	0.115
Topic Entropy	0.067	-0.022	-0.187	0.478	0.171
Video: Anger	0.093	0.710	0.358	-0.069	-0.456
Video: Contempt	0.072	0.386	0.223	0.618	0.486
Video: Disgust	0.082	0.727	0.499	0.009	-0.043
Video: Fear	0.758	0.267	-0.333	-0.281	0.083
Video: Happiness	0.341	-0.723	0.385	0.325	-0.303
Video: Neutral	-0.835	0.308	-0.418	-0.129	0.098
Video: Sadness	0.293	-0.132	0.411	-0.457	0.677
Video: Surprise	0.708	0.187	-0.583	0.019	-0.064

Note: Displayed are the loadings of the component variables on the first five factors of the factor analysis, with given names for the factors. Loadings greater than 0.3 are highlighted in a lighter shade, and loadings less than -0.3 are highlighted in a darker shade. The dataset, when we last accessed it (on 10.15.2018) had 115 interview transcripts but only 69 of these interviews had an accompanying video given that the video making process started in 2012 and between 2008 and a large part of 2012, only audio interviews were conducted. Given that our analysis requires the synthesis of text and facial image data, we based our analysis on the 69 interviews, where we had both text and video data. The factors remain similar if only the sample of 46 active CEOs used in the correlational acquisitions analysis is used for the factor analysis.

Table 2. Estimated Coefficients from Linear Regression of Number of Acquisitions on CEO Communication Style

	DV: Completed Acquisition within *x* Years of Interview		
	x = 1 year	*x* = 3 years	*x* = 5 years
	Model 1	Model 2	Model 3
Excitable	0.04 (0.12) p = 0.74	0.18 (0.16) p = 0.27	0.52 (0.41) p = 0.20
Stern	−0.05 (0.06) p = 0.44	−0.06 (0.10) p = 0.57	−0.05 (0.15) p = 0.74
Dramatic	−0.26 (0.18) p = 0.14	−0.39 (0.19) p = 0.04	−0.56 (0.29) p = 0.06
Rambling	0.05 (0.09) p = 0.58	0.08 (0.12) p = 0.49	0.15 (0.18) p = 0.41
Melancholy	−0.04 (0.07) p = 0.62	−0.08 (0.10) p = 0.40	−0.10 (0.13) p = 0.45
Year FE	Yes	Yes	Yes
Region FE	Yes	Yes	Yes
Gender	Yes	Yes	Yes
Observations	46	46	46
Adjusted R-squared	0.33	0.32	0.39

Note: Each cell displays the OLS estimated coefficient with robust SE in parentheses and p-value underneath. Models control for gender, region, and year of interview. Of the 69 videos in our sample, this analysis utilizes a subsample of interviews related to 46 "active" CEOs, that is, those in our sample who were still performing the role of CEO at the time of their interviews.

Table 3. Linear Regression Models Demonstrating Value of Synthesis

	DV: Completed Acquisitions within 5 Years of Interview				
	Model 1	Model 2	Model 3	Model 4	Model 5
Negative Text Sentiment	−3.72 (4.24) p = 0.38			−2.09 (4.25) p = 0.63	
Text Sentiment Variance	−1.04 (4.83) p = 0.83			4.25 (8.61) p = 0.63	
Average Answer Length		0.01 (0.01) p = 0.26		0.01 (0.01) p = 0.32	
Topic Entropy		0.65 (0.97) p = 0.51		1.17 (1.11) p = 0.29	
Video: Anger			−7.26 (5.11) p = 0.16	−7.47 (5.77) p = 0.20	
Video: Contempt			−4.35 (13.79) p = 0.76	−11.38 (20.77) p = 0.59	
Video: Disgust			−5.40 (19.79) p = 0.79	−8.11 (22.02) p = 0.72	
Video: Fear			118.28 (61.69) p = 0.06	123.47 (61.48) p = 0.05	
Video: Happiness			1.26 (1.83) p = 0.50	1.12 (1.94) p = 0.57	
Video: Sadness			−6.27 (3.80) p = 0.10	−6.01 (3.62) p = 0.10	
Video: Surprise			2.23 (7.19) p = 0.76	1.48 (7.35) p = 0.84	
Excitable					0.52 (0.41) p = 0.20
Stern					−0.05 (0.15) p = 0.74
Dramatic					−0.56 (0.29) p = 0.06
Rambling					0.15 (0.18) p = 0.41
Melancholy					−0.10 (0.13) p = 0.45
Year FE	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes
Gender	Yes	Yes	Yes	Yes	Yes
Observations	46	46	46	46	46
R2	0.26	0.30	0.40	0.47	0.39
Adjusted R-squared	-0.01	0.04	0.03	-0.0001	0.08

Note: Each cell displays the OLS estimated coefficient with robust SE in parentheses and p-value underneath. Models control for gender, region, and year of interview.

Figure 1. Overview of Methodological Approach

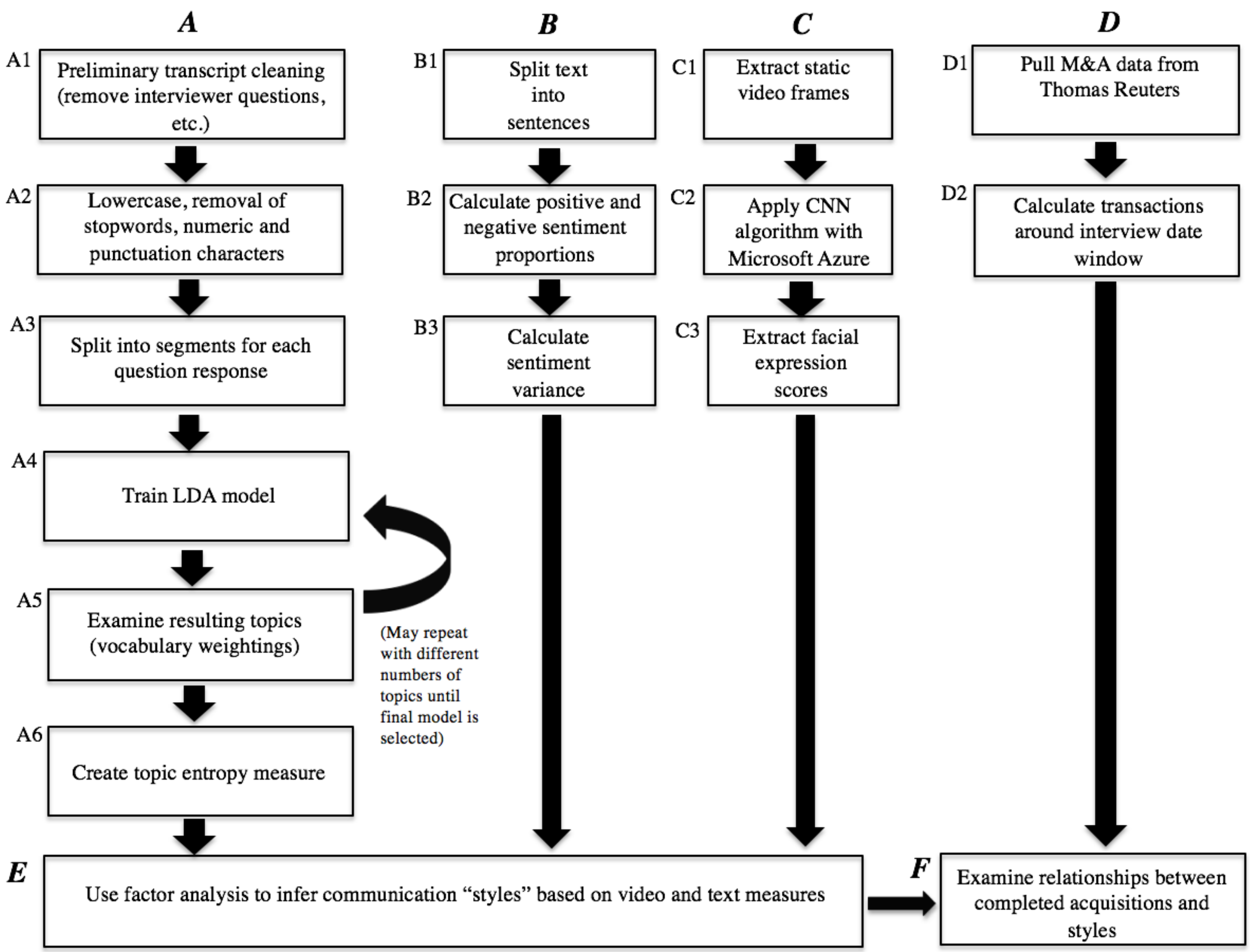


Figure 2. Examples of Static Frames Representing the Eight Facial Expressions

Note: Score for corresponding emotion coded by Microsoft Face API displayed in bold text.

ONLINE SUPPLEMENT

A1. Evaluating Microsoft Face API Coded Emotions against Human Coders

The Microsoft Face API platform allowed us to code facial expressions from 264,186 total frames of videos extracted from interviews with 61 different individuals. Although we have already summarized the efficiency advantages of our automated approach for coding videographic data compared to human observation, a question remains about the validity of the Face API's detection. To what extent does a facial expression from a video snapshot coded by the Face API as "happiness" actually match how a typical individual would describe the same snapshot? Although the Face API's algorithm for facial expression detection was trained by using millions of observations from human-evaluated facial image data, there is reason to believe, discrepancies might exist between how individuals perceive the faces in our videographic data and how the Face API algorithm would classify them.

One such discrepancy comes from the debate in the psychology literature on the cross-cultural universality of the so-called *basic emotions* that the Face API algorithm detects. Ekman and Friesen (1971) first proposed that the human face could express seven basic emotions that persisted across world cultures—anger, disgust, fear, happiness, sadness, surprise, and contempt—and an eighth category—neutral—is frequently evoked to describe the absence of emotional facial expression. However, some work in cross-cultural psychology has called into question whether such emotions are expressed in the same way for certain cultures as they are for others (Matsumoto, 1992; Russell, 1994; Tottenham et al., 2009). This suggests that some facial expressions might be construed as different emotions depending on the cultural or ethnic background of the individual being viewed. The Microsoft Face API algorithm is based on training data that is representative of faces from all different cultural and ethnic backgrounds; thus, its classification of a face as "happy" is based on what the *average* happy face looks like based on a large, diverse sample of faces. In our data, individuals come from emerging markets and form a nonrandom set of ethnic backgrounds that are not necessarily representative of the same sample of facial data on which the Face API was trained. Therefore, how the Face API codes a facial image in our dataset might be different from how a set of human judges would classify the same image.

To address this concern, we asked a group of 100 human coders to view 12 randomly selected facial images, each of which were drawn from a different video in our data (see Table A1). In five of these images, the Face API detected one clear dominant emotion (Bazan, Boyner, Ibrahim, Mody, Vaghul in Table A1). In another five, the Face API detected two primary emotions, with one being clearly more dominant (Burman, Estevez, Fernando, Ghandour, and Simabaqueba in Table A1). And in the remaining two, the Face API detected two primary emotions with almost equal weighting (Dudeja and Mahindra in Table A1).

INSERT TABLE A1 ABOUT HERE

Our 100 human coders were recruited from the Amazon MTurk platform. We asked each coder to choose the primary emotion expressed by each of the 12 images in Table A1 via an online survey. Because our intention was to compare how the Microsoft Face API and humans classify facial expressions, we gave coders the same set of eight emotions that are available to the Face API: anger, disgust, fear, happiness, sadness, surprise, contempt, and neutral. In addition, we gave no other information to our human coders about what a certain emotion looks like (or ought to look like) on a given face because we did not want our own interpretations to interfere with or bias the coders' classifications (Tottenham et al., 2009). For each image shown to a coder, we asked the coder to indicate the primary emotion expressed by the face. We also gathered basic demographic information about the coders in our sample (Mean Age = 34.11, SD of Age = 8.99; Proportion Female = 0.31; Proportion with Bachelor's Degree or above = 0.56).

INSERT FIGURE A1 ABOUT HERE

Figure A1 reports the results of our survey. Each panel in Figure A1 represents one of the 12 images presented in Table A1. In each panel, the histogram reports the proportion of survey respondents who identified a given emotion as the primary emotion expressed by the facial image. For example, for Bazan (in the upper-left corner in Figure A1), 59.6% of respondents identified "anger" as the primary emotion, 21.1% identified "disgust," and 7.1% identified "contempt." The Face API classified this same image as 99.6% "anger." Therefore, although our human coders exhibited some ambiguity in how they classified the emotion of the same image, their overall consensus that the image represents "anger" was consistent with the API.

In fact, for the five images in which the Face API identified one clear primary emotion (Bazan, Boyner, Ibrahim, Mody, and Vaghul), the emotion receiving the most human coder nominations matched the primary emotion identified by the Face API. Among the five images in which the Face API identified two primary emotions with one being more dominant (Burman, Estevez, Fernando, Ghandour, and Simbaqueba), there were four images in which the two primary emotions identified by human coders overlapped by at least one emotion with the two primary emotions identified by the Face API (Burman, Estevez, Fernando, Simbaqueba). Finally, in the images in which two primary emotions were identified with equal weighting by the Face API (Dudeja, Mahindra), there was overlap with the two primary emotions identified by the human coders. This evidence shows that although the human coders in our sample do not align perfectly with the Face API's classification of facial expressions, there is considerable overlap. As a result, we take these results to indicate that we can treat the facial expressions coded by the Microsoft Face API with reasonable validity.

A2. Details of LDA Topic Number Selection

Choosing the optimal number of topics for a topic model to produce over a set of documents is often described as more of an art than a science. Measures of a model's fit to the corpus, such as perplexity and log likelihood, can provide some guidance. It is worth noting that these measures do not always line up exactly with human judgments of semantic coherence (Chang et al., 2009). Coherence is typically best determined by examining the most likely terms for each topic: a good model should allow an observer to intuitively assign a title to each of the topics with a quick glance at the most probable terms. In addition to subjective coherence judgments, we turned to the *ldatuning* package, which compares different fit metrics side by side.

Figure A2 shows four different metrics from prior literature used to guide topic number selection. The four measures, computed over the collection of documents, are plotted against each other as the x-axis varies the number of topics. The metric depicted by the triangle points, "CaoJuan2009," computes a metric based on topic density, minimizing the average cosine similarity between topics. The square points show a measure from Arun et al. (2010), which computes a Kullback–Leibler divergence measure to minimize.

INSERT FIGURE A2 ABOUT HERE

In the bottom panel, the figure shows two metrics to maximize. The circular points indicate a measure from Griffiths and Steyvers (2004), which shows the harmonic mean of the log likelihood computed at various values of k. Finally, the cross points show a measure from Deveaud et al. (2014), which maximizes the information divergence between all pairs of LDA topics. They do this by computing the Jensen-Shannon divergence between all pairs of topics and maximizing the average divergence over difference values of *k*.

In each of the panels, the best value of *k* within the given range is indexed at one, and the other values within the range are plotted on a relative basis to that value. Not all the measures will be useful for a given problem, necessarily, but comparing the metrics side by side is useful. Based on the previous figure, we selected 100 topics as the best value for *k*.

INSERT FIGURE A3 ABOUT HERE

Figure A3 displays the top 10 most likely words for each topic in the final model.

A3. Parallel Analysis

This Online Supplement provides some additional information on the decision of the number of factors to retain following the factor analysis. Figure A4 shows the results of Horn's (1965) parallel analysis run on our sample of interviews. In brief, parallel analysis uses Monte Carlo simulations to generate normally distributed random uncorrelated data "parallel" to the true dataset, computing eigenvalues for each. The factors for which the eigenvalue for the actual dataset is greater than that for the simulated dataset are retained. The R package *paran* computes this by adjusting the eigenvalues downward by subtracting the mean eigenvalue from the simulated parallel data. Factors with adjusted eigenvalues greater than zero are then retained.

INSERT FIGURE A4 ABOUT HERE

The figure displays the results of this exercise on the new incorporated data, showing the factors retained for the 69 observations in our data. The red line shows the original scree plot, while the blue line shows the eigenvalues for the randomly generated data. The black line shows the "adjusted" eigenvalues, subtracting the latter from the former. The results suggest that 12 factors should be retained. However, only the first five factors have eigenvalues above one, and these first five already have a cumulative explanatory value of 0.87. Adding three more factors would add little additional explanatory power and would come at the expense of brevity and interpretability. In weighing these trade-offs, we elected to follow the Kaiser-Guttman guidelines and retain only five factors.

Online Supplement Table A1. Images used for MTurk Survey

Image Label	Primary Emotions	Microsoft Face API Coding of Emotions								Image
		Anger	Contempt	Disgust	Fear	Happiness	Neutral	Sadness	Surprise	
Estevez	Contempt, Sadness	0.000	0.728	0.012	0.000	0.001	0.039	0.219	0.000	
Fernando	Disgust, Anger	0.336	0.005	0.631	0.000	0.000	0.001	0.027	0.000	
Bazan	Anger	0.996	0.000	0.001	0.000	0.003	0.000	0.000	0.000	
Simbaqueba	Fear, Disgust	0.007	0.01	0.104	0.735	0.007	0.006	0.035	0.097	
Ibrahim	Happiness	0.000	0.000	0.000	0.000	1.000	0.000	0.000	0.000	

Image Label	Primary Emotions	Microsoft Face API Coding of Emotions								Image
		Anger	Contempt	Disgust	Fear	Happiness	Neutral	Sadness	Surprise	
Boyner	Neutral	0.000	0.001	0.000	0.000	0.000	0.999	0.001	0.000	
Vaghul	Sadness	0.000	0.000	0.000	0.000	0.000	0.002	0.997	0.000	
Mody	Surprise	0.001	0.000	0.001	0.002	0.000	0.002	0.000	0.994	
Burman	Disgust, Sadness	0.040	0.001	0.513	0.000	0.000	0.133	0.313	0.000	
Ghandour	Fear, Surprise	0.013	0.002	0.022	0.522	0.000	0.089	0.066	0.286	

		Microsoft Face API Coding of Emotions								
Image Label	Primary Emotions	Anger	Contempt	Disgust	Fear	Happiness	Neutral	Sadness	Surprise	Image
Mahindra	Neutral, Happiness	0.000	0.001	0.000	0.000	0.499	0.500	0.001	0.000	
Dudeja	Sadness, Neutral	0.000	0.000	0.000	0.000	0.000	0.500	0.500	0.000	

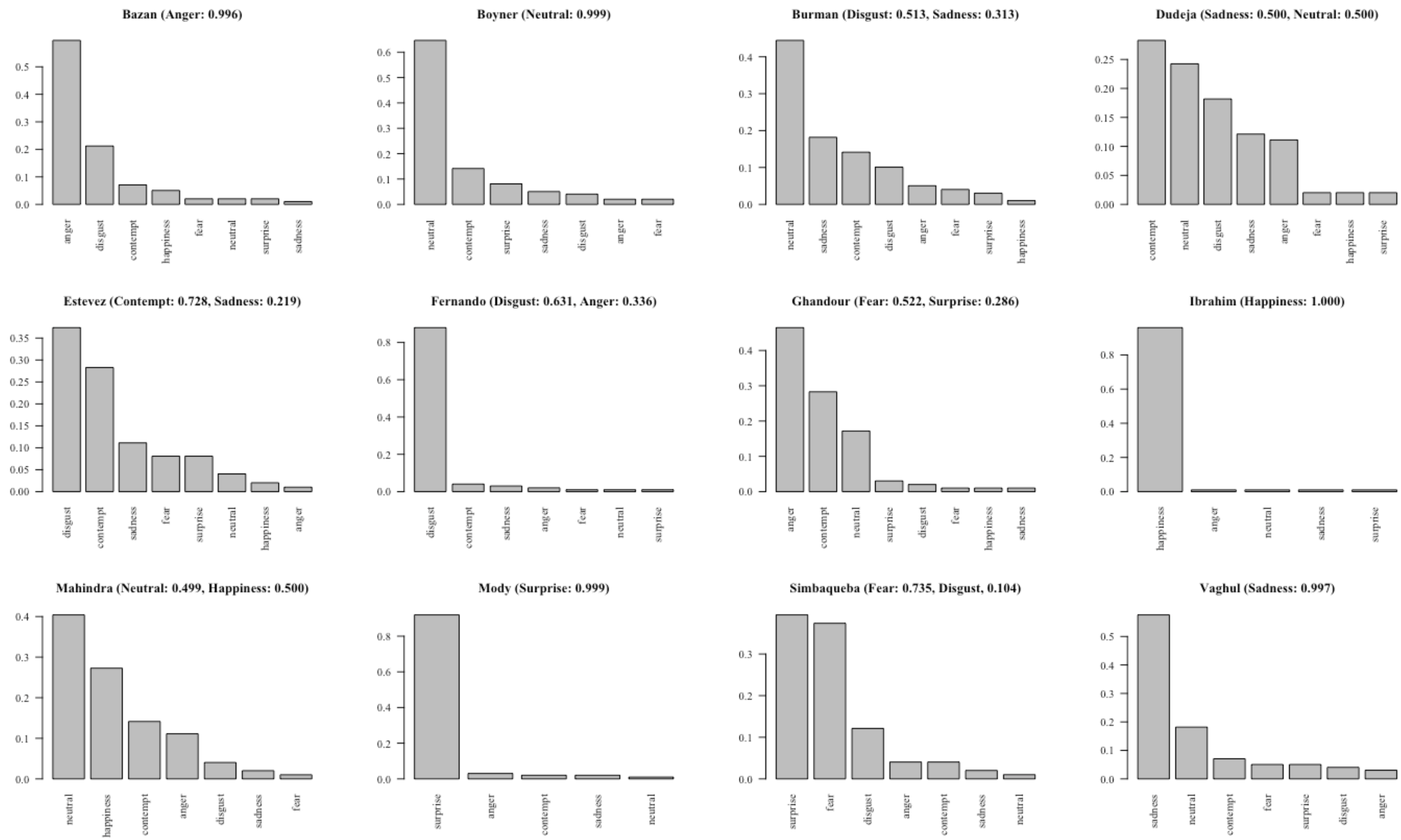
Online Supplement Table A2. Biographical Information for All Emerging Markets CEOs used in Analysis

Interviewee Name	Date of Interview	Country	Title and Company	Industry	Active
Abed, Fazle Hasan	4/24/14	Bangladesh	Founder and Chair, BRAC	Microfinance, Development	Yes
Aga, Anu	2/14/17	India	Thermax Private, Ltd.	Equipment Manufacturing	No
Akbarally, Abbas	12/24/15	Sri Lanka	Chairman, Akbar Brothers	Tea; Diversified	Yes
Akın, Hamdi	2/11/15	Turkey	Founder and Chairman, Akfen Holding	Construction, infrastructure	Yes
Ayala, Jaime Augusto Zobel de	11/8/16	Philippines	Ayala Corporation		Yes
Azeri, Gülsüm	4/29/14	Turkey	Group President, Şişecam; CEO, OMV Petrol Ofisi	Chemicals and glass; Petroleum	Yes
Aziz, Seema	10/18/16	Pakistan	Founder, CARE Foundation; Managing Director, Sefam	Education and Retail	Yes
Azmi, Shabana	11/30/15	India	Actress	Cinema	No
Bajaj, Rahul	7/8/14	India	Chair, Bajaj Group	Diversified	Yes
Bansal, Sanjay	4/27/18	India	Chairman & Managing Director, Darjeeling Organic Tea Estates Pvt. Ltd.	Tea, Agribusiness	No
Bazan, Rosario	5/27/17	Peru	Danper	Canning, Agriculture	No
Benegal, Shyam	11/16/17	India	Filmmaker	Cinema	Yes
Bhatt, Ela	7/13/17	India	Founder and Former General Secretary, Self-Employed Women's Association	Microfinance	No
Boyner, Cem	9/16/14	Turkey	President, Boyner Holding	Retail	Yes
Burman, Anand	12/21/17	India	Chairman, Dabur India Limited	Consumer products	Yes
Celia, Antonio	3/2/17	Colombia	CEO, Promigas	Natural Resources	Yes
Chalhoub, Patrick	3/21/18	UAE	Co-CEO, Chalhoub Group	Luxury, Retail	No
Chandaria, Manu	6/13/14	Kenya	Chair and CEO, Comcraft Group	Steel and Aluminum	Yes
Chandra, Subhash	10/20/16	India	Chairman, Essel Group	Media, Entertainment	Yes
Chaudhary, Binod	7/25/18	Nepal	Chairman, Chaudhary Group	Diversified	Yes
Chetti, Nalli Kuppuswami	6/28/14	India	Chair, Nalli Silk Sarees	Textiles, retail	Yes
Cortes, Jose Alejandro	3/2/17	Colombia	President, Board of Directors, Grupo Bolívar	Diversified	No

Cunha, Paulo	7/3/13	Brazil	Chair, Grupo Ultra	Petroleum and Natural Gas; Chemicals	Yes
Danso, Hubert	4/17/15	South Africa	CEO and Vice Chair, Africa Investor	Financial Services, Media	Yes
Dato' Sri Prof. Dr. Tahir	1/24/17	Indonesia	Founder, Chair, & CEO Mayapada Group	Financial Services	Yes
Dudeja, Shamlu	4/27/18	India	Kantha Revivalist; Director, Malika's Kantha Collection & Trading Pvt. Ltd.; Chairperson, SHE Foundation, Calcutta Foundation	NGO; textiles	Yes
Esteves, Andre	7/1/13	Brazil	Former CEO, BTG Pactual	Financial Services	Yes
Fernando, Merrill	12/24/15	Sri Lanka	Founder and Chairperson, MJF Group	Tea	Yes
Gerdau, Jorge	7/2/13	Brazil	Chairman, Gerdau Advisory Council; former CEO, Grupo Gerdau	Steel	Yes
Ghandour, Fadi	7/4/17	UAE	Founder and Former CEO, Aramex	Shipping & Logistics	No
Godrej, Adi	5/2/13	India	Chair, Godrej Group	Diversified	Yes
Grimoldi, Alberto	5/19/16	Argentina	Grimoldi, S.A.	Clothing, Shoes, Retail	Yes
Hamied, Yusuf	4/29/13	India	CEO, Cipla	Pharmaceutical s	No
Hochschild, Eduardo	5/26/17	Peru	Hochschild Group	Mining	Yes
Husain, Shahnaz	3/31/16	India	Founder & CEO, Shahnaz Herbals Inc.	Beauty	No
Ibrahim, Mo	9/15/17	Sudan	Founder and Chairman, Mo Ibrahim Foundation	Telecoms, NGO	Yes
Jain, Anil	12/11/17	India	Vice Chairman and CEO, Jain Irrigation Systems Limited	Agribusiness	Yes
Kamdani, Shinta Widjaja	11/28/16	Indonesia	Owner and CEO, Sintesa Group	Consumer Products, Energy	Yes
Kapur, Ranjan	8/15/15	India	Country Manager, WPP	Advertising	No
Koç, Rahmi M.	2/12/15	Turkey	Honorary Chairman, Koç Holding	Diversified	Yes
Krishna, Suresh	12/19/12	India	Chair, Sundram Fasteners	Metal products	Yes
Kumar, Ritu	1/14/15	India	Ritika Private Limited	Fashion, textiles, retail	No
Lorentzen, Erling	7/4/13	Brazil	Former CEO, Aracruz Celulose	Pulp and Paper	No
Mahindra, Keshub	7/24/13	India	Former Chair, Mahindra Group	Diversified	No
Martins, Carlos "Wizard"	10/7/15	Brazil	Founder, Grupo Multi	Education	No

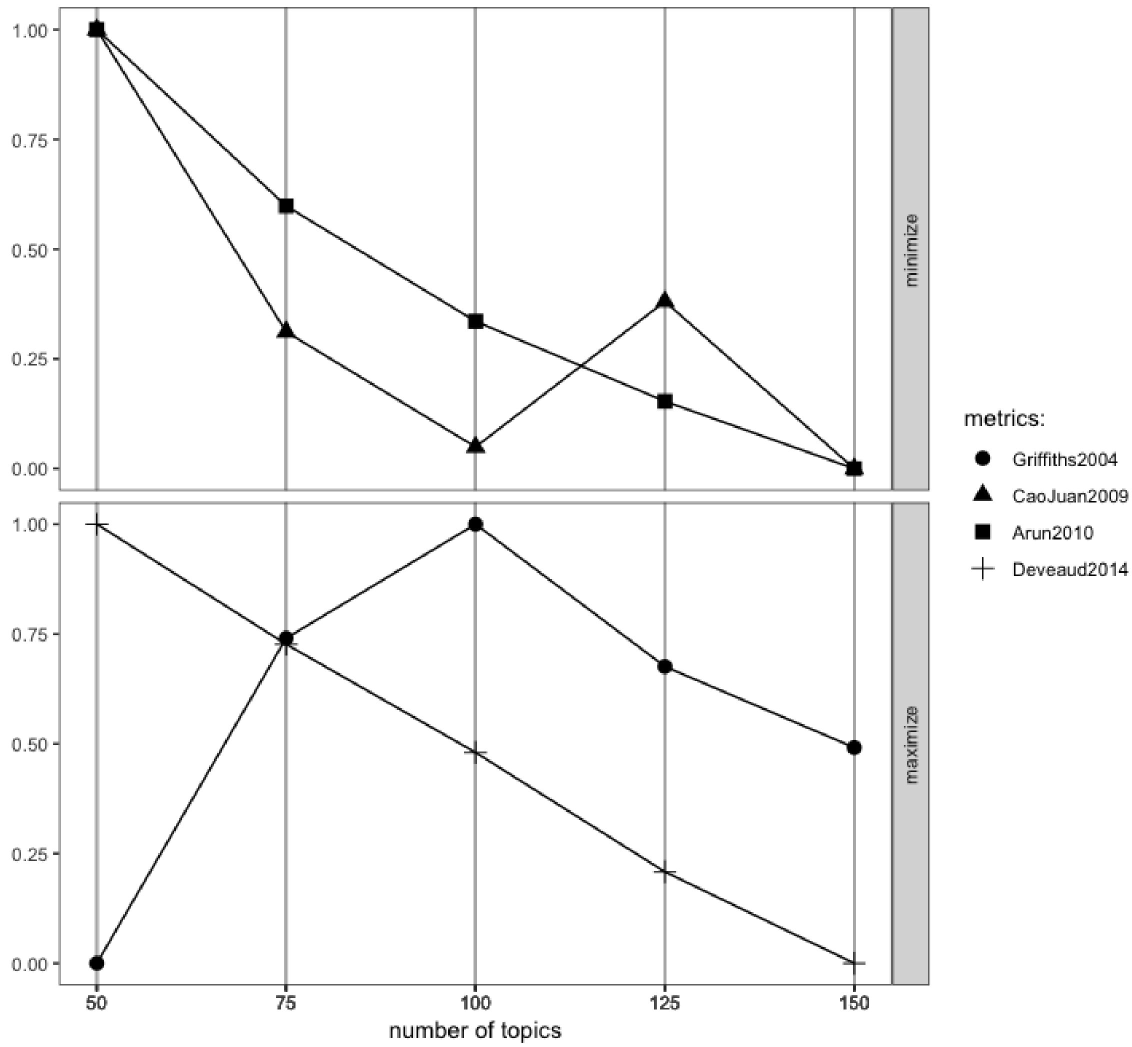
Maziya, Savannah	4/17/15	South Africa	CEO, Bunengi Holdings; Chair, Parsons Brinckerhoff Africa	Infrastructure, Mining	Yes
Mazumdar-Shaw, Kiran	6/4/18	India	Chairperson and Managing Director, Biocon Limited	Pharmaceutical s	Yes
Mittal, Sunil Bharti	11/17/17	India	Founder and Chairman, Bharti Enterprises	Telecommunic ations	Yes
Mody, Zia	2/14/17	India	AZB & Partners	Corporate Law	Yes
Muraya, Eva	11/1/13	Kenya	Group CEO, Brand Strategy and Design Ltd	Advertising and Marketing	No
Nxasana, Sizwe	5/23/17	South Africa	National Student Financial Aid Scheme (NSFAS), First Rand, Ltd., Telkom	Finance, telecoms	Yes
Oberoi, Prithvi Raj Singh	8/25/15	India	Executive Chairperson, EIH Limited	Hospitality, tourism	Yes
Okelo, Elizabeth Mary	2/27/15	Kenya	Founder, Kenya Women Finance Trust and Makini Schools	Financial services; Education	Yes
Okomo-Okello, Francis	2/28/14	Kenya	Chair, Barclays Bank of Kenya and TPS Eastern Africa Limited-Serena Group	Financial Services; Hotels	No
Özyeğin, Hüsnü	9/16/14	Turkey	Chair, FIBA Holding	Financial Services	Yes
Pestonjee, Aban	7/13/17	Sri Lanka	Founder and Chairman, Abans Group	Diversified	Yes
Purie, Aroon	10/24/17	India	Chairman and Editor-in-Chief, India Today Group	Media, Entertainment	Yes
Rao, Jaithirth (Jerry)	6/1/16	India	Founder, Chairman, Value and Budget Housing Corporation	Real Estate; IT; Banking	Yes
Reddy, Prathap C.	4/29/14	India	Founder and Chair, Apollo Hospitals	Healthcare	Yes
Reddy, Y.V.	7/2/17	India	Reserve Bank of India (RBI)	Banking	No
Restrepo, Gonzalo	11/20/17	Colombia	Former President and CEO, Almacenes Éxito	Retail	No
Sabancı, Güler	5/23/14	Turkey	Chair, Sabancı Holding	Diversified	Yes
Sarabhai, Mallika	12/15/16	India	Darpana Academy of Performing Arts	Arts, Media, Entertainment	No
Shetty, Devi	10/10/17	India	Founder and Chairman, Narayana Health	Healthcare	Yes
Simbaqueba, Lilian	11/7/17	Colombia	Founder and President, Grupo LiSim	IT, microfinance	Yes
Subbiah, M.V.	4/25/16	India	Executive Chairman, Murugappa Group	Sugar, Agribusiness, Bicycles, Insurance	No
Tata, Ratan Naval	4/27/15	India	Former Chair, Tata Group; Chair, Tata Trust	Diversified	No
Vaghul, Narayanan	10/26/17	India	Former Chairman, ICICI Bank Limited	Banking, finance	No
Vargı, Murat	9/17/14	Turkey	Founder and Chair, MV Holding	Diversified	Yes

Online Supplement Figure A1. Histograms Summarizing Results from Human Coders' Classification of Facial Emotions



Note: Each panel's title corresponds to the label of the image found in Table A1. The scores listed after the title refer to the one or two primary emotions detected by the Face API, which are also reported in Table A1.

Online Supplement Figure A2. Fit Metrics for Topic Number Selection



Note: Figure displays four different measures of fit at various numbers of topics for our topic model estimation. The top panel shows two metrics to be minimized for best fit, while the bottom panel shows two metrics to be maximized for best fit. Fit measures are scaled between 0 and 1, with the best value indexed at 1. See Section A2 for more details.

Online Supplement Figure A3. Top 10 Keywords Associated with Each Topic in Final LDA Topic Model

[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]	[13]	[14]	[15]	[16]	[17]	[18]	[19]	[20]
office	money	experience	people	university	level	remember	stock	home	investment	growth	plant	believe	political	saris	manager	culture	gone	sector	sell
balance	funds	learned	thank	school	organization	contract	shares	leave	opportunity	grow	plants	bad	party	shop	sales	values	huge	private	buy
close	raise	learn	heart	engineering	people	ship	shareholders	stay	investments	growing	nepal	groups	politics	sari	marketing	employees	run	public	customers
head	spend	car	care	students	create	war	control	house	investors	economy	paper	mistakes	democracy	customers	branch	believe	sort	enterprise	sold
inside	amount	learning	god	study	issue	shipping	exchange	left	invest	start	produce	strong	system	days	charge	respect	grew	basis	customer
front	coming	taught	health	universities	believe	port	share	days	assets	opportunities	trees	makes	member	color	staff	itaú	start	opportunity	selling
career	borrow	life	hospital	studies	sense	equipment	sold	stayed	infrastructure	grown	dream	strongly	politicians	power	moved	performance	department	develop	buying
beginning	lend	mistake	healthcare	degree	organizations	german	stake	couple	fund	acquisitions	cellulose	views	discussion	visit	engineer	structure	happened	body	bought
finally	free	wrong	whatever	college	entrepreneur	machine	bought	dad	equity	diversify	tree	field	opinion	street	weeks	unibanco	people	resources	offer
sheet	bankrupt	helped	happy	studying	entrepreneurial	paid	held	gone	capital	largest	production	prove	parliament	hand	guy	difference	times	information	sale

[21]	[22]	[23]	[24]	[25]	[26]	[27]	[28]	[29]	[30]	[31]	[32]	[33]	[34]	[35]	[36]	[37]	[38]	[39]	[40]
world	stores	period	future	friends	project	society	plan	course	clients	national	significant	idea	successful	bank	technology	foreign	board	social	quality
western	store	difficult	question	kantha	projects	role	size	developed	service	tourism	institutions	research	success	banks	global	export	members	responsibility	name
wrong	retail	lost	happen	soon	example	play	decided	developing	services	park	focus	center	third	banking	standards	exports	executive	corporate	reputation
true	sell	transition	happens	send	construction	feel	ago	start	example	stuff	insurance	ideas	operation	central	world	import	directors	responsible	looked
fine	concept	continued	hand	french	develop	entrepreneurs	strategic	basically	provide	nature	managed	innovation	entire	loans	available	exchange	holding	involved	fabric
benefit	selling	ready	past	paris	huge	impact	strategy	boston	client	tour	financial	willing	results	banco	singapore	local	committee	sustainable	exactly
wait	chain	80s	answer	fashion	based	talk	scale	account	provided	tours	result	call	operate	loan	brought	manufacture	independent	environmental	expensive
chance	supermarket	late	comes	hold	problems	giving	twenty	industrial	providing	san	housing	using	entrepreneur	bankers	continue	imports	run	issues	people
main	shopping	meant	matter	friend	reason	ago	company's	institute	software	cst	created	talking	fourth	deposits	standard	abroad	governance	sustainability	suppliers
feel	el	managed	necessarily	love	opportunity	played	possible	vision	support	natural	key	innovative	canada	credit	globally	due	executives	impact	matter

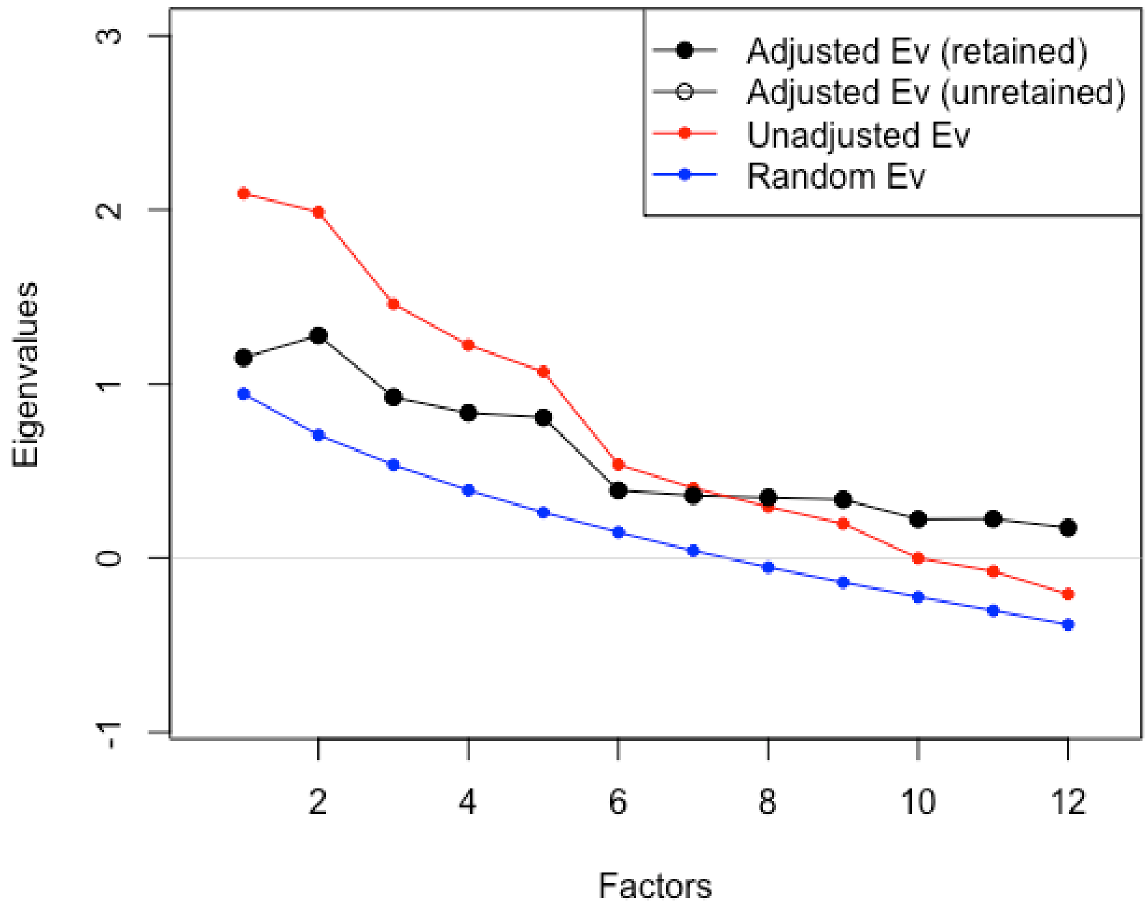
[41]	[42]	[43]	[44]	[45]	[46]	[47]	[48]	[49]	[50]	[51]	[52]	[53]	[54]	[55]	[56]	[57]	[58]	[59]	[60]
leaders	women	partner	create	development	call	percent	days	real	job	million	result	decision	production	father	management	school	price	workers	happened
support	woman	partners	value	economic	license	rate	week	land	months	dollars	coffee	decided	factory	brother	team	schools	cost	union	helped
leadership	men	bought	created	resources	internet	rates	meet	city	position	billion	1970s	forward	glass	grandfather	managers	children	prices	labor	suddenly
leader	village	partnership	creating	human	phone	term	morning	involved	offered	half	1980s	step	biggest	died	top	girls	costs	relationship	stop
talking	access	talent	businessmen	terms	mobile	obviously	months	estate	spent	dollar	1990s	move	chemicals	brothers	hired	teachers	low	unions	exactly
regional	rural	local	jobs	manner	network	short	sent	strong	happy	value	proved	cut	produce	uncle	hire	class	increase	industrial	guys
integration	means	acquired	continue	practices	system	words	hours	decided	run	worth	economy	decisions	supply	father's	teams	teaching	profit	strike	strength
various	coming	deal	capacity	example	office	able	letter	paulo	especially	population	focused	moving	line	parents	manage	teach	profits	relations	period
talked	respect	option	added	drive	story	properly	lunch	são	continue	debt	economic	steps	factories	lived	managed	college	lower	relationships	tremendous
position	unless	total	coming	resource	commission	thirty	wrote	rio	boss	currency	grown	ready	market	age	hiring	students	margin	european	ran

[61]	[62]	[63]	[64]	[65]	[66]	[67]	[68]	[69]	[70]	[71]	[72]	[73]	[74]	[75]	[76]	[77]	[78]	[79]	[80]
person	government	problem	tea	people	water	change	hotel	product	english	people	east	energy	market	brand	challenge	history	process	financial	pay
director	governments	issues	darjeeling	training	food	changed	people	products	read	understand	middle	oil	competition	brands	easy	course	knowledge	crisis	cash
chairman	businessmen	problems	industry	program	farmers	changes	travel	care	speak	community	region	gas	share	market	manage	ones	engineers	system	credit
managing	power	issue	organic	trained	whatever	systems	hotels	raw	book	feel	eventually	distribution	compete	consumer	risk	truth	beginning	inflation	tax
senior	lost	talk	agriculture	train	farm	changing	abroad	hair	books	understanding	local	power	international	strong	challenges	true	experience	crises	paid
guy	military	deal	trade	talk	fish	adapt	lose	personal	language	start	able	natural	competitive	example	taking	laughs	technical	vision	taxes
head	air	corruption	produced	jobs	agriculture	technological	agents	materials	write	reasons	space	advantage	domestic	consumers	basis	involved	start	hit	month
appointed	officials	able	fair	mba	eat	brought	whatever	based	written	word	build	electricity	products	share	faced	believe	entire	payment	paying
ceo	situation	major	association	skill	entire	example	report	chemical	spoke	character	core	ago	markets	marketing	biggest	including	complex	strong	debt
retired	changed	address	estate	beyond	farming	experienced	attention	mainly	reading	comfortable	built	fuel	players	fast	based	telling	factor	credit	income

[81]	[82]	[83]	[84]	[85]	[86]	[87]	[88]	[89]	[90]	[91]	[92]	[93]	[94]	[95]	[96]	[97]	[98]	[99]	[100]
industry	people	view	able	children	capital	life	law	people	terms	operations	family	president	hard	education	minister	mining	build	media	film
steel	recruit	policy	environment	son	markets	live	court	firm	example	moved	professional	met	times	foundation	finance	iron	building	information	television
venture	human	sense	south	mother	international	people	property	running	communities	fishing	generation	club	difficult	basic	meeting	content	built	advertising	story
joint	hours	common	looking	child	emerging	living	laws	kept	impact	copec	members	council	tough	support	happened	cerro	trust	agency	happening
industries	willing	long-term	opportunity	daughter	model	poor	legal	instance	talking	bunge	professionals	invited	remember	programs	prime	mines	realized	digital	particularly
bigger	course	policies	opportunities	wife	terms	nice	act	black	start	largest	families	savings	remain	improve	government	returned	institution	agencies	art
manufacturing	listen	reform	continent	married	access	born	passed	coming	using	owned	join	remember	complicated	focus	chief	operating	none	data	looking
ventures	city	prepared	local	husband	developed	poverty	regulations	professional	local	north	including	especially	understand	involved	governor	peruvian	decided	people	completely
automotive	established	means	understanding	life	base	reason	comes	sort	especially	lived	member	relationships	situation	lives	agreed	lose	roads	press	absolutely
motors	couple	advice	coming	home	key	free	control	accounting	ago	trading	separate	cmpc	immediately	educational	economy	ago	sense	news	stories

Note: Topics are labeled with numbers in parentheses above each set of associated keywords.

Online Supplement Figure A4. Results of Parallel Analysis for Choice of Number of Factors in Factor Analysis Model



Note: The plot displays the results of this exercise on the new incorporated data, showing the factors retained for the 69 observations in our data. The red line shows the original scree plot, while the blue line shows the eigenvalues for the randomly generated data. The black line shows the "adjusted" eigenvalues, subtracting the latter from the former. The results suggest that 12 factors should be retained. See Section A3 for more details.

Online Supplement References

Arun R., Suresh V., Veni Madhavan C.E., Narasimha Murthy M.N. (2010) On Finding the Natural Number of Topics with Latent Dirichlet Allocation: Some Observations. In: Zaki M.J., Yu J.X.,

Ravindran B., Pudi V. (eds) Advances in Knowledge Discovery and Data Mining. PAKDD 2010. Lecture Notes in Computer Science, vol 6118. Springer, Berlin, Heidelberg

Chang, J., Gerrish, S., Wang, C., Boyd-Graber, J. L., & Blei, D. M. (2009). Reading tea leaves: How humans interpret topic models. In *Advances in Neural Information Processing Systems* (pp. 288-296).

Deveaud, R., SanJuan, E. & Bellot, P. (2014). Accurate and effective latent concept modeling for ad hoc information retrieval. *Document numérique*, vol. 17(1), 61-84. doi:10.3166/DN.17.1.61-84.

Ekman, P., & Friesen, W. V. (1971). Constants across cultures in the face and emotion. *Journal of Personality and Social Psychology, 17*(2), 124-129. http://dx.doi.org/10.1037/h0030377

Griffiths, T. L., & Steyvers, M. (2004). Finding scientific topics. *Proceedings of the National Academy of Sciences,101*(Supplement 1), 5228-5235. doi:10.1073/pnas.0307752101

Horn, J. L. (1965). A rationale and test for the number of factors in factor analysis. *Psychometrika,30*(2), 179-185. doi:10.1007/bf02289447

Matsumoto, D. (1992). American-Japanese Cultural Differences in the Recognition of Universal Facial Expressions. *Journal of Cross-Cultural Psychology*, *23*(1), 72–84. https://doi.org/10.1177/0022022192231005

Russell, J. A. (1994). Is there universal recognition of emotion from facial expression? A review of the cross-cultural studies. *Psychological Bulletin, 115*(1), 102-141. http://dx.doi.org/10.1037/0033-2909.115.1.102

Tottenham, N., Tanaka, J. W., Leon, A. C., Mccarry, T., Nurse, M., Hare, T. A., . . . Nelson, C. (2009). The NimStim set of facial expressions: Judgments from untrained research participants. *Psychiatry Research,168*(3), 242-249. doi:10.1016/j.psychres.2008.05.006

ONLINE SUPPLEMENT: ***Oral History Archives***

Archive Name	**Source**
Harvard University Creating Emerging Markets Initiative	http://www.hbs.edu/creating-emerging-markets/interviews/Pages/default.aspx
UCLA Center for Oral History	http://oralhistory.library.ucla.edu/Browse.do?coreDescCvPk=27901&Subject=Business
Columbia University Oral History Archives	http://library.columbia.edu/locations/ccoh.html
World Bank Oral history archive	http://oralhistory.worldbank.org/
Indiana University Center for the Study of History and Memory	http://www.indiana.edu/~cshm/alphalist.html
University of California Berkeley Oral History Collection	http://www.lib.berkeley.edu/libraries/bancroft-library/oral-history-center/search-oral-histories
University of Connecticut Oral History	http://www.oralhistory.uconn.edu/catalog.html
University of Kentucky Louie B. Nunn Center for Oral History	https://kentuckyoralhistory.org/
The British Library	https://www.bl.uk/collection-guides/oral-histories-of-business-and-finance
The History Factory	http://www.historyfactory.com/
History Associates	https://www.historyassociates.com/who-we-serve/our-clients/
University of Florida Oral History Collections	http://ufdc.ufl.edu/ohfbl