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A Computational Framework for Understanding Firm Communication During Disasters

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Abstract. Large firms are leaders in disaster response and communication. We study how firms communicate on social media during various disasters and the relationship between their communication and public engagement using a computationally intensive theory construction framework. The framework incorporates a novel natural language processing (NLP) approach, Semantic Projection with Active Retrieval (SPAR), as a key component of the method lexicon. Drawing on the two dimensions (*internal* versus *external* and *stable* versus *flexible*) of the Competing Values Framework (CVF) as our theoretical lexicon, we examine Facebook posts of Russell 3000 firms on multiple disasters between 2009 and 2022. We find that social media messages that are internal- and stable-oriented, or emphasize operational continuity, are more likely to elicit engagement from the public during biological disasters. By contrast, messages that are external- and flexible-oriented, or stress the innovations to adapt to the disaster, induce more engagement in weather-related disasters. The study offers theoretical implications and methodological support for the research and design of social media messages in disasters and other contexts.

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1. Introduction

The private sector and social media are two integral parts of modern disaster response (Houston et al. 2015, Izumi and Shaw 2015, Chandra et al. 2016, Kryvasheyeu et al. 2016, Arora and Chakraborty 2021). Large firms, with their extensive information technology (IT) resources and social media accounts with millions of followers, are natural leaders of disaster communication. Their social media presence offers an efficient and reputable channel to broadcast information and shape public understanding in disrupted environments (Guan and Zhuang 2015, Ballesteros et al. 2017, Arora and Chakraborty 2021, Athey et al. 2023). Successful social media outreach during crises can also generate long-lasting positive impacts on firms' image, allowing firms to create values for broader stakeholders (Roshan et al. 2016, Borah et al. 2020, Wang et al. 2021). Moreover, since the literature has documented a link between firms' social media activities and stock returns (Luo et al. 2013, Bartov et al. 2018, Peng et al. 2022), effective social media strategies generating substantial public engagement have the potential to channel financial resources to firms facing funding challenges during disaster response and recovery (Chandra et al. 2016).

However, although firm-generated content has become a central topic for information science (IS) research (Gunarathne et al. 2017, Lee et al. 2018, Bai et al. 2020, Sun et al. 2021, Kumar et al. 2022), the emerging phenomenon of firm disaster communication on social media remains underexplored. Current research predominantly addresses firm social media communication in normal times (Dou et al. 2013, Miller and Tucker 2013, Chung et al. 2020, Nian and Sundararajan 2022) and firm-specific crises (Gwebu et al. 2018, He et al. 2018, Gao et al. 2022). The few existing studies that are on disaster-related communication mainly focus on nonprofit and governmental organizations (Oh et al. 2013, Yan and Pedraza-Martinez 2019) and deal with a single or nonspecific disaster (Liu et al. 2020, Mirbabaie et al. 2020). This lack of theory and empirical evidence guiding businesses' social media communication in various natural disasters is particularly concerning, given the crucial role of effective communication during crises.

This study thus examines firms' disaster communication practices on social media and evaluates their effects on public engagement in various disasters. We focus on public engagement with firms' social media messages because it reflects the effectiveness of firm communication and has been widely used as an important outcome variable in IS research (Mallipeddi et al. 2021, Kumar et al. 2022). Our research questions are the following:

RQ1: How do firms communicate on social media during natural disasters?

RQ2:

(a) How does firms' disaster-related social media communication affect public engagement? and

(b) does the effect differ in different disasters?

We follow the recent call in IS to conduct computationally intensive theory construction (Berente et al. 2019, Johnson et al. 2019, Miranda et al. 2022b) and develop a computational framework to answer the aforementioned research questions. Despite the abundance of data provided by social media, their unstructured nature poses difficulties for conducting theory-driven research using the hypothetico-deductive approach (Howison et al. 2011, Berente et al. 2019). Computationally intensive theory construction research explores new data sources with computational methods to generate theoretical implications for emerging IS phenomena. This approach acknowledges the challenges in applying existing theories to unstructured big data and allows for flexibility in theoretical applications, without letting data dictate research questions, design, or analysis.

The theory construction process synthesizes three lexicons: *practice, method*, and *theoretical*. The practice lexicon is situated in the empirical phenomenon being studied. Method lexicons are determined by the methods researchers apply. Theoretical lexicons are embedded in the theoretical framework the scholars employ. The practice lexicon of our study is contextualized in firm disaster communication on social media. We adopt natural language processing (NLP) as our primary method lexicon to analyze the texts of firms' social media posts. We introduce a novel language embedding approach, Semantic Projection with Active Retrieval (SPAR), for deriving latent categories and associations. SPAR uses large language models (LLMs) to represent both latent theoretical concepts and text data in the same semantic space, allowing researchers to progressively retrieve relevant data that best exemplify the concepts and measure the documents using their similarity with the retrieved data. By integrating language embedding, text retrieval, and active learning, SPAR capitalizes on the strengths of both LLMs and human coding to aid theory-driven exploration of large textual data.

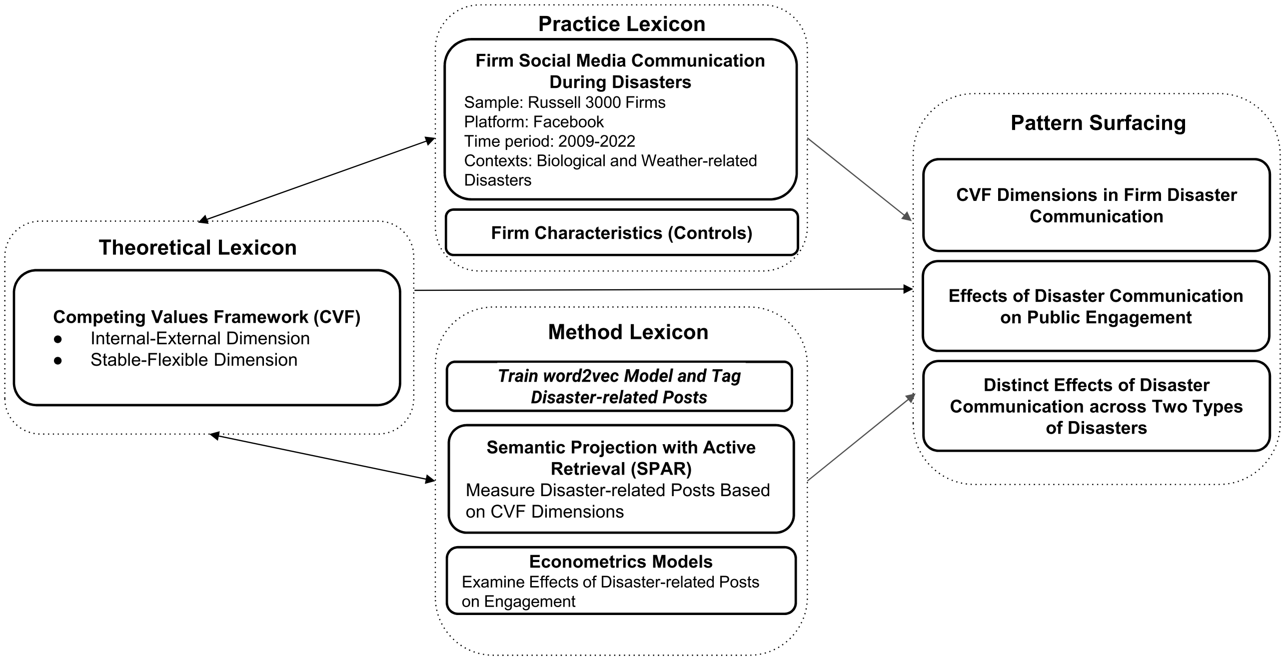
To guide our computational effort, our framework builds on the dimensions of the Competing Values Framework (CVF) (Quinn and Rohrbaugh 1983, Cameron 2006, Cameron and Quinn 2011) as our theoretical lexicon. Although CVF was validated in internal corporate communication (Quinn et al. 1991, Rogers and Hildebrandt 1993, Belasen and Frank 2010), it has not been applied to understand firm disaster communication or evaluate communication effectiveness. We measure the orientations of firms' social media posts along the two competing dimensions: *internal* versus *external* and *stable* versus *flexible*. The two dimensions underscore the basic contradictions firms face in disasters. Disaster messages that are *internal*-oriented focus on operations, employees, and communities, whereas *external*-oriented messages emphasize a firm's response to the business environment. On the *stable* versus *flexible* dimension, *stable*-oriented messages highlight firms' actions to maintain production and service, while *flexible*-oriented messages underline new adaptations and innovations to respond to the disaster.

We analyze disaster-related Facebook posts of Russell 3000 firms from 2009 to 2022. After measuring firms' social media communication on the two competing dimensions, we apply econometric models to examine the relationship between firm communication orientations and public engagement on social media in two different types of disasters—biological disasters (e.g., pandemics) and weather disasters (e.g., hurricanes). We find that firms' social media communication shapes public engagement differently in the two types of disasters. In biological disasters that disrupt daily interactions, social media messages that are *internal-* and *stable*-oriented, or those emphasizing firms' measures to continue their operations and protect employees, attract higher public engagement. Quite the opposite, in weather-related disasters, messages that are *external-* and *flexible*-oriented, or those highlighting firms' ability to create new products and adapt to the environment, lead to higher public engagement. Figure 1 summarizes our computational framework.

Our work constitutes the "*patterns with theoretical implications*" contribution in computationally intensive theory construction, as outlined by Miranda et al. (2022b). The findings of the current research offer original insights. First, we show that firms' disaster communication on social media can be meaningfully characterized based on two competing dimensions (*internal* versus *external*; *stable* versus *flexible*), which are new to the existing literature on organizational communication (Kim et al. 2009, Kusumasondjaja 2018, Yousaf et al. 2020) and CVF (Quinn and Rohrbaugh 1983, Quinn et al. 1991, Cameron and Quinn 2011).

Second, we are among the first to confirm the impacts of these dimensions on social media engagement during disasters and reveal the potential boundary conditions of the effects. Whereas existing research typically addresses one type of disaster (Oh et al. 2013, Yan and Pedraza-Martinez 2019), our study demonstrates that the impact of firm disaster communication on public engagement is contingent on disaster types. Our interviews with 16 national leaders in disaster response confirm the applicability of the

Figure 1. A Computational Framework to Extract Theoretical Patterns of Firm Disaster Communication on Social Media



Source. Adapted from figure 1 in Miranda et al. 2022b.

two competing dimensions in understanding firm disaster communications and support the validity of the observed patterns in firm message orientations and user engagement. Therefore, we contribute to our theoretical lexicon, CVF, by adding new relationships not established in the literature before (Miranda et al. 2022b). Our observations also offer implications to further develop the CVF to specify the boundary of the competing dimensions' effects. In addition, prior research has studied CVF dimensions in corporate communication and culture separately, implying that the two practices may not be identical. Our study thus raises the question about the alignment between firms' communication orientation in disasters and organizational value orientation, offering opportunities for new theorizing of organizational practices using CVF.

Finally, our study provides future researchers with a novel approach for computationally intensive theory construction with textual data (Berente et al. 2019, Johnson et al. 2019, Miranda et al. 2022b). The approach synthesizes human judgment with multiple existing computational methods to identify theoretical patterns in unstructured textual data. Its analytical logic and measures are flexible and easy to interpret, even for researchers with limited training in machine learning. The application of the method is not limited to disaster communication or CVF but can be extended to a variety of contexts and theories. We provide an open-source Python package to facilitate other scholars' use of SPAR in their research.

2. A Computational Framework of Firm Disaster Communication on Social Media

2.1. Computationally Intensive Theory Construction of Firm Disaster Communication

Social media provide abundant and accessible data on firms' communication during disasters. However, the data are unstructured and large in scale. This means disaster communication data from social media do not conform to extant theoretical constructs or validated measures, making it hard for researchers to apply and develop extant theories following the traditional hypothetico-deductive approach (Howison et al. 2011, Abbasi et al. 2018, Berente et al. 2019). Therefore, IS scholars have recently called for computationally intensive theory construction to support the exploration of emerging phenomena with the goal of theory development (Berente et al. 2019, Johnson et al. 2019, Miranda et al. 2022b).

The process of computationally intensive theory construction involves reconciling and integrating three lexicons: *practice*, *method*, and *theoretical* (Miranda et al. 2022b). Inherent to the empirical phenomenon under study, the practice lexicon reflects languages laden with contextualized understanding. Method lexicons, which are prescribed by the analytical tools employed, influence researchers' assumptions and inferences of empirical evidence. Theoretical lexicons are theoretical discourses that scholars use to elucidate their research based on concepts and their relations. In the following sections, we explain our computational framework to extract theoretical patterns in firm disaster communication by elaborating on the three lexicons of our study.

2.2. Practice Lexicon: Firm Disaster Communication on Social Media

We study the phenomenon of firm disaster communication on social media, that is, the sharing of disaster-related information, actions, and perspectives by companies to engage with the public. We focus on the two most common types of natural disasters—biological and weather-related disasters (Below et al. 2009). Biological disasters, which often take the form of epidemics or pandemics of infectious diseases, are scenarios where a disease spreads widely among humans due to certain pathogens (e.g., viruses). By contrast, weather-related disasters, such as hurricanes and wildfires, are destructive natural events as a result of weather or climate fluctuations. Both disaster types have resulted in significant losses. For example, Covid-19 has killed 6.5 million people worldwide, and over the past 50 years, weather disasters on average killed 115 people each day and caused US$202 million in daily losses (WMO 2021).

Anecdotal evidence points to the value of firms' social media communication in disasters. During Hurricane Sandy, large firms such as JetBlue and Con Edison were lauded for their effective utilization of social media (Gabbatt 2013). Their social media presence offered reassurance and satisfaction to the public and gained significant followers for the firms. The real-time updates were widely shared, helping the firms interact with people and adapt their practices during and after the storm. As the chief executive officer (CEO) of RankSecure emphasized in a *Forbes* quote: "Whether you're updating customers about hours of operation, offering support or aid to your community, or just passing along information that might be useful, social media can be a huge asset for your business during any crisis" (Segal 2021).

For firms, effective communication that stimulates public engagement can cultivate stronger relationships with customers and other stakeholders. Firms engaging in online communication can foster a sense of belonging and shared identity, which in turn enhances customer loyalty and advocacy (Bhattacharya and Sen 2003). Addressing stakeholders' needs and expectations during disasters is also vital for maintaining corporate reputation (Palttala et al. 2012). This improved reputation can lead to positive word-of-mouth and, ultimately, better financial performance (Fombrun and Shanley 1990). In addition, the network nature of social media (Qiu et al. 2015) enables engaged audiences to further share information by exposing their connections to the content. This cascading effect may lead to a rapid and broad spread of useful information during disasters. A recent field experiment has demonstrated the cost-effectiveness of social media messages in influencing public attitudes and behaviors (Athey et al. 2023), which further underscores the potential of optimizing firm communication for engagement in times of disaster.

2.3. Method Lexicon: SPAR

In computationally intensive theory construction, the lack of applicable theories for emerging IS phenomena requires a flexible assembly of practice, method, and theoretical lexicons and iterative alignment of the three (Berente et al. 2019, Miranda et al. 2022b). During this process, fast and scalable alignment between theoretical concepts and domain-specific text data is crucial. Our method lexicon, SPAR, offers flexibility and supports this process.

The SPAR framework integrates multiple well-established computational techniques, including language embedding, semantic projection, and active learning. It leverages the representation power of LLMs, while remaining computationally efficient to support theory development. It builds on recent literature demonstrating the effectiveness of *semantic projection* in measuring theoretical constructs from texts (Bolukbasi et al. 2016, Li et al. 2021, Grand et al. 2022). Specifically, language embedding captures text semantics as dense embedding vectors in a multidimensional space (Ebrahimi et al. 2022, Yang et al. 2023a). If a meaningful *feature subspace* can be defined based on a theoretical concept within this multidimensional space, the encoded values in the text can be recovered by projecting its embedding vector to this subspace (i.e., computing the dot product of the embedding vector and the subspace) and used as a measure of the construct. Usually, the feature subspace is a one-dimensional scale—a straight line in the embedding space on which the value in the text can be ordered. Research shows that even highly abstract concepts such as gender, religiosity, intelligence, and valence can be measured using this method and the results are consistent with human judgment (Bolukbasi et al. 2016, Grand et al. 2022).

In the literature, the feature subspaces are defined using the difference between pairs of word embedding vectors with opposing meanings to define a feature subspace, for example, $\overrightarrow{\boldsymbol{she}} - \overrightarrow{\boldsymbol{he}}$ defines the *gender* subspace, and $\overrightarrow{\boldsymbol{smart}} - \overrightarrow{\boldsymbol{stupid}}$ defines the *intelligence* subspace. We expand on this idea by employing a human-in-the-loop approach, where a theoretical lexicon guides the active search for exemplary social media posts to define the feature subspaces. The main novelty of our approach is that it combines the notions of active learning (Settles 2012, pp. 3–4) and semantic search so that researchers can efficiently and progressively find contextually relevant posts.[1] These modifications respond to the call for incorporating human activities and intellect in the computational theory discovery process (Berente et al. 2019).

Figure 2 depicts the two main steps of SPAR. The first step is *active retrieval*, which aims to identify exemplary social media posts that align with concepts in a theoretical lexicon. To accomplish this, we use an LLM to embed the posts into dense vectors in a semantic space. The resulting vectors are normalized to unit length. We employ the same LLM to embed the theoretical lexicon seeds, which are generic sentences describing theoretical concepts. The dot product between the embeddings of the posts (documents) and the embeddings of the seeds (queries) provides a relevance score for semantic search. A semantic search engine returns the indexed posts that are most relevant to the seeds, and researchers then judge their relevance to the theoretical concepts. Exemplary posts that align with the concepts are retained. The process is repeated by using these exemplary posts as new queries. Once a sufficient number of exemplary posts have been collected, we proceed to the second step by computing theoretical scales using exemplary post embeddings. Each post is then measured by projecting it onto the scale.

We provide an open-source Python package at https://pypi.org/project/spar-measure/ to facilitate the application of SPAR. The package contains a user-friendly graphical user interface (GUI) and implements a complete pipeline of text embedding, active retrieval, and measurement. Online Appendix A8 provides a tutorial on the package. Section 5.2 discusses how SPAR is connected to other widely used NLP approaches, as well as its advantages and limitations.

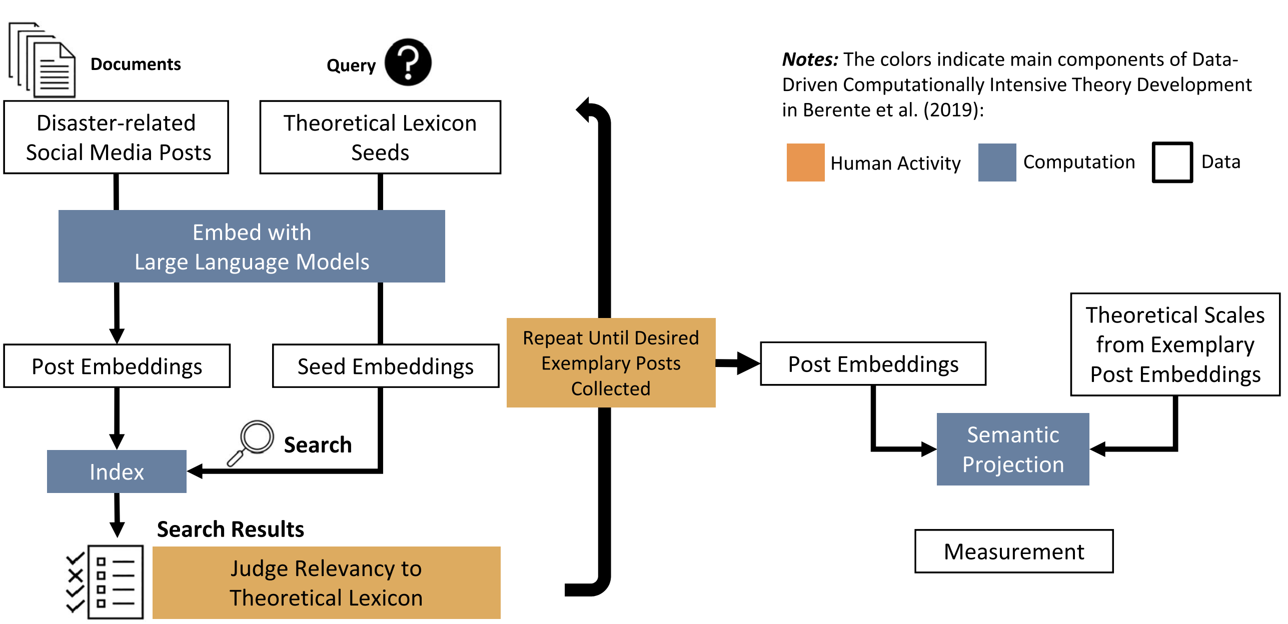
2.4. Theoretical Lexicon: CVF

We draw on the dimensions of the CVF (Quinn and Rohrbaugh 1983, Cameron 2006) as our theoretical lexicon to inform our analysis of firms' social media disaster communication. The central tenets of CVF state that firms' actions can be understood based on two competing value orientations (i.e., what the firms believe will generate values)—*internal* versus *external*, and *flexible* versus *stable* (Buenger et al. 1996, Cameron 2006, Hartnell et al. 2011). The two dimensions reflect two basic dilemmas faced by organizations—how do organizations balance internal versus external effectiveness and address change versus stability (Quinn and Rohrbaugh 1983)? Therefore, CVF offers a dialectical view of organizational practices, highlighting the tensions and complexity inherent in organizational processes and their relations to the environment.

Whereas often seen in research on organizational culture, CVF was developed as a general framework for the analysis of organizational effectiveness (Quinn and Rohrbaugh 1983, Cameron and Quinn 2011). Over the years, the framework was found to be applicable across a wide variety of organizational phenomena, including leadership, organizational design, and communication (Cameron 2009). Scholars have shown that the two competing dimensions of CVF (i.e., *internal* versus *external*, and *flexible* versus *stable*) are the core principles inherent in corporate communication (Quinn et al. 1991, Belasen and Frank 2010) and have used the framework to characterize firm communication practices (Rogers and Hildebrandt 1993, Belasen 2008). Nonetheless, research on CVF in communication has been limited and not extended to firms' social media communication in disasters.

CVF is suitable for corporate communication because different from interpersonal communication, corporate communication is "more goal oriented and situationally constrained" (Quinn et al. 1991, pp. 218) and needs to make "multifaceted communication decisions involved in dealing with conflicts" (Rogers and Hildebrandt 1993,

Figure 2. (Color online) Flowchart of SPAR



Notes: The colors indicate main components of Data-Driven Computationally Intensive Theory Development in Berente et al. (2019):

pp. 123). When communicating, organizations need to make trade-offs and respond to "contradictory and often inconsistent expectations" that are "vital for building a strong identity and sustaining a credible organizational image" (Belasen 2008, pp. 11). This is particularly true in disasters, when the event disrupts the stability of firms both internally to their routine operations and externally to the customers and markets (Chandra et al. 2016, Arora and Chakraborty 2021, Guo and Cannella 2021). During weather-related disasters such as Hurricane Katrina, numerous businesses in flooded regions are forced to close (Lam et al. 2012). In pandemics like Covid-19, measures such as the isolation of infected individuals and social distancing hinder the efficiency and continuity of business operations and customer service (Donthu and Gustafsson 2020). Thus, the competing dimensions reflect the two fundamental dilemmas in firms' communication to the public during disasters: should firms emphasize their internal operations and employees or customers and community stakeholders? Should they focus on stabilizing their operations or adapting to the changing environment?

On the internal-external dimension, firms' social media communication with an internal orientation may stress their own operations, internal stakeholders, and community members (e.g., employees and partners) in disasters (Buenger et al. 1996, Cameron 2006). The recovery of operations and protection of employees are primary goals for firm disaster response (Izumi and Shaw 2015). Internal-oriented firm messages would highlight their operational adeptness and highlight human relationships, teamwork, and doing things together during disasters (Cameron 2006, Hartnell et al. 2011). In pandemics like Covid, for example, internal-oriented firm communications may underscore their protection and support for their employees and related communities in disaster response in their communication (e.g., sharing financial and other support for the local hospitals and medical workers during pandemics).

By contrast, external-oriented disaster messages emphasize the environment, market, and customers (Quinn and Rohrbaugh 1983, Cameron 2006). In the disaster context, this means an emphasis on the firms' service to their customers and performance despite the negative environmental conditions, such as storefronts or distribution sites being destroyed or closed (Donthu and Gustafsson 2020). Thus, firms' external-oriented messages would emphasize the actions they take to adapt to the environment, recover market order, and ensure the quality of their service to their clients during the disaster—for example, prioritizing digital services and phone orders if the disaster prevents clients from traveling to their physical locations.

On the stable-flexible dimension, a stable orientation favors control and consistency instead of change and spontaneity in situations of disasters. Stable-oriented messages focus on problem solving, routine effectiveness, and continuity (Quinn et al. 1991, Buenger et al. 1996) during disasters. When firms send out stable-oriented disaster messages, they would like to demonstrate that things are under their control. These messages may focus on the measures implemented to reduce disaster impacts and maintain their routines. For example, stable-oriented firm communications may discuss their determination to ensure operational continuity and stable service to their clients (Fernandes 2021).

In comparison, flexible-oriented disaster messages posted by firms would highlight organizational resilience and adaptation, as well as the firms' visions for new changes at a challenging time. These messages may announce new partnerships the firm has built with other organizations in response (Izumi and Shaw 2015, Shi 2020). Firms may also discuss the innovative technologies or products the firms are working on to tackle the difficulties during the disaster. For instance, in disasters such as wildfires, flexible messages may discuss the new solutions the firm is working on to reduce fire risks and combat climate change. In pandemics, firms may discuss their application of new remote-work technologies, or their support for the development of new medications and vaccinations.

When extending CVF to understand corporate communication, Quinn et al. (1991) proposed the framework as a tool for evaluating corporate effectiveness. However, although research has shown CVF as a useful framework to characterize corporate communication (Quinn et al. 1991, Rogers and Hildebrandt 1993, Belasen and Frank 2010), little is known about how the competing value orientations in firms' communication may impact public engagement on social media or in disasters. It is also unclear to what extent the impact of value orientations in firms' social media communication may depend on disaster types. Prior research has suggested that value orientations reflected in communication, such as socio-emotional and task orientation, may influence the effectiveness of the communication (Brown and Starkey 1994, Yousaf et al. 2020). Value orientations in messages may affect public engagement because they can influence how people perceive the legitimacy of the information (Leidner and Kayworth 2006) and provide a shared cognitive map that unites individuals into collective actions (Langfield-Smith 1992). These qualities are critical during disasters due to the fluidity of the situation (Chen et al. 2019) and the need for disseminating information, coordinating response, and alleviating grief (Leong et al. 2015). The current research thus investigates this question and explores how competing value orientations in firms' social media communication are effective in different disasters.

3. Extracting Competing Dimensions in Disaster Communication

Taken together, to answer our *RQ1*, we use SPAR to analyze firms' disaster communication on social media with the guidance of CVF dimensions. In this process, we undertake *concept operationalization*, a crucial step in computationally intensive theory construction that involves linking abstract concepts to measurable observations. As a result, firms' disaster communication on social media can be quantified based on the two latent CVF dimensions (*internal* versus *external*; *stable* versus *flexible*). We explain the details of the procedure.

We acquire Facebook business page data from CrowdTangle, a public insights tool from Meta (a company brand for Facebook applications and technologies) that supports the analysis of public content on social media.[2] We choose firms that are in the Russell 3000 index as of July 1, 2019, as our firm sample. We manually search for these firms' Facebook business pages by business names, web addresses, and links from the firms' websites. We are able to locate 1,946 firms' business pages on Facebook. We then use CrowdTangle's historical data feature to download all firms' posts and engagement information from July 2009 to June 2022. There are a total of 3,452,528 posts. We remove all empty posts, non-English posts, and paid promotions, which account for 1.48% of the total posts.[3] After excluding observations with missing firm financial variables (which account for approximately 9.96% of the posts), the final sample contains 3,057,490 posts from 1,759 firms, representing 88.55% of the total posts.[4] The time frame encompasses many major disasters such as Covid-19, Hurricane Sandy, and the 2021 Texas Winter Storm. Because the data set covers the largest public companies in the United States that are active on Facebook across various disasters, it provides a comprehensive and representative sample to justify and generalize inference.

We use a set of keywords to identify posts relevant to biological and weather-related disasters. For biological disasters, we use the keywords suggested by Hassan et al. (2023). These keywords include the main outbreak of epidemic diseases in our sample period, that is, Covid-19, H1N1 (swine flu), Middle East respiratory syndrome (MERS), Ebola, Zika, and influenza. For weather-related disasters, we develop our own set of disaster keywords by training a word2vec model (Mikolov et al. 2013) to find the words and phrases that are most relevant to the phrase "weather-related disasters." We then cross-check our list with the list of weather disasters on the National Oceanic and Atmospheric Administration website to ensure completeness.[5] Online Appendix A1 lists the final word list. In total, we include 45,324 biological disaster posts and 17,868 weather-related disaster posts.

We measure the CVF dimensions in disaster messages using the textual content of posts. We start by concatenating a post's main message, text description (for links), and text on images (with text recognition provided by CrowdTangle). We then use an off-the-shelf Sentence-Transformer model (Reimers and Gurevych 2019) to embed the text.[6] Sentence-Transformer is a modification of transformer-based pretrained LLMs, of which the best known is Bidirectional Encoder Representations for Transformers (BERT) (Devlin et al. 2019).[7] By fine-tuning a pretrained transformer LLM on semantic textual similarity tasks using supervised data, Sentence-Transformer excels at measuring the meaning of sentences and short documents, such as Facebook posts.

After embedding the text, we begin the semantic search with a generic set of theoretical lexicon seeds as initial queries. We first generated the initial seed sentences based on the theoretical definitions of the competing dimensions (Table 1). For example, according to CVF (Belasen and Frank 2010, Cameron and Quinn 2011), high external and flexible orientation focuses on the external environment and change. Thus, the messages should emphasize adaptivity and innovation. Based on this, we created the seed sentence "*We should adapt and innovate*" for the *external & flexible* orientation. Next, we observe that the specific manifestation of the theoretical concept indeed varies with each type of disaster, which justifies the need for active retrieval. For example, "*holding hands*" may be an appropriate way to express the *internal & flexible* orientation in a flood, but not necessarily during a pandemic. In each round of query and search, we progressively annotate the top posts returned by the semantic search engine. In the end, we retain 25 final exemplary posts (a total of 100) that represent each CVF orientation separated by the two competing dimensions. We define $\overrightarrow{\{external\ \&\ flexible\}} = mean[\vec{s}_1, \ldots, \vec{s}_{25}]$, where $\vec{s}_k$ is a post embedding vector for exemplary post k generated by the LLM, and likewise for the other dimensions. Table 1 displays example posts along the two competing message dimensions in each disaster type. Online Appendix A2 provides additional details of the procedure.

Next, we define two scales (feature subspace) that correspond to two competing dimensions in CVF. The two competing dimensions in CVF are naturally provided by the geometry of the orientations separated by the two dimensions (Figure 3). Specifically, along each dimension of the CVF, the "positive" and "negative" ends represent opposing concepts of the scale. For example, for external-internal scale, the first and fourth quadrants of Table 1 denote the "positive" or external end of the spectrum, emphasizing concepts like adaptation and innovation, swift responses, and customer service. In contrast, the second and third quadrants of Table 1 with concepts including empathy, collaboration, control, and stability encapsulate the "negative" or internal end of

Table 1. Theoretical Lexicon Seeds and Exemplary Disaster Posts

	Internal	*External*
Flexible	**Seed:** We should empathize and collaborate. **Biological disaster:** Through education, community partnerships, and promotion of good habits, Centene's Fluvention® program works to increase flu vaccination rates. **Weather-related disaster:** Together, we can make a difference. We are hand in hand to help the hurricane victims tonight at 8/7c.	**Seed:** We should adapt and innovate. **Biological disaster:** For all of the chaos of the past few months, there is a lot of reason to feel optimistic. We have all recognized the need to be more digital and to automate as much as possible. **Weather-related disaster:** The rise in severe weather events across the US has underscored the urgent need to address the nation's resilience to climate change. Talking with Kelly Evans on @CNBC's 'The Exchange', Patrick Decker discusses the role digital solutions play in solving water for a more sustainable world.
Stable	**Seed:** We should control and stabilize. **Biological disaster:** Here's a special update from our leadership team on the potential impact of coronavirus to Connection's operations, and measures the company is taking to protect the safety and well-being of our workforce. Statement on COVID-19: **Weather-related disaster:** All but a few of our Florida employees have been reached. All of our employees in Puerto Rico remain safe and accounted for, as well. Hurricane Irma impacted employees are reminded to check-in with their supervisors to the best of their abilities.	**Seed:** We should respond swiftly and serve customers. **Biological disaster:** How has your business communicated to customers during the pandemic? Here are 5 ways to offer excellent customer service during this time. **Weather-related disaster:** Our thoughts are with those impacted by the recent wildfires in California. We are here to assist you. - We are waiving certain fees and charges for customers who've been impacted and contact us for assistance.

the spectrum. Accordingly, we can compute scales by taking their difference:

$$\begin{aligned} external \leftrightarrows internal &= \{external \ \vec{\&}\ flexible\} + \{external \ \vec{\&}\ stable\} \\ &\quad - \{internal \ \vec{\&}\ flexible\} - \{internal \ \vec{\&}\ stable\}, \\ flexible \leftrightarrows stable &= \{external \ \vec{\&}\ flexible\} + \{internal \ \vec{\&}\ flexible\} \\ &\quad - \{external \ \vec{\&}\ stable\} - \{internal \ \vec{\&}\ stable\}, \end{aligned}$$

where $external \leftrightarrows internal$ is the external-internal scale, $flexible \leftrightarrows stable$ is the flexible-stable scale, and $\{external \ \vec{\&}\ flexible\}$ is the mean embedding vector for exemplary sentences that exemplifies both flexible and external orientations, such as creation, adaptation, and innovation.

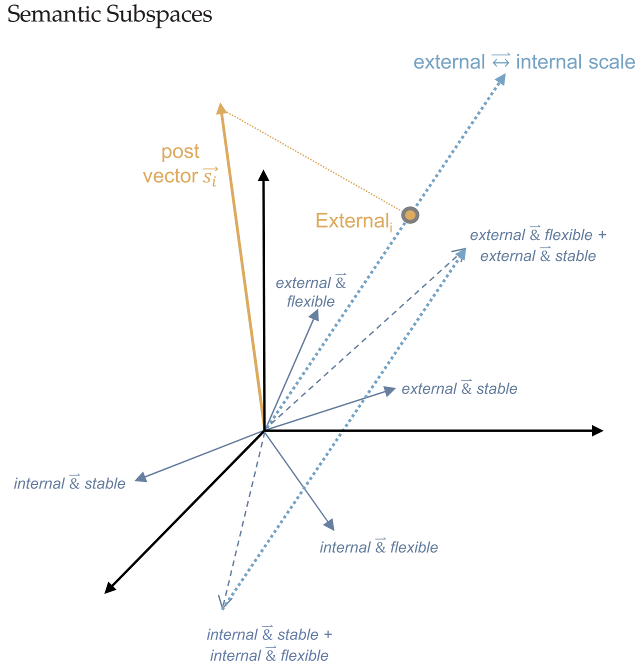
Finally, we measure each post i's score on two latent CVF dimensions by projecting its embedding vector $\vec{s_i}$ onto the two scales:

$$External_i = \vec{\boldsymbol{s}_i} \cdot external \leftrightarrows internal,$$

$$Flexible_i = \vec{\boldsymbol{s}_i} \cdot flexible \leftrightarrows stable.$$

Concept operationalization can be challenging in computationally intensive theory construction given the nature of the process (Miranda et al. 2022b). Our operationalization of the CVF dimensions suggests that it is important to establish clear conceptual distinctions among the scales when selecting the seeds and exemplary posts. In Online Appendix A3, we present robustness studies and diagnostic metrics to help guide this process. The results suggest that, at least in our context, both posts with the "positive" and "negative" keywords of the theoretical dimensions are needed to define the scales. Importantly, it is preferable to craft "negative" seeds and search exemplary posts guided by theory (as we have done) while maintaining an affirmative sentence structure, rather than relying on simple syntactic negations (e.g., adding "not" to seed sentences). Finally, SPAR is robust to semantic variations and the inclusion or exclusion of individual exemplary posts.

Figure 3. (Color online) Competing Value Dimensions as Semantic Subspaces



To further ensure the reliability and validity of our measures, a series of validation tests were conducted and documented in Online Appendix A4. These tests ensure the rigor of concept operationalization, an essential part of stopping rules in computationally intensive theory construction (Miranda et al. 2022b). Based on word clouds and distributions of the firms, the method is shown to have high face validity. The messages' CVF orientations agree with human judgments according to normalized Discounted Cumulative Gain (nDCG). Compared with the Linguistic Inquiry and Word Count (LIWC) variables, the message orientations are consistent with psychometric measurements of text.

4. Econometrics Models and Results

4.1. Dependent Variable

After uncovering the latent theoretical dimensions of firms' social media communication in disasters, we build econometric models to answer our *RQ2*, which seeks to evaluate the impacts of firm disaster communication on public engagement in biological and weather-related disasters. *Public engagement* is reflected in a variety of user responses to social media posts (i.e., comments, likes, and shares), so it is often measured as a multidimensional construct (Lee et al. 2018, Huang et al. 2021). In addition to comments and shares, Facebook posts can also receive several emotional reactions: *like*, *love*, *haha*, *wow*, *care*, *sad*, and *angry*. Shares and comments may include both positive and negative engagements. So, to measure the level of positive public engagement with firms' social media posts, our main dependent variable is *log(Positive Engagement)*, which is defined as the logarithm of the total number of positive emotional reactions received by posts (*like, love, haha, wow, care*). Following prior research (Lee et al. 2018), we also compute an alternative dependent variable to reflect the overall public engagement—*log(Total Interaction)*, defined as the logarithm of a post's number of *shares*, *comments*, and all emotional responses combined (including negative emotional reactions *sad* and *angry*).

4.2. Control Variables

We include several other post-level control variables in our analysis. The indicator variables *Photo* and *Video* control if the post contains any multimedia content. *Text length* is the log number of words in the post. The indicator *Verified* takes one if the page has a verified badge. *Subscribers* is the log number of page subscribers at the time of posting. *Like Growth* is the log number of likes the account accumulated in the most recent week. To control for the other contents of posts, we use topic modeling, which is commonly used for quantifying text content for inclusion into econometric models (Yang et al. 2023b). Topic models are fitted using only the verbs and nouns because they are more likely to convey a post's purpose and function rather than the underlying value orientations. As Online Appendix A5 shows, a 10-topic solution can distinguish different types of posts such as information sharing (join, register), appreciation (thank, support), and sweepstakes (win, chance). Based on the topic modeling results, we compute both the post-level topic prevalence and week-level prevalence to control for weekly trending topics.

We also include firm-level financial variables, environmental, social, and governance (ESG) ratings, and disaster impact variables as controls. All firm-level financial variables are computed on a quarterly basis, while ESG ratings and disaster impact are computed yearly. The financial variables include firms' size, revenue, research and development (R&D) expenditure, return on assets (ROA), sector-adjusted stock return, liquidity, and industry concentration. Firms' ESG ratings are provided by Refinitive and are designed to transparently and objectively measure firms' ESG performance based on publicly reported data. Firms' disaster impact variable is computed following Hassan et al. (2023). Firm characteristics are related to both firms' value orientation and social media engagement (Zhang et al. 2010, Saxton et al. 2019, Chu et al. 2020, Gillan et al. 2021). Additionally, a disaster's impact on a firm can affect its social media disclosures and engagement, as stakeholder interest in the firm's response may vary based on the extent of the impact. As such, we include these variables as controls because they can potentially confound the relationship under study. The details of these variables are available in Online Appendix A1. Table 2 provides the definitions of all the variables and summary statistics.

4.3. Regression Models

To examine if the CVF dimensions expressed in firms' social media messages during natural disasters impact public engagement, we estimate the following regression model:

$$
\begin{aligned}
&log(Positive\,Engagement)_{ij}\\
&= \beta_0 + \beta_1 External_i + \beta_2 Flexible_i + \gamma PostControls_i\\
&\quad + \delta FirmCharacteristics_j + \zeta TopicContent_i + \eta TrendingTopic_t\\
&\quad + YearFE + MonthFE + IndustryFE + \epsilon_{ij},
\end{aligned}
$$

where the main independent variables *External* and *Flexible* are the measurements obtained using the method described in Section 3. We control for observed covariates including post controls, firm controls, topic content controls, and time and industry fixed effects (FEs) in the baseline Ordinary Least Square (OLS) model.

We adopt several techniques to address endogeneity issues that could bias the estimates in the baseline OLS model. First, we add page (firm)-level FEs. The page FEs account for all time-invariant unmeasured and unobserved confounders at the firm level, thus allowing us to

Table 2. Variable Definition and Summary Statistics

		Biological disasters					Weather-related disasters				
Variable	Variable definition	Mean	S.D.	Q1	Med	Q3	Mean	S.D.	Q1	Med	Q3
log(Positive Engagement)	Logarithm of a post's number of positive emotional responses (*like, love, haha, wow, care*)	2.96	1.46	1.95	2.77	3.76	3.19	1.58	2.08	3.04	4.14
log(Total Interaction)	Logarithm of a post's number of shares, number of comments, and number of all emotional responses combined (including sad and angry)	3.17	1.54	2.08	3	4.01	3.54	1.67	2.3	3.4	4.54
External	A post's message orientation on the external-internal axis (normalized)	0	1	−0.69	−0.01	0.67	0	1	−0.83	−0.03	0.82
Flexible	A post's message orientation on the flexible-stable axis (normalized)	0	1	−0.66	−0.04	0.64	0	1	−0.89	−0.13	0.86
Photo	1 if the post is a photo type	0.44	0.5	0	0	0	0.4	0.49	0	0	0
Video	1 if the post is a video type	0.12	0.32	0	0	0	0.08	0.27	0	0	0
Text length	Logarithm of the number of words in a post	4.03	0.46	3.69	4.03	4.36	3.99	0.66	3.58	3.99	4.36
Verified	1 if the page is verified by Facebook	0.21	0.41	0	0	0	0.26	0.44	0	0	0
Subscribers	Logarithm of the number of page subscribers at the time of posting	8.84	4.08	8.03	9.78	11.42	4.36	5.38	0	0	10.19
Like Growth	Logarithm of the total number of new likes accumulated for a page in the week prior to the disaster-related post	2.48	2.41	0	2.2	4.22	2.33	2.97	0	0	4.38
Firm Size	Logarithm of firm size (variable ATQ)	8.72	1.68	7.57	8.69	9.82	9.08	1.65	7.77	9.09	10.5
R&D	Logarithm of research and development expenditures (variable XRDQ)	1.47	2.04	0	0	3.08	0.44	1.1	0	0	0
Adj. Return	Sector-adjusted quarterly return (from CRSP security monthly data)	−0.03	0.18	−0.16	−0.02	0.09	−0.01	0.12	−0.08	0	0.06
ROA	Return on asset, calculated as the ratio of operating income (OIBDPQ) to book value of total assets (ATQ)	0.02	0.02	0.01	0.02	0.04	0.02	0.02	0.01	0.02	0.03
Liquidity	Ratio of long-term debt (LCTQ) to total asset (ACTQ)	0.54	0.38	0.26	0.54	0.8	0.7	0.55	0.15	0.68	1.12
Revenue	Logarithm of revenue (REVTQ)	5.91	2.66	4.87	6.36	7.73	6.37	2.37	5.58	6.78	7.97
ESG	Firm's Refinitive ESG score (yearly)	0.47	0.17	0.34	0.47	0.6	0.4	0.22	0.28	0.41	0.57
HHI	Hirschman-Herfindahl index, a measure of industry concentration; higher HHI indicates lower competition	0.22	0.16	0.09	0.19	0.29	0.19	0.17	0.04	0.14	0.26
Disaster Impact	Firm's exposure to natural disasters as indicated by the log counts of disaster-related keywords in each year's earnings-call transcripts, normalized by transcript length	2.71	1.91	1.54	2.34	3.58	0.41	0.58	0	0.18	0.59
Topic Content$_j$	The prevalence of topic j in a post, j = 1 … 10	See Online Appendix A5									
Trending Topics$_j$	The prevalence of topic j among all the posts in a week, j = 1 … 10										

Note. Adj., adjusted; Med, median; S.D., standard deviation; Q1, the first quartile; Q3, the third quartile.

identify the relationship between changes in message dimensions and changes in engagement by leveraging within-firm variations in message dimensions. For instance, it may be that firms in a particular region are more susceptible to disasters and thus attract a larger number of highly engaged followers. Page FEs eliminate the effects of such confounders. In addition, adding page FEs accounts for endogenous group formation on social media, that is, individuals with similar preferences choose to follow the same pages (Park et al. 2018).

Second, we use a Heckman bias correction technique to address the possible sample selection issues at the post level.[8] Our study faces incidental truncation, a type of sample selection problem where certain variables are observed only if other variables take on particular values (Wooldridge 2010). Specifically, we can measure the CVF values in the two disaster samples only when firms post disaster-related content. However, a firm may choose not to post disaster-related information, or our keywords may not detect the post even if it is relevant to the disaster. We apply Heckman's two-stage analysis to show that potential sample selection issues do not have a material impact on our conclusions. For each type of disaster, we first fit a Probit model using the full post sample with nonmissing controls to determine the probability that a post is selected in that disaster sample (i.e., contains one of the disaster-related keywords). We then control for the inverse Mills ratio in our second-stage regressions.[9]

Our third approach is to use two instrumental variables (IVs). First, we use firms' main competitors' disaster message orientations as an IV, where the main competitors are defined following Hoberg and Phillips (2016).[10] For each firm, we find its closest yearly competitor and use its last available daily average message orientation as an instrument. Second, we use lagged daily values of the independent variables as an instrument (Ghose 2009, Mu et al. 2022). The two IVs satisfy the relevance criterion because firm value orientations are industry dependent and persistent, so both competitors' and a firm's lagged message orientations should correlate with their current message orientations. Additionally, they should satisfy the exclusion restriction, as they are unlikely to impact later engagement after considering control variables. These IVs help eliminate unobserved variation in message orientations that may confound engagement effects.

While the *EdgeRank* algorithm used by Facebook for promoting content to user feeds may introduce additional unobserved heterogeneity in post views (Lee et al. 2018), our sample excludes ads and paid promotional content. In addition, we follow Yang et al. (2019) to control for post views in several ways. We use the number of subscribers to control the page-level popularity. We account for the weekly trending topics and the type of posts through topic modeling. To mitigate the possible issue of correlated unobservables (Park et al. 2018), that is, any simultaneous shock to message CVF dimensions and engagement to all users on the platform, we include both year and month FEs. We also use *Like Growth* to control for other unobserved factors at the page and time level; because the variable is computed immediately prior to the posting time, it helps absorb any shorter-term shocks.

4.4. Effects of Disaster Communication Dimensions

Table 3 reports the results on the effects of disaster message orientations on engagement during biological disasters. In column 1 we report results from the baseline OLS model. In column 2 we add the firm-level control variables. In column 3 we include firm FEs. Because the firm FEs noticeably depress the magnitude of the estimates, possibly due to unobserved page-level confounders, we prefer this more conservative estimate. In model 4, we add the Heckman bias correction term. The fact that the inverse Mills ratio is significant indicates sample selection bias. However, after controlling for the selection bias, the negative relationships between the two competing dimensions and engagement still hold. In model 5, we add the two sets of instrumental variables and find that both the direction and the magnitude of the estimates are consistent.[11]

According to all specifications in Table 3, high *External* and *Flexible* orientations in firms' Facebook posts concerning biological disasters negatively predict positive engagement. A one-standard-deviation increase in the *External* orientation decreases post shares by 3.6% ($p <$ 0.01), and one standard deviation of increase in the *Flexible* orientation decreases shares by 2.1% ($p < 0.01$). Combining both dimensions, we find that the *internal and stable orientations* in firms' posts promoted public engagement, whereas the *external and flexible orientations* decreased engagement. In other words, for biological disasters, the public prefers firms' social media communication emphasizing operational stability and continuity over posts promoting change and innovation.

We next test the effect of disaster message orientations on social media engagement in weather-related disasters. According to Table 4, firm posts expressing high *External* orientation positively predicted public engagement. A high *Flexible* orientation in weather-related disaster posts also positively predicts engagement. Taken together, in weather-related disasters, the most popular type of social media posts is both external- and flexible-oriented, or stressing innovation and adaptation. The findings suggest that the effect of disaster message orientations is not universal across all disasters.

4.5. Robustness Checks

To ensure the rigor of statistical inferences, another important part of the stopping rules in computationally intensive theory construction, we conduct several robustness

Table 3. Message Orientations and Social Media Engagement: Biological Disasters

	Dependent variable: log(positive engagement)				
	(1) OLS	(2) OLS	(3) Page FE	(4) Page FE + Heckman	(5) IV
External	−0.145 (0.006)***	−0.082 (0.005)***	−0.036 (0.004)***	−0.036 (0.004)***	−0.051 (0.004)***
Flexible	−0.187 (0.005)***	−0.133 (0.005)***	−0.021 (0.004)***	−0.021 (0.004)***	−0.034 (0.005)***
Post controls					
Photo	0.347 (0.012)***	0.369 (0.011)***	0.223 (0.009)***	0.223 (0.009)***	0.219 (0.009)***
Video	0.331 (0.018)***	0.321 (0.017)***	0.049 (0.012)***	0.049 (0.012)***	0.043 (0.013)***
Text length	0.244 (0.012)***	0.338 (0.011)***	0.098 (0.009)***	0.098 (0.009)***	0.078 (0.009)***
Verified	0.651 (0.014)***	0.230 (0.016)***			
Subscribers	0.066 (0.002)***	0.059 (0.002)***	0.001 (0.003)	0.001 (0.003)	0.007 (0.003)***
Like Growth	0.098 (0.002)***	0.067 (0.002)***	0.015 (0.002)***	0.015 (0.002)***	0.019 (0.002)***
Topic Content	Yes	Yes	Yes	Yes	Yes
Trending Topics	Yes	Yes	Yes	Yes	Yes
Firm controls					
Firm Size		0.120 (0.004)***	0.182 (0.024)***	0.184 (0.024)***	0.159 (0.024)***
R&D		0.022 (0.003)***	0.006 (0.009)	0.010 (0.009)	0.030 (0.009)***
Adj. Return		0.008 (0.029)	0.021 (0.021)	0.029 (0.021)	0.063 (0.020)***
ROA		−0.376 (0.255)	−1.868 (0.416)***	−1.856 (0.416)***	−2.782 (0.421)***
Liquidity		−0.016 (0.016)	−0.063 (0.036)*	−0.053 (0.037)	0.072 (0.037)*
Revenue		0.060 (0.003)***	0.002 (0.014)	0.002 (0.014)	−0.023 (0.014)
ESG		−0.249 (0.036)***	0.063 (0.085)	0.038 (0.085)	−0.110 (0.059)*
HHI		0.349 (0.032)***	−0.090 (0.132)	−0.081 (0.132)	0.204 (0.131)
Disaster Impact		0.057 (0.003)***	0.019 (0.006)***	0.007 (0.007)	0.001 (0.006)
Inv Mills Ratio				−0.074 (0.022)***	
Constant	0.609 (0.077)***	−0.520 (0.309)*	–	–	–
Industry FE	No	Yes	–	–	–
Page FE	No	No	Yes	Yes	Yes
Year and month FE	Yes	Yes	Yes	Yes	Yes
Observations	45,324	45,324	45,324	45,324	44,790
R^2	0.325	0.400	0.189	0.190	0.161

Note. Cluster-robust standard errors reported in parentheses. Adj., adjusted; Inv, inverse.
$^*p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

tests. First, we use *log(Total Interaction)* as an alternative dependent variable. An expression of sadness or anger in times of disaster can be empowering since it conveys a sense of belonging and empathy. Additionally, the alternative dependent variable provides a more direct reflection of information dissemination by including the number of shares. We find the effects of the disaster message orientations are in line with the main results. Second, we performed Propensity Score Matching (PSM), Coarsened Exact Matching (CEM), and Covariate Balancing Propensity Score (CBPS) weighting as alternative methods of estimating treatment effects. The results are reported in Online Appendix A6. Third, our results are consistent when a different transformer model is used. For our main study, we used the measurement generated by pretrained Sentence-Transformer distill-RoBERTa$_{\text{base}}$ (Sanh et al. 2020). We reestimate the model where the disaster message orientation measures are constructed using the second-best transformer model (all-MiniLM-L6-v2). We find that the correlations of the measures generated by the two transformer models are high ($\rho = 0.86$ for *External*; $\rho = 0.84$ for *Flexible*). In addition, results from the regression models are consistent when an alternative transformer model is used.

To validate and explore the theoretical and practical implications of our framework and findings, we interviewed a total of 16 renowned experts and leaders in the U.S. disaster management community. The feedback we received from these domain experts lends strong support to the validity and applicability of the theoretical dimensions to characterize firms' disaster communication and their effects in different disasters. A detailed summary of the interview can be found in Online Appendix A7.

5. Discussion and Conclusion

In this study, we examine how firms communicate on social media and their effects on public engagement in different types of natural disasters. Taking the computationally intensive theory construction approach (Berente et al. 2019, Miranda et al. 2022b), we propose a framework to understand firms' disaster communication (practice lexicon). We introduce SPAR as the basis of our method lexicon to analyze unstructured online textual data. We apply the dimensions of the CVF as our theoretical lexicon to guide our data exploration. The two competing dimensions—(1) *internal* versus *external*, and (2) *stable* versus *flexible*—reflect the constant tensions

Table 4. Message Orientations and Social Media Engagement: Weather-Related Disasters

	Dependent variable: log(positive engagement)				
	(1) OLS	(2) OLS	(3) Page FE	(4) Page FE + Heckman	(5) IV
External	0.036 (0.011)***	0.042 (0.011)***	0.052 (0.010)***	0.057 (0.010)***	0.034 (0.011)***
Flexible	0.256 (0.011)***	0.210 (0.012)***	0.159 (0.011)***	0.165 (0.011)***	0.148 (0.011)***
Post controls					
Photo	0.274 (0.023)***	0.250 (0.023)***	0.241 (0.020)***	0.352 (0.020)***	0.244 (0.020)***
Video	0.387 (0.040)***	0.312 (0.039)***	0.183 (0.032)***	0.290 (0.033)***	0.205 (0.033)***
Text length	0.113 (0.018)***	0.126 (0.017)***	0.118 (0.015)***	0.114 (0.015)***	0.106 (0.015)***
Verified	0.787 (0.024)***	0.415 (0.028)***			
Subscribers	0.016 (0.002)***	0.046 (0.004)***	−0.027 (0.004)***	0.000 (0.002)	−0.039 (0.003)***
Like Growth	0.148 (0.004)***	0.114 (0.004)***	0.045 (0.004)***	0.070 (0.003)***	0.049 (0.004)***
Topic Content	Yes	Yes	Yes	Yes	Yes
Trending Topics	Yes	Yes	Yes	Yes	Yes
Firm controls					
Firm Size		0.023 (0.034)	0.191 (0.010)***	0.056 (0.033)*	−0.087 (0.034)***
R&D		−0.017 (0.019)	0.008 (0.010)	0.029 (0.019)	0.038 (0.019)**
Adj. Return		−0.111 (0.073)	−0.091 (0.086)	0.004 (0.073)	−0.021 (0.073)
ROA		2.307 (1.007)**	8.716 (0.689)***	1.595 (1.028)	2.330 (1.022)**
Liquidity		0.073 (0.044)*	0.043 (0.022)**	0.179 (0.045)***	0.122 (0.044)***
Revenue		0.040 (0.029)	0.028 (0.006)***	0.045 (0.029)	0.029 (0.028)
ESG		0.043 (0.092)	−0.209 (0.066)***	0.817 (0.072)***	0.488 (0.073)***
HHI		−0.022 (0.216)	0.880 (0.066)***	0.247 (0.221)	0.150 (0.217)
Disaster Impact		0.042 (0.022)*	−0.077 (0.019)***	−0.039 (0.022)*	−0.017 (0.021)
Inv Mills Ratio				0.056 (0.033)*	
Constant	1.728 (0.078)***	−1.138 (1.310)	–	–	–
Industry FE	No	Yes	–	–	–
Page FE	No	No	Yes	Yes	Yes
Year and month FE	Yes	Yes	Yes	Yes	Yes
Observations	17,868	17,868	17,868	17,868	17,790
R^2	0.262	0.324	0.194	0.151	0.129

Note. Cluster-robust standard errors reported in parentheses. Adj., adjusted; Inv, inverse.
$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

that firms face when communicating to the public in highly dynamic and complex disaster situations.

Examining the disaster-related messages from the Facebook pages of Russell 3000 firms, we show that firms' disaster communication can be understood based on the two competing dimensions. This analysis allows further investigation of the impact of the competing dimensions in firms' disaster communication on public engagement, showing that the effect of firms' communication is contingent on the type of disaster. Our results highlight the need for firms to use different communication strategies depending on the disaster type. The analytical approach can also be adopted by IS scholars to conduct computationally intensive research for new theory construction and uncover theoretical patterns in unstructured textual data in other contexts.

5.1. Theoretical Implications

The emerging IS literature on computational theory development recognizes that not all phenomena can be studied with the classic, heavy theory-based, deductive formal hypothesis-driven setup (Agarwal and Dhar 2014, Berente et al. 2019, Grover et al. 2020). Our study follows the computationally intensive theory construction approach to study firm communication during disasters. Our work falls under the "*patterns with theoretical implications*" stage. We derive theoretical patterns related to the two competing dimensions (*internal* versus *external* and *stable* versus *flexible*) in firm disaster communication, generating "*latent categories and associations*" as described in table 1 of Miranda et al. (2022b).

The patterns that we uncover are *original* and *important*, which are considered critical when assessing theoretical contributions (Miranda et al. 2022b, pp. ix). The *originality* of the work refers to the novelty of the focal phenomenon or the surprise elicited by the surfaced patterns (Robinson 2019). Our theoretical lexicon, CVF, was proposed as a general framework for the analysis of organizational effectiveness. Prior research has shown the applicability of the CVF for corporate communication in internal and routine practices because the theory captures the fundamental conflicts (i.e., *internal* versus *external*; *stable* versus *flexible*) when firms make communication decisions (Quinn et al. 1991, Belasen and Frank 2010).

However, extant literature has not validated CVF dimensions in firm disaster communication or examined how the dimensions impact public engagement on social media. We are the first to (1) show that the competing dimensions also characterize firm communication on social media and in disasters and (2) confirm the impact of the dimensions on engaging external stakeholders on social media in different disasters. Our research therefore extends the CVF literature into the disaster context and suggests a new theoretical approach to study firm disaster communication. By demonstrating the CVF dimensions' impacts on public engagement and disaster types as boundary conditions, our findings also contribute to CVF "by adding novel concepts and relationships" not previously theorized by the framework (Miranda et al. 2022b).

The *importance* of research refers to the likelihood of a study in stimulating future research or altering theory or practice (Miranda et al. 2022b). The patterns that we discover are important because they help the research community conceive new streams of scholarly inquiries. First, the alignment between communication and disaster types would warrant future theorizing around firm disaster communication and disaster communication in general based on CVF. Our results show disaster types as the contingency of the CVF dimensions' effects on user engagement. Future research can further extend this finding to develop a thorough understanding of the boundary of the competing dimensions' impacts. Beyond these observations, researchers can explore the reasons (*why*) for these interesting boundary conditions. For example, the subject domain experts that we interviewed (Online Appendix A7) have shared some possible distinctions between the two disaster types (e.g., "hazard tangibility"), which may be interesting to scholars who want to explore this stream of research.

Second, it bears theoretical significance to investigate the potential alignment between firms' communication orientation in disaster and organizational value orientation. The competing dimensions of CVF have been studied in discrete organizational phenomena, such as organizational culture and communication, but not together. This implies that CVF dimensions manifested in firms' social media communication in disasters may not equal those of their core culture (Quinn et al. 1991, Belasen 2008). Firm disaster communication may be influenced by firms' core value orientations. For instance, firms with an internal-oriented culture could be more likely to communicate with a stronger internal orientation, highlighting their employees and workplace. Firms' social media communication could also differ from firms' core culture, because social media communication may require less resource investment and firms can be strategic and selective when communicating to the public. For example, a firm may communicate with a flexible orientation in disasters to emphasize its adaptability but its core orientation is more stable.

Hitherto, little research has investigated the alignments of CVF dimensions across different organizational practices. As a potential theoretical extension to the CVF literature, a new research question emerges: "To what extent can firms' core cultural value orientation shape their public communication in disaster or different contexts?" Miranda et al. (2022b) comment that patterns that surfaced from a very novel phenomenon may not resonate immediately with an established theory. In the case of the present research, addressing the earlier research question can help us extend the knowledge of CVF. Beyond an exploration of the direct relationship between the two, there exist great opportunities to enrich the literature. For example, research can compare the alignment between a firm's public communication on different communication channels and its core cultural value orientation in different crises, along with the impacts of these alignments.

In conclusion, Miranda et al. (2022b) noted in their editorial that "describing patterns with theoretical implications can be strong contributions too. For instance, you may realize that a pattern you identified connects in interesting ways to many theoretical discourses in the field, but it may not be clear to you yet how it contributes to each and every one" (pp. vii). As our research uncovers novel patterns that are not established in CVF literature and warrant future theorizing in important directions, it makes significant contributions to the literature.

5.2. Methodological Implications

To generate theoretical implications on firm disaster communication via computational analysis, we propose a new NLP approach which we term SPAR to analyze firms' communication data. SPAR synthesizes several computational techniques, thus adhering to the *methodological pluralism* principle advocated for computationally intensive theory construction (Miranda et al. 2022b). The approach is flexible and facilitates efficient assembly of theoretical, method, and practice lexicons entailed in theory construction, supporting researchers' *reflexivity* of and *epistemic attention* to various components of a research process. It can be used by IS scholars to analyze other large textual data sets with various theoretical frameworks in diverse contexts. We hereby discuss SPAR's advantages and limitations compared with other popular NLP methods for computationally intensive theory construction, broadly divided into four categories: (1) lexicon-based method (e.g., LIWC) (Tausczik and Pennebaker 2010), (2) topic modeling (e.g., latent Dirichlet allocation) (Miranda et al. 2022a), (3) static word embedding (e.g., word2vec) (Bachura et al. 2022), and (4) fine-tuning LLMs (e.g., BERT) (Yang et al. 2023a).

The first approach, lexicon-based methods, relies on predefined word lists to measure the presence of certain concepts in the text (Tausczik and Pennebaker 2010). Despite their simplicity and interpretability, they may not effectively capture the complexity and nuances of language, particularly when dealing with abstract theoretical constructs. Additionally, lexicon-based methods require careful adaptation for different contexts, which can be labor intensive. SPAR facilitated domain adaptation by empowering researchers to dive into the raw data, search, and retrieve relevant passages. Such an active approach facilitates the understanding of how theoretical concepts manifest in the data and allows for a more nuanced, context-specific measurement.

The second approach, topical modeling, can help identify latent themes in textual data without predefined labels. But it is largely unsupervised, so the alignment of topics with theoretical constructs is unpredictable and requires post hoc coding (Bachura et al. 2022, Syed and Silva 2022). In comparison, SPAR reconciles data-driven and theory-driven approaches by embedding the theoretical lexicon and the practice lexicon (i.e., domain-specific text data) in a shared semantic space and finding alignment between the two, which makes it more likely to generate theoretical implications.

Recent IS researchers have turned to the latter two language embedding approaches, which SPAR also fits into. Static word embeddings such as word2vec (Mikolov et al. 2013) learn the semantics of words in a corpus and allow researchers to measure text by constructing a domain-specific lexicon related to a set of theoretical constructs (Li et al. 2021, Bachura et al. 2022). Its limitation lies in learning only word and phrase embeddings, which may not capture the context of an entire message. The limitation is more salient when sentence structure and composition, such as idiomatic expressions, are crucial for understanding the underlying theoretical construct. Also, the sensitivity to word form variations of static embeddings can be an issue when dealing with social media texts due to the prevalence of nonstandard expressions like slang and abbreviations (Nguyen and Grieve 2020).

Because SPAR builds on pretrained LLMs, the embeddings capture linguistic and world knowledge from large amounts of general-purpose documents. Compared with static word embeddings, LLMs typically use subword tokenization, which handles nonstandard expressions more effectively (Devlin et al. 2019). They also utilize contextual embeddings, thus providing a richer representation of the entire sentence by taking into account the relationships between words. However, SPAR departs from the prevalent LLM paradigm that involves fine-tuning LLMs with domain-specific data (Bai et al. 2020, Gao et al. 2022, Yang et al. 2023a). When analyzing emerging IT phenomena, because of a lack of existing theories, researchers often face uncertainties regarding appropriate theories, suitable theory variations for the context, and the need for adaptation of existing theories. If a fine-tuning LLM approach were to be used, each round of such theory testing and adaptation would require (1) updating the parameters of the model (training cost) and (2) applying the model to the entire corpus (inference cost). Due to the high computational costs and requirements for specialized hardware for LLMs, this can be challenging for time- or resource-constrained social science researchers and practitioners. In contrast, SPAR uses a frozen LLM without model training or parameter updating. The bulk of the computation occurs during the initial embedding of the corpus, which is performed only once; embedding queries and the measurement both require minimal computation. As a result, SPAR improves *discursive flexibility* (Miranda et al. 2022b) for researchers because it can be applied iteratively to adapt multiple theories and adjust empirical measures and analysis with no additional training or inference cost.

SPAR has several limitations in comparison with existing methods. First, it may not be suitable for longer or more complex documents since it represents a document using a single vector. Second, sentence embeddings are derived from higher layers of transformers, which primarily capture semantic features (Tenney et al. 2019). As such, it may not be suitable for theoretical constructs that rely primarily on syntactic features. Third, pretrained LLMs may not have up-to-date world knowledge or specialized vocabulary. To address this limitation, we used word2vec to construct disaster-related lexicons. Finally, because semantic projection is a linear operation, SPAR may not perform as well as fine-tuning approaches in capturing nonlinear patterns in training data.

5.3. Practical Implications

First, our study advocates the practical value of two competing dimensions (*internal* versus *external* and *stable* versus *flexible*) in disaster communication. We also establish the connection between the dimensions and message engagement within the disaster context. Our findings suggest that firms can be strategic and design their messages to maximize their impact. They can adopt the competing dimensions as a framework to guide their design of disaster messages on social media.

Moreover, the findings of this research can help firms develop their social media communication strategies in different types of disasters to both facilitate disaster response and promote their businesses. Rather counterintuitively, our results suggest that a popular firm disaster communication such as announcing financial aid to stakeholder communities is not the most effective communication to attract public engagement. In biological disasters that disturb social interactions, the best social media communication strategy for firms is to focus on their own operations and deliver messages that showcase their abilities to maintain their businesses despite the negative circumstances. As much as it may seem appealing, advocating for potential innovations and framing the disaster as an opportunity for change is not a prudent strategy when people are still grappling with the potential spread of infectious diseases. On the contrary, firms may lean more toward the external environment and changes in their social media posts during weather-related disasters. The most popular type of social media messages may discuss their future vision and their plan to develop new technologies to respond to the disaster.

5.4. Limitations and Future Research Directions

Our study focuses on public engagement with firms' disaster communication on social media, which includes metrics of likes, comments, and shares. While these metrics can provide some insights into the dissemination of firm messages, we do not investigate the full extent of the messages' dissemination or their impact on other public behavior. To further understand the effects of firm communication in disasters, future studies can track the chain of information dissemination and evaluate how public response to disasters is shaped by firm communication. We further caution that the relationship between disaster communication and public engagement may still be correlational rather than causal, despite our best efforts to address the endogeneity issues in a multitude of methods.

Disasters are dynamic events that are fast-evolving. Future research can examine if there are longitudinal changes in firm communication and public engagement throughout the course of various disasters and explore to what extent firms learn from disasters and adapt their communication over time. For example, after experiencing one biological disaster, do firms change their messages on social media in future biological disasters?

In addition, firms' operations may be impacted by disasters differently (Hassan et al. 2023) and some firms may even benefit from disasters (e.g., pharmaceutical companies and remote working tool and software providers during Covid-19). It is also possible that the effect of the competing dimensions on user engagement depends on the industry of the firms. For example, IT firms may attract higher engagement if they communicate with an external and flexible orientation, because they are technology companies that are expected to innovate. On the other hand, medical companies that produce personal protective equipment (PPE) or utility companies may gain more popularity if their messages are stable and internal, since their continued operation is a reassurance of effective disaster response. Researchers can study to what extent firms' social media strategies and their effectiveness may be influenced by firms' industries and categories.

While SPAR holds potential in various other contexts, its effectiveness is inherently tied to the ability of a pretrained LLM to adequately represent and differentiate theoretical constructs in the embedding vectors. For future endeavors utilizing this computational framework, we advocate for a three-pronged approach to ensure validity: robust theoretical guidance, particularly for frameworks that provide well-defined, orthogonal constructs; informed human judgment supplemented by diagnostic metrics during the data interaction phase; and rigorous postmeasurement validity assessments.

The empirical findings of this study are limited by the data collected, which offers potential avenues for future research. First, we focus on the social media messages from large public firms. However, small to medium businesses also play a significant role in disaster prevention and recovery, especially in local communities. The difference in disaster message orientations and their impacts deserves further study. Second, we only collect data from two common and general types of disasters (i.e., biological and weather disasters). Future studies can extend the framework and examine firms' communication strategies and effectiveness in other disaster types such as geophysical disasters (e.g., earthquakes) and terrorist attacks (e.g., massive shootings) to test the propositions we develop. Moreover, our transformer-based LLM is monolingual, so we removed non-English posts from our analysis. Because Hispanics and other minority communities often suffer disproportionately during disasters due to cultural and language barriers (Bethel et al. 2013), future research may analyze non-English posts with multilingual LLMs. Lastly, the mechanisms of the effects may be explored through surveys that gauge public perceptions and experiments that control the different communication dimensions in firms' social media messages.

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Endnotes

[1] The goal of active learning is to judiciously and economically improve the performance of a model in a particular domain (Saar-Tsechansky and Provost 2007). Semantic search ranks documents using the relevancy between the query and each document without relying on exact term matching.

[2] For details, please visit https://help.crowdtangle.com/en/articles/4201940-about-us.

[3] These posts have a special sponsor identification (ID) tag that indicates their association with an external marketing campaign that seeks to promote products, brands, or sponsors. Because they are not intended for creating social benefit, and their engagement is mostly driven by advertising budgets, they are excluded.

[4] The missing firm controls are due to ticker changes, mergers, and acquisitions, which prevents us from uniquely matching the firm's Facebook pages to firm IDs in the Compustat database.

[5] https://www.ncei.noaa.gov/access/billions/events.

[6] We choose a fine-tuned version of distill-RoBERTa$_{\text{base}}$ (Sanh et al. 2020) after benchmarking against other models. The technical details of the models are available in Online Appendix A2.

[7] A transformer-based LLM like BERT is a deep neural network model that predicts a missing word given previous words in a sentence or surrounding words. Once the LLM is pretrained using a

large corpus, its stacked layers of transformers can dynamically map words (or tokens) into numeric vectors that capture their meanings according to the sentence context. The word vectors are known as contextual word embeddings. The word embeddings in a post can be further aggregated into a post embedding by taking the average. Our SPAR package supports other text embedding methods such as OpenAI embeddings (OpenAI 2022); however, we leave the comparison of these methods to future studies.

[8] Sample selection concerns may also arise at the account level, which is not addressed by Heckman correction. Among all Russell 3000 firms, we are able to identify Facebook accounts and merge with firm-level controls for 58% of them. We compare the Russell 3000 firms with and without accounts. We observe that the firms with accounts are larger, have better performance and fewer liquidity issues, and invest more in ESG. Readers should be aware that our research is not able to determine, had we observed disaster-related posts from these firms, what the relationship between message orientations and engagement would be.

[9] The Heckman correction necessitates an exclusion restriction: at least one exogenous variable in the first-stage selection model must be excluded from the second-stage model. We tally the monthly count of disaster-related posts from firms sharing the same headquarter state or industry, as these could exogenously influence a firm's disaster-related disclosure on social media. These variables are included only in the first-stage model.

[10] The data define firms' peers using similarity of firms' product descriptions in 10-K annual filings. We use a firm's competitors in 2019 for 2020–2022 since the data are only updated to 2019.

[11] We perform several validity tests for the instrument. We regress the CVF variables on the two instruments and find both are highly significant, indicating that they pass the relevance criteria. In addition, we perform an underidentification test, a weak identification test, and an overidentification test. The Anderson LM statistic rejects the null hypothesis of underidentification. The Kleibergen-Paap *rk* Wald F statistic is greater than the threshold of 10% maximal IV size, suggesting that the instruments are rather strong (Hong et al. 2021). Sargan's statistic fails to reject the null hypothesis that the instruments are valid.

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Online Appendix

A Computational Framework for Understanding Firm Communication During Disasters

A1. Details on Firm-Level Measures and Sample Selection

The firm-level covariates include R&D expenditure, firm size, adjusted excess quarterly return, return on assets, liquidity, revenue, and HHI. R&D expenditure is measured using research and development expenses (variable XRDQ from Compustat). We compute these variables at the firm-quarter level. Firm size is measured as the log total assets of a firm (ATQ). The sector-adjusted excess quarterly return is calculated by taking the difference in the quarterly returns of a firm and the average return of its sector in the same quarter. Return on assets is the ratio of a firm's operating income (OIBDPQ) to its book value of total assets (ATQ). Liquidity is the ratio of long-term debt (LCTQ) to total assets (ACTQ). Revenue is the total revenue of a firm (REVTQ). HHI is the Hirschman-Herfindahl index, a measure of industry concentration, calculated using the sum of squared market shares of firms with the same SIC code. The market share is defined as the ratio of sales revenue (REVTQ) to total industry revenue of firms in the same sector. We winsorize the firm-level measures at 1% and 99% levels. The adjusted return variable is the only variable computed from Compustat monthly security data while all other financial variables are calculated using the quarterly data. The disaster impact measure is computed at the firm-year level. For each year, we count the number of times the disaster-related keywords appear in the firm's earnings call transcripts, then divide the count by the total number of words in the transcript.

Table A1-1 compares the firm's characteristics with and without Facebook accounts. Table A1-2 lists the keywords and phrases we used to identify posts relevant to biological and weather-related disasters.

Table A1-1. Comparison of Firm Characteristics with and without Facebook Accounts

	R&D	Firm Size	Adj. Return	ROA	Liquidity	Revenue	ESG	HHI
With accounts	0.822	8.004	-0.049	0.023	0.491	5.656	0.445	0.234
Without Accounts	1.118	8.716	-0.044	0.027	0.555	6.437	0.530	0.276

Table A1-2. List of Keywords for Tagging Biological and Weather-Related Disasters

	Biological Disasters	Weather-Related Disasters
Keywords	covid, pandemic, coronavirus, H1N1, swine flu, MERS, influenza, Ebola, Zika virus	affected by the storm, drought, extreme heat, extreme weather, flooding, freezing rain, freezing temperature, gusty wind, heat wave, heatwave, hurricane, ice storm, impacted by the storm, landfall, major storm, prepare for the storm, severe storm, severe thunderstorm, severe weather, snow storm, snowstorm, storm damage, storm hit, storm surge, strong wind, thunderstorm, tornado, tropical storm, tsunami, wildfire, wind gust, winter storm

A2. Additional Details on Measurement Methods

Our Semantic Projection with Active Retrieval (SPAR) approach starts with a large collection of disaster-specific Facebook posts (documents). We combine active learning and semantic search to identify the feature subspace for two CVF dimensions (i.e., stable-flexible, internal-external). We start with a generic set of *seed* statements that define CVF quadrants (theoretical concepts) as initial queries. In each round of active learning (query and search), we progressively annotate the top posts returned by the semantic search, i.e., judging their relevance to the quadrants. We retain the most relevant ones as the new seeds until a predetermined number of final exemplary seed posts are reached. Table A2-1 provides examples of the posts that scored high by the semantic search but were excluded by human judgment. Table A2-2 provides examples of the final seed posts.

Theoretically, our semantic projection approach is designed to preserve the contrasts between the four quadrants made up by the two dimensions. For example, a post that highlights creation and innovation (Q1 of CVF) would score high in the external/flexible quadrant, and a post that emphasizes control and continuity (Q3 of CVF) would score high in the internal/stable quadrant. Despite this, empirically there is no guarantee that the external and flexible directions in the sentence embedding space are orthogonal, as the CVF theory suggests. Therefore, we apply whitening to orthogonalize the empirical measurements of two dimensions. Whitening transforms a vector of random variables into a new vector whose covariance is an identity matrix. We use Mahalanobis whitening (ZCA), which is commonly applied to improve text representations in the embedding space.

Sentence-Transformers provide a general way to generate post embeddings that is useful for both semantic search and semantic projection. It can encode Facebook posts into a fixed-sized, dense vector space. It is a modification of transformer-based pre-trained large language models (LLMs), of which the most well-known is Bidirectional Encoder Representations for Transformers (BERT) (Devlin et al. 2019). Given a sentence i with N tokens: $s_i = [w_1, w_2, \dots, w_N]$, a transformer LLM turns this sentence to $[\overrightarrow{[CLS]}_i, \overrightarrow{w_{i1}}, \overrightarrow{w_{i2}}, \dots, \overrightarrow{w_{iN}}]$, where each $\overrightarrow{w_{in}}$ is a k dimensional contextual word embedding vector and $\overrightarrow{[CLS]_i}$ is the embedding vector for a special token that marks the beginning of sentence i. A typical transformer LLM, such as BERT, was trained in an unsupervised way using general corpus including Wikipedia and books. They excel at many language tasks such as parsing, translation, and classification. However, an important limitation of the BERT model is that it does not perform well at the semantic textual similarity (STS) task, i.e., automatically measuring the meaning similarity of a pair of Facebook posts. When either using the special $\overrightarrow{[CLS]}$ vector or averaging the contextual word embeddings, a BERT sentence embedding is often worse than averaging non-contextual word embeddings such as GloVe or word2vec (Reimers and Gurevych 2019).

Sentence-Transformer model overcomes the challenge by fine-tuning pre-trained transformer LLM on STS tasks using supervised data. Training data from prior studies on sentence similarity, natural language inference, and question & answering includes pairs of sentences that are labeled to be semantically relevant to each other. These sentence pairs $[s_i, s_j]$s enter a siamese network structure, i.e., two transformer LMs with parameters weights constrained to be identical. The output embeddings of the siamese networks, $[\overrightarrow{[CLS]}_i, \overrightarrow{w_{i1}}, \overrightarrow{w_{i2}}, \dots, \overrightarrow{w_{iN}}]$ and $[\overrightarrow{[CLS]}_j, \overrightarrow{w_{j1}}, \overrightarrow{w_{j2}}, \dots, \overrightarrow{w_{jN}}]$ are averaged individually, resulting in a sentence vector pair $\overrightarrow{s_i}, \overrightarrow{s_j}$. Then the sentence vector pair enters a softmax layer that predicts if sentence i and j are labeled to be similar. After the above training process, a BERT model's weight is calibrated so that two similar sentences, once encoded, would have high cosine similarity $cos(\overrightarrow{s_i}, \overrightarrow{s_j})$. We use author-released Sentence-Transformer models that are pre-trained and fine-tuned to embed each Facebook post directly.[1]

A natural concern of using a pre-trained Sentence-Transformer model to represent social media posts is domain adaptability. Because the vocabulary and general writing styles of the Facebook posts are different from the training data of the language models, there might be a degradation in performance. Thus, we investigate two unsupervised domain adaptation strategies for Sentence-Transformer: Simple Contrastive Learning of Sentence Embeddings (SimCSE) (Gao et al. 2021) and Transformers and Sequential Denoising Auto-Encoder (TSDAE) (Wang et al. 2021).

SimCSE uses contrastive learning to finetune a pre-trained language model on the task of predicting if two sentences s_i and s_j are similar. Specifically, we can construct a training set that consists of pairs of sentences

[1] Available at https://www.sbert.net/

$[s_i, s_i + \delta]$ and $[s_i, s_j]$ from the Facebook corpus. The positive samples $[s_i, s_i + \delta]$ are random sentences s_i and itself with added noise δ, whereas the negative samples $[s_i, s_j]$ are randomly drawn sentence pairs. The rationale for this training set is that if we apply dropout noise (e.g., deleting or removing a few words) on an input sentence s_i, the result $s_i + \delta$ should have a similar meaning compared with another random sentence s_j. Such positive examples do not need human labelers, so they are less expensive to acquire. SimCSE then fine-tunes a pre-trained language model using the training set.

TSDAE addresses the sentence similarity task using an encoder-decoder architecture. It also works in an unsupervised fashion by first corrupting input sentences s_i with noise δ using operations such as deleting and swapping words. The encoder-decoder architecture then uses a transformer model to embed the corrupted sentence into a vector $\overrightarrow{s_\iota + \delta}$ and attempts to reconstruct the original sentence s_i from the corrupted sentence vector. We use the full Facebook dataset and the code released by the authors to train SimCSE and TSDAE based on three models: BERT (Devlin et al. 2019), DistilRoBERTa (Sanh et al. 2020), and MiniLM (Wang et al. 2020) to adapt the generic pre-trained models to the Facebook domain. Code for training SimCSE is available at https://github.com/princeton-nlp/SimCSE. Code for training TSDAE is available at https://www.sbert.net/examples/unsupervised_learning/TSDAE/README.html. We use the default hyperparameters for training. Trained models are available upon request.

Nevertheless, the benefit of using the above methods needs to be weighed against the fact that pre-trained Sentence-Transformers are fine-tuned in a supervised fashion using a large collection of human-labeled STS and NLI dataset. The quality of the STS and NLI datasets are likely superior to the training sets constructed in an unsupervised way, even though the latter can produce a larger amount of in-domain training data inexpensively. We experimented with nine candidate Sentence-Transformers models, three each with pre-trained, SimCSE, and TSDAE methods. For pre-trained models, we use DistilRoBERTa-base, all-MiniLM-L6, all-mpnet-base. For both SimCSE and TSDAE, we fine-tune bert-base-uncased, DistilRoBERTa-base, and MiniLM-L6-H384-uncased. In our validation studies, we find that neither SimCSE and TSDAE are better than the pre-trained model on our dataset in terms of improving normalized Discounted Cumulative Gain (nDCG) (Table A3-1).

Table A2-1. Example of Excluded Sentences During Active Learning

Quadrant	**Disaster**	**Excluded**	**Reason for Exclusion**
Internal & Flexible	Biological	Some of the needed responses to the COVID-19 pandemic are simple, others not so much. Read our CEO Peter Altabef's latest blog post about how all are important - and all need to be infused with compassion.	Collaboration and human connection are not the focus
External & Flexible	Biological	Here at Exela, we will always value passionate people. #Technology #Automation #DigitalTransformation #Innovation #BusinessTransformation #Tech #Coronavirus #Covid #COVID19 #Pandemic	Hashtags not related to message
Internal & Stable	Biological	We hope everyone is keeping safe in these unprecedented times. As the COVID-19 situation continues to evolve, we are learning right alongside you.	Message too broad Actions are vague
External & Stable	Biological	During this time of uncertainty due to COVID-19, we are prioritizing the health and safety of our employees, customers and partners.	More related to control
Internal & Flexible	Weather	It's #FocusFriday! How many tools, platforms, gadgets and gizmos do you use to be more "productive?" Don't be embarrassed, you can tell us! :) David Sable, Y&R's global CEO shares his thoughts on productivity for this week's #FocusFriday, asking us to be an island of calm amidst the tsunami of information flooding our minds.	Natural disaster as metaphor
External & Flexible	Weather	A year on from the Japanese tsunami, what lessons have been learned about shielding the world's technology needs from natural disasters?	Not relevant to the value itself
Internal & Stable	Weather	Check it out - a great opinion piece from The Washington Times - "Finding Economic Security in Shale" Reliance on politically unstable countries for energy imports puts America at the mercy of the pendulumlike swings in the commodities market. Gas and oil prices shoot upward practically every time a	Not directly related to natural disaster

		disruptive event elsewhere in the world (civil unrest, tropical storms, etc.) causes investors to fear…	
External & Stable	Weather	Wishing the very best to all our associates, customers and suppliers who are affected by Hurricane Florence. Be safe.	Not specific to the value

Table A2-2. Examples of Final Seed Sentences

a. Biological Disasters

Quadrant	Final Seed Sentences
Internal & Flexible	● HPE CCO Jennifer Temple on how leaders can show empathy during this pandemic, when team members are juggling more than just work projects. ● The #influenza virus is still on the rise. @CDCgov reports on age groups and flu subtypes Get coverage and let's #fight the #flu together
External & Flexible	● "For all of the chaos of the past few months, there is a lot of reason to feel optimistic. We have all recognized the need to be more digital and to automate as much as possible." -- Ken Lamneck, CEO, Insight #TechJournal #ITtrends #COVID19 ● Our employees are working tirelessly to design and rapidly scale solutions for COVID-19 through their ingenuity, perseverance and passion. We are proud of their efforts for rising to this global challenge! New challenges. New priorities. New innovations.
Internal & Stable	● In response to #COVID19, we have taken the following actions to protect the health and safety of our employees. We continue to add to this list based on the latest CDC and WHO recommendations and governmental regulations. ● We're practicing social distancing on every job, every day to keep our workers and our customers safe. If you see a worker in your area, please don't break that 6 ft. distance we're allowing to stop the spread of #COVID-19.
External & Stable	● How has your business communicated to customers during the pandemic? Here are 5 ways to offer excellent customer service during this time: ● We are living in unprecedented times as businesses and consumers learn to navigate the challenges of COVID-19. As businesses begin to open back up, business owners are looking for new ways to offer excellent customer service. Here are some ways businesses can offer great customer service during this time

b. Weather-Related Disasters

Quadrant	Final Seed Sentences
Internal & Flexible	● Seeing Americans pull together to donate time, supplies, food & more to their neighbors made us so proud to be a part of helping families in need in the wake of Hurricane Harvey. We are all #BetterTogether. ● Together, we can make a difference. We are hand in hand to help the hurricane victims tonight at 8/7c.
External & Flexible	● Manufacturers need to build a culture of adaptability. Resilience and rapid response is the universal storm protection. #Adaptability #Disruption #HurricaneSeason Manufacturers must be able to recognize expected disruption and prepare for unexpected disruption. Assess your business' adaptability. ● How can we build a better world in which we have more accurate hurricane forecasting and better carbon footprint monitoring? #L3Harris' Rob Mitrevski proposes that it starts from outer space. To hear more about this panel discussion at SXSW, cast your vote here: #SXSW2020 #SXSW A discussion on the ways that data is being collected and systems are being supported from new, smaller, more affordable innovations in space. From more accurate hurricane forecasting to better carbon footprint monitoring to forest fire prevention, many of human "blind spots" can be monitored
Internal & Stable	● All but a few of our Florida employees have been reached. All of our employees in Puerto Rico remain safe and accounted for, as well. Hurricane Irma impacted employees are reminded to check-in with their supervisors to the best of their abilities. ● Find out how to protect the safety of your employees during hurricane season: You can't stop a natural disaster, but you can minimize the threat with careful planning and thoughtful action.
External & Stable	● We will make every effort to ship product to you. #hurricanedorian #staysafe #integrainspired ● Even during a hurricane, our customers trust us to ensure we address their waste management needs. Learn more about how we prepare for hurricane season. The ice storm is affecting ~200 customers. Thank you for your patience as our crews continue to work as quickly as safety allows to restore power to all.

A3. Additional Insights on Exemplary Posts

In the SPAR framework, ensuring the appropriateness of seed queries and exemplary posts is vital. Although human judgment serves as the primary standard, and careful validity checks should be performed after the measurement, additional quantitative insights could be helpful, especially during the interactive process. Here, We propose three diagnostic metrics that provide additional insights into the selection of exemplary posts.

The first metric is the reciprocal condition number $\frac{1}{\kappa(B^T B)}$, where $B = [\vec{b}_1, \ldots, \vec{b}_m]$, a matrix consisting of all the final scales. This metric ranges from 0 to 1 and provides insights into the LLM's ability to distinguish between the constructs in the form of embedding vectors. The rationale for this metric is based on the theory of orthogonal projection (Golub and Van Loan, 2013). Our measurement can be seen as projecting post vectors in $\mathbb{R}^n$, where n is the embedding vector's dimension, onto a general subspace $U \in \mathbb{R}^m$, where m is the number of scales. The final scales can be seen as a set of basis B in U that encapsulates the theoretical constructs in the semantic space. In our application, $n = 768, m = 2$, and $B = [external \overrightarrow{\leftarrow} internal, flexible \overrightarrow{\leftarrow} stable]$. The condition number of the Gram matrix of the basis reflects their orthogonality or collinearity. A $1/\kappa$ close to 1 indicates that the scales are near orthogonal to each other, and the underlying theoretical constructs do not overlap significantly. Conversely, a $1/\kappa$ near 0 indicates collinearity in the scales. This could stem from either a lack of discriminant validity between constructs, or an inadequacy in the LLM's expressive power to capture the distinctions between the constructs based on the exemplary posts. In such instances, it is advisable to 1) revisit the theoretical framework, 2) consider testing with a more capable language model, or 3) deliberate on the selection of seed sentences and exemplary posts. The final exemplary post for the biological sample has $1/\kappa = 0.89$, and for the weather sample has $1/\kappa = 0.47$.

The second metric C serves as a quantifiable measure for assessing the validity of exemplary posts via the lens of similarity metrics. For an individual exemplary post i, we compute two similarities: a, the average cosine similarity between post i and post vectors within the same dimension, and b, which signifies the average cosine similarity between the vector of post i and vectors of posts belonging to other dimensions. The metric C then given by the ratio of $a/(a + b)$. When C is close to 1, the exemplary post aligns well with its own dimension and is dissimilar to others. Conversely, a C close to 0 suggests that the exemplary post is almost equally similar to its own dimension and other dimensions, indicating potential concerns in either convergent or discriminant validity.[2] We can calculate the average value across all posts as a unified metric; it also serves to identify individual problematic posts. The final exemplary post for the biological sample has $C = 0.55$, and for the weather sample has $C = 0.58$.

The third metric ρ quantifies the Pearson correlation with the measure employed in this study. Assuming the measure's validity (as substantiated by results in A4), a high correlation value in a given seed set serves as an indicator of the seed set's validity. We compute the correlation for two axes separately, denoted as ρ_1(external) and ρ_2 (flexible).

With the three metrics defined, we undertake the following empirical investigations to evaluate the influence of seed queries and exemplary posts on the effectiveness of SPAR measures. We report the results from the biological sample, noting that results from the weather sample are similar.

1. Are results sensitive to exemplary post selection? Given that the scale of the metric derives from the average of the final exemplary posts, coupled with the interactive procedure utilized for their selection, we hypothesize that a few posts are unlikely to have a disproportionate influence on the results. To empirically validate the robustness of exemplary post selection, we execute 500 bootstrap samples of the final exemplary posts, thereby quantifying the uncertainty associated with the measures. The bootstrap samples yield average values of $1/\kappa = 0.79$, $C = 0.56$, $\rho_1 = 0.95$, and $\rho_2 = 0.93$, respectively. These results suggest that the measurements are not sensitive to the inclusion or exclusion of individual exemplary posts.

2. Are exemplary posts robust to semantic variations? To evaluate the robustness of exemplary posts to semantic variations—a term to describe subtle lexical or syntactic alterations that maintain core meaning—we employ the GPT-4 (gpt-4-0613) model to paraphrase each of the exemplary posts.[3] For example, the post "*How #SmartCity #innovation may soon help us guard against natural disasters - Hurricane Sandy. Derecho of 2012. Typhoon Bopha*." is paraphrased to "*Innovations in smart city technologies hold promise for protecting us against natural*

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[2] Although the cosine similarity theoretically spans from -1 to 1, empirical observation indicates that negative values rarely occur. This is because the exemplary posts under examination pertain specifically to a particular class of natural disasters.

[3] The prompt we used is: "The following are companies' Facebook posts addressing natural disasters. Paraphrase each post to preserve the meaning of the main idea and value advocated by the post."

disasters like Hurricane Sandy and Typhoon Bopha.” Employing these paraphrased exemplary posts, we conduct the same measurement and compare the results with the current exemplary posts (bootstrapped). Figure A3-1 indicates that the four metrics undergo minor deterioration but maintain overall high values. Thus, we conclude that the measurements are robust to semantic variations in exemplary posts.

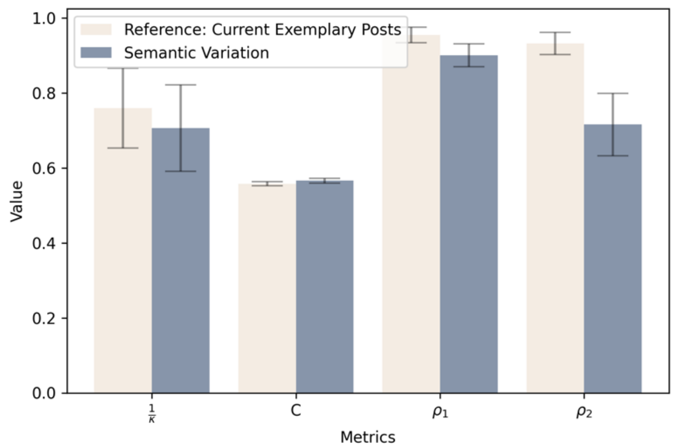


Figure A3-1: Exemplary Posts with Semantic Variation

3. Are both ends of the scales needed? In our study, we define the CVF scales using both “positive” and “negative” exemplary posts. For example, the $external \leftrightarrows internal$ axis is defined as the difference between $\{external \overrightarrow{\&} flexible\}, \{external \overrightarrow{\&} stable\}$ (i.e., notions related to adaptation and serving customers) and $\{internal \overrightarrow{\&} flexible\}, \{internal \overrightarrow{\&} stable\}$ (i.e., notions related to stabilization and collaboration). We study if both ends are needed to define the scale. First, we only retain the “positive” end of the exemplary posts. That is, the scales are defined as:

$$external \leftrightarrows internal = \{external \overrightarrow{\&} flexible\} + \{external \overrightarrow{\&} stable\}$$
$$flexible \leftrightarrows stable = \{external \overrightarrow{\&} flexible\} + \{internal \overrightarrow{\&} flexible\}.$$

We then only retain the “negative end of the exemplary posts. That is, the scales are defined as:

$$external \leftrightarrows internal = -\{internal \overrightarrow{\&} flexible\} - \{internal \overrightarrow{\&} stable\}$$
$$flexible \leftrightarrows stable = -\{external \overrightarrow{\&} stable\} - \{internal \overrightarrow{\&} stable\}.$$

Given this new definition of axes with single ends, we compute the metrics. Figure A3-2 indicates a significant drop in 1/κ, ρ_1, and ρ_2 when only either the positive or negative end is used. Thus, relying on a single end of the scale may potentially compromise the validity of the measurement.

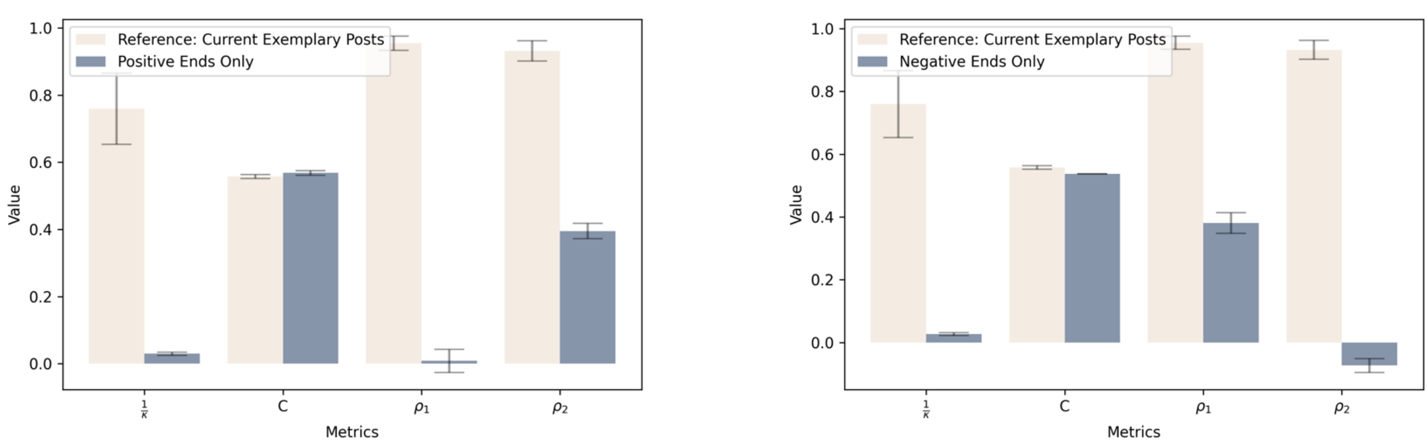


Figure A3-2: Defining Scale by Using Only Positive or Negative Ends

4. Can we simply negate the positive end? If both ends were indeed needed to define our scales, we study if it is possible to craft the exemplary posts by simply negating the "positive" exemplary posts. Again, we employ GPT-4 to negate the exemplary post in each quadrant.[4] For example, the post "*The pandemic pushed businesses to act urgently, intensifying the need for innovation, but the technologies put into place should remain relevant beyond current health concerns.*" is negated to "*The pandemic has encouraged businesses to act complacently, diminishing the need for innovation; these technologies may become obsolete after the current health concerns subside*." Accordingly, we can define the axes as follows:

$$external \overrightarrow{\leftarrow} internal = \{external \overrightarrow{\&} flexible\} + \{external \overrightarrow{\&} stable\} - NOT(\{external \overrightarrow{\&} flexible\}) - NOT(\{external \overrightarrow{\&} stable\})$$

$$flexible \overrightarrow{\leftarrow} stable = \{external \overrightarrow{\&} flexible\} + \{internal \overrightarrow{\&} stable\} - NOT(\{external \overrightarrow{\&} flexible\}) - NOT(\{internal \overrightarrow{\&} stable\}),$$

where $NOT(.)$ indicates that the exemplary posts are negated.

We find that even the state-of-the-art generative AI fails to effectively find the opposing values based on the posts' content. Rather, GPT-4 relies on simple syntactic rules, such as adding "not" to the posts. As the metrics in Figure A3-3 show, this is not an effective approach for generating the negative ends of scale.

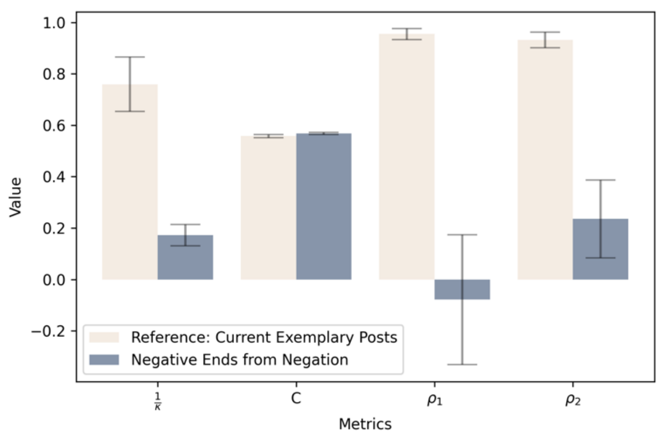


Figure A3-3: Defining Negative Ends using Negation

Overall, our results confirm that SPAR is robust to semantic variation and the inclusion or exclusion of individual exemplary posts. Additionally, at least in our context, both the "positive" and "negative" ends of the CVF scales are needed. Finally, a theoretical framework is crucial for crafting "negative" seeds and exemplary posts, so that the exemplary posts should encapsulate the opposite values while maintaining an affirmative sentence structure, rather than using syntactic negations such as "not."

[4] The prompt we used is: "The following are companies' Facebook posts addressing natural disasters. Negate each post to convey the opposite meaning. Focus on finding the opposite meaning of the main idea and value advocated by the post and not minor details."

A4. Validation of Disaster Message Orientations

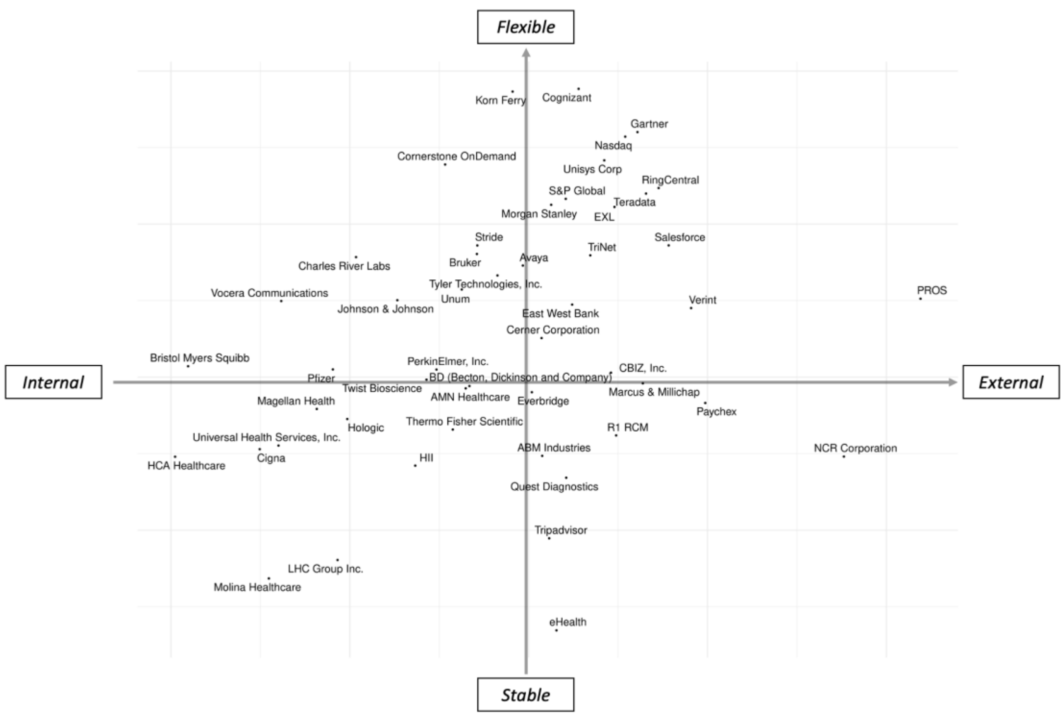
First, we demonstrate disaster message orientations' high face validity by summarizing the content of the posts. We generate word clouds using posts that are on the top and bottom quartiles of the two dimensions (Figure A4-1). We remove the top words that describe disasters rather than the message orientations (e.g., covid, hurricane) to highlight the differences between the quadrants. Several observations are worth highlighting. First, the two competing dimensions clearly separate the posts into four quadrants, with high-frequency words matching the definitions of the quadrants. For example, the external/flexible quadrant contains words that highlight technology and changes. Second, the word cloud demonstrates that the measurement of disaster message orientations is different from topic modeling in that exclusivity of words is not necessary. It is possible to have different disaster message orientations for posts with similar topics or content. Third, the top words differ by disaster type. To illustrate, biological disasters' internal/stable quadrant highlights vaccination and stopping disease spreading, whereas weather-related disaster's internal/stable quadrant highlights better protection and evacuation.

Second, we show that the distribution of the firms also has high face validity. We plot 50 firms in our sample with the most posts and their firm-level disaster message orientations by averaging all posts (Figure A4-2). For biological disasters, we notice that IT firms such as Salesforce and Teradata are more inclined to send messages that highlight flexible and external orientations; healthcare firms such as HCA Healthcare and Hologic are more likely to emphasize internal and stable orientations; and business service firms such as ABM Industries and NCR are more likely to stress external and stable orientations. This observation is consistent with the role that different industry sectors are expected to play in a biological disaster – we rely on healthcare firms to stop the spread of diseases, as well as IT firms to help us adapt to a new way of doing business. On the other hand, for weather-related disasters, renewable and alternative energy firms such as Sunrun and Boom Energy score high on flexible and external orientations, whereas more traditional utility firms such as PSEG and OG&E rank high on flexible and stable orientations. Most insurance firms rank highly on internal and stable orientations. Across two types of disasters, firms such as HCA Healthcare are in the internal/stable quadrant for biological disasters but have moved to the internal/flexible quadrant for weather-related disasters. This is a reasonable adjustment as healthcare firms' role shifts from controlling epidemics in biological disasters to raising donations to support community-based relief efforts in weather-related disasters.

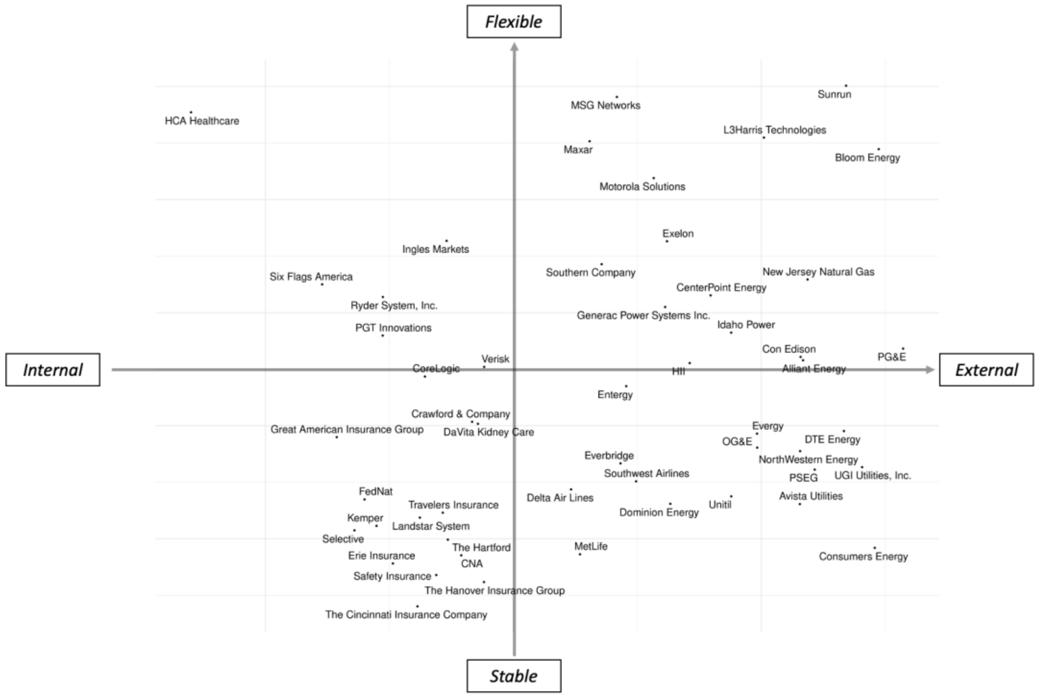
(a) Biological Disasters

(b) Weather-Related Disasters

Figure A4-1: Word Cloud of Posts Projected on Disaster Message Orientations



(a) Biological Disasters



(b) Weather-Related Disasters

Figure A4-2: Most Active Firms on Facebook and Message Orientations

Third, we use normalized Discounted Cumulative Gain (nDCG) as the evaluation metric to determine if the measurements agree with human judgments (Table A4-1). nDCG is a common measure of ranking quality in information retrieval. It is a normalized version of Discounted Cumulative Gain, which is defined as $\Sigma_{i=1}^{k} \frac{rel_i}{log_2(i+1)}$. The intuition is that given an automatically ranked list of k documents and human-assigned relevancy score to these documents, DCG penalizes the documents that are rated high by humans but low by the automated measure. nDCG divides DCG by the best possible score from a perfect ranking. Thus, nDCG scores are always between 0 and 1, with 1 indicating a perfect ranking.

A human rater evaluates 100 posts for each disaster on the two orientations using a scale of [0, 1, 2], where 2 indicates most relevant and 0 indicates not relevant. We then compare the disaster message orientation given by the all-distilroberta-v1 transformer model with the human-rated performance using the nDCG – in other words, if the human ranking agrees with the ranking given by our automated measure. Overall, we find that the automated measure provides a ranking that is in accordance with the human rater (average nDCG = 0.87 for biological disasters and average nDCG = 0.84 for weather-related disasters) for all analyses.

Fourth, to validate our measure of the competing dimensions, we applied the Linguistic Inquiry and Word Count (LIWC) (Tausczik and Pennebaker 2010) to gauge the language used in the two orientations. LIWC is a dictionary-based text analysis tool widely used to assess language features. It contains a set of predefined word categories that were shown to be indicative of social and psychological processes such as affiliation and certainty. We regressed the two dimensions (i.e., external and flexible) on pairs of word categories in LIWC that contain opposite meanings (Table A4-2). The LIWC results support the validity of our disaster message orientation measures. A high external orientation focuses on success in the external environment. The orientation highlights the firms' competitive advantage and financial performance rather than social relationships and community amid disasters. Thus, it is positively related to words indicating differentiation ($\beta = 0.049/0.097$, $p < 0.01$) for biological/weather-related posts respectively) and negatively related to words denoting affiliation ($\beta = -0.077/-0.019$, $p < 0.01$). A high external orientation is also positively associated with words concerning money and finance ($\beta = 0.152/0.064$, $p < 0.01$) and negatively associated with family ($\beta = -0.235/0.292$, $p < 0.01$). On the other hand, a high flexible orientation tends to be optimistic and advocates for change during disasters while remaining tentative and spontaneous. The regression results support these characteristics and show that the message orientation is positively related to the use of words suggestive of rewards ($\beta = 0.044/0.065$, $p < 0.01$) and negatively associated with words indicating risks (β = − 0.189/-0.179, p < 0.01). A flexible orientation is also associated with less use of language demonstrating certainty (β = − 0.086/-0.040, p < 0.01) and more frequent use of words suggesting causation (β = 0.097/0.053, p < 0.01), implying open-ended estimations rather than firm conclusions.

Table A4-1: Comparing Normalized Discounted Cumulative Gain of Models

	Collaborate	**Compete**	**Control**	**Create**	**Average**
Pre-trained Models					
DistilRoBERTa-base	0.842	0.874	0.758	0.814	0.822
all-MiniLM-L6	0.859	0.872	0.654	0.756	0.785
all-mpnet-base	0.848	0.838	0.695	0.771	0.788
Unsupervised Domain Adaptation (SimCSE)					
bert-base-uncased	0.805	0.845	0.736	0.704	0.772
DistilRoBERTa-base	0.815	0.755	0.582	0.761	0.728
MiniLM-L6-H384-uncased	0.834	0.840	0.592	0.763	0.757
Unsupervised Domain Adaptation (TSDAE)					
bert-base-uncased	0.754	0.744	0.646	0.726	0.717
distilroberta-base	0.758	0.796	0.641	0.679	0.719
MiniLM-L6-H384-uncased	0.726	0.771	0.662	0.768	0.732

Table A4-2: Validation with LIWC Measure

(a). External-Internal Axis (Biological)

	Dependent variable: External	
	(1)	(2)
liwc_differ	0.049*** (0.004)	
liwc_affiliation	-0.077*** (0.002)	
liwc_family		-0.235*** (0.008)
liwc_money		0.152*** (0.002)
Flexible	0.074*** (0.005)	0.112*** (0.004)
Constant	0.157*** (0.006)	-0.147*** (0.005)
Observations	45,324	45,324
R^2	0.060	0.116

(b). Flexible-Stable Axis (Biological)

	Dependent variable: Flexible	
	(1)	(2)
liwc_reward	0.044*** (0.004)	
liwc_risk	-0.189*** (0.005)	
liwc_cause		0.097*** (0.003)
liwc_certain		-0.086*** (0.005)
External	0.085*** (0.005)	0.069*** (0.005)
Constant	0.070*** (0.006)	-0.074*** (0.006)
Observations	45,324	45,324
R^2	0.038	0.030

(c). External-Internal Axis (Weather)

	Dependent variable: External	
	(1)	(2)
liwc_differ	0.097*** (0.005)	
liwc_affiliation	-0.019*** (0.003)	
liwc_family		-0.292*** (0.016)
liwc_money		0.064*** (0.003)
Flexible	-0.176*** (0.008)	-0.197*** (0.007)
Constant	-0.042*** (0.009)	-0.021*** (0.008)
Observations	17,868	17,868
R^2	0.068	0.080

(d). Flexible-Stable Axis (Weather)

	Dependent variable: Flexible	
	(1)	(2)
liwc_reward	0.065*** (0.008)	
liwc_risk	-0.179*** (0.006)	
liwc_cause		0.053*** (0.005)
liwc_certain		-0.040*** (0.007)
External	-0.199*** (0.007)	-0.220*** (0.007)
Constant	0.110*** (0.009)	-0.032*** (0.009)
Observations	17,868	17,868
R^2	0.093	0.050

A5. Controlling for Posting Content with Topic Modeling

Topic Number	FREX Keywords	Average Proportion
1	look, good, create, check, plan, forward, job, feel, see, day	7.09%
2	win, chance, enter, want, leave, follow, end, give, tell, post	6.46%
3	home, love, add, shop, store, new, ready, offer, come, enjoy	9.13%
4	available, get, online, find, sign, open, explore, free, close, question	5.07%
5	join, register, meet, learn, discuss, build, benefit, hear, design, challenge	12.01%
6	watch, live, take, video, talk, play, share, thing, ceo, story	7.30%
7	use, need, save, time, help, start, tip, know, money, let	14.22%
8	customer, read, business, say, company, drive, power, increase, announce, lead	12.08%
9	thank, community, support, celebrate, honor, proud, employee, serve, team, work	11.39%
10	click, stay, information, include, link, visit, detail, excited, event, host	4.00%

Note: We compare 5, 10, and 20-topic solutions and choose a 10-topic model based on overall interpretability.

A6. Robustness Checks with Matching and Weighting Analysis

We consider two matching methods: nearest neighbor Propensity Score Matching (PSM) using a logistic regression propensity score with a matching ratio of 1-1, and five-bin Coarsened Exact Matching (CEM) (Iacus et al. 2012). We match on post controls, firm controls, and topics using PSM but drop firm controls from matching covariates for CEM as it is too restrictive. We examine the distributions of propensity scores in both the treatment and control groups and find them to be similar. A value near zero for the maximum eCDF suggests that the treated and control groups are balanced. In biological-disaster and weather-disaster samples, the maximum eCDF values were 0.0577 (for firm control variable log revenue in PSM) and 0.058 (for firm control variable liquidity in PSM), respectively. We observe that all the other covariates' maximum eCDF values are in closer proximity to zero, which implies that the covariates are balanced after matching.

As matching analyses require a binary treatment, we construct the treatment dummy variables: *high internal and stable* and *high external and flexible*. The former takes a value of 1 if both CVF axes' values are smaller than 0, and the latter takes a value of 1 if both CVF axes' values are greater than 0. In Table A6-1 Panel (a), we present the results of our matching analyses. Panel (a) shows that the treatment of high internal and stable value has a positive effect on positive engagement for both PSM and CEM samples for biological disaster-related posts. Conversely, high external and flexible value, the opposite treatment, has a positive effect on positive engagement for both matching samples for weather disaster-related posts.

To avoid dichotomizing the main independent variable, we adopt the Covariate Balancing Propensity Score (CBPS) method, a weighting method as an alternative to matching (Imai and Ratkovic 2014). CBPS gives more weight to covariates that are predictive of the treatment assignment according to the propensity score, resulting in a better balance of covariates and a more accurate estimation of treatment effects. CBPS has two advantages: it mitigates the effect of potential misspecification of a parametric propensity score model and can be extended to non-binary treatments such as continuous values (Imai and Ratkovic 2014). We use the adjusted correlations between the covariates and the treatment to assess the weighting quality and find that all adjusted correlations between the covariates and the treatment are close to 0. The largest unbalanced covariate (in absolute value) is topic content #9 (see Table A5) in the biological disaster sample, with an adjusted correlation of 0.0231, and ROA in the weather disaster sample, with an adjusted correlation of -0.0013. CBPS achieves good covariate balance between the treatment and control.

In Table A6-1, Panel (b), we present the results of our CBPS analysis, which is used to estimate the treatment effect of external + flexible, a continuous treatment variable. Our CBPS analysis indicates that the treatment has a negative effect on positive engagement for biological-related disasters, and a positive effect for weather-related disasters. These findings, along with the results of our matching analyses, provide further evidence of the robustness of our main findings to potential covariate imbalance.

Table A6-1: Robustness Checks Using Matching and Weighting Methods

(a). Results from Matching

	Dependent variable: log (Positive Engagement)			
	Biological		Weather-Related	
	(1)	(2)	(3)	(4)
Matching Method	PSM	CEM	PSM	CEM
Treatment				
High Internal and Stable	0.184 (0.013)***	0.156 (0.027)***	--	--
High External and Flexible	--	--	0.170 (0.032)***	0.142 (0.035)***
Post Controls				
Photo	0.420 (0.016)***	0.365 (0.036)***	0.320 (0.037)***	0.293 (0.036)***
Video	0.344 (0.023)***	0.421 (0.060)***	0.384 (0.055)***	0.386 (0.066)***
Text length	0.325 (0.015)***	0.094 (0.043)**	0.162 (0.028)***	0.201 (0.030)***
Verified	0.304 (0.022)***	0.150 (0.050)***	0.357 (0.046)***	0.352 (0.048)***
Subscribers	0.059 (0.002)***	0.050 (0.004)***	0.057 (0.006)***	0.053 (0.005)***
Like Growth	0.068 (0.003)***	0.034 (0.007)***	0.118 (0.006)***	0.100 (0.007)***
Topic Content	Yes	Yes	Yes	Yes

Trending Topics	Yes	Yes	Yes	Yes
Firm Controls				
Firm Size	0.110 (0.006)***	0.106 (0.013)***	0.187 (0.018)***	0.199 (0.015)***
R&D	0.019 (0.004)***	0.000 (0.008)	0.027 (0.012)**	0.039 (0.014)***
Adj. Return	-0.005 (0.040)	-0.034 (0.076)	-0.004 (0.128)	-0.041 (0.126)
ROA	-0.529 (0.350)	-3.319 (0.695)***	7.152 (1.064)***	8.756 (1.008)***
Liquidity	0.061 (0.021)***	0.210 (0.045)***	-0.002 (0.036)	-0.019 (0.033)
Revenue	0.057 (0.004)***	0.043 (0.009)***	0.048 (0.015)***	0.045 (0.009)***
ESG	-0.202 (0.048)***	-0.174 (0.100)*	-0.540 (0.104)***	-0.371 (0.099)***
HHI	0.418 (0.043)***	0.161 (0.093)*	0.912 (0.093)***	0.821 (0.097)***
Disaster Impact	0.051 (0.005)***	0.097 (0.010)***	-0.096 (0.028)***	-0.086 (0.026)***
Page FE	No	No	No	No
Year & Month FE	Yes	Yes	Yes	Yes
Observations	24,958	6,184	6,890	7,737
R^2	0.409	0.351	0.311	0.265

Note: Cluster-robust standard errors reported in parenthesis. *p<0.1; **p<0.05; ***p<0.01

(b). Results from Covariate Balancing Propensity Score (CBPS) Weighting

	Dependent variable: log (Positive Engagement)	
	(1)	(2)
	Biological	Weather-Related
Treatment		
External + Flexible	-0.101 (0.003)***	0.121 (0.008)***
Post Controls		
Photo	0.383 (0.011)***	0.263 (0.023)***
Video	0.327 (0.017)***	0.320 (0.039)***
Text length	0.337 (0.012)***	0.127 (0.017)***
Verified	0.221 (0.016)***	0.441 (0.028)***
Subscribers	0.058 (0.002)***	0.045 (0.004)***
Like Growth	0.066 (0.002)***	0.112 (0.004)***
Topic Content	Yes	Yes
Trending Topics	Yes	Yes
Firm Controls		
Firm Size	0.128 (0.004)***	0.196 (0.010)***
R&D	0.014 (0.003)***	0.016 (0.009)*
Adj. Return	-0.047 (0.029)	-0.027 (0.086)
ROA	-0.578 (0.254)**	9.015 (0.693)***
Liquidity	-0.002 (0.016)	-0.011 (0.022)
Revenue	0.058 (0.003)***	0.030 (0.006)***
ESG	-0.383 (0.036)***	-0.246 (0.066)***
HHI	0.308 (0.033)***	0.955 (0.066)***
Disaster Impact	0.066 (0.003)***	-0.068 (0.018)***
Page FE	No	No
Year & Month FE	Yes	Yes
Observations	45,324	17,868
R^2	0.398	0.318

Note: Cluster-robust standard errors reported in parenthesis.
*p<0.1; **p<0.05; ***p<0.01

A7. Interviews with the Domain Experts

In this section, we provide information on one-on-one interviews conducted with domain experts.

Background

Because this paper explores an understudied research area with little established literature, we resort to domain experts to validate our research assumptions and findings. As we take the perspective of online users to understand the drivers of their engagement on firms' messages, we interviewed disaster management experts who have directly served the public and who are knowledgeable about their needs during the time of disastrous events. The U.S. disaster response practice takes a whole community approach, involving the public sector, private sector, non-governmental organizations, and the public (FEMA 2011). As a result, leaders of the U.S. disaster management field are familiar with the feelings and demands of the public, rendering them appropriate experts for us to consult.

We were able to recruit an outstanding expert panel that represents 16 national leaders of the U.S. in disaster management. These experts have been selected based on their experience and reputation in the field. The panelists are either currently taking or have taken presidential or gubernatorial-appointed positions, or have been a chairman elected of national disaster associations. In performing their job duties, these interviewees have served a huge number of citizens, through developing national, state, and municipal disaster response plans, overseeing disaster response operations (e.g., evacuation, sheltering and food supplies), and allocating disaster relief funds in billions USD. Many are top experts in weather disasters (e.g., hurricanes, earthquakes, and flooding) or trained professionals in emergency health management (e.g., mental health, emergency medical services, and hospital patient care). Some have written articles on how to communicate with citizens during crises, closely related to the current study. Others have been deployed as experts to help the victims of the 9/11 attack and those of other major disasters, showing their ability to understand the emotional and cognitive needs of the public. Well-respected by their peers, these panelists have chaired numerous national policy committees and given congressional testimonies. They have frequently spoken at major disaster management events (e.g., the International Disaster Conference and Expo, National Disaster Resilience Conference, and NATO Civil Emergency Planning Committee forum). They have frequently shared knowledge with the scientific community (e.g., speaking at the "Resilient America" Roundtable Workshop of the National Academies of Sciences, Engineering, and Medicine, teaching in the Harvard University Kennedy School of Government's Program on Crisis Leadership, and writing articles for the Center of Excellence of the Homeland Security Emergency Management). Appendix Table A7-1 contains their example qualifications.

One author conducts all the interviews mainly via Zoom.[5] The interview starts with the interviewer presenting the research background, motivation, frameworks used, and key findings. Next, the interviewer solicits interviewee feedback to understand (a) applicability of CVF in disaster research; (b) differences between biological disasters and weather disasters; and (c) experts' take on the observed findings: whether interviewees agree with our research findings or not, their reasoning is collected. Their participation is completely voluntary, and interviewees don't receive any compensation.

Interview Questions

1. In this study, we've applied the Competing Value Framework (CVF) to categorize the message orientations of firms' disaster related Facebook posts. Following CVF, firms' social media messages may be crafted to display an internal focus (e.g., employees and operations) or an external focus (e.g., products and services for customers). They may also be crafted to display a stable focus (e.g., continuous production and operation) or a flexible focus (e.g., adaptations and innovations).

In your opinion, to what extent does the CVF describe firms' disaster communication?

2. Milliken (1987) identified three types of uncertainties in events: (1) State Uncertainty: the inability to accurately predict an event; (2) Effect Uncertainty: the inability to predict the impact of an event on people's life; (3) Response Uncertainty: the difficulty in understanding and evaluating what actions one should take to respond to an event.

[5] This author has 17 years of experience in interviewing disaster management practitioners at local, state, and federal levels. He has visited many disaster zones to interview the responders (e.g., interviewing responders of the 2005 Hurricane Katrina, the 2020 Midwest Derecho, and the 2021 Surfside Building Collapse). He has traveled to many disaster management events, and Washington D.C., to interview the leaders of the U.S. disaster community.

Between weather disasters (e.g., hurricane, tornado, and flooding) and biological disasters (e.g., pandemic), which one displays high State Uncertainty? Which one displays high Effect Uncertainty? Which one displays high Response Uncertainty?

3. By analyzing over 60,000 disaster-related firm Facebook posts, we found the following results: (A) in biological disasters, the internal focus and stable focus are effective in helping posts receive positive reactions. (B) for weather disasters, the external focus and flexible focus are effective in helping posts receive positive reactions.

Based on your professional experience, how do you evaluate the above results? What part of the results will you agree to? And what part of the results will you not agree to?

Key Findings

First, all interviewees except one agree on the utility of CVF in identifying firm communications during disasters.[6] They comment that "it does make sense", "I can barely spell CVF, but it made sense to me," and "I think the way you have applied the framework to those two threats makes perfectly good sense." While the experts have no prior knowledge of CVF, they concur that the two message orientations capture important attributes of firm crisis communication to the public.

Multiple experts add that the two message orientations of CVF are easy to use and understand, which is important in helping companies communicate to the public:

- "I've never seen it [CVF] before. But it makes perfectly good sense. It's easy to read, and easy to understand. And could be very good in guiding and crafting your messages to the left of bang, and also analyzing the results of your messages to the right of bang. Ease of use and application are really important. And you know in our world, because time is our enemy, we'd be able to have messages to use this to pre-craft messaging. And also in the moment, look at your message messaging, just going out and to see, you know, does the messaging meet these criteria? Or were these guiding points? I looked at it right away, and I was able to understand it."

The interviewees also express strong support for the differences between the two disaster types. Responses are such as "I think I do agree with that," "between those two types of events, it totally makes sense," "I tend to agree with that," and "I would agree to that." Interviewees share their reasoning with us, citing examples such as:

- "[for weather disasters] there is an element of effect and response uncertainty, but it is far localized. And it is far more based on perception, than it is on science or other things, like it may be for biological disasters." That is, weather disasters display low levels of effect uncertainty and response uncertainty, which remain high in biological disasters, owing to the difficulty in developing a scientific understanding of the viruses. "But when you deal with weather, I think oftentimes most people know that weather is just part and parcel to our very existence, right? I mean we get it, we get it with regularity. We generally tend to know what the outcome is… So I think people are not having such a fear factor or grim reality associated with weather related events. Unless, you are talking about your category 5 hurricanes and different things like that. Even the hurricanes, even when people live in hurricane regions, they're so accustomed to the steps that need to be taken, and how to protect themselves, and the storm surge and all of those things that take place. So I think, you know, on the weather side people have grown more accustomed to these types of events versus this major pandemic."

- "I think the Covid-19 pandemic presented to many people many unknowns of the impact and response. This is the first time many people ever experienced a pandemic of this manganite. You had H1N1, H5N1, but it was nowhere near as impactful as Covid-19. For many people, there was a fear factor." "People haven't grown accustomed to those types of events, Covid-19 events. And this thing was so new to people, too. People were still trying to learn about it as it was taking place. So I mean again a lot of unknowns [of the effect and the response], you know, on the biological side."

[6] This interviewee agrees that the CVF values are useful. The person expresses a concern because he/she thinks that our CVF framework will limit a firm to craft all of its messages to be either stable-focused or flexible-focused. This is not true because what the CVF framework really suggests is that a firm's messages may be categorized into one of the two focuses. The framework doesn't require that all messages of a firm must display one single focus. We consider that this reflects a misunderstanding, but not a real criticism of the framework.

- “I can see how the natural hazards are [of] high state uncertainty,” “those [weather] hazards are largely dependent on where it strikes (more populated areas vs. more rural areas),” “weather incidents change a lot,” and “Hurricanes forecasts are highly uncertain specifically when the forward speed of the storm is below 12 mph. Intensity and rainfall forecasts are two of the hardest factors to predict as well. The Fema Hurricane Liaison Team located at the Hurricane Center always says: It’s a highly dynamic situation that requires constant monitoring.”
- “I'd agree that there is low uncertainty around that particular pathogen,” “there is less of a chance of genetic change amongst the host population,” and “biological incidents generally have a more consistent impact of vulnerability where it tends to impact the elderly, the really young, and the immunocompromised the worst.”

Multiple interviews underscore a novel perspective of “hazard tangibility.” They suggest that the fact biological disasters cannot be seen or felt results in more perceived uncertainty in disaster response.

- “There's a different sense of fright or heightened awareness, or for something that, though that we can't see, feel, taste, or touch. As a firefighter I hated going on a hazmat incident because I couldn't reach out and grab it. And I think, with pandemic or bio, we were worried about it here. I talked about pandemics probably 10 years ago, probably one of the worst threats that we could have here, because we couldn't see it coming. Well, just in a very simplistic sense, you couldn't see it coming like you could have fire or flood: at least as human beings, from my perspective I could see it, I could touch it. Flooding is the single most costly disaster in the country. Annually, every state has a flooding challenge, you know. But compared to a bio issue, it's tangible. You know germs are bad things. We can't see it coming. And pandemic level stuff, you know, moves at the speed of the modern transportation conveyances. In 1918 influenza moved at the speed of steamships and locomotives. Fast forward to 2020, Covid moved at 500 miles an hour on an airplane, you know, but we couldn't see it coming. You know, I've seen a fire rolling up the hill, you know, or water flashing across a room. I've seen a flood you know increase and cars start to float. I think it has to do with the tangibility, or you know, can a human process it?”

Finally, the domain experts express unanimous support for the reported patterns between weather types and the effects of firm message orientations (e.g., the internal and stable orientations help Facebook posts receive more positive reactions in biological disasters). Responses are such as “This makes sense,” “I don't see any issues here,” and “How they are opposite to each other, it makes sense. It makes a lot of sense,” “Does that [the specific research findings] make sense? Absolutely,” “I think that totally makes sense,” and “I think that's a perfect alignment of how the messaging would sort of follow a disaster.” In the case of weather disasters, expert comments are such as:

- “On the weather disaster part, it makes total sense. It is consistent with the things that I’ve seen.”
- “Walmart, Home Depot, Lowes, and hardware stores, their facilities may be damaged. But they will put up posts or they will advertise that we got all of our inventory out in the tents in the parking lots. You can still shop. It’s not gonna be pretty, but you can still shop here and get what you need to rebuild your house.”
- “There was a lot of push to try to make known: ‘Hey, we are still open, we are still here.’ Even as recently as in eastern Kentucky [July 26-30, 2022 Eastern Kentucky Flooding, killing 39 people], there were lots of instances where there were hotels, camp sites, and other recreational areas that have had lots of cancellations. Because folks coming in from out of the region saw all the news coverage, [they think] Shoot! I am not gonna go to a place that is covered up in flood water, I cannot get around if there is no power. There is no cell coverage, then forget it. Not knowing what the effects are, they self-eliminated them and were out of the market. That creates economic injury to the businesses that are there.”

In the case of biological disasters, experts underscore “hope” and “continuity/resilience” as two potential reasons that may explain the reported research findings. These factors help mitigate the perceived uncertainty.

- Hope as a reason: “At times, there was a lot of information presenting the grim reality of the outcome and potential outcome of what this Covid-19 can do, if certain steps were not being taken, social distancing, masking, vaccination, all these different things. So, I think in that context, when people started to get any sort of good news, with relation to, hey, in the midst of this pandemic, we are still operational, we are still stable, I think that is a breadth of fresh air for people to hear, right? So, yeah naturally they are going to respond positively to those kinds of messages that have come up. Because they have been hearing nothing but negativity or the grim reality of this thing. There's a fear factor there.”

- Continuity and resilience as a reason: "I think people wanna know continuity, which is a good thing important. I think you know another word that obviously is critical in today's disaster environment is resiliency. You can't necessarily have good resilience, unless you have good continuity. So, you know, people knowing that your company has a very effective continuity plan that allows for the resiliency of your operation: whether that's supply chain management, or whether you have mechanisms in place, whether it's companies on retainer or things like that, where you can get products in. People wanna know "Hey! You know, these companies have the wherewithal to survive in these types of crisis situations. I think that also, you know, gives people reassurance knowing that companies have taken the steps to ensure continuity to ensure resiliency. So, I think that's just another critical aspect."
- "[when] it is a bio emergency, so, the emphasis is on continuity and order, conservative and cautious." and "Covid is a perfect example of this. You know, everybody was looking for stability, because their entire world from where they went to school, where they went to work, where they, how they grocery shop. Everything was turned on its head."

Table A7-1: Example Qualifications of the Interviewees

P	F	S/C/A	Disaster Management Experience
X	X	X	Appointed by a U.S. president and approved by the Senate, he served as the **Administrator of the Federal Emergency Management Agency** (FEMA) of the U.S. Department of Homeland Security. Director of Emergency Management of the **State of Florida**.
X	X	X	Appointed by a U.S. president and approved by the Senate, she served as the Deputy/Associate Administrator of **FEMA**. Championed the development of National Disaster Recovery Framework, Recovery Support Functions, Federal Disaster Recovery Coordinators, and Sandy Recovery Improvement Act. Assistant Director for the Division of Emergency Management of the **State of Arizona**.
X	X	X	Appointed by a U.S. president, he served as the Associate Administrator of **FEMA**. President of **the National Emergency Management Association** (NEMA). Member of the FEMA National Advisory Council. Administrator of the Homeland Security & Emergency Management Division of the **State of Iowa**.
X	X		Appointed by a U.S. president, he served as the Director for Preparedness Policy of the **White House National Security Council Staff**, where his work led to a Presidential Memorandum and associated National Action Plan. Recovery Coordinator of the U.S. **Economic Development Administration**. Acting Director of the Recovery Division in the U.S. **Department of Health and Human Services**. Director of Disaster Resilience and Recovery Planning at the U.S. **Small Business Administration** (SBA).
P: an interviewee receiving a presidential appointment. F: an interviewee leading federal government agencies. S/C/A: an interviewee taking leadership role in state, city/county, or national disaster management association.			

A8. A Tutorial on Using the SPAR Package for Measurement

This section provides a tutorial on using our open-source SPAR (Semantic Projection with Active Retrieval) package for measuring CVF values and other semantic measurements.

Launching on Google Colab: SPAR can be launched on Google Colab without installation using the link.

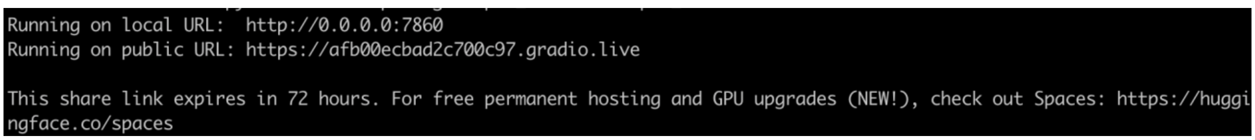
Installation: SPAR is available as a pip package (https://pypi.org/project/spar-measure/), a package installer for Python. It can be installed by running the following command in the terminal (Unix/Linux/MacOS) or command prompt (Windows):

```
pip install -U spar-measure
```

Running: SPAR offers two access modes: local (which is the default) and public. The public access mode generates a shareable link, so it is advisable to add a username and password for security purposes. They can be respectively launched as follows:

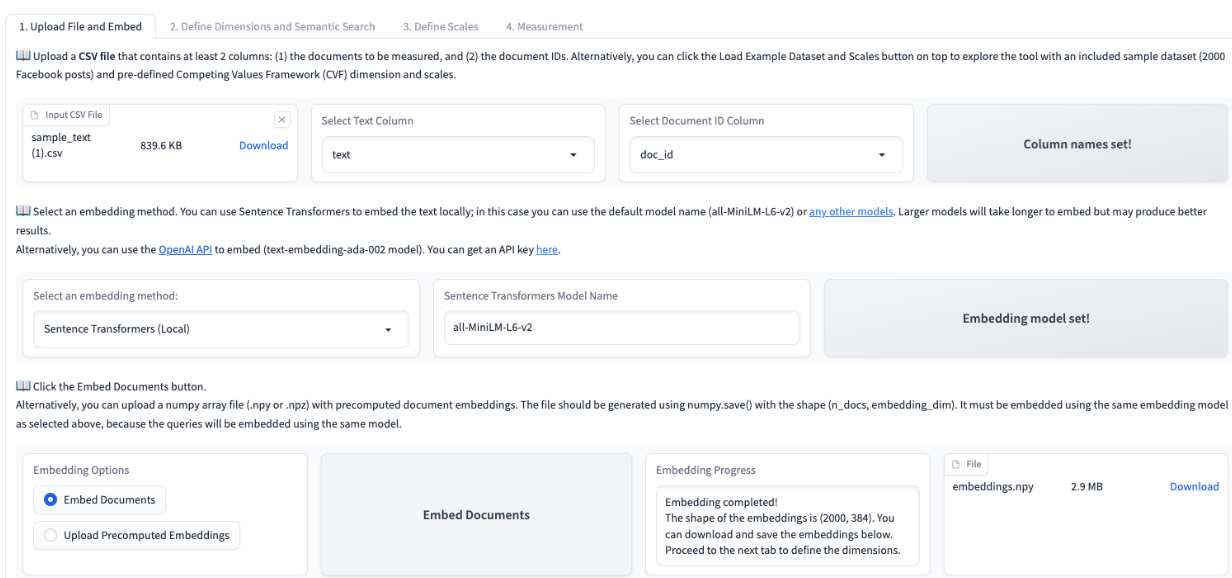
```
python -m spar_measure.gui
python -m spar_measure.gui --mode=public --username=user --password=password
```

Once launched, the interface can be accessed in a web browser locally via http://0.0.0.0:7860/ or a public URL as shown below.



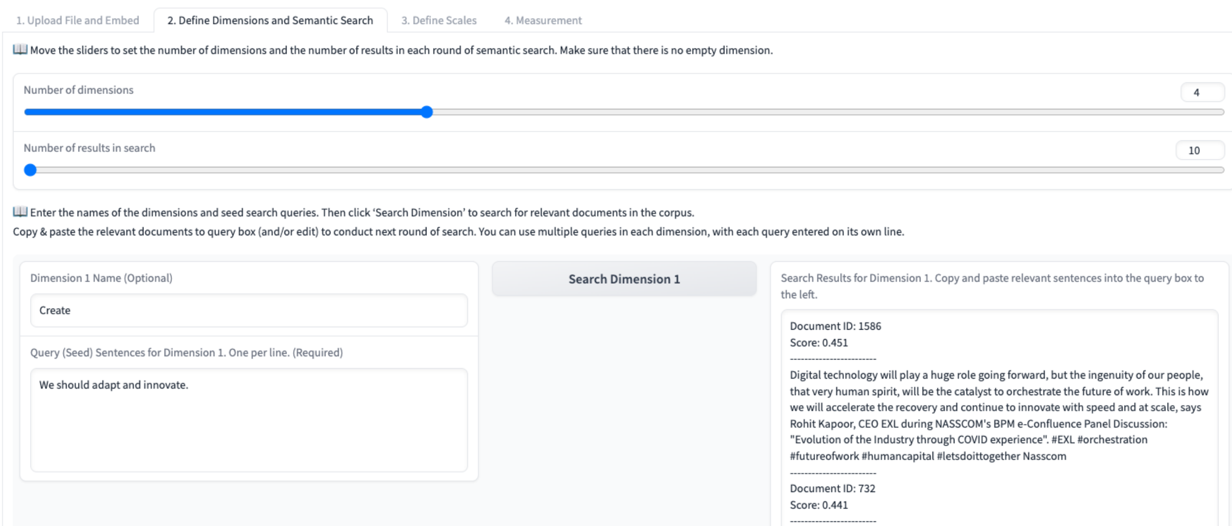
Measurement: The measurement process consists of four steps, each of which is located in its own tab. To help new users navigate the functions and steps, we provide a "💡 Load Example Dataset and Scales" button at the top of the interface. Clicking this button will load an example dataset of 2000 Facebook posts and their corresponding embeddings. The settings for Tabs 1 through 3 will be automatically filled in using CVF as an example.

Step 1 In the first tab of the application, the user is prompted to upload a CSV file containing at least two columns: one for the document ID and one for the actual document. Each document should be in its own line. For document embeddings, the user has three options: 1) Choosing a pre-trained sentence transformer model to embed the text. 2) Using the OpenAI embedding API to embed the text. If this option is selected, the user must enter an OpenAI API key or set it as an environment variable. 3) Uploading a pre-computed embedding matrix in the form of a NumPy file. Once the embedding is completed, users can download the embedding matrix as a NumPy file.



Step 2 The second tab of the application allows users to select dimensions and provide seed queries. The example dataset uses the CVF dimensions: create, collaborate, control, and compete. Users have the flexibility to choose a different number of dimensions and seed queries. To retrieve the top semantically related documents to the seed queries for each dimension, the user can click the "search dimension i" button, where "i" refers to the number of the selected dimension. After this step, users can manually add and refine the queries in the query box and conduct the next round of search.

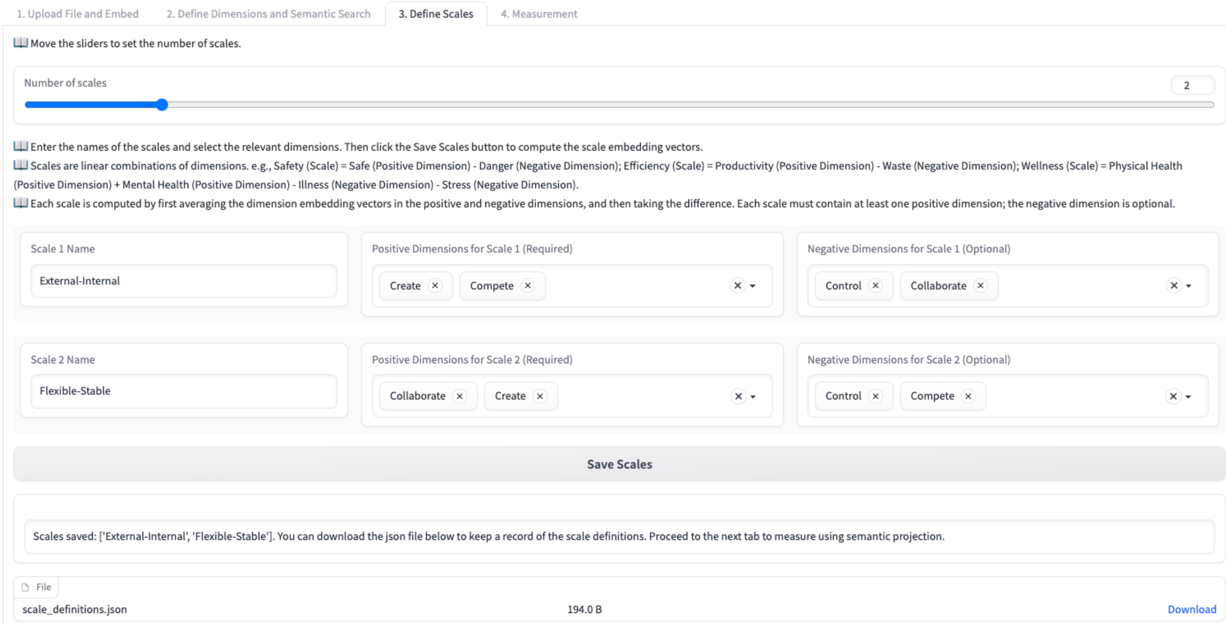
In each round, the average embedding vector of the queries will be used to retrieve relevant documents. Once the user has finalized the exemplary sentences, they should click the "Embed Queries and Save Dimensions" button. This step will embed the final exemplary queries, and users can save them as a JSON file.



Step 3 The third tab of the application allows users to define scales based on the selected dimensions. For instance, our paper uses the External-Internal and Flexible-Stable scales. The External-Internal scale can be computed by using the formula: Create + Compete – (Control + Collaborate). As such, for this scale, we can choose Create and Compete as the positive dimensions and Control and Collaborate as the negative dimensions. Similarly, we define the Flexible-Stable scale.

The application allows users to define other scales to measure documents. For example, an "Intelligence" scale can be measured by using the "Smart" as the positive dimension, and the "Stupid" dimension as the negative dimension. Note that it is not necessary to define both opposite "ends" of the scale. One can use the dimensions defined in Tab 2 as the scales if no opposite or composition is needed.

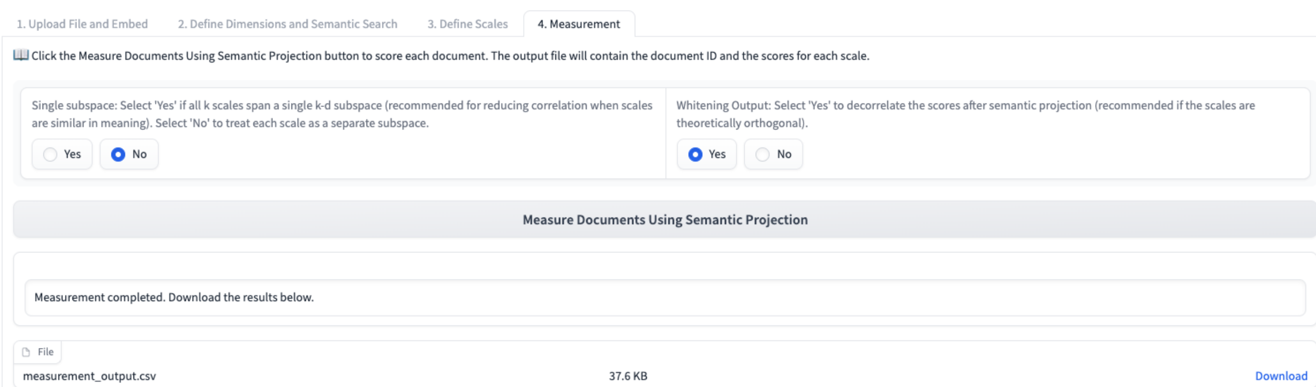
Once the user has finalized the scale definitions, they should click the "Save Scales" button. This step will compute the semantic vectors for the scales. The scale definitions are downloadable as a JSON file.



Step 4

In the final tab of the application, users can choose whether to conduct projection onto general subspaces or ZCA whitening for the semantic projection measures. Whitening is used to decorrelate the scores of the semantic projection and improve the accuracy of the results. Once users have selected the desired whitening option, they can click the "Measure Documents using Semantic Projection" button. This step should be relatively fast compared to the embedding step, which can be time-consuming without a GPU.

The measurement results, in the form of document IDs selected in Tab 1 and their corresponding scale values, will be downloadable as a CSV file. This allows users to further analyze and interpret the results in their preferred statistical or visualization software.



doc_id	External-Inte	Flexible-Stable
0	0.9621	-1.1246
1	-0.0609	0.1685
2	-1.0033	1.6859
3	0.1487	0.1166
4	-0.7253	0.227
5	-1.1128	0.9298
6	-0.1005	0.0884

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