Weakening Cultural Strength: Environmental Fit, Uncertainty, and Cultural Norm Consensus in Firms *

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Abstract

Prior research largely ignores how the external environment impacts the ability of firms to nurture or maintain a strong culture. As such, how and why corporate culture systematically changes over time is not well understood. This article proposes that cultural strength decreases when organizational members experience uncertainty resulting from perceptions of poor organization-environment fit. Uncertainty reduces norm consensus, or the extent to which members hold congruent perceptions of the cultural norms that guide how work is done in the organization. I theorize that this relationship is mediated by disruption to existing routines, which reduces the behavioral consistency required to foster shared perceptions of dominant norms. Support for the argument is found using novel, time-varying measures of norm consensus developed via a language-based model that identifies cultural content in employee reviews of nearly 500 publicly traded firms on the website Glassdoor.com. One important implication is that strong corporate culture may be an outcome rather than simply a determinant of performance, suggesting the need for dynamic models that account for the endogenous relationship between these constructs.

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Whether deliberatively cultivated or naturally arising, every organization develops a culture—a system of meanings and norms shared by its members. The culture of a firm can have important consequences for the success of its members and the organization as a whole through its effects on individual motivation and commitment, interpersonal coordination, and group creativity and innovation (for a review, see Chatman and O'Reilly (2016)). Although organizational scholars often ask how the content of organizational culture relates to performance—for example, how different beliefs and norms promote or inhibit various outcomes—a growing literature has been focused on the effects of shared cultural beliefs on organizations’ performance and vitality. Strong culture, defined as “a set of norms and values that are widely shared and strongly held throughout the organization” (O'Reilly and Chatman, 1996, pp. 166), is thought to increase firm performance (Sørensen, 2002; Denison and Mishra, 1995). Moreover, strong cultures can enhance employee morale and well-being (Jehn et al., 1999; Schneider et al., 2013).

Given that cultural strength is presumably linked to higher performance and positive workplace outcomes, both scholars and practitioners are interested in understanding how organizations develop and maintain a strong culture. However, the dynamics of how corporate culture develops, changes, evolves, or persists over time are not well understood, largely due to a lack of systematic, longitudinal data (Schneider et al., 2013; Chatman and O'Reilly, 2016). How and why does culture fluctuate in strength over time?

Existing literature focuses almost exclusively on how leaders can develop, maintain, and transform their firms’ cultures, a determinant of cultural strength which is internal to the firm (O'Reilly et al., 2014). As such, it largely takes a closed system perspective, whereby variation in cultural strength is solely attributable to the efficacy with which leaders, managers, and peers socialize organizational members. This closed view is surprising given today's dominant macro-organizational theories presume that understanding how organizations function in the broader environment as open systems is essential for explaining organizational behavior. And while formal models allow changes in cultural strength to be driven by the interplay between internal socialization forces
and employee demographic processes, the broader environment only impacts cultural strength in so much as it affects employee mobility into and out of the organization (Harrison and Carroll, 2006). These models do not consider whether environmental shifts can have a direct impact on the processes by which shared cultural norms among employees develop or are maintained.

In contrast, this paper adopts an open system perspective, which considers how the fit between an organization and its external environment drives organizational behavior (Thompson, 1967). High environmental fit means the organization’s internal processes are aligned with the demands of the current environment, such that organizational outputs are consistently rewarded by resource holders (Thompson, 1967; Hannan and Freeman, 1977). Little is known about how an organization’s environment influences cultural strength. How does environmental fit affect the ability of firms to nurture or maintain a strong culture?

This question is important for at least three reasons. First, our understanding of the determinants of cultural strength is necessarily incomplete if environmental forces have an impact above and beyond internal factors. Advances in dominant open system theories have shown that many macro-organizational outcomes cannot be fully understood without consideration of the organization-environment relationship. Second, the findings could inform how leaders are evaluated during periods of cultural change – observers may be incorrectly attributing increases and decreases in cultural strength solely to leaders when broader environmental conditions are in part responsible. Third, if poor environmental fit as reflected by volatile firm performance decreases cultural strength, then cross-sectional associations indicating a positive effect of culture on performance may be upwardly biased.

To answer the question of how environmental fit affects culture, I focus on understanding how uncertainty faced by firms impacts one primary component of cultural strength. Firms experience uncertainty when they have difficulty predicting how current policies and strategies will translate into future performance. Uncertainty is fundamentally driven by perceptions of a lack of organization-environment fit. A common theme across foundational theories of organizational
behavior is that organizations attempt to mitigate, manage, and cope with uncertainty in order to adapt to changing environmental demands (Thompson, 1967; Pfeffer and Salancik, 1978; Williamson, 1981). The inability for an organization to identify strategies, routines, and processes that produce consistent, reliable performance is an existential threat (Hannan and Freeman, 1984).

Uncertainty reduces cultural strength by inhibiting norm consensus. Norm consensus is a state in which firm members hold congruent perceptions of the cultural norms that guide how work is done in the organization. The degree of norm consensus, or the extent to which members agree about the norms that impact behavior in the firm, is a primary indicator of a culture’s strength (Chatman and O’Reilly, 2016). High norm consensus increases organizational performance by enhancing employee coordination and motivation (Sørensen, 2002). I theorize that this negative relationship between uncertainty and norm consensus is mediated by disruption to existing routines and a reduction in the behavioral consistency required to entrench dominant norms.

An empirical test of the relationship between uncertainty and cultural strength requires longitudinal data on culture for a large sample of firms. However, the methods most commonly used to study organizational culture—chiefly direct and indirect self-reports (O’Reilly et al., 1991) or participant-observation (Kunda, 2009; Turco, 2016)—are impractical for generating fine-grained, dynamic measures. Traditional culture surveys are often unwieldy, yielding low response rates, and can only be feasibly collected on an intermittent basis. At best, they yield static snapshots of changing organizational culture.

I overcome this limitation by leveraging the language that employees use when describing their firms to others as a window into corporate culture. I develop a novel, time-varying measure of norm consensus by identifying cultural content in employee reviews of nearly 500 publicly traded firms with profiles on the website Glassdoor.¹ I combine these data with measures of firm-level uncertainty used in prior work, and estimate within-firm models. The empirical results support my argument.

Beyond the value of uncovering a major external determinant of changing cultural strength, evidence of a link between uncertainty and cultural strength is important because it calls into question whether strong culture actually increases performance. Scholars have speculated that cross-sectional estimates of the effect of strong culture on firm performance may be biased by reverse causality (Van den Steen, 2010; Sørensen, 2002). If the certainty and behavioral consistency stemming from high, consistent performance facilitates cultural strength, and there is some degree of temporal persistence in performance, then cross-sectional associations between cultural strength and high performance could be observed even if culture has no performance-enhancing effect. While causation between performance and culture might flow in both directions, these results nevertheless suggest the need for more sophisticated models that can capture any endogeneity between these constructs.

ORGANIZATIONAL CULTURE AND CULTURAL STRENGTH

I follow Pettigrew (1979, p. 574) in defining culture as a “system of publicly and collectively accepted meanings” that operates and influences social behavior within groups—including organizations. These meanings manifest in the form of deeply rooted assumptions and beliefs, norms and values, and artifacts (Schein, 2010). Together, these cultural components create normative expectations for the behavior of group members and are reflected in the language they use when interacting with one another and when describing the group to others (Pinker, 2007).

The culture of an organization can be characterized in a variety of ways. One common approach, implemented through instruments such as the Organizational Culture Profile (O’Reilly et al., 1991) and the Denison Organizational Culture survey (Denison, 1990), focuses on specific, predefined organizational features such as innovation or adaptability that are reflective or not of prevailing norms. Another widespread tradition, on which the present study builds, instead focuses on cultural strength. Strong cultures are characterized by “a set of norms and values that are widely shared
and strongly held throughout the organization” (O’Reilly and Chatman, 1996).

Strong corporate culture, exemplified by widespread agreement among members about the most important norms and values that guide work, has been theorized to be positively related to performance for four main reasons. First, cultural strength is thought to promote goal alignment, which in turn makes it easier for employees to coordinate tasks (Kreps, 1996). Second, the strength of culture is believed to promote behavioral consistency (Gordon and DiTomaso, 1992), which can improve the speed and quality of strategy execution. Next, researchers have assumed that firms with a strong culture can exercise social control over group members more cost effectively than can firms with a weaker culture (O’Reilly and Chatman, 1996). Finally, firms with stronger cultures are thought to provide a more conducive environment for employee commitment and motivation to achieving agreed-upon goals than are firms with anemic cultures.

Given the presumed link between cultural strength and performance, practitioners and scholars are interested in learning how organizations can develop, maintain, and transform their cultures (Deal and Kennedy, 1982; Trice and Beyer, 1991). However, how and why corporate culture changes over time is not well understood, despite popular narratives that “cultures do evolve over time – sometimes slipping backward, sometimes progressing” (Katzenbach et al., 2012). How and why does culture fluctuate in strength over time? Given organizations are open systems, how do external environmental forces affect the ability of firms to nurture or maintain a strong culture? A lack of answers to these questions is surprising given: 1) today’s dominant macro-organizational theories assert that many important organizational processes and outcomes can only be fully understood with reference to the organization-environment interface, and 2) an emphasis on the connection between environmental conditions and the development of culture in broader societies (Gelfand et al., 2011; Boyd and Richerson, 2005).

One view represented by organizational ecologists is that cultural elements are relatively stable over time. Founders establish preferred norms and processes when building their organizations (Baron and Hannan, 2002) and socialize employees. These organizing logics lock-in norms and
structures that persist even after the founder(s) depart – the content of founding blueprints are predictive of the subsequent adoption of particular human resource policies (Baron et al., 1996) and the existence of certain administrative structures (Baron et al., 1999). This view suggests the content of corporate culture, the core norms and values that are established early in an organization’s life, is relatively invariant and reflects the predispositions of founding members and/or environmental conditions at the time of founding (O’Reilly et al., 2014; Johnson, 2007).

Another perspective is that organizational culture is more fluid, not necessarily because core cultural content changes, but because cultural strength can fluctuate (Harrison and Carroll, 2006). Changes in cultural strength reflect variation in the degree to which cultural beliefs and values are widely shared and strongly held among current organizational members. I define norm consensus as a state in which firm members hold congruent perceptions of the cultural norms that guide how work is done in the organization. The degree of norm consensus is one primary component of a culture’s strength (Chatman and O’Reilly, 2016; Sørensen, 2002).

However, prior work examining variation in norm consensus largely takes a closed-system view of organizations (Scott and Davis, 2015), whereby the environment external to the firm does not impact internal enculturation processes. Instead, variation in norm consensus has been attributed almost exclusively to an internal firm factor: the efficacy with which leaders and peers socialize employees. Leaders and peers provide information and signals about the preferred normative order to lower-level employees (O’Reilly and Chatman, 1996; Schein, 2010). Formal methods of socialization include mission statements, orientations, employee handbooks, and human resource programs designed to impress appropriate beliefs and values on employees (Kunda, 2009). Informal methods involve signaling important beliefs and values through the use of symbols, such as language, rituals, ceremonies, and role models whom exemplify desirable behavior (Deal and Kennedy, 1982). These socialization forces are directed not only to new employees, but also to current ones because cultural beliefs likely decay over time (Harrison and Carroll, 1991).

An influential research program by Harrison and Carroll (for an overview, see Harrison and
Carroll (2006)) made an important contribution by theorizing that norm consensus depends not just on the intensity of socialization forces, but also their interplay with employee demographic processes. Employee mobility into and out of the firm alters the distribution of cultural beliefs across current members. Mobility also influences the distribution of employee tenure, which likely alters the effectiveness of socialization forces – employees with less tenure are more susceptible to socialization (Harrison and Carroll, 2006).

However, this work stops short of adopting a true open system view of employee enculturation. It posits that the broader environment only impacts cultural strength in so much as it affects employee mobility into and out of the organization. Their models do not consider whether environmental shifts can have a direct impact on the processes by which shared cultural norms among employees develop or are maintained. Socialization proceeds in the same direction with the same intensity, regardless of the organization’s current fit with the environment and the ability of current routines and processes to reliably secure resources from external resource holders (Harrison and Carroll, 2006).

This closed system focus is surprising because modern organizational theory is based on an open system view, which examines how fit with the environment impacts internal firm processes and organizational behavior more broadly. For example, organizations alter their core internal production processes in ways that buffer them from environmental uncertainty (Thompson, 1967). Organizations also change their governance structures to reduce dependence on resource holders and increase autonomy (Pfeffer and Salancik, 1978). The behavioral theory of the firm posits that organizations are more likely to make significant and sometimes risky changes to internal processes when performance in the current environment falls below managers’ aspiration levels (Bromiley, 1991; Cyert and March, 1963). Most notably, organizations shift from exploitation to exploration strategies, or from refining existing to searching for new routines and competencies, when current processes fail to produce outputs that are consistently valued by external resource holders (March, 1991; Sitkin, 1992).
How, then, might consideration of environmental fit enhance our understanding of how and why norm consensus changes over time within firms? A limited set of theoretical work suggests that an organization’s experience interfacing with its environment can affect cultural processes. First, Trice and Beyer (1991) theorize that certain leadership qualities are more conducive to maintaining corporate culture during periods of environmental stability, while others are more beneficial for instilling new cultural norms and values when routines and processes need to be radically altered. Since strategy and culture are tightly coupled (Lorsch, 1986), this argument implies that environmental shifts may induce cultural changes. Second, Van den Steen (2010) formally models how the environment affects norm consensus as mediated by direct environmental performance feedback. Leaders can foster shared beliefs by selecting the organizational actions and environmental payoffs from which employees learn. An implication is that cultural beliefs are shaped by how organizational actors attend to, interpret, and respond to environmental performance signals about the efficacy of current routines and processes. Third, Schein (2010) theorizes that environmental feedback may influence norm consensus through a more emergent process. He writes that organizational culture accumulates as a “pattern of shared basic assumptions learned by a group as it solved its problems of external adaptation and internal integration, which has worked well enough to be considered valid and, therefore, to be taught to new members as the correct way to perceive, think, and feel in relation to these problems” (Schein, 2010, pp. 18). In other words, shared cultural norms and assumptions develop over time as the organization works to cope with a changing organizational environment.

However, no prior work has provided a systematic account of how organizational members’ perceptions of environmental fit drive changes in norm consensus and ultimately cultural strength. In the next section, I call upon a large, diverse body of evidence supporting the idea that norm consensus is significantly enhanced by behavioral consistency. An implication is that perceptions of the organization-environment relationship that facilitate behavioral consistency within the firm should promote norm consensus and cultural strength, while perceptions that induce inconsistent
behavior should decrease cultural strength.

**NORM CONSENSUS AND BEHAVIORAL CONSISTENCY**

Organizations are conceptualized as bundles of routines (Cyert and March, 1963; Hannan and Freeman, 1989; Nelson and Sidney, 1982). Routines are repetitive, recognizable patterns of interdependent behavior (Feldman and Pentland, 2003), which help organizational actors perform tasks consistently by standardizing behavior (Becker, 2004). In other words, the enactment of a stable set of routines amounts to behavioral consistency among organizational actors.

For several reasons, social groups whose members exhibit consistent behavior are more likely to develop high levels of consensus about important norms and values. First, behavioral consistency helps leaders more effectively socialize employees, increasing an organization’s ability to foster and maintain congruent perceptions of dominant norms. The development of norm consensus requires the continual reinforcement of behavior that is aligned with the firm’s core norms and values (O’Reilly and Chatman, 1996). Norm internalization is slow, and requires intense and sustained socialization (Morris et al., 2015). Leaders manage the information employees process by “minimizing mixed or inconsistent messages to help members develop shared interpretations of events” (O’Reilly and Chatman, 1996, pp. 175) in order to enhance informational and normative influence. Managers can reinforce norms by repeatedly exposing members to consistent behavioral practices, which can increase perceptions that norms are familiar and typical to other group members (Morris et al., 2015; Kwan et al., 2015). Perceptions that behaviors are common makes members more likely to infer that the behaviors are also normatively approved by leaders and peers (Eriksson et al., 2015).

Widely shared norms require behavioral consistency in order to form. Observations of behavioral regularities, consistent sanctioning behavior, and institutionalized rules lead actors to perceive the presence of norms – these perceptions impact subsequent attitudes and behavior in a self-reinforcing
cycle. Norms develop from the bottom-up – useful behaviors discovered by a few group members are imitated and ultimately become imbued with value in and of themselves (Morris et al., 2015; Zucker, 1977). Behavioral consistency also allows ample opportunity for cultural norms and values to be legitimated through performance feedback. Cultural conventions perceived by a group as functional through performance feedback are more likely to become widely shared. Schein (2010) writes, “Only those beliefs and values that can be empirically tested and that continue to work reliably in solving the group’s problems will become transformed into assumptions” (pp. 26). Consistent performance is key – “When a solution to a problem works repeatedly, it comes to be taken for granted. What was once a hypothesis supported only by a hunch or a value, gradually comes to be treated as a reality” (pp. 27-28).

One socialization technique is for leaders to interpret events as being causally linked to the firm’s norms to highlight the culture’s value to employees, which is particularly effective given the high level of ambiguity in organizations (O’Reilly and Chatman, 1996; March et al., 1991). Formal modeling suggests that beliefs about performance-enhancing norms more quickly converge in the presence of positive, consistent performance feedback. Positive feedback allows members to attribute successful outcomes to an existing norm, while negative feedback only narrows the search for a performance-enhancing norm by one (Van den Steen, 2010).

A second way that behavioral consistency drives norm consensus is that the consistent enactment of behaviors can directly lead to attitude change (O’Reilly and Chatman, 1996; Cialdini, 1993; Schlenker, 1982). While behavior is commonly thought to reflect actors’ attitudes and beliefs, the reverse can also be true. Behavior often drives beliefs, values and attitudes (Cialdini, 1993). Sustained and incremental behavioral participation can lead to attitude and subsequent behavior change (O’Reilly and Chatman, 1996). Individuals are apt to justify their actions to themselves and others by altering their values to be consistent (O’Reilly and Chatman, 1986).

At the group level, the consistent enactment of routines allows shared understandings to develop among collaborators. Turner and Rindova (2012) find that the consistent performance of routines
allows tacit agreements to emerge among coworkers. These shared understandings increase team coordination and efficiency by reducing the need for negotiation and debate about work processes. Moreover, they find consistent routines also help members more effectively police norm violations – observations of these sanctioning events serve to increase norm consensus even further.

A third way that behavioral consistency can increase norm consensus is that the repeated execution of stable routines can mask latent cultural disagreements across subgroups within an organization. The mere perception of norm consensus in a firm harboring latent cultural disagreement can enhance goal alignment and motivation and ultimately promote performance. Deeply held cultural assumptions can be latent in that they are not exposed until the organization is forced to deal with a crisis that threatens its survival (Schein, 2010).

Organizations are often composed of political coalitions with conflicting interests (Cyert and March, 1963; Rotemberg and Saloner, 1995) and cultural beliefs (Martin, 1992), but these disagreements may only surface if existing routines are disrupted. Existing routines represent “truces” that facilitate coordination even when subgroups have conflicting beliefs about how to respond to environmental challenges, so long as only minor strategic compromises are required (Zbaracki and Bergen, 2010). Unexpected events, however, can surface latent tensions in peoples’ belief systems, akin to breaching experiments that illuminate real differences in behavior that are unobservable during more routine periods (Bonikowski, 2016).

For example, Zbaracki and Bergen (2010) found that the marketing and sales departments of a manufacturing firm held conflicting beliefs about how to price products so as to maximize profit. The marketing department believed that the firm could increase market share by reducing product list prices. In contrast, the sales department believed that sales and revenue would increase if price decreases were negotiated on a customer-by-customer basis. During routine operations, the two departments successfully collaborated to make minor price adjustments. However, this latent disagreement surfaced when a reduction in production costs for one product line called for a substantial price reduction. These disparate beliefs created conflict and undermined coordination...
moving forward (Zbaracki and Bergen, 2010).

This evidence shows that organizations whose members exhibit consistent behavior are more likely to develop and maintain high levels of consensus about important norms and values. In the next section, I focus on a fundamental challenge, uncertainty, that confronts firms trying to adapt to changing environmental demands, and examine how the experience of uncertainty reduces cultural strength by inhibiting behavioral consistency and the formation of norm consensus among employees.

UNCERTAINTY AND BEHAVIORAL INCONSISTENCY

Uncertainty is the subjective perception that the future cannot be accurately predicted. Firms and work groups experiencing uncertainty perceive that they cannot accurately predict how their current behavior will translate into future performance (Beckman et al., 2004; Mosakowski, 1997; Milliken, 1987; Duncan, 1972). Uncertainty among organizational decision makers can stem from a variety of sources, including internal changes such as new market entry, acquisitions, and top management turnover, and external changes involving relationships with exchange partners or broader changes in technology or market conditions (Beckman et al., 2004; McGrath, 1997; Wiersema and Bantel, 1993). Changes in any elements of a firm’s task environment, which includes customers, competitors, suppliers, regulatory groups, and technological standards (Duncan, 1972), can induce uncertainty.

Each of these proximate sources of uncertainty signal that the external environment has changed or is changing, calling into question the fit between the organization’s internal processes and the offerings rewarded by resource holders in the external environment. Uncertainty is characterized by a lack of clear information, unpredictable outcomes, the inability to ascertain causal relationships between organizational action and environmental feedback, and difficulty in predicting how envi-
ronmental conditions will affect future performance (Lawrence and Lorsch, 1967; Duncan, 1972). Podolny (2001) nicely encapsulates uncertainty among producers as egocentric uncertainty, which is uncertainty about market opportunities and the resources that can most effectively take advantage of those opportunities. He uses the example of an automobile producer that faces egocentric uncertainty over how hiring, supplier, and production decisions will impact whether the company produces a vehicle valued by buyers.

Environmental volatility, or the variability of environmental change, is a driver of particularly high levels of uncertainty (Child, 1972). Operating in a dynamic, volatile environment, in which the nature and/or timing of environmental shifts themselves are hard to predict, greatly increases uncertainty for decision makers (Dess and Beard, 1984; Duncan, 1972). Environmental volatility makes it difficult to establish and maintain organization-environment fit. Particularly vexing for producers is that volatile environments are often characterized by unstable consumer preferences (March, 1978; Tripsas, 2008). Sorenson (2000) provides an example from computer workstation markets. In some of these markets, sales of the same products fluctuated wildly from one year to the next, making it difficult for firms to predict which products to produce and when. As such, environmental volatility inhibits the ability of firms to sustain competitive advantage (D’Aveni et al., 2010).

Individuals and organizations are fundamentally driven to attempt to reduce uncertainty so as to develop confidence in how to react to and behave in their environment (Hogg and Terry, 2000). Overcoming uncertainty is the fundamental problem facing decision makers in organizations (Thompson, 1967) – firms seek to reduce uncertainty in an effort to better regulate how their behavior is rewarded by the environment.

In particular, firms have a strong incentive to reduce uncertainty accompanied by firm performance variability. Variable firm performance is a strong signal that internal routines and processes have fallen out of alignment with the changing environment. Performance variability may make it more difficult for firms to buffer their cores from environmental volatility in order to effectively
plan and make decisions (Thompson, 1967), or reduce dependence on resource holders (Pfeffer and Salancik, 1978). Corporate finance research finds that highly variable cash flows reduce firm competitiveness due to underinvestment in promising projects (Froot et al., 1993). Highly variable performance is also a direct existential threat to organizations – organizational ecologists argue that firms that perform haphazardly are at a higher risk of mortality because resource holders demand consistent performance in and of itself (Hannan and Freeman, 1984). Furthermore, simple models predict that firms with more variable performance are more likely to run out of resources and die (Levinthal, 1991).

Uncertainty is important in the context of cultural strength because the ways firms attempt to mitigate, manage, and cope with uncertainty reduce the behavioral consistency required to foster norm consensus. Echoing prior arguments that changing environmental conditions disrupt current routines and processes (Baum and Shipilov, 2006), I argue that these responses to uncertainty disrupt existing routines because they are all ultimately efforts to realign internal routines and processes with current environmental demands.

For example, buffering, collusion, long-term contracts, and vertical integration, strategies and tactics that firms use to cope with uncertainty (Dess and Beard, 1984), each initially disrupt existing routines by shifting resources and structure from core production tasks to efforts to manage the organization-environment interface. For example, buffering involves adding administrative functions that protect core production processes from environmental changes (Thompson, 1967), or amassing slack resources that can be used for exploratory search and innovation so that production processes can be realigned with the changing environment (Cyert and March, 1963).

More generally, firms experiencing uncertainty shift activity away from exploitation, refining existing routines and capabilities, and towards exploration, or the search for new processes that better align with the environment and produce reliable performance. Given the trade-off between exploitation and exploration, increased search behavior disrupts existing routines designed to exploit a stable environment. Organizations that perceive high organization-environment fit and little
environmental ambiguity are likely to stick with the routines and processes that produce reliable outcomes, and less likely to engage in problemistic or exploratory search for new routines (Sitkin, 1992). In contrast, uncertainty casts doubt on whether current organizational routines and processes will produce reliable outputs moving forward in time. Uncertainty, and any firm performance variability associated with it, are cues that an organization’s existing routines have fallen out of alignment with the current environment. Because lack of organization-environment fit is an existential threat, firms respond to these cues by engaging in exploratory search for new routines or processes that can meet changing environmental demands.

For example, firms experiencing uncertainty decrease capital investment, hiring, and advertising, but increase R&D spending, consistent with this shift from exploitation to exploration (Stein and Stone, 2013). Uncertainty also leads to experimentation with alternative network arrangements and structures – firm-specific uncertainty prompts firms to seek out new information about the changing environment by broadening the scope of their network partners or diversifying into new markets (Beckman et al., 2004; Mizruchi and Stearns, 1988; Podolny, 2001; Brealey et al., 2012). Additionally, volatile performance that dips below managers’ aspiration levels is more likely to lead to risk-taking behavior that in turn worsens performance (Bromiley, 1991; Cyert and March, 1963).

These two links, one between behavioral consistency and norm consensus and the other between uncertainty and behavioral inconsistency, suggest that uncertainty inhibits the development of shared norms in organizations. As such, I predict that uncertainty reduces norm consensus among firm members. This argument accords with culture’s theorized role in action in more versus less volatile societies. Swidler (1986) argues that new cultural norms and values take time to be learned in uncertain periods. During “settled times,” the cultural resources available to actors and the problems that can be solved using cultural tools are taken-for-granted. Actors have “familiar strategies of action for which they have the cultural equipment” (Swidler, 1986, pp. 281). However, actors during “unsettled times,” or periods of social transformation, have to learn new strategies of action and practice “unfamiliar habits until they become familiar” (Swidler, 1986, pp. 278).
other words, new cultural elements have to be learned through consistent practice and behavior until they become widely shared and ultimately taken-for-granted.

**HYPOTHESIS 1 (H1):** Periods of higher uncertainty are associated with subsequent decreases in the level of norm consensus within the firm.

I posit that the link between uncertainty and norm consensus is mediated by responses to uncertainty that disrupt existing routines and reduce behavioral consistency within the firm. As such, drastic responses to particularly threatening manifestations of uncertainty should be more disruptive to existing routines and have a larger effect on norm consensus.

I argue that the perceived threat of uncertainty is likely moderated by the firm’s recent performance trend. Firms use past performance trends to predict future performance (Downey and Slocum, 1975). While uncertainty is always problematic to some degree, it is more threatening if a firm’s recent performance is trending downward. Compared to firms with increasing performance, firms exhibiting declining performance are less able to secure resources from the environment to grow and survive. Moreover, work on the behavioral theory of the firm provides extensive evidence that firms are more likely to take risks and make significant organizational changes when performance falls below managers’ aspiration levels (Bromiley, 1991; Cyert and March, 1963). This leads to the prediction that the effects of uncertainty on norm consensus will be particularly acute when the organization is experiencing an overall performance decline.

**HYPOTHESIS 2 (H2):** The negative association between uncertainty and norm consensus is amplified during periods of declining performance.
METHOD

Language as a Window into Cultural Agreement

In measuring norm consensus, I begin with the premise that organizational culture can be detected in the language used by members (Pinker, 2007; Cremer et al., 2007). Insofar as culture sets normative expectations for group members, it also prescribes a set of linguistic conventions that people who seek to fit in to an organization typically aim to follow. For example, Srivastava et al. (2017) and Goldberg et al. (2016) develop a language-based measure of cultural fit and, using an email corpus and personnel records from a mid-sized firm, examine its relationship to individual attainment. Srivastava et al. (2017) demonstrate that this measure can be used to trace distinct “enculturation trajectories” for employees who exit voluntarily, leave involuntarily, and remain employed. In particular, those who fail to learn and conform to the organization’s linguistic code face greater risk of involuntarily exit, and those who cease to invest in staying normatively compliant are more likely to subsequently choose to exit on their own. Similarly, Goldberg et al. (2016) show that, although linguistic alignment with colleagues is generally positively related to attainment, this relationship is contingent upon a person’s position within the structure of the intraorganizational network.

Building on these insights, I propose that organizational culture can not only be detected by observing the degree of linguistic compliance that members exhibit when communicating with each other—for example, in emails or text messages—but also in the language they use to describe the organization as a whole. In particular, I focus on the topics that members use when describing their culture to each other and to outsiders. Unlike previous conceptions of organizational culture or climate that focus on categories such as innovation or transparency that are predefined by researchers or informants (e.g., senior leaders in the firm) (Ehrhart and Naumann, 2004; O’Reilly et al., 1991), mine neither privileges one set of cultural topics over others nor assumes that researchers and informants understand the culture better than the typical organizational member does. Instead, the
approach assumes that all topics used in discourse about the organization’s culture are potentially informative. This permits not only the detection of norms and values that are directly espoused by employees (ex. “the company has a fun-loving, laid-back culture”), but also key cultural artifacts that reflect espoused values as well as more deeply-held cultural assumptions (ex. “coworkers socialize on Friday afternoons by playing ping pong and drinking beer”) (Schein, 2010). As such, this measurement strategy can capture some richer cultural manifestations that previously were only attended to by qualitative work (Schneider et al., 2013).

Empirically, the methods most commonly used to study organizational culture—chiefly direct and indirect self-reports (O’Reilly et al., 1991) or participant-observation (Kunda, 2009; Turco, 2016)—are often unwieldy, yielding low response rates, and can only be feasibly collected on an intermittent basis. At best, they yield static snapshots of changing organizational culture. In part for this reason, prior work examining the link between culture and firm performance has tended to rely on cross-sectional designs and simply side-stepped questions about the causal relationship between the two.

To overcome these limitations, I apply the tools of computational linguistics to derive novel, time-varying measures of norm consensus for a sample of nearly 500 publicly traded companies on Glassdoor (www.glassdoor.com)—a career intelligence website that allows employees to evaluate and comment on their firms. Given that cultural content can appear in a wide variety of reviews, I use unsupervised learning to identify distinct cultural topics in the nearly one million sentences that contain the word culture and its synonyms. I then train a topic model, which I fit to all employee reviews in the sample, and derive the culture measure based on these identified topics.

Cultural Agreement

I measure norm consensus by assessing the level of cultural agreement exhibited by employees writing about their organization. Given a set of topics that organizational members use to describe culture in a given period, I define cultural agreement as the similarity of topics that group members
mention in their characterizations. In other words, organizations exhibit greater cultural agreement when their members tend to agree with each other when describing the culture.

Although this linguistic approach has the advantages described above over survey-based measures, it is also similar in some key ways to established tools like the Organizational Culture Profile (OCP). First, both approaches presume that members of strong cultures can accurately describe attitudes, beliefs, norms, and values that are approved of by other members (Chatman and O’Reilly, 2016). Second, both approaches elicit the norms and values that respondents consider most intensely held throughout the organization. The OCP forces respondents to choose several norms that are most characteristic of the organization. My approach reasonably assumes that the cultural topics that are worth mentioning in written comments of limited length are likely the ones perceived as most intensely held.

**Data Sources and Sample**

The data include all employer reviews written by employees in the United States from January 2008 to July 2015 on the website GlassDoor. GlassDoor is a career intelligence website that attracts a diverse audience primarily as a job search platform. It has an estimated 17 million unique users per month. While their identities as employees are authenticated by GlassDoor, reviewers are anonymous and thus the reviews are less susceptible to bias stemming from fear of retribution. Reviews are either unsolicited or contributed by users searching for jobs in exchange for unlimited site access (see Appendix C for details).

While recent work uses similar employee review text to construct longitudinal culture measures, my approach differs. Popadak (2013) and Moniz (2016) track changes in cultural content, such as results- and performance-orientation, which requires the researcher to predefine cultural categories that are generalizable across a diverse set of firms. In contrast, I discover the topics that organizational members consider germane to culture using unsupervised learning, consistent with

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a distributive approach to culture that considers cultural content to be relatively idiosyncratic to
individual firms (Harrison and Carroll, 2006).

I restricted analyses to reviews for publicly-traded companies for which I have access to perform-
ance data from Compustat. Additionally, I limited the sample to firms with at least 50 employee
reviews in one or more quarters to ensure that there were a sufficient number of reviews to calculate
the culture measure.3 The initial analytic sample contains 512,246 reviews over 492 organizations. I
lag all predictors by one quarter to assuage concerns of reverse causality. In addition, I standardized
the culture measure.

Measures

Dependent Variable

I measure cultural agreement by assessing the degree to which a firm’s employees in a given
quarter characterize the firm using similar cultural topics. This measurement strategy first requires
a method to identify cultural topics discussed by employees.

Language-Based Measure of Cultural Agreement

I develop a language-based measure of cultural agreement using free response text written by
employees reviewing the firm. Following prior text analysis work, I treat each review as a “bag of
words,” which assumes that I can identify topical content even after discarding word order. I then
represent each review as a vector of unigram counts, which identifies how many times the review
includes individual words. Together, these individual words comprise a set of the most popular
words that appear across the entire text corpus.

My empirical strategy consists of two primary steps: 1) training a linguistic topic model to iden-
tify distinct dimensions of organizational culture, and 2) fitting that model to my analytic sample

3I later restricted to reviews with at least five words given weight by the LDA culture model, which marginally
reduced the number of available reviews in some firm/quarters. Only firm/quarters with at least 25 reviews were
used in all analytical models.
to identify the cultural dimensions mentioned in each employee review. I use a Latent Dirichlet Allocation (LDA) topic model (see Appendix A for technical details). LDA inputs a document-term matrix, for which the rows are reviews and the columns are unigram counts, and identifies distinct topics across the corpus by observing words that tend to co-occur frequently within each review across many reviews. LDA then outputs a document-topic matrix, for which each review is assigned to a probabilistic mixture of topics, or a probability distribution giving the percentages across all topics $c \in C$ that the model estimates comprising the review. The model predicts that two reviews with similar probability distributions contain similar content.

### Identifying a Set of Cultural Dimensions

Training the LDA model allows me to learn what topics employees across many organizations collectively consider germane to organizational culture. My model training approach requires a key assumption: when employees write about firm culture, they sometimes explicitly use the word “culture” or a synonym, and sometimes do not. Regardless, I can use the presence of a culture synonym as a label that indicates a given sentence contains content relevant to culture. Training the LDA model on text with these explicit references allows the model to identify a set of cultural topics. The model is then fit to reviews in my analytic sample to identify the cultural topics in text containing either explicit or implicit culture references (see Appendix A for details).

The topics identified by the LDA model have face validity as cultural dimensions that capture beliefs, norms, and artifacts. One way to validate LDA topics is to examine the words that are most highly weighted within each topic. Table 1 shows the highest-weighted words for four hand-picked and four randomly selected LDA topics. The first set were hand-picked based on their highly distinctive culture content and refer to emphasis on quality versus quantity in production, the entrepreneurial environment, travel and multiculturalism, and the nature of social interactions, respectively. The randomly selected set is representative of average LDA topics. These topics refer to how employee performance is recognized, the cultural dynamics of mergers, fun and laid-back
coworkers, and challenging work, respectively. The LDA topics are clearly germane to organizational culture, which supports my approach of training the linguistic model on sentences that contain a culture synonym.

In simply inspecting the 500 culture topics, it is sometimes difficult to identify exactly what distinguishes one topic from others. My goal, however, is not to select LDA model parameters (e.g., the number of topics to output) that maximize the coherence or distinctiveness of the topics. I am not interested in the cultural content *per se* but the extent to which reviewers agree or disagree about the content. As such, I output a large number of topics to ensure I tease apart conceptually meaningful distinctions between cultural topics. My cultural agreement measures are highly-correlated and the results consistent using different numbers of topics (i.e. 25, 50, 100, and 250), which indicates that measuring cultural agreement with regards to the same linguistic baseline is what is required to make comparisons between and within organizations.

*Measuring Cultural Agreement*

I measure cultural agreement by assessing the degree to which a firm’s employees in a given quarter characterize the firm using similar cultural topics (Appendix B provides a series of measurement validation checks). After fitting the LDA model to the reviews in my analytic sample, each review $i$ is represented as a probability distribution $p$ indicating the relative proportion of each cultural topic $c$ estimated as present in the review text.

I define cultural agreement for a given firm/quarter as one minus the mean Jensen-Shannon (JS) divergence between the LDA probability distributions for all unordered pairs of reviews $i, j$ for that firm/quarter, formally:

$$A = 1 - \frac{\sum_{i,j} JS(p_i, p_j)}{\sum_{i,j}}, \text{ for all } \{i, j \mid i < j\}$$

\[ 1 \]
where the JS-divergence between the two probability distributions is defined as:

$$JS(p_i, p_j) = \frac{1}{2} KL(p_i, M) + \frac{1}{2} KL(p_j, M)$$

and where $M = \frac{1}{2}(p_i + p_j)$ and $KL(p_i, M)$ is the Kullback-Leibler divergence of $M$ from $p_i$:

$$KL(p_i, M) = \sum_{c \in C} p_i(c) \log_2 \frac{p_i(c)}{M(c)}$$

JS-divergence is a symmetric measure of the dissimilarity of two probability distributions. It is well-suited for comparing sparse, power-law distributions of words observed in natural language and has been used previously to measure the similarity of organizational members’ language use (Goldberg et al., 2016; Srivastava et al., 2017).

This language-based model of cultural agreement has two advantages over survey-based culture measures. First, it allows me to measure dimensions of organizational culture longitudinally for a large, diverse set of organizations, which would be extremely difficult using more expensive and logistically-demanding survey methods. Second, the model inductively identifies topics that employees consider germane to organizational culture – it does not require the researcher to make a priori assumptions about the cultural topics that broadly characterize organizations. Corritore et al. (2017) show that, consistent with prior literature on cultural strength, this measure of cultural
agreement is associated with firm performance. In other words, firms exhibit higher performance in periods in which employees are in agreement about the most important norms and values.

Since the employees who write Glassdoor reviews were not selected through random sampling from the population of firm employees, Appendix D includes robustness checks to address the impact of any non-random selection of employees into writing Glassdoor reviews that could bias the findings.

Independent Variables

Performance volatility reflects managers’ perceptions of uncertainty and thus impacts decision making (Lang and Lockhart, 1990; Bourgeois, 1985). As such, I follow Beckman et al. (2004) in using firm stock price volatility as a measure of firm-specific uncertainty. Economists also use stock market volatility to capture firm level uncertainty (Bloom et al., 2007; Stein and Stone, 2013).

Stock price is an appropriate performance metric for at least two reasons. First, it reflects investors’ assessments of companies’ future earnings prospects, and so is a relatively accurate indicator of the ability of large, publicly-traded companies to secure resources from their environments moving forward in time. For this reason, stock price volatility should impact uncertainty perceptions among decision makers more than backward-looking, accounting-based performance measures, such as return on assets. Second and related, it captures organization-environment fit rather than simply the efficiency with which a firm’s internal processes convert inputs into outputs. This study aims to capture uncertainty stemming from the mismatch between a firm’s offerings and the often unpredictable and fickle tastes of consumers and other market actors.

For each firm/quarter, I examine variability over the past 12 months in the firm’s monthly closing price. I then create two measures: 1) the coefficient of variation of the stock price, and 2) the sum of the squared residuals around a bivariate OLS regression line that assesses the overall trend in the firm’s stock price as time passes over the past 12 months.

The coefficient of variation, or the standard deviation of the monthly stock prices over the
mean of the stock prices, is a conventional way of capturing volatility (Beckman et al., 2004). However, this measure fails to delineate truly unpredictable performance variability from more predictable variance attributable to increasing or decreasing performance trends (Bourgeois, 1985). Firms use past performance trends to predict future performance (Downey and Slocum, 1975) – performance increasing or decreasing at a consistent rate is more predictable and thus should not drive uncertainty.

For example, consider Figure 1. Both firms a and b are exhibiting consistent performance, but a is consistently increasing and b is consistently flat. Nevertheless, a has a positive coefficient of variation, while b has a zero coefficient of variation.

To delineate performance variability from trend, I run a local bivariate OLS regression of past performance on time for each observation, as illustrated by firm c in Figure 1. I measure the performance trend as the slope of the fitted regression line through the data points. I measure variability as the sum of the squared residuals around this fitted trend line. This measurement strategy allows me to interact variability and trend in the models, so as to assess whether performance variability is more detrimental to cultural agreement in cases in which overall performance is trending downward versus upward. This “detrend” step follows the logic of disambiguating volatility from major performance trends (Bourgeois, 1985; Downey and Slocum, 1975).

Control Variables

Cultural Topic Breadth

This measurement strategy captures variation in the number or diversity of cultural topics that employees individually or collectively discuss in their reviews, which likely reflects the breadth or diversity of an organization’s culture. It may be that cultural agreement is more difficult to foster in a company with a broad, diverse, multidimensional culture as opposed to one with a more focused culture (Corritore et al., 2017). As such, I measure cultural topic breadth by assessing the degree to which a firm’s employees collectively concentrate discussion around a broad versus narrow set
of cultural topics. First, I sum the cultural topic probability distributions across reviews and normalize to obtain a cultural topic probability distribution, $P$, at the firm/quarter level. Formally, I aggregate over all $p_i$ within a firm/quarter to produce the normalized probability of cultural topic $c$ for a firm/quarter:

$$P_c = \frac{\sum_i p_{c_i}}{\sum_{k \in C} \sum_i p_{k_i}}$$ (4)

This distribution $P$ indicates the cultural topics that employees collectively consider as descriptive of a firm’s culture. I apply the Herfindahl index, a popular measure of concentration, to this probability distribution. After taking the inverse, high values indicate that a firm during a given quarter is described by a broader range of cultural topics, while low values indicate a narrower, concentrated set of topics. I take the natural log of the Herfindahl Index because the measure has a highly right-skewed distribution. Cultural topic breadth for a firm/quarter is formally defined as:

$$B = 1 - \ln \sum_{c \in C} (P_c)^2$$ (5)

Other Controls

The cultural agreement measure may be sensitive to the number of review pairs used to calculate it. I account for this by controlling for the log of the number of reviews contributed by employees on Glassdoor during a given firm/quarter.

I also include important firm-level controls. It is important to control for performance level
because it might be related both to performance variability and cultural changes. For example, it is plausible that firms in a general state of dysfunction exhibit volatile performance and suffer declines in norm consensus. I control for past performance level, both in terms of productivity and market evaluation. Productivity is measured using Return on Assets (ROA), defined as income before extraordinary items over total assets. Market evaluation is measured using the closing stock price.

In addition, I control for firm size using the log of total assets. I also control for the number of business segments in which the firm operates to account for internal segmentation that could either facilitate consensus within divisions or inhibit it across divisions. Finally, all models include year and quarter fixed effects.

**Analytical Strategy and Estimation**

My longitudinal measures of cultural agreement allow me to model how this primary component of cultural strength varies within firms over time in response to changes in the level of uncertainty that firms experience. I leverage this longitudinal data by estimating models with firm fixed effects that examine within firm variance in uncertainty and cultural agreement. An advantage of this approach is that the models control for time-invariant firm characteristics that may impact the estimated relationship between uncertainty and cultural agreement. This is important because there may be stable components of a given company’s culture that make it resistant to fluctuations in the level of uncertainty, i.e. norms and values specifically pertaining to appropriate responses to uncertainty or the general effectiveness with which the firm socializes employees. The sample of observations with complete data is highly unbalanced, primarily due to the consistent availability of enough Glassdoor reviews to compute the cultural agreement measure over time. Consequently, all models restrict to firms with at least six quarterly observations to ensure I have enough within-firm variance to estimate the firm fixed effects.
RESULTS

Tables 2 and 3 provide summary statistics and pairwise correlations, respectively, for the final analytical sample. Contrary to my prediction, cultural agreement has a small, positive correlation with stock price variation. Note, however, that cultural agreement is highly correlated with firm size and segmentation. My two measures of uncertainty, the coefficient of variation and separating the variance from the trend, have a strong positive correlation.

Table 4 reports findings using the coefficient of variation to measure uncertainty. All specifications include firm and period fixed effects. More variable performance over the past year is associated with a subsequent lower level of cultural agreement, providing preliminary support for hypothesis 1. The number of Glassdoor reviews has a marginally significant negative association with cultural agreement, which is unsurprising given the sensitivity of the measure to the number of review pairs used in its estimation. Also, the diversity of the cultural topics discussed collectively by employees has a negative association with agreement, suggesting it is more difficult to foster agreement in firms organized around a broad, diverse set of cultural topics. Additionally, the number of business segments has a negative association with cultural agreement, consistent with the notion that an increase in structural segmentation in a firm leads to the development of more differentiated subcultures.

Table 5 replaces the coefficient of variation with the alternative measure of uncertainty, which disentangles performance variability from performance trend. Controlling for performance trend, stock price variability still has a negative association with cultural agreement, providing continued support for hypothesis 1. While controlling for variability, performance trend has a negative association with cultural agreement. Holding variability constant, firms with a positive performance trend exhibit lower cultural agreement. I refrain from interpreting this main trend effect, since
the intuition when interacting variability and trend is clearer. Model 5 is the fully specified model with the interaction term included. The positive and significant coefficient for the interaction between performance variability and trend means that the negative effect of variability is attenuated when performance trends upward. Figure 2 shows the marginal effect of performance variability on cultural agreement across the range of performance trend slopes observed in the data. The model predicts that the negative effect of performance variability is stronger the more negative the performance trend. Moreover, the variability effect is significant only below a performance trend slope of about 0.5. This evidence supports hypothesis 2, that the negative association between uncertainty and cultural agreement is amplified during periods of declining performance.

DISCUSSION AND CONCLUSION

The goal of this article is to gain a purchase on how and why corporate culture changes over time as a function of the perceived fit between an organization and its external environmental. I do so by focusing on the experience of uncertainty as a fundamental challenge that organizations must overcome, and link uncertainty to a weakening of cultural strength in the form of reduced norm consensus among organizational members of the most important norms and values that guide work in the organization. I propose that behavioral inconsistency mediates the negative relationship between uncertainty and norm consensus – firms seek to reduce uncertainty, but in the process disrupt existing routines and the behavioral consistency required to maintain and foster shared perceptions of dominant norms. To overcome the limitations of traditional approaches to measuring organizational culture—for example, indirect self-reports such as the Organizational Culture Profile (O’Reilly et al., 1991)—I used unsupervised learning to discern cultural content in employee reviews of nearly 500 publicly traded firms on the Glassdoor website. I then develop a novel, time-varying measure of norm consensus based on these identified cultural topics. The empirical results support my propositions. In contrast with prior work that adopts a closed system perspective by focusing on
Changes in Organizational Culture Strength

Previous research largely relies on static snapshots of corporate culture. As such, the dynamics of how corporate culture develops, evolves, persists, or changes over time are not well understood. This study leverages systematic, longitudinal data on culture for a diverse set of large firms to examine the dynamics of how corporate culture changes over time in response to environmental forces. It tackles this broad question by focusing on the role that uncertainty plays in leading to decreases in norm consensus, a primary facet of cultural strength. The results suggest that an additional challenge facing firms as they confront uncertainty is maintaining the performance-enhancing benefits of norm consensus. The study also provides a foundation for future inquiries that require longitudinal data on corporate culture. For example, future work might ask how trajectories in the cultures of merging firms affect post-merge outcomes.

Organizational Culture and Firm Performance

Evidence of the effect of strong culture on firm performance has been called into question over concerns of reverse causality – it is plausible that a strong culture is more likely to develop in firms that are experiencing periods of strong, consistent performance (Van den Steen, 2010; Sørensen, 2002). This proposition, however, has not been explored theoretically by organizations theorists or tested empirically. I show that norm consensus, a primary component of cultural strength, varies in response to the level of uncertainty being experienced by a firm. As such, it calls into question whether strong culture causes improved performance, or whether the cross-sectional association is observed in part because strong, consistent performance facilitates the development of shared beliefs, norms, and values among employees via stable routines and behavioral consistency. Future
work using longitudinal data that estimates the effect of culture on performance should examine dynamic panel modeling strategies, which allow current realizations of cultural strength to be impacted by prior realizations of performance (Wintoki et al., 2012).

**Language as a Window into Culture**

This work also has important implications for the burgeoning literature that uses language as a window into culture (Goldberg et al., 2016; Kramsch, 1998; Pinker, 2007). Whereas prior work has drawn inferences about how individuals fit into the social groups and organizations to which they belong based on analyses of interactional language use with other group members (e.g., Srivastava et al., 2017), the present study derives measures of organizational culture based on the language that employees use in describing culture to each other and to the outside world.

In addition, given that culture is a multifaceted construct that people invoke in a variety of different ways, my analytical approach, which relies on unsupervised learning, provides a means to inferring cultural content from variegated textual descriptions of organizations. Additionally, the approach to measuring culture does not rely on cultural categories defined by informants or researchers (Denison, 1984; O’Reilly et al., 1991). Instead, it allows cultural categories to emerge from the full set of naturally occurring topics that employees use in describing organizational culture. To put it differently, the method provides a means to identifying cultural content even when people have varying conceptions and definitions of culture as a construct.

**Limitations and Directions for Future Research**

This study has a number of limitations that suggest directions for future research. One is that I do not consider the long-run temporal dynamics of cultural strength. While uncertainty is associated with subsequent decreases in an important facet of cultural strength, an open question is whether cultural cohesion continues to deteriorate for these firms or whether it eventually recovers. One possibility is that a temporary weakening of the culture is the first step towards necessary cultural
change as the firm adapts to new environmental demands. These data can be extended over a longer time period to develop a descriptive picture of how corporate culture evolves long-term. This question is particularly interesting given work on cultural evolution in broader societies that posits that “tight” cultures with higher norm consensus are associated with exposure to uncertain environmental threats (Gelfand et al., 2011).

Another limitation is identification. My firm fixed effects approach accounts for unobserved time-invariant heterogeneity across firms. This is an improvement over existing work, which relies on cross-sectional data. However, it does not control for unobserved heterogeneity that varies over time within firms. One prime candidate is CEO turnover. While CEO turnover represents one type of internal change that is associated with uncertainty more broadly, many other factors drive uncertainty, and I would not expect the effect of performance variability to be completely washed out when accounting for it. A promising future direction is to instrument for the effect of uncertainty on cultural agreement using market or industry shocks that are plausibly exogenous to the firm (Stein and Stone, 2013; Bloom et al., 2017).

I also leave it to further research to directly measure strategic changes in response to uncertainty. One possibility is to identify strategic change initiatives formally announced in company communications such as 10-K statements and earnings calls.

Finally, although I report robustness checks that help to dispel concerns that the findings can be accounted for by compositional shifts in the kinds of employees who choose to comment about firm culture after periods of uncertainty, I cannot fully rule out the potentially confounding role of selection effects. I leave to future research the task of more thoroughly accounting for selection dynamics in employee reviews. For example, researchers could draw on national survey panels to identify a representative set of employees at firms included in the Glassdoor data and ask them to rate their firms using the same questions used by Glassdoor.
Conclusion

This study paves the way for novel investigations of the temporal dynamics of corporate culture and the role that broader environmental forces play in influencing those dynamics. It highlights that cultural strength, or the degree to which employees hold similar views of the most important norms and values that characterize the firm, can fluctuate over time as the firm seeks to overcome uncertainty. Moreover, it highlights the value of language as a window into changing organizational culture.
## TABLES

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Table 2: Summary Statistics

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L. prefix denotes one quarter lag

Table 3: Correlations

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L. prefix denotes one quarter lag

* p < 0.05, ** p < 0.01, *** p < 0.001
Table 4: Cultural Agreement on Uncertainty

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<tbody>
<tr>
<td>Stock Price Variability (coef of var)</td>
<td>-0.080**</td>
<td>-0.084**</td>
<td>-0.084**</td>
</tr>
<tr>
<td></td>
<td>(2.63)</td>
<td>(2.82)</td>
<td>(2.81)</td>
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<td>-0.084+</td>
<td>-0.084+</td>
</tr>
<tr>
<td></td>
<td>(3.57)</td>
<td>(1.95)</td>
<td>(1.95)</td>
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<tr>
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<td>0.075</td>
<td>0.086</td>
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<tr>
<td></td>
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<td>(0.95)</td>
<td></td>
</tr>
<tr>
<td>L.# Business Segments</td>
<td>-0.051***</td>
<td>-0.050***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(3.88)</td>
<td>(3.75)</td>
<td></td>
</tr>
<tr>
<td>Cultural Topic Breadth</td>
<td>-0.15**</td>
<td>-0.15**</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(3.22)</td>
<td>(3.20)</td>
<td></td>
</tr>
<tr>
<td>L.Stock Price</td>
<td></td>
<td></td>
<td>-0.00022</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(0.76)</td>
</tr>
<tr>
<td>L.ROA</td>
<td></td>
<td></td>
<td>0.00067</td>
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<td></td>
<td></td>
<td></td>
<td>(0.15)</td>
</tr>
<tr>
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<td>1.12</td>
<td>1.01</td>
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<td>(8.96)</td>
<td>(1.33)</td>
<td>(1.11)</td>
</tr>
<tr>
<td>Year FEs</td>
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<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>Quarter FEs</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>Firm FEs</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>Firm/Quarters</td>
<td>2442</td>
<td>2442</td>
<td>2442</td>
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</tbody>
</table>

Absolute t statistics in parentheses
Standard errors clustered by firm
L. prefix denotes one quarter lag
+ $p < 0.10$, ∗ $p < 0.05$, ∗∗ $p < 0.01$, ∗∗∗ $p < 0.001$
Table 5: Cultural Agreement on Uncertainty

<table>
<thead>
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<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
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<td>Stock Price Variability</td>
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<td>-0.018*</td>
<td>-0.023*</td>
<td>-0.025**</td>
<td>-0.021*</td>
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<tr>
<td>(OLS residuals)</td>
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<td>(2.01)</td>
<td>(2.60)</td>
<td>(2.70)</td>
<td>(2.32)</td>
</tr>
<tr>
<td>Stock Price Trend</td>
<td>-0.0069*</td>
<td>-0.090**</td>
<td>-0.0060*</td>
<td>-0.0085*</td>
<td>-0.088**</td>
</tr>
<tr>
<td></td>
<td>(2.48)</td>
<td>(2.78)</td>
<td>(2.31)</td>
<td>(2.15)</td>
<td>(2.75)</td>
</tr>
<tr>
<td>ln(# reviews)</td>
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<td>-0.15***</td>
<td>-0.090*</td>
<td>-0.091*</td>
<td>-0.091*</td>
</tr>
<tr>
<td></td>
<td>(3.73)</td>
<td>(3.70)</td>
<td>(2.10)</td>
<td>(2.13)</td>
<td>(2.12)</td>
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<tr>
<td>L.In(assets)</td>
<td>0.070</td>
<td>0.042</td>
<td>0.040</td>
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<tr>
<td></td>
<td>(0.83)</td>
<td>(0.44)</td>
<td>(0.42)</td>
<td></td>
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</tr>
<tr>
<td>L.# Business Segments</td>
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<td>-0.050***</td>
<td>-0.050****</td>
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<tr>
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<td>(3.75)</td>
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<td>(3.75)</td>
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</tr>
<tr>
<td>Cultural Topic Breadth</td>
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<td>-0.16**</td>
<td>-0.15**</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(3.23)</td>
<td>(3.25)</td>
<td>(3.20)</td>
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</tr>
<tr>
<td>L.Stock Price</td>
<td>0.00050</td>
<td>0.00054</td>
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<td></td>
<td>(1.07)</td>
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</tr>
<tr>
<td>L.ROA</td>
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<td></td>
<td></td>
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</tr>
<tr>
<td></td>
<td>(0.39)</td>
<td>(0.61)</td>
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</tr>
<tr>
<td>Variability X Trend</td>
<td>0.0042**</td>
<td></td>
<td></td>
<td>0.0040*</td>
<td></td>
</tr>
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<td></td>
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<td>(2.57)</td>
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<tr>
<td>Constant</td>
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<td>1.66*</td>
<td>1.93*</td>
<td>1.88+</td>
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<td>(10.48)</td>
<td>(10.12)</td>
<td>(2.02)</td>
<td>(1.99)</td>
<td>(1.95)</td>
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<td>Year FEs</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>Quarter FEs</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>Firm FEs</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>Firm/Quarters</td>
<td>2442</td>
<td>2442</td>
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<td>2442</td>
<td>2442</td>
</tr>
</tbody>
</table>

Absolute t statistics in parentheses
Standard errors clustered by firm
L. prefix denotes one quarter lag
+ p < 0.10, * p < 0.05, ** p < 0.01, *** p < 0.001
FIGURES

Figure 1: Stylized Example of Distinguishing Performance Variability and Trend

Figure 2: Marginal Effects of Uncertainty on Cultural Agreement
Appendix A : Measuring Cultural Agreement Using Latent Dirichlet Allocation

All analyzed text was first preprocessed according to standard text analysis conventions. I removed common stop words and punctuation, discarded word order, and stemmed the words using the Porter stemming algorithm.

To train the Latent Dirichlet Allocation (LDA) model, I constructed a document-term matrix for which the rows represent distinct sentences observed across all available reviews for all organizations that contain the word “culture” or a close synonym (environment, atmosphere, attitude, climate, value, philosophy, belief). This results in 904,613 sentences. I identify the 4,000 most popular unigrams in these sentences. Less popular words outside of this set were increasingly proper noun references, badly misspelled, or nonsense words. After manually removing proper nouns, the document-term matrix tracked the frequency of 3,870 words.

This set of training sentences was analyzed using LDA. LDA is a model of the probabilistic generation of a text corpus. Documents are represented as random mixtures of topics, and each topic is characterized as a probability distribution over words (Blei et al., 2003). I parameterized LDA to identify 500 topics present in these culture sentences. Each topic is characterized by a weighted set of words that tend to co-occur within documents.

After identifying cultural topics using this training set of sentences with explicit cultural references, I fit the LDA model to the reviews in our analytic sample. In contrast to clustering methods, LDA is a mixed membership approach, which assigns each document to a probability distribution over multiple topics. Figure 3 illustrates LDA’s assignment of each review in the analytic sample to a mixture of multiple culture topics.
The measure of cultural agreement is constructed using these topic probability distributions over each review. Figure 4 illustrates that firm/quarters with high cultural agreement feature reviews with more similar topic probability distributions. Conversely, low cultural agreement firm/quarters have reviews with more dissimilar topic probability distributions.
Figure 4: Stylized Example of Cultural Agreement

<table>
<thead>
<tr>
<th>Review</th>
<th>High Cultural Agreement</th>
<th>Low Cultural Agreement</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td></td>
<td></td>
</tr>
<tr>
<td>2</td>
<td></td>
<td></td>
</tr>
<tr>
<td>3</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Appendix B : Validating the Cultural Heterogeneity Measures

Measure Variation

Organizational culture is stable but not invariant over time (Kotter and Heskett, 1992). As such, I examine the sources of variation in the cultural agreement measure. Table 6 decomposes the variance in the measure into three components: within a firm over time, across firms within an industry, and across industries. 60 percent of the variation in cultural agreement occurs between and within industry, consistent with evidence that corporate culture is more similar within than between industries, but still exhibits variance within industry (Chatman and Jehn, 1994). 40 percent of the variance is over time within firms. This accords with the notion that cultural strength, as reflected by cultural agreement, can vary over time in response to the firm-environment relationship and any internal conflict it may produce. Figure 5 plots the within firm variation in cultural agreement, respectively, moving from time $t - 1$ to $t$. This visual evidence shows that cultural agreement is relatively stable but not invariant over time.

Table 6: Variance Decomposition of Cultural Agreement Measure

<table>
<thead>
<tr>
<th>By Total Variation</th>
<th>Cultural Agreement</th>
</tr>
</thead>
<tbody>
<tr>
<td>Within Firms</td>
<td>40%</td>
</tr>
<tr>
<td>Within Industries</td>
<td>32%</td>
</tr>
<tr>
<td>Between Industries</td>
<td>28%</td>
</tr>
</tbody>
</table>
Figure 5: Within Firm Variation in Cultural Agreement
Additionally, I examine the within-firm temporal stability of the cultural agreement measure across the full distribution of the measures. Figure 6 plots the kernel density estimate of the distribution of the culture agreement measure moving within-firm from time $t - 1$ to $t$. The Kolmogorov-Smirnov test fails to reject the null hypothesis that the two distributions are different, providing statistical evidence that the culture measure exhibits relative stability over time.

Figure 6: Time Variation in Cultural Agreement
Construct Validity

Beyond the face validity of the cultural topics that I demonstrated in Table 1, my cultural agreement measure itself exhibits construct validity as capturing variation along this culture dimension. Table 7 shows the firms in the most represented industry in the data that score highest and lowest on cultural agreement. Firms are split into large and small firms because cultural agreement is moderately correlated with firm size. Facebook has high cultural agreement. This is consistent with the company’s well-known emphasis on maintaining a startup culture focused on innovation, autonomy, and open collaboration. Conversely, Xerox has low cultural agreement. This accords with lay accounts of Xerox’s culture in the study period, during which a newly appointed CEO vowed to redefine the culture.

<table>
<thead>
<tr>
<th>Highest Cultural Agreement</th>
<th>Large Firms</th>
<th>Small Firms</th>
</tr>
</thead>
<tbody>
<tr>
<td>Amdocs</td>
<td></td>
<td>National Instruments</td>
</tr>
<tr>
<td>Facebook</td>
<td></td>
<td>Sapient</td>
</tr>
<tr>
<td>Wipro</td>
<td></td>
<td>Cornerstone OnDemand</td>
</tr>
<tr>
<td>Lowest Cultural Agreement</td>
<td>Xerox</td>
<td>Kelly Services</td>
</tr>
<tr>
<td></td>
<td>SAP</td>
<td>Convergys</td>
</tr>
<tr>
<td></td>
<td>Paypal</td>
<td>TeleTech</td>
</tr>
</tbody>
</table>

Notes: Restricted to firms with at least 3 quarterly observations. Large and small firms delimited by industry median size.
Appendix C : Glassdoor Data Details

Employees reviewing their company are required to enter both positive (“pro”) and negative (“con”) comments. Since my objective was to identify the general cultural dimensions mentioned by employees without regard to valence, I combined the pro and con text when analyzing the reviews. Examining the most highly-weighted words for each LDA culture topics reveals that the model identifies cultural topics that are largely agnostic with respect to valence. In other words, both positive and negative review text contribute to most of the culture topics. A close reading of the review text for several firms revealed that pro and con text often characterize the culture the same way, even if an individual reviewer is mentioning a given topic because she believes it is either a positive or negative aspect of the culture. Most visitors come to Glassdoor first and foremost to search for jobs rather than to post an employer review. Glassdoor employs a “give to get” model to solicit employer reviews from users. In order to receive unlimited access to the site’s content, users have to submit an anonymous employer review. Internal Glassdoor research has found that this method mitigates ratings bias by reducing the prevalence of extremely positive and negative reviews.
Appendix D : Variation in Glassdoor Reviewer Composition

Since the employees who write Glassdoor reviews were not selected through random sampling from the population of firm employees, a concern is that systematic variation in the number or composition of reviewers is driving the observed associations between uncertainty and cultural agreement. I examined the robustness of the results to potentially non-random selection of employees into writing Glassdoor reviews by modeling within-firm variation in the number and composition of reviews as a function of the independent variables and controls. The sample includes firms with at least six quarterly observations so as to have enough within-firm observations to include firm fixed effects.

Table 8 shows within-firm models of the number and composition of reviews used when calculating the cultural agreement measure. These models test whether the number or composition of reviewers systematically changes during periods of uncertainty, which could bias the calculation of cultural agreement. I examined reviewer composition by measuring the percentage of reviews in a given firm/quarter written by employees in managerial positions as opposed to lower-level employees, as indicated by non-missing job title information. Model 1 shows that the number of Glassdoor reviews does not vary as a function of stock price variability, although the coefficient for stock price trend is negative and significant. However, model 2 shows that when interacted, neither stock price variability nor trend are associated with the number of reviews. Specifications 3 and 4 model the percentage of managers writing reviews as function of uncertainty while controlling for number of reviews and other covariates. Reviewer composition is insensitive to my measure of uncertainty. In addition, inclusion of the percentage manager variable as a control in the main models has virtually no impact on the findings.
<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
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</thead>
<tbody>
<tr>
<td></td>
<td>ln(# reviews)</td>
<td>ln(# reviews)</td>
<td>% Managers</td>
<td>% Managers</td>
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<td>(1.17)</td>
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<td>(0.19)</td>
<td>(1.83)</td>
<td>(0.60)</td>
</tr>
<tr>
<td>ln(# reviews)</td>
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<td></td>
<td>0.0020</td>
<td>0.0020</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(0.39)</td>
<td>(0.38)</td>
</tr>
<tr>
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<td>(2.26)</td>
<td>(2.26)</td>
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<td>(0.85)</td>
</tr>
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<td>0.029**</td>
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<td>(2.59)</td>
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</tr>
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<td></td>
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<td>(1.26)</td>
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<td>(0.13)</td>
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<td>0.000027</td>
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<td>(1.87)</td>
<td>(0.54)</td>
<td>(0.50)</td>
</tr>
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<td>Quarter FEs</td>
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<td>yes</td>
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<tr>
<td>Firm FEs</td>
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</tbody>
</table>

Absolute t statistics in parentheses
Standard errors clustered by firm
L. prefix denotes one quarter lag
+ p < 0.10, * p < 0.05, ** p < 0.01, *** p < 0.001
References


Popadak, J. A. 2013 “A corporate culture channel: How increased shareholder governance reduces firm value.”


