Inferring Employees' Social Media Perceptions of Goal-Setting Corporate Cultures and the Link to Firm Value

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ABSTRACT

We present a novel social media dataset and employ an automated computational linguistics technique to infer employees' perceptions of corporate culture. In particular, we provide an empirical test of 'goal-setting theory' which states that the extent to which employees perceive their roles to be challenging directly impacts their job satisfaction and firm performance. Our findings are consistent with the organizational view that firms realise greater value by aligning employee goals to strategic objectives rather than the pursuit of employee satisfaction alone. This value only appears to be recognized by financial analysts during earnings announcements, creating systematic "errors-in-expectations" of firms' cash flows. Our study highlights the merits of textual analysis for automated corporate culture analysis and builds on the growing body of evidence which suggests that intangible information is not fully exploited by investors.

JEL Classification: G10, G14, J3, L21

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1 Introduction

"Culture is not just one aspect of the game, it is the game"
- *Lou Gerstner, former CEO of IBM*

In a global knowledge-based economy, firms often perceive their human resources to be critical source of competitive advantage (Barney 1991; Barney and Wright 1998; Zingales 2000; Ravasi et al. 2012). Within the Resource Based View (RBV) of a firm, human capital theories suggest that employees add value by inventing new products and building client relationships which in turn manifest into organizational technology and culture (Barney 1991; Russo and Foots 1997; McGregor 1960; Edmans 2011). These theories assume that employees are fully 'aligned' with a firm's strategic vision and understand how to implement a firm's goals to achieve its chosen direction (Pearce and Robinson 2007, Gagnon and Michael 2003). By contrast, if employees maximise their own utility, for example by prioritising personal career advancement or an individualistic need for recognition (Hofstede 1980), the misalignment of employee interests may even be detrimental to the firm (Witt 1998; Boswell 2006). This principal-agent problem may have even exacerbated (Jensen and Meckling 1976; Ichniowski and Shaw 1999) in recent years as the working practices of many Western countries have encouraged employees to pursue greater discretion and autonomy in their actions (Appelbaum and Batt 1994; Zingales 2000; Triandis et al. 1988). To ensure that employees are strategically aligned with the firm, organizational literature recommends that managers adopt an implementation strategy consisting of 'communication, interpretation, adoption, and enactment of strategic plans' (Noble 1999; van Riel et al. 2009; Gagnon and Michael 2003). The misalignment of employee interests has important implications both for corporate managers and investors and is the primary aspect investigated in this paper.

In this study we infer employees' perceptions of corporate culture by employing textual analysis using a novel social media dataset. The term 'social media' describes a variety of "new and emerging sources of online information that are created, initiated, circulated and used by consumers intent on educating each other about products, brands, services, personalities and issues" (Blackshaw and Nazzaro 2006). Social media allow individuals to share their opinions, criticisms and suggestions in public. To the best of our knowledge, prior reputation and sentiment analysis studies have mostly captured the perspectives of the media and consumers. This study seeks to infer the perceptions of a potentially overlooked stakeholder group, namely, the firm's employees (Moniz and de Jong 2014). We retrieve 417,645 posts for 2,237 U.S. companies from the career community website *Glassdoor.com*. Reviewers' discussions are a potentially rich source of information for corporate culture analysis and provide an insight into employees' perceptions and future behavior (James and Jones 1974; van Riel et al. 2009). By drawing upon Information Retrieval (IR) and Natural Language Processing (NLP) literature, we provide a methodology to infer the latent dimensions of corporate culture and quantify the impact on firm earnings. In particular, we provide an empirical test of 'goal-setting theory', a widely regarded motivational theory, which seeks to link employee motivation, employee satisfaction and firm performance (Yukl and Latham 1978; Shane et al. 2003; Anderson et al. 2010). Goal-setting theory suggests that the extent to which people are motivated by challenging tasks directly impacts their job satisfaction, self-esteem and sense of contributing towards the organization (Beach 1980; Locke 1966; Locke and Latham 1990). Prior organizational psychology literature concludes that individuals exert more effort and work more persistently to attain difficult goals than they do when they attempt to attain less difficult goals or simply "do their best". To test the validity of these claims we employ textual analysis using a well-known probabilistic topic modeling technique known as Latent Dirichlet Allocation (LDA) (Blei et al. 2003). LDA is a dimension reduction technique which seeks to model the latent dimensions in text. In particular, we infer one dimension which appears to capture employees' perceptions of organizational goal-setting behavior. We examine the relation between this 'topic cluster' and future firm earnings and test the hypothesis that goal-setting behavior is a more important determinant of firm earnings than suggested by prior studies based on employee satisfaction alone (Levering and Moskowitz 1993; Levering and Moskowitz 1994; Edmans 2011). Our key finding is that the value-relevance of goal-setting behavior only appears to be recognized by investors once it manifests into tangible outcomes post earnings announcements. We provide evidence to suggest that financial analysts systematically underestimate the intangible benefits of corporate culture.

We provide three important contributions to the literature. First, we contribute a methodology to analyse the dimensions of corporate culture. Culture is often defined as "a set of values, beliefs, and norms of behavior shared by members of a firm that influences individual employee preferences and behaviors" (Besanko et al. 2000). The intangible nature of corporate culture has generated much controversy regarding the creation of a valid construct (Cooper et al. 2001; Pinder 1998; Ambrose and Kulik 1999). Prior organizational literature either relies upon measures that lack sufficient depth or contain substantial measurement errors (Waddock and Graves 1997; Daines et al. 2010). To address these criticisms, we employ an automated approach to corporate culture analysis (see also Popadak 2013). In recent years, the development of NLP techniques has enabled researchers to automatically organize, summarize, and condense unstructured text data and, from this text, extract key themes from vast amounts of data. From an organizational stance, social media enables managers to quickly identify stakeholders' perceptions to measure reputational sentiment (Li et al. 2014). Language is the principal means whereby we achieve social interaction. The words people use in communication reflect their expressions, ideas, beliefs and points of view (Elahi and Monachesi 2012). Our findings suggest that employees' discussions provide greater insight into corporate culture than possible using structured data (financial) alone.

Second, we contribute to prior literature on investors' underreaction to information. A growing body of research finds that the stock market fails to fully incorporate intangible information (e.g. Edmans 2011; Lev and Sougiannis1996; Chan et al. 2001; Derwall 2005). Under a mispricing channel, an intangible asset only affects the stock price when it subsequently manifests in tangible outcomes which are valued by the market. This finding is attributed to the "lack-of-information" hypothesis (Edmans 2011). Recent empirical literature provides evidence to suggest that intangibles are not incorporated by the stock market because investors lack information on their value. In particular, this study contributes to literature on the "errors-in-expectations" in investors' evaluations of corporate culture and human capital management (Edmans 2011; Rajan and Zingales 1998; Carlin and Gervais 2009; Berk et al. 2010). Our approach is closely related to the employee satisfaction study of Edmans (2011). Our findings, however, suggest that firms should focus their efforts to ensure that employees are strategically aligned rather than seek to maximise employee satisfaction.

The remainder of the paper is organized as follows. Section 2 outlines related literature, drawing upon goal-setting theory to develop a potential link to financial performance. Section 3 describes the Glassdoor corpus of employee reviews. Section 4 provides an overview of probabilistic topic modelling and computational techniques to infer the latent dimensions of corporate culture. Section 5 provides empirical results testing the relation between goal-setting behavior and firm earnings. Finally, Section 6 concludes.

2 Literature Review

This paper is related to organizational literature on employee alignment and goal-setting, and financial asset pricing literature on investors' underreaction to intangible information.

2.1 Goal-setting theory

Various mechanisms exist to align employees' interests, ranging from regular communications in the form of open book management and town meetings to performance management systems (Boswell 2006). In particular, a number of studies have shown that employees are motivated by specific and challenging objectives and goals (Spector 2003; Bellenger et al. 1984; Coster 1992). Goals motivate high performance by focusing employees' attention, increasing effort and persistence, and encourage innovative solutions to address difficult tasks (Locke and Latham 1990). Goal-setting theory suggests that specific rather than abstract goals increase performance and that difficult goals, when accepted by employees, result in higher firm productivity (Latham and Locke 1984). From an employee's perspective, challenging goals often lead to valuable rewards such as recognition, promotions, and/or increases in income from one's work (Latham and Locke 2006). Attaining goals creates a heightened sense of efficacy (personal effectiveness), self-satisfaction, positive affect, and sense of well-being (Wiese and Freund 2005), which in turn increases employee commitment (Tziner and Latham 1989), and reduces staff turnover (Wagner 2007).

2.2 Value relevance of intangible information

The principal-agent problem (Jensen and Meckling 1976) challenges investors' abilities to assess firm value. To address this information asymmetry, firms often publish financial corporate disclosures (Myers and Majluf 1984) to mitigate investors' risks of adverse selection and attempt to create higher market valuations (Healy and Palepu 2001). Despite these disclosures, deciphering the "value relevance" of intangible information remains a challenge (Derwall et al. 2005; Borgers et al. 2013). Typically, a firm's human capital management policies may be published in its Corporate Sustainability Responsibility (CSR) report (Kolk 2008) or evaluated in external surveys such as Fortune's "100 Best Companies to Work for in America" list (Edmans 2011). These sources, however, suffer from a number of drawbacks. First, CSR disclosures are voluntary in nature and firms' motivations for publishing such disclosures are often unclear. Recent evidence suggests that firms publish CSR reports merely for symbolic purposes to bolster their social images with consumers (Marquis and Toffel 2012; McDonnell and King 2013; Eberle et al. 2013) rather than to increase transparency and accountability to investors (Moniz and de Jong 2015). In the case of Fortune's Best Places to Work For List, firms pay to participate in the survey which creates perverse incentives for firms to manipulate survey responses (Popadak 2013). Second, CSR may be endogenous with respect to financial performance - companies may only publish CSR reports if they are more profitable or expect their future profitability to be higher. This relation may hinder investors' abilities to disaggregate the value-relevance of extra-financial information (Flammer 2013b). Third, CSR disclosures may be subject to a selection bias if firms' discussions of CSR topics are influenced by institutional pressures (Marquis and Toffel 2012). For instance, non-governmental organizations (NGOs) often scrutinize Wal-Marts' labor relations policies (Bhatnagar 2004; Lobel 2007; Tilly 2007; Rao et al. 2011), and Nike attracts attention on supplier working conditions (Locke et al. 2007; Greenberg and Knight 2004). NGOs' lobbying pressures may bias the topics discussed in disclosures and hinder investors' abilities to make comparisons across firms (Marquis and Toffel 2012). Fourth, firms typically publish CSR disclosures with substantial delay versus accounting related information, hindering the investment relevance of the disclosures (Kolk 2008). One explanation is that CSR reports are often seen as a 'relatively low priority for companies'

(Gray et al. 1995). While survey-based measures of corporate culture seek to address some of these drawbacks (for example, by comparing companies against a standardized set of questions), they too suffer from drawbacks. Surveys are typically manually constructed and thus limited in scope by the number of questions they can ask, the number of companies they can cover and suffer in their timeliness to collect and process responses. For instance, Fortune's survey collects information on an annual basis, is limited to 100 firms of which only around half are publically-listed (Popadak 2013), and only composite scores are published potentially obscuring information within the construct (Daines et al. 2010). Consequently, investors have limited ability to "see inside a company" and are often reliant upon inferring value relevant intangible information once the benefits manifest into tangible outcomes post earnings announcements (Edmans 2011; Derwall 2005).

Textual analysis of social media datasets seeks to overcome many of these drawbacks and offers a significant advancement for corporate culture analysis across a vast number of firms (Popadak 2013). Nonetheless, textual analysis is not without its own set of challenges. The high costs associated with gathering and processing unstructured data suggests that intangible information may even be overlooked by investors compared to more structured datasets. While accounting information is typically organized in a standardized fashion so that financial analysts can process numbers quickly and efficiently (Da et al. 2011), text may not be easy to process and often requires a sophisticated understanding of language and tone (Engelberg 2008; Tetlock 2008; Loughran and McDonald 2011). Thus, even if intangible information is available, investors may ignore it if it is not salient (Edmans 2011).

2.3 Probabilistic topic modeling

A topic model is a statistical model for learning abstract "topics" in documents. Topic models have played an important role in a variety of data mining tasks, within computer science (Blei et al. 2003; Griffiths and Steyvers 2004; Ramage et al. 2010; Liu et al. 2009), social and political science (Ramage et al. 2009; Grimmer 2010), and humanities (Mimno 2012) for the categorization and summarization of texts. The intuition behind LDA is that documents are represented as random mixtures over latent topics, where each topic is characterized by a distribution over words. LDA is most easily described by its generative process which models the way documents arise. For each document, we generate the words in a two-stage process:

1. Randomly choose a distribution over topics.
2. For each word in the document:

    a. Randomly choose a topic from the distribution over topics in step #1.

    b. Randomly choose a word from the corresponding distribution over the vocabulary.

Each document exhibits topics in different proportions (step #1); each word in each document is drawn from one of the topics (step #2b), where the selected topic is chosen from the per-document distribution over topics (step #2a). Figure 1 provides an extract of an employee review to illustrate the methodology. Terms semantically associated with different topics have been manually color coded in the text. For instance, a discussion about an employee's working environment may include references to 'colleagues', 'co-workers', and 'teams' (highlighted in green). By contrast, a discussion about employee performance may include the terms: 'recognition' and 'promotion' (highlighted in yellow). The goal of topic modeling is to automatically discover these topics from a collection of documents. While the documents are observed, the topic structure (the topics, per-document topic distributions, and the per-document per-word topic assignments) are hidden structure (Blei et al. 2003).

More formally, LDA is a two-level Bayesian generative model, which assumes that topic distributions over words and document distributions over topics are generated from prior Dirichlet distributions. This assumption facilitates Bayesian inference due to the fact that the Dirichlet distribution is a conjugate to the multinomial distribution. By reversing the generative process of LDA, one obtains a predictive model by means of the posterior distribution. The model is appealing for noisy data because it requires no annotation and discovers themes in a corpus solely from the learning data without any supervision. To the best of our knowledge, extant organizational studies analyse the dimensions of corporate culture based on heuristic approaches (O'Reilly et al. 1991; O'Reilly et al. 2012). By contrast, we let the data 'speak for itself' and seek to infer employee perceptions of corporate culture. The total probability of the LDA topic model is given by:

$$P(\boldsymbol{W},\boldsymbol{Z},\boldsymbol{\theta},\emptyset;\alpha,\beta) = \prod_{k=1}^{K} P(\emptyset_k\,;\beta) \prod_{j=1}^{M} P(\theta_j\,;\alpha) \prod_{t=1}^{N_j} P(Z_{j,t}|\theta_j)P(W_{j,t}|\,\emptyset_{Zj,t}) \tag{1}$$

where K is the number of topics, M number of documents, N_j the number of words in document j. The distribution of words in topic k is given by $P(\emptyset_k;\beta)$; a multinominal with Dirichlet prior with uniform parameter β. The topic distribution for document j is given by $P(\theta_j;\alpha)$; a multinomial distribution with Dirichlet prior with uniform parameter α. The standard approach is to set α = 50/K and β = 0.1 (Griffiths and Steyvers 2004). The assignment of a topic for t^{th} word in document j is represented by $P(Z_{j,t}|\ \theta_j)$. Finally, $P(W_{j,t}|\emptyset_{Zj\,,t})$ represents the probability of word t in document j given topic $Z_{j,t}$ for the t^{th} word in the document. The task of parameter estimation is to learn both what the topics are, and which documents employ them in what proportions. The key inferential problem that we need to solve in order to use LDA is the posterior distribution of the hidden variables given a document:

$$P(\theta, \emptyset, z | w, \alpha, \beta) = \frac{P(\theta, \emptyset, z, w | \alpha, \beta)}{P(w | \alpha, \beta)} \quad \textbf{(2)}$$

To solve the maximum likelihood estimation, Gibbs sampling is applied to construct a Markov chain that converges to the posterior distributions on topic *Z*. The results are then used to infer *Φ* and *θ* variables indirectly (see Blei et al. 2003 for further details).

3 Data and sample construction

In this section we outline the process to retrieve online employee reviews, discuss the challenges associated with automated cultural analysis and describe the social media corpus.

3.1 Description of online career community websites

While there are a number of different career community websites (see Jeaneau et al. 2013; Popadak 2013), we choose to retrieve employee reviewed posted only to Glassdoor.com for a number of reasons. First, the website appears to attract the most diverse set of reviewers, potentially providing a more representative view of a company's culture than other websites which focus on specific types of employees. For instance, one alternative website provider identifies that its average user is 43 years old with an annual income of $106,000; a second provider states that its niche market is college students and young professionals (see Popadak 2013). By contrast, Glassdoor has an estimated 19 million unique users each month and appears to benefit from the most diverse audience. To assess whether the dataset is representative if variations in corporate culture perceptions, we retrieve web traffic statistics from Quantcast.com, a website which specializes in audience measurement. Quantcast relies upon pixel trackers installed on the pages of websites to measure audience data. These trackers are used to compile visitor profiles and build a detailed picture of web audiences[1]. Table 1 reports descriptive statistics on the average profile of users of the Glassdoor website. Users' profiles appear to be fairly distributed across different sections of society in terms of age, income, education and ethnicity, suggesting that online reviews should be representative of an average employee's perceptions of a firm.

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[2] See http://www.theguardian.com/technology/2012/apr/23/quantcast-tracking-trackers-cookies-web-monitoring)

A second advantage of Glassdoor's corpus is its claim to data integrity[2]. The website states that it seeks to provide honest, authentic and balanced employee reviews. Each review must meet strict community guidelines before it is published. Reviewers are required to provide commentary on both the 'pros' and 'cons' of a company to ensure a balanced profile (see for example Figure 2). These comments are reviewed by website editors before they are publically posted to prevent reviewers from posting defamatory attacks and from drifting off-topic, which may otherwise hinder sentiment analysis (Moniz and de Jong 2014). The editors authenticate reviewers' identities to prevent individuals from posting repeat comments or fake reviews. Identities are anonymized to assure reviewers from fear of company reprisals (Popadak 2013). Approximately 15% of reviews are rejected by the website editors because they do not meet their guidelines. We evaluate the integrity of the dataset and implications for textual analysis in Section 3.3.

A third advantage of the Glassdoor corpus is its rich set of structured data ('star ratings') and associated metadata. Reviewers provide an Overall Score for a firm on a scale of 1-5 and rate companies across five dimensions: Culture & Values, Work/Life Balance, Senior Management, Comp & Benefits and Career Opportunities. Since many of these star ratings only begin in 2012, we rely predominately upon the text supplied in reviewers' comments which available from 2008 onwards, and use the star ratings to validate the quality of user comments (discussed in Section 3.3). The corpus further includes the date stamp of each review, employees' number of years' work experience, job titles, employment status (part-time/full-time), and work location. We use the metadata to validate the integrity of the corpus by statistically testing for differences in sentiment between groups of cohorts within the dataset.

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[2] See http://www.cbsnews.com/news/can-your-boss-force-you-to-write-a-glassdoor-review/)

3.2 Matching firms to articles

One of the primary challenges for unstructured data analysis is an absence of company identifier mappings to link retrieved company information to more traditional financial datasets (such as the CSRP database). To address this, we design a retrieval algorithm to match between company names in Glassdoor reviews and the CRSP database. Our approach addresses the 'synonym detection problem' typically incurred when string matching company names in text (see Engelberg 2008). For instance, the company name International Business Machines in the CRSP database is more commonly referred to as IBM, while AMR Corp is often referred to by its popular subsidiary American Airlines. Our algorithm detects companies' popular names from companies' websites, Wikipedia and the Open Directory Project (ODP) before matching the Glassdoor page. The algorithm then trawls through Glassdoor's subdomains to retrieve all employee reviews for each company. As a robustness check, the linkages in the CRSP-Glassdoor company identifier mapping table were manually inspected to ensure the accuracy of the matches. The retrieval algorithm generates a total of 417,645 reviews for 2,237 U.S. companies over the period January 2008 to April 2015. Table 2 displays descriptive statistics of the sample dataset. Panel A shows that the number of reviews has steadily increased over time. Employees outside of North American account for only a small proportion of the reviews in U.S. companies, alleviating a potential concern that our results may be affected by differences in perceptions between domiciled versus offshore employees (Hofstede 1980). Panel B reports that 60% of the sample consists of posts from individuals stating that they are current employees of the firm while the remaining 40% are former employees. Of those identified by the metadata, only a minority (6.9%) of reviewers state that they are part-time employees. Panel C shows that reviewers have worked in their companies for an average of 1-3 years. Finally Panel D reports the coverage of reviews across different sectors, obtained by matching companies in Glassdoor.com to GICS classifications available in the Compustat database. While all sectors are covered, just over half of reviews are from the Information Technology and Consumer Discretionary sectors. We do not view this as a concern and instead believe it validates the merits of the dataset for corporate culture analysis. As competitive advantage has moved away from investment in physical assets to investment in knowledge-based assets such as R&D, brand value, human and organizational capital (Lev 2001), corporate culture perceptions of service-based sectors are arguably better captured by our dataset. Taken together, the descriptive statistics highlight the benefits of social media datasets for cultural analysis across a large cross-section of companies.

3.3 Validating the corpus

One of the main criticisms levied against textual analysis is the potential for selection bias that results from inferring user perceptions. The bias refers to the misrepresentative selection of reviews which may hinder statistical inference and cultural analysis conclusions. The underlying premise is that textual analysis can be influenced by differences in reviewers' native languages, cultures and human emotional experiences, which may result in unintended consequences when automatically inferring sentiment (see Hogenboom et al. 2013; Pang and Lee 2004; Wierzbicka 1995). For instance, former employees have greater incentive to post negative comments about their previous employers (see Jeaneau et al. 2013). Alternatively, junior and part-time employees may feel more detached from their companies compared to their full-time counterparts, impacting their evaluations of the firm (Boswell and Boudreau 2001).

To address this concern we compute a "language-independent" sentiment measure adopted from the field of NLP. A language-independent measure combines information expressed in reviewers' star ratings to supplement text-based measures. This approach assumes that star ratings are universal classifications of the sentiment that people intend to convey and are independent of potential language, cultural or emotional differences. Regardless of a reviewer's background, one should expect to observe a monotonically increasing relationship between a user's star rating and their expression of sentiment (Hogenboom et al. 2013). This relation can be used to map sentiment to a language-independent measure. Specifically, we estimate a panel regression where the dependent variable is the reviewer's Overall star rating for a firm and the independent variables are features extracted from the reviewer's text. The remaining star rating dimensions are included in the regression as control variables. COMP is the 'Comp & Benefits' star rating, WORKLIFE is the 'Work/Life Balance' rating, MGT is reviewers' 'Senior Management' rating, CULTURE refers to the 'Culture & Values' star rating and CAREER is the 'Career Opportunities' rating. We create an indicator variable, *Part-time*, which equals one if a reviewer is a part-time worker and an indicator variable, *Former*, which equals one if a reviewer is a former. These features are computed by detecting keywords provided in reviewers' metadata. We include company fundamentals to control for a potential 'halo' effect (Fryxell and Wang 1994). This is because reviewers may implicitly infer their perceptions of corporate culture from publically available information. Fundamental variables are constructed from standard data sources. The price related variables are obtained from CRSP; accounting information is obtained from COMPUSTAT and analyst information is obtained from I/B/E/S. The regressions control for analyst revisions (Analyst Revisions), price momentum (Pmom) and one-year historic sales growth (SG). Analyst revisions is the 3-month sum of changes in the median analyst's forecast, changed by the firm's stock price in the prior month (Chan et al. 1996). Pmom is the (signed) stock's return measured over the previous 12 months. We include past sales growth in the regression to control for the growth characteristics of companies in the sample and because sales growth has been shown to be positively related to company valuation (Hirsch 1991). Finally we control for differences in firm size. This is because prior organizational studies suggest that employees working in small companies often have more responsibility and are more closely aligned to management's goals than their counterparts in large companies (Hofstede 1980). We include firm size (Log(Market Equity)) and book-to-market (Log(Book/Market)), both measured at the end of the preceding calendar year (following Fama and French 1992).

Table 3 displays the regression results. The results suggest that, on average, star ratings are significantly lower for former employees while part-time employees are significantly more optimistic. For the subsequent regression analysis we choose to exclude former and part-time employees' reviews from the corpus. While this approach reduces the number of observations in our dataset, it alleviates the need to consider potential interaction effects between different cohorts and allows for more meaningful recommendations by focusing on the implications of corporate culture analysis for current, full-time employees.

4 Inferring corporate culture

In this section we infer the latent dimensions of corporate culture discussed in reviewers' texts. We identify one 'topic cluster' which appears to capture goal-setting behavior and examine the fundamental characteristics of goal-setting firms.

4.1 Topic model of corporate culture

In two pre-processing steps, we first tokenize documents, converting each term into lower-case, removing punctuation characters, numbers, and stop words[3]. This is a standard practice to limit the size of the vocabulary (Wallach et al. 2009). Next we parse text into unigrams, bigrams and trigrams, defined respectively as sequences of one, two and three adjacent elements in each string of tokens (each sentence). This step is intended to detect phrases in text such as 'career path', 'senior management', 'team building' and 'work/life balance'

[3] Stop word lists are obtained from: http://www3.nd.edu/~mcdonald/Word_Lists.html

which are otherwise not detected by the standard unigrams implementation of LDA. We remove the space separators between the most frequently detected phrases in the corpus so that they are interpreted by LDA as single terms and can be used in the standard implementation. The goal is to aid readers' interpretability by creating more coherent topic clusters using domain specific language (Titov and McDonald 2008).

One of the challenges of LDA is the interpretation of the inferred topic clusters. While a document classification score of 100% indicates that the text reflects only one topic, a classification score greater than 0% and less than 100% indicates a mixture of topics. To avoid the potential for ambiguity when interpretating topics we decide to follow a heuristic approach and to manually label[4] the cluster names by drawing upon prior cultural analysis studies (see Berthon et al. 2005; Hofstede 1980). The five highest probability document terms inferred for each topic cluster are ranked in decreasing order of approximately how often they occur in text before allocating topic labels. Figure 3 displays a randomly selected sample of employees' reviews for each topic[5] to aid readers' interpretation. We label one topic cluster 'social value', which appears to capture employees' perceptions of friendly, team-orientated, work environments. Another topic cluster, labelled 'development value' appears to capture perceptions of career-enhancing opportunities. Economic value is the perception that organizations provide above-average remuneration, job security and career prospects. Application value captures the perception that an employee can apply his/her acquired skills and knowledge in the workplace. A fifth topic cluster, labelled 'organizational structure'

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[4] As a robustness check we employ an automated approach to label the LDA topic clusters following an approach taken from information retrieval. We enter the top five document terms associated with each topic cluster into a Google search query and retrieve related urls (following the approach of Lau et al 2011). The most commonly occurring terms retrieved by the online query and used to automatically generate a topic label. In the case of the "goal-setting" topic cluster the automated approach generates the label "performance measurement".

[5] To aid readers' interpretation, the displayed texts have a 100% classification score to their associated topic and 0% classification scores to all other topics.

appears to capture employees' perceptions of the openness of the corporation and the extent they feel they can talk to higher management (consistent with Hofstede's (1980) definition of power distance). A final topic cluster appears to capture perceptions of goal-setting behavior and includes employees' discussions of 'planning', 'goals' and 'performance'. Table 4 presents the resulting six topic clusters inferred by the LDA model[6]. Each cluster is represented as a distribution of words which form semantically similar concepts.

4.2 Data and summary statistics

In this section we provide an insight into the characteristics of goal-setting firms by matching company reviews to fundamental data retrieved from the Compustat database. To align the reporting frequency of the quarterly/annual accounting variables to reviewers' comments, we create a composite document per firm per quarter by aggregating reviewers' comments between firms' successive earnings announcement dates. We winsorize firm characteristics at the 1% level to eliminate the impact of outliers. Panel A of Table 5 reports the median fundamental characteristics of firms when sorted into quartiles by their 'goal-setting' topic probability score. The last column illustrates the statistical significance of a difference of means t-test between top and bottom quartile firms for each fundamental characteristic. Companies with reviews in the highest goal-setting topic probability quartile exhibit significantly higher growth than firms in the lowest goal-setting quartile. This finding is consistent across asset, employee, and sales growth. Panel B of Table 5 reports the Spearman rank correlations between the average Glassdoor star ratings and the goal-setting topic probability, labelled GOAL. The correlations identify relatively high positive correlations between the individual star ratings and the overall composite star rating, yet a substantially

[6] The output of the LDA algorithm is a matrix of dimensions K topics x N documents, where the number of topics is inferred by maximizing the likelihood of fitting the LDA model over the corpus (following Steyvers and Griffith 2007).

lower correlation with the goal-setting topic probabilities. One interpretation is that goal-setting captures a different dimension of corporate culture to the information captured by the star ratings.

4.3 Validating the GOAL measure

Next we regress firms' GOAL topic probability scores on Glassdoor 'star ratings' to examine whether the information inferred from reviewers' texts is incremental to the information provided in star ratings and to a more traditional measure of reviewer sentiment. We compute TONE by counting the number of positive (P) versus negative (N) terms in each review matched within the General Inquirer dictionary (see Tetlock 2008; Stone 1966). We include firms' value, growth, size and momentum characteristics to provide an insight into the types of firms captured by the goal-setting measure. We control for firms' corporate social responsibility attributes to assess the claim that goal-orientated firms undertake unethical behavior due to the high financial incentives associated with meeting performance targets (Jensen 2003; Schweitzer et al. 2004). Following prior studies (see Waddock and Graves 1997; Hillman and Keim 2001; Statman and Glushkov 2009), we proxy this behavior by including an "employee relations" metric obtained from the KLD database. In line with standard practice, we calculate net employee strengths by summing all identified strengths and subtracting all identified weaknesses in a given year (see Verwijmeren, 2010). Finally, we include Edman's (2011) employee satisfaction measure to evaluate whether the characteristics of goal-setting firms differ from the information published in Fortune magazine's "100 Best Companies to Work for in America" list. We create an indicator variable, BC, equal to one if a company was listed in the Fortune list at each point in time, and zero otherwise. Following Petersen (2009), standard errors are clustered by firm to correct for time series dependence in standard errors. Table 6 reports the regression results.

Column 2 identifies a positive correlation between firms with high goal-setting behavior and Glassdoor star ratings for management quality and opportunities, and a negative relation between goal-setting and compensation. These findings are consistent with the view that goal-setting firms seek to incentivize individuals by providing a larger proportion of their total compensation in variable pay (Gneezy et al. 2011; Kamenica 2012), making the fixed component relatively unattractive versus competitors (Gerhart et al. 1995; Adams 1963). Column 2 also identifies a positive correlation to one-year historic sales growth and price momentum confirming that goal-setting firms are typically growth companies. Finally, Column 3 controls for CSR metrics and suggests that goal-setting behavior is not subsumed by employee relations or employee satisfaction, consistent with the view that goal-setting is a distinct dimension of corporate culture.

5 Empirical Results

This section presents the main empirical findings testing the "error-in-expectations" hypothesis. First, we establish that a relation exists between goal-setting behavior and firm value. We then investigate the relation between goal-setting behavior and future cash flows.

We compute Tobin's Q as a measure of firm value, defined as the market value of the firm divided by the replacement value of the firm's assets. The market value of assets is measured as the sum of the book value of assets and the market value of common stock outstanding minus the sum of the book value of common stock and balance sheet deferred taxes. Replacement value is represented by the book value of assets (Kaplan and Zingales 1997). We control for sector, region and year effects and run pooled OLS regressions to estimate models of Tobin's Q. We test for the significance of the coefficients using standard errors that are robust to heteroskedasticity clustered by firm (Petersen 2009). The pooled regression results are reported in Table 8.

Column 1 identifies a positive and highly statistically significant coefficient for GOAL, suggesting that goal-setting firms tend to be more profitable. The regression results suggest that the relation between GOAL and firm valuation is not explained by the qualitative information otherwise contained by TONE. Column 4 controls for the employee satisfaction . Despite the finding that employee satisfaction is valued by the stock market, the magnitude of the coefficient of GOAL is greater than that of BC, indicating that goal-setting behavior is incremental and a relatively more important determinant of firm value than employee satisfaction as suggested by Edman (2011). Our finding is consistent with the view that the combination of goal-setting and employee satisfaction achieve 'strategically aligned behavior' (van Riel et al. 2009; Gagnon and Michael 2003) and are required to enhance shareholder value.

Next we provide a direct test of the "errors-in-expectations" hypothesis. If analysts overlook intangible information, potentially due to its lack of salience or processing complexity, we would expect that positive benefits are only recognized by investors once they manifest into tangible outcomes post earnings announcements (see Edmans 2011). Our main test computes each firm's standardized unexpected earnings (SUE) using a seasonal random walk with trend model for each firm's earnings (Bernard and Thomas 1989):

$$UE_t = E_t - E_{t-4}$$

$$SUE_t = \frac{UE_t - \mu_{UEt}}{\sigma_{UEt}} \tag{3}$$

where E_t is the firm's earnings in quarter t, and the trend and volatility of unexpected earnings (UE) are equal to the mean (μ) and standard deviation (σ) of the firm's previous 20 quarters of unexpected earnings data, respectively. Following Tetlock (2008), we require that each firm has non-missing earnings data for the most recent 10 quarters and assume a zero trend for all firms with fewer than 4 years of earnings data. We use the median analyst forecast from the most recent statistical period in the I/B/E/S summary file prior to the earnings announcement. We winsorize SUE and all analyst forecast variables at the 1% level to reduce the impact of estimation error and extreme outliers, respectively. We create a composite document for each firm to align different frequencies of data by aggregating Glassdoor reviews between consecutive earnings announcement dates. We require a minimum of 30 reviews per company between quarterly earnings announcements to avoid drawing statistical inferences using a limited and potentially unrepresentative set of employee comments (see Moniz and de Jong 2014). For control variables we include firms' lagged earnings, size, book-to-market ratio, analysts' earnings forecast revisions, and analysts' forecast dispersion. We measure firms' lagged earnings using last quarter's SUE. We compute analysts' forecast dispersion (Forecast Dispersion) as the standard deviation of analysts' earnings forecasts in the most recent time period prior to the announcement scaled by earnings volatility (σ).

Finally, we compute a metric, *Difficulty*, to test the hypothesis that difficult and challenging goals inspire greater employee effort, commitment, and firm productivity (Latham and Locke, 1984; Sitken et al. 2011). We proxy perceptions of difficult goals by employing LDA to infer reviewers' attributions towards goal-setting behavior. We employ the same LDA algorithm as before, this time restricting the model's classifications to the 'cons' section of reviewers' comments rather than the full corpus. The output is a vector of topic probabilities which implictly captures the interaction between goal-setting behavior and the reviewers' expression of negative sentiment. Figure 3 provides examples of such text which includes references to the terms: 'difficult', 'hard', 'pressure', and 'stress'. Table 8 reports the regression results. Standard errors are clustered by calendar quarter (following Petersen 2009).

Column 2 identifies a positive and highly statistically significant coefficient for GOAL, suggesting that the measure contains incremental information for predicting earnings surprises beyond those of company fundamentals or the reviewer sentiment measure, TONE. Column 3 provides evidence to suggest that firm which employees perceive to have tough goals are positively associated with future earnings surprises, appearing to corroborate goal-setting theory (Locke, 1966; Locke and Latham, 1990). Column 4 includes the Fortune survey measure, BC, and highlights a mildly negative association, suggesting that GOAL's predictive power is not subsumed by employee satisfaction (Edmans 2011). Taken together, our findings are consistent with the view that corporate culture and specifically goal-setting behaviour is an under-recognized intangible asset and a potential source of competitive advantage.

6 Conclusion

To date, employees' perceptions of corporate culture have been difficult to collect without resorting to manual, labor and time intensive surveys. We seek to overcome these limitations by employing an automated Bayesian computational linguistics technique to infer latent perceptions expressed via social media.

Our results provide evidence in support of extant motivational theories. Specifically, we test the hypothesis that goal-setting behavior is value-relevant for firms. We provide evidence to suggest that firms which set more challenging goals benefit from significantly higher future earnings. Our findings indicate that goal-setting reflects a different dimension of corporate culture than captured by employee satisfaction and more traditional CSR metrics.

From an asset pricing perspective, we find that the value-relevance of goal-setting corporate cultures is only recognized by financial analysts once it manifests into tangible outcomes post earnings announcements. Our findings point to systematic "errors-in-expectations" of firm cash flows, consistent with the growing body of evidence which suggests that intangible assets are not fully incorporated by the stock market. More broadly our study highlights the merits of textual analysis of social media datasets to gain a more timely and holistic insight into a company's culture.

References

Aboody, D., Lev, B., (1998), The value relevance of intangibles: the case of software capitalization. Journal of Accounting Research 36, 161–191.

Adams, J.S, (1963), Toward an understanding of inequity, Journal of Abnormal and Social Pyschology, 67, 422-436.

Ambrose, M. L., Kulik, C. T., (1999), Old friends, new faces: Motivation in the 1990s. Journal of Management, 25, 231–292.

Anderson, S. W., Deker, H. C., Sedatole, K. L. (2010), An empirical Examination of Goals and Performance-to-Goal Following the Introduction of an Incentive Bonus Plan with Participative Goal-setting, Management Science, 56, 90-109.

Appelbaum, E., Batt, R. (1994), The new American workplace: Transforming work systems in the United States. Ithaca, NY: ILR Press.

Barney J., (1991), Firm resources and sustained competitive advantage. Journal of Management 17(1): 771–792.

Barney, J.B., Wright, P.M., (1998), On becoming a strategic partner: The role of human resources in gaining competitive advantage. Human Resource Management, 37: 31- 46.

Baucus, M. S., (1995), Halo-adjusted residuals–Prolonging the life of a terminally ill measure of corporate social performance, Business & Society, 34: 227–235.

Beach, D.S., (1980), Personnel: The management of people at work (4th ed.), New York: Macmillan Publishing Co. Inc.

Bellenger, D.N., Wilcox, J.B. & Ingram, T.N. (1984). An examination of reward preferences for sales managers. Journal of Personal Selling and Sales Management, 4(2):1–6.

Berk, J., Stanton, R., Zechner, J., 2010. Human capital, bankruptcy, and capital structure. Journal of Finance 65, 891–926.

Berthon, P., Ewing, M., Hah, L., (2005), Captivating company: dimensions of attractiveness in employer branding, International Journal of Advertising, 24(2), 151- 172.

Bernard, V., Thomas, J., (1989), Post-earnings-announcement drift: delayed price response or risk premium? Journal of Accounting Research 27, 1–36.

Besanko, D, Dranove, D., Shanley, M., (2000), Economics of Strategy, John Wiley & Sons.

Bhatnagar, R., (2004), Dukes v. Wal-Mart as a catalyst for social activism. Berkeley Women's Law Journal, 19(1): 246-256.

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

Blei, D., McAuliff, J., (2007), Supervised topic models. Neural Information Processing Systems 21, 2007.

Blei, D., (2012), Probabilistic Topic Models, Communications of the ACM, April 2012, vol. 55 no. 4.

Borgers, A., Derwall, J., Koedijk, K., ter Horst, J., (2013), Stakeholder Relations and Stock Returns: On Errors in Expectations and Learning, Journal of Empirical Finance, vol. 22(1), 159-175.

Boswell, W. R., (2006). Aligning employees with the organization's strategic objectives: out of 'line of sight', out of mind, International Journal of Human Resource Management, 17, 1489-511.

Boswell, W. R., Boudreau, J. W., (2001), How leading companies create, measure, and achieve strategic results through "line of sight.", Management Decision, 39, 851-859.

Brown, B., Perry, S., (1994), Removing the financial performance halo from Fortune's Most Admired companies, Academy of Management Journal, 37, 1347-1359.

Burnett, M., Best, R.J., (2011), Employee Satisfaction And Shareholder Returns, J. Bus. Econ. Res. Jber 2. p. 35-41.

Carlin, B., Gervais, S., 2009. Work ethic, employment contracts, and firm value. Journal of Finance 64, 785–821.

Chan, L., Lakonishok, J., Sougiannis, T., (2001), The stock market valuation of research and development expenditures. Journal of Finance 56, 2431–2456.

Cooper, C.L., Cartwright, S, Cartright, S, Earley, C. P., (2001), The International Handbook of Organizational Culture and Climate, John Wiley and Sons Ltd.

Coster, E.A. (1992). The perceived quality of working life and job facet satisfaction. Journal of Industrial Psychology, 18(2):6–9.

Da, Z., Engelberg, J., Gao, P., (2011), In search of attention, Journal of Finance 66(5) 1461-1499.

Daines, R. M., Gow, I., D., Larcker, D. F., (2010), Rating the Ratings: How Good are Commercial Governance Ratings?, Journal of Financial Economics 98, no. 3 439–461.

Davis, A.K, Guenther, D.A, Krull, L.K, Williams, B.M, (2013), Taxes and Corporate Accountability Reporting: Is Paying Taxes Viewed as Socially Responsible?, Working Paper, Lundquist College of Business.

Deng, Z., Lev, B., Narin, F., (1999), Science and technology as predictors of stock performance. Financial Analysts Journal 55, 20–32.

Derwall, J., Guenster, N., Bauer, R., Koedijk, K., (2005), The Eco-Efficiency Premium Puzzle, Financial Analysts Journal, vol. 61(2).

Derwall, J., Koedijk, K., Ter Horst, J., (2011), A tale of values-driven and profit-seeking social investors. J. Bank. Finance 35, 2137–2147.

Dowell, G.A., Hart, S., Yeung, B., (2000), Do Corporate Global Environmental Standards Create or Destroy Market Value? Management Science, 46(8): 1059-1074.

Du Plessis, S. (2003), Purpose is alive and well and living inside you: Key feature. Career Success, 3(1), 1-2.

Easterwood, J., Nutt, S., (1999), Inefficiency in analysts' earnings forecasts: Systematic misreaction or systematic optimism? Journal of Finance 54, 1777–1797.

Eberle, D., Berens, G.A.J.M., Li, T., (2013), The impact of interactive corporate social responsibility communication on corporate reputation. Journal of Business Ethics, 118 (4), 731-746.

Edmans, A., (2011), Does the stock market fully value intangibles? Employee satisfaction and equity prices. JFE 101, 621–640.

Elahi, M., F., Monachesi, P., (2012), An Examination of Cross-Cultural Similarities and Differences from Social Media Data with respect to Language Use, Proceedings of the Eight International Conference on Language Resources and Evaluation (LREC'12).

Engelberg, J., (2008), Costly information processing: Evidence from earnings announcements, Working paper, Northwestern University.

Fama, E. F., French, K.R., (1992), The cross-section of expected stock returns, Journal of Finance 47, 427–465.

Flammer, C., (2013b), Does corporate social responsibility lead to superior financial performance? A regression discontinuity approach,Working paper, University of Western Ontario.

Fombrun, C. J., Shanley, M., (1990), What's in a name? Reputation building and corporate strategy, Academy of Management Journal, 33, 2, pp. 233-258.

Fryxell, G. E., Wang, J. (1994), The Fortune corporate reputation index: Reputation for what?, Journal of Management, 20, pp. 1-14.

Gagnon, M. A., Michael, J. H., (2003), Employee strategic alignment at a wood manufacturer: An exploratory analysis using lean manufacturing. Forest Products Journal, 53, 24-29.

Gerhart, B., Rynes, S. L., (2003), Compensation: Theory, evidence, and strategic implications. Thousand Oaks, CA: Sage.

Gneezy, U., Meier, S., Rey-Biel, P., (2011), When and Why Incentives (Don't) Work to Modify Behavior, Journal of Economic Perspectives, 25(4), 191-210.

Gompers, P., Ishii, J., Metrick, A., (2003), Corporate governance and equity prices, Quarterly Journal of Economics 118, 107–155.

Gray, R., Kouhy, R., Lavers, S., (1995a), Corporate Social and Environmental Reporting: A Review of the Literature and a Longitudinal Study of UK Disclosure, Accounting, Auditing and Accountability, Vol. 8, No. 2, 47–77.

Greenberg, J., Knight, G., (2004), Framing sweatshops: Nike, global production, and the American news media. Communication and Critical/Cultural Studies, 1(2): 151-175.

Griffiths, T. L., Steyvers, M., (2004). Finding scientific topics. Proceedings of the National Academy of Science, 101, 5228-5235.

Grimmer, J., (2010), A bayesian hierarchical topic model for political texts: Measuring expressed agendas in senate press releases. Political Analysis, 18(1):1–35.

Guiso, L., Sapienza, P., Zingales, L., (2013), The value of corporate culture, Journal of Financial Economics.

Hall, E.T., (1976), Beyond culture. New York, NY: Knopf Doubleday Publishing Group.

Healy, P. M., Palepu, K. G., (2001), Information Asymmetry, Corporate Disclosure and the Capital Markets: A review of the Empirical Disclosure Literature, Journal of Accounting and Economics, 31 (1): 405-440.

Hertzberg, F., (1959), The Motivation to Work, J. Wiley & Sons, New York.

Hillman, A.J., Keim, G.D., (2001), Shareholder value, stakeholder management, and social issues: What's the bottom line? Strategic Management Journal 22, 125-139.

Hirsch, B.T., (1991), Union Coverage and Profitability among U.S. Firms., Review of Economics and Statistics 73 (1) 69-77.

Hofstede, G., (1980), Culture's consequences. Beverly Hills, CA: Sage.

Hogenboom, A., Bal, M., Frasincar, F., Bal, D., (2012), Towards Cross-Language Sentiment Analysis through Universal Star Ratings. KMO 2012: 69-79

Hogenboom, A., Bal, M., Frasincar, F., Bal, D., Kaymak, U., de Jong, F., (2014), Lexicon based sentiment analysis by mapping conveyed sentiment to intended sentiment. Int. J. Web Eng. Technol. 9(2): 125-147.

Ichniowski, C., Shaw, K., (1999), The effects of human resource management on economic performance: An international comparison of US and Japanese Plants. Management Science 45(5), 704–723.

James, L. R. and Jones, A. P., (1974), Organizational climate: A review of theory and research. Psychological Bulletin, 81, 1096-1112.

Jeaneau, H., Hudson, J., Zlotnicka, E., T., (2013), Corporate culture: Relevant to investors?

UBS Investment Research.

Jegadeesh, N., Titman, S., (1993), Returns to buying winners and selling losers: Implications for stock market efficiency, J. Finance 48, 65–91.

Jensen, M., Meckling, W., (1976), Theory of the firm: managerial behavior, agency costs and ownership structure, Journal of Financial Economics 3, 305–360.

Johnson, R.A., Greening, D.W., 1999. The effects of corporate governance and institutional ownership types on corporate social performance. Academy of Management Journal 42, 564-576.

Kamenica, E., (2012), Behavioral Economics and Psychology of Incentives, Annual Review of Economics, 4, 427-452.

Kaplan, S.N., Zingales, L., (1997), Do Investment-Cash Flow Sensitivities Provide Useful Measures of Financing Constraints? Quarterly Journal of Economics, 112: 169-215.

Konar, S., Cohen, M.A., (2001), Does the Market Value Environmental Performance? Review of Economics and Statistics, 83(2): 281-289.

Lau, J. H., Grieser, K., Newman, D., Baldwin , T., (2011), Automatic Labelling of Topic Models. Proceedings of the 49th Annual Meeting of the Association for Computational Linguistics.

Lev, B., (2001), Intangibles: Management, Measurement, and Reporting, Brookings Institution Press, Washington, D.C.

Lev, B., Sougiannis, T., (1996), The capitalization, amortization, and value relevance of R&D, Journal of Accounting and Economics 21, 107–138.

Levering, R., Moskowitz, M., (1993), The 100 Best Companies to Work for in America. Plume, New York, NY.

Levering, R., Moskowitz, M., Katz, M., (1984), The 100 Best Companies to Work for in America. Addison-Wesley, Reading, MA.

Li, T., Berens, G.A.J.M., Maertelaere, M. de, (2014), Corporate Twitter Channels: The Impact of Engagement and Informedness on Corporate Reputation. International Journal of Electronic Commerce, 18 (2), 97-125.

Liu, Y., Niculescu-Mizil, A., Gryc, W., (2009), Topic-link LDA: joint models of topic and author community. In Proceedings of the 26th Annual International Conference on Machine Learning, pp. 665–672. ACM.

Lobel, O., (2007), Big-box benefits: The targeting of giants in a national campaign to raise work conditions. Connecticut Law Review, 39: 1685-1712.

Locke, E. A., Latham, G.P., (2002), Building a practically useful theory of goal-setting and task Motivation: A 35-year odyssey, American Psychology, 57, 705-717.

Locke, E. A., (1966), The relationship of intentions to level of performance. Journal of Applied Psychology, 50, 60-66.

Locke, E. A., Latham, G. P., (1990), A theory of goal-setting and task performance, Englewood Cliffs, NJ: Prentice Hall.

Locke, E. A., Latham, G. P., (2006), New directions in goal-setting theory. Association for Psychlogical Science, 15(5), 265-270.

Locke, E. A., Latham, G. P., (2007), New developments in and directions for goal-setting research, European Psychologist, 12(4), 290-300.

Locke, E.A., & Henne, D., (1986), Work motivation theories. In C. Cooper & I. Robertson (Eds.), International review of industrial and organizational psychology, Wiley Ltd.

Locke, R. M., Qin, F., Brause, A., 2007, Does Monitoring Improve Labor Standards? Lessons from Nike. Industrial & Labor Relations Review, 61(1): 3-31.

Loughran, T., McDonald, B., (2011), When is a liability not a liability? textual analysis, dictionaries, and 10-ks,The Journal of Finance, 66(1):35–65.

Mănescu, C., 2011, Stock returns in relation to environmental, social and governance performance: Mispricing or compensation for risk?, Sustainable Development, John Wiley & Sons, Ltd., vol. 19(2), 95-118.

Marquis, C., Toffel, M., (2012), When Do Firms Greenwash? Corporate Visibility, Civil Society Scrutiny, and Environmental Disclosure, Harvard Business School Discussion Paper 12-43.

Maslow, A., (1943), A theory of human motivation. Psychological Review 50, 370–396.

McDonnell, M.H., King, B., 2013, Keeping up Appearances Reputational Threat and Impression Management after Social Movement Boycotts. Administrative Science Quarterly, 58(3), 387-419.

McGregor, D., (1960), The Human Side of Enterprise. McGraw-Hill, New York.

Mimno, D., (2012), Computational historiography: Data mining in a century of classics journals. Journal on Computing and Cultural Heritage (JOCCH), 5(1):3.

Moniz, A. and de Jong, F., (2014), Sentiment Analysis and the Impact of Employee Satisfaction on Firm Earnings. Advances in Information Retrieval - 36th European Conference on IR Research, ECIR 2014, Springer 2014 Lecture Notes in Computer Science.

Myers, S.C., Majluf, N.S., (1984), Corporate financing and investment decisions when firms have information investors do not have, Journal of Financial Economics, 13, 187-221.

Noble, C. H., (1999), The eclectic roots of strategy implementation research, Journal of Business Research, 45, 119-34.

O'Reilly, C., Chatman, J., Caldwell, D., (1991), People and Organizational Culture: A Profile Comparison Approach to Assessing Person-Organization Fit, The Academy of Management Journal 34, 487–516.

O'Reilly, C., Chatman, J., Caldwell, D., Doerr, B., (2012), The Promise and Problems of Organizational Culture: CEO Personality, Culture, and Firm Performance, Working Paper.

Ordóñez, L. D., Schweitzer, M. E., Galinsky, A. D., Bazerman, M. H., (2009), On Good Scholarship, Goal-setting, and Scholars Gone Wild, Academy of Management Perspectives, 23(1), 6-16.

Pang, B., Lee, L., (2004), A Sentimental Education: Sentiment Analysis using Subjectivity Summarization based on Minimum Cuts, 42nd Annual Meeting of the Association for Computational Linguistics (ACL 2004), 271–280, Association for Computational Linguistics.

Pearce, J. A., Robinson, R. B., (2007), Strategic Management: Formulation, Implementation and Control, Irwin: McGraw Hill International.

Petersen, M., (2009), Estimating standard errors in finance panel data sets: comparing approaches, Review of Financial Studies 22: 435-480.

Pinder, C. C., (1998), Work motivation in organizational behavior. Upper Saddle River, NJ: Prentice-Hall.

Popadak, J., (2013), A Corporate Culture Channel: How Increased Shareholder Governance Reduces Firm Value, Duke University working paper.

Rajan, R., Zingales, L., 1998. Power in a theory of the firm. Quarterly Journal of Economics 113, 387–432.

Ramage, D., Dumais, S., Liebling, D., (2010) Characterizing microblogs with topic models, ICWSM.

Ramage, D., Rosen, E., Chuang, J., Manning, C. D., McFarland, D. A., (2009), Topic modeling for the social sciences, NIPS 2009 Workshop on Applications for Topic Models: Text and Beyond.

Rao, H., Yue, L. Q., Ingram, P., (2011), Laws of Attraction. American Sociological Review, 76(3): 365-385.

Ravasi, D., Rindova, V.P., Dalpiaz, E., (2012), The Cultural Side of Value Creation. Strategic Organization 10(3), 231-239.

Rothmann, S., Coetzer, E. P., (2002), The relationship between personality dimensions and job satisfaction, Bestuursdinamika, 11(1), 29– 42.

Russo, M.V., Fouts, P.A., (1997), A resource-based perspective on corporate environmental performance and profitability. Academy of Management Journal 40(3): 534–559.

Schein, E.H., (1990), Organizational culture, American Psychologist, 42, 109-119.

Schweitzer, M. E., Ordóñez, L., Douma, B., (2004), Goal-setting as a Motivator of Unethical Behavior. Academy of Management Journal, 47(3), 422-432.

Shane, S., Locke, E. A., Collins, C. J., (2003), Entrepreneurial motivation, Human Resource Management Review, 13, 257-279.

Spector, P.E., (2003), Industrial and organizational psychology – Research and practice (3rd ed.), New York: John Wiley & Sons, Inc.

Statman, M., Glushkov, D., (2009), The Wages of Social Responsibility, Financial Analysts Journal 65, 33–46.

Stinson, J.E., Johnson, T.W., (1977), Tasks, individual differences, and job satisfaction. Industrial Relations, 16(3):315-325.

Stone, P., Dumphy, D. C., Smith, M. S., Ogilvie, D. M., (1966), The General Inquirer: A Computer Approach to Content Analysis, The MIT Press.

Tetlock, P., M., Saar-Tsechansky, M., Macskassy, S., (2008), More than words: Quantifying language to measure firms' fundamentals, Journal of Finance 63 (3): 1437-1467.

Tilly, C., (2007), Wal-Mart and its workers: Not the same all over the world. Connecticut Law Review, 39: 1805-1823.

Titov, I, McDonald, R.T., (2008), Modeling online reviews with multi-grain topic models. Proceedings of the 17th international conference on World Wide Web, 111-120, 253.

Triandis, H. C, Bontempo, R., Villareal, M. J., Asai, M., Lucca, N., (1988), Individualism and collectivism: Cross-cultural perspectives on self-ingroup relationships, Journal of Personality and Social Psychology, 54, 323-338.

Tziner, A., Latham, G. P., (1989), The effects of appraisal instrument, feedback and goalsetting on worker satisfaction and commitment, Journal of Organizational Behavior, 10, 145–153.

Verwijmeren, P., Derwall, J., (2010), Employee Well-Being, Firm Leverage, and Bankruptcy Risk, Journal of Banking and Finance, 2010.

Waddock, S. A., S. B. Graves, (1997), The corporate social performance- financial performance link, Strategic Management Journal, 18 (4): 303-319.

Wagner, C. M., (2007), Organizational commitment as a predictor variable in nursing turnover research: Literature review, Journal of Advanced Nursing, 60(3), 235–247.

Wallach, H, Mimno, D., McCallum, A., (2009), Rethinking LDA: Why Priors Matter, NIPS, 2009.

Wierzbicka, A., (1995), Emotion and Facial Expression: A Semantic Perspective. Culture

Psychology 1(2), 227–258.

Wiese, B. S., Freund, A. M., (2005), Goal progress makes one happy, or does it? Longitudinal findings from the work domain, Journal of Occupational and Organizational Psychology, 78, 287–304.

Witt, L.A., (1998), Enhancing Organizational Goal Congruence: A solution to Organizational Politics, Journal of Applied Psychology, 83: 666-74.

Yukl, G. A., Latham, G. P., (1978), Interrelationships among employee participation, individuals differences, goal difficulty, goal acceptance, goal instrumentality, and performance. Personnel Psychology, 31, 305–323.

Figure 1 Illustrative example of LDA for an employee review

This figure has been adapted from (Blei 2012) and is intended to illustrate the premise of probabilistic topic modelling. LDA assumes that a number of topics which are distributions over words exist for the whole collection (far left). Each document is assumed to be generated as follows: First choose a distribution over the topics (the histogram at right); then, for each word, choose a topic assignment (the colored circles) and choose the word from the corresponding topic.

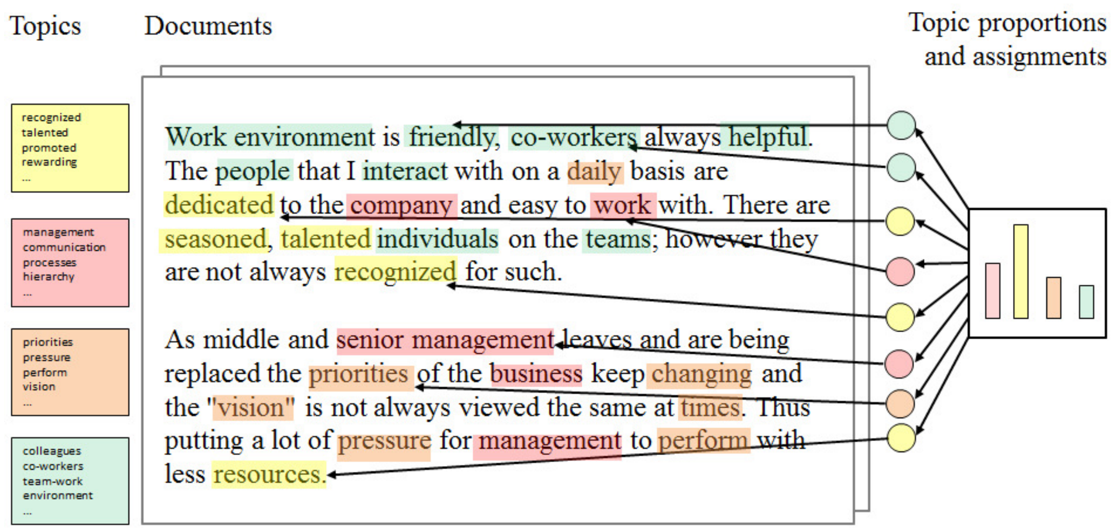

Table 1: Descriptive statistics on the user profiles of Glassdoor.com

This table reports descriptive statistics on the user profiles for Glassdoor.com, obtained from quantcast.com as at June 2015. Quantcast.com relies upon tracking pixels that publishers install on the pages of their sites to measure audience data, which is then used to compile visitor profiles and build a detailed picture of web audiences. The profile of a typical web surfer is evaluated across multiple characteristics including Gender, Age, Household Income, Education Level and Ethnicity.

Characteristic	**Category**	**Percentage of web traffic**
Gender	Male	50%
	Female	50%
Age	< 18	11%
	18-24	18%
	25-34	25%
	35-44	20%
	45-54	17%
	55-64	7%
Household Income	65+	2%
	$0-50k	47%
	$50-100k	30%
	$100-150k	13%
	$150k+	10%
Education Level	No College	27%
	College	51%
	Grad School	22%
Ethnicity	Caucasian	65%
	African American	13%
	Asian	10%
	Hispanic	10%
	Other	2%

Figure 2: Illustrative examples of Glassdoor reviews

This figure provides two examples of employee reviews written for IBM. Reviewers are required to provide balanced feedback on the Pros and Cons of a company. Each review contains metadata which identifies whether a reviewer is a current or former employee, the employee's job title, location and number of years' service at the company.

"Excellent place to earn rewards for performance. "

Current Employee - Supervisor in Tampa, FL

I have been working at IBM full-time (more than 8 years)

Pros High calibre employees, good rewards for individual achievement, solid education opportunities.

Cons Sometimes short-sighted with talent retention.

"Bad & Bureaucratic Culture "

Former Employee - Business Analyst in Bangalore (India)

I worked at IBM India full-time (more than an year)

Pros Work from Home option, a good Brand Name, exposure

Cons Bureaucracy, Politics among different levels of management, weak HR

Table 2: Summary Statistics of Glassdoor.com dataset

Panel A: Overview of dataset by reviewers' stated region of domicile

This table provides descriptive statistics of reviewers' metadata divided by region and year the review was posted. Regions are standardized using MSCI classifications sourced from https://www.msci.com/market-classification

Region	2008	2009	2010	2011	2012	2013	2014	2015	Total	% of Total
Asia	189	285	926	1,330	6,311	6,264	7,798	2,551	25,654	6%
Europe	307	257	796	435	1,196	1,849	2,949	1,619	9,408	2%
North America	13,139	10,136	15,637	18,068	30,100	45,821	71,444	25,698	230,043	55%
Other	40	53	97	130	632	751	967	429	3,099	1%
Anonymous	1,537	5,001	11,760	13,798	20,931	25,552	46,429	24,433	149,441	36%
Total	15,212	15,732	29,216	33,761	59,170	80,237	129,587	54,730	417,645	
% of Total	3.6%	3.8%	7.0%	8.1%	14.2%	19.2%	31.0%	13.1%	100.0%	100.0%

Panel B: Overview of dataset by employment status

This table provides descriptive statistics of reviewers' metadata divided by region and employment status. The Anonymous category refers to posts where employment status was not provided by reviewers.

Region	Full-time employee	Part-time employee	Anonymous	Total	Current employee	Former employee	Total reviews
Asia ex Japan	18,954	224	6,276	25,454	17,228	8,226	25,454
EMEA	1,121	49	388	1,558	956	602	1,558
Europe	5,787	296	3,325	9,408	6,038	3,370	9,408
Japan	118	9	73	200	109	91	200
Latin America	1,124	18	399	1,541	987	554	1,541
North America	119,506	21,290	89,247	230,043	133,114	96,929	230,043
Anonymous	56,464	6,798	86,179	149,441	93,480	55,961	149,441
Total	203,074	28,684	185,887	417,645	251,912	165,733	417,645
% of Total	48.6%	6.9%	44.5%	100.0%	60.3%	39.7%	100.0%

Panel C: Overview of dataset by years' of experience

This table provides descriptive statistics of reviewers' metadata divided by region and number of years' experience. Years of experience are standardized based on conducting a textual analysis of reviews. The Anonymous category refers to posts where the number of years' experience not provided by reviewers.

Region	<1 year experience	1-3 years' experience	5+ years' experience	10+ years' experience	Anonymous	Total	% of Total
Asia	3,675	12,800	3,591	591	4,997	25,654	6%
Europe	1,254	3,422	1,348	628	2,756	9,408	2%
North America	33,242	69,275	30,072	17,326	80,128	230,043	55%
Other	330	1,384	616	185	584	3,099	1%
Anonymous	7,829	24,252	13,282	7,383	96,695	149,441	36%
Total	46,330	111,133	48,909	26,113	185,160	417,645	
% of Total	11.1%	26.6%	11.7%	6.3%	44.3%	100.0%	100.0%

Panel D: Overview of dataset by sector

This table provides descriptive statistics of reviewers' metadata by sector and employment status. Sector classifications are determined by matching companies to the GICS sector classifications available in the Compustat database.

Sector	Current employee	Former employee	Total reviews	% of Total	Number of unique firms
Energy	5,753	3,445	9,198	2.2%	113
Materials	4,295	2,670	6,965	1.7%	110
Industrials	27,616	18,150	45,766	11.0%	317
Consumer Discretionary	54,387	45,415	99,802	23.9%	343
Consumer Staples	14,736	9,560	24,296	5.8%	92
Health Care	16,643	11,488	28,131	6.7%	309
Financials	25,600	18,318	43,918	10.5%	317
Information Technology	89,197	46,903	136,100	32.6%	482
Telecommunication Services	2,359	1,521	3,880	0.9%	28
Utilities	1,734	936	2,670	0.6%	52
Unclassified	9,592	7,327	16,919	4.1%	74
Total	251,912	165,733	417,645	100.0%	2,237

Table 3: Regression analysis of Glassdoor scores

This table reports regression results to assess the fundamental characteristics associated with the Glassdoor ratings. The dependent variable is Overall star rating score provided by Glassdoor reviewers. Former is an indicator variable equal to one if the reviewer is a former employee of the company, and zero otherwise. Part-time is a dummy variable equal to one if the reviewer is a part-time worker, and zero otherwise. Log(Market Equity) is the natural log of the market capitalization of equity during the previous month, in thousands of dollars. Log(Book/Market)) is the natural log of the book-to-value of equity measured as at the end of the preceding calendar year, following Fama and French (1992). Analyst revisions is the 3-month sum of changes in the median analyst's forecast, changed by the firm's stock price in the prior month. SG is one-year historic sales growth. Pmom is the (signed) stock's return measured over the previous 12 months. The fundamental data comes from COMPUSTAT Fundamentals Annual Database apart from Analyst revisions which comes from I/B/E/S and Pmom from CRSP. For presentational reasons, the following control variables are hidden from the table: COMP is the 'Comp & Benefits' star rating provided by Glassdoor reviewers,WORKLIFE is the Glassdoor 'Work/Life Balance' rating, MGT is reviewers' 'Senior Management' rating, CULTURE refers to the 'Culture & Values' star rating and CAREER is the Glassdoor 'Career Opportunities' rating. Standard errors are clustered by firm following Petersen (2009). For each variable we report the corresponding robust t-statistic (in parentheses). Sample period: 2008-2015.

	(1)	**(2)**	**(3)**
Intercept	0.006	0.040	0.012
	(2.320)	(1.657)	(1.300)
Former	-0.058	-0.059	-0.058
	(-4.863)	(-4.754)	(-3.193)
Part-time	0.053	0.053	0.050
	(5.296)	(5.875)	(2.057)
Log(Book/Market)		0.004	0.004
		(1.663)	(1.731)
Log(Market Equity)		0.000	0.000
		(2.099)	(2.937)
Analyst revisions		0.632	0.594
		(2.312)	(2.994)
SG		0.006	0.009
		(0.170)	(0.974)
Pmom		0.009	0.008
		(1.417)	(1.629)
R^2	0.734	0.744	0.745

Table 4: Topic clusters inferred by LDA model

This table reports the top five terms for each topic cluster and their associated probabilities inferred using the Latent Dirichlet Allocation (LDA) algorithm (Blei et al 2003). In LDA, a topic is modeled as a probability distribution over a set of words represented by a vocabulary and a document as a probability distribution over a set of topics. We implement standard settings for LDA hyperparameters with $\alpha = 50/K$ and β=.01 following (Griffiths and Steyvers 2004). The number of topics, K, is inferred by maximizing the likelihood of fitting the LDA model over the corpus of documents. Topic labels are manually annotated to aid the reader's interpretation by drawing upon extant cultural analysis literature (see Berthon et al. 2005). We infer one cluster, labelled *'social value'*, which appears to capture employees' perceptions of team-orientated work environments. *Development value* refers to the perception of career-enhancing opportunities. *Economic value* refers to working conditions and job benefits. *Application value* is the perception that an employee can apply his/her acquired skills and knowledge in the workplace. *Organizational structure* captures the extent to which employees feel they can talk to higher management, consistent with Hofstede's (1980) power distance. The final topic cluster, '*goal-setting'*, appears to capture perceptions of goal-setting behavior.

'social value'		*'development value'*		*'economic value'*	
word	**prob.**	**word**	**prob.**	**word**	**prob.**
friends	0.18	opportunity	0.24	work life	0.18
team building	0.14	career opportunities	0.22	conditions	0.07
co-workers	0.12	advancing	0.13	benefits	0.05
team	0.09	professional development	0.07	diversity	0.04
working environment	0.07	initiatives	0.07	location	0.03

'application value'		*'organizational structure'*		*'goal-setting'*	
word	**prob.**	**word**	**prob.**	**word**	**prob.**
encouragement	0.28	manager	0.27	planning	0.16
responsibilities	0.10	changes	0.17	goals	0.14
talented	0.07	processes	0.12	incentives	0.13
promoted	0.07	senior management	0.10	performance	0.13
rewarding	0.05	communications	0.08	direction	0.01

Figure 3: Illustrative examples of Glassdoor comments for each topic cluster

This figure provides illustrative examples of employee reviews classified into topics based on the outputs of the LDA model. Topic labels are manually annotated and are described in Table 4. To aid readers' interpretation, we randomly select and report five reviewers' comments within the 'pros' and 'cons' sections.

'social value' topic cluster

Pros	Cons
Co-workers were great and very supportive	People, Gossips, Enviorement, Hostility to co-workers, bullying from other areas
Great co-workers. Good environment. Made a lot of friends. Pay Decent.	No pride shown by coworkers.
great culture, wherever you go you will gain a family	Negative co-workers and too much gossip mill.
You get to socialize with alot of people	Door slams, and sometimes people randomly yell at me.
family environment	Some people are very intelligent but a little geeky and tougher to socialize with.

'development value' topic cluster

Pros	Cons
Can move between different job functions wtihin the company. Professional and personal development are encouraged for all employees. A company where you can keep learning.	No career progression, even if you actively pursue it.
Training opportunities are available	A lot of lip service is given regarding advancement opportunitties
Great opportunities to learn different aspects of the business.	Opportunities for advancement in our division are few.
Plenty of opportunity for expanded roles and advancement.	No real room for growth
Excellent Training, Good pay, Resume builder	Limited opportunities for growth and development

'economic value' topic cluster

Pros	Cons
good bonuses, steady job with great co-workers	Offers a lower starting salary than some competitive companies with less
Great gym, good location - center of Silicon Valley.	Pay system is odd. You have minimal control over how much money you
Decent starting salary, 401K program, health benefits	Don't get many holidays.
incredible perks, amazing insurance, gym, cafeteria, education benefits	Horrible working conditions, building falling apart, chairs worn out, bad
Benefits are spectacular. Health, dental, vision, transportation	No perks; cafeteria food is at best OK;

'application value' topic cluster

Pros	Cons
They gave me lots of responsibility right off the bat.	Skewed recognition- the very best receive many many accolades, rewards, etc
recognized for my contributions and promoted Multiple times	Nepotism almost seems encouraged, leading to many unfair circumstances.
Performance based promotions, do what you are supposed to do and you will get promoted...	Diminishing reward system with minimal promotion/Salary increases given downsizing
Meritocracy; evaluated based on impact, not how much your manager likes you.	Miscommunication among departments, which often leads to confusion and finger pointing.
They respect me for my talents.	finger pointing, local leadership not interested to improve

'organizational structure' topic cluster

Pros	Cons
Strong management process	Entrenched in old processes, some decisions are more political than objective.
Horizontal hierarchy, somewhat easy to navigate.	Sometimes politics and red tape can be frustrating
Effective communication with management	The management is the "good ole boy system"
Very good well manage organization when it comes to Sr management	Complex organization structure
Upper management was very accessible.	amount of red tape in the company grows exponentially.

'goal-setting' topic cluster

Pros	Cons
Good foundation in place, with a common goal understood by everyone.	The most hardest thing here is hitting your numbers. If you don't reach the desired goal of the company, they will get rid of you.
if your hard working, its a good place to work. it weeds out the lazy people and the people that dont want to work.	Not a very good work life balance and aggressive deadlines.
Good people that have same goal	The fact that the end goal of JPM is always bottom line, the workload and hours are very intense but the work is exciting and worth it
Great place to work if you are not lazy.	Fast pace and high stress of goal for achievement and sucess.
well planned work habits, good company culture	Long work hours, stressful sometimes, had to work in weekends to meet

Table 5: Summary firm fundamental characteristics

Panel A: Fundamental characteristics

This table reports the median fundamental characteristics of firms when sorted into quartiles by the degree to which employees perceive the company to exhibit goal-setting behavior. We create a composite document per firm per quarter to align the reporting frequency of accounting variables (quarterly/annual) with reviewers' comments (daily) by aggregating reviewer comments between earnings announcement dates (sourced from IBES). We winsorize all firm characteristics at the 1% level to eliminate the impact of outliers. OVERALL is the overall star rating score provided by Glassdoor reviewers, averaged between consecutive earnings announcement dates per company. All fundamental data comes from COMPUSTAT Fundamentals Annual Database. The sample covers the period 2008-2015. The final column of the table indicates the statistical significance of a difference of means t-test between top and bottom quartile firms for each fundamental characteristic where *** indicates statistical significance at the 1% level, ** at the 5% level and * at the 10% level.

Characteristic	**1st.Quartile**	**2nd.Quartile**	**3rd.Quartile**	**4th.Quartile**	**Diff of means T-test (Q1 vs. Q4)**
Accruals	-0.044	-0.035	-0.043	-0.042	
Asset growth (yoy)	0.037	0.051	0.086	0.087	***
Employee growth (yoy)	0.021	0.028	0.046	0.052	***
Financial leverage	0.429	0.510	0.318	0.307	
Market capitalisation (US$ mn)	13,329	17,178	22,289	28,408	***
Prior price momentum	0.148	0.164	0.150	0.198	*
ROA	0.146	0.149	0.149	0.162	***
Sales growth (yoy)	0.038	0.045	0.057	0.069	***
Tobin's Q	1.329	1.474	1.620	1.837	***
GOAL	0.040	0.072	0.099	0.145	
OVERALL	3.231	3.308	3.505	3.500	***

Panel B: Correlation of Glassdoor.com star rating scores

This table reports the Spearman rank correlations between the star ratings provided by Glassdoor reviews and the goal-setting topic probability inferred from reviewers' text. GOAL is the proportion of reviews that refer to goal-setting behavior as inferred by the LDA topic model. OVERALL is the overall star rating score provided by Glassdoor reviewers. COMP is the 'Comp & Benefits' star rating provided by Glassdoor reviewers. WORKLIFE is the Glassdoor 'Work/Life Balance' rating. MGT is reviewers' 'Senior Management' rating. CULTURE refers to the 'Culture & Values' star rating and CAREER is the Glassdoor 'Career Opportunities' rating. The sample covers the period 2008-2015.

	GOAL	OVERALL	COMP	WORKLIFE	MGT	CULTURE	CAREER
GOAL	1.00						
OVERALL	0.04	1.00					
COMP	0.12	0.58	1.00				
WORKLIFE	0.05	0.76	0.56	1.00			
MGT	0.01	0.74	0.44	0.63	1.00		
CULTURE	0.00	0.60	0.41	0.49	0.54	1.00	
CAREER	0.03	0.76	0.54	0.74	0.65	0.49	1.00

Table 6: Goal-setting characteristics regression

This table reports the relation between GOAL and company characteristics. The dependent variable is the topic probability associated with goal-setting behavior inferred by the LDA model. OVERALL is the Glassdoor Overall star rating provided by Glassdoor reviewers, COMP is the 'Comp & Benefits' star rating. WORKLIFE is the Glassdoor 'Work/Life Balance' rating. MGT is reviewers' 'Senior Management' rating, CULTURE refers to the 'Culture & Values' star rating and CAREER is the Glassdoor 'Career Opportunities' rating. TONE is a measure of document polarity computed by counting the number of positive (P) versus negative (N) terms using the General Inquirer dictionary (Stone et al. 1966). Log (Book/Market) is the natural log of the book-to-value of equity as of the previous year end. SG is one-year sales growth. Analyst revisions is the 3-month sum of changes in the median analyst's forecast, changed by the firm's stock price in the prior month. ROA is net income before depreciation scaled by total assets as at the previous year end. Pmom is the (signed) stock's return measured over the previous 12 months. SG is one-year sales growth. The fundamental data comes from COMPUSTAT Fundamentals Annual Database apart from Analyst revisions which comes from I/B/E/S and Pmom from CRSP. KLD is a measure of employee relations metric obtained from the KLD database and is defined as the difference between employee strengths and concerns over the past year. BC is an indicator variable equal to one if the company is in Fortune magazine's "100 Best Companies to Work for in America" list, and zero otherwise (Edmans 2011). Standard errors are clustered by firm following Petersen (2009). For each variable we report corresponding robust t-statistic (in parentheses). Sample period: 2008-2015.

	(1)	(2)	(3)
OVERALL	0.012	0.078	0.011
	(2.867)	(5.663)	(2.63)
TONE	0.023	0.026	0.009
	(0.798)	(0.986)	(0.312)
COMP		-0.047	
		(-11.505)	
WORKLIFE		-0.002	
		(-1.92)	
MGT		0.032	
		(5.581)	
CULTURE		0.001	
		(0.308)	
OPPORTUNITIES		0.022	
		(3.853)	
Log(Book/Market)	-0.003	0.001	-0.002
	(-1.078)	(0.463)	(-0.786)
ROA	0.027	-0.004	0.028
	(1.117)	(-0.175)	(1.19)
SG	0.056	0.030	0.055
	(4.213)	(2.39)	(3.986)
Analyst revisions	0.147	0.070	0.095
	(1.21)	(0.634)	(0.721)
Pmom	0.009	0.009	0.007
	(2.288)	(2.724)	(1.874)
KLD			-0.003
			(-2.734)
BC			-0.018
			(-0.885)

Table 7: Regression of goal-setting and firm value

This table reports the results of running quarterly regressions of firm value on a set of independent variables. The dependent variable is Tobin's Q, defined as the market value of the firm divided by the replacement value of the firm's assets. We compute the market value of assets as the sum of the book value of assets and the market value of common stock outstanding minus the sum of the book value of common stock and balance sheet deferred taxes. GOAL is the proportion of reviews that refer to goal-setting behavior as inferred by the LDA topic model. A composite document is computed for each firm by aggregating Glassdoor reviews between consecutive earnings announcement dates for each firm. Earnings announcement dates are sourced for I/B/E/S. A minimum of 30 reviews are required to create a composite document per firm. OVERALL is the Glassdoor Overall star rating averaged across reviews with the composite document. TONE is a measure of document polarity computed by counting the number of positive (P) versus negative (N) terms using the General Inquirer dictionary (Stone et al. 1966). The definitions for the fundamental variables are described in the text and come from COMPUSTAT Fundamentals Annual Database apart from Analyst revisions which comes from I/B/E/S and Pmom from CRSP. KLD is a measure of employee relations metric obtained from the KLD database and is defined as the difference between employee strengths and concerns over the past year. BC is an indicator variable equal to one if the company is in Fortune magazine's "100 Best Companies to Work for in America" list, and zero otherwise (Edmans 2011). . Standard errors are clustered by firm following Petersen (2009). For each variable we report corresponding robust t-statistic (in parentheses). Sample period: 2008-2015.

	(1)	(2)	(3)
GOAL	1.624	1.400	1.720
	(2.691)	(2.023)	(2.823)
TONE	-0.374	-0.034	-0.166
	(-0.701)	(-0.046)	(-0.311)
OVERALL	0.328		0.322
	(4.472)		(4.393)
COMP		-0.211	
		(-1.848)	
WORKLIFE		0.143	
		(1.181)	
MGT		0.261	
		(1.679)	
CULTURE		-0.102	
		(-1.007)	
OPPORTUNITIES		0.300	
		(1.738)	
log(Book/Market)	-0.762	-0.744	-0.699
	(-2.634)	(-2.488)	(-2.69)
ROA	4.348	4.057	4.725
	(3.364)	(3.282)	(3.192)
SG	2.846	2.635	2.736
	(2.941)	(2.921)	(2.255)
KLD			-0.073
			(-3.727)
BC			1.130
			(2.978)

Table 8: Predicting earnings surprises from GOAL

This table provides the OLS regression estimates of the goal-setting topic probability score's ability to predict quarterly earnings (SUE). The dependent variable, SUE, is a firm's standardized unexpected quarterly earnings. GOAL is the proportion of reviews that refer to goal-setting behavior as inferred by the LDA topic model. A composite document is computed for each firm by aggregating Glassdoor reviews between consecutive earnings announcement dates for each firm. Earnings announcement dates are sourced for I/B/E/S. A minimum of 30 reviews are required to create a composite document per firm. OVERALL is the Glassdoor Overall star rating averaged across reviews with the composite document. TONE is a measure of document polarity computed by counting the number of positive (P) versus negative (N) terms using the General Inquirer dictionary (Stone et al. 1966). KLD is a measure of employee relations metric obtained from the KLD database and is defined as the difference between employee strengths and concerns over the past year. BC is an indicator variable equal to one if the company is one of Fortune magazine's "100 Best Companies to Work for in America", and zero otherwise (Edmans 2011). Regressions include control variables for lagged firm earnings, firm size, book-to-market, trading volume, past stock returns, and analysts' quarterly forecast revisions and dispersion (see text for details). Standard errors are clustered by firm following Petersen (2009). For each variable we report corresponding robust t-statistic (in parentheses). Sample period: 2008-2015.

	(1)	(2)	(3)	(4)
lagged dependent	-0.012	-0.015	-0.013	-0.012
	(-0.358)	(-0.423)	(-0.38)	(-0.351)
Forecast dispersion	-2.700	-2.806	-2.283	-2.581
	(-3.196)	(-3.318)	(-2.656)	(-2.916)
OVERALL	0.067	0.053	0.061	0.079
	(0.761)	(0.505)	(0.582)	(0.755)
GOAL		1.770	4.665	4.477
		(2.536)	(3.931)	(3.751)
TONE		0.054	1.652	1.714
		(2.071)	(1.735)	(1.796)
Difficulty			14.780	14.180
			(3.008)	(2.892)
Analyst revisions	15.130	14.730	13.910	18.050
	(4.749)	(4.622)	(4.369)	(5.173)
Log(Market Equity)	0.000	0.000	0.000	0.000
	(-1.078)	(-1.021)	(-1.183)	(-1.552)
Log(Book/Market)	-0.006	-0.018	0.001	-0.053
	(-0.096)	(-0.294)	(0.009)	(-0.857)
Pmom	0.716	0.738	0.742	0.774
	(7.411)	(7.612)	(7.689)	(8.007)
KLD				0.055
				(1.904)
BC				-0.974
				(-1.699)