How Employee Voice Inform Firm Valuation: Evidence from Glassdoor

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Abstract

This paper investigates whether and how employee-generated reviews inform market participants' perceptions of credit risk in the credit default swap (CDS) market. While prior literature has primarily explored the role of employee perceptions, captured via sentiment, satisfaction ratings and textual reviews, in equity markets, we argue that CDS spreads offer a cleaner setting to isolate downside risk signals associated with their perceptions. Leveraging a novel dataset of high-frequency employee reviews from Glassdoor, we construct a weekly CDS valuation metric that integrates numerical ratings, sentiment, and risk-related indicators extracted from written comments. Our model improves the cross-sectional explanatory power of CDS spreads by nearly 18%, outperforming traditional structural and ESG-adjusted benchmarks. We identify two distinct informational channels through which employee reviews affect credit spreads: a sentiment-based behavioral channel and an informational channel through which employees disclose latent risks before such issues are reflected in formal financial statements or ESG ratings. Using exogenous affective shocks, blockbuster movie releases and aviation fatalities, as instruments, we provide the first causal evidence that shifts in employee sentiment influence CDS pricing independently of firm fundamentals and ESG ratings. Furthermore, heterogeneity analyses reveal that the credit relevance of human capital varies across sectors and ESG components, with particularly strong effects in labor-intensive industries and during periods of heightened uncertainty. Our findings reposition human capital from a peripheral ESG consideration to a dual-channel, firm-level determinant of credit risk, offering a scalable framework for integrating soft information into credit valuation models.

Keywords: Human capital, credit default swap spreads, employee sentiment, insider information, social media

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1. Introduction

Over the past decade, increasing literature establishes that human capital has evolved from a managerial notion to a core intangible asset in finance, shaping firm valuation and investor perception in meaningful ways. A growing body of literature conceptualizes human capital through proxies like employee satisfaction, corporate culture, organizational loyalty and managerial practices. These studies find strong associations between such measures and stock performance, financial resilience, and long-term firm value (Edmans, 2011; Green et al., 2019; Guiso et al., 2015; Graham et al., 2022; Shan and Tang, 2023), affirming the role of human capital in shaping firm value through the lens of equity markets. Yet stock prices reflect a combination of heterogeneous investor beliefs, macroeconomic shocks, and sentiment-driven flows (Bordalo et al., 2022; Li et al., 2022; Laudenbach et al., 2024; Benhabib et al., 2016). Because these forces intermingle in the price-formation process, the distinctive signals that stem from a firm's internal human capital conditions become difficult to isolate. As a consequence, employee-level soft information maybe underweighted in equity valuations, even though it reflects operational realities that remain hidden from most outside investors. Our study shifts the focus from equity to credit default swap (CDS) market, which we argue it offers a cleaner environment for assessing how intangible human capital inputs are priced. We demonstrate that incorporating employee-level information into CDS valuation models increases explanatory power by 18% relative to structural benchmarks through both sentiment and risk-related signals channels. Further, using a Bayesian shrinkage framework and an instrumental variable strategy, we provide the first causal evidence that such intangible inputs affect credit risk through employee sentiment channel.

Before investigating how human capital shapes firm value, it is important to first clarify what human capital represents for a firm. Traditionally, human capital is conceptualized as the stock of knowledge, skills, and abilities embedded in individuals that contribute to firm productivity and value creation (Becker, 1964). In the context of corporate finance, human capital is often measured by education, experience, or firm-level labor expenditures (Chemmanur et al., 2013; Graham et al., 2023)[1].

However, such structural indicators may not fully capture the intangible aspects of human capital, and employee perception [2] has emerged as a particularly informative dimension, reflecting internal conditions not visible through structural metrics. Recent research has already highlighted how employees' subjective perceptions of their work environment serve as meaningful indicators of human capital conditions. For example, Graham et al. (2023) show that trust and morale, forms of non-contractible human capital, significantly amplify the economic cost of corporate bankruptcy beyond what structural variables like tenure and wages can explain. Similarly, Li et al. (2021) demonstrate that firms with stronger organizational culture fared significantly better during the COVID-19 crisis, despite such cultural strength being absent from formal financial metrics. Edmans (2011) finds that employee satisfaction, an intangible reflection of workplace quality, strongly predicts long-term stock returns. Likewise, studies such as Fedyk and Hodson (2023) confirm that skill-based and relational human capital, rather than payroll size alone, drives firm innovation and productivity. Collectively, these studies confirm that employees' perceptions, whether expressed as trust, cultural alignment, satisfaction, or relational expertise, carry distinct information about firm health. And these findings suggest that structural indicators may overlook the deeper, perception-based elements of human capital that are vital to assessing a firm's human capital quality.

Given these insights, a critical empirical challenge emerges regarding how to effectively quantify employees' subjective experiences and perceptions of their work environment that are otherwise difficult to quantify. Addressing this measurement challenge is crucial, as employee perceptions may provide the missing link connecting structural proxies of human capital to intangible organizational attributes.

[1] Chemmanur et al. (2013) use average employee pay, calculated as total labor expense divided by number of employees, as a proxy for firm-level human capital costs, and examine how leverage affects this measure. Graham et al. (2023) measure human capital loss by tracking changes in individual worker earnings before and after corporate bankruptcy, using matched employer-employee data from the U.S. Census Bureau's LEHD program.

[2] We define employee perception is how workers evaluate and interpret their workplace environment.

The finance and accounting literature has typically addressed this issue by operationalizing employee perceptions using single, readily observable metrics, most often overall satisfaction or sentiment scores. For example, Edmans (2011) relies on the 'Great Place to Work' list, which provides one numeric ranking of workplace quality; Green et al. (2019) track changes in a firm's Glassdoor ratings to predict stock returns; and Huang et al. (2020) use the 'Business Outlook' rating from Glassdoor to study post-earnings-announcement drift. A more recent contribution by Campbell and Shang (2022) develops a text-based measure of corporate misconduct risk using employee written comments on Glassdoor.

However, while these studies demonstrate that even a single perception metric contains value-relevant information, they typically analyze employee sentiment, cultural tone, or internal outlook in isolation. Focusing solely on one aggregate score limits researchers' ability to disentangle conceptually distinct channels, such as employee morale versus perceived organizational risk, and may mask heterogeneity across critical workplace dimensions (e.g., compensation, leadership, and work–life balance). Moreover, numeric ratings alone fail to capture the nuance embedded in free-form employee narratives, while text-only sentiment measures often disregard the comparative structure and scale provided by numerical ratings.

Our study addresses these gaps by constructing a multidimensional employee-perception proxy from Glassdoor. We combine (i) the platform's nine numeric ratings that cover discrete aspects of the workplace with (ii) machine-learned sentiment and risk indicators extracted from the full corpus of textual reviews (Figure 1 shows an example of an employee review from Glassdoor). This integrated measure preserves the comparability of structured scores while capturing the subtle cues contained in written comments. By linking this richer proxy to firm valuation through credit-market outcomes, CDS spreads [3], we provide new evidence on how the qualitative side of human capital is priced in CDS markets, and we show that Glassdoor-based information complements, rather than duplicates, traditional structural financial indicators.

[3] We will explain our rationale to use CDS spreads as a proxy of firm valuation later.

Specifically, we document significant linkage between Glassdoor-based metrics and CDS spreads on a weekly basis across U.S. firms from 2012 to 2023. This granular integration improves the cross-sectional explanatory power of CDS spreads by 2.8 percentage points (R^2 from 76.0% to 78.8%) beyond ESG scores, demonstrating that employee perspectives uniquely capture latent credit risks omitted by conventional models. Although ESG scores incorporate aspects of human capital, particularly through metrics related to labor standards, diversity and workplace safety, they are largely constructed from firm-disclosed data and tend to reflect static, policy-level attributes rather than real-time operational realities. Moreover, ESG assessments are typically updated infrequently (often annually or quarterly), limiting their responsiveness to emerging workplace conditions. In contrast, employee reviews on Glassdoor are posted continuously and reflect the lived experiences of workers as they unfold. This higher update frequency, coupled with bottom-up origin, allows Glassdoor reviews to capture time-sensitive signals of internal risk and provide a more dynamic view of human capital quality from the perspective of employees themselves.

Our results also reveal that timeliness matters for how employee perceptions translate into credit pricing. Using the same firm–week CDS panel, we estimate Glassdoor-adjusted valuations at three horizons: weekly, lagged-quarterly (45-day window), and a blend of the two, and compare their marginal fit. Weekly aggregation, which aligns reviews with CDS quotes in real time, raises mean explanatory power to 77.39%, while quarterly aggregation alone climbs slightly higher to 77.63%, indicating that slower-moving reviews still encode durable fundamentals. Crucially, combining both frequencies delivers the best performance 77.78% and the lowest AIC/BIC specifications. The evidence suggests that quarterly aggregation filters noise and embeds persistent cultural trends, whereas contemporaneous reviews can capture fast-unfolding operational shocks to some extent. Integrating these horizons therefore maximises the informational bandwidth of employee discourse, reconciling immediacy with signal stability and further underscoring why Glassdoor data outperform slower, policy-oriented ESG updates in credit-risk models.

We further find two potential channels through which the information influences CDS spreads: (i) employee sentiment as a behavioral indicator and (ii) textual risk signals as early-warning insider information. We find that employee reviews not only serve as a sentiment-signal but also reflect risk-related information. By decomposing these informational pathways, we show that employee reviews are not merely expressions of sentiment but contain forward-looking signals that precede significant increases in future CDS spreads. These predictive patterns position employee perceptions as an informal yet informative disclosure channel, akin to early signals conveyed by corporate insiders.

Further, to identify the causal impact of employee sentiment on credit spreads, we leverage two exogenous affective shocks: blockbuster movie releases and aviation fatalities. These shocks are orthogonal to firm-specific fundamentals and capital market conditions, but have been shown to systematically influence individual affective states [4]. As such, they serve as valid instruments for employee sentiment, affecting CDS spreads only through their impact on how employees evaluate and report their workplace experiences. By isolating variation in sentiment that is driven by external mood fluctuations rather than endogenous firm conditions, we identify a causal pathway from employee sentiment to perceived credit risk in CDS markets, providing clean identification of the emotional transmission mechanism into shaping investors' perception in CDS markets.

Additionally, our analysis explores critical heterogeneity in how human capital informs CDS spreads, which lend support to the underlying mechanism. First, sector-level decomposition demonstrates that workforce dynamics explain 85.72% of CDS spreads in labor-intensive sectors (e.g., Consumer Goods, Healthcare) on average, compared to only 53.68% in regulation-constrained industries like the financial sector, a divergence attributable to the relative importance of operational stability versus regulatory arbitrage in driving default risk. Second, CDS valuation adjusted for ESG scores identifies social factors as the dominant component (mean weight = 42.47%) in pricing stakeholder risk

[4]These shocks, drawn from the literature on emotional contagion and mood spillovers, are known to induce generalized mood states in the population (Hirshleifer and Shumway, 2003; Edmans et al., 2007), which employees internalize in their workplace perceptions and reviews.

premiums, substantially exceeding environmental (19.80%) and governance (31.87%) weights. Notably, governance factors exhibit crisis-sensitive amplification, with their contribution rising by 22% during systemic shocks. Together, these findings reorient the 'S' in ESG from a peripheral compliance metric to a central risk factor, quantifying its materiality through two channels: (i) labor intensity as a sectoral moderator and (ii) social capital as the primary conduit for pricing stakeholder-driven default risk.

Our study first contributes to the growing literature examining how human capital affects firm valuation by providing a clearer empirical environment for identifying such effects. Much of the existing evidence on human capital's impact has been derived from equity markets, with a focus on proxies like employee sentiment and job satisfaction influencing stock returns, volatility, and firm reputation (Edmans, 2011; Green et al., 2019; Chemmanur et al., 2021). However, because equity markets aggregate diverse sources of uncertainty, including investor sentiment, heterogeneous expectations, and macroeconomic shocks, firm-specific signals related to human capital become easily obscured or distorted (Lamont and Stein, 2006; Baker and Wurgler, 2007; Benhabib et al., 2016; Da et al., 2015; Baker et al., 2016) [5]. Stock prices frequently respond to transient sentiment fluctuations or speculative demand, making it difficult to distinguish fundamental updates driven by genuine changes in workforce quality from short-term market noise. Consequently, isolating the valuation impact of subtle, internal factors such as employee morale, organizational culture, or workplace stability is inherently challenging in equity markets.

In light of these limitations, we turn to the credit default swap (CDS) market, where pricing is driven by institutional investors with stronger incentives to incorporate high-frequency credit signals and firm-level soft information through active hedging strategies

[5] For example, Benhabib et al. (2016) demonstrate that sentiment-driven equilibria can cause persistent deviations in asset prices unrelated to fundamentals, while Da et al. (2015) show that equity markets react strongly to ambient anxiety, even in the absence of firm-specific news. Similarly, Baker et al. (2016) model how belief dispersion leads to speculative mispricing. These dynamics imply that firm-specific soft information, such as employee perceptions of workplace stability or internal morale, may be easily overwhelmed by market-level noise, making it difficult to isolate the informational content of human capital in equity prices.

[6]. Meanwhile, CDS spreads more directly reflect downside risk, and their monotonic relationship with deteriorating fundamentals allows CDS pricing to detect internal risk signals that equity markets often obscure. As shown by Campello et al. (2019), Ham and Koharki (2016), and Tran et al. (2024), CDS valuations respond predictably to worsening fundamentals, while remaining relatively insensitive to managed earnings or optimistic equity sentiment. Augustin and Izhakian (2020) further demonstrate that under uncertainty, CDS investors assess risk more consistently, focusing primarily on potential losses rather than growth expectations. These features collectively make CDS markets a more effective environment for isolating internal downside risks and enable us to identify the valuation implications of human capital with greater precision than in equity-based settings.

We also consider our Glassdoor-based metrics as a methodological advancement in the measurement of human capital. Existing proxies, such as firm-level payroll expenditures, average compensation, or single-dimensional satisfaction scores, may overlook the richness and heterogeneity of how human capital is experienced and perceived inside the organization. Therefore, we integrate both structured (numeric) and unstructured (textual) employee inputs to form a joint perception-based measure that reflects distinct dimensions of human capital. Besides, our use of machine learning to extract sentiment and risk-related information from textual reviews enables us to move beyond surface-level satisfaction scores and recover latent perceptions tied to operational risk. Furthermore, unlike traditional ESG-based human capital metrics, our data reflect continuous, bottom-up assessments by employees with direct knowledge of internal conditions. This shift from reported to experienced human capital not only improves granularity and timeliness but also helps uncover the mechanisms through which employee sentiment and risk awareness shape external valuation.

[6] Coughlan et al. (2022) show CDS markets are overwhelmingly dominated by institutional investors, who account for over 85% of trading volume according to CFTC data. As Zhao et al. (2022) document, this structure enables superior price discovery, particularly in the tail of the risk distribution, because capital-at-risk creates stronger incentives for accurate and timely valuation compared to markets driven by sentiment or speculation.

Our methodological contribution lies in adapting the Bayesian shrinkage framework developed by Bai and Wu (2016) to the context of human capital valuation.[7] We extend this approach by first orthogonalising the multidimensional Glassdoor-based metrics with respect to traditional CDS spreads determinants and then treating the residual components as latent, valuation-relevant signals [8]. This two-step set-up allows us to quantify how much of the residual variation in CDS spreads is attributable to Glassdoor-based metrics, over and above what traditional financial fundamentals and ESG scores explain.

Alternative methods, such as cross-sectional OLS regressions or principal component analyses (PCA), face limitations in high-dimensional settings. These approaches are prone to overfitting, particularly when incorporating text-derived employee sentiment variables that vary substantially across firms and time (Harvey et al., 2016; McLean and Pontiff, 2016). Moreover, traditional methods like OLS and lasso perform poorly in high-dimensional asset pricing due to overfitting or excessive sparsity, such as baseline CDS spreads or firm-level risk profiles (Kozak et al., 2020; Freyberger et al., 2020). They also offer limited ability to discipline noisy, sparse data, especially when firm coverage is imbalanced or employee reviews are irregularly distributed (Green et al., 2017). By embedding the orthogonalised human-capital signals in a structured prior, the Bayesian shrinkage framework disciplines noisy inputs via posterior precision, accommodates firm-specific heterogeneity, and allows for partial updating around a baseline, yielding an empirically tractable way to embed human capital signals into firm value measured by CDS spreads.

Our separation of the two potential channels through which employee reviews influence firm valuation represents a novel contribution to the literature. While prior studies have established that employee sentiment can predict market outcomes (Edmans, 2011;

[7]In their original application, Bai and Wu use this framework to explain variation in CDS spreads by anchoring them to a structural benchmark and sequentially incorporating firm-level characteristics.

[8]Formally, we regress each Glassdoor metric on the baseline CDS covariates and carry the residuals into the shrinkage step. This residualisation removes mechanical correlations with fundamentals, ensuring that the Bayesian update reflects incremental human-capital information rather than re-scaled financial ratios. Full details and robustness checks appear in Appendix A.

Green et al., 2019; Huang et al., 2020), they generally do not distinguish between distinct informational mechanisms. This distinction is critical because one pathway reflects a behavioral channel, whereby collective mood or morale, regardless of its objective accuracy, affects market perception and CDS spreads; the other reflects a conventional informational channel, in which employees possess and communicate early signals of deteriorating internal conditions, akin to informal insider disclosures. And we use textual analysis of employee reviews to separate the impact of overall sentiment from the impact of specific risk-related information, making it possible to tell whether CDS pricing reflects mood or actual internal problems.

Importantly, our results indicate that both channels operate simultaneously. On one hand, aggregated employee sentiment predicts changes in CDS spreads in a pattern consistent with behavioral biases in investor belief updating. On the other hand, textual reviews contain predictive signals that anticipate future credit deterioration, even after controlling for financial covariates and market sentiment. This suggests that employees can possess material, forward-looking information that is not captured through standard disclosure mechanisms, and are willing to share such information on platforms like Glassdoor. These findings extend the literature on soft information and investor learning by showing that employee reviews serve not only as mood signals but also as early warning indicators of firm-specific risk.

Finally, we contribute to the literature by documenting interesting heterogeneity in how human capital information is priced in CDS markets. Our findings show that the influence of Glassdoor-based metrics varies systematically across industries, depending on their reliance on labor as a core production input. Moreover, by integrating ESG dimensions into CDS valuation, we demonstrate that the Social score plays a central role in shaping credit risk perceptions. These insights help reframe the role of human capital and social capital in CDS markets, positioning them as critical inputs in default risk pricing rather than peripheral disclosure metrics.

The remainder of this paper is structured as follows: Section 2 describes data and sample construction, Section 3 outlines our methodology, Section 4 presents empirical results, and Section 5 concludes.

2. Data collection and Sample Construction

We collect data on U.S. publicly traded corporations from multiple sources. Our dataset begins with the universe of firms with available credit default swap (CDS) data in the Markit database, which we then match with financial statement information from Compustat, stock option implied volatilities from Ivy DB OptionMetrics, and stock market data from the Center for Research in Security Prices (CRSP). Then, we incorporate environmental, social, and governance (ESG) scores from MSCI ESG Ratings and employee review data from Glassdoor.

A firm is included in our final sample if it satisfies the following criteria: (i) it has a valid five-year CDS spread quote, (ii) its financial statements contain book value of debt and total assets, (iii) it has at least one year of daily stock return history to compute realized volatility and market capitalization, and (iv) it has non-missing observations in both MSCI ESG and Glassdoor databases. We use the weekly Wednesday data as a proxy for the full week data (from Monday to Friday) like Bai and Wu (2016). Meanwhile, due to the structural limitations of the MSCI ESG database, the coverage of available company data has significantly expanded since 2012. Additionally, the OptionMetrics IvyDB database, which undergoes periodic updates, only provides option data up to August 31, 2023.

To ensure consistency in data availability and to meet the requirements for our empirical analysis, we define our sample period from August 2012 to August 2023, aligning with the expansion of MSCI ESG coverage and the latest available option data from OptionMetrics. And finally we identify a subset of 417 publicly traded U.S. firms with complete financial fundamental information, ESG scores and Glassdoor information.

2.1 CDS and Firm Fundamentals

Credit default swaps (CDS) are over-the-counter contracts that provide protection against credit events of a reference entity. The buyer of protection makes periodic premium payments to the seller until either the contract reaches maturity or a credit event occurs, triggering a settlement. Unlike credit ratings, which distinguish between temporary shocks and permanent shocks to a company's value, and will only change in the event of a permanent shock (Gredil et al., 2022), CDS spreads incorporate real-time market perceptions of a firm's ability to meet its financial obligations, consider the temporary shock which may trigger contractual terms affecting a firm's ability to purchase raw materials from suppliers and its production, making them a forward-looking indicator of firm value.

Our CDS data are sourced from Markit, which aggregates and filters quotes from multiple contributors (banks and brokers) to generate consensus CDS spreads for each reference entity. The dataset provides CDS spreads across various contract terms, currencies, and documentation types. Consistent with prior literature (Bai and Wu, 2016), we focus on five-year CDS contracts denominated in U.S. dollars with modified restructuring (MR) clauses, as this contract type is the most liquid. To ensure reliability, we exclude observations with CDS spreads exceeding 10,000 basis points, as such extreme values often indicate illiquid or distressed trading conditions.

The Markit CDS database contains CDS spreads for 1,487 unique U.S. company names from 2012 to 2023. To integrate CDS data with firm fundamentals, we match each entity to its financial statement information retrieved from Compustat. We also exclude financial firms with Standard Industrial Classification (SIC) codes between 6000 and 6999 to mitigate regulatory differences. Through this matching process, we identify a subset of 476 publicly traded U.S. firms with complete financial fundamental information. And also given the limited ESG coverage in earlier years and our requirement that each firm has complete ESG information, our final dataset remains 417 publicly traded firms after integrating ESG ratings into the broader dataset.

For consistency, we sample CDS data on a weekly basis, selecting Wednesday as the reference date each week, covering a total of 706 active weeks. Following prior literature (Bai and Wu, 2016), we match financial statement data with market-based variables using the 45-day rule, ensuring that financial statement information from the most recent quarter is available before it is linked to CDS spreads, stock market variables and Glassdoor information. Specifically, we match CDS spreads and stock market data between:

- **May 15 to August 14** with Q1 balance sheet data,
- **August 15 to November 14** with Q2 balance sheet data,
- **November 15 to February 14** with Q3 balance sheet data, and
- **February 15 to May 14** with Q4 balance sheet data.

This matching rule accounts for the typical lag in financial reporting and ensures that the financial statement information used in our analysis is publicly available at the time of CDS spread valuation.

2.2 ESG Data from MSCI

To incorporate environmental, social, and governance (ESG) considerations into our analysis, we obtain MSCI ESG Ratings, a widely used measure of firms' sustainability and governance practices. MSCI assigns ESG scores to companies based on a combination of industry-specific risk exposure and firm-level policies. These ratings are updated on a monthly basis, ensuring that they capture evolving ESG-related risks and improvements over time.

One challenge in integrating MSCI ESG data into our dataset is that the comprehensiveness of ESG coverage improved significantly following a major database update in 2012. Prior to this update, ESG ratings were available for only a subset of firms, primarily large-cap publicly traded corporations. However, after the update, coverage expanded to include more mid-cap and smaller publicly traded firms, leading to a more complete dataset. As a result, while ESG ratings are available for most firms in recent years, historical ESG data are more sparse, particularly for firms that were not included in MSCI's initial coverage universe.

To align ESG data with firm fundamentals and CDS spreads, we follow a two-step matching procedure:

- Firm-Level Matching: We use Compustat firm identifiers to match ESG scores with financial statement and CDS data, ensuring consistency in firm coverage;
- Time Alignment: Since MSCI ESG scores are updated monthly, we apply a quarterly aggregation. Specifically, for each firm-quarter, we take the last available ESG rating before the financial quarter-end to ensure that the information used in our analysis reflects what was available to investors at that time.

Table 1 provides descriptive statistics for fundamental firm characteristics across CDS spread quintiles. The average CDS spread across all firms is approximately 136 basis points. Notably, firms in the lowest CDS quintile (Q1) have a mean spread of only about 29 basis points, whereas firms in the highest quintile (Q5) exhibit a significantly elevated mean spread of over 405 basis points, emphasizing the substantial heterogeneity in perceived default risk. Financial leverage, a critical determinant of default risk, is prominently reflected in these quintile differences. The mean total debt-to-market capitalization ratio is modest at 0.184 in the lowest quintile and rises sharply to 1.544 in the highest quintile. This monotonic increase is consistent with the notion that firms with higher leverage face greater credit risk. Other key financial metrics demonstrate similar relationships with CDS spreads.

In addition to examining firm characteristics across CDS quintiles, we further analyze these characteristics by industry sector classifications based on the Sustainable Industry Classification System (SICS) developed by the Sustainability Accounting Standards Board (SASB). Table 2 summarizes key financial and ESG metrics across different sectors, highlighting important industry-specific attributes that influence credit risk assessments.

The SICS sector classification identifies substantial heterogeneity in CDS spreads and firm characteristics across industries. Firms within the Renewable Resources & Alternative Energy sector exhibit notably lower average CDS spreads (approximately 55 basis points), reflecting both lower financial leverage (average total debt-to-market capitalization ratio of 0.295) and superior ESG scores (average ESG overall score of 5.120). In contrast, firms in sectors such as Transportation and Technology & Communications have substantially higher average CDS spreads (approximately 208 and 180 basis points, respectively), coinciding with significantly higher leverage and comparatively lower ESG scores.

Overall, these descriptive statistics across CDS quintiles and SASB industry sectors illuminate key financial and ESG characteristics that systematically relate to market perceptions of firm creditworthiness. Understanding these patterns is critical not only for investors and credit analysts aiming to accurately price risk but also for corporate managers seeking to enhance firm value through strategic financial management and sustainability initiatives.

2.3 Employee Review Data from Glassdoor

Glassdoor is an influential online platform that provides employees with the opportunity to anonymously review their employers. Since its inception in 2008, Glassdoor has emerged as a pivotal source of real-time, crowdsourced insights into workplace conditions, employee satisfaction, corporate culture, and managerial effectiveness. Employees offer assessments through both structured numerical ratings and unstructured textual commentary, thus capturing nuanced aspects of firm internal dynamics that traditional corporate disclosures frequently miss.

Our analysis utilizes Glassdoor reviews as indicators of firm-level human capital quality and employee sentiment. We extract both numerical ratings and written reviews. And from reviews, we measure employee sentiment scores and risk-related information to comprehensively assess the role of employee-generated information in shaping firm valuation and perceived risk.

Specifically, employees rate their firms across several dimensions on a scale from 1 to 5, with ratings available for Overall Firm Rating and six detailed categories reflecting workplace conditions: Work-Life Balance, Career Opportunities, Compensation and Benefits, Senior Management, Corporate Culture and Values, and Diversity and Inclusion. Employees further provide categorical ratings on broader dimensions including Business Outlook, CEO Approval, and the likelihood of recommending the company to peers. Business Outlook and CEO Approval ratings use a ternary coding scheme (positive = 1, neutral = 0, negative = –1), while Recommendation ratings adopt a binary measure (yes = 1, no = –1).

However, it is important to note that the Diversity and Inclusion metric was only introduced on the Glassdoor platform in 2020. As a result, this dimension contains substantial missing data throughout most of the sample period. To maintain consistency in our empirical analysis and ensure comparability across firms and time, we exclude this variable from our baseline specifications and primary inferences.

Table 3 summarizes the Glassdoor review statistics in our dataset, which comprises 3,628,342 daily employee reviews across publicly traded U.S. firms. Panel A presents the overall means across all companies and sectors. The Overall Rating averages approximately 3.61 on a 1-to-5 scale, reflecting moderate employee satisfaction across the entire sample. Approximately one-third of employees (33.5%) hold positive perceptions about their firms' Business Outlook, while CEO Approval and Recommend ratings average at 35.5% and 33.9%, respectively. Among specific workplace categories, Senior Management receives the lowest average score (2.420), indicating widespread concerns regarding managerial effectiveness. Work-Life Balance and Compensation and Benefits exhibit slightly higher averages (2.639 and 2.726, respectively), albeit with significant variation, suggesting heterogeneity in employee experiences across firms.

Panel B of Table 3 disaggregates these ratings by Sustainability Accounting Standards Board (SASB) Industry Classification System (SICS) sectors. Notable cross-sector variation is apparent. Firms within Technology & Communications, and Services sectors receive relatively higher Overall Ratings (3.744 and 3.733, respectively), suggesting favorable employee sentiment in industries characterized by innovation and growth opportunities. In contrast, Food & Beverage and Consumer Goods sectors report lower ratings (3.435 and 3.521), indicating potential issues relating to employee morale or work environment in these traditionally labor-intensive sectors. CEO Approval and Recommendation ratings similarly exhibit significant sectoral differences, with Financials and Technology sectors demonstrating higher employee endorsement, while Renewable Resources & Alternative Energy and Food & Beverage sectors lag.

The Sentiment Score, a normalized index derived from textual reviews, further enriches our assessment of employee perceptions. Sectors such as Financials, Services, and Technology & Communications record higher sentiment scores (0.184, 0.182, and 0.179 respectively), suggesting generally positive employee commentary in these dynamic sectors. In contrast, Food & Beverage and Consumer Goods show notably lower sentiment (0.090 and 0.095), indicative of prevalent negative sentiment or dissatisfaction in these industries.

Table 4 provides the correlation matrix for Glassdoor ratings, underscoring the consistency and internal coherence of employee reviews. The Overall Rating demonstrates strong positive correlations with the Recommend Rating (0.731), Business Outlook (0.624), and CEO Approval (0.599). These correlations underscore the interconnectedness of general employee satisfaction with specific leadership and outlook perceptions. Additionally, the strong inter-correlations among workplace dimensions, notably between Culture & Values and Senior Management (0.874), Career Opportunities (0.832), and Compensation & Benefits (0.807), reflect how employees' assessments of management quality and organizational culture align closely with perceived career and compensation outcomes.

Interestingly, the Sentiment Score, although positively correlated with numerical ratings, shows somewhat lower correlations with dimensions such as Compensation & Benefits (0.197) and Work-Life Balance (0.243). This suggests that textual sentiment captures subtle aspects of employee experiences that might not be fully reflected in structured numerical ratings, providing complementary information regarding the intangible aspects of workplace conditions.

3. Methodology

3.1 Sentiment Analysis for Textual Comments

In brief, we pursue text mining and sentiment analysis to analyze the information within the employees' reviews. Figure 1 shows a typical layout of an employee review on Glassdoor. Firstly, we apply text mining techniques to clean and normalize the

Glassdoor reviews. This involves removing stop words, punctuation, non-text characters, and converting the text to lowercase.

Our sentiment analysis is based on a machine learning model, specifically BERT (Bidirectional Encoder Representations from Transformers). Machine learning-based sentiment models have become increasingly prevalent in financial research due to their ability to capture context-sensitive meanings and complex linguistic structures (Gentzkow et al., 2019; Huang et al., 2023).

Unlike static lexicons, BERT is pre-trained on large text corpora and fine-tuned on sentiment classification tasks, making it more adaptable to various textual inputs, including informal or nuanced language used in Glassdoor reviews. BERT's bidirectional training enables it to consider both preceding and succeeding words in a sentence, which significantly improves its ability to assess sentiment in employee reviews.

The Sentiment score is computed as the difference between the proportions of positively and negatively classified sentences:

$$\text{Sentiment} = \%\text{Positive} - \%\text{Negative} \tag{1}$$

This measure captures the overall tone of employee commentary, with higher values indicating greater positive sentiment toward the firm. Machine learning-based sentiment models have been applied in finance to extract sentiment from news articles, analyst reports, and earnings call transcripts (Huang et al., 2023; Tetlock, 2007; Gentzkow et al., 2019). These models have demonstrated superior accuracy compared to dictionary-based methods, particularly in settings where context significantly affects the sentiment conveyed (Loughran and McDonald, 2011).

Although our baseline analysis relies on the BERT-derived sentiment scores due to their superior ability to handle contextual information and linguistic nuance, we also experimented with dictionary-based sentiment scores using the Harvard-IV lexicon. These supplementary results, available upon request, show no significant differences in direction or statistical significance compared to the BERT-based results, supporting the robustness of our sentiment-based findings.

3.2 Measuring Risk-related Indicators from Textual Comments

Beyond sentiment analysis, we aim to assess whether employee reviews contain meaningful information related to firms' risk-related events. While traditional financial disclosures and credit ratings provide retrospective assessments of financial stability and creditworthiness, employee reviews may serve as an early warning signal by revealing firm-specific operational or governance concerns before they materialize in financial statements or market valuations. To capture this information, we construct a Risk Index using Multinomial Inverse Regression (MNIR), a text-mining approach that extracts words and phrases statistically associated with future increases in credit risk (Campbell and Shang, 2022; Taddy, 2013).

A firm's risk event at time t is defined based on the relative change in its CDS spread between time t and $t+1$. Specifically, we calculate the standardized change in CDS spread, denoted as ΔCDS, as the difference between the firm's CDS spread at $t+1$ and at t, scaled by its CDS spread at t:

$$\Delta CDS_{t+1} = \frac{CDS_{t+1} - CDS_t}{CDS_t}. \tag{2}$$

We then classify a firm as having experienced a risk-related event at time $t+1$ if ΔCDS_{t+1} exceeds the cross-sectional median of ΔCDS across all firms at time t. This classification captures firms that face an unusually large deterioration in perceived creditworthiness relative to their peers, consistent with the notion that sharp CDS spread increases reflect rising concerns about a firm's financial stability and risk exposure. By using this definition, we identify potential risk events at $t+1$ and retrospectively examine whether employee reviews at time t contain textual signals, such as risk-related disclosures, that may have anticipated these future risk developments.

To extract the textual signals predictive of these risk events, we analyze employee reviews on Glassdoor, focusing on three distinct sections: Pros, Cons, and Advice to Management. Each of these sections reflects different aspects of workplace conditions and managerial effectiveness. Importantly, the same word may carry different connotations depending on the section in which it appears. For instance, the term 'growth' in the Pros section may indicate positive career advancement opportunities, whereas in the Cons section, it may suggest instability or excessive turnover. Similarly, the word 'pressure' could imply strong performance incentives in the Advice section but signify a toxic work environment in the Cons section. Thus, by analyzing these sections separately, we ensure that our Risk Index accurately reflects the different dimensions of employee-expressed concerns.

To extract the Risk Index, we apply the MNIR method, which models the probability distribution of word occurrences as a function of credit risk exposure. This statistical transformation allows us to project high-dimensional textual data onto a lower-dimensional space where words are assigned coefficients indicating their association with future CDS spread movements. The MNIR model takes the following functional form:

$$W_{j,i,t} = \frac{d_{j,i,t}}{N_{i,t}} \times \ln\left(\frac{N_{i,t}}{1 + d_{j,i,t}}\right) \tag{3}$$

$$E(W_{j,i} \mid x_{i,t}, v_{i,t+1}) = \exp\left(\alpha_j + \beta_j x_{i,t} + \phi_j v_{i,t+1}\right) \tag{4}$$

Where, $d_{j,i,t}$ is the number of all Glassdoor reviews for a given firm i at quarter t containing word j; $N_{i,t}$ is total number of words in reviews for firm i at quarter t; $W_{j,i,t}$ is the relative importance of word j across all Glassdoor reviews for a given firm i at quarter t; $x_{i,t}$ is a vector of controls for firm i in quarter t; $v_{i,t+1}$ is a dummy for whether firm i encounter a risk-related event at time $t+1$, as we defined above.

The resulting Risk Index is constructed as a weighted sum of the extracted word scores:

$$\text{Risk\_index}_{i,t} = \frac{\phi_1 W_{1,i,t}}{\sum_{j=1} W_{j,i,t}} + \frac{\phi_2 W_{2,i,t}}{\sum_{j=1} W_{j,i,t}} + \cdots + \frac{\phi_j W_{j,i,t}}{\sum_{j=1} W_{j,i,t}} \tag{5}$$

A higher Risk Index suggests that the vocabulary used in employee reviews is indicative of heightened credit risk exposure, allowing us to quantify the extent to which employee-generated insights serve as leading indicators of financial distress.

3.3 Bayesian Shrinkage Estimation

Our empirical strategy builds upon the structural framework introduced by Merton (1974), which provides a fundamental linkage between a firm's credit risk and its underlying asset volatility and leverage through the well-known distance-to-default metric. Although Merton's structural model offers an intuitive and theoretically grounded starting point for analyzing credit spreads, it faces practical constraints due to its restrictive assumptions regarding debt structure, default thresholds, and its omission of non-financial dimensions like ESG considerations and employee-related information.

To address these limitations while retaining the foundational logic of structural credit risk modeling, we adopt a Bayesian shrinkage methodology developed by Bai and Wu (2016). This approach systematically integrates traditional financial fundamentals with previously overlooked non-financial information derived from ESG scores and employee-generated Glassdoor information. The intuition underlying our methodology is to progressively extend the model by layering additional information, and each step is carefully designed to ensure only incremental explanatory power is considered without introducing redundancy or multicollinearity issues.

We begin our valuation approach by employing the structural credit risk model introduced by Merton (1974) as a baseline framework to estimate firms' CDS spreads. Further, we predict the CDS spreads based on the baseline framework and three different information layers: firm fundamentals, ESG scores, and Glassdoor information, sequentially. Each process is designed to isolate incremental information while mitigating overfitting:

1. Baseline Valuation (MCDS): First, we construct a baseline valuation of firms' CDS spreads, using the Merton model's distance-to-default approach. This measure, labeled MCDS, serves as our baseline model for subsequent analysis. Recognizing the common bias inherent in structural models documented by prior literature (Eom et al., 2004), we employ a nonparametric local quadratic regression to calibrate MCDS to actual market-observed CDS spreads. This adjustment method allows us to flexibly correct for model misspecifications without enforcing rigid parametric assumptions, effectively aligning

theoretical valuations closer to observed market conditions.

2. Fundamental Augmentation (FCDS): Second, we extend the baseline MCDS valuation by incorporating additional financial fundamentals, described in Section 2. These characteristics are first orthogonalized relative to the MCDS predictions using local linear regressions separately, isolating the incremental informational content of each fundamental factor relative to the benchmark MCDS valuation. The unique contributions from these fundamentals are then integrated into the valuation via a Bayesian shrinkage estimation. This method aggregates the information from various characteristics into a weighted-average CDS valuation (FCDS), with the weights determined via Bayesian updating.

Crucially, the Bayesian approach dynamically updates the weights assigned to each characteristic, smoothing temporal fluctuations in coefficients by using prior estimates derived from historical information. This intertemporal stability is achieved by imposing a Bayesian shrinkage prior, mitigating erratic shifts in parameters that commonly arise due to transient noise in financial data.

Additionally, our methodology effectively addresses missing data, common in large cross-sectional datasets, employing reliability-based imputation developed by Bai and Wu (2016). Specifically, missing values for particular characteristics are filled using weighted averages of available characteristics, with weights determined by historical predictive accuracy (measured through R^2 statistics). Thus, characteristics with historically greater explanatory power exert a stronger influence on the imputed values, further enhancing robustness and minimizing measurement error.

The resulting FCDS valuation synthesizes MCDS with orthogonalized fundamentals, effectively decomposing CDS spreads into a Merton-driven baseline and incremental fundamental adjustments.

3. Non-Financial Integration (ECDS & GCDS): Third, after incorporating firm fundamentals into the valuation (FCDS), we further enrich our model by adding non-financial data, ESG ratings from MSCI and Glassdoor-derived metrics. Each additional set of information, first ESG and subsequently Glassdoor information, is integrated using

a similar orthogonalization and Bayesian weighting approach. The rationale is to isolate the incremental explanatory power of these non-financial indicators beyond traditional financial metrics. At the same time, we also separate the human capital reflected in traditional ESG scores from the employee information reflected in Glassdoor. ESG ratings reflect firm sustainability and governance quality, while Glassdoor information captures real-time employee sentiment and potential insider-based risk-related perceptions.

ESG factors are first orthogonalized with respect to the residual variation not explained by financial fundamentals, and we generate an ESG-adjusted CDS (ECDS); Glassdoor metrics, including numerical ratings, employee sentiment (Sentiment), and textual risk signals (Risk Index), are subsequently orthogonalized relative to ESG-adjusted valuations, generating a Glassdoor-adjusted CDS (GCDS). This disciplined sequential approach guarantees that each layer of data provides unique, additive insights into firm value dynamics, free from contamination by previously integrated variables.

The resulting final valuation metric (GCDS) embodies four distinct yet interconnected components of CDS spreads: (1) structural leverage-volatility risks as captured by Merton's model, (2) incremental signals derived from detailed firm-specific financial analysis, additional non-financial insights, reflecting (3) ESG practices and (4) employee perception from Glassdoor. Conceptually, our Bayesian shrinkage methodology aligns closely with Merton's original structural insight, CDS spreads reflect evolving market assessments of a firm's total risk profile, encompassing both measurable financial risks and qualitative dimensions such as organizational culture and sustainability commitments.

In comparison to traditional linear regression methods, the Bayesian framework exhibits two principal advantages. First, the Bayesian updating mechanism ensures intertemporal stability of estimates, essential for high-dimensional data contexts where parameter volatility can obscure meaningful signals. Second, its robust approach to missing data imputation surpasses conventional strategies like simple mean substitution, explicitly accounting for each characteristic's predictive reliability.

The table above provides a clear summary of the different layers of our CDS valuation measures, each capturing distinct aspects of firm-specific risks. It outlines how we

Descriptions of CDS Measures

Variables	Interpretation
MCDS	Structural Anchors: Market-implied pricing of leverage and volatility risks.
FCDS	Fundamental Adjustments: Incremental signals from financial statement analysis.
ECDS	ESG Adjustments: Incremental signals from ESG scores and ESG compliance costs.
GCDS	Employee View Adjustments: Incremental signals from Glassdoor information and employee-related risk exposures.

progressively adjust the baseline structural model (MCDS) by incorporating additional information, including firm fundamentals (FCDS), ESG factors (ECDS), and Glassdoor information (GCDS). Detailed implementation procedures, technical derivations, and equations are provided in Appendix.

3.4 Instrumental Variables

We extend our analysis to examine whether the relationship between employee sentiment (captured by Glassdoor information) and CDS spreads reflects a causal effect. To address potential endogeneity concerns, we employ an instrumental variables (IV) approach using two distinct exogenous instruments: the number of blockbuster movie releases ($Release$) and global aviation fatalities ($Fatalities$). Blockbuster movie releases generate positive sentiment shocks by enhancing general mood and enjoyment, while aviation fatalities induce immediate negative emotional reactions through widespread media coverage and increased anxiety.

We utilize weekly counts of blockbuster movie releases ($Release$) from 2012-2023 as our first IV, sourced from Box Office Mojo. Hong and Wei (2025) find a significant positive correlation between blockbuster movie releases and US stock market returns in the subsequent week, because movies can improve investors' mood by generally providing enjoyment and escapism. Inspired by this, we consider that blockbuster movies may improve employees' emotion and have a possible impact on employee sentiment, while the release of movies cannot affect one firm's valuation directly. Followed the measurement of Hong and Wei (2025), we also define the blockbuster movie as the movie which has released in over 4,000 theaters on the release dates. Following this threshold, there are 169 unique movies considered as a blockbuster, about 14 movies per year.

Figure 2 shows the number of blockbuster movie releases per year, and reveals COVID-19's transient suppression effect (2020-2021) followed by a steady recovery, with a mean of 2 movies per week in 2020 and 5 for the whole sample. Crucially, the temporal design aligns this week's movie releases with next week's Glassdoor sentiment scores, capturing the natural delay in mood propagation: employees typically view films during weekends, with emotional effects persisting into subsequent workdays. This one-week lag structure ensures contemporaneous firm operations remain unaffected while isolating sentiment transmission mechanisms. For robustness check, we also conduct the same instrumental variable tests on the sub-samples from 2012 to 2019, and their results are not significantly different from those of the full sample.

Our second IV uses weekly global aviation fatality ($Fatalities$) counts from the Aviation Safety Network. Prior research, such as Kaplanski and Levy (2010), has shown that aviation disasters trigger immediate and widespread public anxiety, largely driven by intense media coverage of such tragic events. These emotional responses are not confined to passengers or the aviation industry but extend broadly to the general public, including employees across various sectors. We argue that such high-profile disasters, while unrelated to firm-specific fundamentals, can negatively affect overall workforce sentiment through heightened feelings of vulnerability, fear, and uncertainty.

Importantly, these events serve as exogenous shocks to employee emotions because they are unexpected, externally driven, and independent of individual firm's operational or financial conditions outside aviation and movie industry . This makes aviation fatalities a valid and powerful instrument for identifying shifts in employee sentiment that are plausibly unrelated to firm-specific factors. Figure 3 illustrates the annual total number of fatalities from aviation safety events worldwide during our sample period, highlighting both periods of relative stability and spikes associated with major aviation incidents. On average, there are 28 fatalities per week, which reflects a non-trivial and recurring source of emotionally salient events that can influence public and workforce sentiment on a regular basis. By leveraging these variations, we aim to isolate the effect of employee sentiment on firm value in a way that addresses endogeneity concerns.

Diagnostic tests for instrument validity, including under-identification, weak identification, and overidentification tests, consistently support the credibility and robustness of our IV approach. The test results are presented in Table 11, and we provide further explanations in Section **??**.

4. Results

4.1 Statistics Analysis of Adjusted CDS Measures

Table 5 presents summary statistics and correlations of various CDS measures. Panel A reports a mean log market CDS (lnCDS) of 4.422 with a standard deviation of 0.882, ranging from 0.883 to 9.175. Adjusted CDS measures demonstrate similar means but notably lower volatility, suggesting their effectiveness in smoothing fluctuations inherent in raw CDS data. Notably, the Fundamental-adjusted and ESG-adjusted CDS exhibit high correlations with the market CDS (0.865 and 0.873, respectively), underscoring their incremental explanatory power over traditional structural models.

Detailed insights into ESG-adjusted CDS (lnECDS) are shown in Table 6. These data reveal substantial heterogeneity in ESG contributions, with social (S) factors holding the largest average weight at 42.47%, governance (G) at 31.87%, and environmental (E) at 19.80%. The overall ESG score itself holds a minor average weight of 5.86%, accompanied by significant variability across firms. This suggests nuanced differences in how ESG dimensions affect credit risk assessments. Figure 4 illustrates temporal shifts in ESG factor weights, including a gradually declining but persistently dominant social factor, heightened governance significance during crises, and steadily increasing attention to environmental factors, reflecting evolving investor priorities.

Panels B–D of Table 5 detail Glassdoor-adjusted CDS (GCDS) across different aggregation frequencies and timing conventions. Panel B (weekly) demonstrates that contemporaneous matching of Glassdoor information with CDS data yields mean ln(GCDS) values of approximately 4.438 and robust correlations (0.879–0.881), indicating that real-time employee reviews effectively capture current credit risk perceptions.

Panel C (quarterly), employing a 45-day lagged aggregation of quarterly Glassdoor information before matching to CDS, also yields mean values close to 4.439 and strong correlations (0.878–0.883), suggesting that lagged employee information retains substantial predictive capability regarding credit risk.

Panel D (weekly + quarterly) combines real-time and lagged quarterly employee information, achieving the highest observed correlation of 0.884, with mean ln(GCDS) at 4.445. This result highlights the enhanced informational advantage derived from utilizing both contemporaneous and historical sentiment insights to assess persistent credit risk.

Finally, Panel E illustrates high inter-scheme correlations (0.994–0.997) across weekly, quarterly, and combined GCDS indices, indicating consistent sentiment patterns regardless of aggregation method. The slight improvement in correlation from single-aggregation schemes (0.882) to combined aggregations (0.884) underscores the value added by integrating multiple data horizons.

4.2 Comparison of Model R^2 Performance

To gauge the cross-sectional explanatory performance of the adjusted CDS valuations, we perform five sets of cross-sectional regressions on each date:

$$ln(\mathrm{CDS}_t^i) = a_t + b_t(\frac{D}{E})_t^i + c_t(\sigma_E)_t^i + e_t^i \tag{6}$$

$$ln(\mathrm{CDS}_t^i) = ln(\mathrm{MCDS}_t^i) + e_t^i \tag{7}$$

$$ln(\mathrm{CDS}_t^i) = ln(\mathrm{FCDS}_t^i) + e_t^i \tag{8}$$

$$ln(\mathrm{CDS}_t^i) = ln(\mathrm{ECDS}_t^i) + e_t^i \tag{9}$$

$$ln(\mathrm{CDS}_t^i) = ln(\mathrm{GCDS}_t^i) + e_t^i \tag{10}$$

All regressions are on the logarithms of CDS for better distributional behaviors. The bivariate linear regression (BLR) in equation (6) creates a benchmark by taking the two Merton model inputs directly as explanatory variables, while ignoring the Merton model's suggestion for combining the two variables into a standardized distance-to-default measure in equation (6). The second regression takes MCDS as the explanatory variable, which takes suggestions from the Merton model in both the inputs and the distance-to-default standardization and removes the average bias at different risk levels via a local quadratic regression, shown in equation (7). The third regression in equation (8) takes the FCDS as the explanatory variable, which combines the Merton-based valuation with a long list of additional firm fundamental characteristics. The fourth regression in equation (9) takes the ECDS as the explanatory variable, which combines the firm-fundamental-adjusted valuation with orthogonalized components in ESG scores. Finally, the last regression in equation (10) takes the GCDS as the explanatory variable, which combines the ESG-adjusted valuation with all available Glassdoor information, including numerical ratings, employee sentiment (Bert_sentiment) and the indicators of risk-related events (Risk_Index) extracted from textual reviews, as described in Section 3. By design, MCDS, FCDS, ECDS and GCDS are not biased. Hence, we set the intercept to zero and slope to one for the last four regressions, with the error term e_t^i directly defined as the log difference between the market observation and the adjusted model valuation.

Table 7 compares the explanatory power (measured by mean R^2) across different CDS valuation models. The Benchmark model achieves an average R^2 of 55.14% with moderate variability. Introducing structural information through the Merton-based CDS significantly improves the mean explanatory power to 60.64%, while further adjustments based on firm fundamentals increase the average R^2 to 74.55%. The ESG-adjusted CDS demonstrates the highest explanatory power with a mean R^2 of 75.97%, supported by the lowest Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC), indicating superior model fit.

Further comparison by frequency and type of Glassdoor data adjustments in Table 8 highlights the incremental explanatory power gained by incorporating employee-generated sentiment and risk indicators. For weekly data (Panel A), incorporating numerical ratings, sentiment scores, and risk indicators achieves the highest mean R^2 (77.39%). Similarly, quarterly aggregations (Panel B) yield slightly higher explanatory power (77.63%) with all factors combined. Notably, the integration of both weekly and quarterly aggregations (Panel C) further enhances the explanatory power, reaching 77.78%, and produces the lowest AIC and BIC, clearly supporting the superior predictive capability and model robustness when utilizing both contemporaneous and lagged employee sentiment data. Therefore, the 'weekly + quarterly' Glassdoor-adjusted CDS will serve as our primary metric in subsequent analyses.

4.3 Comprehensive Analysis of Model R^2 and Sector-Specific Performance

Figure 8 illustrates the cross-sectional explanatory power (R^2) of various CDS valuation models from August 2012 to August 2023. The benchmark bivariate linear regression (BLR) serves as a baseline, consistently yielding the lowest explanatory power over the period. Each subsequent enhancement significantly improves model performance: the Merton-based CDS valuation (MCDS), the fundamental-adjusted CDS (FCDS), and particularly the ESG-adjusted CDS (ECDS) incrementally elevate the R^2. Ultimately, the Glassdoor-adjusted CDS (GCDS) demonstrates the highest explanatory power, clearly surpassing other models and confirming the incremental informational value provided by incorporating employee sentiment and risk indicators.

Table 9 provides a detailed breakdown of normalized weights assigned to specific Glassdoor variables in constructing the GCDS measure. The weights are estimated through a Bayesian shrinkage procedure and reflect the average contribution of each variable to the GCDS over time. All weights are standardized to sum to one across categories within each time window.

Panel A focuses on textual risk indicators, showing that the 'Pros' term consistently receives the highest weight (mean = 19.85%), followed by 'Advice' and 'Cons.' Figure 5 visualizes the time series of these weights. It shows that the influence of the 'Pros' term increases significantly during periods of heightened market volatility (e.g., 2015–2016, early 2020), while negative indicators ('Cons') tend to carry smaller or even negative weights during the same windows, suggesting a shifting emphasis on positive insider narratives during stress events.

Panel B examines weekly Glassdoor variables. The sentiment score contributes the most (26.48%), followed by Compensation & Benefits (10.18%) and CEO rating (9.72%). Variables such as Work-Life Balance and Business Outlook receive moderate weights. Figure 6 plots the temporal evolution of these weekly components. While sentiment remains the most influential factor throughout, some variables (e.g., Culture & Values, Career Opportunity) display declining weights over time, implying a relative reduction in their incremental informational value.

Panel C shifts to quarterly Glassdoor inputs, where sentiment score again dominates (28.01%), followed by Business Outlook (15.57%). Several variables, including Overall Rating and Career Opportunity, receive negative weights on average, indicating that, conditional on other information, they are inversely associated with credit risk perceptions. Figure 7 illustrates the time-varying weights for these quarterly variables, showing that periods of elevated market uncertainty coincide with increased reliance on sentiment and business outlook, while the role of conventional satisfaction ratings diminishes.

Sector-specific analysis in Table 10 demonstrates substantial variability in model explanatory power across Sustainability Industry Classification System (SICS) sectors. GCDS consistently exhibits superior explanatory power across most sectors, notably in Consumer Goods (85.72%), Transportation (81.83%), and Health Care (79.82%). However, substantial sectoral differences emerge, with lower explanatory performance noted in Financials (53.68%) and Services (59.27%). Renewable Resources and Alternative Energy demonstrate negative R^2 values, reflecting potential model misspecification or extreme volatility in these sectors. Overall, GCDS achieves the highest total sector-aggregated R^2 (73.62), emphasizing its robustness and effectiveness as a comprehensive credit risk measure across diverse industry contexts.

4.4 The Causality Between Glassdoor Information and CDS Spreads

Our baseline analysis establishes a robust correlation between workforce sentiment and CDS spread. To advance from correlation to causation, we employ an instrumental variables (IV) approach using two distinct instruments: blockbuster movie releases ($Release$) and aviation fatalities($Fatalities$). At the same time, in order to ensure the exogeneity of the instrumental variables, we excluded firms in the film and entertainment industry and the aviation industry from the sample, which contain 25 unique companies and 9,725 observations from our main sample. These instruments leverage exogenous variations in sentiment that are plausibly unrelated to firm-specific fundamentals, ensuring that changes in workforce sentiment reflect external emotional shocks rather than endogenous firm dynamics.

To integrate all the information in Glassdoor information into one dimension, we employ principal component analysis (PCA). The PCA reduces the dimensionality of the data by creating one composite factor ($PCA\_glassdoor$), which represents all ten numerical ratings, sentiment score as well as risk indicators provided on the Glassdoor platform. This technique ensures that the regression model remains robust while capturing the key information embedded in the Glassdoor information, without the risk of overfitting the model due to the high correlation among the individual items.

The first-stage regression, reported in Table 11, demonstrates that both instruments significantly predict Glassdoor information, as captured by the principal component factor (PCA_glassdoor). The coefficient on blockbuster movie releases is -0.002 (t=-5.27), indicating that an increase in the number of movie releases in a given week is associated with a statistically significant improvement in employee sentiment in the subsequent week. This result is consistent with prior literature documenting the broader mood-enhancing effects of entertainment, where increased exposure to cinematic experiences improves overall emotional well-being and, by extension, workplace morale. Importantly, the lag structure, where movie releases from one week predict employee sentiment in the following week, ensures that this channel operates through sentiment propagation rather than contemporaneous firm operations.

Similarly, the coefficient on aviation fatalities is 0.001 (t=11.76), suggesting that weeks with a higher number of aviation-related deaths lead to a significant decline in employee sentiment. This finding aligns with prior research on emotional contagion, which suggests that tragic events with widespread media coverage induce anxiety and risk aversion among individuals, including employees who may generalize negative sentiment to their professional environments. Unlike movie releases, which operate with a lag, aviation fatalities exhibit an immediate effect on workforce sentiment, as they trigger real-time psychological reactions.

The second-stage regression, where PCA_glassdoor is instrumented and included alongside ln(ECDS) as explanatory variables for ln(CDS), provides compelling evidence that employee sentiment exerts a causal impact on firm valuation. The coefficient on PCA_glassdoor in the second stage is 0.101 (z=1.68), suggesting that, after accounting for endogeneity, positive workforce sentiment is associated with lower CDS spreads, implying improved firm creditworthiness. This result is consistent with the premise that firms with more engaged and satisfied employees tend to experience lower operational risk, greater stability, and enhanced strategic adaptability, which translates into more favorable credit market perceptions.

Several diagnostic tests confirm the validity of our IV approach. The Kleibergen-Paap rk LM statistic of 168.057 strongly rejects the null hypothesis of under-identification, indicating that the instruments are sufficiently correlated with the endogenous variable. The Cragg-Donald Wald F statistic of 85.991 far exceeds conventional weak instrument thresholds, confirming that our instruments are strong predictors of workforce sentiment. Furthermore, the Hansen J statistic of 0.115 (p=0.7349) suggests that the overidentification restriction is not violated, meaning that the instruments are exogenous and do not directly influence CDS spreads beyond their impact on sentiment.

Taken together, these results provide strong support for the hypothesis that workforce sentiment plays a direct and economically meaningful role in shaping firm valuation in credit markets. While our baseline OLS regressions demonstrated a robust correlation between employee sentiment and CDS spreads, concerns about reverse causality and omitted variable bias necessitated an IV approach. The identification strategy employed here strengthens the interpretation of employee sentiment as a fundamental determinant of firm risk perception, rather than a mere reflection of existing firm conditions.

In summary, our IV approach confirms that employee sentiment has a causal impact on firm valuation, with higher sentiment associated with lower CDS spreads and improved credit market perceptions. By employing blockbuster movie releases and aviation fatalities as exogenous sentiment shocks, we mitigate endogeneity concerns and establish a robust causal link between workforce morale and financial risk. These findings reinforce the growing recognition that human capital is not merely an operational consideration but a fundamental driver of firm financial stability and market valuation.

5. Discussion and Conclusion

This study offers novel insights into how human capital shapes firm valuation in credit markets by leveraging a high-dimensional, real-time dataset of employee reviews from Glassdoor. While prior literature underscores the importance of human capital for firm productivity and performance, our work extends this line of research by examining how market participants use employee-generated insights to evaluate credit risk. By integrating structured numerical ratings, sentiment indicators, and unstructured textual risk disclosures, we construct a dynamic and granular measure of human capital that complements and augments traditional financial and ESG-based metrics.

Our empirical results confirm that Glassdoor-derived human capital indicators significantly enhance the explanatory power of firm credit risk models. Using a Bayesian shrinkage framework, we show that incorporating employee sentiment and risk-related textual disclosures improves the prediction accuracy of CDS spreads beyond what can be achieved with fundamentals or ESG scores alone. Notably, our approach demonstrates superior cross-sectional explanatory power, especially during periods of heightened uncertainty—such as the 2013–2014 taper tantrum, the late 2015 market dislocation, and the COVID-19 crisis. These findings highlight the salience of employee-generated information in assessing firm creditworthiness during turbulent times.

Crucially, we identify two distinct channels through which Glassdoor information influences firm valuation: (i) employee sentiment as a behavioral indicator and (ii) textual risk signals as early-warning insider information. High employee sentiment—reflecting trust in management, workplace satisfaction, and morale—is associated with tighter CDS spreads, suggesting lower perceived credit risk. This supports the view that a motivated and engaged workforce enhances firm stability and resilience. In parallel, textual risk disclosures—covering operational breakdowns, leadership concerns, or resource constraints—function as timely, insider-like alerts of potential financial distress. These disclosures offer external investors access to firm-specific soft information that would otherwise remain obscured, consistent with the literature on asymmetric information in credit markets.

Methodologically, our paper contributes to the expanding field of text-based financial analysis by implementing a robust Bayesian shrinkage technique to integrate noisy and high-dimensional textual data into credit risk modeling. This approach allows us to extract economically meaningful signals from unstructured employee reviews while mitigating overfitting and multicollinearity. Importantly, our methodology ensures that Glassdoor-derived indicators enhance rather than duplicate the explanatory content of financial and ESG variables.

The findings carry several implications for different stakeholders. For investors and credit analysts, the results suggest that incorporating employee sentiment and risk disclosures can materially improve valuation accuracy and risk assessment, particularly in volatile periods. For corporate managers, the results underscore that workplace conditions and internal transparency not only affect operational outcomes but are also priced by financial markets. Firms that foster high morale and minimize internal frictions are perceived as less risky. Finally, for policymakers, our study points to the potential benefits of integrating more standardized and systematic reporting on human capital metrics—an area still underdeveloped in ESG frameworks despite its predictive power.

Nonetheless, our study has limitations that offer opportunities for future work. Our dataset is focused on U.S. publicly listed firms where Glassdoor coverage is relatively deep; extending this framework to international firms could reveal how institutional and labor market differences moderate the observed effects. Moreover, while this paper emphasizes credit market valuations, future research could explore the role of human capital in influencing other firm outcomes such as long-term investment behavior, innovation trajectories, or M&A decisions.

6. Tables and Figures

6.1 Tables

Table 1: **Descriptive Statistics by different CDS quintiles**

Variable	Mean	Std. dev.	Mean at CDS Quintiles				
			Q1	Q2	Q3	Q4	Q5
CDS	135.946	241.259	28.957	50.075	74.919	120.303	405.484
Total debt/Market cap	0.555	1.430	0.184	0.254	0.361	0.430	1.544
Realized volatility	0.308	0.156	0.224	0.244	0.288	0.326	0.457
Liability/Market cap	0.664	0.919	0.294	0.400	0.496	0.564	1.566
Total debt/Total assets	0.341	0.161	0.310	0.312	0.327	0.341	0.414
EBIT/Interest expense	12.948	14.084	20.600	15.602	12.302	10.034	6.203
Working capital/Total assets	0.104	0.132	0.090	0.090	0.114	0.120	0.108
EBIT/Total assets	0.030	0.021	0.038	0.034	0.029	0.029	0.021
Retained earnings/Total assets	0.292	0.410	0.444	0.351	0.330	0.281	0.055
ln(Market cap)	9.890	1.434	11.321	10.540	9.868	9.305	8.413
Stock market momentum	0.150	0.354	0.188	0.171	0.137	0.165	0.087
ln(Implied/Realized vol)	0.110	0.193	0.167	0.152	0.103	0.083	0.047
ESG overall score	4.061	1.501	4.436	4.284	4.152	3.895	3.538
ESG Environmental score	4.938	2.511	5.569	5.042	4.877	4.568	4.635
ESG Social score	4.093	1.810	3.914	4.165	4.069	4.246	4.071
ESG Governance score	5.291	2.026	5.346	5.468	5.301	5.218	5.122

Notes: This table presents descriptive statistics for key financial and ESG variables, reported both at the full-sample level and across quintiles of CDS spreads. The quintiles (Q1 to Q5) are formed based on the level of CDS spreads, from lowest to highest.

Table 2: **Descriptive Statistics by SICS Sector**

Variable	SICS Sector				
	Renewable Resources & Alternative Energy	Food & Beverage	Financials	Resource Transformation	Health Care
CDS	55.169	65.348	66.560	102.243	108.664
Total debt/Market cap	0.295	0.320	0.263	0.353	0.648
Realized volatility	0.283	0.225	0.235	0.279	0.264
Liability/Market cap	0.228	0.382	0.318	0.482	0.644
Total debt/Total assets	0.367	0.449	0.268	0.333	0.306
EBIT/Interest expense	5.568	10.394	11.385	12.359	14.721
Working capital/Total assets	0.071	0.018	0.129	0.135	0.115
EBIT/Total assets	0.027	0.039	0.032	0.032	0.029
Retained earnings/Total assets	0.011	0.369	0.374	0.394	0.279
ln(Market cap)	9.971	10.484	9.506	9.761	10.634
Stock market momentum	0.068	0.139	0.179	0.162	0.174
ln(Implied/Realized vol)	0.117	0.155	0.162	0.125	0.148
ESG overall score	5.120	4.322	5.053	4.273	3.939
ESG Environmental score	4.914	4.631	5.595	4.890	5.645
ESG Social score	6.514	3.999	4.788	3.872	3.865
ESG Governance score	6.301	5.514	6.013	5.540	4.640

Variable	Infrastructure	Extractives & Mineral Processing	Consumer Goods	Services	Technology & Communications	Transportation
CDS	110.196	138.556	157.056	162.878	179.733	207.685
Total debt/Market cap	0.953	0.439	0.403	0.943	0.521	1.183
Realized volatility	0.279	0.388	0.320	0.325	0.331	0.366
Liability/Market cap	0.926	0.497	0.599	0.908	0.739	1.365
Total debt/Total assets	0.430	0.288	0.341	0.388	0.300	0.373
EBIT/Interest expense	7.431	10.730	17.719	10.359	15.432	8.514
Working capital/Total assets	0.048	0.116	0.144	0.033	0.137	0.043
EBIT/Total assets	0.023	0.020	0.038	0.028	0.029	0.026
Retained earnings/Total assets	0.131	0.268	0.384	0.165	0.197	0.178
ln(Market cap)	9.669	9.758	9.786	9.025	9.976	9.457
Stock market momentum	0.135	0.149	0.125	0.173	0.146	0.137
ln(Implied/Realized vol)	0.125	0.034	0.103	0.125	0.096	0.085
ESG overall score	3.848	3.440	4.269	3.694	4.175	3.901
ESG Environmental score	3.848	3.126	5.178	5.247	5.664	4.965
ESG Social score	4.601	4.510	4.024	3.775	4.696	3.565
ESG Governance score	5.964	4.964	5.352	5.276	5.051	5.832

Notes: This table reports the mean values of selected financial and ESG variables by SICS (Sustainability Industry Classification System) sectors. The sectors span twelve major industry groups.

Table 3: **Overall Means of Daily Glassdoor Reviews by SICS Sector**

Panel A: Overall Daily Glassdoor reviews

	Overall rating	Business outlook	CEO rating	Recommend	Work Life & Balance
Mean	3.609	33.5%	35.5%	33.9%	2.639
	Culture & Values	**Senior management**	**Career opportunity**	**Compensation & Benefits**	**Sentiment Score**
Mean	2.722	2.420	2.687	2.726	0.130

Panel B: By SICS Sector

SICS Sector	Overall rating	Business outlook	CEO rating	Recommend	Work Life & Balance
Consumer Goods	3.521	30.8%	29.6%	27.8%	2.476
Extractives & Mineral Processing	3.620	23.3%	31.5%	34.9%	2.771
Financials	3.672	49.8%	48.9%	41.2%	2.864
Food & Beverage	3.435	23.9%	27.0%	17.4%	2.197
Health Care	3.586	38.6%	38.1%	33.2%	2.784
Infrastructure	3.653	39.3%	46.7%	38.7%	2.856
Renewable Resources & Alternative Energy	3.489	32.1%	16.4%	23.7%	2.907
Resource Transformation	3.675	36.8%	39.1%	41.5%	2.943
Services	3.733	38.0%	40.3%	42.6%	2.826
Technology & Communications	3.744	39.9%	43.2%	43.5%	2.980
Transportation	3.593	35.4%	30.5%	32.8%	2.564
SICS Sector	**Culture & Values**	**Senior management**	**Career opportunity**	**Compensation & Benefits**	**Sentiment Score**
Consumer Goods	2.572	2.352	2.623	2.642	0.095
Extractives & Mineral Processing	2.689	2.521	2.786	3.120	0.130
Financials	2.724	2.633	2.764	2.784	0.184
Food & Beverage	2.166	2.056	2.269	2.189	0.090
Health Care	2.698	2.483	2.701	2.882	0.131
Infrastructure	2.893	2.714	2.933	3.215	0.142
Renewable Resources & Alternative Energy	2.493	2.446	2.704	3.022	0.107
Resource Transformation	2.770	2.604	2.913	2.991	0.155
Services	2.849	2.623	2.821	2.733	0.182
Technology & Communications	2.831	2.629	2.909	2.957	0.179
Transportation	2.534	2.381	2.728	2.887	0.119

Notes: A shows the overall sample means for eleven Glassdoor-based variables, including five numerical ratings (1–5 scale), four positive response percentages, and a standardized sentiment score derived from textual reviews. Panel B provides the sector-level means of the same variables, grouped by SICS sector.

Table 4: **Correlation Matrix of Daily Glassdoor Ratings**

	Overall rating	Business outlook	CEO rating	Recommend	Work Life & Balance
Overall rating	1				
Business outlook	0.624***	1			
CEO rating	0.599***	0.590***	1		
Recommend rating	0.731***	0.624***	0.575***	1	
Work Life & Balance	0.330***	0.414***	0.413***	0.493***	1
Culture & Values	0.402***	0.524***	0.531***	0.600***	0.830***
Senior management	0.419***	0.536***	0.538***	0.581***	0.815***
Career opportunity	0.377***	0.507***	0.469***	0.545***	0.772***
Compensation & Benefits	0.289***	0.401***	0.383***	0.433***	0.770***
Sentiment Score	0.629***	0.518***	0.505***	0.592***	0.243***
	Culture & Values	Senior management	Career opportunity	Compensation & Benefits	Sentiment Score
Culture & Values	1				
Senior management	0.874***	1			
Career opportunity	0.832***	0.820***	1		
Compensation & Benefits	0.807***	0.784***	0.824***	1	
Sentiment Score	0.301***	0.325***	0.276***	0.197***	1

Notes: This table reports the pairwise Pearson correlations among Glassdoor-based employee rating variables and sentiment scores. Variables include both numerical ratings and binary-response items. The matrix shows how closely different dimensions of employee perception are associated. Only the lower triangle and diagonal are shown. All coefficients marked with *** are statistically significant at the 1% level.

Table 5: **Summary Statistics and Correlations for CDS Measures**

Panel A: Value-adjusted CDS Measures					
Variable	Mean	Std. dev.	Min	Max	Correlation
ln(CDS)	4.422	0.882	0.883	9.175	1
ln(Merton-based CDS)	4.421	0.697	3.123	8.610	0.783***
ln(Fundamental-adjusted CDS)	4.451	0.756	2.628	8.614	0.865***
ln(ESG-adjusted CDS)	4.407	0.755	2.619	8.647	0.873***
Panel B: Weekly CDS Aggregations (Glassdoor-adjusted CDS, GCDS)					
Variable	Mean	Std. dev.	Min	Max	Correlation
ln(GCDS): Only Numerical Ratings	4.437	0.755	2.503	8.602	0.879***
ln(GCDS): Only Sentiment Scores	4.427	0.755	2.622	8.617	0.877***
ln(GCDS): Numerical + Sentiment	4.438	0.756	2.532	8.596	0.880***
ln(GCDS): Numerical + Sentiment + Risk Indicator	4.445	0.758	2.508	8.602	0.881***
Panel C: Quarterly CDS Aggregations (Glassdoor-adjusted CDS, GCDS)					
Variable	Mean	Std. dev.	Min	Max	Correlation
ln(GCDS): Only Numerical Ratings	4.439	0.759	2.500	8.599	0.880***
ln(GCDS): Only Sentiment Scores	4.427	0.758	2.571	8.617	0.878***
ln(GCDS): Numerical + Sentiment	4.439	0.760	2.500	8.591	0.881***
ln(GCDS): Numerical + Sentiment + Risk Indicator	4.446	0.760	2.447	8.578	0.883***
Panel D: Weekly + Quarterly Aggregations (Glassdoor-adjusted CDS, GCDS)					
Variable	Mean	Std. dev.	Min	Max	Correlation
ln(GCDS): Numerical + Sentiment + Risk Indicator	4.445	0.760	2.439	8.622	0.884***

Panel E: Correlation Matrix			
ln(GCDS): Numerical + Sentiment+ Risk Indicator	Weekly + Quarterly	Weekly	Quarterly
Weekly + Quarterly	1		
Weekly	0.996***	1	
Quarterly	0.997***	0.994***	1

Notes: This table presents summary statistics and pairwise correlations for log-transformed CDS measures. Panel A includes the raw CDS spread, Merton-based CDS (MCDS), fundamental-adjusted CDS (FCDS), and ESG-adjusted CDS (ECDS). Panels B–D report results for different aggregation schemes of Glassdoor-adjusted CDS (GCDS): using weekly, quarterly, and combined Glassdoor data, with varying combinations of numerical, sentiment, and textual risk indicators. Panel E provides the correlation matrix among the weekly, quarterly, and combined GCDS series.

Table 6: **Normalized Weights of ESG Scores in ESG-adjusted CDS**

Variable	Mean	Std. dev.	Min	Max
ESG Overall	5.86%	0.110	-17.66%	24.10%
E Score	19.80%	0.079	2.54%	35.16%
S Score	42.47%	0.087	18.37%	57.41%
G Score	31.87%	0.086	20.41%	58.09%

Notes: This table shows the normalized weights of overall ESG scores and their environmental (E), social (S), and governance (G) components in constructing the ESG-adjusted CDS measure. The weights are estimated from a Bayesian shrinkage procedure and reflect the relative contribution of each ESG component in explaining variation in CDS spreads across firms and over time. All weights are standardized to sum to one across categories within each time window.

Table 7: **Model R^2 Performance and Information Criteria**

Variable	Mean R^2	Std. dev.	Min R^2	Max R^2	AIC	BIC
Benchmark	55.14%	0.0636	39.03%	67.65%	215191.1	215219.7
Merton-based CDS	60.64%	0.0538	47.10%	73.11%	166127.0	166146.0
Frim Fundamental-adjusted CDS	74.55%	0.0512	58.15%	82.35%	122286.9	122305.9
ESG-adjusted CDS	75.97%	0.0478	60.38%	83.59%	116689.2	116708.3

Notes: This table reports the mean cross-sectional R^2 values, standard deviations, and model fit criteria (Akaike Information Criterion and Bayesian Information Criterion) for five CDS valuation models: a benchmark structural model, Merton-based CDS, fundamental-adjusted CDS, and ESG-adjusted CDS.

Table 8: **Comparison of R^2 and Information Criteria by Frequency of Glassdoor-adjusted CDS**

Panel A: Weekly Glassdoor-adjusted CDS (GCDS)						
	Mean	Std. dev.	Min	Max	AIC	BIC
Only Numerical Ratings	77.01%	0.046	61.80%	0.84486	112098.3	112117.3
Only Sentiment Scores	76.72%	0.047	61.49%	0.84139	113555.6	113574.6
Numerical + Sentiment	77.17%	0.046	62.05%	0.84598	111380.2	111399.2
Numerical + Sentiment + Risk Indicator	77.39%	0.046	62.61%	0.85588	110287.8	110306.8
Panel B: Quarterly Glassdoor-adjusted CDS (GCDS)						
	Mean	Std. dev.	Min	Max	AIC	BIC
Only Numerical Ratings	77.21%	0.045	61.66%	0.84595	111241.9	111261.0
Only Sentiment Scores	76.81%	0.045	60.65%	0.84172	113127.8	113146.9
Numerical + Sentiment	77.40%	0.045	61.51%	0.84736	110367.6	110386.7
Numerical + Sentiment + Risk Indicator	77.63%	0.045	61.38%	0.85091	109141.3	109160.3
Panel C: Weekly + Quarterly Glassdoor-adjusted CDS (GCDS)						
	Mean	Std. dev.	Min	Max	AIC	BIC
Numerical + Sentiment + Risk Indicator	77.78%	0.044	61.24%	0.85256	108424.5	108443.6

Notes: This table compares the R^2 values and information criteria for Glassdoor-adjusted CDS models under different input combinations and temporal aggregation frequencies. Panel A uses only weekly Glassdoor data, Panel B uses quarterly data with a 45-day publication lag, and Panel C combines both. Each panel evaluates specifications using numerical ratings, sentiment scores, and textual risk indicators, individually and in combination.

Table 9: **Normalized Weights of Glassdoor Information in Glassdoor-adjusted CDS**

Variable	Mean	Std. dev.	Min	Max
Panel A: Risk Indicators				
Risk Indicator (Pros)	19.85%	0.107	0.33%	59.25%
Risk Indicator (Cons)	9.03%	0.088	-31.61%	40.44%
Risk Indicator (Advice)	9.26%	0.071	-1.04%	43.61%
Panel B: Weekly Glassdoor Information				
Overall rating	-4.58%	0.046	-19.67%	9.82%
Business outlook	7.68%	0.030	-0.26%	20.17%
CEO rating	9.72%	0.035	1.64%	26.18%
Recommend rating	-0.67%	0.039	-19.40%	7.07%
Career opportunity	1.90%	0.039	-7.66%	18.07%
Compensation & Benefits	10.18%	0.034	3.03%	22.46%
Culture & Values	-2.74%	0.032	-14.20%	2.15%
Senior management	-3.47%	0.044	-22.74%	7.75%
Work Life & Balance	6.95%	0.039	-1.52%	31.82%
Sentiment Score	26.48%	0.109	9.85%	65.43%
Panel C: Quarterly Glassdoor Information				
Overall rating	-18.14%	0.134	-76.44%	1.83%
Business outlook	15.57%	0.114	-3.37%	74.82%
CEO rating	1.12%	0.110	-36.66%	25.91%
Recommend rating	2.88%	0.076	-25.73%	26.50%
Career opportunity	-17.22%	0.114	-69.61%	2.15%
Compensation & Benefits	5.20%	0.129	-46.06%	49.33%
Culture & Values	1.13%	0.109	-42.79%	23.06%
Senior management	-4.39%	0.095	-43.16%	22.59%
Work Life & Balance	-3.72%	0.087	-33.32%	8.47%
Sentiment Score	28.01%	0.123	6.06%	64.46%

Notes: This table reports the normalized weights of individual Glassdoor-derived variables in constructing the Glassdoor-adjusted CDS (GCDS). Panel A includes weights for risk indicator terms extracted from textual review sections (Pros, Cons, and "Advice). Panels B and C list the weights for weekly and quarterly Glassdoor variables, respectively, including numerical ratings, sentiment scores, and topic-specific perceptions such as compensation and leadership. All weights are standardized to sum to one across categories within each time window.

Table 10: **Model R^2 by SICS Sector**

SICS Sector	Benchmark	Merton-based CDS	Fundamental-adjusted CDS	ESG-adjusted CDS	Glassdoor-adjusted CDS	Obs
Consumer Goods	50.74%	73.64%	83.85%	84.35%	85.72%	16,181
Extractives & Mineral Processing	25.34%	42.62%	65.98%	66.85%	70.09%	10,855
Financials	42.47%	51.70%	49.38%	54.12%	53.68%	1,011
Food & Beverage	15.56%	24.76%	56.74%	57.49%	59.36%	8,903
Health Care	46.71%	56.17%	77.40%	79.71%	79.82%	13,044
Infrastructure	61.05%	52.74%	57.07%	56.40%	59.34%	2,538
Renewable Resources & Alternative Energy	20.13%	-151.67%	-63.23%	-58.25%	-56.02%	494
Resource Transformation	32.87%	49.44%	71.67%	74.24%	75.66%	18,919
Services	26.29%	44.02%	51.71%	56.64%	59.27%	6,811
Technology & Communications	37.19%	56.73%	69.45%	69.68%	73.22%	13,758
Transportation	41.92%	70.66%	78.36%	79.72%	81.83%	8,944
Total	36.86%	52.89%	70.14%	71.69%	73.62%	

Notes: This table shows the mean R^2 values from five different CDS valuation models, calculated separately for each SICS sector. The models include the benchmark, Merton-based, fundamental-adjusted, ESG-adjusted, and Glassdoor-adjusted CDS. The final column reports the number of firm-week observations per sector. The table facilitates comparison of model performance across industries.

Table 11: **First and Second Stage Regression Results**

	Regression Results	
Variable	First Stage	Second Stage
lnECDS	-0.178***	1.103***
	(-51.38)	(99.03)
PCA_glassdoor		0.101*
		(1.68)
Release	-0.002***	
	(-5.27)	
Fatalities	0.001***	
	(11.76)	
Constant	0.773***	-0.429***
	(50.19)	(-8.72)
Adj R-squared	0.0237	0.5636
Underidentification test (Kleibergen-Paap rk LM Statistic)	168.057 p = 0.0000	
Weak identification test (Cragg-Donald Wald F statistic)	85.991 25% maximal IV size = 7.25	
Overidentification test (Hansen J statistic)	0.115 (p = 0.7349)	

Notes: This table presents results from the instrumental variable (IV) regression analysis, designed to establish a causal relationship between employee sentiment and CDS spreads. The first-stage regression results show how two instrumental variables, the number of blockbuster movie releases (*Release*) and global aviation fatalities (*Fatalities*), predict employee sentiment (captured by the principal component, *PCA_glassdoor*, which integrates employee numerical ratings, sentiment scores, and textual risk indicators).

6.2 Figures

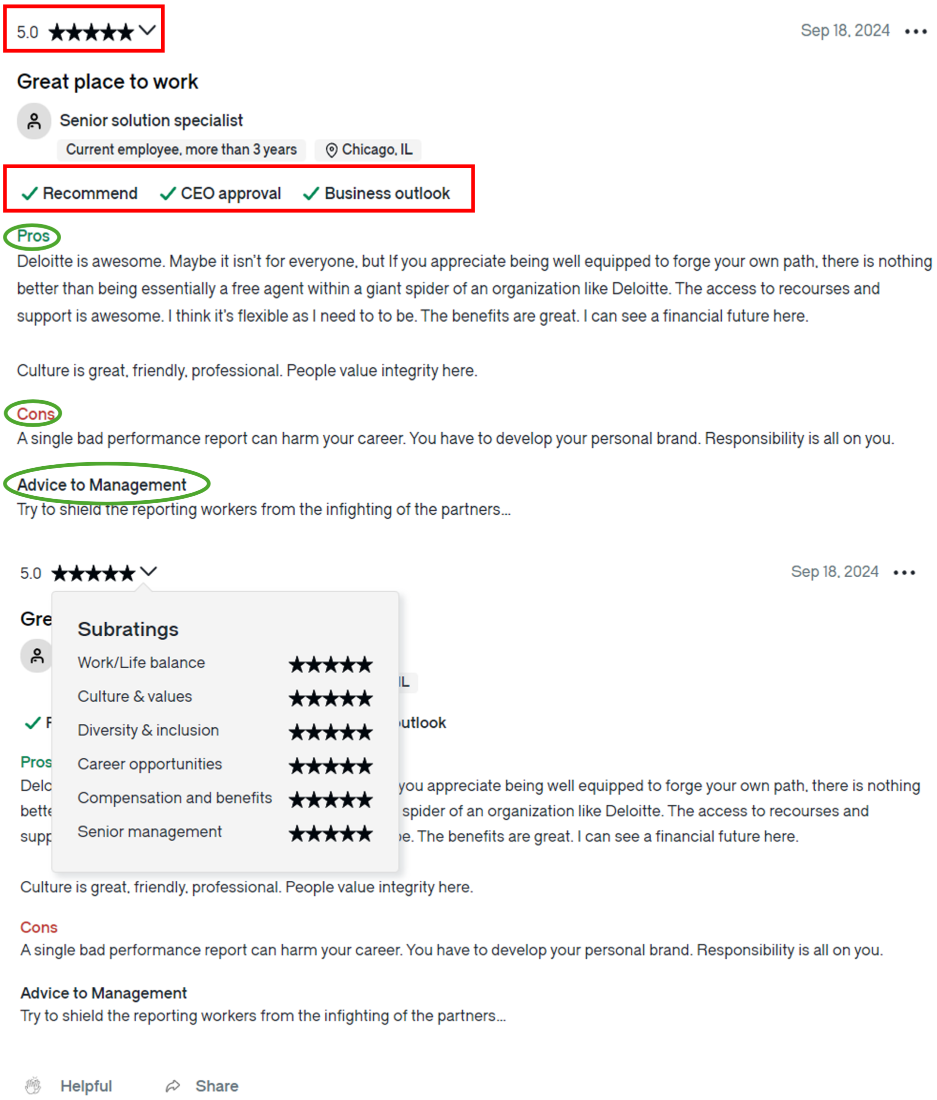

Figure 1: **An example of an employee review on Glassdoor**

Notes: This screenshot illustrates a typical layout of an employee review on Glassdoor, highlighting key information such as overall rating and review comments.

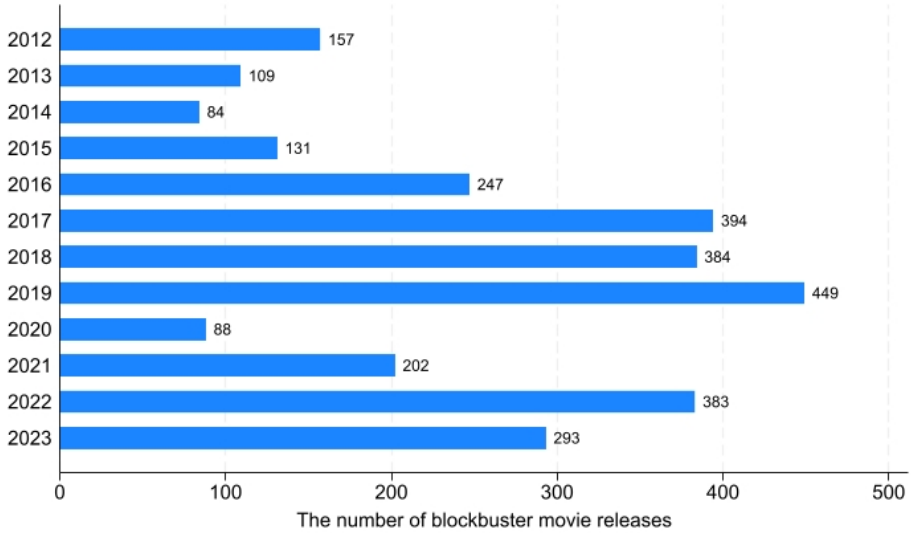

Figure 2: **The number of blockbuster movie releases per year**
Notes: This figure illustrates the annual number of blockbuster movie releases in the United States from 2012 to 2023, based on Box Office Mojo data. A blockbuster is defined as a movie released in more than 4,000 theaters nationwide.

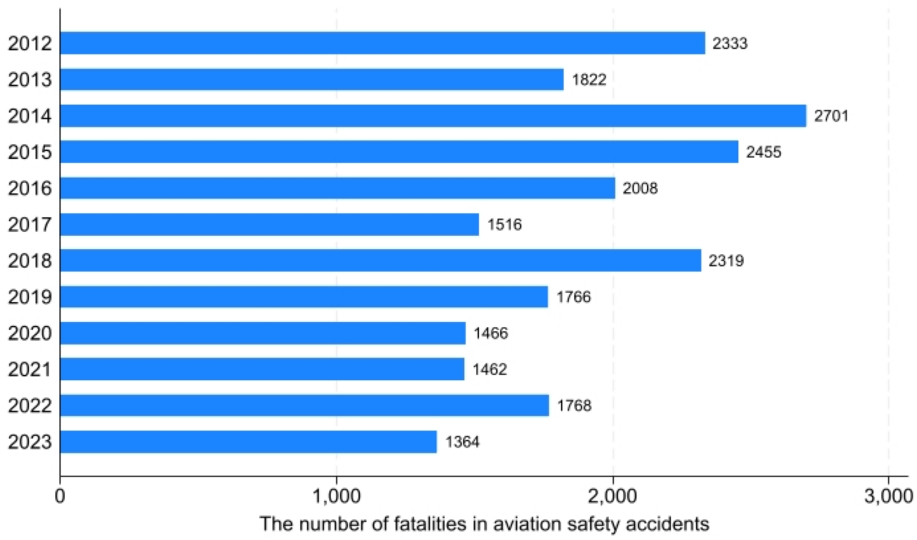

Figure 3: **The number of fatalities in aviation safety per year**
Notes: This figure presents the annual number of fatalities resulting from aviation safety incidents worldwide, covering the period from 2012 to 2023. The data are sourced from the Aviation Safety Network and reflect all reported fatal events in the civil aviation sector.

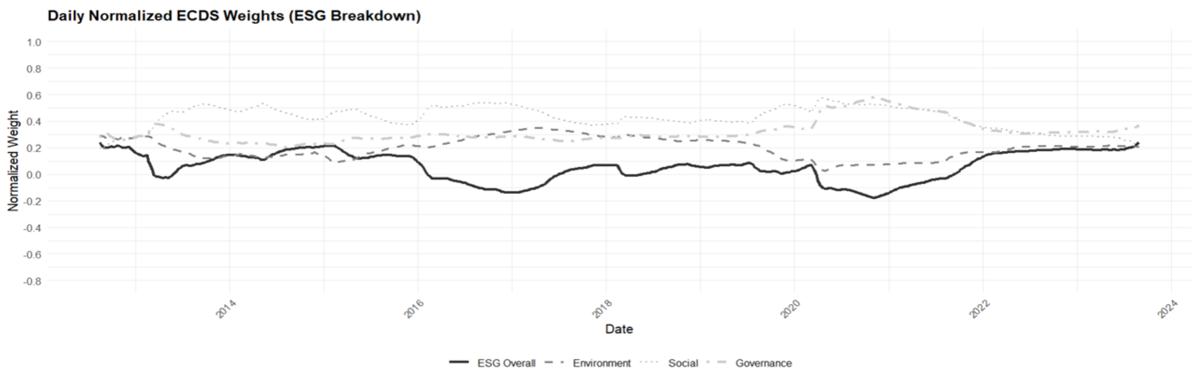

Figure 4: **Daily Normalized ESG-based CDS Weights (ESG Breakdown)**

Notes:

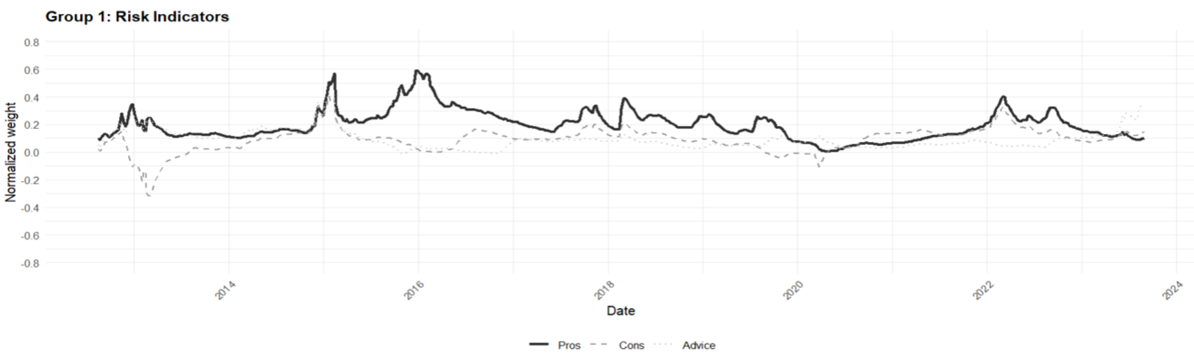

Figure 5: **Group 1: Risk Indicators**

Notes:

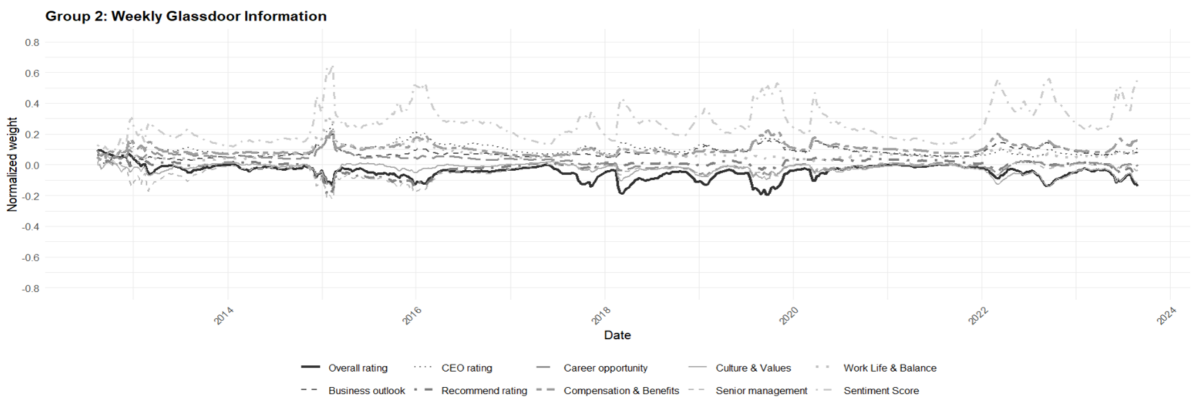

Figure 6: **Group 2 Weekly Glassdoor Information**

Notes:

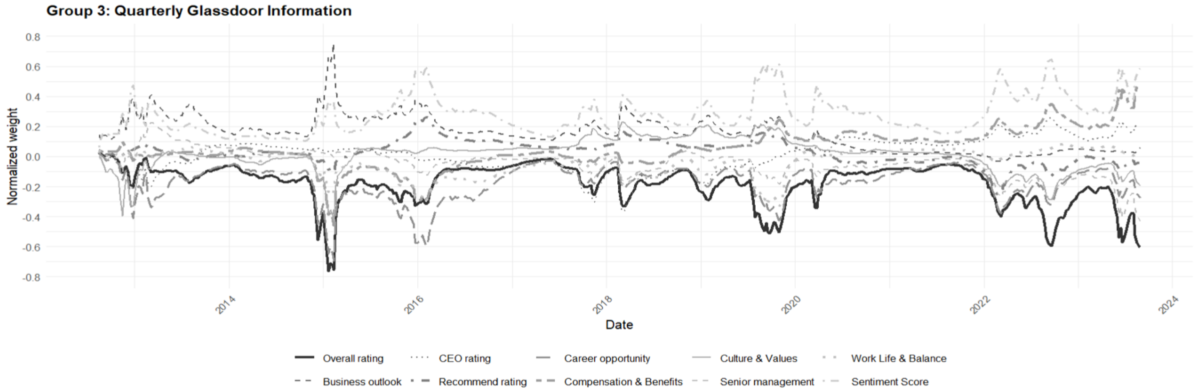

Figure 7: **Group 3: Quarterly Glassdoor Information**

Notes:

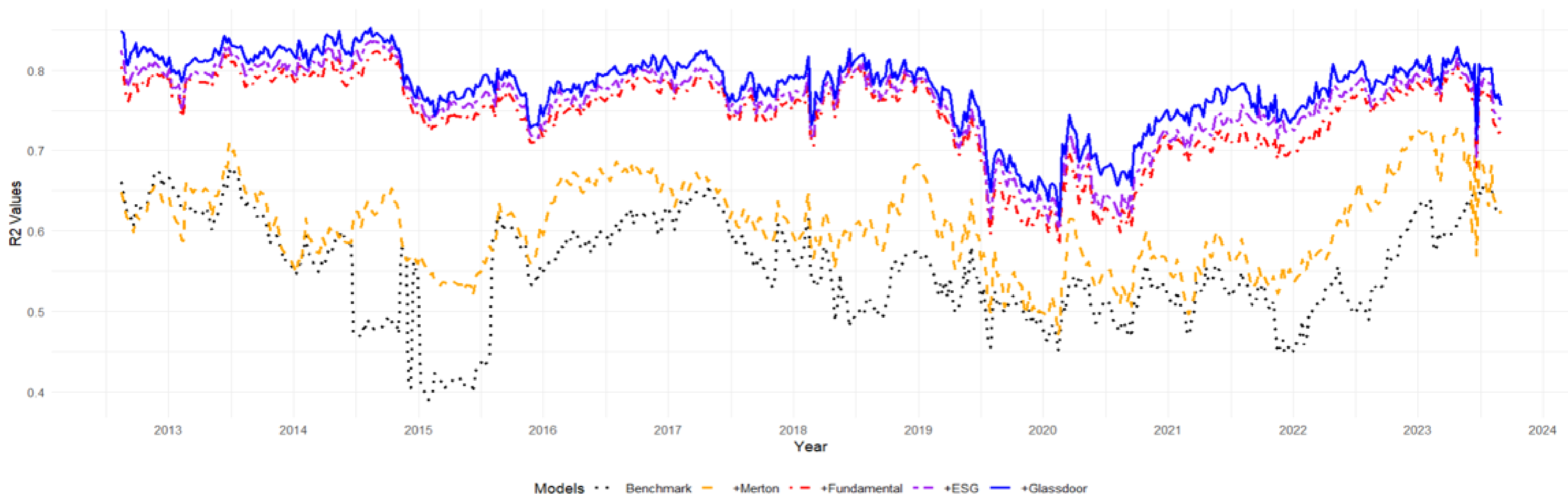

Figure 8: **The time series of R-squared estimates from cross-sectional regressions**

Notes: This figure displays the time series of cross-sectional R^2 estimates from different valuation models of credit default swap (CDS) spreads, covering 706 weeks from August 2012 to August 2023. The black dotted line represents the benchmark bivariate linear regression (BLR), the orange dashed line the Merton-based CDS valuation (MCDS), the red dotdash line the fundamental-adjusted CDS (FCDS), the purple twodash line the ESG-adjusted CDS (ECDS), and the blue solid line the Glassdoor-adjusted CDS (GCDS).

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Appendix A. Bayesian Shrinkage Estimation

In our research, we use a robust methodology proposed by Bai and Wu (2016) . By leveraging the Merton (1974) structural model, we incorporate a comprehensive set of firm-specific fundamental characteristics, as well as non-financial indicators to investigate the additional explanatory power of Glassdoor information. This methodology involves a series of steps, including the conversion of distance-to-default measures into raw CDS valuations, the correction of valuation biases via local quadratic regression, and the integration of additional firm fundamentals and non-financial factors using a Bayesian shrinkage method. The results are weighted average CDS valuation, which demonstrates superior cross-sectional explanatory power and stability over time, significantly improving upon traditional models.

Appendix A.1 Valuing CDS spreads based on firm fundamentals

To generate valuations on the five-year CDS spread, we start with the classic structural model of Merton (1974). Merton (1974) assumes that the total asset value (A) of a company follows a geometric Brownian motion with instantaneous return volatility σ_A, the company has a zero-coupon debt with a principal value D and time-to-maturity T, and the firm's equity (E) is a call option on the firm's asset value with maturity equal to the debt maturity and strike equal to the principal of the debt. We compute the distance-to-default measure from the Merton model using the total debt to market capitalization ratio and the stock return realized volatility as inputs:

$$\text{Distance to default} = \frac{\ln(\frac{A}{D}) + (r - \frac{1}{2}\sigma_A^2)T}{\sigma_A\sqrt{T}} \tag{A.1}$$

To compute a firm's distance to default, we take the company's market capitalization as its equity value E, the company's total debt for the zero-coupon bond D, and the one-year realized stock return volatility as an estimator for stock return volatility σ_A. We further assume zero interest rates ($r = 0$) and fix the debt maturity at $T = 10$ years for all firms:

$$E = A \cdot N(d + \sigma_A \sqrt{T}) - D \cdot N(d) \tag{A.2}$$

$$\sigma_E = N(d + \sigma_A \sqrt{T}) \sigma_A A / E \tag{A.3}$$

We solve for the firm's asset value A and asset return volatility σ_A from the two equations in (A.2) and (A.3) via an iterative procedure, starting at $A = E + D$. With the solved asset value and asset return volatility, we compute the standardized distance to default according to equation (A.1). Then we convert the distance-to-default into a raw CDS valuation based on a constant hazard rate assumption and a 40% recovery rate:

$$RCDS = -6000 \cdot \ln(N(d))/T \tag{A.4}$$

where d is distance-to-default we calculated from equation (A.1), and $RCDS$ is a raw credit default spread (RCDS) measure based on Bai and Wu (2016), to retain the key contributions of the Merton model while avoiding its limitations in predicting actual defaults. The fixed 40% recovery rate is a standard simplifying assumption in the CDS literature. To the extent that the recovery rate can also vary across firms, this simple transformation does not capture such variation.

To explain the cross-sectional variation of market CDS observations, at each date we estimate the raw CDS valuation (RCDS) on the whole universe of chosen companies, and map the RCDS to the corresponding market CDS observation via a cross-sectional local quadratic regression:

$$\ln(CDS) = f(\ln(RCDS)) + R \tag{A.5}$$

where CDS denotes the market CDS from Markit, $f(\cdot)$ denotes the local quadratic transformation of the RCDS value, and R denotes the regression residual from this mapping. We use $RCDS$ rather than distance-to-defualt directly is because the transformation in (A.4) moves the distance-to-default measure closer to the actual CDS observation so that the local quadratic regression in (A.5) becomes more stable numerically. Meanwhile, the local quadratic regression has significant advantages in handling nonlinear relationships and data with complex structures over the ordinary regression. By fitting a quadratic polynomial near each data point, it can better capture local features of the data, providing more accurate and flexible fitting. And we use a Gaussian kernel for the local quadratic regression and set the bandwidth to twice as long as the default choice to reduce potential overfitting. Finally, we label the local-quadratic transformed Merton model-based CDS valuation as MCDS, $\ln(\text{MCDS}) = \hat{f}(\ln(\text{RCDS}))$.

Next, we use a long list of firm fundamental characteristics mentioned in section 2 that are not included in the Merton-based valuation but have been shown to be informative about a firm's credit spread. We use a Bayesian shrinkage method to combine the Merton-based valuation with the information from this long list of additional fundamental characteristics to generate a weighted average CDS valuation.

Formally, let F_t denote an $(N \times K)$ matrix for N companies and K additional credit-risk informative firm fundamental characteristics at date t. At each date, we first regress each characteristic cross-sectionally against MCDS to orthogonalize its contribution from the Merton prediction:

$$F_t^k = f_k(\ln(MCDS_t)) + x_t^k, \qquad k = 1, 2, \ldots\ldots, K \tag{A.6}$$

where $f_k(\cdot)$ denotes a local linear regression mapping and x_t^k denotes the orthogonalized component of F_t^k, which means that after removing the part related to $MCDS$, the remaining part of each feature is orthogonal to other features. This orthogonalization process can effectively reduce the multi-collinearity problem between features. And we use the local linear regression to accommodate potential nonlinearities in the relation further.

Second, we regress the Merton prediction residual, $R\_merton_t = ln(CDS_t/MCDS_t)$, cross-sectionally against each of the K orthogonalized characteristic x_t^k via another local linear regression:

$$R\_merton_t^k = f_k(x_t^k) + e_t^k, \qquad k = 1, 2, \ldots\ldots, 9 \tag{A.7}$$

Through this local linear regression, we generate a set of K residual predictions, $R\_m\hat{e}rton_t^k, k = 1, 2, \ldots\ldots, K$, from the K characteristics. The two local linear regressions in (A.6) and (A.7) remove the potential nonlinearity in the relations and orthogonalize each characteristic's contribution to the original Merton valuation.

Third, we stack the K predictions to an N × K matrix, $X_t = [R\_m\hat{e}rton_t^1, R\_m\hat{e}rton_t^2, \ldots, R\_m\hat{e}rton_t^K]$, and estimate the weight among them via the following linear cross-sectional relation:

$$R\_merton_t = X_t\, W_t + e_t \tag{A.8}$$

with W_t denoting the weights on the K firm fundamental characteristics.

To perform the stacking regression in (A.8), we need all K predictions to be available. However, for a given company, it is possible that only a subset of the K characteristics, and hence only a subset of the K predictions, are available. We fill the missing predictions with a weighted average of the other predictions on the firm, where the relative weights are determined by the R-squared of the regressions in (A.7) for each available variable,

$$R\_merton_t^{i,j} = \sum_{k=1}^{\tilde{K}} w_t^k R\_merton_t^{i,k} \tag{A.9}$$

$$w_t^k = e^\top (ee' + \mathrm{diag}\langle 1 - R^2 \rangle)^{-1} \tag{A.10}$$

where $R\_merton_t^{i,j}$ represents the missing residual prediction for firm i from the j-th variable at time t; $\tilde{K}$ denotes the subset of available residual predictions on the firm i; w_t^k represents the weight for the k-th variable at time t; e is a vector of error term from equation (A.7); and R^2 values are the R-squared values from regressions of each characteristic in equation (A.7). This weighting scheme is motivated by the Bayesian principle, where the prior prediction is set to zero, and the relative magnitude of the measurement error variance for each available residual prediction is proportional to 1 −

R^2. This method helps in managing missing data by effectively borrowing strength from available data while accounting for the reliability of the predictions based on their R^2 values.

Equations (A.6) and (A.7) each contains K separate univariate local linear regressions on the cross section of N firms at date t. The cross-section can be smaller than N when there are missing values for a variable. Once the missing values are replaced by a weighted average, the time-t weightings (W_t) among the K predictions in equation (A.8) can be estimated in principle via a simple least square regression; however, to reduce the potential impact of multi-collinearity and to increase intertemporal stability to the weight estimates, we perform a Bayesian regression update by taking the previous day's estimate as the prior:

$$\hat{W}_t = (X_t^T X_t + P_{t-1})^{-1}(X_t^T R\_merton_t + P_{t-1}\hat{W}_{t-1}) \tag{A.11}$$

$$P_t = \text{diag}\langle(X_t^T X_t + P_{t-1})\phi\rangle \tag{A.12}$$

where ϕ controls the degree of intertemporal smoothness that we impose on the weights. We start with a prior of equal weighting and choose $\phi = 0.98$ for intertemporal smoothing.

In the final step to combine firm fundamental characteristics with Merton CDS, we add the weighted average prediction of the residual back to the MCDS valuation to generate a new CDS valuation, which we label as WCDS:

$$ln(FCDS)_t = ln(MCDS)_t + X_t\hat{W}_t \tag{A.13}$$

In constructing the FCDS, we could have treated MCDS as just one of the firm characteristics. Instead, we separate its effect by treating MCDS as the benchmark CDS valuation and choose other firm characteristics based on their additional contribution to the CDS valuation. Our analysis in later sections shows that MCDS represents a good benchmark as it can explain a large proportion of the market observed CDS variation across firms.

Appendix A.2 Valuing CDS Spreads based on ESG and Glassdoor ratings

To assess the additional explanatory power of ESG and Glassdoor information, we extend our framework by sequentially incorporating MSCI ESG ratings and Glassdoor data. Each dataset is orthogonalized to the prior model residual:

$$ESG_t^e = f(\ln(FCDS_t)) + esg\_orth_t^e, \quad e = 1, 2, 3, 4, \tag{A.14}$$

$$R\_fcds_t = f(esg\_orth_t) + e_t, \tag{A.15}$$

$$\ln(ECDS)_t = \ln(FCDS)_t + R\_\hat{fcds}_t \hat{W}_t. \tag{A.16}$$

where $f(\cdot)$ denotes a local linear regression mapping and esg_orth_t denotes the orthogonalized component of ESG_t from MSCI ESG (including overall score, E score, S score and G score), with W_t denoting the weight on ESG score. Because our sample excludes firms without ESG scores, there is no need to adjust for missing values in ESG scores, and we use the similar Bayesian regression update in equation (A.11) and (A.12).

Next, we apply the same process to Glassdoor information, which includes numerical ratings in table **??**, sentiment scores, and textual risk signals in table **??**:

$$Glassdoor_t^g = f_g(\ln(ECDS_t)) + glass\_orth_t^g, \quad g = 1, 2, \ldots, 15, \tag{A.17}$$

$$R\_ecds_t = f_g(glass\_orth_t) + e_t, \tag{A.18}$$

$$\ln(GCDS)_t = \ln(ECDS)_t + R\_\hat{ecds}_t \hat{W}_t. \tag{A.19}$$

The final valuation, GCDS, incorporates both fundamental and non-financial factors, demonstrating the additional predictive value of ESG and employee reviews in explaining CDS spreads.