CAN TEXTUAL DISCLOSURES MEASURE RISK BETTER THAN VOLATILITY?

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Motivation

Financial economics has long relied on volatility as the standard measure of risk, yet volatility is symmetric, capturing both upside and downside deviations, and therefore fails to isolate the downside losses that matter most to investors. Recent work in textual analysis has shown that management sentiment and disclosure language in corporate filings can forecast returns and volatility, but little research has examined whether risk-related language predicts downside risk specifically. The Risk Factor sections of 10-Ks and 10-Qs contain forward-looking narratives about threats to firm performance, which may provide early signals of tail events. Prior literature (e.g., Loughran & McDonald, 2011) highlights the value of domain-specific sentiment dictionaries, while more recent approaches apply transformer-based embeddings to financial text. However, existing work has largely focused on sentiment and volatility, leaving a gap in connecting risk disclosures to realized drawdowns and crash risk. This gap is particularly salient given recent arguments that conventional variance-based risk measures are conceptually limited and fail to reflect the fear of loss that drives investor behavior (Arnott & McQuarrie, 2025). This project aims to address that gap by directly linking textual risk narratives to downside risk outcomes.

Research Question + Method

Our main question is: Can textual risk disclosures in corporate filings predict downside risk (e.g., maximum drawdown, tail losses) more effectively than volatility (standard deviation)? To investigate, we will extract risk-related text from WRDS filings (2005–2025), apply both dictionary-based sentiment/risk measures and transformer-based embeddings, and link these textual features to realized measures of downside risk. The novelty lies in shifting the focus from volatility and returns prediction to downside risk prediction, using risk disclosures as forward-looking indicators.

Hypothesis / Expected Results

We expect that firms with more negative or risk-focused disclosures will experience higher realized downside risk in subsequent periods. More importantly, we hypothesize that text-based measures of risk will outperform volatility (standard deviation) in predicting tail outcomes such as drawdown. We anticipate that the advantage of text-based predictors will be most evident during crisis regimes (e.g., the 2008 financial crisis, the 2020 COVID crash). Overall, our hypothesis is that corporate risk narratives systematically encode forward-looking information about future downside risk that variance alone cannot capture.

Experimental Design

Data will be drawn from WRDS, including 10-K and 10-Q filings for the period 2005–2025. Text preprocessing will involve section extraction, tokenization, and embedding generation. We will compute multiple risk metrics: downside semivariance and maximum drawdown. Models will include linear regressions and tree-based methods, with text features as predictors. Evaluation will focus on out-of-sample predictive accuracy and incremental R^2 over volatility. Compute requirements are considerable, we have access to a remote machine with a Threadripper CPU, 512 GB of RAM and an RTX 4090 GPU; If this isn't enough then we will utilize cloud computing. embeddings can be generated with pre-trained transformer models (e.g., FinBERT, Sentence-BERT) using GPU inference but without full training.

Project Timeline and Roles - Weeks 1–2: Data extraction and cleaning. - Weeks 3–4: Feature engineering: dictionary-based scores and embeddings. - Weeks 5–6: Model estimation and evaluation against baseline volatility. - Weeks 7–8: Interpretation of results, write-up, and revisions (with mentor feedback). The students will carry out data processing, modeling, and analysis. The mentor will give feedback on results.

References

Rob Arnott and Edward F. McQuarrie. Fear, not risk, explains asset pricing. Working paper. Revised May 2025, February 2025.

TIM LOUGHRAN and BILL MCDONALD. When is a liability not a liability? textual analysis, dictionaries, and 10-ks. *The Journal of Finance*, 66(1):35–65, 2011. doi: https://doi.org/10.1111/j.1540-6261.2010.01625.x. URL `https://onlinelibrary.wiley.com/doi/abs/10.1111/j.1540-6261.2010.01625.x`.