

Summary

From Transcripts to Insights: Uncovering Corporate Risks Using Generative AI

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1. What are the research questions?

- Can generative AI help investors uncover firms' regulatory, environmental, and AI-related risks?

2. Why are the research questions interesting?

- Corporations face multifaceted risks that extend far beyond traditional financial metrics
 - Regulatory, environmental, and AI risks have strong implications for growth and stakeholder value.
- Generative language models particularly attractive in the analysis of corporate risk
 - Could go beyond the given text by leveraging general knowledge acquired from related documents.
 - Could extract information into coherent, understandable narratives

3. What is the paper's contribution?

- Contribute to a nascent and actively developing body of work on the value of LLMs
 - Prior studies: Use generative LLMs for other purposes, such as analyzing complex, unstructured information(Kim et al.)
- Contribute to literature that uses corporate disclosures to construct firm-level measures of risk exposure
 - Prior studies: Rely on topic-based bigram dictionaries. Hassan et al. (2019) construct overall political risk by defining training libraries of political text and nonpolitical text.
 - Extension: Use AI-based technology to analyze risks, which can understand the deeper context
- Contribute by establishing the value of general AI for understanding complex topics like risk
 - Prior studies: Limited to the information contained within the text.
 - Extension: Show LLMs can use general knowledge to analyze firm risks from given context.

4. What hypotheses are tested in the paper? list them explicitly

- H1: If GPT based risk measures are valid, there will be some risk-related capital market consequences
- H2: If GPT based risk measures are valid, it could predict firms' actions.

(a) Do these hypotheses follow from and answer the research questions?

Yes

(b) Do these hypotheses follow from theory or are they otherwise adequately developed? Please explain the logic of the hypotheses (use visualization if possible)

- H1:
 - A valid measure of risk must exhibit association with volatility (Engle, 2004).
 - We use two forward-looking firm-level volatility metrics: implied volatility derived from option prices(Sautner et al., 2023), and abnormal realized volatility(Loughran and McDonald, 2014).

- H2:
 - In theory, riskier firms experience higher financing costs and value the option of waiting (Dixit and Pindyck, 1994).
 - However, for technology-related risks, the effect is less clear because addressing AI challenges requires significant investments in new technology.

5. Sample: comment on the appropriateness of the sample selection procedures

They can enlarge the window and conduct random sampling to increase credibility.

6. Dependent and independent variables: comment on the appropriateness of variable definition and measurement (focus on the key dependent variables and independent variables)

- Independent variable: Using the ratio of processed to original text length directly as a proxy indicator for risk is not sufficiently convincing.
- Both dependent variables in the regression has ample literature support.

7. Regression/prediction model specification: comment on the appropriateness of the regression/prediction model specification

- Conduct industry and time fixed effects and industry \times time fixed effects reasonably.

8. What difficulties arise in drawing inferences from the empirical work

- Effectiveness outside GPT's training period
- 2018.1-2023.3 is a short window, and most of this period is during the COVID-19 pandemic, which may lead to bias.

9. Describe at least one publishable and feasible extension of this research

- Other information receiver: fund managers, analyst
- Use chatgpt4

参考文献

Alex G. Kim, Maximilian Muhn, and Valeri V. Nikolaev. Bloated disclosures: Can chatgpt help investors process information?

Tarek A Hassan, Stephan Hollander, Laurence Van Lent, and Ahmed Tahoun. Firm-level political risk: Measurement and effects*. 134(4):2135–2202, 2019.