

Can news predict firm bankruptcy?

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Siyu Bie, Guanhao Feng, Naixin Guo, Jingyu He

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Overview

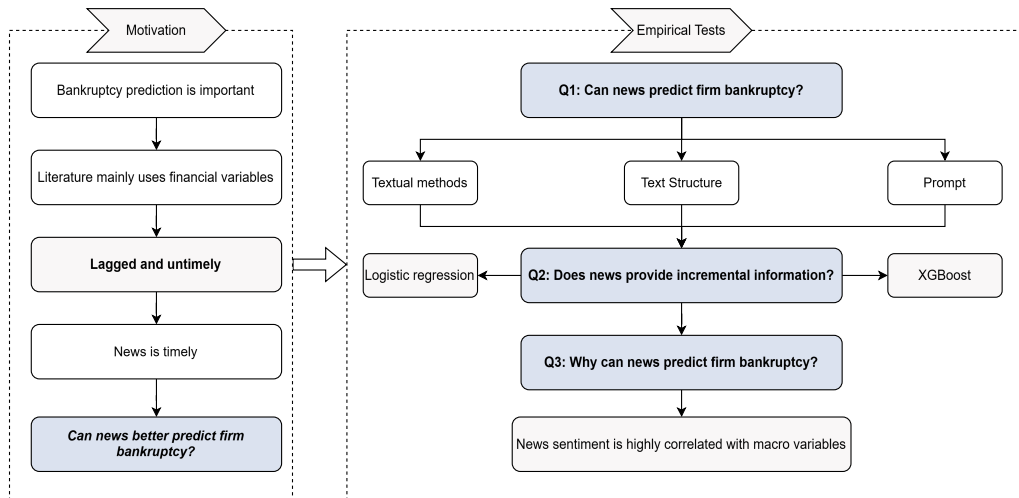
1. Introduction

2. Design

3. Result

4. Idea

Framework



Question

- Q1: Can news predict firm bankruptcy?
- Q2: Does news provide incremental information?
- Q3: Why can news predict firm bankruptcy?

Motivation

- Firm bankruptcy is rare but can lead to substantial financial losses for investors
- Existing bankruptcy prediction methods heavily rely on financial-related information
 - Altman, 1968, JF; Shumway, 2001, RFS; Campbell et al., 2008, JF
- **Challenges:** Financial-related information is usually lagged and untimely
- Business news provides timely insights into a company's status
- **This paper: Can news better predict firm bankruptcy?**

Marginal contribution

- Predict firm bankruptcy
 - Prior studies
 - Use financial-related information (Campbell et al., 2008, JF; BAO et al., 2019, JAR; Li et al., 2023, TAR)
 - This paper
 - Use news text data and finding it can provide incremental predictive power
- Applications of generative AI
 - Prior studies
 - Focus on pricing (Chen et al., 2025, SSRN), analysts' information processing (Bertomeu et al., 2025, JAE), peer-firm identification (Breitung and Müller, 2025, JFE), firm value (Eisfeldt et al., 2023, NBER), and dissecting corporate culture (Li et al., 2025, RFS)
 - This paper
 - Extend to bankruptcy prediction

Hypothesis

- H1: News-related information significantly predicts bankruptcy rates
- H2: News can provide incremental information
- H3: News sentiment is significantly correlated with contemporaneous macroeconomic variables
 - News sentiment significantly affects investors' macroeconomic expectations and confidence (Obaid and Pukthuanthong, 2022, JFE)

Use ChatGPT to predict bankruptcy

- Step 1: Generate sentiment scores and bankruptcy probabilities via prompting
 - Forget all previous instructions. Analyze according to the given text of firm [firm] as a credit risk and bankruptcy prediction expert:
 1. **Sentiment score** (−1 to 1, −1 is most negative, 0 is neutral, 1 is most positive)
 2. 3 keywords/phrases significantly affecting sentiment
 3. **Estimated bankruptcy probability of this firm in the month after 1 month, 1 quarter, 1 year, and 3 years** from when the text was released
 4. Important: Base your analysis solely on the information provided in the text. Do not use external knowledge, future information, or data not explicitly stated in the content.
Respond in this format:
 - Output example: a. 0.2 b. [sentiment keywords] c. [0.01,0.05,0.21,0.42]
- Step 2: Compute average monthly sentiment scores and bankruptcy probabilities

Estimate sentiment via FinBERT and dictionary methods

- Dictionary-based method (Loughran and McDonald, 2011, JF)

$$Sentiment_{dic} = \frac{N_{pos} - N_{neg}}{N_{pos} + N_{neg}} \quad (1)$$

- Use FinBERT to classify each article into positive, neutral, or negative

$$Sentiment_{bert} = \begin{cases} P & \text{if } Class = \text{Positive} \\ 0 & \text{if } Class = \text{Neutral} \\ -P & \text{if } Class = \text{Negative} \end{cases} \quad (2)$$

- Where P is the probability of the most likely class

Data

- News text
 - The databases of the Dow Jones Newswires
 - Exclude articles tagged with non-economic topics such as sports or arts to maintain a focus on finance
- Firm bankruptcy data
 - CRSP, Compustat and Florida-UCLA-LoPucki Bankruptcy Research Database (BRD)
 - A firm is classified as bankrupt if it meets any of the following criteria:
 1. a CRSP delisting code of 574
 2. a Compustat delisting reason code of 02 or 03
 3. a recorded filing under Chapter 7 or Chapter 11 in the BRD
 - Focus on predicting a firm's initial bankruptcy filing and exclude all observations following the first recorded event
- Sample period: 1998-2023

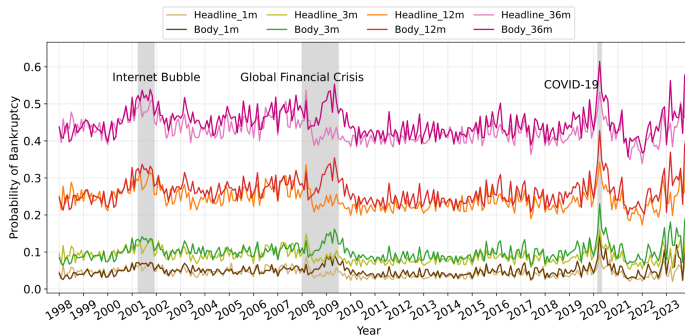
Data

- After merging the firm bankruptcy data and news data, approximately **45% of the bankrupt firms were excluded**

Year	Before merge			After merge		
	Total	Bankruptcy	Active	Total	Bankruptcy	Active
1998	6047	24	6023	1708	0	1708
1999	5626	37	5589	1891	4	1887
2000	5465	66	5399	2222	6	2216
2001	5007	109	4898	2165	43	2122
2002	4367	73	4294	2090	28	2062
2003	3963	55	3908	2044	25	2019
2004	3773	33	3740	1865	19	1846
2005	3740	23	3717	1909	8	1901
2006	3662	14	3648	2172	4	2168
2007	3609	9	3600	2121	7	2114
2008	3529	34	3495	2583	22	2561
2009	3262	96	3166	2578	67	2511
2010	3095	23	3072	2520	19	2501
2011	2993	22	2971	2440	16	2424
2012	2894	27	2867	2401	24	2377
2013	2790	24	2766	2349	19	2330
2014	2853	21	2832	2422	16	2406
2015	2912	31	2881	2479	22	2457
2016	2827	35	2792	2460	21	2439
2017	2732	23	2709	2426	13	2413
2018	2747	15	2732	2472	13	2459
2019	2781	30	2751	2527	27	2500
2020	2801	50	2751	2568	44	2524
2021	2976	6	2970	2757	5	2752
2022	3180	18	3162	2977	14	2963
2023	3100	26	3074	2899	23	2876

Measure validation: Monthly average bankruptcy probability

- Bankruptcy probabilities are elevated during market crises
- Bankruptcy probabilities and their volatility increase with longer horizons
- Probabilities derived from article bodies consistently exceed those based on headlines



Predictive model setting

- To evaluate the predictive power of business news, authors adopt a logistic regression framework

$$P(y_{i,t+\tau} = 1) = \frac{\exp(\beta_{0\tau} + \beta'_{1\tau} \mathbf{X}_{i,t} + z_i + \eta_t)}{1 + \exp(\beta_{0\tau} + \beta'_{1\tau} \mathbf{X}_{i,t} + z_i + \eta_t)} \quad (3)$$

- $y_{i,t+\tau} = 1$ indicates that firm i does not experience a bankruptcy within τ months, but does experience a bankruptcy event at time $t + \tau$
- $\tau = 1, 3, 12$, and 36 months
- z_i and η_t are the industry and year-fixed effects, respectively

Q1: Can news alone predict firm bankruptcy?

- All news-based variables exhibit significant predictive power across horizons
- Sentiment scores are negatively associated with bankruptcy risk
- The predictive power of news variables declines as the forecast horizon increases

	Headline				Body			
	1m	3m	12m	36m	1m	3m	12m	36m
Panel A: ChatGPT								
<i>Sentiment score</i>	-3.42*** (-11.95)	-2.24*** (-10.54)	-1.68*** (-4.84)	-1.22*** (-4.73)	-4.86*** (-17.69)	-3.43*** (-13.31)	-2.93*** (-10.25)	-1.54*** (-3.03)
Pseudo- R^2	0.14	0.09	0.06	0.05	0.22	0.12	0.08	0.05
AUC	0.85	0.80	0.75	0.74	0.89	0.84	0.79	0.73
<i>1m-probability</i>	8.48*** (9.53)				9.69*** (17.29)			
<i>3m-probability</i>		5.86*** (14.24)				7.12*** (17.32)		
<i>12m-probability</i>			3.74*** (6.32)				5.42*** (14.14)	
<i>36m-probability</i>				3.34*** (5.80)				4.03*** (6.96)
Pseudo- R^2	0.14	0.08	0.06	0.05	0.19	0.11	0.08	0.06
AUC	0.83	0.81	0.75	0.74	0.87	0.84	0.79	0.76
Panel B: FinBERT								
<i>Sentiment score</i>	-0.66*** (-6.58)	-0.55*** (-2.74)	-0.86*** (-3.10)	-0.71*** (-3.33)	-1.16*** (-7.78)	-1.24*** (-5.19)	-0.67*** (-5.45)	-0.62*** (-3.47)
Pseudo- R^2	0.08	0.06	0.05	0.05	0.09	0.08	0.05	0.05
AUC	0.79	0.78	0.76	0.73	0.81	0.80	0.75	0.73
Panel C: LM								
<i>Sentiment score</i>	-1.59*** (-9.92)	-1.01*** (-6.38)	-0.49*** (-3.01)	-0.66*** (-4.19)	-1.62*** (-6.45)	-1.11*** (-6.37)	-0.60*** (-3.58)	-0.40*** (-2.60)
Pseudo- R^2	0.11	0.07	0.04	0.05	0.10	0.08	0.05	0.04
AUC	0.82	0.80	0.74	0.73	0.83	0.80	0.74	0.74
Observations	246,439	238,541	226,522	242,181	246,439	238,541	226,522	242,181

Q1: Does ChatGPT do a better job?

- ChatGPT outperforms FinBERT and dictionary-based methods

	Headline				Body			
	1m	3m	12m	36m	1m	3m	12m	36m
Panel A: ChatGPT and FinBERT								
<i>ChatGPT sentiment</i>	-3.80*** (-12.38)	-2.47*** (-7.16)	-1.96*** (-11.47)	-0.91*** (-2.65)	-4.93*** (-19.99)	-3.12*** (-13.07)	-2.86*** (-10.61)	-1.25** (-2.13)
<i>FinBERT sentiment</i>	0.64*** (6.30)	0.32 (1.15)	-0.15 (-0.58)	-0.40 (-1.59)	0.13 (0.80)	-0.49** (-2.26)	-0.03 (-0.18)	-0.37* (-1.92)
Pseudo- R^2	0.15	0.09	0.07	0.05	0.22	0.12	0.08	0.05
AUC	0.85	0.80	0.79	0.74	0.89	0.85	0.80	0.73
Panel B: ChatGPT and LM								
<i>ChatGPT sentiment</i>	-2.88*** (-8.28)	-1.90*** (-7.78)	-1.63*** (-4.25)	-0.92*** (-3.00)	-4.64*** (-11.82)	-3.15*** (-8.95)	-2.88*** (-8.43)	-1.36** (-2.27)
<i>LM sentiment</i>	-0.74*** (-3.95)	-0.48** (-2.56)	-0.08 (-0.50)	-0.45*** (-2.58)	-0.38 (-1.13)	-0.43* (-1.86)	-0.06 (-0.33)	-0.21 (-1.05)
Pseudo- R^2	0.15	0.09	0.06	0.05	0.22	0.12	0.08	0.05
AUC	0.86	0.81	0.75	0.74	0.89	0.84	0.79	0.73
Observations	246,439	238,541	226,522	242,181	246,439	238,541	226,522	242,181

Q1: Do article bodies improve predictive performance?

- Article bodies provide stronger predictive power than headlines

	<i>Sentiment score</i>				<i>τ-month probability</i>			
	1m	3m	12m	36m	1m	3m	12m	36m
Headline	−1.08*** (−2.82)	−0.78** (−2.11)	−0.50 (−1.41)	−0.85*** (−3.69)	4.53*** (6.36)	2.23*** (2.81)	0.86 (1.19)	1.79*** (2.87)
Body	−4.24*** (−11.98)	−2.97*** (−6.92)	−2.62*** (−8.14)	−1.00* (−1.80)	7.99*** (13.80)	6.17*** (10.76)	5.05*** (11.38)	3.26*** (5.03)
Pseudo- R^2	0.22	0.12	0.08	0.05	0.20	0.12	0.08	0.06
AUC	0.90	0.84	0.79	0.74	0.88	0.84	0.79	0.76
Observations	246,439	238,541	226,522	242,181	246,439	238,541	226,522	242,181

Q1: Prompt engineering for ChatGPT

- Bankruptcy probabilities exhibit strong predictive power at longer horizons

	Headline				Body			
	1m	3m	12m	36m	1m	3m	12m	36m
<i>Sentiment score</i>	-2.21*** (-11.25)	-1.49*** (-3.90)	-1.12** (-2.02)	0.21 (0.41)	-2.04*** (-5.83)	-1.15*** (-3.92)	-0.55 (-1.41)	-0.44* (-1.74)
<i>1m-probability</i>	4.87*** (5.86)				7.70*** (15.10)			
<i>3m-probability</i>		2.99*** (3.08)				5.94*** (9.30)		
<i>12m-probability</i>			1.64 (1.47)				4.90*** (8.62)	
<i>36m-probability</i>				3.72*** (3.06)				3.64*** (5.83)
Pseudo- R^2	0.16	0.09	0.06	0.05	0.21	0.12	0.08	0.06
AUC	0.85	0.81	0.75	0.74	0.89	0.84	0.79	0.76
Observations	246,439	238,541	226,522	242,181	246,439	238,541	226,522	242,181

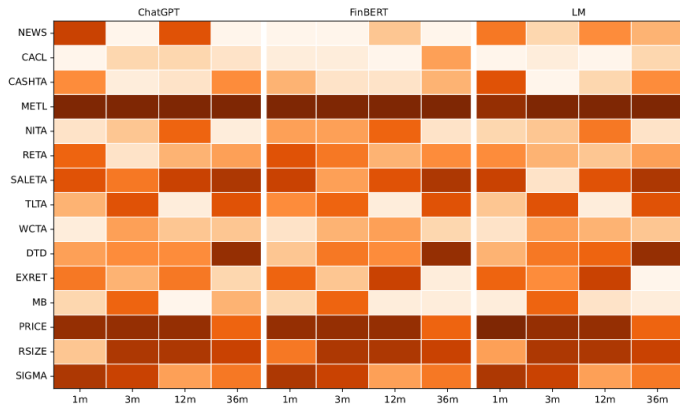
Q2: Importance of news in the linear model

- News sentiment adds incremental predictive power beyond financial indicators

	Panel A: Baseline model				Panel B: ChatGPT body				Panel C: FinBERT body				Panel D: LM body			
	1m	3m	12m	36m	1m	3m	12m	36m	1m	3m	12m	36m	1m	3m	12m	36m
CACI	0.13*** (4.78)	0.12*** (5.35)	0.08*** (2.73)	0.03 (1.23)	0.11*** (3.89)	0.12*** (5.26)	0.07*** (2.50)	0.03 (1.18)	0.13*** (4.84)	0.12*** (5.37)	0.08*** (2.71)	0.03 (1.19)	0.12*** (4.41)	0.12*** (4.92)	0.08*** (2.70)	0.03 (1.15)
CASHITA	2.93** (2.36)	0.97 (0.80)	0.09 (0.12)	-0.26 (-0.36)	2.54** (2.35)	0.97 (0.81)	0.05 (0.06)	-0.25 (-0.37)	2.96** (2.46)	1.00 (0.81)	0.10 (0.13)	-0.25 (-0.36)	2.90** (2.45)	0.96 (0.80)	0.09 (0.12)	-0.25 (-0.36)
METL	0.01*** (3.08)	0.02*** (2.86)	0.01 (0.38)	0.02*** (2.63)	0.01** (2.53)	0.02** (2.55)	0.00 (0.38)	0.02*** (2.65)	0.01*** (3.10)	0.02*** (2.70)	0.01 (0.41)	0.02*** (2.70)	0.01*** (3.05)	0.02*** (2.69)	0.00 (0.38)	0.02*** (2.64)
NITA	-0.23 (-0.17)	-0.11 (-0.13)	-1.31 (-1.12)	-1.40 (-1.32)	0.09 (0.07)	0.21 (0.23)	-1.08 (-0.92)	-1.31 (-1.21)	-0.22 (-0.16)	-0.06 (-0.07)	-1.22 (-1.02)	-1.33 (-1.28)	-0.18 (-0.14)	-0.03 (-0.04)	-1.28 (-1.09)	-1.36 (-1.27)
RETA	0.12 (0.71)	0.12 (1.14)	0.13* (1.84)	0.01 (0.16)	0.10 (0.70)	0.10 (1.05)	0.12* (1.73)	0.01 (0.11)	0.11 (0.68)	0.11 (1.01)	0.12* (1.72)	0.01 (0.11)	0.11 (0.69)	0.11 (1.11)	0.13* (1.82)	0.01 (0.13)
SALETA	-0.82** (-2.00)	-0.38 (-0.75)	-1.54*** (-2.79)	-2.97*** (-4.32)	-0.48 (-1.09)	-0.30 (-0.59)	-1.50*** (-2.66)	-2.96*** (-4.33)	-0.78* (-1.92)	-0.34 (-0.65)	-1.50*** (-2.70)	-2.94*** (-4.38)	-0.64 (-1.58)	-0.31 (-0.62)	-1.52*** (-2.76)	-2.96*** (-4.33)
TLTA	3.99*** (5.91)	3.70*** (5.52)	3.62*** (7.73)	3.38*** (4.99)	3.60*** (5.02)	3.56*** (4.92)	3.49*** (7.16)	3.36*** (4.81)	3.95*** (5.85)	3.62*** (5.30)	3.55*** (7.62)	3.36*** (4.91)	3.86*** (6.00)	3.64*** (5.35)	3.59*** (7.66)	3.37*** (4.94)
WCTA	-1.97** (-2.22)	-1.17 (-1.08)	-0.18 (-0.31)	-0.18 (-0.22)	-1.88** (-2.46)	-1.17 (-1.09)	-0.15 (-0.27)	-0.18 (-0.22)	-2.04** (-2.40)	-1.25 (-1.12)	-0.24 (-0.44)	-0.20 (-0.25)	-1.88** (-2.28)	-1.12 (-1.03)	-0.17 (-0.30)	-0.17 (-0.21)
DTD	0.24*** (2.99)	-0.07 (-0.53)	-0.22** (-2.43)	-0.27*** (-3.34)	0.23*** (3.53)	-0.06 (-0.48)	-0.21** (-2.44)	-0.27*** (-3.51)	0.24*** (3.10)	-0.07 (-0.54)	-0.22** (-2.47)	-0.27*** (-3.33)	0.23*** (2.90)	-0.07 (-0.52)	-0.22** (-2.42)	-0.27*** (-3.34)
EXRET	-2.69*** (-3.78)	-1.21*** (-3.89)	-0.98*** (-2.69)	-0.47 (-1.10)	-1.95*** (-2.93)	-0.94*** (-3.00)	-0.75** (-2.16)	-0.41 (-0.84)	-2.55*** (-3.56)	-1.03*** (-3.14)	-0.84** (-2.49)	-0.40 (-0.92)	-2.55*** (-3.62)	-1.15*** (-3.61)	-0.95*** (-2.59)	-0.45 (-1.04)
MB	-0.10 (-0.68)	-0.12 (-1.32)	-0.12 (-1.14)	-0.03 (-1.14)	-0.07 (-0.64)	-0.11 (-1.35)	-0.11 (-1.10)	-0.03 (-1.14)	-0.09 (-0.69)	-0.11 (-1.39)	-0.11 (-1.15)	-0.03 (-1.12)	-0.09 (-0.67)	-0.11 (-1.32)	-0.12 (-1.13)	-0.03 (-1.13)
PRICE	-1.28*** (-11.52)	-1.07*** (-4.40)	-0.59*** (-4.97)	-0.08 (-0.53)	-1.16*** (-8.66)	-1.03*** (-4.20)	-0.56*** (-4.48)	-0.07 (-0.44)	-1.27*** (-10.88)	-1.06*** (-4.28)	-0.59*** (-4.85)	-0.08 (-0.52)	-1.26*** (-10.58)	-1.06*** (-4.32)	-0.59*** (-4.79)	-0.08 (-0.50)
RSIZE	-0.31 (-1.51)	-0.04 (-0.17)	-0.07 (-0.65)	-0.09 (-1.30)	-0.29 (-1.47)	-0.05 (-0.20)	-0.08 (-0.72)	-0.09 (-1.35)	-0.31 (-1.52)	-0.04 (-0.18)	-0.07 (-0.61)	-0.09 (-1.26)	-0.30 (-1.53)	-0.04 (-0.18)	-0.07 (-0.66)	-0.09 (-1.31)
SIGMA	-0.18 (-0.84)	0.39** (2.10)	0.01 (0.06)	-0.02 (-0.06)	-0.26 (-1.28)	0.33* (1.75)	-0.06 (-0.27)	-0.04 (-0.13)	-0.18 (-0.87)	0.37** (2.00)	0.00 (0.00)	-0.03 (-0.10)	-0.19 (-1.00)	0.36** (1.97)	0.00 (0.02)	-0.03 (-0.09)
Sentiment	-	-	-	-	-2.51*** (-13.05)	-1.10*** (-6.28)	-1.20*** (-3.61)	-0.40 (-0.70)	-0.57*** (-3.39)	-0.74*** (-2.73)	-0.61*** (-2.91)	-0.37** (-2.02)	-0.89*** (-4.16)	-0.53** (-2.54)	-0.20 (-1.14)	-0.16 (-1.00)
Pseudo- R^2	0.37	0.29	0.19	0.13	0.41	0.30	0.19	0.13	0.38	0.30	0.19	0.13	0.38	0.30	0.19	0.13
AUC	0.98	0.96	0.91	0.86	0.98	0.96	0.91	0.86	0.98	0.96	0.91	0.86	0.98	0.96	0.91	0.86
Observations	246,439	238,541	226,522	242,181	246,439	238,541	226,522	242,181	246,439	238,541	226,522	242,181	246,439	238,541	226,522	242,181

Q2: Importance of news in the nonlinear model

- Relative importance of variables from the XGBoost model
- Darker shades indicate higher importance
- News is more important than most financial variables



Economic gain

- Firms with higher bankruptcy probabilities are associated with lower cross-sectional expected returns

Portfolio	Low(1)	2	3	4	5	6	7	8	9	High(10)	LS1090	LS2080
Panel A: Portfolio summary statistics and alphas												
Average returns	1.67 (3.36)	1.10 (2.86)	1.03 (2.68)	0.81 (2.55)	0.37 (0.92)	0.81 (1.89)	1.02 (2.31)	0.49 (0.87)	-0.06 (-0.10)	-2.71 (-3.26)	4.39 (5.34)	1.99 (3.05)
CAPM alpha	0.59 (1.99)	0.15 (1.05)	0.09 (0.51)	-0.11 (-0.49)	-0.49 (-2.77)	-0.10 (-0.61)	0.04 (0.18)	-0.48 (-1.22)	-0.94 (-1.88)	-4.09 (-6.16)	4.68 (5.34)	1.91 (2.63)
FF3 alpha	0.53 (2.97)	0.13 (1.00)	0.07 (0.39)	-0.10 (-0.48)	-0.49 (-2.72)	-0.10 (-0.56)	0.07 (0.37)	-0.41 (-1.43)	-0.83 (-1.91)	-3.80 (-7.46)	4.33 (7.19)	1.72 (3.45)
Sharpe ratios	0.98	0.78	0.72	0.57	0.27	0.58	0.67	0.31	-0.04	-1.06	2.11	1.38
Panel B: Portfolio news-based variables												
ChatGPT headline sentiment	0.242	0.244	0.246	0.246	0.246	0.241	0.235	0.231	0.222	0.193	-	-
ChatGPT body sentiment	0.321	0.307	0.301	0.296	0.289	0.279	0.271	0.263	0.246	0.200	-	-
ChatGPT headline 1m-prob	0.026	0.026	0.026	0.026	0.026	0.027	0.027	0.028	0.029	0.033	-	-
ChatGPT body 1m-prob	0.024	0.024	0.025	0.025	0.025	0.026	0.027	0.028	0.031	0.039	-	-

Q3: news sentiment and macro variables

$$\text{Macro}_t = \alpha_{00} + \alpha_{01} \text{SentimentScore}_t + \epsilon_t \quad (4)$$

- Macro variables: CBOE Volatility Index (VIX); Real GDP Growth (GDPG); Industrial Production Growth (IPG), and recession probability (SRP)
- Sentiment exhibit significant correlations with contemporaneous macro variables

	Panel A: VIX			Panel B: GDPG		
	Coef	t-stat	R ²	Coef	t-stat	R ²
ChatGPT headline	-22.04	-2.60	0.04	0.02	1.26	0.01
ChatGPT body	-40.65	-3.92	0.11	0.03	2.28	0.02
FinBERT headline	-27.88	-4.37	0.06	0.03	2.92	0.02
FinBERT body	-25.29	-4.62	0.08	0.02	2.23	0.01
LM headline	-6.39	-1.00	0.01	0.01	1.05	0.00
LM body	-3.31	-0.86	0.01	0.00	0.80	0.00

	Panel C: IPG			Panel D: SRP		
	Coef	t-stat	R ²	Coef	t-stat	R ²
ChatGPT headline	0.00	-0.20	0.00	-0.02	-0.08	0.00
ChatGPT body	0.01	1.35	0.00	-0.71	-2.51	0.05
FinBERT headline	0.01	2.46	0.01	-0.39	-1.88	0.01
FinBERT body	0.01	1.10	0.00	-0.23	-1.44	0.01
LM headline	0.00	1.21	0.00	-0.21	-2.04	0.02
LM body	0.00	0.73	0.00	-0.11	-1.50	0.01

Q3: macro variables and bankruptcy rate

$$\text{BankruptcyRate}_t = \alpha_{10} + \alpha_{11} \text{Macro}_{t-\text{lag}} + \epsilon_t \quad (5)$$

- Macro variables significantly predict future bankruptcy rate

	Panel A: Lag 1m			Panel B: Lag 3m		
	Coef	<i>t</i> -stat	<i>R</i> ²	Coef	<i>t</i> -stat	<i>R</i> ²
<i>VIX</i>	0.0001	3.77	0.08	0.0001	4.66	0.14
<i>GDPG</i>	−0.0285	−2.85	0.06	−0.0327	−2.55	0.08
<i>IPG</i>	−0.0133	−1.23	0.01	−0.0315	−2.67	0.05
<i>SRP</i>	0.0023	3.01	0.09	0.0027	3.69	0.13

Extension

1. Predict firm bankruptcy using daily news
2. Examine the role of the interaction between numerical financial variables and narrative contextual information in corporate bankruptcy prediction (Kim and Nikolaev, 2024, JAR)
3. Use ChatGPT to predict alternative credit events