The News in Earnings Announcement Disclosures: Capturing Word Context Using LLM Methods

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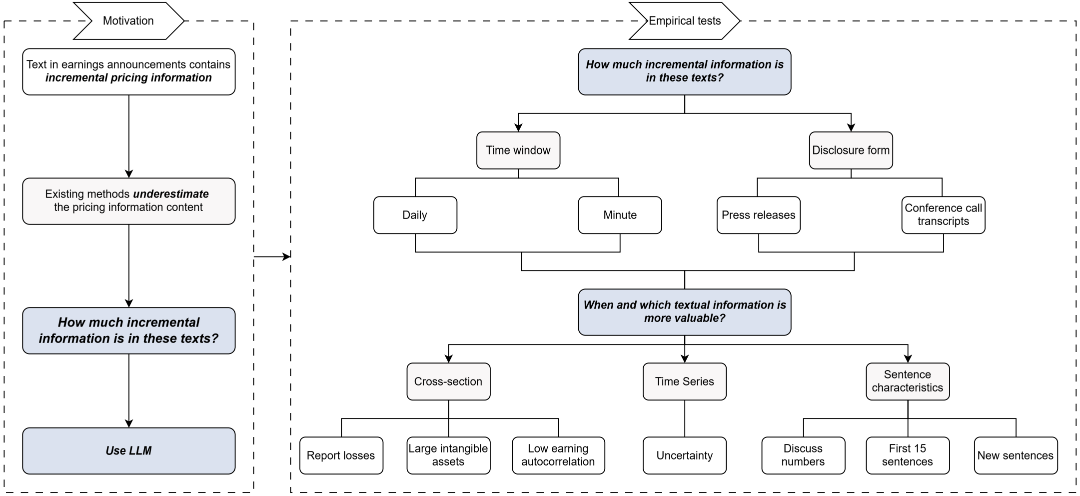
Overview

Framework


Motivation
Text in earnings announcements contains *incremental pricing information*
Existing methods *underestimate* the pricing information content
How much incremental information is in these texts?
Use LLM
Empirical tests
How much incremental information is in these texts?
Time window
Disclosure form
Daily
Minute
Press releases
Conference call transcripts
When and which textual information is more valuable?
Cross-section
Time Series
Sentence characteristics
Report losses
Large intangible assets
Low earning autocorrelation
Uncertainty
Discuss numbers
First 15 sentences
New sentences

Question

- Q1: How much incremental information is in earnings announcement text beyond accounting numbers?
- Q2: When and which textual information in earnings announcements is more valuable for investors?

Motivation

- Text in earnings announcements conveys important pricing information beyond numbers
  - Tone (Huang et al., 2014, TAR)
  - Readability (Lee, 2011, CAR)
  - Cybersecurity risk (Florackis et al., 2023, RFS)
- Existing methods underestimate the pricing information content in earnings announcement text
  - Ignore word context (Frankel et al., 2022, MS)
    - Dictionary
    - Traditional ML
- **How much incremental pricing information is in earnings announcement text?**
- **LLMs can effectively capture information from word context**
  - Attention-based transformers
  - Large-scale training

Marginal contribution

- Explanatory power of earnings announcement text for short-window stock returns
  - Frankel et al., 2022, MS
    - Using traditional methods that ignore word context, texts in earnings press explain only **4.5%** of the cumulative abnormal returns (CAR[0,1])
  - This paper
    - Using a LLM, texts in earnings press explain **14.9%** of the cumulative abnormal returns (CAR[0,1])

Hypothesis: Q1

- How much incremental information is in earnings announcement text?
  - H1: Text in earnings announcements contains incremental pricing information beyond numbers
  - H2: LLMs outperform conventional methods that ignore word context in extracting pricing information from earnings announcement text

Hypothesis: Q2

- When and which textual information in earnings announcements is more valuable?
  - H3: During periods of high uncertainty, textual information is more valuable
    - Investors pay more attention to unstructured information (Loh and Stulz, 2018, JF)
  - H4: Textual information is more valuable for firms with lower earning persistence: reporting losses, having large intangible assets, and exhibiting low earnings autocorrelation
    - Losses are often driven by one-time or nonrecurring events (Hayn, 1995, JAE)
    - Timing mismatch between recognized costs and revenues (Lev and Zarowin, 1999, JAR)
  - H5: Sentences that directly discuss numbers, appear at the beginning of the text, and contain new content are more valuable

Data

- **Earnings press releases** from 8-K filings obtained through the SEC EDGAR
- Earnings call transcripts are obtained from Capital IQ
- Daily stock returns are sourced from CRSP, and after-hours and pre-market returns are sourced from TAQ
- Quarterly fundamentals are sourced from Compustat
- Analyst quarterly estimates, management guidance, and earnings announcement (conference call) timestamps are obtained from I/B/E/S
- Out-of-sample period: 2014–2023

Use LLM to extract textual information

- Step 1 : Obtain firm-quarter earnings press releases via the SEC's EDGAR database
- Step 2: Filter the textual content
  - Exclude texts with fewer than 10 sentences or 250 total words
  - Exclude generic cautionary statements and tables
- Step 3: Split the dataset
  - Fine-tuning: 2006-2013
  - Out-of-sample test: 2014-2023

Use LLM to extract textual information

- Step 4: Fine-tune a BERT model
  - Input: earnings press releases
  - Output: two-day cumulative abnormal stock returns (CAR[0,1])

- Step 5: Obtain out-of-sample CAR[0,1] (CAR LLM EA)
  - Aggregate all pricing information contained in the text

Use traditional methods to extract information

- Textual information
  - Dictionary-based textual proxies
    - *Tone*, *Length*, *Fog*, *Numbers* and *Future*
  - Non-LLM machine learning–based textual proxy (CAR GB EA)
    - Use gradient boosting to map textual features to CAR[0,1]
- Numerical information
  - Use gradient boosting to map 12 influential financial surprise variables to CAR[0,1] (CAR GB FSA)

Main regression model

- Explaining CAR:

$$\begin{aligned} \text{CAR}_{[0,1],iq} = \alpha_2 &+ \delta_1 \textbf{CAR LLM EA}_{iq} \\ &+ \delta_2 \text{Alternative Text Measure}_{iq} \\ &+ \delta_3 \text{Financial Statement Surprises}_{iq} \\ &+ \delta_4 \text{Controls}_{iq} + \text{Fixed Effects}_i + \chi_{iq} \end{aligned} \tag{1}$$

- CAR LLM EA represents the LLM-predicted CAR
- Alternative Text Measure is the non-LLM-predicted CAR
- Financial Statement Surprises are 12 numerical account variables

Q1: How much incremental information is in EA text?

- Text in EA explains 14.9% of the variation in CAR
- H1: Text in EA contains incremental pricing information
- H2a: LLMs outperform dictionary-based methods in extracting pricing information

	Dependent variable: *CAR [0,1]*							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Comparison with dictionary-based measures and financial surprise variables								
CAR LLM EA	1.01***				0.95***	1.11***		1.00***
Tone		0.56***		0.46***	0.01		0.66***	0.05
Fog		−0.01		−0.01 *	−0.01		−0.03***	−0.03**
Length		−0.10		−0.02	0.14***		−0.14	0.00
Numbers		0.01***		0.01***	−0.01***		0.01***	0.00
Future		−0.07		−0.04	−0.05		−0.14	0.04
Earn Surp			2.39**	2.85***	2.63***		2.46***	2.57***
Sales Surp			2.07***	1.84***	1.10***		1.79***	1.12***
Ebitda Surp			6.55***	6.31***	3.51***		6.48***	3.60***
Ebit Surp			1.56***	1.54***	1.06***		1.73***	1.20***
Pre-Tax Surp			2.25***	2.18***	1.20**		2.20***	1.18***
Gaap Surp			1.07***	0.69 *	0.32		0.57	0.18
Cfo Surp			8.46***	8.70***	7.12***		8.21***	6.70***
Earn Surp (GA)			0.01***	0.01***	0.01**		0.01***	0.01**
Earn Surp (GQ)			0.01***	0.01***	0.01***		0.01***	0.01***
Sales Surp (GA)			0.29***	0.08	−0.01		0.14	0.11
Sales Surp (GQ)			1.98***	1.84***	0.75		1.62***	0.69
Ebitda Surp (GA)			2.04**	1.84**	1.10		1.67**	0.92
Spec Items			−0.11***	−0.09***	−0.00		−0.03	0.01
Size			0.05**	−0.02	−0.13***		−0.99***	−1.17***
N	98,171	98,171	98,171	98,171	98,171	97,942	97,942	97,942
Fixed effects	No	No	No	No	No	Firm	Firm	Firm
Adjusted R^2	14.9%	1.6%	4.9%	5.9%	16.6%	16.7%	8.6%	18.3%
Within R^2	—	—	—	—	—	14.4%	6.2%	16.3%

Q1: How much incremental information is in EA text?

- Comparison with non-LLM machine learning measures derived from text and financial surprise variables
- H1: Text in EA contains incremental pricing information
- H2b: LLMs outperform non-LLM machine learning in extracting pricing information

	Dependent variable: $CAR[0,1]$							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
CAR LLM EA	1.01***				0.78**	1.07***		0.81***
CAR GB EA		0.61***		0.39***	0.01		0.39***	0.04*
CAR GB FSA			0.80***	0.74***	0.52**		0.78***	0.55***
N	98,171	98,171	98,171	98,171	98,171	97,942	97,942	97,942
Fixed effects	No	No	No	No	No	Firm	Firm	Firm
Adjusted R^2	14.9%	3.1%	11.5%	12.7%	19.0%	16.1%	14.6%	20.3%
Within R^2	—	—	—	13.9%	12.4%	—	—	18.3%

Q1: How much incremental information is in EA text?

- Immediate price revisions
- H1: Text in EA contains incremental pricing information

	Dependent variable: RET 5M EA			Dependent variable: RET 30M EA			Dependent variable: RET 2H EA		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
ET LLM EA	2.04***		1.16***	2.18***		1.28***	1.55***		0.99***
ET GB FSA		1.08***	0.91***		1.12***	0.92***		1.09***	0.86***
N	63,249	63,249	63,249	63,249	63,249	63,249	63,249	63,249	63,249
Fixed effects	No	No	No	No	No	No	No	No	No
Adjusted R^2	8.0%	14.6%	16.8%	9.4%	15.5%	18.3%	10.2%	14.2%	17.7%

Q1: How much incremental information is in EA text?

- Conference calls analyses
- H1: Text in EA contains incremental pricing information
- H2: LLMs outperform non-LLM machine learning in extracting pricing information

Panel A: Two-day price revisions

	Dependent variable: $CAR[0,1]$		
	(1)	(2)	(3)
CAR LLM CC	2.54***		0.89**
CAR LLM EA		0.83***	0.43***
CAR GB FSA		0.55**	0.45***
N	56,670	56,670	56,670
Fixed effects	No	No	No
Adjusted R^2	18.9%	20.8%	24.1%

Panel B: One-hour price revisions

	Dependent variable: $RET\ 1H\ CC$		
	(1)	(2)	(3)
RET LLM CC	2.91***		2.08***
RET LLM EA		0.54***	0.11***
RET GB FSA		0.80***	0.66***
N	33,618	33,618	33,618
Fixed effects	No	No	No
Adjusted R^2	12.1%	11.9%	15.5%

Q2: When and which textual information is more valuable?

- H3: During periods of high uncertainty, textual information is more valuable
- H4: Textual information is more valuable for firms that report losses, have large intangible assets, and exhibit low earnings autocorrelation

Panel A: Cross-sectional tests: Incremental disclosure news and earnings persistence

	Loss (1)	Profit (2)	High R&D firms (3)	Other firms (4)	Low earn AR (1) firms (5)	Other firms (6)
Incremental Adjusted R^2 of CAR LLM EA	9.4%	5.6%	9.0%	6.7%	8.8%	6.5%
p-value (1) > (2)	0.00***					
p-value (3) > (4)			0.00***			
p-value (5) > (6)					0.00***	
N (firm-quarters)	29,803	68,368	18,980	63,074	17,771	71,053

Panel B: Time series tests: Incremental disclosure news and changes in aggregate uncertainty

	Dependent variable: Δ *Incremental Adjusted R^2* Changes in aggregate uncertainty			
	COVID-19 (1)	Trade war (2)	Financial crisis (3)	Enron scandal (4)
I(Event)	0.07**	0.06**	0.06**	0.06 *
p-value	(0.04)	(0.01)	(0.05)	(0.08)
N (month-years)	288	288	288	288

Q2: When and which textual information is more valuable?

- H5: Sentences that directly discuss numbers, appear at the beginning of the text, and contain new content are more valuable

	Dependent variable: *CAR [0,1]*						
	First partition: Discussion of numbers ($N=98{,}171$)			Second partition: Location of text ($N=87{,}406$)		Third partition: Novel contents ($N=85{,}342$)	
	Sentences discussing numbers (#s included) (1)	Sentences discussing numbers (#s excluded) (2)	Other sentences (3)	First 15 sentences (4)	Last 15 sentences (5)	New sentences (6)	Stale sentences (7)
R^2 *of CAR LLM EA*	11.7%	10.9%	6.1%	15.1%	2.4%	12.7%	3.9%
p-value (1) > (3)		0.00***					
p-value (2) > (3)		0.00***					
p-value (4) > (5)				0.00***			
p-value (6) > (7)						0.00***	

Extension

- Use LLMs to identify textual features
  - logical and causal reasoning errors
  - Readability
- Compare textual and numerical signals
  - Horizon effect of predictive power