Discussion of “Theory Meets Textual Analysis: Measuring Firm-Level Labor Cost Pressures and Inflation Pass-Through”

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FRB Vienna Macro Workshop

May 7, 2026

What the Paper Does

Big Picture: Important contribution to measuring firm-level labor cost pressures

1. **Primary Goal:** Measure firm-level *marginal* labor costs
   - Challenge: Compustat lacks direct wage data
   - Solution: Infer from textual analysis of 248,437 earnings calls (2002–2025)
   - Classify labor discussions into 8 topics via supervised approach
   - Regress intermediate input share on topics → use fitted values as measure
2. **Key Results:**
   - Aggregate index outperforms traditional slack measures in forecasting inflation
   - Pass-through to prices: highest for services, near-zero for manufacturing
   - Firm-level evidence: automation mitigates labor cost pressures

Overview of My Discussion

1. **KO Methodology:** How theory-weighted textual analysis works

2. **Methodological Extension:** AI-enhanced continuous measures as the next step

1. Understanding KO Methodology: The Measurement Strategy

Core challenge: Measure firm-level marginal labor costs without wage data

Step 1: Count keywords by topic (8 topics total)

- Supervised approach: authors define 5 core topics from reading transcripts
- Labor costs $\uparrow/\downarrow$, Headcount $\uparrow/\downarrow$, Shortages, Efficiency $\uparrow/\downarrow$, Agreements
- Each topic: count sentences containing keywords, normalize
- $\text{Topic}_{k,it} = \%$ of sentences mentioning topic k in firm i's call at time t

Step 2: Theory-motivated regression

- Intuition: When labor costs rise $\rightarrow$ firms substitute toward materials
- Regress intermediate input share on 8 topic counts:

$$\Delta \log(\text{M-share}_{it}) = \sum_{k=1}^{8} \beta_k \cdot \text{Topic}_{k,it} + \text{controls} + \varepsilon_{it}$$

Step 3: Use fitted values as labor cost measure

- $\lambda_{it} = \hat{\beta}_1 \cdot \text{Topic}_1 + \ldots + \hat{\beta}_8 \cdot \text{Topic}_8$ (weights from data, not theory)

Strengths and Limitations of This Approach

Strength: Using text to filter M-share changes

- **Problem:** M-share changes from many sources (supply shocks, tech, etc.)
- **Solution:** Topics identify which changes are labor-driven
- **Result:** Does well in forecasting inflation

Limitations:

1. **Inference relies on imputed wages**
   - Compustat lacks good firm-level wage and employment data
   - Authors use: (annual firm employment) $\times$ (industry avg wage QCEW)
   - Noise in wage imputation affects M-share construction
2. **Supervised topic classification is subjective**
   - 8 topics defined by authors' judgment and manual reading
   - May miss nuanced or emerging labor themes
3. **Theory motivates regression, data provides weights**
   - $\hat{\beta}_k$ coefficients come from empirical estimation, not first principles

2. Extension: Where Will Textual Analysis Go?

KO approach (keyword counts + manual topic definition):

- Count sentences by predefined topic categories
- $\text{Topic}_{k,it}$ = % of sentences mentioning topic k
- Treats all mentions equally within a topic

AI/LLM enhancement:

- **Context-aware scoring**: "costs remain low" $\neq$ "costs crushing us"
- **Intensity measurement**: How concerned? (0 to 1 scale)
- **Investment responses**: Direct extraction of capex plans (-1 to +1 scale)
- **No manual topic definition**: LLM interprets semantic meaning directly

Advantages of AI over keyword-based approaches:

1. **Semantic understanding**: Captures meaning, not just word presence
2. **Multi-dimensional**: Extract multiple measures simultaneously
3. **Less subjective**: No predefined topic categories required

The Prompt: What AI Can Do for You

```
PROMPT = """
You will be analyzing snippets of earnings calls transcripts to identify mentions of wages,
salaries, or labor costs.

For each snippet, extract three pieces of information:

    1. TOPIC: Is the company discussing labor costs or not?

    2. LABOR COST SENTIMENT (LCS): Construct an index of labor costs concerns for the firm given
the discussion in the call, ranging from 0 to 1 (in 0.1 increments), where 0 indicates no labor
cost concerns, 1 indicates maximum level of labor cost or labor cost concerns.

    3. INVESTMENT INTENTIONS (II): Construct an investment intentions score ranging from -1 to 1
(in 0.1 increments) based on whether the firm plans to change investment/capex/R&D/mergers/market
entry in response to labor costs (only score if labor costs index is non-zero).
       - Score -1 if firm definitely plans to DECREASE investment
       - Score 0 if firm mentions NO CHANGE or does not mention investment plans
       - Score 1 if firm plans to INCREASE investment

Examples
1. We continue to mitigate very high inflationary cost pressures introduced by labor shortages,
and plan to replace workers with capex spending going forward. LCS: 1, II:1
```

AI-Enhanced Analysis

LLM approach: For each transcript snippet, ask Claude to extract:

1. **Labor Cost Sentiment (LCS):** Score from 0 to 1
   - 0 = no labor cost concerns
   - 1 = maximum labor cost concerns

2. **Investment Intentions (II):** Score from -1 to 1
   - -1 = plan to decrease investment in response to labor costs
   - 0 = no change or not mentioned
   - +1 = plan to increase investment (e.g., automation)

Advantage: Measure captures intensity and nuances

Why Continuous Measures Matter: Two Examples

Both mention "higher wages" — but very different concern levels:

Example 1: SPAR Group (2022) — **Low Concern (0.2)**

"...A couple of comments on the impact of RISING WAGES ... that's happening ... around the world. ... We're already paying a very competitive wage..."

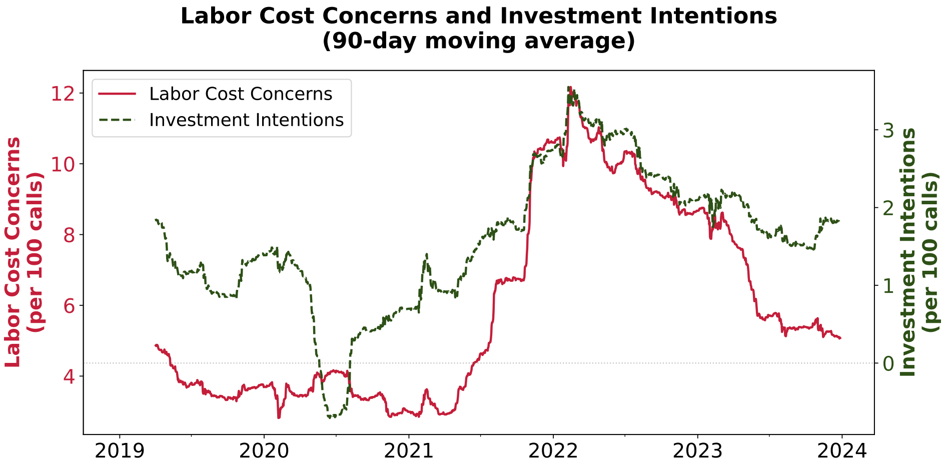
→ **Binary approach:** "higher wages" mentioned = 1
→ **LLM approach:** Concern = 0.2 (acknowledges trend, not worried)

Example 2: FedEx (2021) — **High Concern (0.9)**

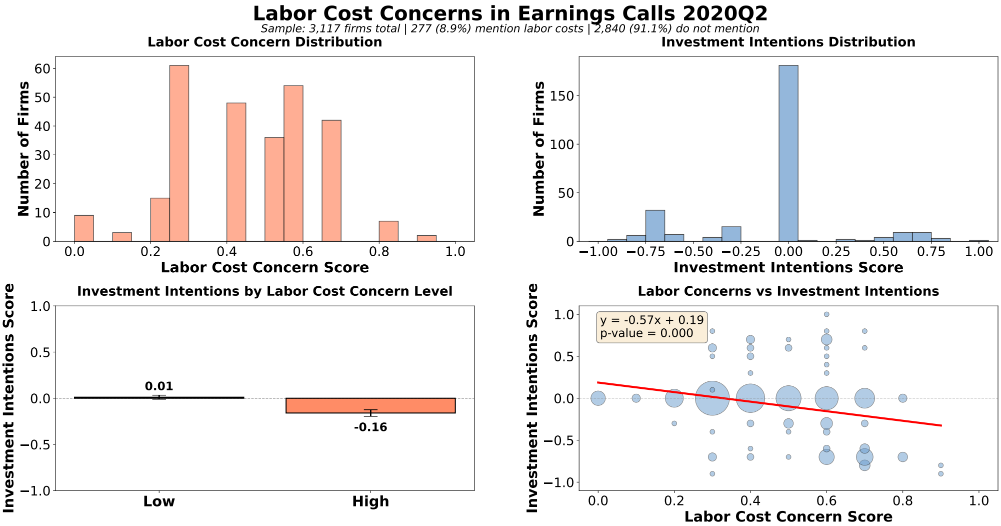
"...I want to break this impact into 2 components: HIGHER WAGES and the impact of network inefficiencies. Of the $450 million, we estimate that $200 million was incurred in HIGHER WAGE and purchase transportation rates..."

→ **Binary approach:** "higher wages" mentioned = 1
→ **LLM approach:** Concern = 0.9 (quantifies massive cost impact)

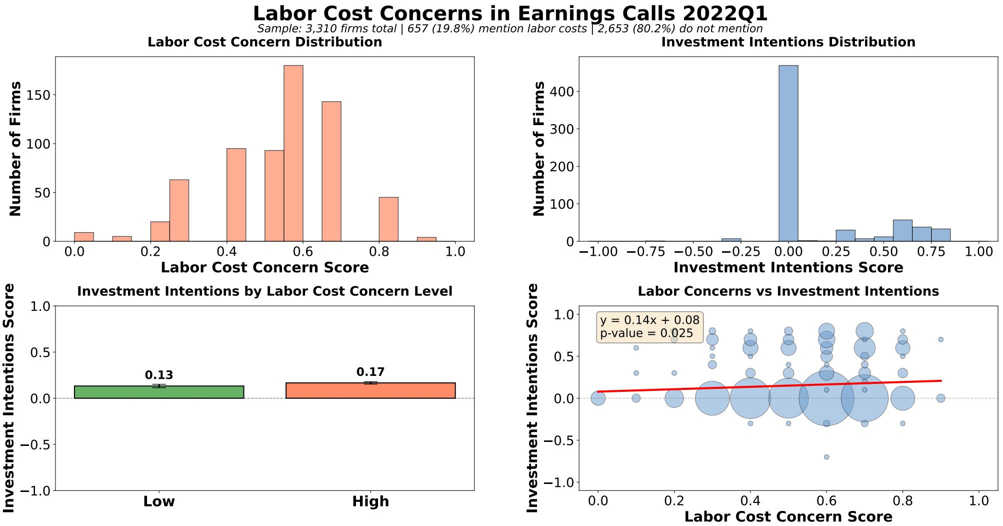
AI-Based Labor Cost Concerns and Investment Intentions



AI-based Results: Labor Cost Concerns in 2020



AI-based Results: Labor Cost Concerns in 2022



Insights from AI-LLM Analysis

1. **Heterogeneity in concern levels**
   - Not just binary mention/no-mention
   - Distribution shows firms experiencing different intensities
   - Some firms face severe pressures, others moderate concerns
2. **Investment (and other) responses are measurable**
   - Time-varying correlation: higher labor costs $\rightarrow$ more investment intentions, BUT not always
3. **Granularity enables firm-level analysis**
   - Can track individual firm responses over time
   - Can link to firm characteristics (size, sector, profitability)
   - Can study pass-through heterogeneity more richly

Why AI-LLMs represent the future

1. **Semantic understanding**
   - Distinguish “labor costs manageable” from “labor costs major headwind”
   - Captures synonyms and variations automatically
2. **Multi-dimensional extraction**
   - Extract multiple variables simultaneously (concern + investment + automation)
   - Can adapt to new questions without re-coding
3. **Scalability**
   - Apply same prompt to millions of documents
   - Consistent scoring across time and firms
4. **Validation and iteration**
   - Can ask AI to provide reasoning (explainability)
   - Easy to refine prompts based on sample outputs

Concluding Remarks

- **Excellent paper** that advances measurement of labor market pressures from text
- **AI-based methods** are the natural next step:
  - Simple keyword matching captures aggregate trends
  - AI can unlock firm-level heterogeneity and investment responses
  - Future research should embrace these tools for richer insights