Discussion
Mental Models and Financial Forecasts

by Francesca Bastianello, Paul Décaire, and Marius Guenzel

Eduardo Dávila

Yale and NBER

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This Paper

- **Broader Question** $\rightarrow$ How do individuals form beliefs?
  Beliefs: perceptions over future values of (endogenous) variables

$$\textbf{Environment} \underset{(1)}{\Longrightarrow} \textbf{Beliefs} \underset{(2)}{\Longrightarrow} \textbf{Outcomes}$$

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- **This Paper** → (1)

  How do equity analysts justify their forecasts?

  - What do they *write*? How do they *reason*?
  - Analyst reports (2000-25) → use LLMs to extract "mental models"
    1. Valuation methods: DCF vs. multiples
    2. Attention: topics, channels, time outlook, sentiment, etc.
  - Models are sparse/rigid & attention is more important

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- **Overall Assessment** → valuable contribution
  - Natural use of LLMs
  - Expands on belief formation literature → complement to surveys
  - Many interesting facts

High-Level Summary

1. Conceptual Framework
2. Data Collection
3. Main Empirical Findings

Discussion $\rightarrow$ Summary with Remarks + Comments

Conceptual Framework

- Single analyst → No equilibrium/strategic interactions
  - Truth: $p = \sum_k v_k x_k$
  - Forecast: $p^m = \sum_k m_k x_k$
  - Signal: $s_k = x_k + u_k$ with $u_k \sim N\left(0, \tau_{sk}^{-1}\right)$

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- Model = *method* + *attention*

Method

$m = \{m_k\}_{k=1}^K$ discrete choice

Attention

$\tau_s = \{\tau_{sk}\}_{k=1}^K$ continuous choice

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- Final stage: choose attention τ_s to minimize MSE

$$V(m) = \min_{\{\tau_s\}} \mathbb{E}\left[\left(\underbrace{p}_{\text{truth}} - \underbrace{\mathbb{E}\left[p^m \mid \{s_k\}_k\right]}_{\text{forecast}}\right)^2\right] \text{ s.t. } \sum_k c_k \tau_{sk} \leq C$$

- Initial stage: choose methods given optimally chosen precisions

$$V^\star = \max_m \{V(m)\}$$

- Heterogeneity in attention and model due to c_k^i, C^i, v_k^i

Model Predictions

1. More attention to dimensions if
   i) more relevant
   ii) more volatile $\rightarrow$ driven by Gaussianity
   iii) easier-to-process
2. Model shaped by individual characteristics
   - e.g. experience yields persistence
3. Attention is *sparse* $\rightarrow$ driven by linear constraint on precisions
4. Misperception $\iff$ over/underreaction
   - Overreaction to salient topics $\rightarrow$ lower realized returns
   - Underreaction to less salient topics $\rightarrow$ higher realized returns

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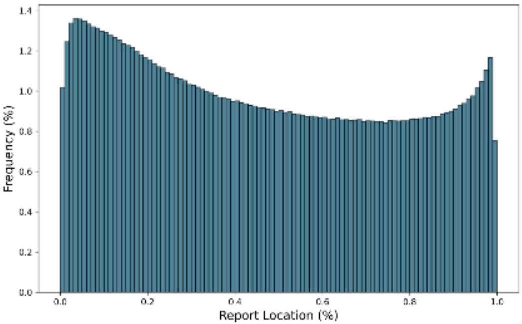
- **Remarks:**
  1. Standard Gaussian rational inattention (with entropy constraint)
     Very rational
  2. Tension in this literature: analyst "knows the true model"
     - Ideally: $m_k = v_k$
  3. Is this the best model to organize the empirical findings?
     - There are many alternative models of belief formation
     - Why not fewer functional/parametric forms?
     - Better connection to measurement?

Data Collection

- **Strategy:** *multi-step* LLM prompting
  - Near-universe of 2.1 million analyst reports (2000-2025)
  - Extract
    1. Valuation method
       DCF, multiples, etc.
    2. Line of reasoning (attention) [39 on average per report]
       Topic + Entities + Valuation Channel + Time Outlook + Sentiment
  - 301,364 reports, 18,284 firms, 8,578 analysts
- **Models**: Gemini 2.0 Flash + Claude 3.5 Sonnet
- Standard question: how good are these procedures?
  - Several robustness checks in paper
    Similarity ≈ 1
  - Cross-validation with alternative LLMs?
  - Better LLMs? $\rightarrow$ $\boxed{\text{Claude Opus 4.5 or GPT-5.2-Codex?}}$

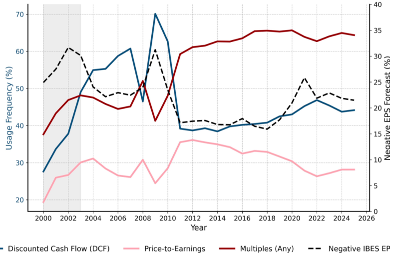
Data Collection

(A) Where Does the AI Collect the Information?.



- Interesting nuggets: Information at beginning and end
- Lots more in the paper

Empirical Findings: Valuation Method



- DCF and multiples are widespread
- Interesting DCF uptick in Global Financial Crisis
  Negative earnings
- Variation across
  - firms: size, age, industry → see paper
  - analysts → see paper

Empirical Findings: Attention

1. Sparsity in topics (16/139 topics in average report)
   - **Remark**: not obvious that every topic applies to every report?
     Examples of topics are: “Product Recall”, “Clinical Trials”, etc.
2. Persistence in
   - Valuation 80% year-on-year overlap
   - Attention: 40% year-on-year overlap
3. Differences explained by attention more than valuation
   - Time-series: 64% attention vs. 36% valuation
   - Cross-section: 83% attention vs. 17% valuation
   - **Remark**: more scope for variation in attention?

Empirical Findings: Attention

4. Analyst vs. Firm
   - Firm characteristics $\rightarrow$ attention
   - Analyst characteristics (training, location) $\rightarrow$ valuation
5. Biased beliefs and return predictability
   - Overreaction to firm-related topics $\rightarrow$ lower realized returns
   - Underreaction to macro-related topics $\rightarrow$ higher realized returns

- **Remarks**:
  1. It would be useful to run CG-style regressions in the/a model
     This would greatly help interpretation of coefficients
  2. What is the economic mechanism for predictability?
  3. Can trading strategies exploit the predictability? Magnitudes?
  4. Can strategic considerations explain overreaction to firm-related information?
     Broader Point: Belief Revelation vs. Persuasion

Final Comments/Remarks

1. It would be great to have direct links to decisions/outcomes

$$\textbf{Environment} \underset{(1)}{\Longrightarrow} \textbf{Beliefs} \underset{(2)}{\Longrightarrow} \textbf{Outcomes}$$

   - (1) is interesting, but we also need (2)
   - Data on actual portfolio positions?
     Do investors follow analysts with particular models?
   - Analyst career outcomes?
   - Return predictability is the closest in the paper $\rightarrow$ more!

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2. What are the normative implications?

$$\textbf{Environment} \underset{(1)}{\Longrightarrow} \textbf{Beliefs} \underset{(2)}{\Longrightarrow} \textbf{Outcomes} \underset{(3)}{\Longrightarrow} \textbf{Welfare}$$

    - Is all of this good or bad? How about (3)?
    - Should analysts be required to provide multiple valuation methods?
    - Should analysts separately disclose firm vs. macro justifications?

Conclusion

- Valuable contribution
  - Natural use of LLMs for belief measurement
  - Rich collection of novel facts about analyst reasoning
- Looking forward
  - Tighter connection between theory and empirics
  - Richer outcome data $\rightarrow$ connecting to revealed preference
  - Normative implications
- Promising area!

$\boxed{\text{Thank you for your attention}}$