Crash Narratives

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The Paper

Really nice paper about asset pricing and behavioral finance:

Research question: how does narratives of rare events (stock market crashes) translate into asset prices and investors behavior?

How?: by studying crash narratives vs 1) variation in market returns and volatility and 2) investor crash beliefs

Methodology: using text data, construct a crash narrative indicator, capturing media attention to stock market crashes.

The Paper

Main findings:

- Strong association between the crash narrative measure and market-based risk, return, fear, disagreement indicators and following day volatility.
- Media crash narratives are predictive of investor attention to stock market crashes, being this effect stronger where attention is persistent.
- Strong association between higher crash narratives in media and attention to the market vs. investor crash probability assessments. No association for institutional investors.

Comments

Robustness checks within the following dimensions:

1. **Measurement**
2. **Inference**

Comment 1: Measurement

- Crash narratives as *"... the retrieval of collective and perhaps personal memories associated with the event."*
- Largest crashes are used as baseline to compute similarities across whole history. This captures the similarity of all articles w.r.t. the narrative of that very same crash.
- **Concept similarity**: similarity between articles and a "dictionary" $\rightarrow$ 1987 crash narrative as a dictionary.
  - Perfect approach for Section 4 of the paper - investor beliefs testing with Shiller survey (expectation formation of crash is made in terms of 1987' and 1929' crashes)
- Also, smart adjustment of measure taking into account pre-crash days, to control for potential changes in structural media writing.

Comment 1: Measurement

- My preferred solution: **concept detection.**
- Hypothesis:
  - Media may be using more catastrophic language nowadays.
  - Different shock types generating different types of crashes (COVID crash), and hence, different crash narratives.
- **Concept detection**: supervised model to predict a characteristic (crash narrative) for every article. Problem $\rightarrow$ **no labeled data** $\rightarrow$ **embeddings** to the rescue.

Comment 1: Measurement

1. **Label data**: encode all history (use Sentence Transformers) and:
   1.1 Hand-pick your top N representative set of articles A of a crash (across whole sample).
   1.2 $\forall a \in A \rightarrow$ cosine similarity to whole embedding and retrieve most similar articles. After **manual inspection**, label them as *crash*. Hack: rely on Argilla interface.
2. **Train model**: follow Hansen et al. (2023) methodology. **Most accurate way of detecting a concept with text data.**
   2.1 Domain-adapt a Transformer to the sample.
   2.2 Fine-tune such pre-trained model with your labeled data.
   2.3 Each article has a probability of being a crash narrative. Adjust for monthly articles and construct time series.

Comment 2: Inference

- Many economics papers using text data, estimate first some phenomena to answer economic-related questions.
- This is done by means of a two-step methodology.
- In this paper:
  1. Model crash narratives with NLP techniques (upstream model).
  2. Econometric model(s) using data from previous step (downstream model).
- **Measurement error**: what if the crash narrative measure is constructed with other newspaper data?

Comment 2: Inference

- Regressions contain estimated rather than true latent variables $\rightarrow$ Measurement error $\rightarrow$ **Biased inference**
  - High bias but no variance (fixed confidence intervals width) in estimates.
- **Solution**: to use a one-step strategy, modeling joint distributions of text data, latent variables and numeric outcomes with maximum likelihood estimation (computing upstream and downstream models jointly).
  - For example, Supervised Topic model with covariates.
- Early stages of exciting literature at the intersection of the use of text data and econometrics Fong and Tyler (2021); Zhang et al. (2023); Allon et al. (2023); Battaglia et al. (2024)

Thank you

References I

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