Does finance benefit society? a language embedding approach

Manish Jha, Hongyi Liu, Asaf Manela

Washington University in St. Louis

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COVID-19

- Financial intermediaries bore most of the blame for 2008 crisis and subsequent recession
- Q: Will the financial sector be perceived more as a hero or villain after COVID-19?

Source: wsj.com
Why care?

“As finance academics, we should care deeply about the way the financial industry is perceived by society. Not so much because this affects our own reputation, but because there might be some truth in all these criticisms, truths we cannot see because we are too embedded in our own world. And even if we thought there were no truth, we should care about the effects that this reputation has in shaping regulation and government intervention in the financial industry. Last but not least, we should care because the positive role that finance can play in society depends on the public’s perception of our industry.”

Zingales (2015, AFA presidential address)
Public perceptions of finance matter

- Mostly survey evidence
  - Trust in bankers fell following the 2007–2008 financial crisis (Sapienza-Zingales 2012)
  - Public perceptions often diverge from those of economists (Sapienza-Zingales 2013)
  - Low trust can hinder insurance market efficiency (Gennaioli-Porta-Lopez-de-Silanes-Shleifer 2020)

- Short time dimension limits our understanding of public perception of finance
Questions

- How does finance sentiment change over time and differ across countries?
- How does it respond to rare disasters like the currently spreading pandemic?
- How do such changes relate to economic and financial outcomes?
Our approach

- Measure sentiment toward finance in an annual panel
- 8 large economies matched to languages from 1870–2009
- Computational linguistics approach applied to the text of millions of books
Main findings

- Persistent differences across languages/countries with ample time-series variation
- Finance sentiment declines after uninsured disasters (epidemics and earthquakes), but rises following insured ones (droughts, floods, and landslides)
- Shocks to finance sentiment have long-lasting effects on economic and financial growth
Related literature

  - We provide a new sentiment toward finance panel spanning centuries and several large economies

- Culture and its effects on economic outcomes (Guiso-Sapienza-Zingales 2006; Spolaore-Wacziarg 2013; Mokyr 2016; McCloskey 2016)
  - We show natural disasters provide one plausibly exogenous cause for cultural changes

- Text used to analyze culture, economics, and finance (Michel et al. 2011; Gentzkow-Kelly-Taddy 2019; Loughran-McDonald 2020)
  - Early work is bag-of-words / dictionary-based ⇒ missing context
  - Kozlowski-Taddy-Evans (2019) show embeddings capture cultural associations better
  - We provide a more efficient method using a pretrained model (BERT)
    - Transfer learning lowers estimation error and computation costs
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Data

- Text from Google Books corpus
  - Annual sentence (5-gram) counts 1870–2009
  - 8 languages: Chinese, German, French, Italian, Russian, Spanish, UK English and US English
  - About 1 billion sentences mentioning “finance”

- Natural disasters data
  - Emergency Events Database from CRED 1900–2009

- Macro data
  - Jorda-Schularick-Taylor macro data for advanced economies
  - Barro-Ursua macro data for Russia and China
Word embeddings

- We rely on recent language model (BERT, Devlin et al. 2018) to measure if “finance” mentions are on average closer to positive versus negative sentences.
- We use BERT to embed sentences in a low dimensional numerical vector (~800d).
- Neural word embeddings produce richer insights into cultural associations than prior methods.
  - e.g. \( \text{king} - \text{man} + \text{woman} \approx \text{queen} \)
- BERT is particularly good at distinguishing context.
- Basic idea
  - e.g. “correcting corruption or financial malpractice”
  - Closer to “finance damages society” than to “finance benefits society”
Measuring of finance sentiment

Step 1: Define positive—negative sentiment dimension
Measuring of finance sentiment

Step 2: Project “finance” mentioning sentence $j$ in language $i$ embeddings on the positivity dimension

Finance sentiment for language $i$ in year $t$ is mean cosine similarity across mentions.
Measuring of finance sentiment

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Finance sentiment for language $i$ in year $t$ is mean cosine similarity across mentions.
## Positive — negative defining sentences (English)

<table>
<thead>
<tr>
<th>Positive sentences</th>
<th>Negative sentences</th>
</tr>
</thead>
<tbody>
<tr>
<td>financial services benefit society</td>
<td>financial services damage society</td>
</tr>
<tr>
<td>finance is good for society</td>
<td>finance is bad for society</td>
</tr>
<tr>
<td>finance professionals are mostly good people</td>
<td>finance professionals are mostly corrupt people</td>
</tr>
<tr>
<td>finance positively impacts our world</td>
<td>finance negatively impacts our world</td>
</tr>
<tr>
<td>financial system helps the economy</td>
<td>financial system hurts the economy</td>
</tr>
</tbody>
</table>
## Sentences assigned most positive and negative finance sentiment (English)

<table>
<thead>
<tr>
<th>Positive sentiment sentences</th>
<th>Negative sentiment sentences</th>
</tr>
</thead>
<tbody>
<tr>
<td>financial support of the science</td>
<td>turmoil in the financial markets</td>
</tr>
<tr>
<td>financial management of the school</td>
<td>instability in the financial markets</td>
</tr>
<tr>
<td>financial support of the research</td>
<td>lack of money to finance</td>
</tr>
<tr>
<td>financial management of the business</td>
<td>a financial panic</td>
</tr>
<tr>
<td>financial support of this project</td>
<td>the financial panic</td>
</tr>
<tr>
<td>financial management initiative</td>
<td>financial panic in the united</td>
</tr>
<tr>
<td>financial support of the work</td>
<td>international financial instability</td>
</tr>
<tr>
<td>understanding of the financial system</td>
<td>lack of funds to finance</td>
</tr>
<tr>
<td>finance for small and medium</td>
<td>my finances falling short</td>
</tr>
<tr>
<td>finance graduate school of</td>
<td>the financial deficit</td>
</tr>
</tbody>
</table>

Repeat for all 8 languages
Sentiment toward finance 1870–2009

Persistent differences across languages/countries despite ample time-series variation
Finance sentiment growth

Focus on percentage growth to detrend

$$\Delta f_{it} = \frac{f_{i,t} - f_{i,t-1}}{|f_{i,t-1}|} \times 100$$
Common concerns

1. Books may not represent average citizen, especially far back in time
   ▶ Yes. But, “literary elite” commands large share of wealth, power, and influence on others’ opinions

2. Spanish is spoken outside of Spain
   ▶ Requires a modest leap of faith
   ▶ We expect it to introduce more error into our measurement toward the end of our sample

3. Language may have changed over time
   ▶ We do assume the meaning of language stays constant
   ▶ But our estimates come from variation in phrase use over time
   ▶ Manela-Moreira (2017) show English language changes over similar period does not affect much ability of ML to predict volatility
Natural disasters as exogenous shocks

Classify disaster as severe if it kills at least 20 per million population
Epidemics, droughts, earthquakes, volcanos are largely uninsured

<table>
<thead>
<tr>
<th>Disaster Group</th>
<th>Type</th>
<th>Disasters</th>
<th>Severe</th>
<th>Mean</th>
<th>Killed</th>
<th>Damage, $M</th>
<th>Insured, %</th>
</tr>
</thead>
<tbody>
<tr>
<td>Biological</td>
<td>Epidemic</td>
<td>46</td>
<td>19</td>
<td>378133</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Climatological</td>
<td>Drought</td>
<td>20</td>
<td>3</td>
<td>783922</td>
<td></td>
<td>1830</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Wildfire</td>
<td>53</td>
<td>0</td>
<td>41</td>
<td></td>
<td>504</td>
<td>37.22</td>
</tr>
<tr>
<td>Geophysical</td>
<td>Earthquake</td>
<td>150</td>
<td>18</td>
<td>7534</td>
<td></td>
<td>1744</td>
<td>21.23</td>
</tr>
<tr>
<td></td>
<td>Volcano</td>
<td>5</td>
<td>0</td>
<td>206</td>
<td></td>
<td>431.6</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Mass movement</td>
<td>8</td>
<td>0</td>
<td>79</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Hydrological</td>
<td>Flood</td>
<td>189</td>
<td>9</td>
<td>38949</td>
<td></td>
<td>859.3</td>
<td>42.97</td>
</tr>
<tr>
<td></td>
<td>Landslide</td>
<td>66</td>
<td>2</td>
<td>321</td>
<td></td>
<td>224.1</td>
<td></td>
</tr>
<tr>
<td>Meteorological</td>
<td>Storm</td>
<td>217</td>
<td>3</td>
<td>951</td>
<td></td>
<td>1132</td>
<td>101.2</td>
</tr>
<tr>
<td></td>
<td>Extreme Temp.</td>
<td>70</td>
<td>5</td>
<td>1068</td>
<td></td>
<td>2233</td>
<td>36.26</td>
</tr>
<tr>
<td></td>
<td>Fog (Smog)</td>
<td>1</td>
<td>1</td>
<td>4000</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Severe natural disasters 1900–2009

Systematic sources of risk may not provide risk sharing opportunities ⇒ high insurance premia and low take-up
Natural disasters affect future finance sentiment

<table>
<thead>
<tr>
<th></th>
<th>Finance sentiment growth_{t+1}</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
</tr>
<tr>
<td>Natural Disasters_{t}</td>
<td>-0.88**</td>
</tr>
<tr>
<td></td>
<td>(0.32)</td>
</tr>
<tr>
<td>War_{t}</td>
<td>0.10</td>
</tr>
<tr>
<td></td>
<td>(0.40)</td>
</tr>
<tr>
<td>Natural Disasters_{t} × Low Insured_{t}</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
</tr>
<tr>
<td>logKilled_{t}</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
</tr>
<tr>
<td>Drought_{t}</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
</tr>
<tr>
<td>Earthquake_{t}</td>
<td>-4.57**</td>
</tr>
<tr>
<td></td>
<td>(1.88)</td>
</tr>
<tr>
<td>Epidemic_{t}</td>
<td>-4.13**</td>
</tr>
<tr>
<td></td>
<td>(1.64)</td>
</tr>
<tr>
<td>Extremetemp_{t}</td>
<td>-0.07</td>
</tr>
<tr>
<td></td>
<td>(0.35)</td>
</tr>
<tr>
<td>Flood_{t}</td>
<td>2.39**</td>
</tr>
<tr>
<td></td>
<td>(0.68)</td>
</tr>
<tr>
<td>Landslide_{t}</td>
<td>5.20***</td>
</tr>
<tr>
<td></td>
<td>(1.08)</td>
</tr>
<tr>
<td>Storm_{t}</td>
<td>-5.87</td>
</tr>
<tr>
<td></td>
<td>(4.90)</td>
</tr>
<tr>
<td>Fog_{t}</td>
<td>3.31</td>
</tr>
<tr>
<td></td>
<td>(2.57)</td>
</tr>
<tr>
<td>Country FE</td>
<td>Yes</td>
</tr>
<tr>
<td>Year FE</td>
<td>Yes</td>
</tr>
<tr>
<td>R^2</td>
<td>0.13</td>
</tr>
<tr>
<td>Obs</td>
<td>851</td>
</tr>
</tbody>
</table>
Natural disasters effect heterogeneity

- Finance sentiment declines by 1% one year after a severe natural disaster
- Hides ample heterogeneity across disaster types
  - Uninsured disasters (epidemics, earthquakes) reduce it by 4%
  - Insured disasters (floods, landslides) increase it by 2–5%
Potential explanation #1
Bankers, love them ex-ante, hate them ex-post

- Finance facilitates risk sharing through insurance, securitization or derivatives
- But financial contracts and intermediaries are often designed to prevent ex-post renegotiation (Diamond-Rajan 2001; Agarwal et al. 2017)
- When insured disasters hit, economic costs are shared broadly, across households and generations
Potential explanation #1

- But COVID-19 pandemic illustrates uninsured disasters
  - damage can be concentrated in parts of the population (Mongey, Pilossoph, and Weinberg, 2020)
  - destroy fragile businesses (Chetty, Friedman, Hendren, and Stepner, 2020)
  - generate resentment against financial intermediaries

Source: New York Times
Potential explanation #2
Insurance claim disputes can affect finance sentiment

- Insurance claims are frequently disputed and result in rejections or lower payments (Gennaioli, Porta, Lopez-de-Silanes, and Shleifer, 2020)

- Sentiment toward insurers may worsen if households learn they are uninsured only after disaster strikes

Source: Wall Street Journal
Other explanations?

- Getting at the exact mechanism is always tricky
- Other unobservables besides insurance could be different across disaster types
Does finance sentiment affect economic growth?

- Before the (old) financial crisis, many economists thought of finance as a “veil”
- If so, does it matter if people perceive the veil as white or red?
- To answer, we estimate impulse responses for GDP and credit growth using local projections (Jorda 2005)
- What are the long term consequences of a shock to finance sentiment controlling for 5 lags of GDP, credit, and sentiment growth, and for country fixed effects?
  - Causality in VAR sense
Impulse response of economic growth and finance sentiment

Finance sentiment shock is followed by higher future GDP growth (left)
Finance sentiment oscillates (right)
Impulse response of economic growth and finance sentiment to shocks

Positive GDP growth shock reduces contemporaneous finance sentiment

GDP growth shock
Impulse response of economic, credit growth and finance sentiment

*Excluding* China and Russia

Finance sentiment shock is followed by higher future GDP and Credit growth
COVID-19 implications

- Beyond the health crisis, COVID-19 may have long-lasting effects on popular sentiment toward finance
- If like previous severe epidemics, all else equal we expect
  - 4pp decline in finance sentiment growth within a year
  - 1pp lower GDP growth over next five years
  - 2pp lower credit growth over next five years
Books allow us to travel through time and across borders, and to document several new facts about finance sentiment

Persistent differences across languages/countries with ample time-series variation

Finance sentiment declines after uninsured disasters but rises after insured ones

Long-lasting effects on economic and financial growth

Word embeddings are underutilized in economics and finance but show promise
Effects on finance sentiment growth robustness to severe disaster cutoff

Natural disaster (any)

Drought

Earthquake
Effects on finance sentiment growth robustness to severe disaster cutoff

Epidemic

Extreme Temperature

Flood
Effects on finance sentiment growth robustness to severe disaster cutoff

Fog

Landslide

Storm
Comparison with dictionary-based approach

- Dictionary-based approach is more common in economics and finance
  - e.g. Tetlock (2007), Loughran-McDonald (2014), Baker et al. (2016)
- Limitations:
  - Hard to capture context with single words (unigrams)
  - Existing word lists are mostly in English
- Our attempts to adapt it to our purposes failed miserably
Comparison with Kozlowski-Taddy-Evans (2019) approach

- Kozlowski-Taddy-Evans (2019) approach
  - fit a word embedding (word2vec, glove) model to each decade for each language
  - measure cosine similarity once for each phrase of interest
  - variation comes from variation in the language model and in term frequencies

- Instead, we
  - use a pretrained BERT language model
  - measure cosine similarity once for each phrase of interest
  - average cosine similarities for each year (and language)
  - variation is only due to term frequencies

- Assumption that language meaning stays the same allows us to measure year over year changes and reduces computation costs considerably