Does finance benefit society? a language embedding approach

Manish Jha
Georgia State University

Hongyi Liu
Washington University in St. Louis

Asaf Manela
Reichman University and Washington University in St. Louis

August 2022

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

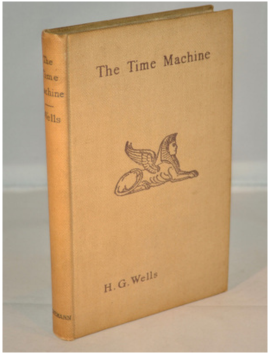
- Mostly survey evidence
  - Trust in bankers fell following the 2007–2008 financial crisis (Sapienza-Zingales 2012)
  - Public perceptions often diverge from those of economists (Sapienza-Zingales 2013)
  - Low trust can hinder insurance market efficiency (Gennaioli-Porta-Lopez-de-Silanes-Shleifer 2020)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

Questions

- How does finance sentiment change over time and differ across countries?
- How do such changes relate to financial crises and to economic growth?

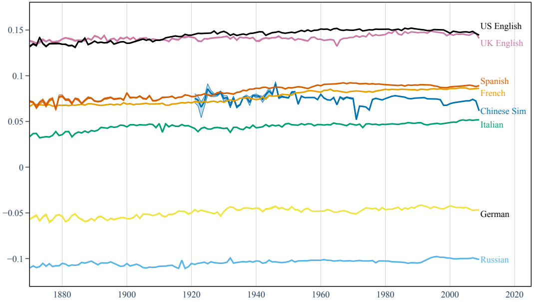
Our approach

- 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

Sentiment toward finance



- Persistent differences across languages/countries with ample time-series variation
- Capitalist countries tend to discuss finance in a more positive context
- Finance sentiment declines one year before financial crises, but not after
- Shocks to finance sentiment have long-lasting effects on economic and financial growth

Related literature

- Measurement of public attitude toward the financial sector (Stulz-Williamson 2003; Guiso-Sapienza-Zingales 2008; Giannetti and Wang 2016; Gurun-Stoffman-Yonker 2018; D'Acunto-Prokopczuk-Weber 2019; Levine-Lin-Xie 2019)
  - We provide a new sentiment toward finance panel spanning centuries and several large economies
- 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

Related literature

- Measurement of public attitude toward the financial sector (Stulz-Williamson 2003; Guiso-Sapienza-Zingales 2008; Giannetti and Wang 2016; Gurun-Stoffman-Yonker 2018; D'Acunto-Prokopczuk-Weber 2019; Levine-Lin-Xie 2019)
  - We provide a new sentiment toward finance panel spanning centuries and several large economies
- 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 $\Rightarrow$ 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

Data

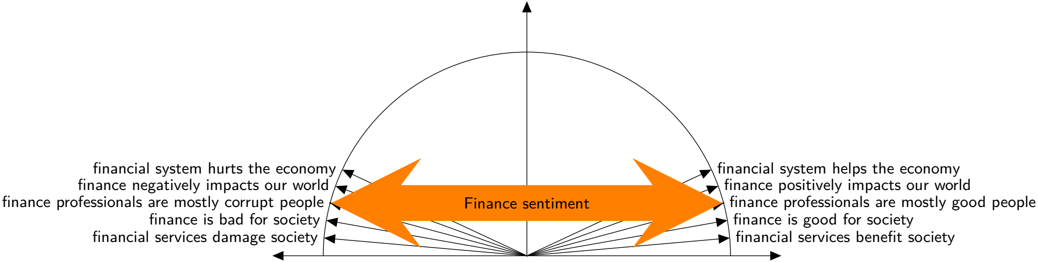
- Text from Google Books corpus
  - Annual sentence (5-gram) counts 1870–2009
  - 8 languages: Chinese, German, French, Italian, Russian, Spanish, UK and US English
  - About 1 billion sentences mentioning “finance”
- Macro data
  - Jorda-Schularick-Taylor macro data for advanced economies
  - Barro-Ursua 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. $\overrightarrow{king} - \overrightarrow{man} + \overrightarrow{woman} \approx \overrightarrow{queen}$
- 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"

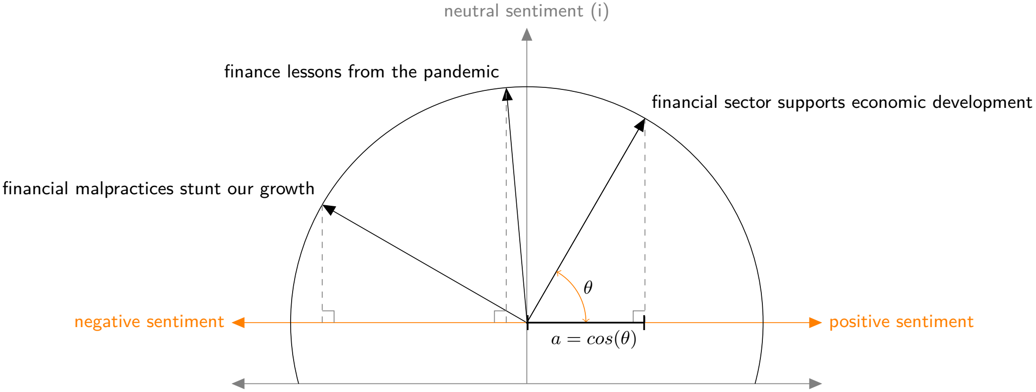
Measuring finance sentiment

Step 1: Define positive–negative sentiment dimension



Measuring finance sentiment

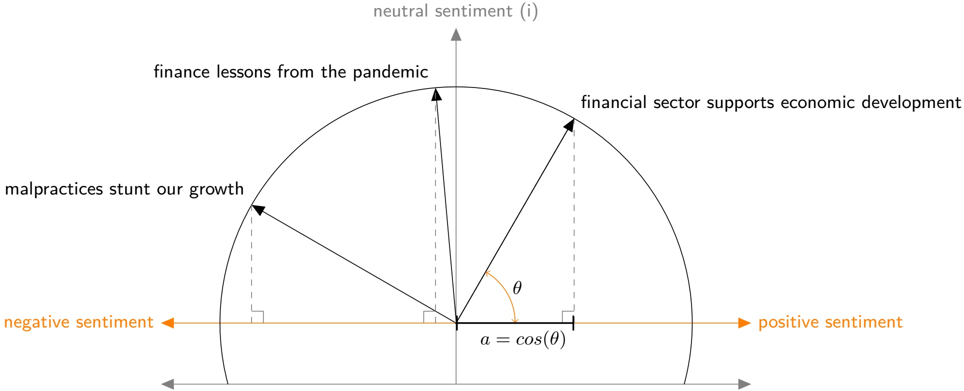
Step 2: Project “finance”-mentioning sentence j in language i embeddings on the positivity dimension



Finance sentiment for language i in year t is mean cosine similarity across mentions

Measuring 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

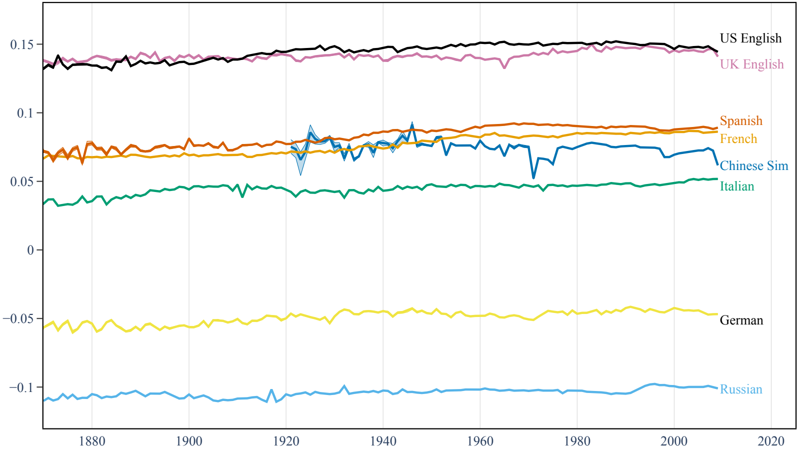
Sentences assigned most positive and negative finance sentiment (English)

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

Repeat for all 8 languages

Sentiment toward finance 1870–2009

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



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

Common concerns

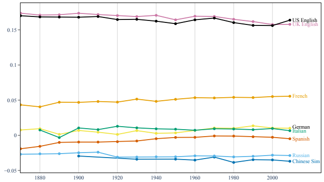
1. Books may not represent average citizen, especially far back in time
   - Yes. But, "literary elite" commands large share of wealth, power, and influence on others' opinions
2. Spanish is spoken outside of Spain
   - Requires a modest leap of faith
   - We expect it to introduce more error into our 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

Common concerns

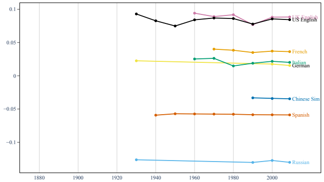
1. Books may not represent average citizen, especially far back in time
   - Yes. But, “literary elite” commands large share of wealth, power, and influence on others’ opinions
2. Spanish is spoken outside of Spain
   - Requires a modest leap of faith
   - We expect it to introduce more error into our 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

Common concerns

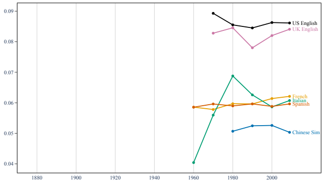
4. Finance is a somewhat broad concept



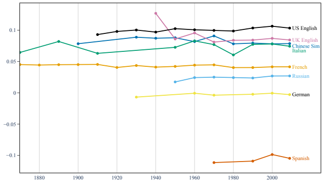
Banks



Stock Markets



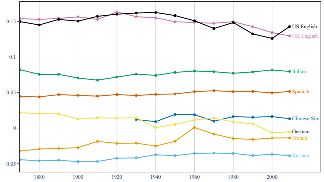
Mutual Funds



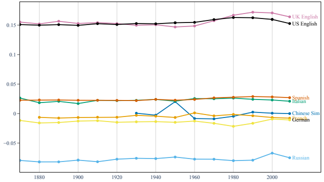
Large Corporations

Common concerns

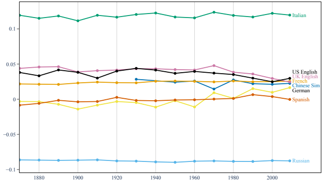
5. Some languages may be generally more positive than others



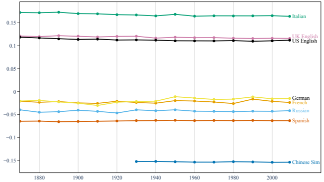
Coal



Paper



Tobacco



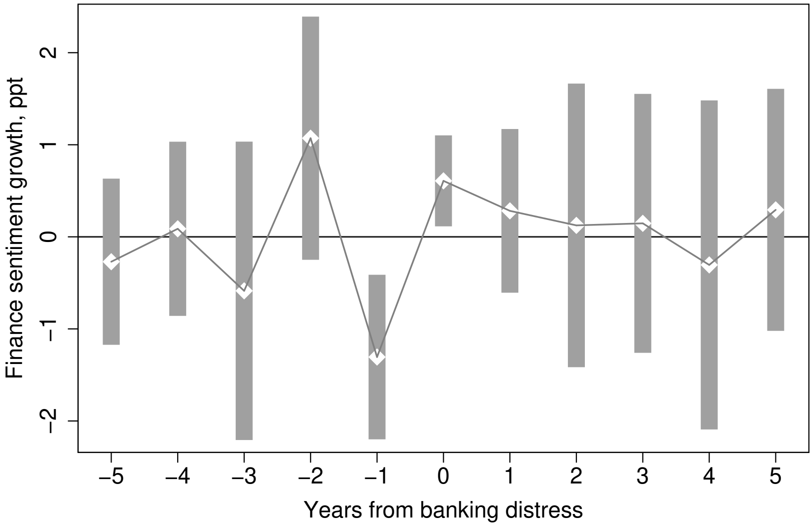
January

How does finance sentiment compare with attitudes toward capitalism?

Finance sentiment is positively correlated with various measures of capitalism

	Finance sentiment score											
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Ideological leaning of government	0.023** (0.01)	0.0005** (0.0002)	0.023** (0.011)	0.0003 (0.0003)								
Preference for private ownership of business					0.031** (0.012)	-0.0014 (0.001)	0.03** (0.012)	-0.0023** (0.0008)				
Difficulty of registering a business									-0.015*** (0.004)	0.00004 (0.0001)	-0.015*** (0.004)	-0.0002 (0.0002)
Country FE		Yes		Yes		Yes		Yes		Yes		Yes
Year FE			Yes	Yes			Yes	Yes			Yes	Yes
Observations	263	263	263	263	18	16	18	16	35	35	35	35
R^2	0.020	0.999	0.044	0.999	0.225	1.000	0.274	1.000	0.221	1.000	0.229	1.000

Finance sentiment declines one year *before* banking distress



Finance sentiment declines one year *before* banking distress

Result holds controlling for two lags of credit growth

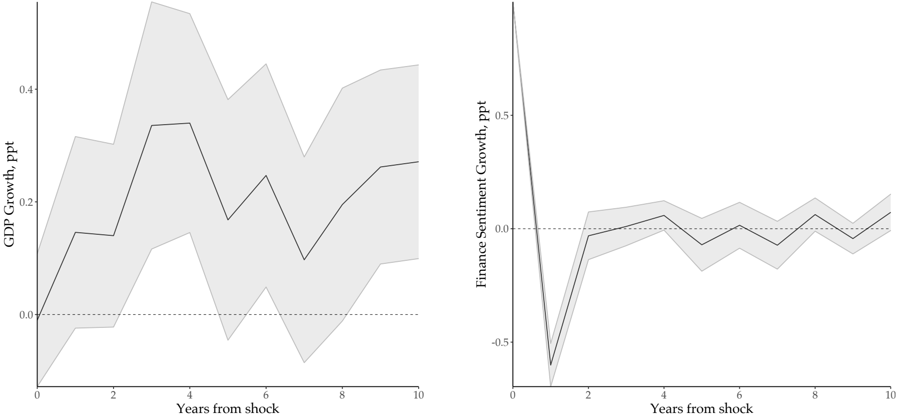
Model	Bank Equity 30% Decline$_{t+1}$				
	Logistic Regression			Linear Probability Model	
	(1)	(2)	(3)	(4)	(5)
Finance sentiment growth$_t$	-7.78***	-6.16**	-9.59**	-0.69**	-0.66**
	(2.74)	(3.00)	(4.47)	(0.22)	(0.23)
Finance sentiment growth$_{t-1}$		5.88	5.56	0.25	0.15
		(4.94)	(7.40)	(0.34)	(0.31)
Credit growth$_t$			-1.12	-0.08	-0.12
			(1.07)	(0.05)	(0.07)
Credit growth$_{t-1}$			3.17***	0.26**	0.21
			(1.04)	(0.07)	(0.12)
Country FE	Yes	Yes	Yes	Yes	Yes
Year FE	No	No	No	No	Yes
Obs	1053	1045	709	709	709

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 3 lags of GDP, credit, and sentiment growth, and for country fixed effects?
  - Causality in VAR sense

Impulse response of economic growth and finance sentiment

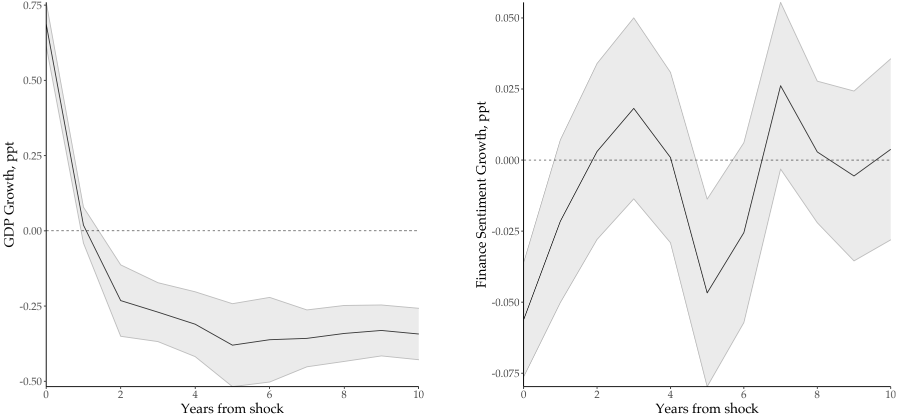
Finance sentiment shock is followed by higher future GDP growth (left)
Finance sentiment oscillates (right)



Finance sentiment growth shock

Impulse response of economic growth and finance sentiment to shocks

Positive GDP growth shock reduces contemporaneous finance sentiment

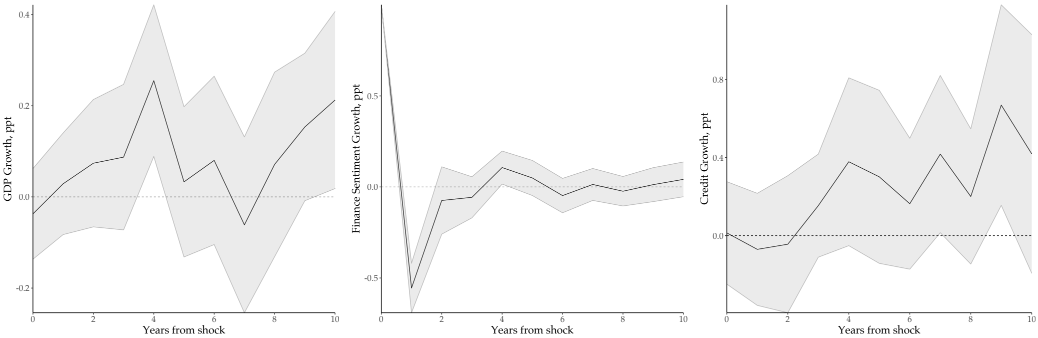


GDP growth shock

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



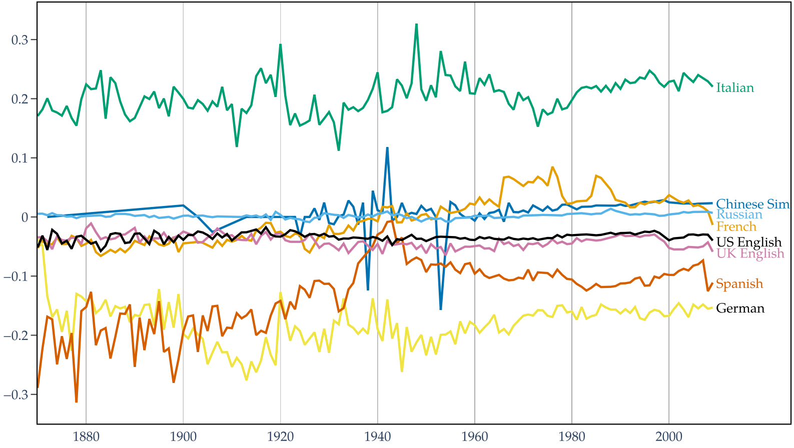
Finance sentiment growth shock

Conclusion

- 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
- More capitalist countries mention finance in a more positive context
- Finance sentiment declines one year before financial crises, but not after
- Long-lasting effects on economic and financial growth
- Word embeddings are underutilized in economics and finance but show promise

Alternative sentiment measures

Bag-of-words / Dictionary approach tends to miss the context and subtleties of language



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

Alternative sentiment measures are noisier

Kozlowski-Taddy-Evans (2019) approach (train embedding model every language-year)

	Bag-of-words	Kozlowski-Taddy-Evans			Our approach
Languages	LM dictionary	Fasttext	Glove	Word2Vec	BERT
Chinese	0.01	0.14	0.05	-0.05	0.07
	(0.03)	(0.30)	(0.17)	(0.10)	(0.01)
French	-0.01	-0.25	-0.14	-0.02	0.08
	(0.04)	(0.04)	(0.09)	(0.05)	(0.01)
German	-0.18	-0.10	-0.02	-0.02	-0.05
	(0.04)	(0.07)	(0.09)	(0.07)	(0.00)
Italian	0.20	-0.09	-0.10	0.10	0.04
	(0.03)	(0.06)	(0.15)	(0.07)	(0.00)
Russian	0.00	-0.05	0.04	0.03	-0.12
	(0.00)	(0.10)	(0.11)	(0.07)	(0.01)
Spanish	-0.13	-0.16	0.05	0.06	0.08
	(0.06)	(0.06)	(0.11)	(0.09)	(0.01)
UK English	-0.04	0.16	0.03	0.08	0.14
	(0.01)	(0.09)	(0.12)	(0.05)	(0.00)
US English	-0.03	0.17	0.01	0.14	0.14
	(0.01)	(0.06)	(0.07)	(0.08)	(0.01)

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

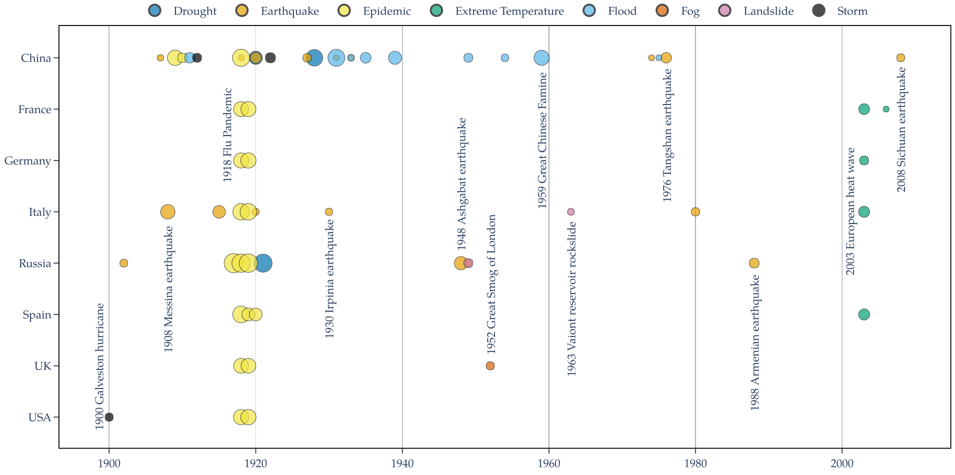
Natural disasters as exogenous shocks

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

Disaster Group	Type	Obs.	Severe	Mean Killed	Damage, $M	Insured, %	Pub. Lag
Biological	Epidemic	46	19	388333			0.58
Climatological	Drought	20	3	783922	1830		0.00
	Wildfire	53	0	41	504	37.22	
Geophysical	Earthquake	150	18	7534	1744	21.23	0.28
	Volcano	5	0	206	431		
	Mass move.	8	0	79			
Hydrological	Flood	189	9	38949	859	42.97	0.00
	Landslide	66	2	321	224		3.50
Meteorological	Storm	217	3	951	1132	101.20	0.00
	Extreme Temp.	70	5	1068	2233	36.26	0.00
	Fog (Smog)	1	1	4000			0.00
All				35662	1116	83	0.38

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

	Finance sentiment growth$_{t+1}$					
	1	2	3	4	5	6
Natural Disaster$_t$	-0.88**	-0.88**	-0.89**			2.01**
	(0.32)	(0.33)	(0.33)			(0.70)
War$_t$		0.10	0.08			
		(0.40)	(0.42)			
Natural Disaster$_t$ $\times$ Low Insured$_t$						-4.44**
						(1.70)
logKilled$_t$			0.10		0.12	
			(0.09)		(0.09)	
Drought$_t$				3.27*	3.60*	
				(1.39)	(1.55)	
Earthquake$_t$				-4.57**	-4.64**	
				(1.88)	(1.92)	
Epidemic$_t$				-4.13**	-4.17**	
				(1.64)	(1.69)	
Extremetemp$_t$				-0.07	-0.05	
				(0.35)	(0.37)	
Flood$_t$				2.39**	2.42***	
				(0.68)	(0.68)	
Landslide$_t$				5.20***	5.41***	
				(1.08)	(1.26)	
Storm$_t$				-5.87	-5.93	
				(4.90)	(5.19)	
Fog$_t$				3.31	3.37	
				(2.57)	(2.50)	
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.13	0.13	0.13	0.16	0.17	0.14
Obs	851	851	851	851	851	851

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

Coronavirus Will Cost Businesses Billions. Insurance May Not Help.

Companies buy insurance that usually pays out when they have to halt operations. But it's usually because of physical damage, not outbreaks.

The coronavirus outbreak has closed suppliers in China, but insurance policies meant to protect companies from business interruptions probably won't cover the losses. Noel Celis/Agence France-Presse — Getty Images

By Mary Williams Walsh

March 5, 2020

Two years ago Munich Re, the reinsurance giant, tried to start underwriting a new kind of insurance — one that would make a company whole if its business tanked in an epidemic. For months, there were no takers.

Then came the coronavirus outbreak.

Source: New York Times

Potential explanation #2

Insurance claim disputes can affect finance sentiment

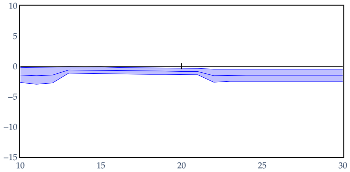
- Insurance claims are frequently disputed and result in rejections or lower payments (Gennaioli, Porta, Lopez-de-Silanes, and Shleifer, 2020)
- Sentiment toward insurers may worsen if households learn they are uninsured only after disaster strikes

Source: Wall Street Journal

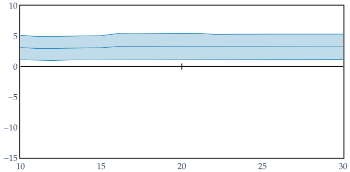
Other explanations?

- Getting at the exact mechanism is always tricky
- Other unobservables besides insurance could be different across disaster types

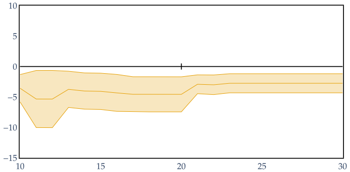
Effects on finance sentiment growth robustness to severe disaster cutoff



Natural disaster (any)

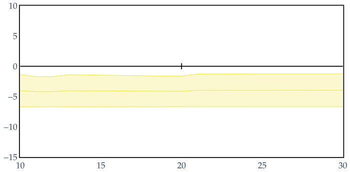


Drought

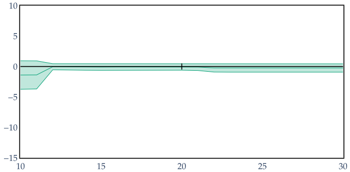


Earthquake

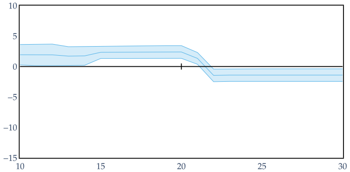
Effects on finance sentiment growth robustness to severe disaster cutoff



Epidemic

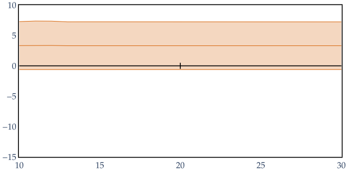


Extreme Temperature

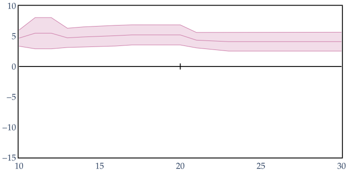


Flood

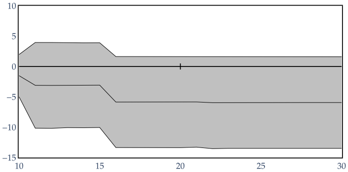
Effects on finance sentiment growth robustness to severe disaster cutoff



Fog



Landslide



Storm