Does Finance Benefit Society?

A Language Embedding Approach

Presenter: Rafael M. Azevedo
Authors: M. Jha, H. Liu and A. Manela

12/09/2023

Motivation Question

How does the public's sentiment toward finance impact society and economic growth?

Motivation Question

How does the public's sentiment toward finance impact society and economic growth?

AFA Presidential Address (2015): Does Finance Benefit Society?

> *" [...] 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."*
>
> —Luigi Zingales

Motivation Question

How does the public's sentiment toward finance impact society and economic growth?

AFA Presidential Address (2015): Does Finance Benefit Society?

> *" [...] 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."*
>
> —Luigi Zingales

Can LLM help to address this issue?

Table of Contents

Introduction

- Zingales, Shiller, Shleifer,..: popular sentiment toward finance
  - Positive: can benefit society
  - Negative: can restrict credit, insurance, risk-sharing and competition
- Large Language Model (LLM) to build a Finance Sentiment Index
  - BERT: sentences into vectors
  - BERT: sentences $\rightarrow [-1, 1]$
  - Annual averages from millions of Books (1870 to 2009)
    - Google Books Ngram Corpus: $\approx 6\%$ of all books

Introduction - Results Preview

Two new empirical facts

1. Fin. Sent. drops one year before periods of banking distress
   - Fin. Sent. predicts a higher probability of banking distress
2. $\uparrow$ Fin. Sent. => $\uparrow$ future GDP and credit growth
   - Impulse response using local projection (Jordà, 2005)

Introduction - Results Preview

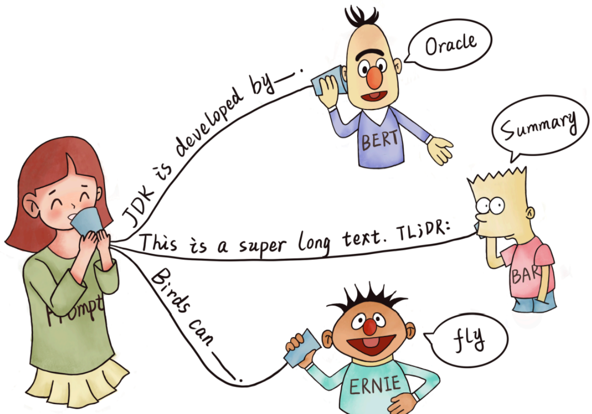
- Validations:
  - Fin. Sent. is more positive in more capitalist countries
  - Fin. Sent. impacted by major historical events
  - Fin. Sent. correlates positively with financial market participation
  - Placebo: paper, coal, tobacco, January
    - Different behavior and order

Language Model Overview

- Language Model: generative likelihood of word sequences, so as to predict the probabilities of future (or missing) tokens.
  - Long history
  - Seminal paper using NN: Bengio et. al (2003)
    - Initiated the use of LM for representation learning
  - Important Contribution: word2vec (2013)
- Pre-trained Language Models (PLM)
  - Initial paradigm: pre-train on large corpora and fine-tune
  - Context-aware word representations
- Large Language Models (LLM): scaling PLMs
  - Emergent Abilities (e.g. math)
  - Brown et al. (2020 - GPT3): prompting instead of fine-tuning
  - GPT-4: possibility of AGI

Language Model Overview

- Seminal paper (2016): "Attention is All You Need!"
  - "meme-yourself to greatness!" (Karpathy in Lex's podcast)
- Names for LLMs (Sesame Street, Simpsons, ...)



Language Model Overview

- Embeddings: high-dimensional vector representing the word or sentence
  - Has a semantic meaning
  - Linear algebra as "semantic operations"
- The "classics": word2vec (2013), GloVe (2014), FastText (2015)
  - Words that occur in the same contexts tend to have similar meanings
  - king − man + woman ≈ queen
- Cosine Similarity
  - Measure the "proximity" between embeddings

$$\text{Cosine Similarity}(\mathrm{u}, \mathrm{v}) = \frac{\mathrm{u} \cdot \mathrm{v}}{\|\mathrm{u}\| \times \|\mathrm{v}\|} = \frac{\sum_{i=1}^{n} u_i \times v_i}{\sqrt{\sum_{i=1}^{n} u_i^2} \times \sqrt{\sum_{i=1}^{n} v_i^2}}$$

BERT: Bidirectional Encoder Representation from Transformers

- word2vec: "bank robbery" vs "bank in a square"
- Transformers solve this issue
- BERT:
  - Transformer architecture
    - Attention is All You Need!
  - Only the enconder
    - Matrix Operations, Softmax, FFN

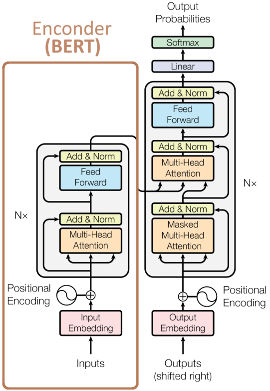


Figure 1: The Transformer - model architecture.

Finance Sentiment

- Positive vector a:
  - Average the embedding of positive sentences in table
  - Average the embedding of negative sentences in table
  - Subtract

Table 2: Positive – negative defining sentences for English

Positive sentences	Negative sentences
financial services benefit society	financial services damage society
finance is good for society	finance is bad for society
finance professionals are mostly good people	finance professionals are mostly corrupt people
finance positively impacts our world	finance negatively impacts our world
financial system helps the economy	financial system hurts the economy

Note: To define the positive minus negative dimension, we average the embeddings of positive sentences less that of their negative counterparts.

Finance Sentiment

- sentences: 5 words sequences containing "finance" in the corpus
- a_{ji} : sentiment toward finance of a sentence
  - a_{ji}: sentiment toward finance of sentence j in language i
  - s_{ji} : sentence j in language i
  - p_i : positivity embedding of language i

$$a_{ji} = \frac{s_{ji} \cdot p_i}{|s_{ji}||p_i|}$$

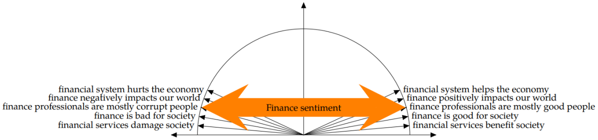
- Annual Finance Sentiment :
  - f_{it}: finance sentiment of language i in year t
  - c_{jit}: times the sentence j of language i appeared in year t

$$f_{it} = \sum_j a_{ji} \times \frac{c_{jit}}{\sum_k c_{kit}}$$

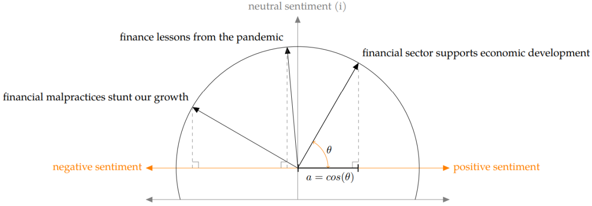
Finance Sentiment

- Example: "financial malpractices stunt our growth"

Figure 1: Conceptual diagram of finance sentiment measurement



(a) Defining the positive minus negative finance sentiment dimension



(b) Projection of sentences onto positive minus negative sentiment dimension

Data Source

- 5-grams containing the stem of "finance" (finance, financial)
- Google Books Ngram Corpus (2012 edition)
  - Words and phrases and their annual usage frequency
  - Around 8 million books (6 %)
  - Since XVI century
  - Authors use from 1870 to 2019

Table 1: Finance mentions across languages

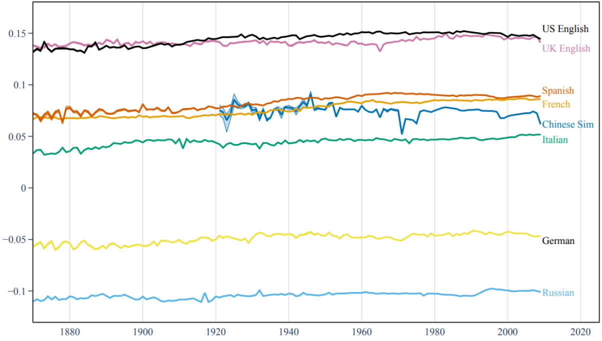
Language	Finance word stem	Unique sentences	Total sentences
American English	financ	220k	79m
British English	financ	48k	15m
Simplified Chinese	金融, 金 融, 金_融	196k	305m
French	financ	100k	43m
German	finanz	28k	7m
Italian	finanz	23k	9m
Russian	финан	187k	250m
Spanish	finan	89k	33m

Note: We report the number of mentions of the word finance, translated and stemmed, in a five-word sequence (5-gram) for each language in the Google Book Ngram Corpus. Our dataset covers the period 1870–2009.

Results - Over Time

- Evolution of finance sentiment over time.

Figure 2: Sentiment toward finance



Results - Summary By Country

- How finance sentiment varies across countries:
  - capitalist countries > communist countries
  - Before 1912: Britain / After 1912: USA
  - Volatility seems to correlate with historical events

Table 4: Finance sentiment and other summary statistics

Country (language)	Variable, %	Mean	Std. Dev.	Obs.
China	Finance sentiment	7.5	0.5	95
(Chinese)	Finance sentiment growth	0.1	7.9	88
	GDP growth	3.2	7.1	119
France	Finance sentiment	7.6	0.7	140
(French)	Finance sentiment growth	0.2	1.3	139
	GDP growth	1.9	6.4	139
	Credit growth	4.9	12.9	101

Go to full table

- Finance Sentiment Growth: $\Delta f_{it} = \frac{f_{it} - f_{it-1}}{|f_{it-1}|} \times 100$

Results -Finance Sentiment and Capitalism

- Finance Sentiment and Capitalism
  - Measures of Di Tella and Macculloch (2009)
  - Positive Association between those measures and sentiment
  - Low R^2 $\implies$ sentiment not spanned by attitudes toward capitalism

Table 5: Finance sentiment and attitudes toward capitalism

	Finance sentiment score											
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Ideological leaning of government	0.023**	0.0005**	0.023**	0.0003								
	(0.01)	(0.0002)	(0.011)	(0.0003)								
Preference for private ownership of business					0.031**	-0.0014	0.03**	-0.0023**				
					(0.012)	(0.001)	(0.012)	(0.0008)				
Difficulty of registering a business									-0.015***	0.00004	-0.015***	-0.0002
									(0.004)	(0.0001)	(0.004)	(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

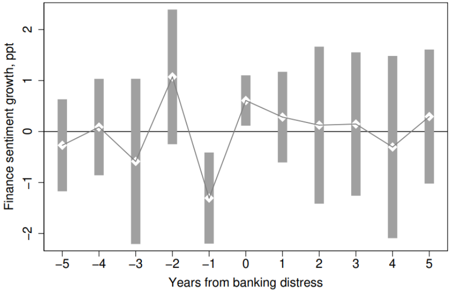
Note: Ideological leaning is based on the ideology of the largest party in government, according to the classification scheme of the Database of Political Institutions, made available via the World Bank. Scale - Left: 0, Center: 0.5, Right:1. Preference for ownership of businesses is based on World Values Surveys. Scale - State: 1, Private: 10. Difficulty of registering a business measures the total number of procedures required for a startup to obtain legal status, obtained from World Development Indicators published by the World Bank. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are in parentheses.

Results - Financial Crises

- Dataset on banking distress and panics: Baron, Verner, and Xiong (2021)
- Sapienza and Zingales (2012)
  - decline in finance sentiment + mild recession =>(possibly) full-blown financial crisis
- Fin. Sent. declines one percentage in previous year
- Boom two years before the distress period (Schularick and Taylor (2012))
- Fin. Sent. relatively flat in the five years following the distress

Results - Financial Crises

Figure 6: Finance sentiment around financial crises



Note: The figure shows how finance sentiment growth evolves around periods of banking distress, when bank equity declines at least 30 percent. The gray histograms represent 90% confidence intervals adjusted for country-level clustering. Estimates are from the following regression: $\Delta f_{it} = c + \beta_1 crisis_{it}^{-5} + \cdots + \beta_{10} crisis_{it}^{+5} + country_i + yr_t + \epsilon_{i,t}$.

Results - Financial Crises

- Logit and Linear Prob. Model suggest:
  - $\downarrow$ finance sentiment => $\uparrow$ prob of banking distress
  - credit growth is higher two years prior to banking distress

Table 9: Finance sentiment declines before bank equity declines

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

Note: This table reports the impact of finance sentiment growth and/or credit growth on predicting banking crises using logistic regression with country fixed effects and linear probability model. The banking crises defined in Baron, Verner, and Xiong (2021) represent that banking equity declines 30% for each country in a year and credit growth is denoted as loan growth as defined in Schularick and Taylor (2012). Model specifications with credit growth exclude China and Russia as credit data of these two countries are unavailable. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors are in parentheses for logistic regression model and linear probability model uses standard errors clustered by country.

Go alternatives definitions of financial crises

Results - Economic Growth

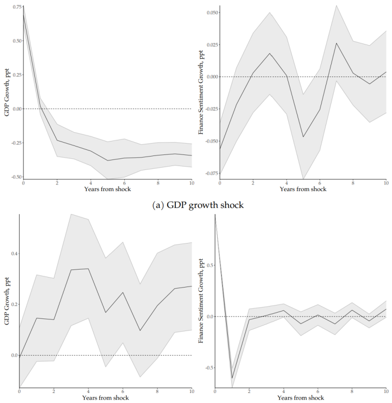
- Local projection-estimated impulse response
  - Country fixed effect

$$\Delta_h y_{i,t+h} = \alpha_i^h + \sum_{k=1}^{3} \beta_k^h \Delta f_{i,t-k} + \sum_{k=1}^{3} \gamma_k^h X_{i,t-k} + \epsilon_{i,t+h}$$

  - All countries: GDP and Fin. Sent.
  - Excluding China and Russia: GDP, credit and Fin. Sent.
- $\uparrow$ 1% Fin. Sent. => $\uparrow$ 0.3% in GDP growth (4 yr, all countries)
- $\uparrow$ 1% Fin. Sent. => $\uparrow$ 0.4% in credit growth (4 yr)
- $\uparrow$ 1% Fin. Sent. => $\uparrow$ 0.2(?) % in credit growth (4 yr)

Results - Economic Growth

Figure 7: Impulse responses of output and finance sentiment growth



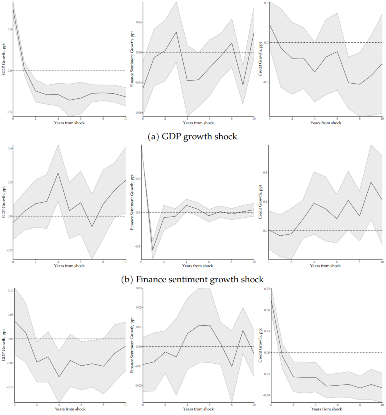
(a) GDP growth shock

(b) Finance sentiment growth shock

Note: Impulse responses estimated via local projections indicate the change of the cumulative response to a one percentage point shock. Bands are 90% confidence intervals based on Driscoll and Kraay nonparametric robust standard errors.

Results - Economic Growth

Figure 8: Impulse responses of output, credit, and finance sentiment growth (without China and Russia)



(a) GDP growth shock

(b) Finance sentiment growth shock

(c) Credit growth shock

Note: Impulse responses estimated via local projections indicate the change of the cumulative response to a one percentage point shock. Bands are 90% confidence intervals based on Driscoll and Kraay nonparametric robust standard errors.

Conclusion

- LLM embedding to analyze millions of books to gauge finance sentiment.
- Results:
  - Persistence of finance sentiment across countries
  - More capitalist countries: finance in a more positive context
  - Finance sentiment declines one year before banking distress
  - Shocks to Fin. Sent. positively affect output and credit growth

External Validation - Credit and Stock Market Participation

- Fin. Sent. positive correlated with credit/stock market participation
- Link exists between finance sentiment and income inequality

Table 6: Credit and stock market participation and income inequality

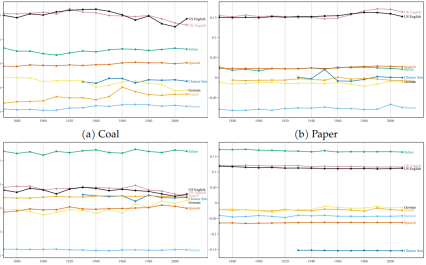
	(1) Households loans / GDP	(2) Non-financial private sector loans / GDP	(3) Equity/ Assets for households	(4) Income inequality
Finance Sentiment	6.096***	3.697***	2.614*	-1.757***
	(0.982)	(1.015)	(1.428)	(0.448)
Country FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	366	735	75	209
R^2	0.824	0.705	0.948	0.872

Note: Total loans to households and total loans to non-financial private sectors as a fraction of gross domestic product are from the Jordà-Schularick-Taylor Macrohistory Database. Equity as a percent of total assets for households is from the OECD and covers five countries: France, Germany, Spain, the United Kingdom, and the United States. Income inequality is Gini coefficient reported from the World Income Inequality Database (WIID), and ranges between 0 and 100. In all four regressions, we standardize finance sentiment for each country. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are in parentheses.

External Validation - Sentiment Towards Other Indutries

- Not Fin. Sent. but sentiment in general?
- No clear uppward trend, different ordering, variations more modest between countries
- Tobacco: differences after 50's

Figure 3: General sentiment



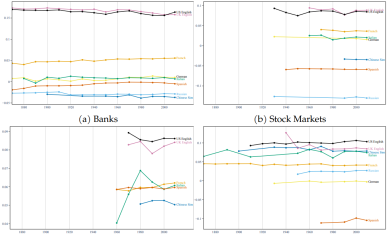
(a) Coal (b) Paper (c) Tobacco (d) January

Note: We report sentiment toward the coal, paper, and tobacco industries as well as toward the fairly generic word "January", by redefining the positivity dimension accordingly and focusing on sentences mentioning these alternatives instead of "finance". For example, sentiment for the coal industry is based on the annual average projection of coal-mentioning sentence embeddings onto the positive minus negative coal sentiment dimension. To define the positivity dimension, we average the difference in embedding for the following tuples (and their translations to each language): [("coal is good for society", "coal is bad for society"),("coal miners are mostly good people", "coal miners are mostly corrupt people "),("coal positively impacts our world", "coal negatively impacts our world"),("coal industry helps the economy", "coal industry hurts the economy"),("coal industry benefits society", "coal industry damages society")]. Between similar ngrams such as "coal miners", "coal producers", we select the ngram with a higher Google search volume. We only report scores for the language where the number of sentences containing the word, in a year, exceeds 1000.

Alternative Text Based Approaches - Robustness and Comparisons

- Sentiment measurement applied to banks, stock markets, mutual funds, and large corporations.
- Restrict do decades because of computational cost
- Similar ordering

Figure 4: Sentiments towards specific financial words



(a) Banks (b) Stock Markets

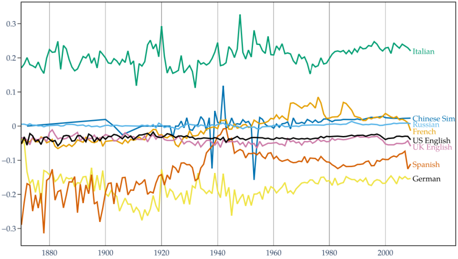
(c) Mutual Funds (d) Large Corporations

Note: We report sentiment toward Banks, Mutual Funds, Stock Markets, and Large Corporations by redefir ing the positivity dimension accordingly and focusing on sentences mentioning these alternatives instead c "finance". For example, sentiment for banks is based on the annual average projection of bank-mentionin sentence embeddings onto the positive minus negative bank sentiment dimension. To define the positiv ity dimension, we average the difference in embedding for the following tuples (and their translations t each language): [("banks are good for society", "banks are bad for society"),("bank managers are mostl good people", "bank managers are mostly corrupt people"),("banks positively impact our world", "bank negatively impact our world"),("banking industry helps the economy", "banking industry hurts the ecor omy"),("banking services benefits society", "banking services damages society")]. For Bank, we only repo scores for languages where the number of sentences containing the word, in a year, exceeds 1000. For th bigrams, because the number of sentences in a year is smaller, we use a cutoff equal to the maximum numbe of sentences for a country across decades divided by 10. The cutoff is bounded between 10 and 1000.

Alternative Text Based Approaches - Robustness and Comparisons

- Dictionary based approach
- More volatile score
- Substantial different ordering (noise/misinterpretation)

Figure 5: Sentiment toward finance using an alternative dictionary-based approach



Note: Dictionary-based finance sentiment is based on the annual average sentiment of finance-mentioning sentences. Sentiment for a sentence is net positive words in a sentence normalized by total positive and negative words in the sentence.

Alternative Text Based Approaches - Robustness and Comparisons

- Alternative Language Embedding Approaches
- Bag of Words
- "Usual" Word Embeddings (isolated word)
- Higher std. var.
- Ordering differ

Table 8: Alternative approaches

	Bag-of-words	Kozlowski-Taddy-Evans			Our approach
Languages	LM Dictionary	fastText	GloVe	Word2Vec	BERT
Chinese	-0.06 (0.10)	0.02 (0.26)	0.03 (0.14)	-0.03 (0.09)	0.03 (0.06)
French	-0.01 (0.04)	-0.25 (0.04)	-0.14 (0.09)	-0.02 (0.05)	0.08 (0.01)
German	-0.18 (0.04)	-0.10 (0.07)	-0.02 (0.09)	-0.02 (0.07)	-0.05 (0.00)
Italian	0.20 (0.03)	-0.09 (0.06)	-0.10 (0.15)	0.10 (0.07)	0.04 (0.00)
Russian	0.00 (0.00)	-0.05 (0.10)	0.04 (0.11)	0.03 (0.07)	-0.10 (0.00)
Spanish	-0.13 (0.06)	-0.16 (0.06)	0.05 (0.11)	0.06 (0.09)	0.08 (0.01)
UK English	-0.04 (0.01)	0.16 (0.09)	0.03 (0.12)	0.08 (0.05)	0.14 (0.00)
US English	-0.03 (0.01)	0.17 (0.06)	0.01 (0.07)	0.14 (0.08)	0.14 (0.01)
Total	-0.02 (0.11)	-0.03 (0.18)	-0.02 (0.13)	0.04 (0.10)	0.05 (0.09)
Average	-0.03 (0.04)	-0.04 (0.09)	-0.01 (0.11)	0.04 (0.07)	0.04 (0.01)

Note: We report the average sentiment and corresponding volatility for each language using different approaches. Total is the pooled mean and standard deviation including all languages, while average is the average across languages of the within-language statistics. Standard deviations are in parentheses.

Full Table 4

Table 4: Finance sentiment and other summary statistics

Country (language)	Variable, %	Mean	Std. Dev.	Obs.
China (Chinese)	Finance sentiment	7.5	0.5	95
	Finance sentiment growth	0.1	7.9	88
	GDP growth	3.2	7.1	119
France (French)	Finance sentiment	7.6	0.7	140
	Finance sentiment growth	0.2	1.3	139
	GDP growth	1.9	6.4	139
	Credit growth	4.9	12.9	101
Germany (German)	Finance sentiment	-4.9	0.5	140
	Finance sentiment growth	0	4.4	139
	GDP growth	2.1	8.1	139
	Credit growth	8.9	17.8	129
Italy (Italian)	Finance sentiment	4.4	0.4	140
	Finance sentiment growth	0.4	5.2	139
	GDP growth	2.0	4.7	139
	Credit growth	6.1	13.9	139
Russia (Russian)	Finance sentiment	-10.4	0.3	140
	Finance sentiment growth	0	1.7	139
	GDP growth	2.0	8.5	139
Spain (Spanish)	Finance sentiment	8.3	0.7	140
	Finance sentiment growth	0.2	3.4	139
	GDP growth	2.1	5.0	139
	Credit growth	7.4	11.1	98
UK (British English)	Finance sentiment	14.2	0.3	140
	Finance sentiment growth	0	1.5	139
	GDP growth	1.5	2.9	139
	Credit growth	4.0	8.2	129
US (American English)	Finance sentiment	14.5	0.6	140
	Finance sentiment growth	0.1	1.3	139
	GDP growth	2.1	5.0	139
	Credit growth	4.5	6.7	129
Total	Finance sentiment	5.0	8.3	1075
	Finance sentiment growth	0.1	3.7	1061
	GDP growth	2.1	6.2	1092
	Credit growth	5.9	12.5	725

Note: The sample spans from 1870 to 2009 for 8 country-language pairs. The corpus of sentences for each language is gathered from the Google Book Ngram Corpus. The connotation for each finance-mentioning sentence is measured based on its cosine similarity with respect to the positive minus negative vector. Finance sentiment is the average cosine similarity of finance-mentioning sentences in each language and year. GDP and credit data are from Jordà, Schularick, and Taylor (2017) and Barro and Ursua (2010) when available.

Go back to partial table

Table 10

- JST(2017): based on narrative accounts.
  - May have different cronology or classify crises differently

Table 10: Alternative definitions of banking crises

Logistic Regression	$Panic_{t+1}$	Bank $Failures_{t+1}$	Bank Equity $Crisis_{t+1}$	BVX $Crisis_{t+1}$	JST $Crisis_{t+1}$
	(1)	(2)	(3)	(4)	(5)
Finance sentiment $growth_t$	-9.36**	-10.22*	-12.57	-8.84**	2.75
	(3.95)	(5.34)	(9.88)	(3.72)	(6.48)
Finance sentiment $growth_{t-1}$	12.17	14.06*	13.60	11.80	12.04***
	(16.84)	(7.54)	(11.82)	(11.19)	(4.30)
Credit $growth_t$	-1.48	-2.56	-2.34	-1.57	-1.37
	(2.03)	(1.67)	(2.54)	(1.86)	(1.42)
Credit $growth_{t-1}$	4.49***	5.59***	5.51***	4.53**	4.35**
	(1.56)	(1.29)	(1.59)	(2.07)	(1.82)
Country FE	Yes	Yes	Yes	Yes	Yes
Year FE	No	No	No	No	No
Obs	709	709	709	709	709

Note: This table shows the robustness result of how finance sentiment growth affects other banking crises using logistic regression with country fixed effects. All other banking crises are defined in Baron, Verner, and Xiong (2021). * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors are in parentheses.

Go back to table 9 (bank equity decline)