

**IFC-Bank of Italy Workshop on "Data science in central banking: enhancing the access to and sharing of data"**

**17-19 October 2023**

**Do anecdotes matter? Exploring the beige book  
through textual analysis from 1970 to 2023<sup>1</sup>**

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Isabel Kitschelt, Seung Jung Lee, Anderson Monken, Dylan  
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Board of Governors of the Federal Reserve System

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<sup>1</sup> This contribution was prepared for the workshop. The views expressed are those of the authors and do not necessarily reflect the views of the Bank of Italy, the BIS, the IFC or the other central banks and institutions represented at the event.

# Do Anecdotes Matter?: Exploring the Beige Book through Textual Analysis from 1970 to 2023

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3rd IFC and Bank of Italy Workshop on  
"Data Science in Central Banking: Enhancing the access to and sharing of data"

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# Overview

1 Motivation

2 Literature

3 Beige Book Modeling

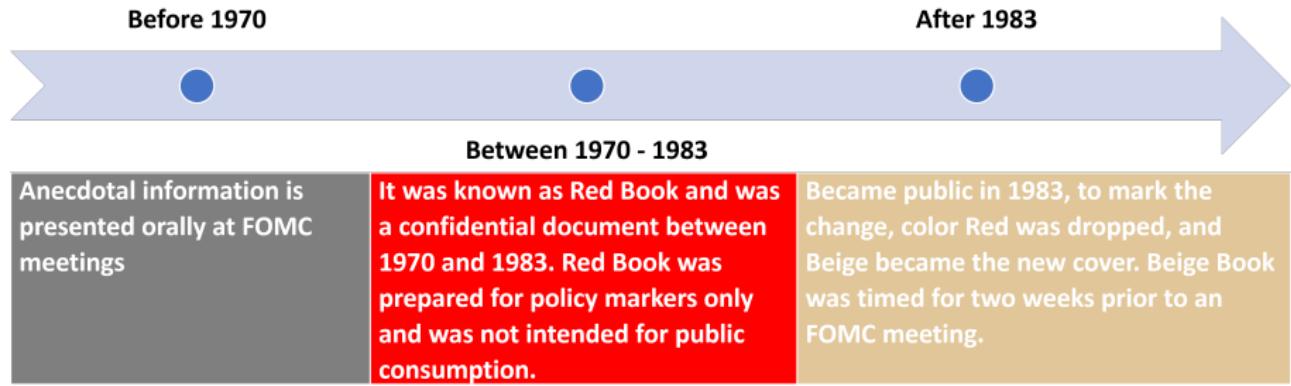
4 Sentiment in Beige Books

5 Topics in Beige Books

6 Conclusion

# Motivation - History of Beige Book

## Beige Book History (1970-2022)



**Figure:** Roughly 40 years after it was made public, and nearly 50 years after it began as a document meant to mirror the condition of the economy, for some the Beige Book has become an important part of the FOMC process.

- Discussions in the Beige Book are useful to understand business sentiment in the US economy.
- **Mostly based on entire body of text/words and dictionary approach.**
- Machine learning approaches.
  - *Fettig, Rolnick, and Runkle (1999)*
  - *Balke and Petersen (2002)*
  - *Fulmer and Zhang (2017)*
  - *Gascon and Werner (2022)*
- **We use BERT-based sentiment and topic modeling.**

# Beige Book Cleaning and Modeling

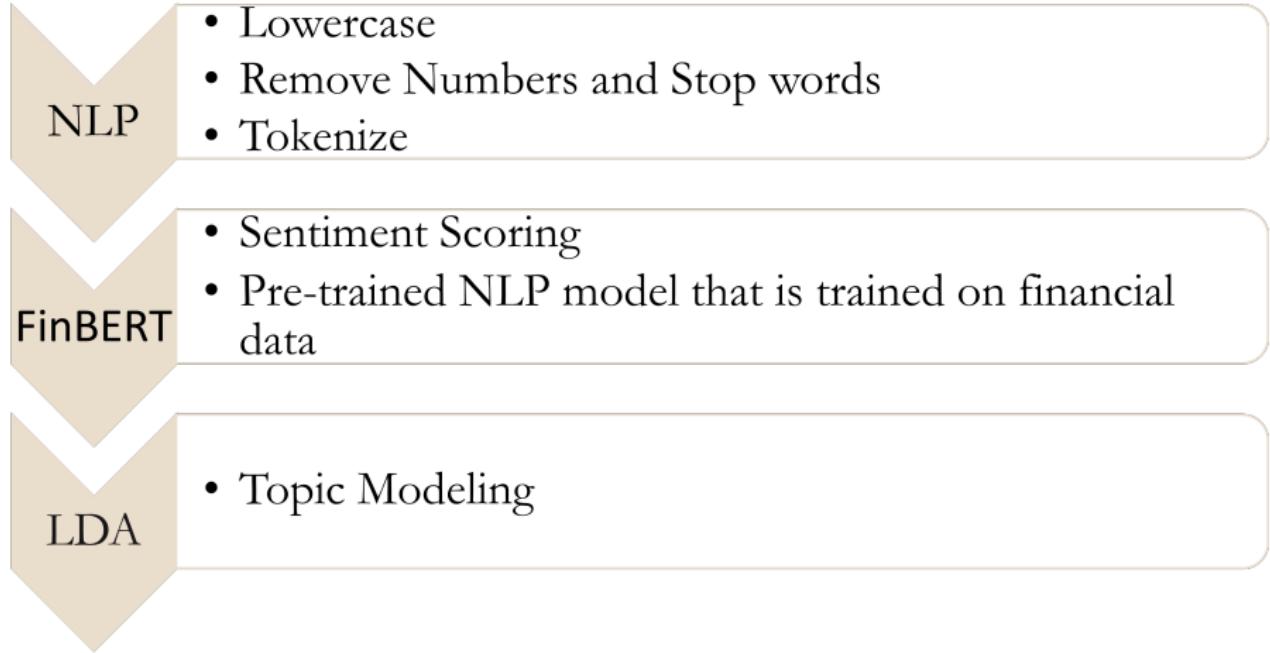
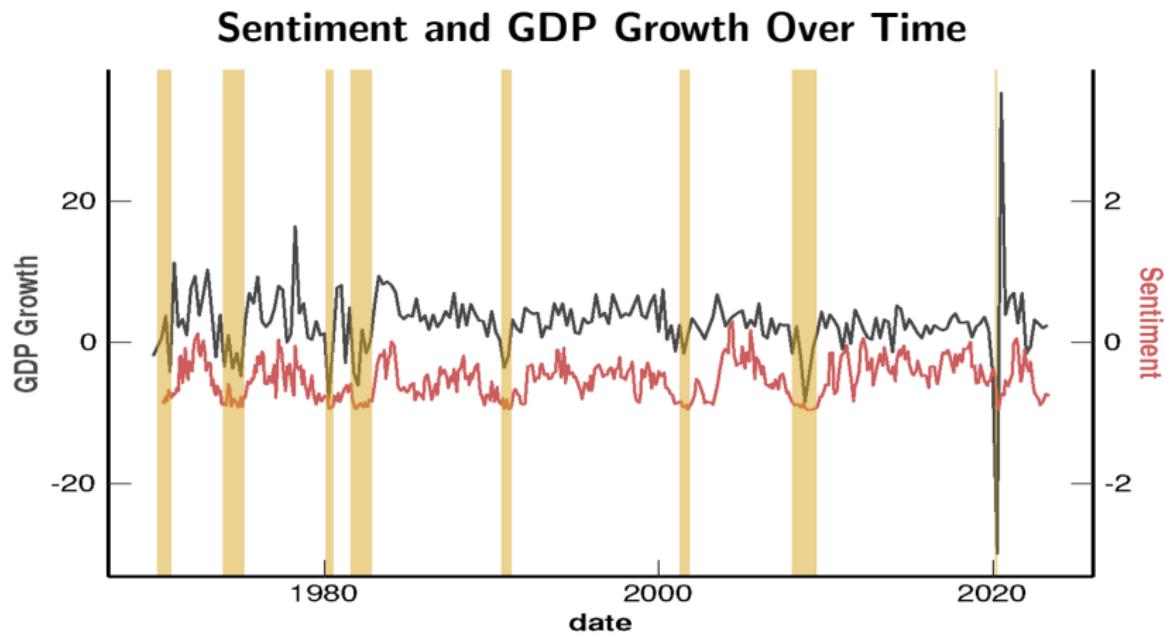


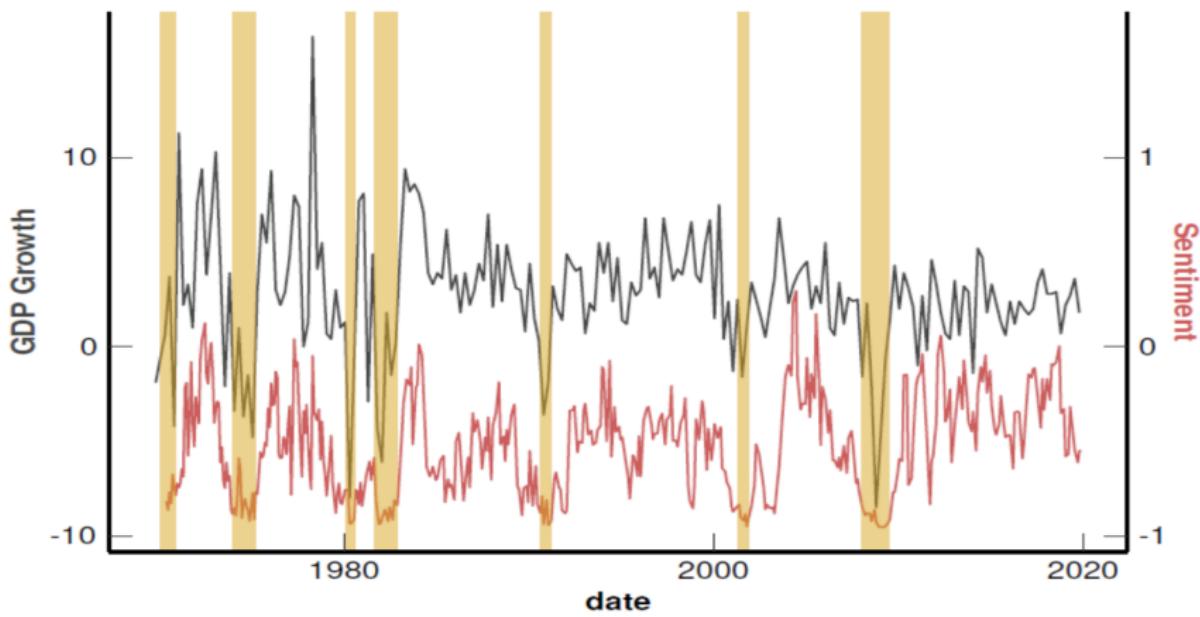
Figure: The Beige Book Model

# Sentiment and GDP Growth Over Time



# Sentiment and GDP Over Time

## Sentiment and GDP Growth Over Time (COVID omitted)



Correlation is 0.44 prior to COVID

# Some Regressions

- Nowcast Real GDP Growth.
  - OLS regression on (lagged) GDP growth, yield spread (2 year – 10 year yield on US Treasuries), Beige Book sentiment, and SF-Fed News sentiment (Shapiro, Sudhof, and Wilson, 2020), separately and together.
- Nowcast Recessions.
  - Logit regression on (lagged) GDP growth, yield spread, Beige Book sentiment, and SF-Fed News sentiment, separately and together.
- Can also forecast.

# Nowcast: BB Sentiment and Real Activity

## Sentiment and GDP Growth Over Time

	Real GDP Growth (seasonally adjusted annual rate)			
	(1)	(2)	(3)	(4)
Lagged Real GDP Growth	0.387*** (0.074)	0.271*** (0.077)	0.289*** (0.074)	0.223*** (0.077)
Yield Spread		-0.206 (0.236)		-0.248 (0.237)
News Sentiment			4.926*** (1.240)	3.070** (1.380)
FinBERT Beige Book (text concatenated)				3.380*** (0.831) 2.778*** (0.927)
Observations	159	159	159	159
R <sup>2</sup>	0.159	0.232	0.236	0.275
Adjusted R <sup>2</sup>	0.148	0.223	0.226	0.256

Note:

\*p<0.1; \*\*p<0.05; \*\*\*p<0.01

Regressions based on 159 observations from 1980:Q2 to 2019:Q4.

# Out-of-Sample RMSE Comparison for Nowcasting

	2020 Q1	2020 Q2	2020 Q3	2020 Q4
Spec. 4 vs Spec. 4 (without BeigeBook)	0.977 <i>0.159</i>	<b>0.975</b> 0.078	<b>0.958</b> 0.057	0.878 0.112
Spec. 3 vs Spec. 3 (without BeigeBook)	<b>0.943</b> <i>0.042</i>	<b>0.941</b> 0.038	<b>0.927</b> 0.049	<b>0.768</b> 0.098
Spec. 4 vs Spec. 3 (without BeigeBook)	<b>0.902</b> <i>0.025</i>	<b>0.903</b> 0.032	<b>0.887</b> 0.050	<b>0.636</b> 0.099
Observations	14	13	12	11

# Nowcast: BB Sentiment and Recessions

## Sentiment and GDP Over Time

	Recession			
	(1)	(2)	(3)	(4)
Lagged Real GDP Growth	-0.685*** (0.145)	-0.489*** (0.168)	-0.491*** (0.187)	-0.552** (0.273)
Yield Spread	0.188 (0.343)			-0.039 (0.540)
News Sentiment		-11.877*** (3.403)		-11.669** (5.221)
FinBERT Beige Book (text concatenated)			-28.823*** (9.531)	-29.295** (11.625)
Observations	159	159	159	159
Akaike Inf. Crit.	75.614	53.509	37.704	33.762

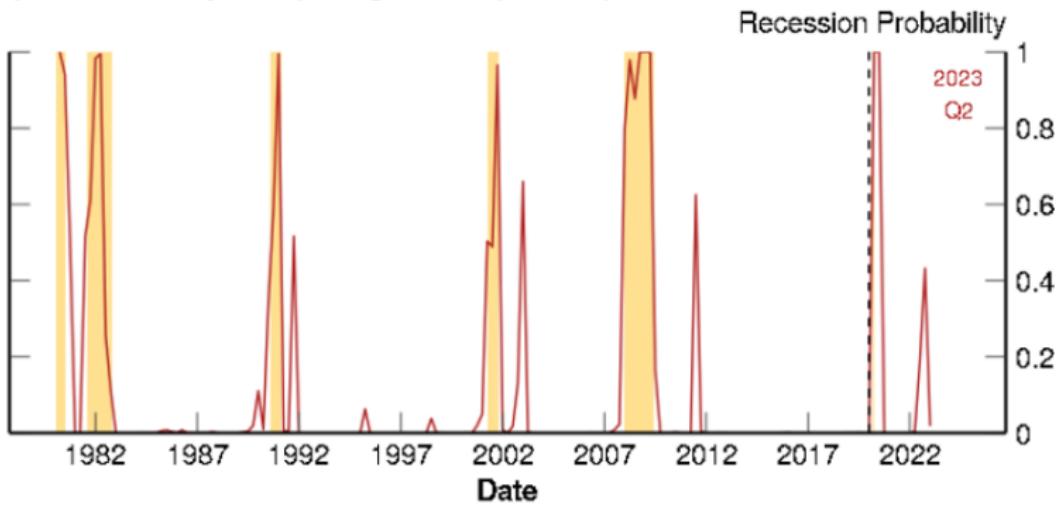
Note:

\*p<0.1; \*\*p<0.05; \*\*\*p<0.01

Regressions based on 159 observations from 1980:Q2 to 2019:Q4.

# Out-of-Sample Comparison Recessions

## Recession: Actual vs Forecast (with Yield Spread, Beige Book, News)



Dashed line marks when our model's out-of-sample forecasts begin,  
highlighted periods are NBER recessions.

# Forecast: BB Sentiment and Real Recessions

## Sentiment and GDP Over Time

	Recession			
	(1)	(2)	(3)	(4)
(Twice) Lagged Real GDP Growth	-0.367*** (0.095)	-0.144 (0.104)	-0.083 (0.109)	0.104 (0.143)
Lagged Yield Spread	-0.414 (0.286)			-1.151** (0.526)
Lagged News Sentiment		-10.071*** (2.623)		-9.159** (3.752)
Lagged FinBERT Beige Book Sentiment (text concatenated)			-17.326*** (4.777)	-21.073*** (7.990)
Observations	159	159	159	159
Akaike Inf. Crit.	97.696	75.748	60.906	51.764

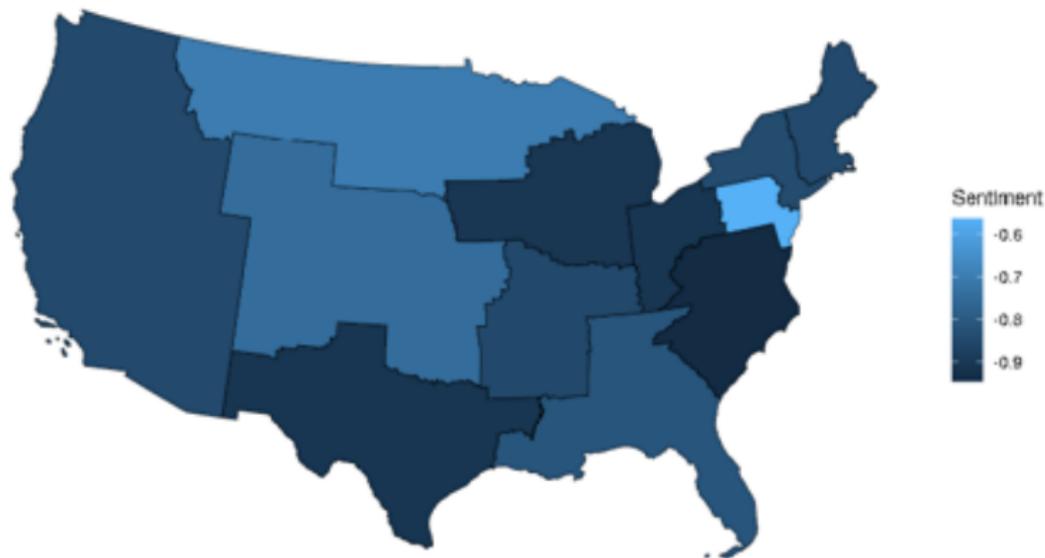
*Note:*

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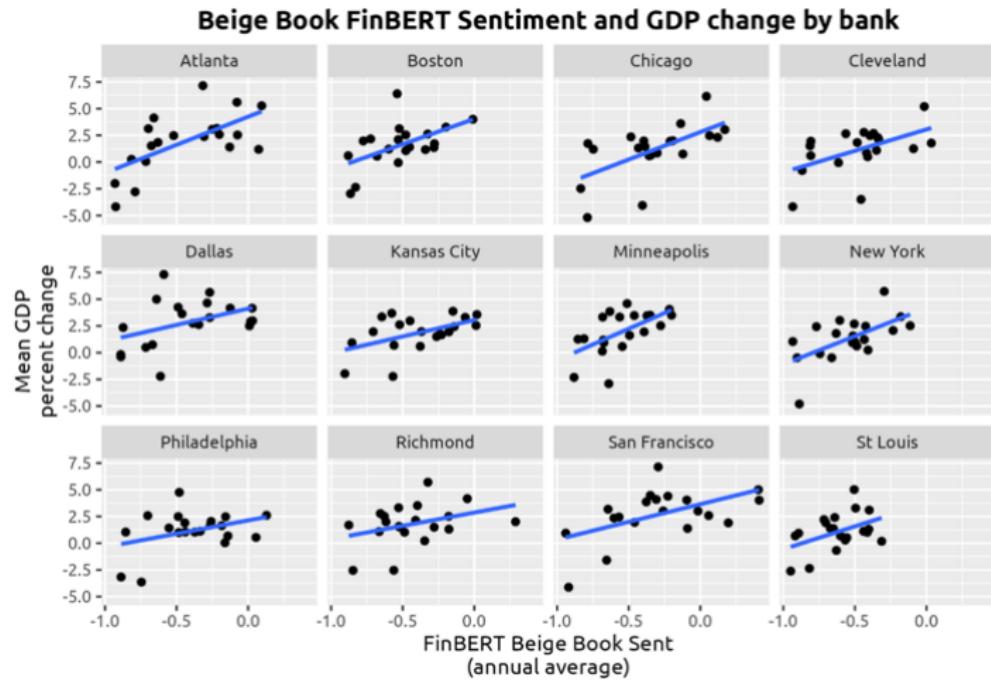
Regressions based on 159 observations from 1980:Q2 to 2019:Q4.

## Regional Differences in Beige Book Sentiment

Belge Book Sentiment In May 2023

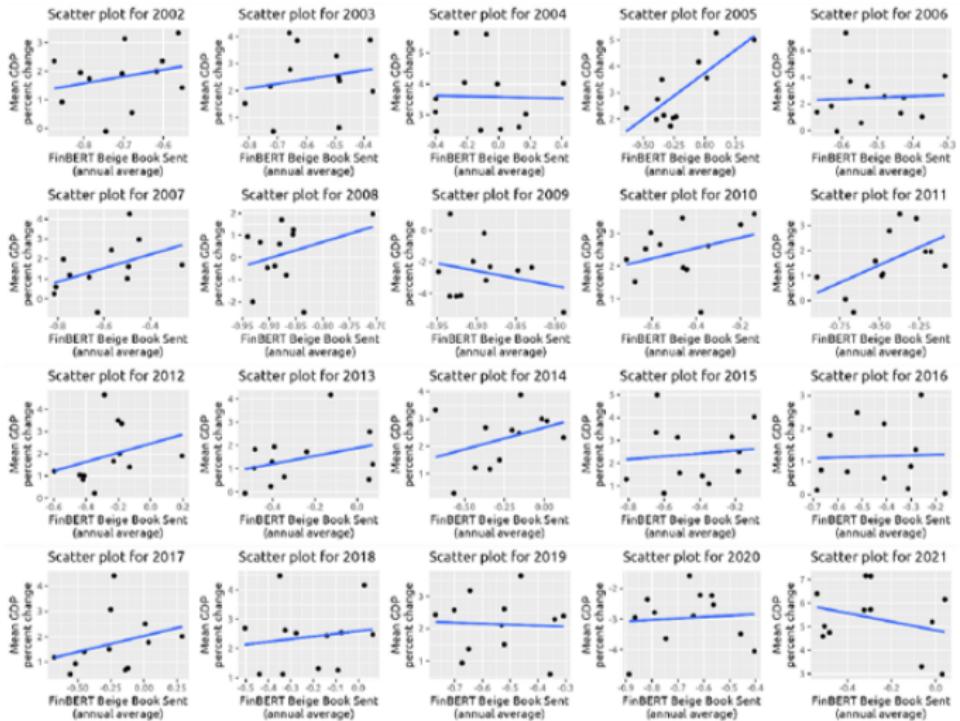


# Regional Differences in Sentiment, by District



# Regional Differences in Sentiment, by Year

## Beige Book FinBERT Sentiment and GDP change by year



# Regional Differences in Sentiment

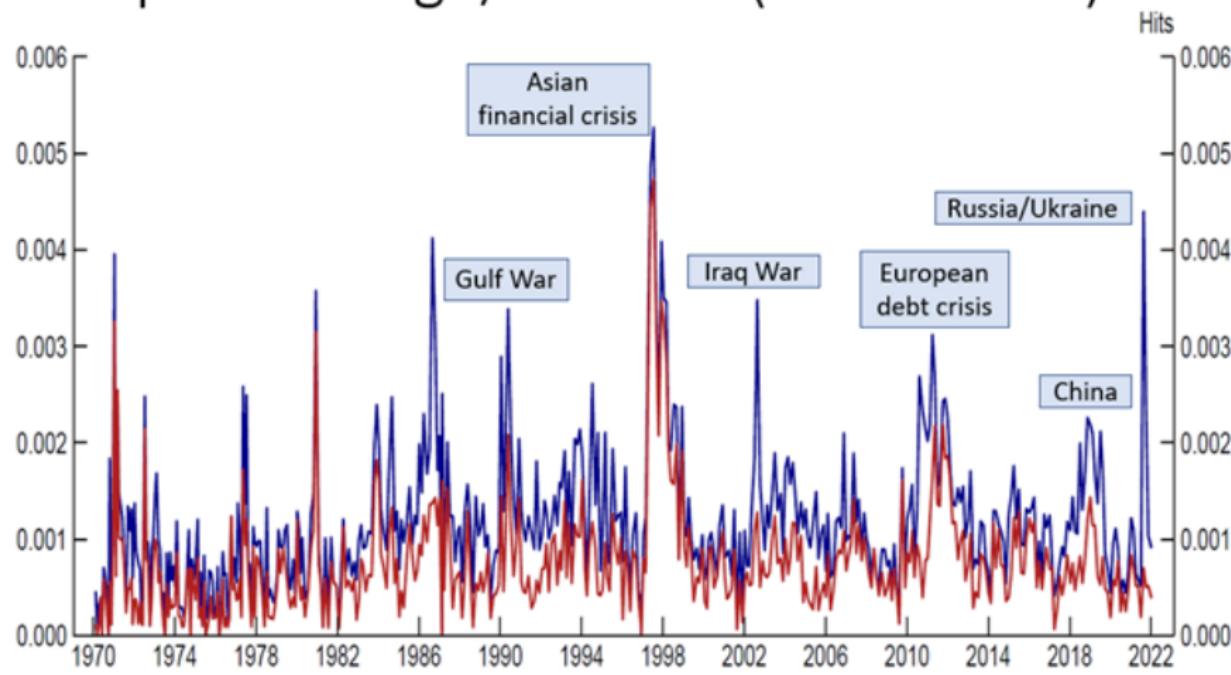
	Real GDP Growth (percent change)	
	(1)	(2)
FinBERT Sentiment (District level)	3.611*** (0.622)	1.490** (0.638)
FinBERT Sentiment (combined excl. District)		3.852*** (0.761)
Constant	3.296*** (0.529)	4.906*** (0.460)
District FE	Yes	Yes
Year FE	Yes	Yes
Observations	240	240
R <sup>2</sup>	0.482	0.384
Adjusted R <sup>2</sup>	0.408	0.349
Residual Std. Error	1.668 (df = 209)	1.749 (df = 226)
F Statistic	6.483*** (df = 30; 209)	10.852*** (df = 13; 226)

Note:

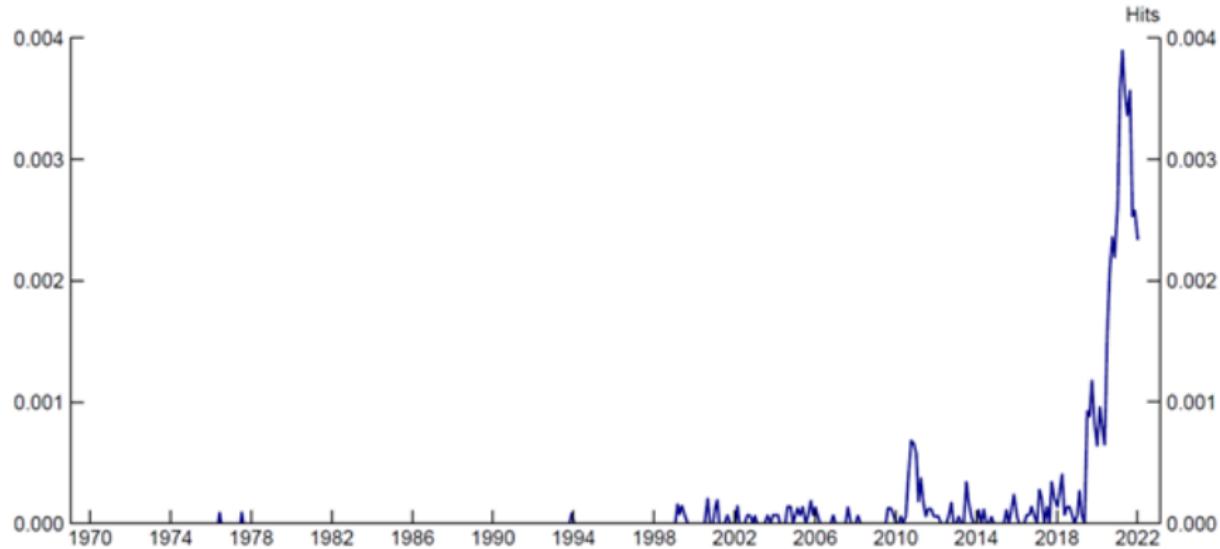
\*p<0.1; \*\*p<0.05; \*\*\*p<0.01

Regressions based on 240 from 2002 to 2021. Method: Concatenated text average.

## Topics: Foreign/Int'l Hits (Normalized)



## Topics: Supply Chain Hits (Normalized)



# Beige Book LDA Analysis

- LDA: ML algorithm that identifies main topics in a group of documents
  - Views each document as a distribution of topics and each topic as a distribution of words
  - Number of topics chosen via coherence scores
- LDavis: Visualization tool for LDA output
  - Displays topics and associated words (or words and associated topics) by prevalence

# Beige Book LDA Results

Recessionary Period	Topics (Negative Sentiment)	Topics (Positive Sentiment)
1972-1974	<ul style="list-style-type: none"><li>Savings, credit, and loans (1)</li><li>Raw materials and prices (2, 5)</li><li>Construction (4, 7)</li><li><b>Fuel and energy prices (8)</b></li></ul>	<ul style="list-style-type: none"><li>Agriculture and food prices (1, 7, 8)</li><li>Consumer and business confidence (2)</li><li>Supply chain (3)</li><li>Employment and labor market (4, 6)</li><li>Construction and loans (5)</li></ul>
2007-2008	<ul style="list-style-type: none"><li>Commercial real estate and construction (1, 5)</li><li>Wages, prices, and costs (2)</li><li><b>Real estate, loans, and credit quality (3)</b></li><li>Business activity and employment (4)</li><li>Cars, inventories, and sales (6)</li></ul>	<ul style="list-style-type: none"><li>Prices and raw materials (1, 2)</li><li>Real estate and construction (3, 5, 6)</li><li>Business activity and employment (4)</li></ul>
2022	<ul style="list-style-type: none"><li>Real estate (1)</li><li><b>Higher prices (2, 4)</b></li><li>Cars and loans (3)</li><li>Wages and labor (5)</li><li>Mortgages and credit quality (6)</li><li><b>Supply chain (7, 8)</b></li></ul>	<ul style="list-style-type: none"><li>Real estate (1)</li><li><b>Travel and consumer activity (4)</b></li></ul>

# Conclusion

- Anecdotes seem to matter
- Sentiment in Beige Books sheds light on macro activity, both in the time series and in the cross-section
- Topics are relatively easy to extract; large language models (LLMs) can help with more nuanced topical analysis going forward

# Thank You!