Whatever it takes to understand a central banker

Embedding their words using neural networks.

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2021-11-01

Text as data

1. Dictionary approaches

> Loughran, McDonalds (2011), Baker, Bloom and Davis (2016), Shapiro and Wilson (2019)

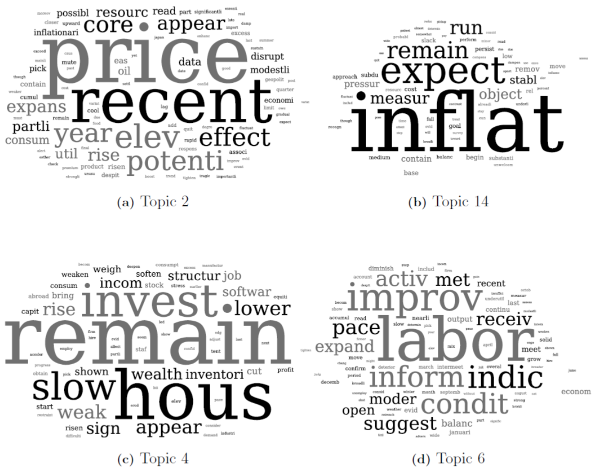
> "Unfortunately, many euro area countries entered the financial crisis and the economic downturn with unnecessarily weak fiscal balances, having missed the opportunity presented by past years' revenue windfalls to consolidate their budgets."
>
> Jose Gonzalez-Paramo (2009)

$$S_{t,i} = \frac{\#positive_j - \#negative_j}{\#positive_j + \#negative_j}$$

Text as data

1. Dictionary approaches
2. LDA model

> Fligstein, Brundage, and Schultz (2014), Hansen and McMahon (2016), Lüdering and Tillmann (2020):

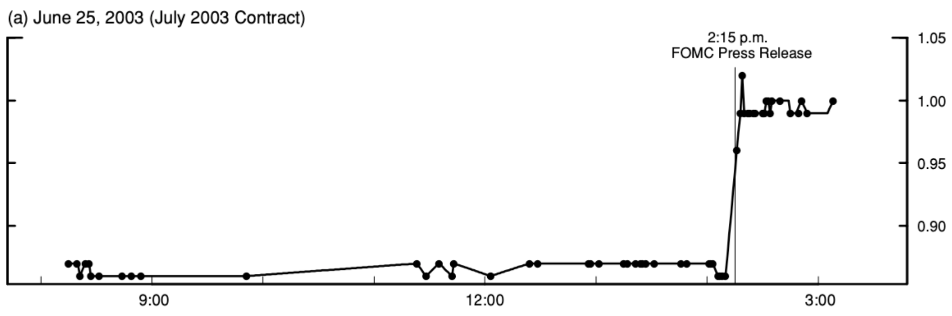


Hansen and McMahon (2016)

Text as data

1. Dictionary approaches
2. LDA model
3. Observing market reactions

> Gürkaynak, Sack and Swanson (2005), Jarociński, Karadi (2020)



Gürkaynak, Sack and Swanson (2005)

Text as data

1. Dictionary approaches
2. LDA model
3. Observing market reactions
4. Word embeddings

> Mikolov, Chen, Corrado, Dean (2013), Pennington, Socher and Manning (2014)

5. Document embeddings

> Le and Mikolov (2014)

$\Longrightarrow$ Each word/document is a point in a vector space, with similar words colocated.

term	dim_1	dim_2	dim_3	...	dim_{300}
ability	-0.02	0.03	0.01	...	0.04
able	-0.01	0.04	0.01	...	0.51
about	0.02	0.04	-0.02	...	0.12
...					...

Embeddings

- In the last years, embeddings have entered the realm of monetary policy:
  - Measure similarity in Twitter tweets (Masciandaro et al., 2020),
  - Improvement of the Euro Area uncertainty index (Azqueta-Gavaldon et al., 2019)
  - Measure central banker disagreement (Apel, Grimaldi, and Hull, 2019)

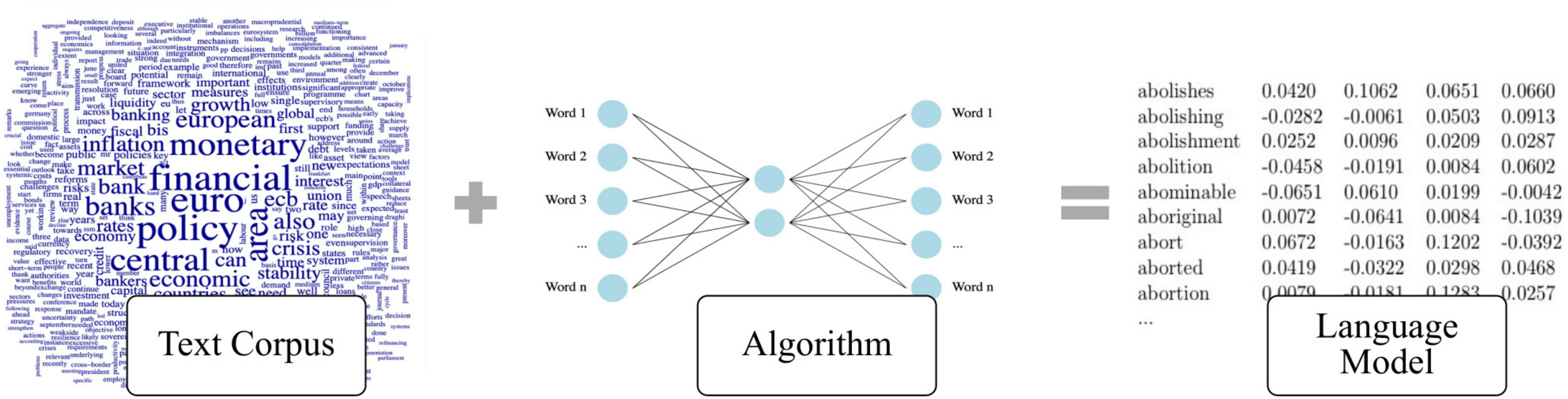
All studies use models based on a general corpus (Twitter, Google News, parliament discussions). They might be too "general" for applications in monetary policy because central banks use a specific language.

This comes with some problems:

- missing relevant monetary policy specific terms (e.g. hicp)
- Homonyms (e.g. Basel - City and Regulation Framework)
- Collocations (e.g. european_central_bank)

> 1. We use a specific monetary/economic text corpus
> 2. We evaluate different algorithms
> 3. We train embeddings on a word level and on a document level to summarize entire texts.
> 4. We apply the language model to a variety of applications.

Embeddings



Text Corpus
Word 1
Word 2
Word 3
...
Word n
Algorithm
Word 1
Word 2
Word 3
...
Word n
abolishes 0.0420 0.1062 0.0651 0.0660
abolishing -0.0282 -0.0061 0.0503 0.0913
abolishment 0.0252 0.0096 0.0209 0.0287
abolition -0.0458 -0.0191 0.0084 0.0602
abominable -0.0651 0.0610 0.0199 -0.0042
aboriginal 0.0072 -0.0641 0.0084 -0.1039
abort 0.0672 -0.0163 0.1202 -0.0392
aborted 0.0419 -0.0322 0.0298 0.0468
abortion 0.0257
...
Language Model

Embeddings

Corpus

Source	Type	n
BIS	Speech	16,627
FED	Minute, Press Conference, Transcript, Agenda, Blue-, Green-, Teal-, Beige- and Red-Book	2,238
BOJ	Minute, Economic Report, Release, Outlook Report	2,187
ECB	Minute, Press Conference, Economic Outlook, Blog	343
Riksbank	Minute, Economic Review, Monetary Policy Report	330
Australia	Minute	159
Poland	Minute	156
Iceland	Minute	101

Embeddings

Algorithms

Count based

```
- LDA
- GloVe
...
```

Prediction based

```
- Word2Vec
- Doc2Vec
- fasttext
...
```

Pre-trained Models

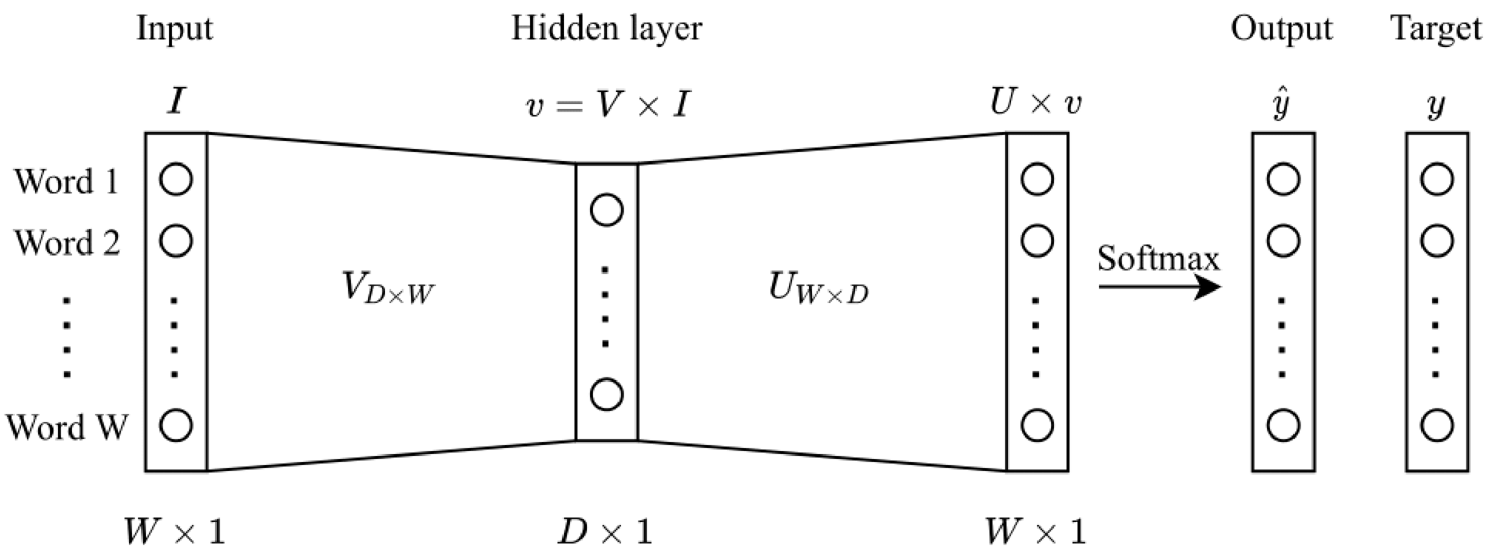
```
- GloVe6B
- GloVe.Twitter
- fastText WIKI
- word2vec GoogleNews
- ...
```

Word2Vec

> "this [......] outlook remains subject to considerable uncertainty"
>
> "this brighter [.....] remains subject to considerable uncertainty"

Word2Vec

> "this [......] outlook remains subject to considerable uncertainty"
>
> "this brighter [.....] remains subject to considerable uncertainty"
>
> "this brighter outlook [.....] subject to considerable uncertainty"



Embeddings

(Word-) Embeddings

> Each word is a point in a vector space, with similar words colocated.

term	dim_1	dim_2	dim_3	…	dim_{300}
a	0.05	0.02	0.02	…	…
ability	-0.02	0.03	0.01	…	…
able	-0.01	0.04	0.01	…	…
about	0.02	0.04	-0.02	…	…
above	-0.02	0.02	-0.01	…	…
abroad	-0.02	0	0.01	…	…
absence	-0.01	0	0.01	…	…
…					

(Document-) Embeddings

> Each document is a point in a vector space, with similar document colocated.

doc_id	dim_1	dim_2	dim_3	…	dim_{300}
doc_1	0.05	0.02	0.02	…	…
doc_2	-0.02	0.03	0.01	…	…
doc_3	-0.01	0.04	0.01	…	…
doc_4	0.02	0.04	-0.02	…	…
doc_5	-0.02	0.02	-0.01	…	…
doc_6	-0.02	0	0.01	…	…
doc_8	-0.01	-0.01	0.01	…	…
…					

Word

inflation

Number of Words:

1 5 20

1 3 5 7 9 11 13 15 17 19 20

The table shows the most similar terms to the target word according to the cosine distance of the underlying word embeddings

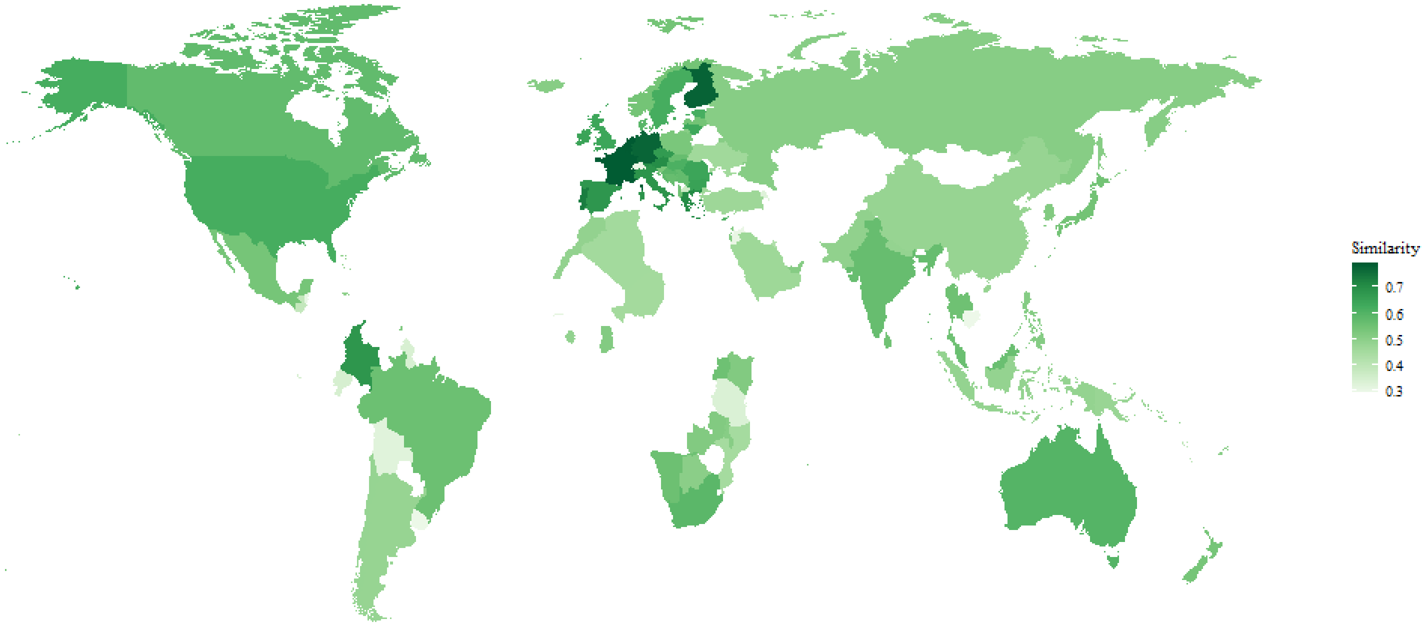
Applications

There is a myriad of potential applications. In the paper we explore the following:

1. Comparing central banks according their objectives
2. Indicator of the ECB's commitment to act as a lender of last resort
3. Evaluate gender bias in the technical language of central bankers
4. Prediction of monetary policy surprises (Altavilla et al. (2019)) by previous speeches

Application 1: Central bank objectives

We investigate factors that influence central bank similarity, using the central bank document similarity (towards the ECB) index as a dependent variable:



Similarity to the ECB

Application 1: Central bank objectives

	Dependent variable:					
	Document similarity to European Central Bank					
	Document embedding			Word embedding		
	(1)	(2)	(3)	(4)	(5)	(6)
Inflation target	0.121***	0.093***	0.091***	0.003***	0.003***	0.003***
	(0.019)	(0.019)	(0.021)	(0.001)	(0.001)	(0.001)
Euro Area Member		0.094***			0.002**	
		(0.024)			(0.001)	
ECB member			0.069***			0.001*
			(0.023)			(0.001)
Constant	0.472***	0.466***	0.466***	0.994***	0.994***	0.993***
	(0.010)	(0.010)	(0.010)	(0.0003)	(0.0003)	(0.0003)
Observations	151	151	151	151	151	151
R^2	0.221	0.294	0.267	0.159	0.182	0.178
Adjusted R^2	0.216	0.284	0.257	0.153	0.171	0.167
Note:				*p<0.1; **p<0.05; ***p<0.01		

Application 2: Whatever it takes

Focus on the effect of central bank communication in times of heightened uncertainty.

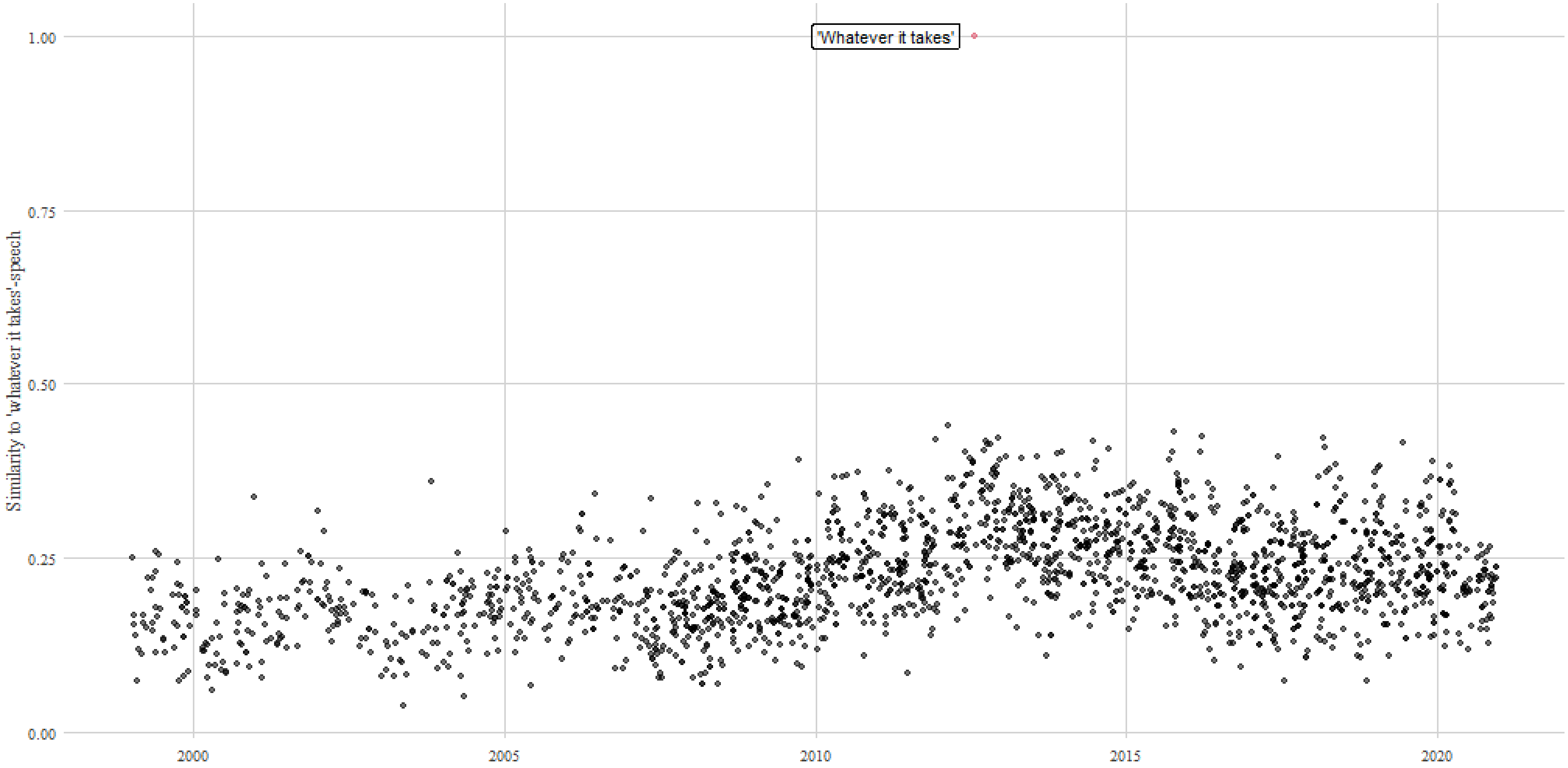
We use the famous speech by Mario Draghi in London on 26 July 2012, containing the iconic quote: *"Within our mandate, the ECB is ready to do whatever it takes"* as a focal point.

The speech is widely interpreted as the ECB signaling its willingness to act as a lender of last resort if necessary.

We calculate the cosine distance between the ECB's remaining speeches to this event, thereby creating a time-series of an lender of last resort index.

$$\text{Cosine similarity: } \frac{\boldsymbol{a} \cdot \boldsymbol{b}}{\|\boldsymbol{a}\|\|\boldsymbol{b}\|}$$

Application 2: Whatever it takes



Application 2: Whatever it takes

To investigate whether the similarity to that speech can calm financial markets in times of heightened uncertainty, we run the following regression:

$$\Delta spread_{10y,t} = wit_{simil,t} + Unc_t + wit_{simil,t} \times Unc_t + X_t + \epsilon_t$$

$\Delta spread_{10y,t}$ = daily change in greek-german ten-year bond spreads

$wit_{simil,t}$ = Whatever it takes similarity index

$Unc_{pd,t}$ = three different specifications of uncertainty before the speech

- VSTOXX
- ECB's daily CISS index (Hollo et. al, 2021)
- Decomposition of the VSTOXX into uncertainty (*UC*) and risk aversion (*RA*) (Bekaert et. al (2021))

X_t = a set of control variables:

- Dummy for the wit speech
- Moodys agency ratings for Greek bonds
- European and U.S. stock prices
- monetary policy surprises (Altavilla et. al, 2019)
- a dummy for the ECB's different central bank presidents

Application 2: Whatever it takes

Regression results: Whatever it takes

	Δ **spread$_{10y}$**		
	Unc = VSTOXX$_{pd}$	**Unc = CISS$_{pd}$**	**Unc = UC$_{pd}$**
wit$_{simil}$	1.42^{***}	0.35^{**}	0.49^{***}
	(0.48)	(0.16)	(0.18)
Unc$_t$	0.02^{***}	0.68^{**}	0.00^{***}
	(0.01)	(0.29)	(0.00)
wit$_{simil}$ * Unc$_t$	-0.07^{***}	-2.91^{**}	-0.02^{***}
	(0.03)	(1.26)	(0.01)
RA$_{pd}$			-0.00
			(0.00)
wit$_{dummy}$	-1.30^{***}	-1.14^{***}	-1.42^{***}
	(0.32)	(0.41)	(0.28)
Constant	-0.32	-0.12	-0.12
	(0.28)	(0.24)	(0.27)
Moodys Rating	Yes	Yes	Yes
MP Shocks	Yes	Yes	Yes
Stock Prices	Yes	Yes	Yes
President Dummy	Yes	Yes	Yes
Adj. R^2	0.11	0.10	0.10
Num. obs.	2028	2028	2028
F statistic	10.53	10.15	10.10

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Coefficients are estimated using an OLS regression. Standard errors are displayed in parentheses. The test statistics are calculated with heteroscedasticity and autocorrelation robust (HAC) standard errors.

WIT regression results

Summary

- Quantifying central bank communication has developed to be a substantial entity in monetary policy, with dictionary approaches at the forefront of current techniques.
- We expand the literature on four fronts:
    1. A text-corpus that is unparalleled in size and diversity.
    2. Introduction of embeddings, a novel approach from computational linguistics to quantifying texts
    3. Provision of high quality text-representations for central bank communication → open source [1]
    4. We show how high dimensional embeddings can be integrated into (low dimensional) social science research through cosine and Euclidean similarity.
- We highlighted the broad applicability illustrating four examples in the fields of measuring objectives, financial uncertainty, gender bias, and policy surprise prediction.

[1] sites.google.com/view/whatever-it-takes-bz2021