Narrative in Macroeconomics

Charl van Schoor[1]
Nicola Viegi[1]

[1]Department of Economics
University of Pretoria

SAMNet Annual Virtual Workshop
November 25, 2020

Purpose

Research Question

What role does central bank narrative play in monetary policy shocks?

Broader Questions

Is narrative important for assessing economic shocks? Can we actually use NLP techniques to accurately and objectively find changes and content of narratives?

Some Context

Literature

- Gentzkow et al. (2019)
- Bholat et al. (2015)
- Calvo-González et al. (2018)
- Hansen & McMahon (2016)
- Shiller (2017)

How can it help economists

- New data source (add narrative metrics to models) for prediction and inference
- Possibly help central banks in emerging countries to assess the impact of the information they provide
- Help us better understand the importance of narrative at a large scale

Defining Narrative

Narrative according to Shiller (2017)

- Narratives are ideas that have found ground in a proportion of the human population
- Important economic narratives might comprise a very small percentage of popular talk
- Narratives constilations are more impactful then single narratives (Narratives are essentially comprised of narratives)
- Narratives can mutate over time
- Reinforcement of narrative matters

The Journey so far

NLP for Narrative

- Sentiment Models: extract sentiment of narratives
- N-grams: explore defining words for narratives
- Latent Dirichlet Allocation: deeper exploration of content and change of narratives
- Word Embeddings: more acccurately explore change in narratives

The Journey so far

NLP Models Explored

- Sentiment Models. Issues are that language changes over time, and word combinations determine sentiment, expecially for economicc information. Some models deal with this issue (Valence), but not trained for the economic context.
- N-grams. Issues are again that language changes over time, and words can have multiple meanings given the context. The issue is framing the context in real time.
- Latent Dirichlet Allocation. Issues are that determining right hyperparameters are difficult, topics can be disaggregated into more topics.
- Word Embeddings through neural networks. Issues are that inference is really difficult and needs to train on a large corpus

Methodology and Dataset

NLP models

- LDA (Latent Dirichlet Allocation) with Gibbs Sampling
- Google's Universal Sentence Encoder for word embeddings

Data

- Unstructured text data from SARB MPC communications
- Bi-Monthly communications from 2000 to 2020

Regressions

- Principal components fitted to Bloomberg tickers with rotational matrix around time of communications to construct short, medium and long term composite factors (Pirozhkova et al., 2020)
- Change in word embbeddings and latent topics extracted from the bi-monthly communications

F2, IRF2

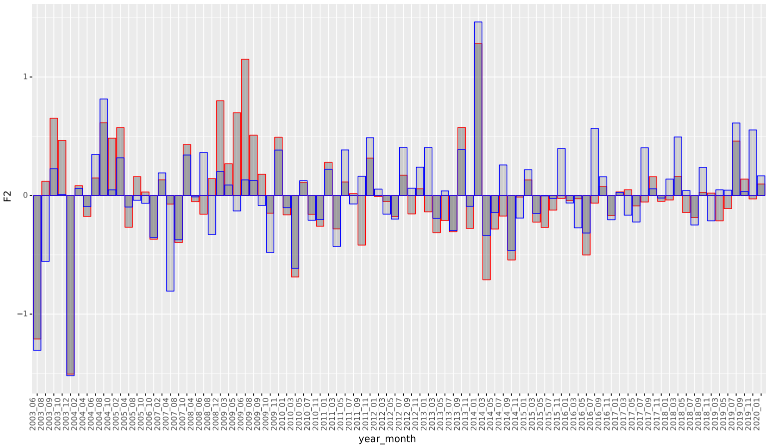


Figure 1: Red: F2; Blue: IRF2

Methodology and Dataset

Procedural Steps

1. Extract word embeddings for all documents and calculate euclidean distance between word embeddings
2. Calculate topic distributions for all documents and compare change in topics with change in word embeddings
3. Select the topic model with the highest correlation with word embeddings
4. Regress both change in word embeddings and change in topics on factors
5. Regress change in optimal topics on factors to identify important topics

Preliminary

Expectations

Hansen & McMahon (2016) sets our expectation quite low, but narrative might play a more prominant role in emerging markets than developed ones.

Finding any relationship between changes in narrative and monetary policy shocks, both derived from unsupervised models, should be interesting and lead to further research.

F2, IRF2 and Euclidean Distance for Word Embeddings

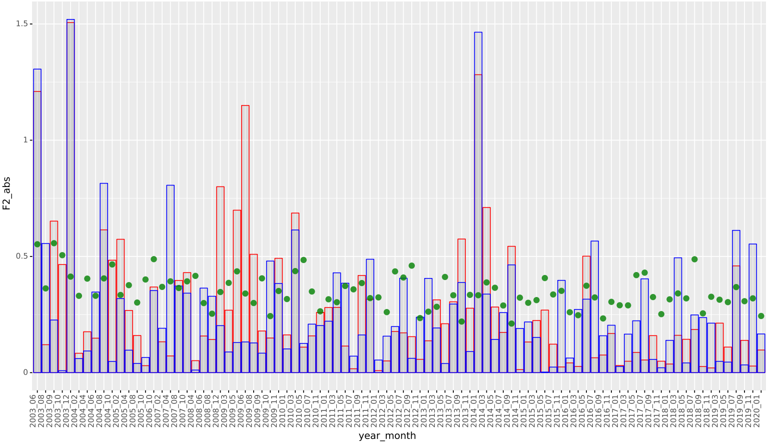


Figure 2: Red: F2; Blue: IRF2; Green: Google USE Word Embedding Distance

Regression Output

	F1_abs	F2_abs	F3_abs	IRF1_abs	IRF2_abs	IRF3_abs	F1_abs	F2_abs	F3_abs	IRF1_abs	IRF2_abs	IRF3_abs
e_dist_use	2.850**	1.320***	0.831	1.318	0.557	-0.084	2.433**	1.077***	1.009	1.005	0.484	-0.033
	(1.119)	(0.448)	(1.018)	(0.802)	(0.520)	(0.569)	(0.943)	(0.374)	(1.010)	(0.710)	(0.434)	(0.582)
change_repo_rate							-0.223	-0.130**	0.096	-0.167	-0.039	0.027
							(0.195)	(0.061)	(0.115)	(0.144)	(0.076)	(0.049)
Adjusted R2	0.066	0.098	-0.001	0.015	0.009	-0.011	0.076	0.134	-0.007	0.023	0.002	-0.022
Obs	88.000	88.000	88.000	88.000	88.000	88.000	88.000	88.000	88.000	88.000	88.000	88.000

Standard errors in parentheses
* $p < .10$, ** $p < .05$, *** $p < .01$

	F1_pos	F2_pos	F3_pos	IRF1_pos	IRF2_pos	IRF3_pos	F1_pos	F2_pos	F3_pos	IRF1_pos	IRF2_pos	IRF3_pos
e_dist_use	0.015	0.459	1.282	-0.600	-0.189	0.867*	0.436	0.239	1.182	-0.176	-0.145	0.934*
	(0.613)	(0.344)	(0.936)	(0.501)	(0.222)	(0.496)	(0.631)	(0.305)	(0.942)	(0.567)	(0.226)	(0.528)
change_repo_rate							0.225*	-0.118**	-0.053	0.227**	0.024	0.036
							(0.122)	(0.055)	(0.121)	(0.108)	(0.046)	(0.061)
Adjusted R2	-0.012	0.006	0.023	-0.003	-0.008	0.018	0.021	0.045	0.014	0.042	-0.017	0.008
Obs	88.000	88.000	88.000	88.000	88.000	88.000	88.000	88.000	88.000	88.000	88.000	88.000

Standard errors in parentheses
* $p < .10$, ** $p < .05$, *** $p < .01$

	F1_neg	F2_neg	F3_neg	IRF1_neg	IRF2_neg	IRF3_neg	F1_neg	F2_neg	F3_neg	IRF1_neg	IRF2_neg	IRF3_neg
e_dist_use	2.835**	0.862	-0.451	1.918**	0.746	-0.951*	1.997**	0.838*	-0.173	1.182**	0.629	-0.967
	(1.156)	(0.526)	(0.989)	(0.809)	(0.569)	(0.548)	(0.790)	(0.453)	(0.990)	(0.587)	(0.484)	(0.588)
change_repo_rate							-0.448**	-0.012	0.149	-0.394***	-0.063	-0.008
							(0.194)	(0.065)	(0.123)	(0.130)	(0.073)	(0.063)
Adjusted R2	0.082	0.056	-0.008	0.054	0.035	0.022	0.174	0.045	-0.004	0.167	0.038	0.011
Obs	88.000	88.000	88.000	88.000	88.000	88.000	88.000	88.000	88.000	88.000	88.000	88.000

Standard errors in parentheses
* $p < .10$, ** $p < .05$, *** $p < .01$

Regression Output

	F1_abs	F2_abs	F3_abs	IRF1_abs	IRF2_abs	IRF3_abs	F1_abs	F2_abs	F3_abs	IRF1_abs	IRF2_abs	IRF3_abs
euc_dist_lda	4.224***	1.217***	0.268	2.608**	0.386	-0.006	4.022***	0.871**	0.526	2.449**	0.265	0.095
	(1.098)	(0.441)	(1.097)	(1.050)	(0.506)	(0.438)	(1.114)	(0.411)	(1.145)	(1.128)	(0.443)	(0.493)
change_repo_rate							-0.069	-0.118	0.088	-0.055	-0.041	0.035
							(0.180)	(0.074)	(0.127)	(0.139)	(0.083)	(0.057)
Adjusted R2	0.161	0.082	-0.011	0.094	-0.001	-0.012	0.153	0.106	-0.018	0.085	-0.009	-0.022
Obs	88.000	88.000	88.000	88.000	88.000	88.000	88.000	88.000	88.000	88.000	88.000	88.000

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

	F1_pos	F2_pos	F3_pos	IRF1_pos	IRF2_pos	IRF3_pos	F1_pos	F2_pos	F3_pos	IRF1_pos	IRF2_pos	IRF3_pos
euc_dist_lda	-0.160	0.742*	1.030	-0.831**	-0.145	0.180	0.547	0.452	0.902	-0.181	-0.072	0.216
	(0.427)	(0.390)	(1.203)	(0.365)	(0.214)	(0.488)	(0.517)	(0.417)	(1.189)	(0.487)	(0.291)	(0.508)
change_repo_rate							0.242*	-0.099	-0.044	0.222*	0.025	0.012
							(0.132)	(0.065)	(0.103)	(0.117)	(0.056)	(0.049)
Adjusted R2	-0.011	0.034	0.011	0.006	-0.009	-0.010	0.022	0.055	0.001	0.042	-0.019	-0.022
Obs	88.000	88.000	88.000	88.000	88.000	88.000	88.000	88.000	88.000	88.000	88.000	88.000

Standard errors in parentheses

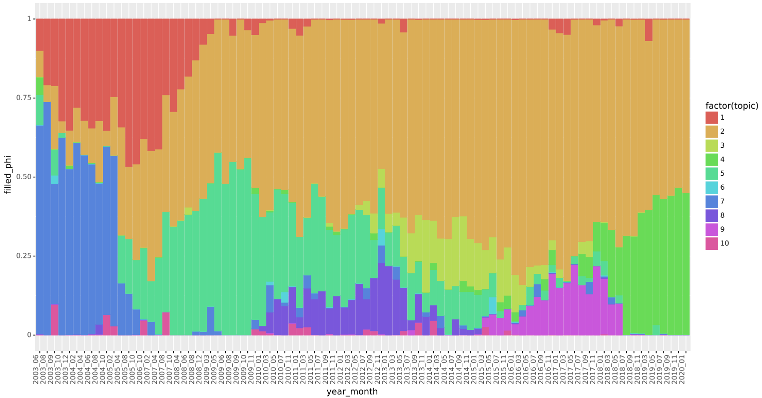
* $p < .10$, ** $p < .05$, *** $p < .01$

	F1_neg	F2_neg	F3_neg	IRF1_neg	IRF2_neg	IRF3_neg	F1_neg	F2_neg	F3_neg	IRF1_neg	IRF2_neg	IRF3_neg
euc_dist_lda	4.385***	0.475	-0.762	3.439***	0.532	-0.186	3.475***	0.418	-0.376	2.629**	0.338	-0.120
	(1.222)	(0.465)	(0.611)	(1.060)	(0.521)	(0.404)	(1.255)	(0.366)	(0.635)	(1.156)	(0.415)	(0.470)
change_repo_rate							-0.311*	-0.019	0.132	-0.277**	-0.066	0.022
							(0.183)	(0.072)	(0.130)	(0.119)	(0.079)	(0.063)
Adjusted R2	0.213	0.009	-0.002	0.202	0.012	-0.010	0.248	-0.001	-0.003	0.246	0.015	-0.021
Obs	88.000	88.000	88.000	88.000	88.000	88.000	88.000	88.000	88.000	88.000	88.000	88.000

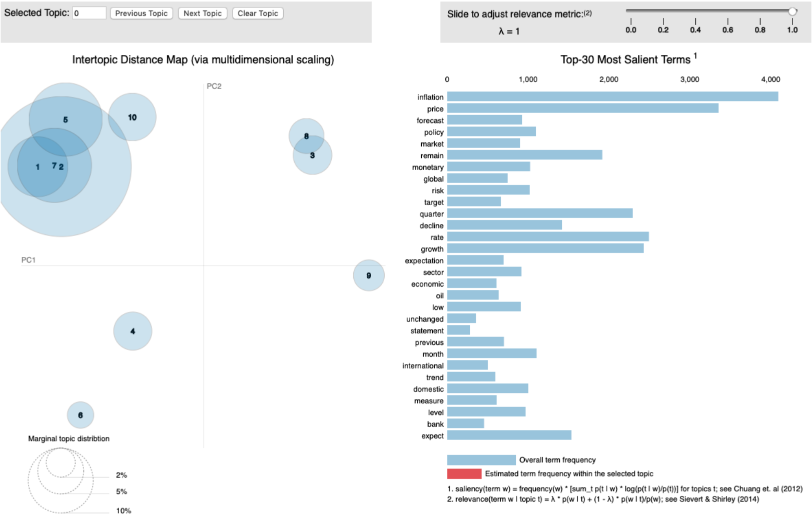
Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Topic Distributions Over Time



Topic Distance and Word Importance



Regression Output

	F1_abs	F2_abs	F3_abs	IRF1_abs	IRF2_abs	IRF3_abs	F1_abs	F2_abs	F3_abs	IRF1_abs	IRF2_abs	IRF3_abs
dist_change_topic1	14.996***	4.024**	2.456	4.912	3.348*	-1.666	13.363***	2.586	2.854	3.481	2.929	-1.513
	(4.588)	(1.858)	(3.012)	(3.406)	(1.938)	(2.298)	(4.477)	(1.746)	(3.265)	(3.370)	(1.923)	(2.441)
dist_change_topic2	10.335***	4.039**	3.275	2.628	3.801**	-1.283	9.322***	3.148**	3.521	1.741	3.541**	-1.188
	(3.306)	(1.628)	(2.188)	(1.672)	(1.612)	(1.608)	(3.134)	(1.350)	(2.307)	(1.822)	(1.537)	(1.684)
dist_change_topic3	5.668	2.292	3.613	-3.267	0.685	-0.780	4.449	1.219	3.909	-4.334	0.372	-0.666
	(4.990)	(2.419)	(4.293)	(3.991)	(2.404)	(3.100)	(4.848)	(2.235)	(4.213)	(3.998)	(2.300)	(3.192)
dist_change_topic4	10.678***	4.160**	0.743	1.441	5.153***	-2.600	9.754**	3.346**	0.968	0.631	4.916**	-2.514
	(3.989)	(1.930)	(2.855)	(2.401)	(1.932)	(2.395)	(3.841)	(1.670)	(2.855)	(2.574)	(1.882)	(2.433)
dist_change_topic5	10.225***	3.803**	1.951	2.773	3.817**	-3.102*	9.101***	2.814*	2.225	1.788	3.529**	-2.997
	(3.523)	(1.705)	(2.395)	(2.040)	(1.670)	(1.781)	(3.431)	(1.488)	(2.522)	(2.227)	(1.649)	(1.862)
dist_change_topic6	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)
dist_change_topic7	8.214**	3.624**	1.677	0.537	3.575**	-2.661	7.104**	2.647*	1.948	-0.435	3.290**	-2.557
	(3.222)	(1.583)	(2.271)	(1.925)	(1.625)	(1.672)	(3.111)	(1.386)	(2.563)	(2.046)	(1.597)	(1.766)
dist_change_topic8	10.895***	3.658**	1.097	1.390	4.450**	-4.463	9.858**	2.745*	1.349	0.482	4.184**	-4.366
	(4.014)	(1.746)	(3.441)	(2.763)	(1.731)	(2.951)	(3.798)	(1.483)	(3.487)	(2.859)	(1.643)	(2.992)
dist_change_topic9	6.548	3.946**	0.301	-0.681	3.702*	-1.122	5.673	3.176*	0.514	-1.447	3.477*	-1.040
	(4.152)	(1.963)	(3.080)	(2.516)	(2.021)	(3.080)	(3.971)	(1.653)	(3.067)	(2.630)	(1.932)	(3.129)
dist_change_topic10	7.344	4.094*	5.569	-2.150	4.130*	-3.445	6.521	3.370	5.769	-2.870	3.918*	-3.368
	(4.688)	(2.420)	(4.171)	(3.806)	(2.194)	(3.102)	(4.792)	(2.406)	(4.159)	(4.060)	(2.240)	(3.144)
change_repo_rate							-0.185	-0.163**	0.045	-0.162	-0.047	0.017
							(0.170)	(0.067)	(0.157)	(0.129)	(0.063)	(0.058)
Adjusted R2	0.078	-0.003	-0.036	0.057	0.095	0.001	0.081	0.061	-0.048	0.063	0.090	-0.011
Obs	88.000	88.000	88.000	88.000	88.000	88.000	88.000	88.000	88.000	88.000	88.000	88.000

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Regression Output

	F1_pos	F2_pos	F3_pos	IRF1_pos	IRF2_pos	IRF3_pos	F1_pos	F2_pos	F3_pos	IRF1_pos	IRF2_pos	IRF3_pos
dist_change_topic1	3.824	2.785**	1.477	-1.063	0.950	-1.654	5.885**	1.523	0.322	0.973	1.073	-1.792
	(2.380)	(1.292)	(2.692)	(2.274)	(1.160)	(2.592)	(2.467)	(1.466)	(2.898)	(2.445)	(1.351)	(2.694)
dist_change_topic2	2.199	1.611*	0.563	-0.324	0.796	-1.500	3.477**	0.828	-0.153	0.938	0.872	-1.586
	(1.663)	(0.965)	(2.067)	(1.551)	(0.833)	(1.993)	(1.668)	(1.119)	(2.023)	(1.581)	(0.902)	(2.048)
dist_change_topic3	-4.683	-0.845	4.850	-8.095*	-1.422	2.028	-3.146	-1.786	3.988	-6.576*	-1.331	1.925
	(3.890)	(1.894)	(3.120)	(4.175)	(2.237)	(3.281)	(3.467)	(1.936)	(3.211)	(3.778)	(2.127)	(3.368)
dist_change_topic4	1.803	1.052	0.445	-0.583	1.713	-1.246	2.969	0.338	-0.209	0.570	1.783	-1.324
	(2.415)	(1.120)	(2.380)	(2.175)	(1.245)	(2.239)	(2.334)	(1.267)	(2.269)	(2.148)	(1.330)	(2.285)
dist_change_topic5	1.127	1.698	-0.025	-1.608	0.526	-2.296	2.545	0.830	-0.819	-0.208	0.611	-2.391
	(1.604)	(1.030)	(2.106)	(1.635)	(0.852)	(2.213)	(1.681)	(1.191)	(2.116)	(1.654)	(0.977)	(2.278)
dist_change_topic6	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)
dist_change_topic7	1.759	1.870*	-0.213	-1.153	0.691	-1.951	3.159*	1.013	-0.998	0.231	0.775	-2.044
	(1.512)	(1.030)	(2.020)	(1.596)	(0.866)	(2.102)	(1.700)	(1.209)	(2.211)	(1.664)	(0.987)	(2.182)
dist_change_topic8	2.261	1.885*	-3.801	-2.140	1.037	-5.753*	3.569**	1.084	-4.534	-0.847	1.115	-5.840*
	(1.780)	(1.108)	(3.003)	(1.950)	(0.991)	(3.195)	(1.776)	(1.223)	(3.071)	(1.930)	(1.036)	(3.249)
dist_change_topic9	0.080	0.224	-0.911	-1.824	-0.054	-0.695	1.185	-0.452	-1.530	-0.733	0.012	-0.768
	(2.746)	(1.161)	(2.823)	(2.398)	(1.366)	(2.152)	(2.587)	(1.242)	(2.762)	(2.280)	(1.390)	(2.195)
dist_change_topic10	4.523	4.515*	4.644	-1.474	2.777	-1.284	5.561	3.880	4.062	-0.448	2.839	-1.353
	(3.646)	(2.268)	(4.296)	(3.885)	(1.956)	(3.861)	(3.356)	(2.411)	(4.043)	(3.672)	(2.032)	(3.874)
change_repo_rate							0.233*	-0.143**	-0.131	0.231**	0.014	-0.016
							(0.121)	(0.057)	(0.144)	(0.107)	(0.044)	(0.067)
Adjusted R2	0.015	0.033	0.071	0.040	0.018	0.076	0.052	0.100	0.076	0.089	0.006	0.065
Obs	88.000	88.000	88.000	88.000	88.000	88.000	88.000	88.000	88.000	88.000	88.000	88.000

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Wordclouds Associated with Contractionary Monetary Shocks

Topic 1

Topic 2

Topic 8

Regression Output

	F1_neg	F2_neg	F3_neg	IRF1_neg	IRF2_neg	IRF3_neg	F1_neg	F2_neg	F3_neg	IRF1_neg	IRF2_neg	IRF3_neg
dist_change_topic1	11.173**	1.239	0.979	5.975*	2.398	-0.012	7.478*	1.062	2.532	2.508	1.856	0.278
	(4.744)	(1.738)	(2.971)	(3.440)	(2.058)	(1.714)	(4.276)	(1.636)	(3.203)	(2.991)	(1.839)	(1.856)
dist_change_topic2	8.136**	2.429	2.712	2.952*	3.005	0.218	5.845**	2.319	3.675	0.803	2.669	0.398
	(3.350)	(1.611)	(2.106)	(1.537)	(1.809)	(1.168)	(2.766)	(1.524)	(2.325)	(1.438)	(1.630)	(1.231)
dist_change_topic3	10.351**	3.137*	-1.237	4.827*	2.108	-2.808	7.596**	3.005*	-0.079	2.242	1.703	-2.591
	(3.965)	(1.643)	(4.205)	(2.648)	(1.825)	(2.384)	(3.355)	(1.590)	(4.056)	(2.412)	(1.671)	(2.354)
dist_change_topic4	8.876**	3.108*	0.298	2.024	3.440*	-1.354	6.785**	3.008*	1.177	0.062	3.133*	-1.190
	(3.710)	(1.818)	(2.701)	(2.008)	(1.920)	(2.029)	(3.044)	(1.730)	(2.753)	(1.840)	(1.752)	(2.061)
dist_change_topic5	9.098**	2.105	1.976	4.381**	3.291*	-0.806	6.557**	1.984	3.044	1.996	2.918*	-0.606
	(3.769)	(1.700)	(2.246)	(2.067)	(1.863)	(1.267)	(3.071)	(1.664)	(2.477)	(1.832)	(1.735)	(1.351)
dist_change_topic6	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)
dist_change_topic7	6.455*	1.754	1.891	1.690	2.884	-0.710	3.945	1.635	2.946	-0.666	2.515	-0.513
	(3.429)	(1.589)	(2.433)	(1.852)	(1.802)	(1.253)	(2.755)	(1.545)	(2.680)	(1.595)	(1.655)	(1.339)
dist_change_topic8	8.633**	1.773	4.898	3.529	3.413*	1.290	6.289*	1.661	5.884*	1.329	3.068*	1.474
	(4.128)	(1.778)	(2.999)	(2.608)	(1.954)	(2.079)	(3.417)	(1.689)	(3.173)	(2.391)	(1.777)	(2.183)
dist_change_topic9	6.468*	3.722**	1.212	1.143	3.756*	-0.427	4.488	3.628**	2.044	-0.715	3.465*	-0.271
	(3.662)	(1.818)	(3.215)	(1.797)	(1.975)	(2.951)	(2.964)	(1.736)	(3.193)	(1.628)	(1.805)	(2.975)
dist_change_topic10	2.821	-0.421	0.925	-0.676	1.352	-2.161	0.960	-0.510	1.707	-2.422	1.079	-2.015
	(4.815)	(1.906)	(4.914)	(3.416)	(2.028)	(2.630)	(4.047)	(1.894)	(4.870)	(2.962)	(1.925)	(2.616)
change_repo_rate							-0.418**	-0.020	0.176	-0.393***	-0.061	0.033
							(0.184)	(0.050)	(0.120)	(0.130)	(0.057)	(0.059)
Adjusted R2	0.086	0.108	-0.041	0.047	0.064	-0.034	0.169	0.098	-0.031	0.163	0.066	-0.045
Obs	88.000	88.000	88.000	88.000	88.000	88.000	88.000	88.000	88.000	88.000	88.000	88.000

Standard errors in parentheses

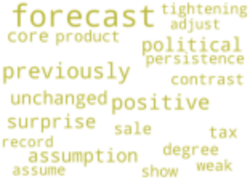
* $p < .10$, ** $p < .05$, *** $p < .01$

Wordclouds Associated with Expantionary Monetary Shocks

Topic 3

Topic 4

Topic 9



Wordclouds

Topic 1
development recent measure policy month target compare price strong expectation cpix continue oil inflation range level rate exchange outlook international
Topic 2
food market previous risk remain expectation quarter exchange rate low policy inflation forecast price level expect growth outlook mpc domestic
Topic 3
previously core eurozone account petrol quarter taper response contrast strike decline record contraction point weak sector month trend normalisation depreciation
Topic 4
monetary continue point headline inflation assess basis remain meeting policy risk low expectation weak shock statement global condition price forecast
Topic 5
inflation level continue quarter compare economy measure month petrol price previous domestic rate trend result index sector decline global monetary
Topic 6
stability level measure interest time monetary index condition target policy financial bank model public change inflation objective effect framework achieve
Topic 7
monetary domestic government month low policy bank economic growth rate price inflation consumer level quarter sector fourth production decline slow
Topic 8
environment mining positive expenditure core risk administer pose sector growth constrain crisis debt economic global fiscal employment month development eurozone
Topic 9
forecast tightening adjust core product political persistence previously contrast unchanged positive surprise sale tax record assumption degree assume show weak
Topic 10
development meeting interest market remain end oil activity financial strong money rate result net bond share international recent economic foreign

Conclusion

Some interesting outtakes

- Some relationship between output from two unsupervised models from both quantitative and qualitative data
- Possible to model narrative in some capacity
- Some slight signs that empricially narrative might have some relationship with shocks

Still a lot of work needs to be done

- Build a panel with more countries
- Explore more text data (twitter)
- Explore more quantitative metrics
- Train economics word embbedding and lda models
- Summarize narratives in "real-time"

Discussion

Bibliography

Bholat, D., Hansen, S., Santos, P., & Schonhardt-Bailey, C. (2015). Text mining for central banks. *Available at SSRN 2624811*.

Calvo-González, O., Eizmendi, A., & Reyes, G. (2018). *Winners never quit, quitters never grow: using text mining to measure policy volatility and its link with long-term growth in latin america*. The World Bank.

Gentzkow, M., Kelly, B., & Taddy, M. (2019). Text as data. *Journal of Economic Literature*, *57*(3), 535–74.

Hansen, S., & McMahon, M. (2016). Shocking language: Understanding the macroeconomic effects of central bank communication. *Journal of International Economics*, *99*, S114–S133.

Shiller, R. J. (2017). Narrative economics. *American Economic Review*, *107*(4), 967–1004.