The ECB's Tracker

Nowcasting the Press Conferences of the ECB

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Motivation

- Financial markets closely scrutinize central banks to price in changes to monetary policy stance.
- Central banks usually announce changes to their monetary policy stance in press conferences.
- However, the interval between two consecutive press conferences can be significantly long.
- Even if macroeconomic and/or financial conditions change abruptly, central bank watchers need to wait the nearest press conference to see confirmed or denied their expectations on central banks' decisions.

Core of the Paper

- This paper provides an econometric framework to infer the monetary policy stance in-between two consecutive press conferences.
  - Dynamic Factor Model (DFM) with mixed-frequency variables
- I use two types of data:
  - Conventional Data:
    - Financial, Macro, Monetary, Surveys, Rates
  - Textual Data:
    - Introductory Statements to Press Conferences
    - ECB Internal Database
- The focus is on the European Central Bank (ECB).

Summary of Findings

- Results:
  - Develop a unified econometric framework to produce real-time estimates of ECB monetary policy stance and decisions.
  - The model provides an accurate tracking of the ECB monetary policy stance and decisions at key historical ECB announcements.
  - The model proves to be useful in forecasting the EONIA rates from January 2008 to December 2009.
  - The model provides higher forecast accuracy than a benchmark model approximated by a “pseudo” Taylor rule.
  - The inclusion of textual variables in the dataset contributes significantly to the improvement of the forecasting from 2015 onwards.

Literature

- First strand on nowcasting:
  - Banbura and Modugno (2014)
  - Banbura et al. (2013)
  - Thorsrud (2020)
  - Cimadomo et al. (2020)
- Second strand on forecasting interest rate decisions:
  - Sturm and de Haan (2011)
  - Picault and Renault (2017)
  - Bennani and Neuenkirch (2017)
  - Bennani et al. (2020)
  - Baranowski et al. (2021)
- Third stream on text analysis techniques in macro:
  - Ke et al. (2019)
  - Ardia et al. (2019)
  - Bybee et al. (2020)
  - Babii et al. (2021)

What's Coming Next

- Data and Textual Methods
- Econometric Methodology
- Results

Data and Textual Methods

Data and Textual Methods

- Two types of textual data:
  - Introductory Statements to Press Conferences
  - ECB Textual Dataset
    - Topic Probabilities
    - Tone Indexes
- Combine mixed-frequency conventional data with textual variables

Data and Textual Methods

- Two types of textual data:

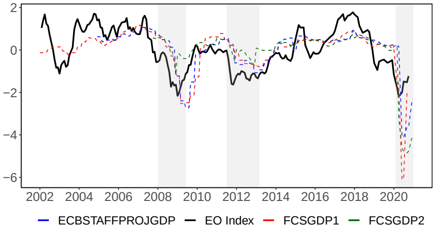
Introductory Statements to Press Conferences

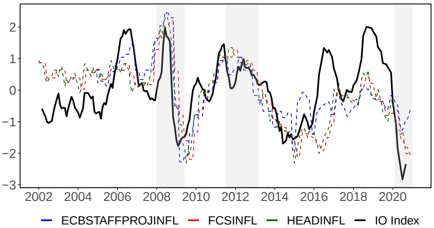
- ECB Textual Dataset
  - Topic Probabilities
  - Tone Indexes
- Combine mixed-frequency conventional data with textual variables

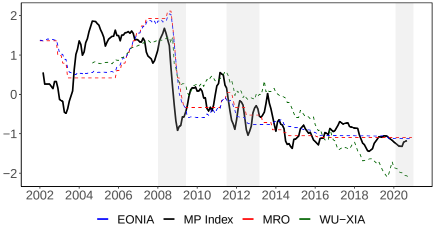
Quantifying Press Conferences

- First, gather press conferences from January 2002 to December 2020 via web-scraping.
- Second, apply Latent Dirichlet Allocation (LDA) model (Blei et al., 2003) LDA I LDA II LDA III LDA IV
  - monetary policy
  - inflation outlook
  - economic outlook
- Third, create ECB-field specific dictionaries for each topic (Picault and Renault, 2017). Alternative Indexes Sample Dictionaries
  - Subset each dataset into *n-gram*s and manually classify each *n-gram* into the topic j with tone i.
  - Compute the probability that every *n-gram* belongs to each of the corresponding category.
  - Each *n-gram* is classified as positive or negative.
- Fourth, measure the tone of a document (Rinker, 2019) Scoring Rule

ECB Press Conferences Indexes







Data and Textual Methods

- Two types of textual data:

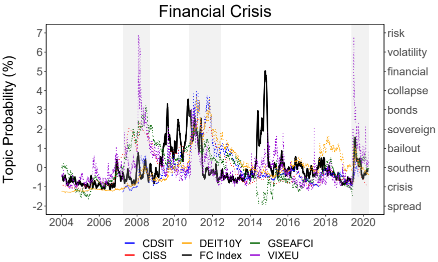
  ECB Textual Dataset

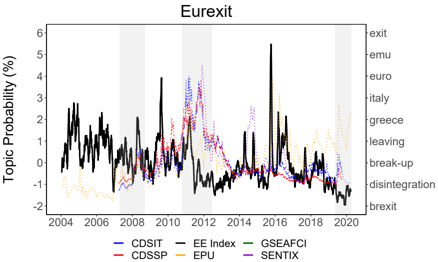
- Combine mixed-frequency conventional data with textual variables

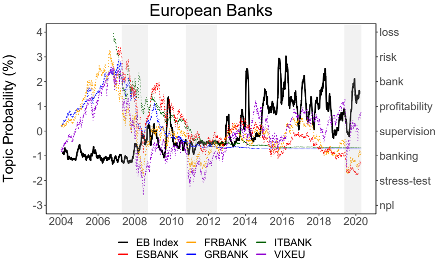
Structuring ECB Textual Data (I)

- ECB internal database Textual Dataset
  - 300,000 documents
  - From 19 September 2004 to 31 December 2020.
- To make this dataset applicable for time series analysis:
  - Decompose the textual corpus into news topics using LDA estimated with $K = 80$.
  - Out of 80 topics, I identify and label 60 of them which I reduce to 40 once filtering for monetary policy relevance.
  - The remaining 40 topics are then clustered into 7 meta-topics on the basis of the similarity among topics.
    - Financial Crisis
    - Eurexit
    - European Banks
    - Inflation Outlook
    - Economic Outlook
    - Monetary Policy
    - Fiscal Policy

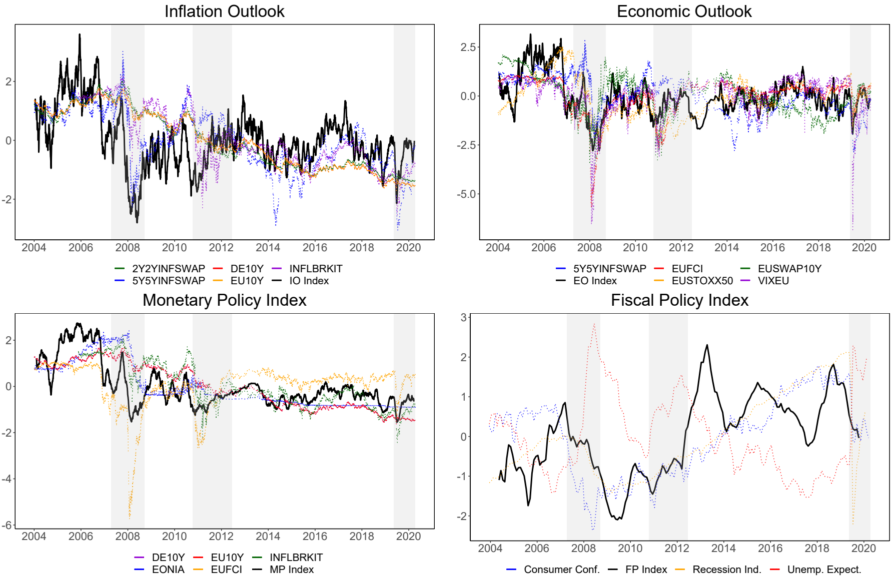
Topic Probabilities







Additional Tone Indexes



Data and Textual Methods

- Two types of textual data:
  - Introductory Statements to Press Conferences
  - ECB Textual Dataset

Combine mixed-frequency conventional data with textual variables

Total Dataset

Block	Timing	Delay	Frequency	Number
Financial	Daily	No delay	Daily	16
Forecasts	Daily	No delay	Daily	6
Rates and Spreads	Daily	No delay	Daily	41
Textual Newspapers	Daily	No delay	Daily	7
Prices	Mid-month	One month	Monthly	9
Output	Mid-month	One month	Monthly	10
Surveys	End of month	No delay	Monthly	14
Mixed	End of month	One Month	Monthly	8
Monetary	End of month	One month	Monthly	19
US	Mixed	Mixed	Monthly	7
Textual PC	Press conferences	No Delay	Irregular	3

Note: The first column reports the block in which the released variable are included. The second column indicates the official dates of the publication. The third one reports the lag with which the data are released. The frequency of the data is reported in the fourth one, while in the last column is displayed the number of variables per group. Data have been collected from Haver and Bloomberg.

What's Coming Next

- Data and Textual Methods

Econometric Methodology

- Results

Econometric Methodology

Econometric Methodology

- I build on Modugno (2013), Banbura et al. (2013) and Banbura and Modugno (2014) to develop a mixed-frequency DFM with flow and stock variables. DFM
- The DFM is however not informative on the expected probability that the ECB, conditional on the incoming data, will actually take a monetary policy decision.
- I therefore augment the model with a multinomial logit model that takes the nowcasts of the DFM as regressors. Multinomial Logit
- I finally compare the performance of the DFM with a forecast-based policy rule (Jansen and De Haan, 2009). Benchmark Model
  - Led by the fact that the ECB is found to set interest rates in a forward-looking manner (see Gerlach, 2007; Gorter et al., 2008)

What's Coming Next

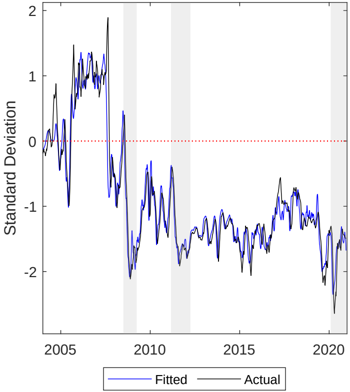
- Data and Textual Methods
- Econometric Methodology

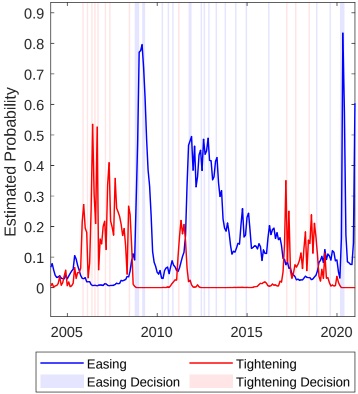
Results

Results

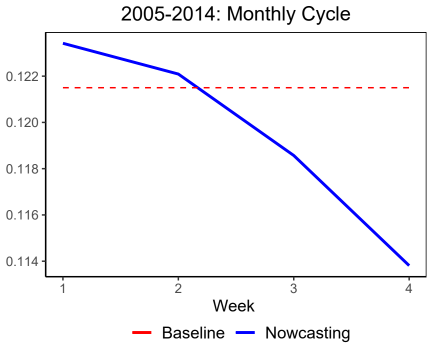
- Results
  - In-Sample
  - RMSFE
  - Average Absolute Contribution
  - Out-of-Sample

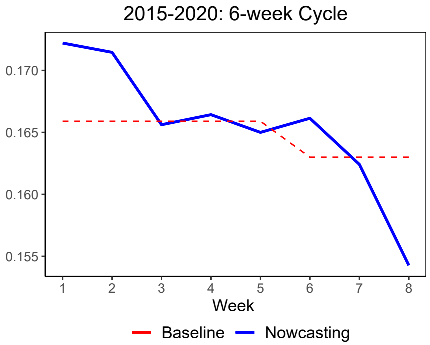
In-Sample Results





Root Mean Squared Forecast Error (RMSFE)



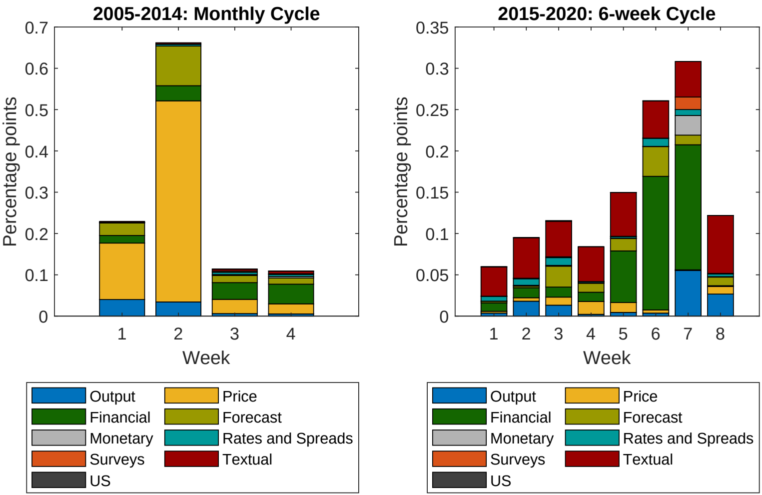


Forecast Evaluation

Horizon	2005-2014		Horizon	2015-2020	
	DFM	BM		DFM	BM
1	0.123	0.121	1	0.172	0.165
2	0.122	0.121	4	0.166	0.165
3	0.118^{**}	0.121	6	0.166^{**}	0.163
4	0.113^{***}	0.121	8	0.154^{***}	0.163

Note: The table shows the RMSE for the DFM and the benchmark model (BM) with the relative result of the Diebold-Mariano test statistic (Diebold and Mariano, 1995). The test-statistics are based on out-of-sample forecast errors for the period 2005-2014 and 2015-2020. The column "Horizon" indicates the number of weeks between two consecutive press conferences. $*$, $**$, and $***$ denote, respectively, the 10%, 5%, and 1% significance level.

Average Absolute Contribution

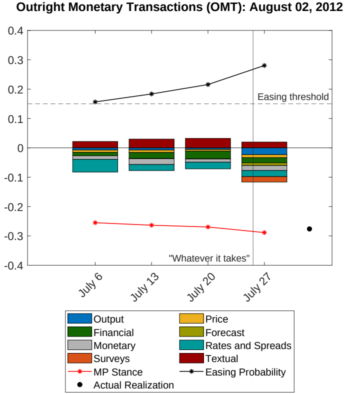


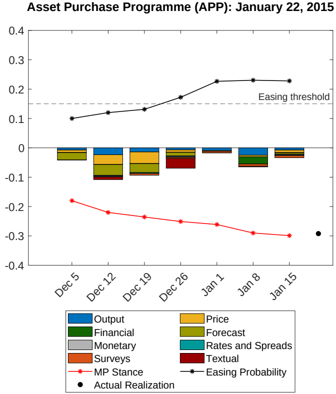
Do Textual Variables Matter?

Horizon	2005-2014		Horizon	2015-2020	
	DFM_{all}	DFM_{notext}		DFM_{all}	DFM_{notext}
1	0.123	0.124	1	0.172^{***}	0.181
2	0.122	0.123	4	0.166^{***}	0.175
3	0.118	0.118	6	0.166^{**}	0.176
4	0.113	0.115	8	0.154^{**}	0.166

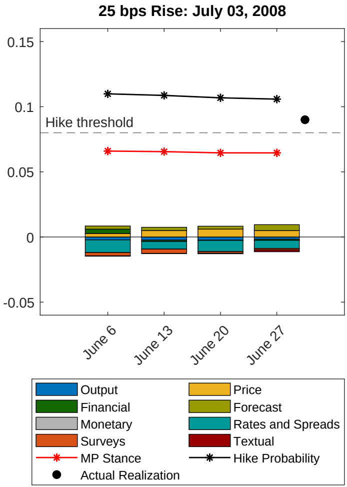
Note: The table shows the RMSE for the DFM with all the variables (DFM_{all}) and the DFM excluding textual variables (DFM_{notext}) with the relative result of the Diebold-Mariano test statistic (Diebold and Mariano, 1995). The test-statistics are based on out-of-sample forecast errors for the period 2005-2014 and 2015-2020. The column "Horizon" indicates the number of weeks between two consecutive press conferences. $*$, $**$, and $***$ denote, respectively, the 10%, 5%, and 1% significance level.

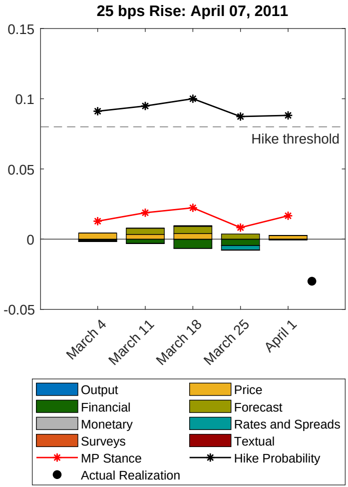
Easing Episodes



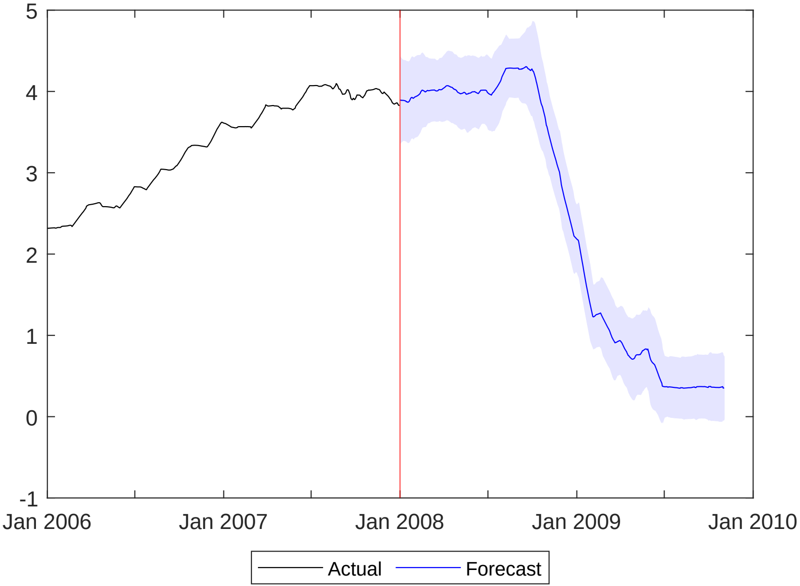


Tightening Episodes





Forecasting EONIA



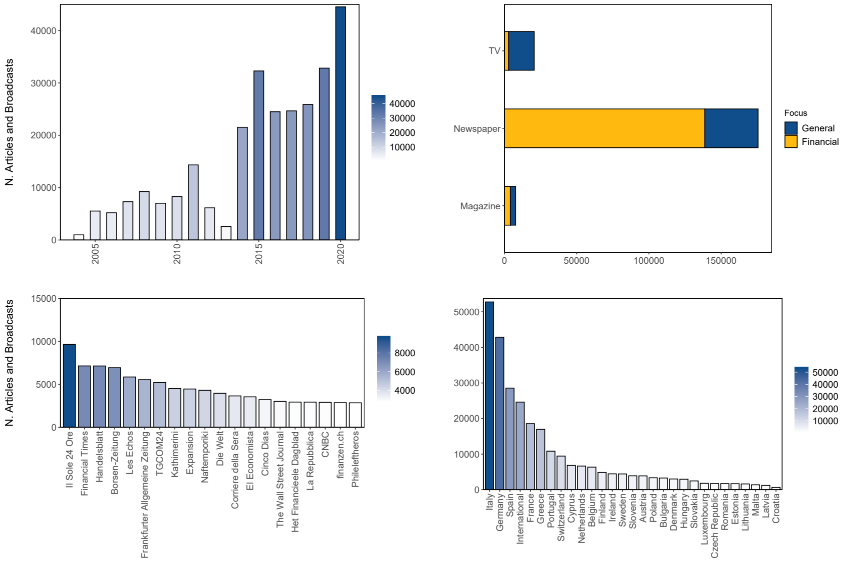
Conclusion

- Financial markets closely watch central banks to track the evolution of monetary policy.
- Central banks, however, update their stance at press conferences.
- The interval in-between two consecutive press conferences can be significantly long.
- I then propose a model that provides contemporaneous forecasts of the ECB's monetary policy stance exploiting conventional and textual data.
- Results:
  - Accurate tracking of ECB MP stance at key events
  - Useful in forecasting EONIA (2008-2009)
  - DFM outperforms competing models
  - Textual variables do improve forecast accuracy

Thank you for your attention

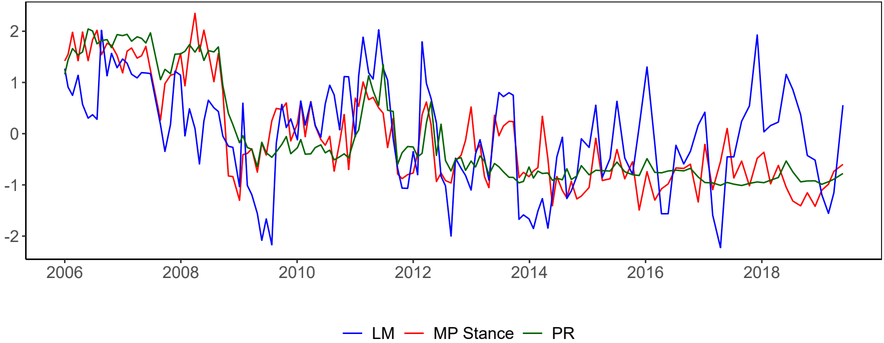
Textual Dataset

Textual Dataset



Alternative MP Indexes

Alternative Indexes



Sample Dictionaries

Sample Dictionaries

Monetary Policy	Economic Outlook	Inflation Outlok
Dovish	Positive	Positive
– favourable financing conditions	– stronger than expected	– tighter labour markets
– additional asset purchases	– growth momentum	– higher than expected
– accommodative stance	– positive outlook	– second round effects
– increase the envelope	– revised upwards	– higher energy price
– reduce interest rates	– strong recovery	– solid wage growth
– heightened alertness	– encouraging	– higher pressure
– extension of credit	– upswing	– higher inflation
– liquidity provision	– impetus	– fast growing
– weakening	– surging	– upside risks
– subdued	– upturn	– build up
Hawkish	Negative	Negative
– higher commodity prices	– negative cyclical momentum	– lower unit labour costs
– increase interest rates	– heightened uncertainty	– higher unemployment
– inflationary pressure	– revised downwards	– lower wage pressures
– strong fundamentals	– downside risks	– unutilised capacity
– counter upside risks	– vulnerabilities	– lower oil prices
– rise in inflation	– decelerating	– disappointing
– end purchases	– disequilibria	– contained
– winding down	– contracting	– fall below
– rising wages	– headwinds	– sluggish
– withdrawal	– softening	– muted

Note: The table shows a sample of n-grams and unigrams for each ECB field-specific dictionary.

Scoring Rule

Scoring Rule

- The algorithm breaks each press conference into sentences and, in turn, each sentence into an ordered bag of words.
- The word w in each sentence τ is then compared to the dictionaries of polarized words.
- These polarized words form a polar cluster $\gamma_{w,\tau}$, that is, a subset of a sentence ($\gamma_{w,\tau} \subset \tau$) where every polarized word (w_γ^p) in the cluster is preceded and succeeded by valence shifters that weight the impact of the reference word by a factor η set by the researcher.
- Amplifiers w_a (de-amplifiers w_d) increase (decrease) the polarity by η in such a way that $w_a = \sum[\eta \cdot (w_\gamma^{neg} \cdot w_\gamma^a)]$ where $w_\gamma^{neg} = (-1)^{2+\sum w_\gamma^n}$ and w_γ^n stands for the n^{th} negator in the j^{th} cluster.

Scoring Rule

- Amplifiers become de-amplifiers w_d if there is an odd number of negators w^n_γ in the cluster.
- An adversative conjunction w_{advcon} *before* the polarized word up-weights the cluster by $1 + [\eta \cdot (w_{advcon})]$, whereas an adversative conjunction *after* the polarized word down-weights the cluster by $1 + [(w_{advcon} - 1) \cdot \eta]$.
- Overall, the score for each sentence s is computed following the equation:

$$\psi_\tau = \frac{\gamma^n_{w,\tau}}{\sqrt{\sum_{n=1}^{N} w_n}} \tag{1}$$

where $\gamma^n_{w,\tau} = \sum[(1 + w_a + w_d) \cdot w^p_\gamma \cdot w^{neg}_\gamma]$ is the sum of single polar clusters and $\sqrt{\sum_{n=1}^{N} w_n}$ is the square root of the total number of words in a sentence.

- To obtain the mean of all sentences within a press conference I simply calculate the average sentiment score $PC^d = \frac{1}{n} \sum \psi_\tau$.

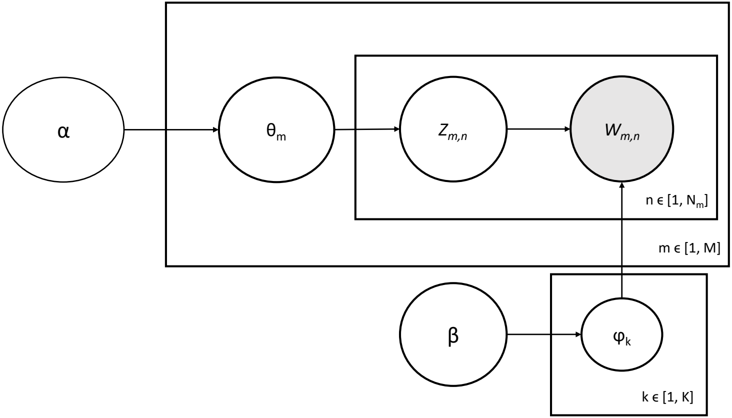
LDA

LDA I

- LDA is a generative probabilistic model of a corpus.
- The basic idea is that documents are represented as random mixtures over latent topics, where each topic is characterized by a distribution over words
- There are three levels in LDA model
  - a document level where every document is a mixture of latent topics
  - a topic level where every document has a probability to belong to a topic
  - a word level where every word has a probability to belong to a topic.

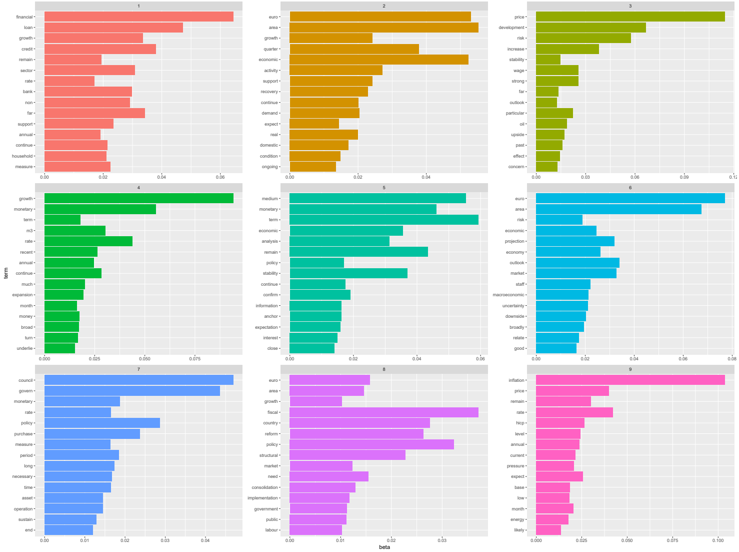
LDA Graphical Representation

LDA II



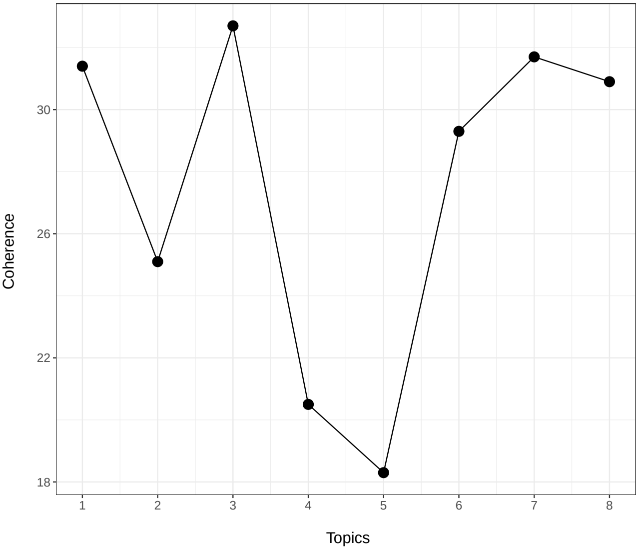
Word-Topic Probability

LDA III



Topics' Coherence

LDA IV



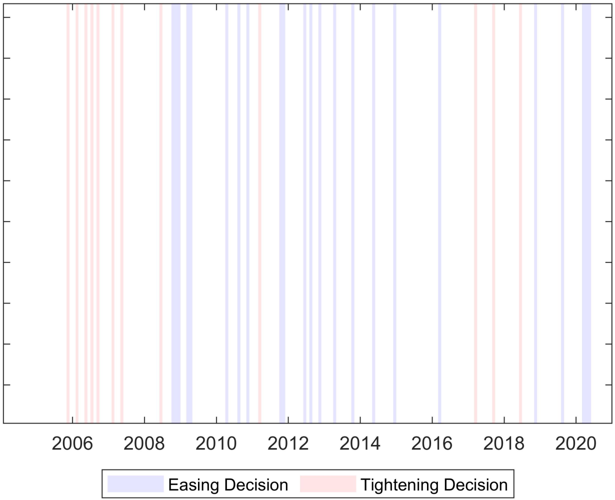
Multinomial Logit (I)

Multi Logit I

- Tightening decisions to be classified as such must contain one (or a combination) of the following announcements:
  - increase in interest rates
  - a reduction in asset purchases
  - a hawkish revision of the forward guidance
- An easing decision to be classified as such must instead include one (or a combination) of the following announcements:
  - an interest rate cut
  - the launch of an asset purchase programme
  - a type of long-term refinancing operations (LTROs)
  - an increase in asset purchases
  - a dovish revision of the forward guidance
  - an extension of the collaterals eligible for repos
- Monetary policy remains constant if no decision in the first or second group is announced.

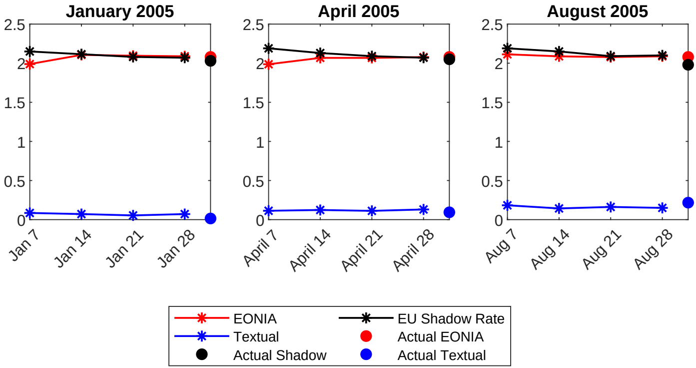
Multinomial Logit (II)

Multi Logit II



Validating DFM

Validating DFM



Mean Estimates of Policy Rules (I)

Alternative Benchmarks I

Rules	**N**	**% of Total**	ρ	r^*	β_π	β_y	**SEE**	R^2
Total Rules	157		0.90	-0.51	1.20	0.90	0.2017	0.9516
			(0.03)	(0.34)	(0.39)	(0.20)		
Forward-looking	46	29.9%	0.91	-1.05	2.11	1.10	0.2134	0.9598
			(0.04)	(0.38)	(0.86)	(0.19)		
Backward-looking	51	32.4%	0.92	-0.36	0.79	0.92	0.2001	0.9511
			(0.03)	(0.32)	(0.14)	(0.25)		
Mixed Rules	60	38.2%	0.91	-0.61	1.52	0.96	0.2211	0.9522
			(0.04)	(0.39)	(0.61)	(0.20)		

Alternative Benchmark Models (II)

Alternative Benchmarks II

2005-2014				
H	1	2	3	4
$DFM\backslash BM_1$	0.75	1.22	1.90^{*}	2.61^{***}
$DFM\backslash BM_2$	1.14	1.45	2.01^{**}	2.37^{**}
$DFM\backslash BM_3$	1.22	1.38	1.79^{*}	3.11^{***}
$DFM\backslash BM_4$	0.98	1.13	1.59	$2.41{**}$
$DFM\backslash BM_5$	0.67	0.94	1.55	2.78^{***}
$DFM\backslash BM_{all}$	1.55	1.58	1.73^{*}	2.26^{**}
$DFM\backslash BM_{for}$	1.41	1.49	1.65^{*}	1.88^{*}
$DFM\backslash BM_{back}$	1.05	1.33	2.11^{**}	2.90^{***}
$DFM\backslash BM_{mix}$	1.15	1.34	2.23^{**}	3.08^{***}
2015-2020				
H	1	4	6	8
$DFM\backslash BM_1$	1.172	1.19	1.71^{*}	3.10^{***}
$DFM\backslash BM_2$	1.16	1.26	1.90^{*}	3.22^{***}
$DFM\backslash BM_3$	1.01	0.163	1.34	3.11^{***}
$DFM\backslash BM_4$	1.15	1.16	1.45	2.99^{***}
$DFM\backslash BM_5$	1.15	1.26	2.33^{**}	2.65^{***}
$DFM\backslash BM_{all}$	1.10	1.16	2.55^{**}	2.76^{***}
$DFM\backslash BM_{for}$	0.78	1.11	1.56	3.01^{***}
$DFM\backslash BM_{back}$	0.98	1.32	2.89^{***}	3.44^{***}
$DFM\backslash BM_{mix}$	1.21	1.44	2.79^{***}	3.21^{***}

Note: The table shows the t-test of the Diebold-Mariano test statistic (Diebold and Mariano, 1995). The test-statistics are based on out-of-sample forecast errors for the period 2005-2014 and 2015-2020. The row "H" indicates the number of weeks between two consecutive press conferences. $*$, $**$, and $***$ denote, respectively, the 10%, 5%, and 1% significance level.

Dynamic Factor Model

Econometric Methodology

- Measurement equation: Validating DFM

$$\begin{bmatrix} Y_t^{i,f} \\ Y_t^{m,f} \\ Y_t^{m,s} \\ Y_t^{d} \end{bmatrix} = \begin{bmatrix} \tilde{\Lambda}^{i,f} & 0 & 0 & 0 \\ 0 & \tilde{\Lambda}^{m,f} & 0 & 0 \\ 0 & 0 & \Lambda^{m,s} & 0 \\ 0 & 0 & 0 & \Lambda^{d} \end{bmatrix} \begin{bmatrix} \tilde{F}_t^{i,f} \\ \tilde{F}_t^{m,f} \\ F_t^{m,s} \\ F_t^{d} \end{bmatrix} + \begin{bmatrix} E_t^{i,f} \\ E_t^{m,f} \\ E_t^{m,s} \\ E_t^{d} \end{bmatrix}$$

- Transition Equation:

$$\begin{bmatrix} I_{2r} & 0 & 0 & \mathcal{W}_t^{i,f} \\ 0 & I_{2r} & 0 & \mathcal{W}_t^{m,f} \\ 0 & 0 & I_r & \mathcal{W}_t^{m,s} \\ 0 & 0 & 0 & I_r \end{bmatrix} \begin{bmatrix} \tilde{F}_t^{i,f} \\ \tilde{F}_t^{m,f} \\ F_t^{m,s} \\ F_t^{d} \end{bmatrix} = \begin{bmatrix} \mathcal{I}_t^{i,f} & 0 & 0 & 0 \\ 0 & \mathcal{I}_t^{m,f} & 0 & 0 \\ 0 & 0 & \mathcal{I}_t^{m,s} & 0 \\ 0 & 0 & 0 & \Xi \end{bmatrix} \begin{bmatrix} \tilde{F}_{t-1}^{i,f} \\ \tilde{F}_{t-1}^{m,f} \\ F_{t-1}^{m,s} \\ F_{t-1} \end{bmatrix} + \begin{bmatrix} 0 \\ 0 \\ 0 \\ U_t \end{bmatrix}$$

Bridge Equation

Econometric Methodology

- The DFM is not informative on the expected probability that the ECB, conditional on the incoming data, will actually take a monetary policy decision.
- I therefore augment the model with a multinomial logit model:
  Multi Logit I Multi Logit II

$$P(y_{t+h} = j | \hat{X}_{t+h}) = \Phi(\alpha + \beta' \hat{X}_{t+h})$$

- where
  - y_{t+h} is a categorical variable that equals 1 if the ECB hikes at time $t+h$, 0 if there is no actual change and -1 if the ECB eases at time $t+h$;
  - α and β are, respectively, a constant and a vector of parameters;
  - $\Phi(\cdot)$ denotes the cumulative distribution function of the logistic distribution;
  - $\hat{X}_{t+1}$ is a vector containing a set of predictors for which the DFM provided the forecasts at time $t+1$.

Benchmark Model

Econometric Methodology

- Compare the DFM with a forecast-based policy rule (Jansen and De Haan, 2009)
  - Led by the fact that the ECB is found to set interest rates in a forward-looking manner (see Gerlach, 2007; Gorter et al., 2008)
- The model: Alternative Benchmarks I Alternative Benchmarks II

$$ECB_t = \alpha + \phi_\pi(\pi_t - \pi^*) + \phi_\gamma(\gamma_t - \gamma_t^*) + \phi_{\pi,h}\mathbb{E}_t\pi_{t+h} + \phi_{\gamma,h}\mathbb{E}_t\gamma_{t+h} + \epsilon_t$$

- where
  - $\pi_t - \pi^*$: difference between growth rate of core inflation and ECB inflation target
  - $\gamma_t - \gamma_t^*$: difference between growth rate of output and output gap
  - π_{t+h} and γ_{t+h}: respectively, the inflation and output growth ECB staff forecasts four quarters ahead ($h = 4$)