The term structure of judgement: interpreting survey disagreement

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What is behind professional forecasts?

The forecasting process is a “black box”, but there is something we can say about it (ECB, 2019, 2024; Stark, 2013):

- At short horizons, respondents rely heavily on models, especially time series and a combination of models
- At every horizon, the majority of respondents incorporates at least some judgement to their model forecasts

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Professionals are well informed agents, yet they disagree: **Q1: why?** Figure

- Because of interpreting information differently?
- Because they have different models?
- Mix of both?

Focus on **interpreting** survey forecasts and disagreement across respondents **structurally**.

A novel way to analyze SPF forecasts

Q2: Which structural shocks do forecasters expect to affect the variables they are forecasting?

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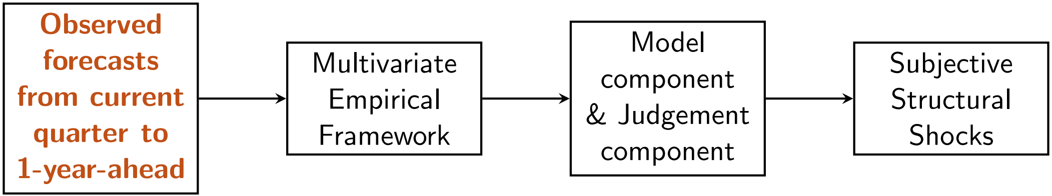
Our Approach



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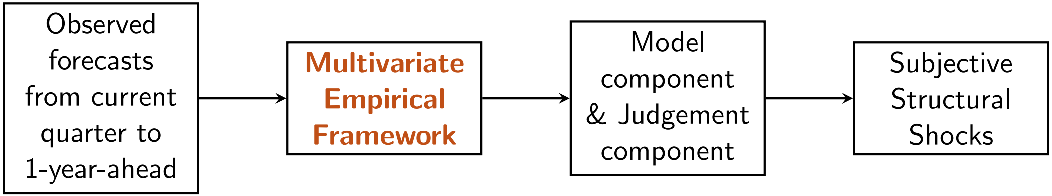

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Observed forecasts from current quarter to 1-year-ahead → Multivariate Empirical Framework → Model component & **Judgement component** → Subjective Structural Shocks

A novel way to analyze SPF forecasts

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Related Literature and Contribution

- **Propose a novel way of combining models and forecasts:** exploit the information contained in the term structure of individual forecasts to estimate and identify coefficients of a VAR model
  - Bańbura, Brenna, et al., 2021; Bańbura, Leiva León, et al., 2021; Ganics and Odendahl, 2021; Monti, 2010; Robertson et al., 2005
- **Offer a deeper look into structural disagreement through time**
  - Andrade et al., 2016; Dovern, 2015; Rich and Tracy, 2021 (empirical); Andre et al., 2022; Herbst and Winkler, 2021 (structural)
- **Shed further light on professional forecasters' expectation formation process**: we do not take a specific stance on the microfoundations behind the process, but model expectations in a flexible, reduced form.
  - Born et al., 2020; Farmer et al., 2021 (sticky information), Casey, 2021 (over-reaction), Dovern and Hartmann, 2017; Giacomini et al., 2020 (heterogeneous forecasters)

Model for the term-structure of forecasts

Each respondent i runs a VAR+SV (here simplified):

$$y_t = \beta y_{t-1} + A_0^{-1} e_t \qquad e_t \sim \mathcal{N}(0, \Lambda_t)$$

The optimal **model** forecast done at time t would correspond to:

$$y_{t+1|t} = \beta y_t \qquad y_{t+h|t} = \beta^h y_t$$

If we assumed agents have:

- same available data
- same model
- same priors

we would not see any disagreement, which however we observe in the SPF forecasts.

Model for the term-structure of forecasts

Each respondent i runs a VAR+SV (here simplified):

$$y_t = \beta_i y_{t-1} + A_{0,i}^{-1} e_{t,i} \qquad e_{t,i} \sim \mathcal{N}(0, \Lambda_{t,i})$$

The optimal **model** forecast done at time t would correspond to:

$$y_{t+1|t,i} = \beta_i y_t \qquad y_{t+h|t,i} = \beta_i^h y_t$$

Instead, we allow for the possibility that forecasters:

- use **different models**

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$$y_{t+1|t,i} = \beta_i y_t + A_{0,i}^{-1} e_{t+1|t,i} \quad y_{t+h|t,i} = \beta_i^h y_t + A_{0,i}^{-1} e_{t+h|t,i} + \ldots + \beta_i^{h-1} A_{0,i}^{-1} e_{t+1|t,i}$$

Instead, we allow for the possibility that forecasters:

- use **different models**
- incorporate some **judgement**

Assumption for the estimation

$$y_{t+1|t,i} = \beta_i y_t + A_{0,i}^{-1} e_{t+1|t,i} \quad y_{t+h|t,i} = \beta_i^h y_t + A_{0,i}^{-1} e_{t+h|t,i} + \ldots + \beta_i^{h-1} A_{0,i}^{-1} e_{t+1|t,i}$$

Formulation of forecasts in this way has its advantages:

- aligns with conditional forecasting methods (Waggoner & Zha, 1999)
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it buys computational convenience but also adheres to structural interpretation

$$y_{t+h|t,i} = \beta_i y_{t+h-1|t,i} + A_{0,i}^{-1} e_{t+h|t,i}$$

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$$y_{t+h|t,i} = \beta_i y_{t+h-1|t,i} + A_{0,i}^{-1} e_{t+h|t,i}$$

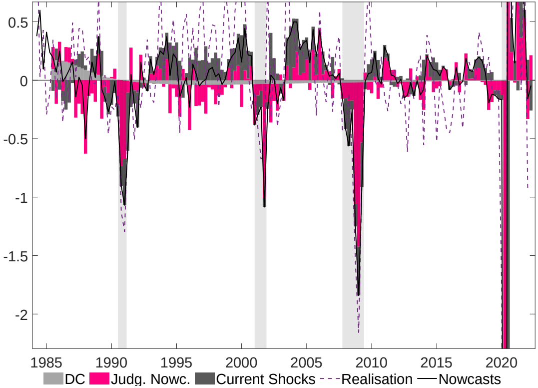
Price: it does not adhere to intricacies of expectation formation literature

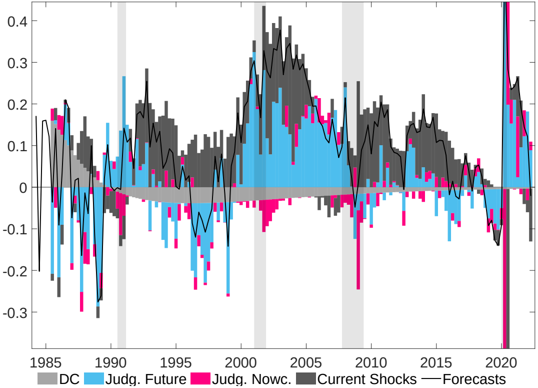
Data and Specifications

- **Philadelphia FED SPF** and **Real Time Dataset for Macroeconomists**: Data
  - sample 1984q2-2022q2
  - **6 variables:** real GDP growth, investment, term spread, AAA-10y spread, CPI inflation, 3-month T-bill
  - For every quarter q, observed data and forecasts between quarter $q-1$ and $q+4$

- Two main specifications:
  - "Average" respondent
  - Individual models (63 respondents)

Historical decomposition of *GDP* **nowcast** and **one-year ahead forecast**





CPI Equation HD

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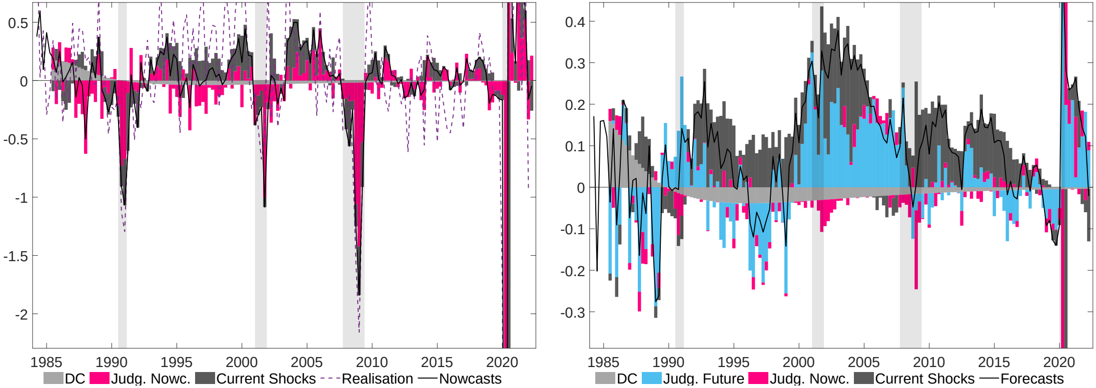
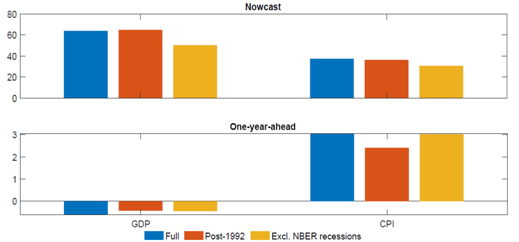


Judgement is **pervasive** in SPF consensus forecasts. But does it help?

CPI Equation HD

Judgement and forecast accuracy

- Yes, judgement aids accuracy at **short horizons** and particularly during crises



Note: The figure shows the percentage gains in terms of root mean squared error (RMSE) for the SPF forecasts compared to model-consistent unconditional forecasts. All

- *Possible explanation:* Judgement about nowcast reflects high-frequency and timely info, which is available between the first macro release and the survey submission

Impulse response functions: shocks' labelling

We exploit **heteroskedasticity** for identification, but we still need to provide an economic interpretation.

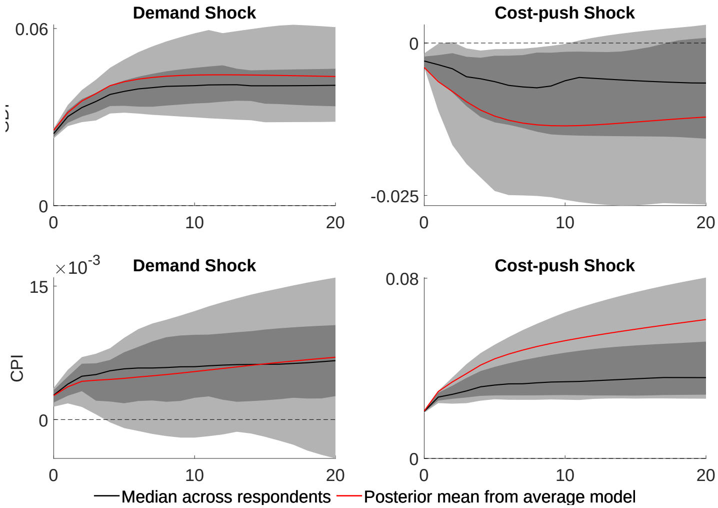
1 $\rightarrow$ label shocks by looking at **signs of impulse responses**
2 $\rightarrow$ compare shocks with 150 others in literature, check if **valid instruments** .

Identified shocks:

1. **Unanticipated demand** (Mertens & Ravn, 2012, 2013; Romer & Romer, 2010)
2. Unanticipated supply
3. Anticipated demand
4. Financial (Bassett et al., 2014; Bloom, 2009; Gilchrist & Zakrajšek, 2012)
5. **Cost-push** (Baumeister, 2023; Känzig, 2021) ..
6. "Interest rate"

IRFs small IRFs all

Impulse response functions: **individual models**



Consensus IRFs All IRFs

Cross-sectional disagreement

IRFs across individual forecasters present some parameter heterogeneity. But how important is it to explain forecasts dispersion?

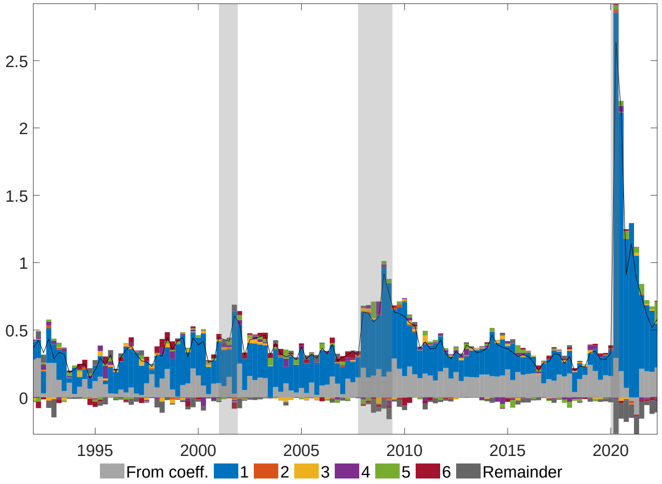
We re-arrange terms to isolate the two effects...

$$y_{t+h|t,i} = \underbrace{\left(\sum_{j=0}^{h-1} \beta_i^j\right) c_i + \beta_i^h y_t + \sum_{k=1}^{N}\left(\sum_{j=1}^{h} \psi_{h-j,i,1}\bar{\varepsilon}_{t+j|t,k}\right)}_{\tilde{y}_{h,t,i}\text{(different coefficients)}} + \underbrace{\sum_{k=1}^{N}\left(\sum_{j=1}^{h} \bar{\psi}_{h-j,1}\varepsilon_{t+j|t,i,k}\right)}_{\tilde{\varepsilon}_{h,t,i}^{(1,\dots,N)}\text{(different expected shocks)}}$$

$$+ \text{"remainder"}$$

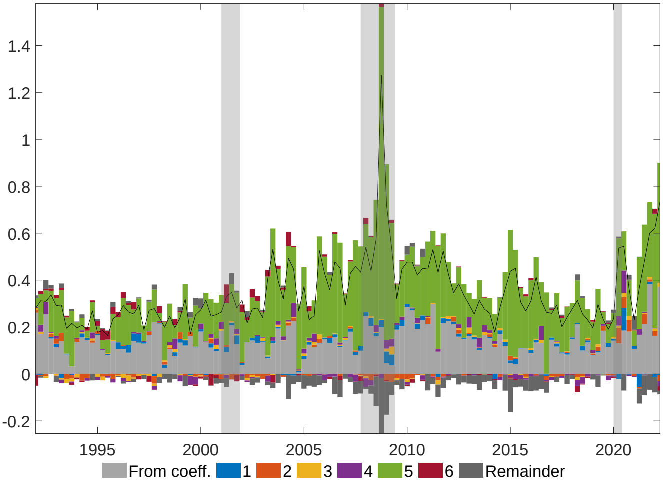
... and calculate the cross-sectional variance as the covariance between each right-hand side term and the left-hand side.

Cross-sectional disagreement of **1-year-ahead GDP forecasts**



Other

Cross-sectional disagreement of **1-year-ahead CPI forecasts**



Other

Conclusions

- We develop a parsimonious and efficient way to incorporate the full term structure of survey forecasts into a VAR model
  - The added information content allows for sharper parameter estimates and inference
  - Our framework allows to extract judgement shocks from survey forecasts and identify them structurally using heteroskedasticity
- Judgement improves accuracy across the sample, more so in turbulent times and for nowcasts
- Two thirds of disagreement due to different judgements, remaining third due to different coefficients
- Disagreement mainly on size of shocks, not on their nature

Thank you!

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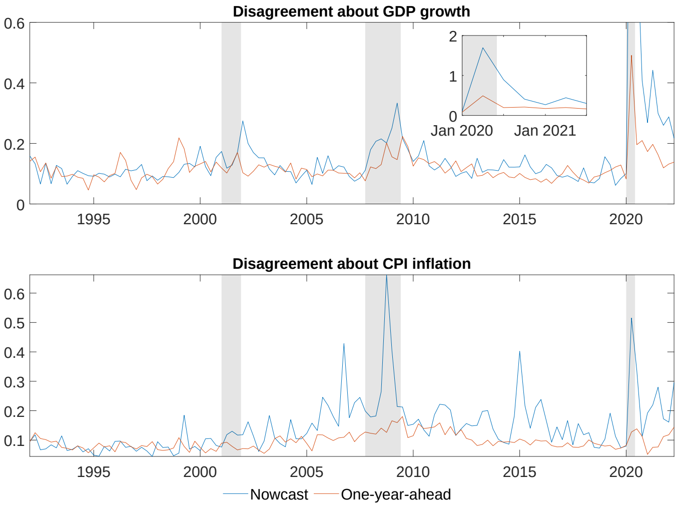
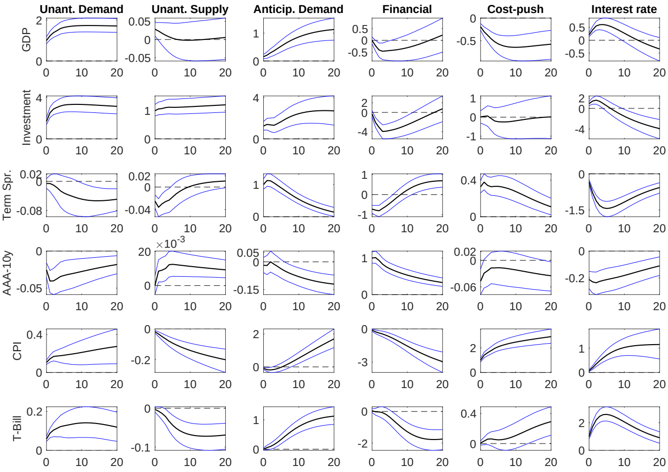
Background slides

Disagreement over time



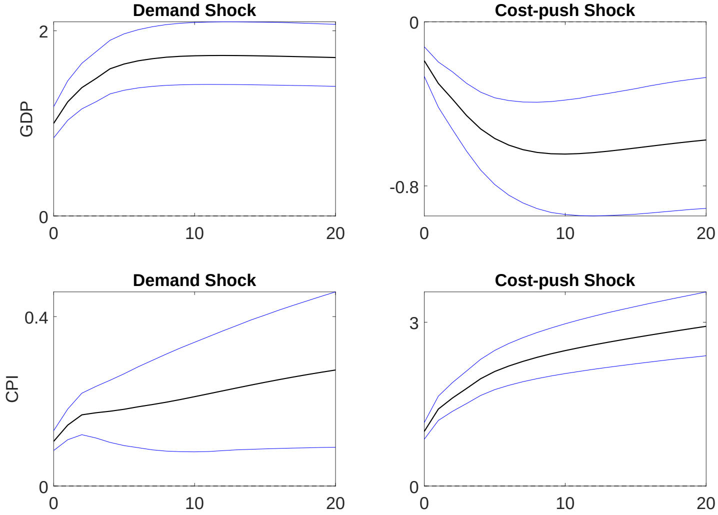
Back to Intro

Impulse response functions: average model



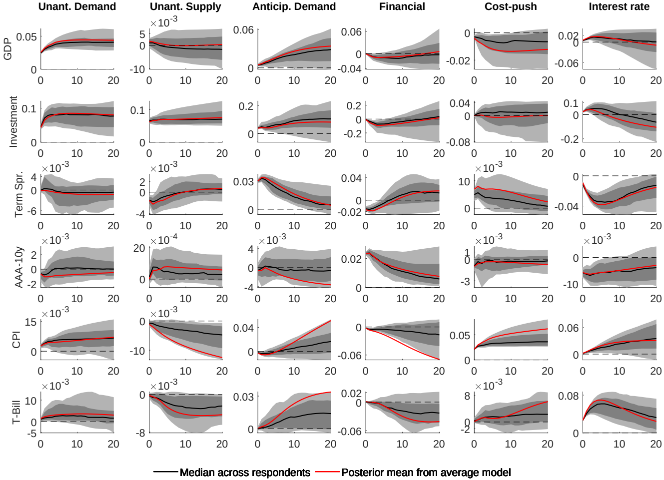
Robustness Back

Impulse response functions: **“average” model**



All IRFs | Back to labelling | Back to Individual

Impulse response functions: **individual models**



Back

External instruments and labelling of structural shocks

Post-estimation procedure to label structural innovations (Bertsche & Braun, 2022; Schlaak et al., 2023) *but extended to a Bayesian setting [accounts for the measurement error]*:

- We assume external shocks w_t are linearly related to our shock estimates, $\hat{\varepsilon}_t$

$$w_t = \psi\hat{\varepsilon}_t + o_t \qquad o_t \sim \mathcal{N}(0, \sigma_o^2) \qquad \hat{\varepsilon}_t \sim p(\varepsilon_t, \Sigma_{\varepsilon,t})$$

- Check relevance, s.t. $\psi_k \neq 0$, and exogeneity $\psi_i = 0$ for all $i \neq k$;
- In the analysis, we exploit more than 100 proxies collected from over 40 studies.

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External shocks related to **unanticipated demand** shock

	RR10exo	MR12unc	MR2013TPI
ψ_1	**-0.024*** **	**-0.02*** **	**-0.023*** **
ψ_2	0.001	0.001	0.001
ψ_3	-0.019**	-0.013*	-0.016*
ψ_4	-0.011	-0.006	-0.004
ψ_5	-0.004	-0.005	-0.005
ψ_6	-0.007	-0.002	-0.002
Candidate	1	1	1
$P(M_r\|y)$	1	1	1
$\log_{10} BF$	7.964	8.827	8.364
LRT	0.139	0.488	0.475

Back

Note: The table presents the coefficients obtained from regressing shocks from the literature on our shock estimates. Asterisks denote levels of high probability density intervals when the zero value is not included (***=99%, **=95%, *=90%). "Candidate" is the shock with the highest absolute coefficient, "$P(M_r|y)$" is the posterior probability of the restricted model (i.e. the model including only the most relevant shock) to be preferred, "$\log_{10}$(Bayes F.)" is the logarithm of Bayes' factor in favour of the restricted model, and "LRT p-value" is the p-value from the likelihood ratio test.

External shocks related to **financial** shock

	BCDZ14	GZ12	NB09	NB09FMT	NB09MMT
ψ_1	-0.003	-0.005	-0.006	0.002	-0.001
ψ_2	0.001	0	0.001	-0.001	-0.001
ψ_3	-0.001	0.006	0.014*	0	0
ψ_4	**0.038****	**0.09*****	**0.064*****	**0.013****	**0.016*****
ψ_5	0.006	-0.004	-0.001	-0.001	0
ψ_6	0.007	0.01	-0.004	0.002	0.002
Candidate	4	4	4	4	4
$P(M_r\|y)$	1	1	1	1	1
$\log_{10} BF$	9.035	9.013	8.731	11.506	11.473
LRT	0.775	0.39	0.249	0.781	0.665

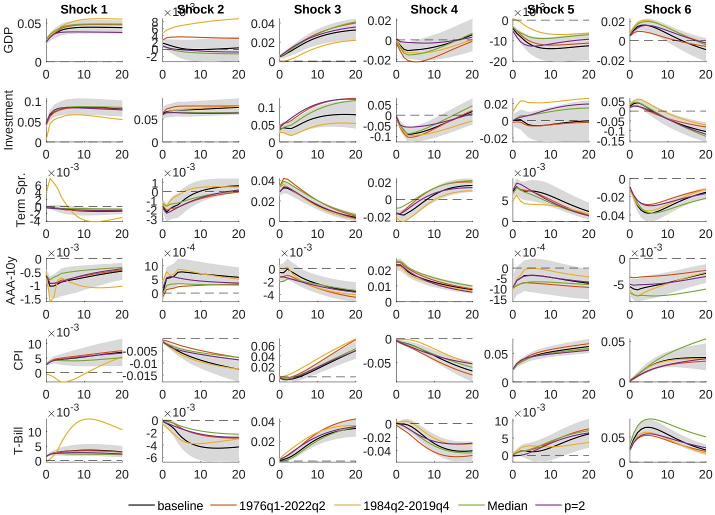
Back

External shocks related to **cost-push** shock

	DK21s	HAM03b	BH2022E	CCI19inst
ψ_1	-0.003	0.001	0	0.006
ψ_2	-0.002	-0.004*	-0.002	0.001
ψ_3	-0.005	0.001	0.004	-0.003
ψ_4	-0.001	0.014	-0.009	0.009
ψ_5	**0.013*** **	**0.013*** **	**0.018*** **	**-0.01** **
ψ_6	0.011	0.001	0.005	0.009
Candidate	5	5	5	5
$P(M_r\|y)$	1	1	1	1
$\log_{10} BF$	8.553	8.746	9.084	8.766
LRT	0.443	0.509	0.815	0.712

Back

Impulse response functions: **robustness**



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Data and transformations

Data Series	Transformation	Available from	Avg Periods	Avg Resp.
Real GDP	log-diff	1968:Q4	61	25 (29)
Investment	log-diff	1981:Q3	57	23 (27)
Term Spread	level	1992:Q1	52	22 (27)
AAA-10y spread	level	1992:Q1	44	18 (23)
CPI Inflation	log	1981:Q3	60	25 (29)
T-bill	diff	1981:Q3	58	24 (28)

Note: The table summarises variables used in the baseline specification, their transformation and the availability of individual responses. “Available from” is the date when forecast information became available in the SPF dataset; “Avg Periods” indicates the average number of quarters in which each respondent reported the forecast for a variable; “Avg Resp.” indicates the average number of respondents at each time point in the sample, with the average from 1992q1 in brackets.

Back

Priors

βs are mostly weakly informative but proper

$$vec(\beta_{avg}) \sim \mathcal{N}(\beta_0, \Sigma_\beta(\kappa)) \qquad vec(\beta_{indiv}) \sim \mathcal{N}(\widehat{\beta}_{avg}, 3 \cdot I)$$

For *consensus*: Chan (2021) and Litterman (1986). For *individual*: slight pooling à la Jarociński (2010) and Zellner and Hong (1992) to ensure comparability.

Similarly A_0s for *consensus* are assumed to follow RW, but slight pooling for *individual*.

$$\forall i = 1, ..., N \quad a_{avg,0,i,i} \sim \mathcal{N}(\widehat{\sigma}^{-1}_{AR,i}, 40) \qquad \forall i \neq j \quad a_{avg,0,i,j} \sim \mathcal{N}(0, 40)$$

$$\forall i, j \quad a_{indiv,0,i,j} \sim \mathcal{N}(\widehat{a}_{avg,0,i,j}, 4)$$

For parameters governing SV a hierarchical set-up is assumed to ensure "fatter-tails"

$$\sigma^2_{u,i} \sim \mathcal{IG}(3/2, S_{u,i}) \qquad S_{u,i} \sim \mathcal{G}(1.6/2, 1)$$

$$\rho_i \sim \mathcal{N}(0.9, 0.09)\mathbb{1}_{(-1<\rho<1)}$$

Back

Historical decomposition

$$y_{t+h|t} = \overbrace{\underbrace{\left(\sum_{j=0}^{t-1} \beta^{j+h}\right) c + \beta^{t+h} y_0}_{\text{deterministic comp.}} + \underbrace{\sum_{j=0}^{t} \beta^{j+h} A_0^{-1} \varepsilon_{t-j}}_{\text{stochastic comp.}}}^{\text{model forecast}}$$

Back

Historical decomposition with conditional forecasts

$$y_{t+h|t} = \overbrace{\underbrace{\left(\sum_{j=0}^{t-1}\beta^{j+h}\right)c + \beta^{t+h}y_0}_{\text{deterministic comp.}} + \underbrace{\sum_{j=0}^{t}\beta^{j+h}A_0^{-1}\varepsilon_{t-j}}_{\text{stochastic comp.}}}^{\text{model forecast}} + \overbrace{\underbrace{\beta^{h-1}A_0^{-1}\varepsilon_{t+1|t}}_{\text{nowcast judg.}} + \underbrace{\sum_{l=2}^{h}\beta^{h-l}A_0^{-1}\varepsilon_{t+l|t}}_{\text{future judg.}}}^{\text{judgement}}$$

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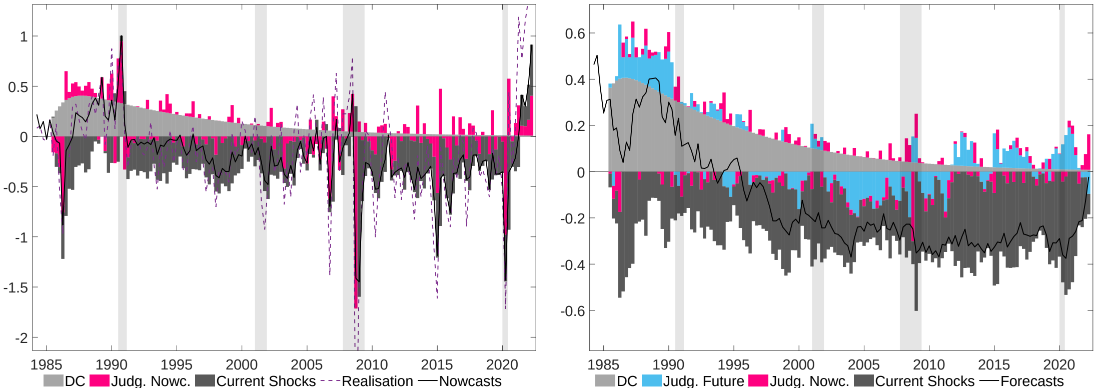
Historical decomposition of *CPI* **nowcast** and **one-year ahead forecast**



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Identification via stochastic volatility

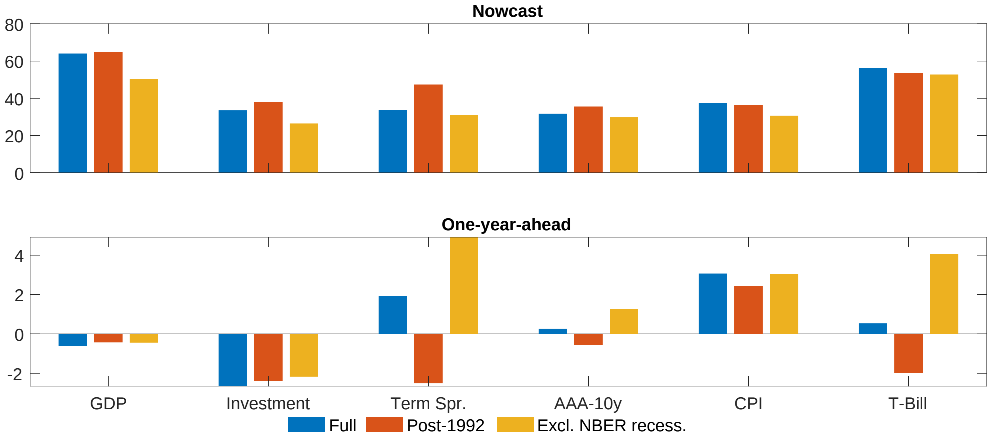
- The model and its estimation capture the whole term-structure of forecasts, but *we also want to identify shocks structurally*
- To do that, we exploit time variation in the volatility of shocks following Bertsche and Braun (2022), Chan et al. (2024), Lewis (2021), and Rigobon (2003)
- We set the law of motion of stochastic volatility to

$$\lambda_{i,t} = \rho_i \lambda_{i,t-1} + u_{i,t} \qquad\qquad u_{i,t} \sim \mathcal{N}(0, \sigma_{u,i}^2)$$

SV Multimodality

BACK

Forecast performance gains of SPF versus unconditional forecasts



Note: The figure shows the percentage gains in terms of root mean squared error (RMSE) for the SPF forecasts compared to model-consistent unconditional forecasts: $100(1 - RMSE_{SPF}/RMSE_{UC})$. Back

Cross-sectional disagreement

IRFs across individual forecasters present some parameter heterogeneity. But how important is it to explain forecasts dispersion?

- Historical shock decomposition for each individual i:

$$y_{t+h|t,i} = \underbrace{\left(\sum_{j=0}^{h-1} \beta_i^j\right) c_i + \beta_i^h y_t}_{y^{(uf)}_{h,t,i} \text{ (model forecast)}} + \underbrace{\sum_{j=1}^{h} \psi_{h-j,i,1}\varepsilon_{t+j|t,i,1}}_{\varepsilon^{(1)}_{h,t,i} \text{ (shock 1 judgement)}} + \ldots + \underbrace{\sum_{j=1}^{h} \psi_{h-j,i,N}\varepsilon_{t+j|t,i,N}}_{\varepsilon^{(N)}_{h,t,i} \text{ (shock N judgement)}}$$

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Cross-sectional disagreement

We re-arrange terms to isolate the two effects...

$$y_{t+h|t,i} = \underbrace{\left(\sum_{j=0}^{h-1} \beta_i^j\right) c_i + \beta_i^h y_t + \sum_{k=1}^{N}\left(\sum_{j=1}^{h} \psi_{h-j,i,1}\bar{\varepsilon}_{t+j|t,k}\right)}_{\tilde{y}_{h,t,i}\text{(different coefficients)}} + \underbrace{\sum_{k=1}^{N}\left(\sum_{j=1}^{h} \bar{\psi}_{h-j,1}\varepsilon_{t+j|t,i,k}\right)}_{\tilde{\varepsilon}_{h,t,i}^{(1,\ldots,N)}\text{(different expected shocks)}}$$

$$+ \underbrace{\sum_{k=1}^{N}\left(\sum_{j=1}^{h}(\psi_{h-j,i,1} - \bar{\psi}_{h-j,1})(\varepsilon_{t+j|t,i,k} - \bar{\varepsilon}_{t+j|t,k})\right)}_{\xi_{h,t,i}\text{ ("remainder" term)}} - \underbrace{\sum_{k=1}^{N}\left(\sum_{j=1}^{h} \bar{\psi}_{h-j,1}\bar{\varepsilon}_{t+j|t,k}\right)}_{\text{constant in the cross-section}}$$

... and calculate the cross-sectional variance as the covariance between each right-hand side term and the left-hand side.

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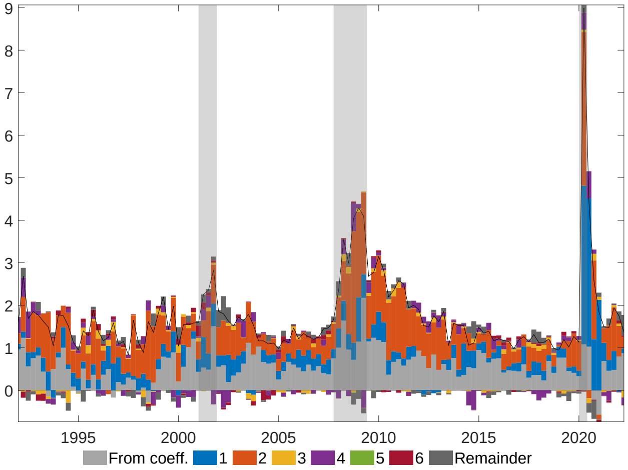
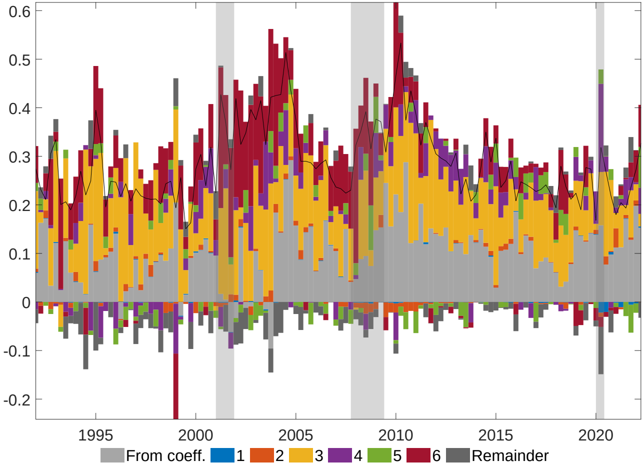
Cross-sectional disagreement of **1-year-ahead Investment forecasts**



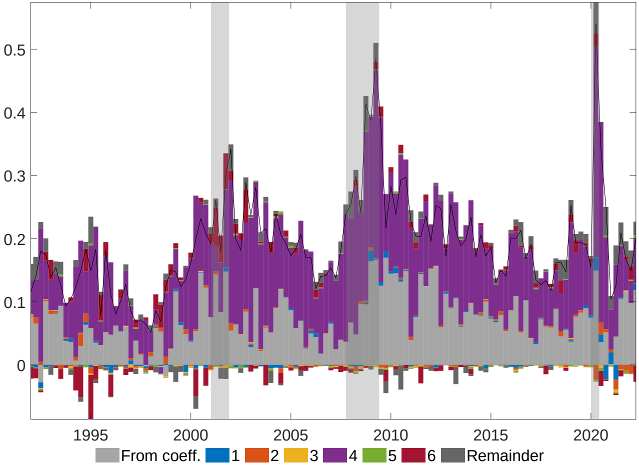
Back Term-Spread AAA-10y T-bill

Cross-sectional disagreement of **1-year-ahead Term-Spread forecasts**



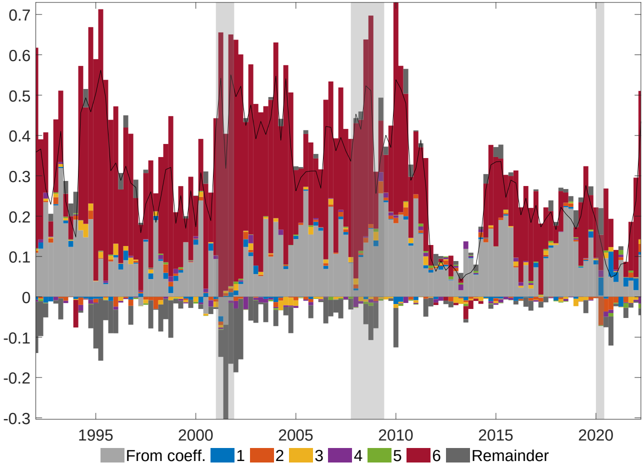
Back Investment AAA-10y T-bill

Cross-sectional disagreement of **1-year-ahead AAA-10y forecasts**



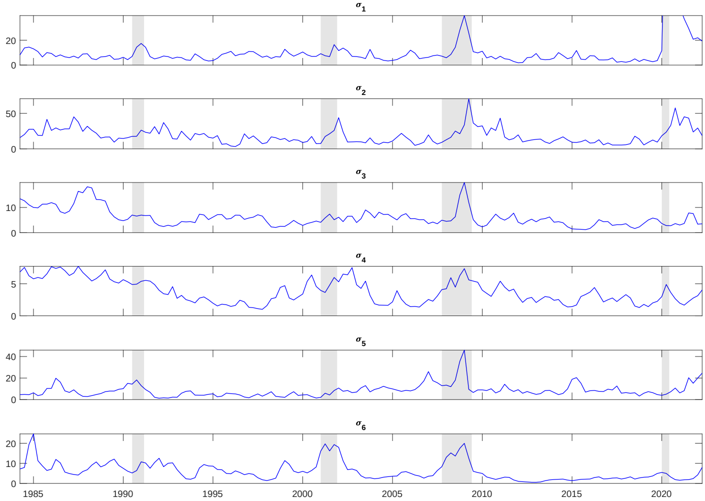
Back Investment Term-Spread T-bill

Cross-sectional disagreement of **1-year-ahead T-bill forecasts**



Back Investment Term-Spread AAA-10y

Estimated stochastic volatility



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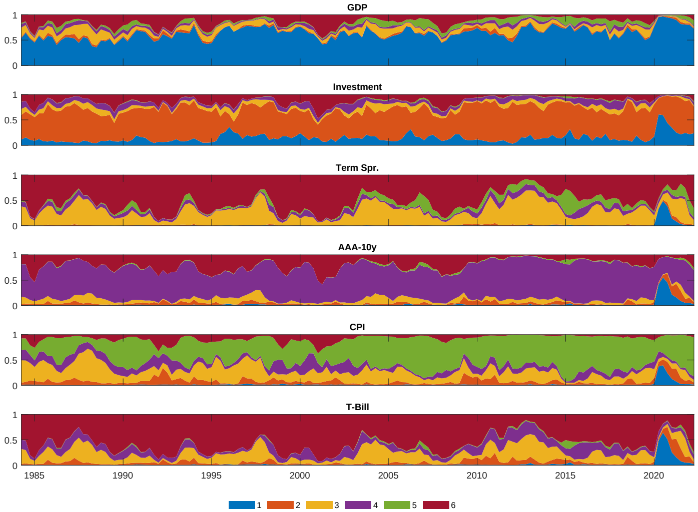
Forecast error variance decomposition, **one-year-ahead**



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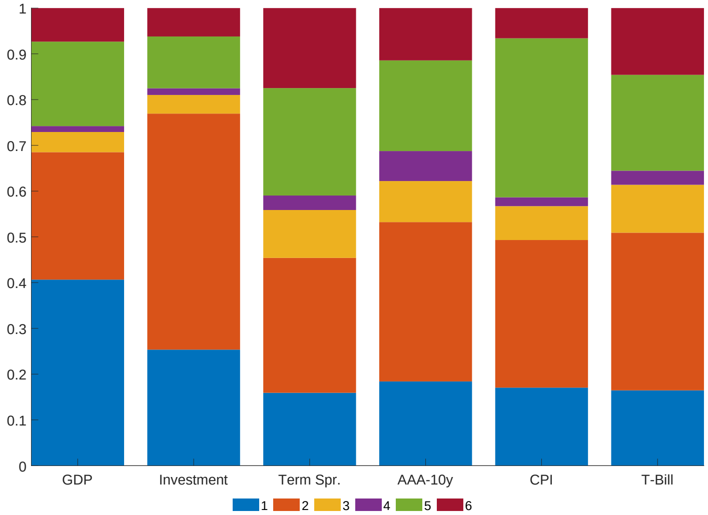
Forecast error variance decomposition, **long-run**



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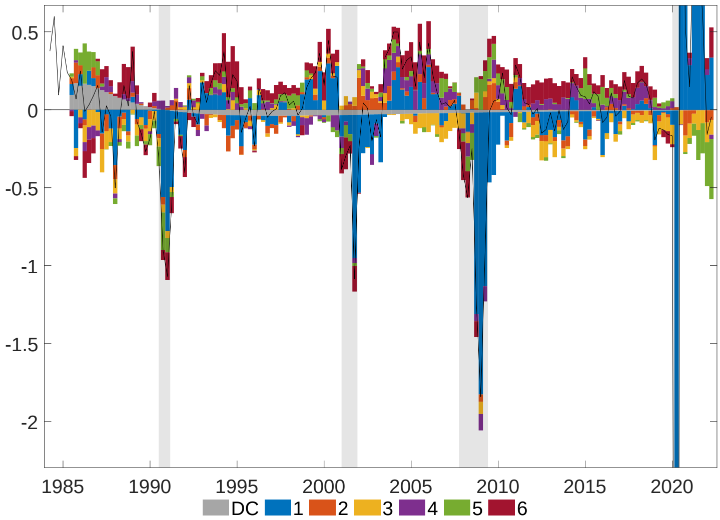
Historical decomposition of **GDP nowcast**



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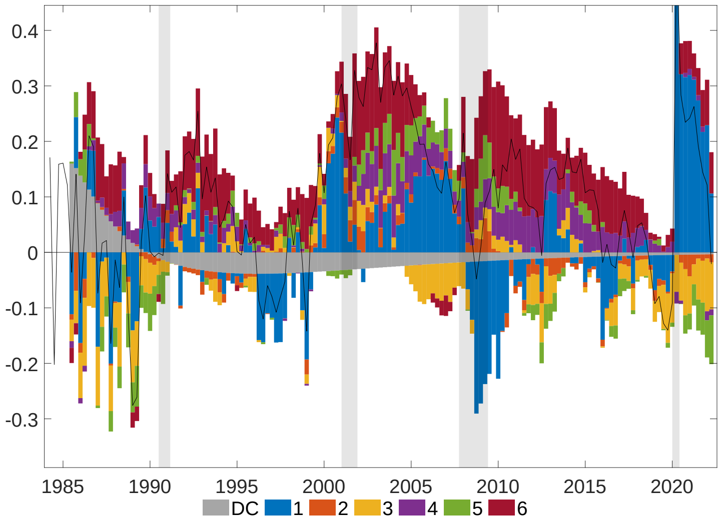
Historical decomposition of **1-year-ahead GDP forecasts**



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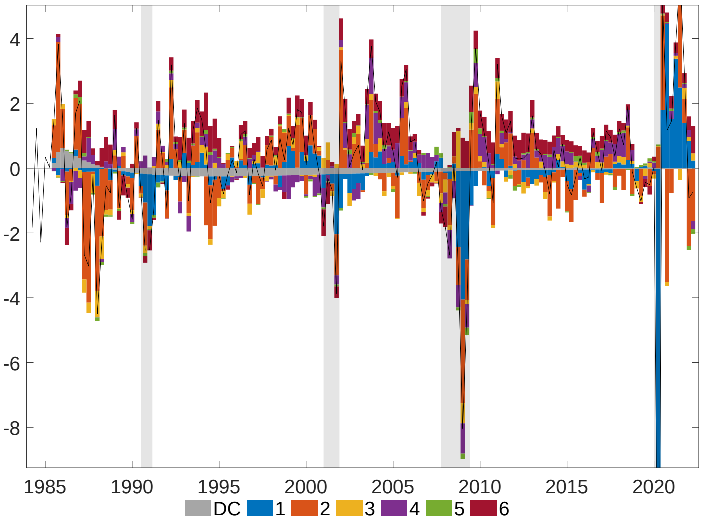
Historical decomposition of **investment nowcast**



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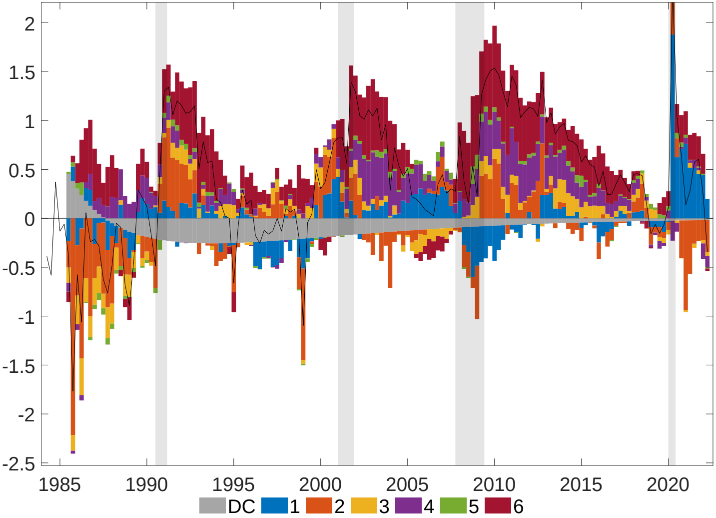
Historical decomposition of **1-year-ahead investment forecasts**



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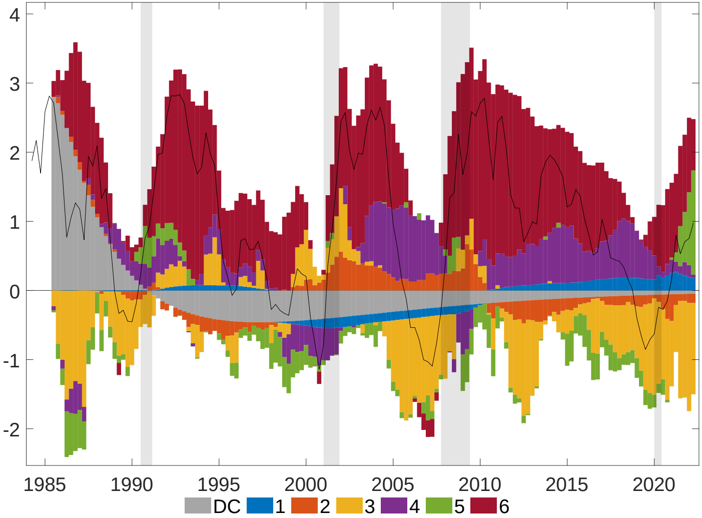
Historical decomposition of **term spread nowcast**



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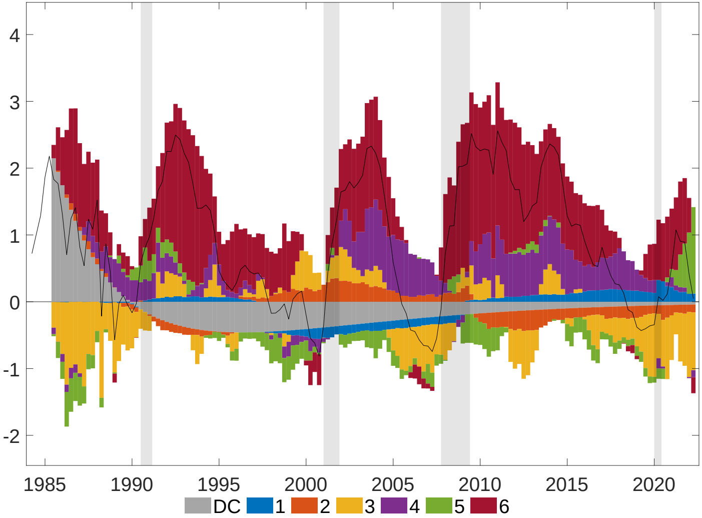
Historical decomposition of **1-year-ahead term spread forecasts**



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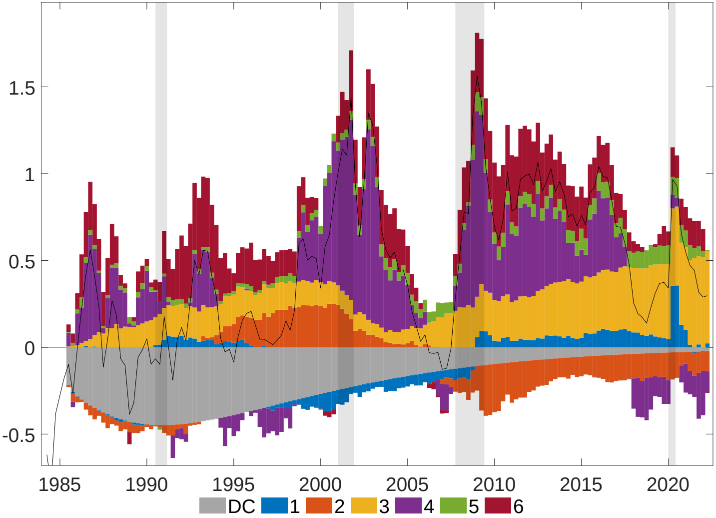
Historical decomposition of **AAA spread nowcast**



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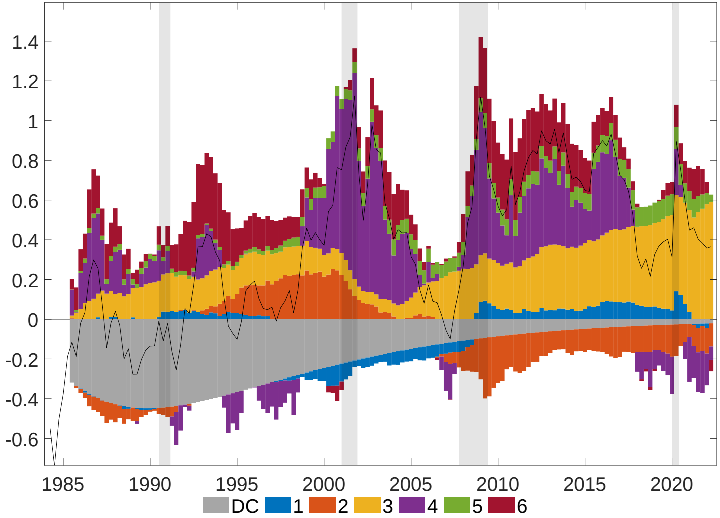
Historical decomposition of **1-year-ahead AAA spread forecasts**



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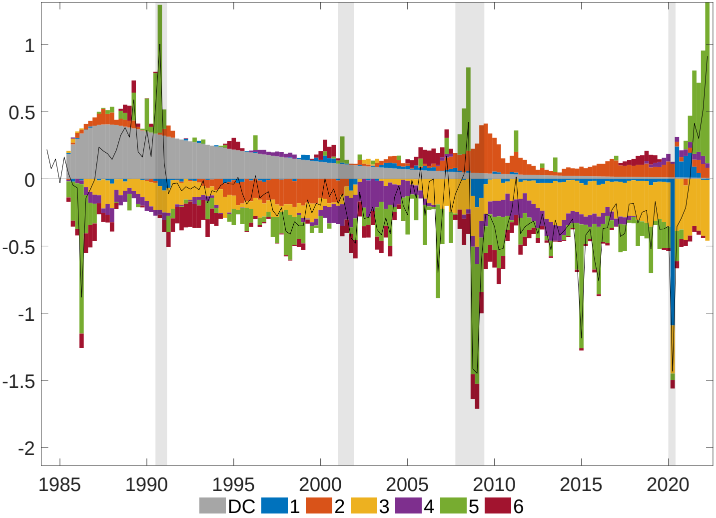
Historical decomposition of **CPI nowcast**



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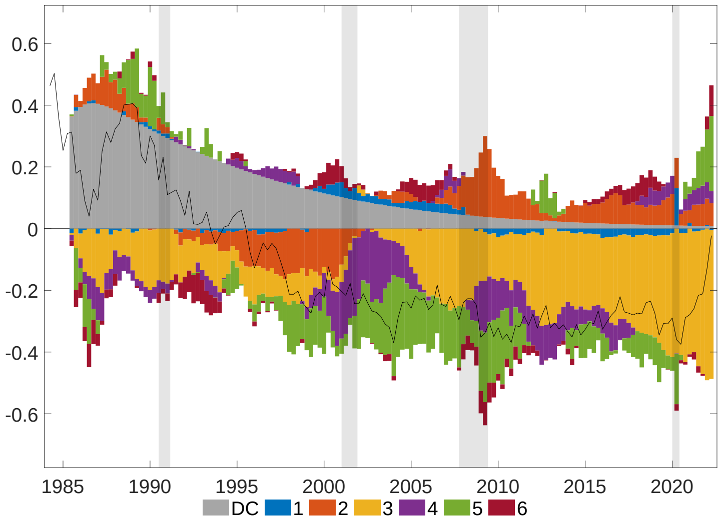
Historical decomposition of **1-year-ahead CPI forecasts**



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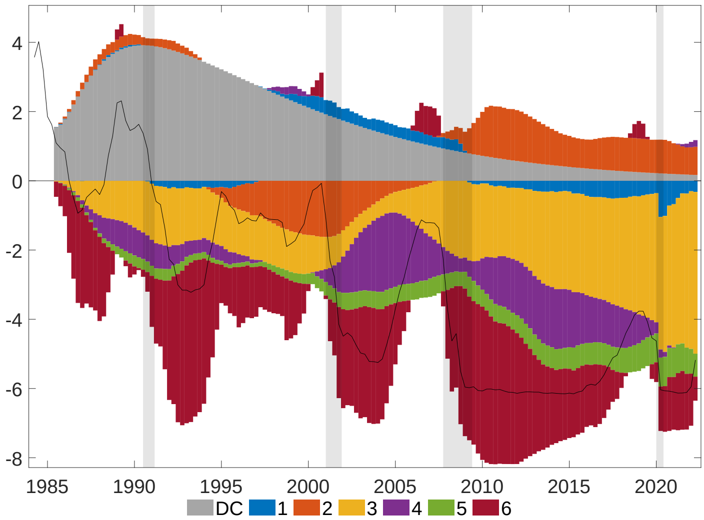
Historical decomposition of **T-bill nowcast**



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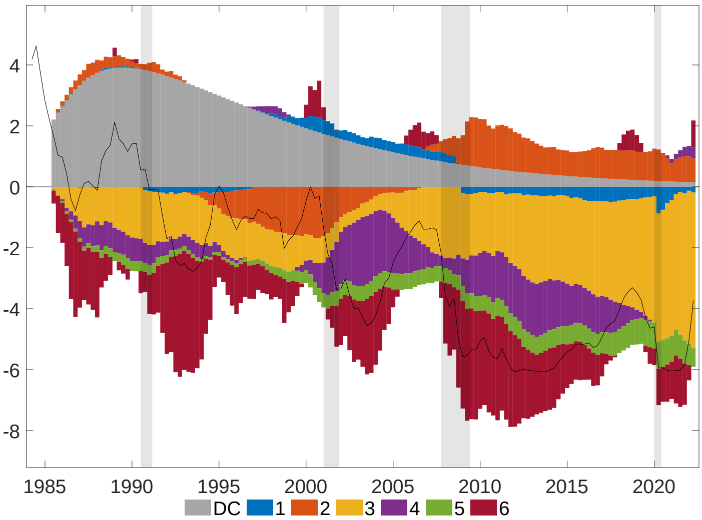
Historical decomposition of **1-year-ahead T-bill forecasts**



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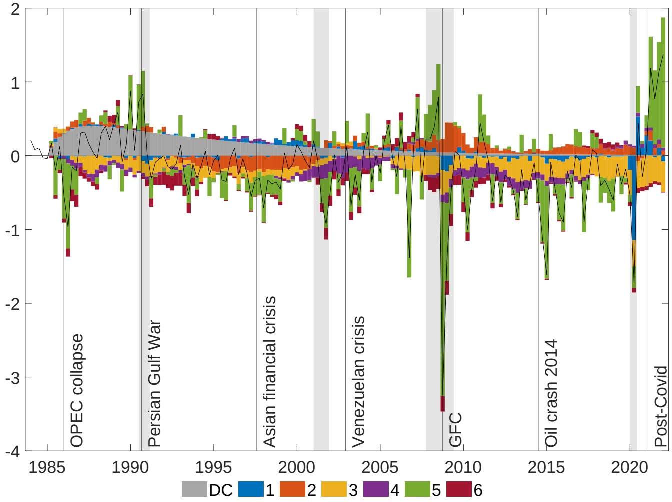
Historical decomposition of **CPI and oil events**



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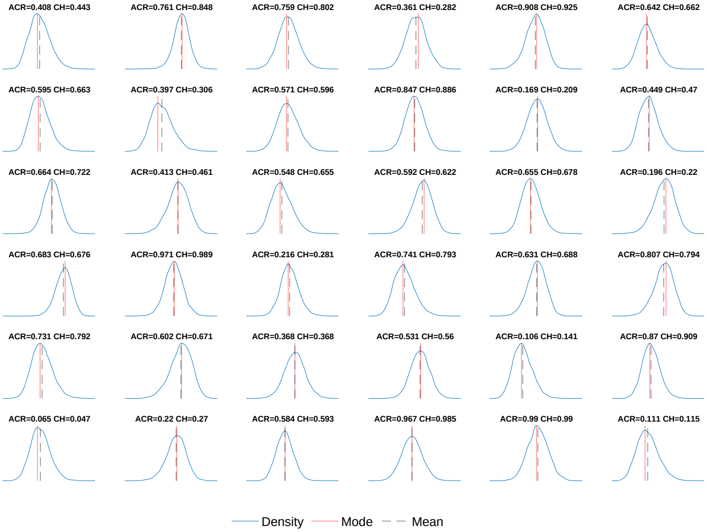
Posterior densities of A_0^{-1} and multimodality



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