Constructing the Term Structure of Uncertainty from the Ragged Edge of SPF Forecasts

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The results presented here do not necessarily represent the views of Federal Reserve Bank of Cleveland, the Federal Reserve System, the Central Bank of Hungary, the Deutsche Bundesbank, or the Eurosystem

NBER Summer Institute 2022 Forecasting & Empirical Methods

RESEARCH AGENDA

Setup

We observe predictions from the SPF (or similar sources) in form of **point and/or density** forecasts

for fixed horizons and/or fixed events

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i.e. term structures of expectations and uncertainty

that are consistent with the SPF?

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Throughout we look at average SPF responses

1) State-space model

Maps arbitrary sets of SPF point forecasts (fixed-event & -horizon)

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- Predictive densities reflect historical forecast errors

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2) We match the SPF histograms with entropic tilting

We replicate the entire "bin" structure instead of selected moments that were imputed

Survey uncertainty based on past forecast errors

- Reifschneider & Tulip (2007/19), Clark, McCracken & Mertens (2020)
- Lahiri & Sheng (2010), Knüppel (2014), Jo & Sekkel (2019)

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Entropic tilting: recent applications

- Krüger, Clark & Ravazzolo (2017), Tallman & Zaman (2020)
- Galvao, Garratt, & Mitchell (2021), Ganics & Odendahl (2021) Banbura, Brenna, Parades & Ravazzolo (2021)

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- SPF data
- State space model for forecasts
- 3 Densities from SPF histograms and model
- Effects of entropic tilting on predictive densities
- 5 Application: SEP-style fan charts
- 6 Conclusions

OUR DATA: U.S. SPF

1) Point forecasts

2) Probabilistic forecasts (histograms)

to be discussed later

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- "Fixed horizons:" Quarters 0 to 4, since 1968Q4
- "Fixed events:" Calendar years 1 to 3, since 1981Q3 (or 2009Q2)

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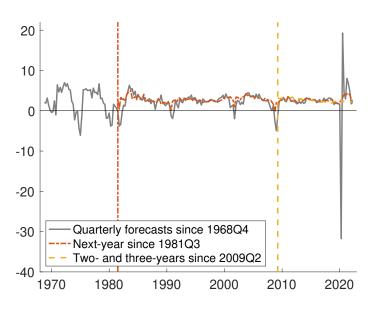
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Today:

Focus on GDP growth results (RGDP)

w/others shown in paper

AVAILABILITY OF SPF POINT FORECASTS



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with C_t known (based on data definitions)

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- **3** Specify DGP for η_t , options:
 - a) Baseline: Martingale difference
 - b) Alternative: Persistent process

with SV or CONST shock variances

An accounting identity for fixed-horizon point forecasts $y_{t+h\mid t}$

Forecast errors (FE)

$$e_t \equiv y_t - y_{t|t}$$

$$e_{t o t+h} \equiv y_{t+h} - y_{t+h|t}$$

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Applied by CMM to fixed-horizon forecasts when observed

Next: state space for fixed-event forecasts

1) Accounting identity from CMM for H steps ahead:

$$y_{t+H} = e_{t+H} + \sum_{i=1}^{H} \mu_{t+H|t+i} + y_{t+H|t}$$

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$$\begin{bmatrix} y_{t-1} \\ y_{t|t} \\ y_{t+1|t} \\ \vdots \\ y_{t+H|t} \end{bmatrix} = \begin{bmatrix} 0 & 1 & 0 & 0 & \dots & 0 \\ 0 & 0 & 1 & 0 & \dots & 0 \\ 0 & 0 & 0 & 1 & \dots & 0 \\ 0 & \dots & 0 & \ddots & 0 \\ 0 & \dots & \dots & 0 & 1 \end{bmatrix} Y_{t-1} + \begin{bmatrix} e_{t-1} \\ \mu_{t|t} \\ \mu_{t+1|t} \\ \vdots \\ \mu_t^* \end{bmatrix}$$

$$T_t$$

Recall: $e_t = y_t - y_{t|t}$ and $\mu_{t+h|t} = y_{t+h|t} - y_{t+h|t-1}$

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 $Y_t = F Y_{t-1} + \eta_t$, $\eta_t \sim \mathsf{TBD}$

Recall: $e_t = y_t - y_{t|t}$ and $\mu_{t+h|t} = y_{t+h|t} - y_{t+h|t-1}$

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Alternative: persistent forecast updates

- ullet $E(\eta_t)=0$: model's prior is centered on SPF
- $\eta_t \sim \mathsf{VAR}(p)$
- ullet Imputed bias: $b_{t+h|t} = y_{t+h|t} E_t y_{t+h}$
- Entropic tilting not applied to this case

Martingale-difference case for forecast updates

Trend and gap shocks with SV

Decompose updates into long-run shifts and cyclical gaps

$$\eta_t = ilde{\eta}_t + 1 \cdot \mu_t^*$$

$$\mu_t^* \sim N(0, \sigma_*^2)$$

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- Combines slow-moving endpoint of term structure with time-varying volatility over near-/medium term
- Low-order factor structure suited for handling of missing observations
- Scale SV invariant to reordering variables in $\tilde{\eta}_t$ (Carriero, Clark & Marcellino, 2016; Chan, 2020)

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- C_t: known, reflects definition of forecast targets, e.g., growth in annual average level of GDP

$$\hat{y}_t = \frac{y_t + 2y_{t-1} + 3y_{t-2} + 4y_{t-3} + 3y_{t-4} + 2y_{t-5} + y_{t-6}}{16}$$

 As in Mariano & Murasawa (2003), Patton & Timmermann (2011), Aruoba (2020)

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- As in Mariano & Murasawa (2003), Patton & Timmermann (2011), Aruoba (2020)
- In Q4: next-year forecasts omitted (since spanned by quarterly forecasts)

ESTIMATION SETUP

- Model applied separately for each outcome variable (RGDP, PGDP, UNRATE)
- Estimated with MCMC over growing samples of real-time data and SPF that start in 1968Q3 (FRB PHIL's Real-Time Data Set for Macroeconomics)
- Generate out-of-sample predictive densities from 1992Q1 onwards
- Predictions evaluated against 2nd release outcomes (for NIPA, and latest data for UNRATE)

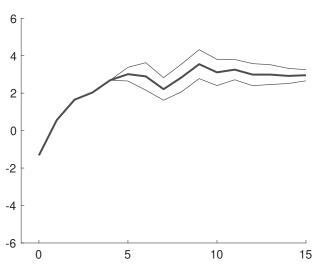
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TERM STRUCTURE OF GDP GROWTH EXPECTATIONS

Quarterly real-time estimates w/68% bands for unobserved values

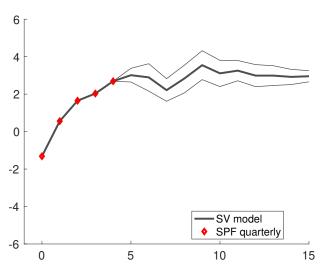




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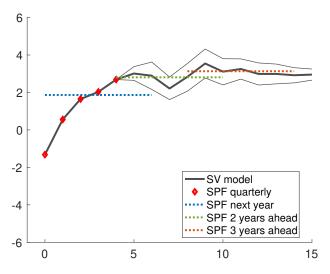




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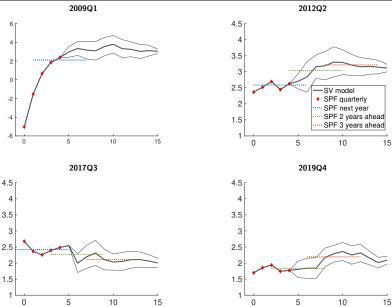




Dotted lines: quarters included in tent-shaped mapping from annual-average to quarterly changes

TERM STRUCTURES OF GDP GROWTH EXPECTATIONS

Quarterly real-time estimates w/68% bands for unobserved values



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FITTED TERM STRUCTURES OF EXPECTATIONS Key feature

We can perfectly match any shape of the term structure of expectations that could be seen in the data

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NON-MDS FORECAST UPDATES

Extended model

Relaxation of MDS assumption

- ullet Persistent forecast errors instead of $E_{t-1}\eta_t=0$
- Transformation from Y_t to η_t still useful: motivates shrinkage to VAR(1)

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Results:

- Similar avg forecast performance (relative to MDS)
- Persistence in η_t matters most at turning points
- ...and is hard to predict in real time

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1) Point forecasts

- "Fixed horizons:" Quarters 0 to 4
- "Fixed events:" Calendar years 1 to 3

2) Probabilistic forecasts (histograms)

- Fixed-event only, calendar years 1 to 3
- Using only predictions since 1992 (b/o data issues)
- To match SPF, we transform draws from log-linear model to actual annual-average changes

Throughout, we look at average forecasts

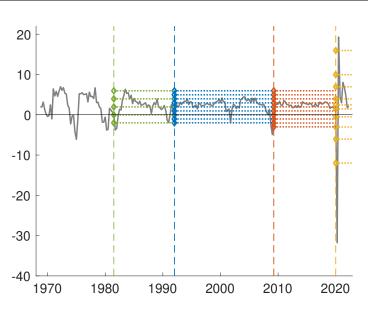
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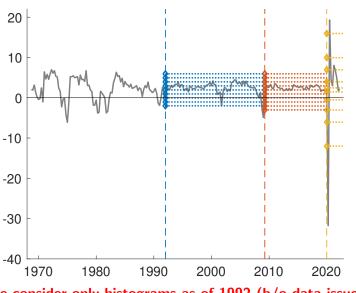
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Nowcast and widths of histogram bins



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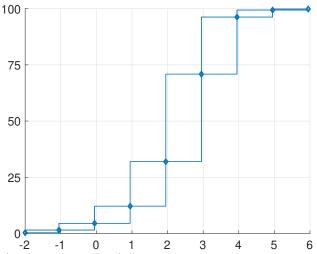
Nowcast and widths of histogram bins



We consider only histograms as of 1992 (b/o data issues)

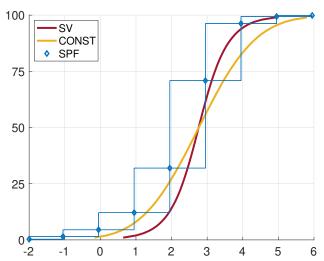
Next-year GDP growth

SPF histograms pin down selected CDF values:



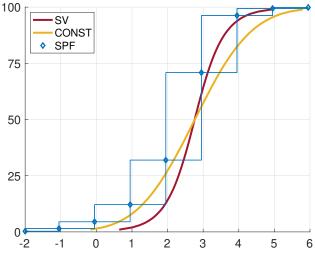
Cumulative densities for next-year GDP growth

By construction, model-based densities have same median . . .



Cumulative densities for next-year GDP growth

... but differ otherwise:



SCORES FOR HISTOGRAM EVALUATIONS

Setup

- Let $b_{j,t}$ denote the upper edge of SPF bin j (at t)
- Histogram provides discrete-valued CDF:

$$P_{j,t} = \mathsf{Prob}_t(y_{t+h} \leq b_{j,t})$$

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Discrete Ranked Probability Scores

$$\mathsf{DRPS}_t = \sum_{j} \left(P_{j,t} - \mathbb{1} \left(y^o_{t+h} \leq b_{j,t}
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where y_{t+h}^o denotes the observed value

- Measures accuracy of predictions to fall into SPF bins
- ullet Depends on specification of SPF bins $(b_{j,t})$

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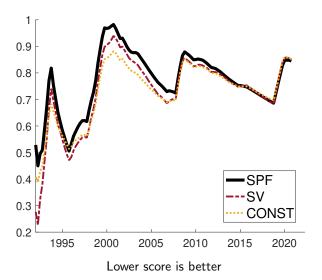
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- Measures accuracy of predictions to fall into SPF bins
- ullet Depends on specification of SPF bins $(b_{i,t})$
- Bin-specific analogue to CRPS

ACCURACY OF PREDICTIONS FOR BIN EVENTS

Avg DRPS scores over growing samples, next-year GDP growth

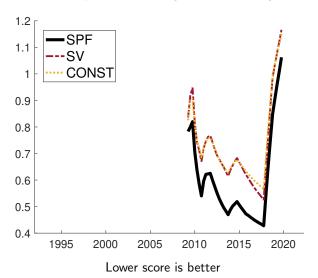
Models better than SPF pre GFC and on par over full sample



ACCURACY OF PREDICTIONS FOR BIN EVENTS

Avg DRPS scores over growing samples, two-years ahead GDP growth

SPF better since GFC also for predictions beyond the next year



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 - Entropic tilting method
 - Average forecast performance w/and w/o entropic tilting
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- ullet Target: moment conditions $E[g(y_{t+h})] = ar{g}$
- ullet Tilting problem: Reweigh draws from f into ar f to match ar g while minimizing KL divergence

$$\min_{ ilde{f} \in \mathbb{F}} \mathsf{KL}(ilde{f}, f)$$
 subject to $E_{ ilde{f}}\left[g(y_{t+h})
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- ullet Target: moment conditions $E[g(y_{t+h})] = ar{g}$
- ullet Tilting problem: Reweigh draws from f into ilde f to match ar g while minimizing KL divergence

$$\mathsf{min}_{ ilde{f} \in \mathbb{F}} \; \mathsf{KL}(ilde{f}, f) \; \mathsf{subject} \; \mathsf{to} \; E_{ ilde{f}} \; [g(y_{t+h})] = ar{g}$$

Key insight for our application

Bin probabilities are predictive moments

for example:

$$\mathsf{Prob}_t \left(2.5 < y_{t+h} \leq 3.0 \right) = E_t \left(\mathbb{1} \left(2.5 < y_{t+h} \leq 3.0 \right) \right)$$

Generic setup

- ullet Given: predictive density draws $f:=\{y_{t+h}^i\}_{i=1}^M$
- ullet Target: moment conditions $E[g(y_{t+h})] = ar{g}$
- ullet Tilting problem: Reweigh draws from f into ilde f to match ar g while minimizing KL divergence

$$\min_{ ilde{f} \in \mathbb{F}} \mathsf{KL}(ilde{f},f)$$
 subject to $E_{ ilde{f}}\left[g(y_{t+h})
ight] = ar{g}$

Key insight for our application

Bin probabilities are predictive moments

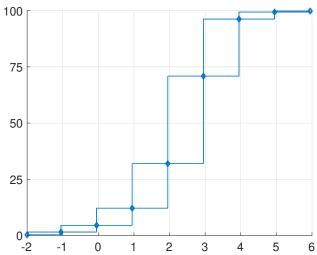
for example:

$$\mathsf{Prob}_t \left(2.5 < y_{t+h} \leq 3.0 \right) = E_t \left(\mathbb{1} \left(2.5 < y_{t+h} \leq 3.0 \right) \right)$$

We target all bin probabilities

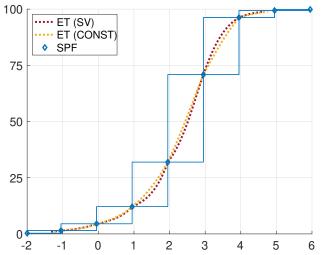
Next-year GDP growth

We use ET to target the SPF probabilities as available for next year and beyond



Cumulative densities for next-year GDP growth

After tilting, SV and CONST densities similar, but not identical:



AGENDA

- SPF data
- 2 State space model for forecasts
- 3 Densities from SPF histograms and model
- Effects of entropic tilting on predictive densities
 - Entropic tilting method
 - Average forecast performance w/and w/o entropic tilting
- **5** Application: SEP-style fan charts
- 6 Conclusions

POINT FORECAST PERFORMANCE

RMSE relative to SV

SV w/ET CONST CONST w/ET

POINT FORECAST PERFORMANCE

CM / E.T.

RMSE relative to SV

	SV w/ET		COI	NST	CONST w/ET		
h	92–22	92–16	92–22	92–16	92–22	92–16	
0							
1							
2							
3							
4							
5							
6							
7							
8							
9							
10							
11							
12							
13							
14							
15							

POINT FORECAST PERFORMANCE

RMSE relative to SV

	SV w/ET		CONST		CONST w/E	
h	92–22	92–16	92–22	92–16	92–22	92–16
0	1.01	1.01*	1.00	1.00	1.01**	1.01*
1	1.00	1.01	1.00	1.00	1.00	1.01
2	1.00	1.00	1.00	1.00	1.00	1.00
3	1.00	0.99	1.00	1.00	1.00	0.99
4	1.00	0.99	1.00	1.00	1.00	0.99
5	1.00	0.98	1.00	1.00	1.00	0.99
6	1.00	0.99	1.00	1.01	1.01	1.01
7	1.00	0.99	1.00	1.01	1.00	1.00
8	1.00	0.99	1.00	1.02	1.00	1.01
9	1.00	0.99	1.00	1.01	1.00	1.00
10	1.00	1.00	1.00	1.02	1.00	1.01
11	1.00	0.99	1.00	1.02^{*}	1.00	1.01
12	1.00	1.00	1.00	1.02	1.00	1.01
13	1.00	1.01^{*}	1.00	1.02	1.00	1.02
14	1.00	1.00	1.00	1.00	1.01	1.00
15	1.00	1.00	1.00	1.00	1.00	1.00

DENSITY FORECAST PERFORMANCE

CRPS relative to SV

		SV w/ET		CONST		CONST w/E7	
	h	92–22	92–16	92–22	92–16	92–22	92–16
	0	1.00	1.00				
	1	1.00	1.00				
	2	0.99	1.00				
	3	0.99	0.99				
	4	0.99	0.99				
	5	0.99	0.98				
	6	0.99	0.99				
	7	1.00	0.99				
	8	1.00	0.99				
	9	1.00	0.99				
	10	1.00	0.99				
	11	0.99	0.98				
	12	0.99	0.99				
	13	1.00	1.00				
	14	1.00	1.00				
	15	0.99*	0.99				

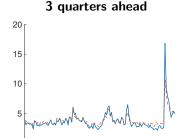
DENSITY FORECAST PERFORMANCE

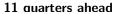
CRPS relative to SV

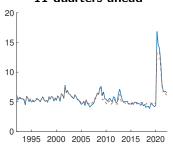
	SV w/ET		CONST		CONST w/ET	
h	92–22	92–16	92–22	92–16	92–22	92–16
0	1.00	1.00	0.99	0.99	1.00	0.99
1	1.00	1.00	1.04	1.01	1.04^{*}	1.02
2	0.99	1.00	1.00	1.02	1.01	1.02
3	0.99	0.99	1.01	1.02	1.01	1.01
4	0.99	0.99	1.01	1.03^{*}	1.01	1.01
5	0.99	0.98	1.01	1.04*	1.01	1.01
6	0.99	0.99	1.03	1.06**	1.03	1.04
7	1.00	0.99	1.03	1.06**	1.03	1.04
8	1.00	0.99	1.03	1.06**	1.03	1.04
9	1.00	0.99	1.03	1.06**	1.03	1.05
10	1.00	0.99	1.03**	1.07^{***}	1.04**	1.06**
11	0.99	0.98	1.04**	1.07^{***}	1.03	1.05^{*}
12	0.99	0.99	1.04**	1.07^{***}	1.03**	1.06**
13	1.00	1.00	1.04***	1.07^{***}	1.04***	1.06***
14	1.00	1.00	1.04**	1.05^{***}	1.04**	1.05^{**}
15	0.99*	0.99	1.04**	1.04**	1.04**	1.04**

EFFECTS OF TILTING ON UNCERTAINTY

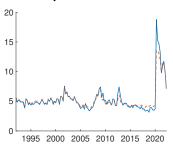
Real growth: SV model before (blue) and after ET (red)





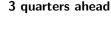


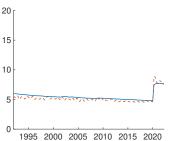
7 quarters ahead



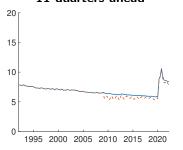
- Uncertainty measured by width of 68% bands
- Not much effect from ET
- Except for narrowing at onset of COVID-19
- Stronger effects on CONST (see next)

Real growth: CONST model before (blue) and after ET (red)

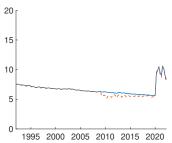




11 quarters ahead



7 guarters ahead

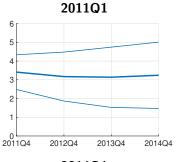


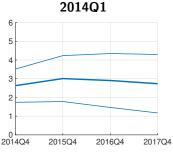
- More visible effects of ET on CONST
- Narrower until COVID
- Recall: Longer-run SPF histograms available only since 2009

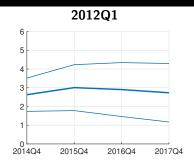
AGENDA

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FAN CHARTS FOR Q4/Q4 GDP GROWTH







- In format of FOMC's SEP
- Generated by SV model
- Next: comparison against SEP uncertainty bands

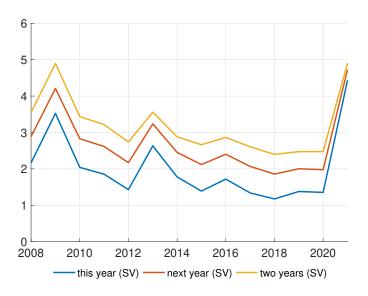
FAN CHART UNCERTAINTY: MODEL VS SEP

SEP setup

- SEP fan-chart bands based on historical forecast errors assume constant variances over last 20-years
- ullet Uncertainty **bands reflect** \pm **RMSE** around forecast
- ... and can differ from FOMC's subjective assessments

FAN CHART UNCERTAINTY OVER TIME

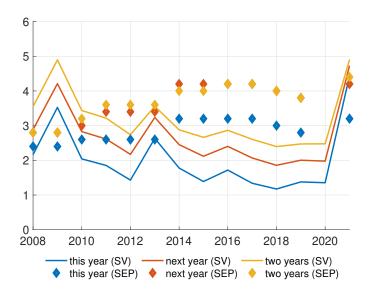
Width of 68% bands from SV model ...



Width of 68% bands for Q4/Q4 forecasts

FAN CHART UNCERTAINTY OVER TIME

Width of 68% bands from SV model vs. SEP's RMSE-based bands



Width of 68% bands for Q4/Q4 forecasts

FAN CHART UNCERTAINTY: MODEL VS SEP

SEP setup

- **SEP** fan-chart bands based on historical forecast errors assume constant variances over last 20-years
- ullet Uncertainty **bands reflect** \pm **RMSE** around forecast
- ... and can differ from FOMC's subjective assessments

Take aways

- SV-model bands more nimble than SEP estimates
- After GFC:
 - SV estimates returned to lower levels
 - while SEP remained elevated

AGENDA

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Our contributions:

Model that transforms an arbitrary set of fixed-event/-horizon SPF data into a consistent term structure

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Findings

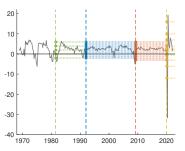
- Calendar-year histograms add some, but mostly occasional value . . .
- ... relative to model centered on SPF point forecasts
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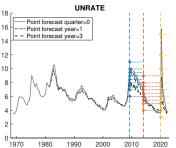
APPENDICES

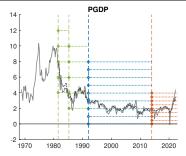
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AVAILABILITY OF SPF PREDICTIONS

Real growth (RGDP), inflation (PGDP), unemployment rate (UNRATE)



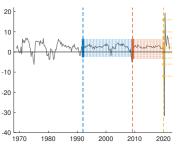


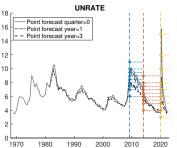


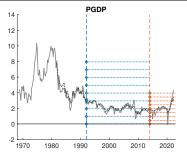
- Point forecasts since 1968
- Next-year bins since 1981 (and since 2009 for UNRATE)
- ... beyond next year since 2009
- But, w/data issues prior 1992
- ...and bin changes throughout

AVAILABILITY OF SPF PREDICTIONS

Real growth (RGDP), inflation (PGDP), unemployment rate (UNRATE)







- Point forecasts since 1968
- Next-year bins since 1981 (and since 2009 for UNRATE)
- ... beyond next year since 2009
- But, w/data issues prior 1992
- ...and bin changes throughout
- Using only bin data since 1992

APPENDICES

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- **8** Details on state space model
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COMMENTS ON STATE EQUATION

$$Y_t = F Y_{t-1} + \eta_t$$

- ullet All rows except last replicate CMM data for η_t
- Transition matrix F is known
- All roots of F are zero except for one unit root
- ullet F implies common trend in outcomes and forecasts (assuming stationary η_t)
- ullet $\operatorname{Var}\left(\mu_{t}^{*}
 ight)
 ightarrow0$ captures (near) stationary Y_{t}
- ullet MDS assumption, $E_{t-1}\eta_t=0$, closes state space
- ullet In extension, we consider VAR for $E_{t-1}\eta_t$ (as in CMM)

Even if not literally true, MDS assumption provides useful shrinkage for VAR in η_t

H-step Wold decomposition for y_t

$$egin{aligned} y_{t} &= e_{t} + \mu_{t|t} + \mu_{t|t-1} + \dots \mu_{t|t-H+1} + y_{t|t-H} \ y_{t+H|t} &= y_{t+H-1|t-1} + \mu_{t}^{*} \end{aligned}$$

 e_t , $\mu_{t+h|t}$, μ_t^* are MDS

Dynamics responses of y_t to shocks encoded in $\operatorname{Var}_t \eta_t$

For example, ignoring nowcast problem, let $y_t = \rho y_{t-1} + \varepsilon_t$:

$$\left(\operatorname{Var}_t \eta_t
ight)^{1/2} = egin{bmatrix} 1 \
ho \
ho^2 \ dots \ 0 \end{bmatrix} \operatorname{Var}_t arepsilon_t$$

- We use **conditionally Gaussian models** for η_t (w/SV)
- Standard Gaussian signal extraction applies (conditional on SV states etc.)
- Kalman filter/smoother would work, but requires many loops
- Precision-based samplers would be faster, but does not apply (Chan & Jeliazkov, 2009)
- Challenge: no noise in measurements leads to ill-defined posterior precision

$$|\operatorname{Var}\left(Y_t|Z^t\right)|=0$$

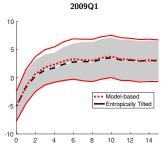
• We use a new precision-based sampler to efficiently draw $m{Y}^t|m{Z}^t$ in this case

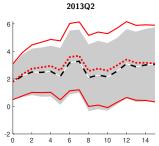
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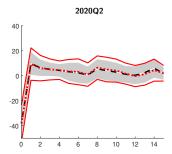
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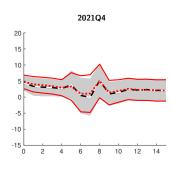
FAN CHARTS FOR GDP GROWTH

SV model before (red) and after entropic tilting (black)









Predictive means and 68% uncertainty bands

APPENDICES

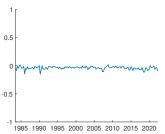
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SKEW INDUCED BY TILTING

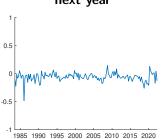
Bowley coefficient

- Our model has zero skew, only ET can induce skew
- Some skewness at targeted annual horizon
- But, w/o carrying over to quarterly term structure

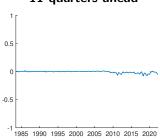
3 quarters ahead



next year



11 quarters ahead

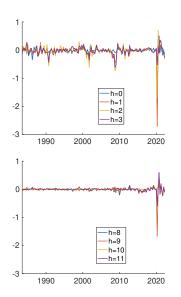


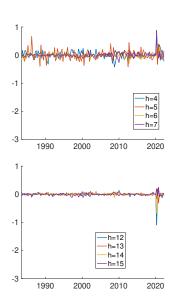
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BIAS IN SPF EXPECTATIONS OF GDP GROWTH

 $\mathsf{Bias}_t = E_t y_{t+h} - y_{t+h|t}$ from non-MDS model





MDS VS NON-MDS MODEL: FORECAST PERFORMANCE

Relative RMSE and CRPS (MDS in denominator)

	RMSE			CRPS				
	SV		CONST		SV		CONST	
h	92–22	92–16	92–22	92–16	92–22	92–16	92–22	92–16
0	1.00	1.00	1.12	1.01	1.01	1.01	1.08	1.01
1	1.02	1.00	1.06	1.01	1.02	1.01	1.04	1.01
2	1.00	0.98^{*}	1.00	0.97^{**}	1.01	0.99^{*}	1.00	0.99
3	1.00	1.00	1.00	0.99	1.02	1.01	1.00	1.00
4	1.00	1.00	1.00	0.99	1.02	1.01	1.01	1.01
5	1.00	1.00	1.00	1.01	1.01	1.00	1.01	1.00
6	1.00	1.00	1.00	1.02	1.00	0.99	1.01	1.01
7	1.00	1.00	1.00	0.99	1.00	0.99	0.99	0.99
8	1.00	1.01	1.00	1.00	1.00	0.99	0.99	0.99
9	1.00	1.01	1.01	1.01	1.00	0.99	1.01	1.01
10	1.00	1.01	1.01	1.02	0.99	0.98	1.01	1.01
11	1.00	1.01	1.00	1.02	1.00	0.98	1.01	1.02
12	1.00	1.00	1.00	1.02	0.99	0.97^{**}	1.01	1.01
13	1.00	1.00	1.01	1.01	0.99	0.97^{**}	1.00	1.00
14	1.00	1.00	1.00	1.00	0.99	0.98	1.00	1.01
15	1.00	1.00	1.00	1.00	0.98*	0.98**	1.00	1.00

FORECAST UPDATES: MDS VS. VAR

Takeaways

Persistence in forecast updates matters mostly at turning points

...and is hard to predict in real time

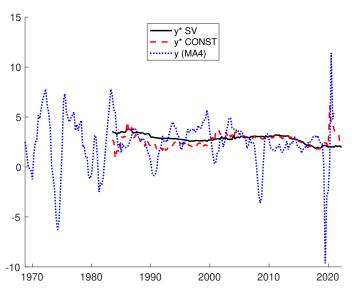
Croushore (2010), Mertens & Nason (2020), Matthes & Foerster (2021), Hajdini and Kurmann (2022), Farmer, Nakamura & Steinsson (2022), Bianchi, Ludvigson & Ma (2022)

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ESTIMATED END POINTS OF TERM STRUCTURE

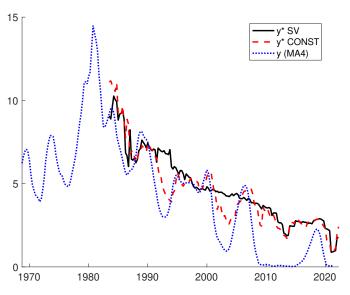
 $y_{t+H|t}$ from SV and CONST model for GDP growth (H=15)



Real-time estimates

ESTIMATED END POINTS OF TERM STRUCTURE

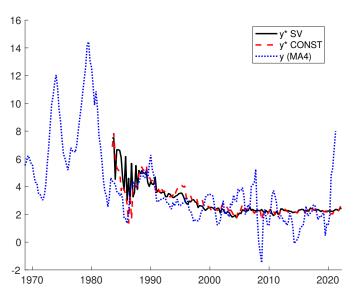
 $\overline{y_{t+H|t}}$ from SV and CONST model for T-bill rate (H=15)



Real-time estimates

ESTIMATED END POINTS OF TERM STRUCTURE

 $y_{t+H|t}$ from SV and CONST model for CPI inflation $\left(H=15
ight)$



Real-time estimates

Our contributions:

Model that transforms an arbitrary set of fixed-event/-horizon SPF data into a consistent term structure

- Matches observed SPF
- Incorporates all SPF bins with entropic tilting

Findings

- Calendar-year histograms add some, but mostly occasional value . . .
- ... relative to model centered on SPF point forecasts
- At onset of COVID-19, narrower uncertainty after tilting