Advances in Nowcasting Economic Activity

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THIS PAPER

- This paper contributes to the literature on nowcasting economic activity
- We propose a bayesian dynamic factor model (DFM), which takes seriously the features of the data:
  1. Low-frequency variation in the mean and variance
  2. Heterogeneous responses to common shocks (lead-lags)
  3. Outlier observations and fat tails
  4. Endogenous modeling of seasonality (not today)
- We evaluate the performance of the model and its new features in a comprehensive out-of-sample evaluation exercise using fully real-time, unrevised data for a number of countries
- The project builds on our earlier work: Antolin-Diaz, Drechsel, and Petrella (2017 *ReStat*)

PREVIEW OF RESULTS

- The real-time nowcasting performance is substantially improved across a variety of metrics (point and density)

  1. Capturing trends and SV improves nowcasting performance significantly across countries
  2. Heterogeneous dynamics deliver substantial additional improvement
  3. Fat tails:
     - Successfully capture outlier observations in an automated way
     - Improve density forecasts of the monthly variables

- Today's talk will present a selection of results

THE MODEL

We start from the familiar specification of a DFM (see, e.g. Giannone, Reichlin, and Small, 2008 and Banbura, Giannone, and Reichlin, 2010)

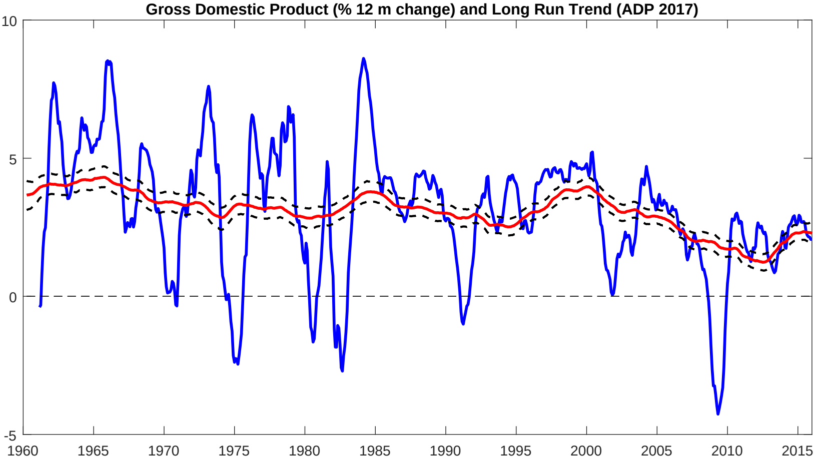
Consider an n-dimensional vector of quarterly and monthly observables $\mathbf{y}_t$, which follows

$$\begin{aligned} \Delta(\mathbf{y}_t) &= \mathbf{c} + \boldsymbol{\lambda}\mathbf{f}_t + \mathbf{u}_t && (1) \\ (I - \Phi(L))\mathbf{f}_t &= \varepsilon_t && (2) \\ (1 - \rho_i(L))u_{i,t} &= \eta_{i,t}, \qquad i = 1, \ldots, n && (3) \end{aligned}$$

$$\begin{aligned} \varepsilon_t &\overset{iid}{\sim} N(0, \boldsymbol{\Sigma}_\varepsilon) && (4) \\ \eta_{i,t} &\overset{iid}{\sim} N(0, \sigma^2_{\eta_i}), \qquad i = 1, \ldots, n && (5) \end{aligned}$$

THE MODEL

WHY EXPLICITLY MODEL LOW FREQUENCY VARIATION? THE US CASE



The UK case

Consider n-dimensional vector of observables $\mathbf{y}_t$, which follows

$$\Delta(\mathbf{y}_t) = \mathbf{c}_t + \boldsymbol{\lambda}\mathbf{f}_t + \mathbf{u}_t, \tag{6}$$

with

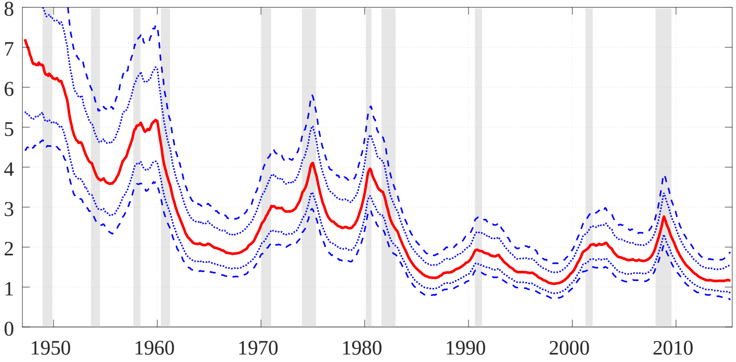
$$\mathbf{c}_t = \begin{bmatrix} \mathbf{B} & \mathbf{0} \\ \mathbf{0} & \mathbf{c} \end{bmatrix} \begin{bmatrix} \mathbf{a}_t \\ 1 \end{bmatrix}, \tag{7}$$

and

$$\begin{aligned} (I - \Phi(L))\mathbf{f}_t &= \boldsymbol{\varepsilon}_t, && (8) \\ (1 - \rho_i(L))u_{i,t} &= \eta_{i,t}, \quad i = 1, \dots, n && (9) \end{aligned}$$

THE MODEL

WHY MODEL CHANGES IN VOLATILITY? THE US CASE



- SV in the common factor captures both secular (McConnell and Perez-Quiros, 2000) and cyclical (Jurado et al., 2014) movements in volatility.

The UK case

Consider n-dimensional vector of observables $\mathbf{y}_t$, which follows

$$\Delta(\mathbf{y}_t) = \mathbf{c}_t + \boldsymbol{\lambda}\mathbf{f}_t + \mathbf{u}_t, \tag{10}$$

with

$$\mathbf{c}_t = \begin{bmatrix} \mathbf{B} & \mathbf{0} \\ \mathbf{0} & \mathbf{c} \end{bmatrix} \begin{bmatrix} \mathbf{a}_t \\ 1 \end{bmatrix}, \tag{11}$$

and

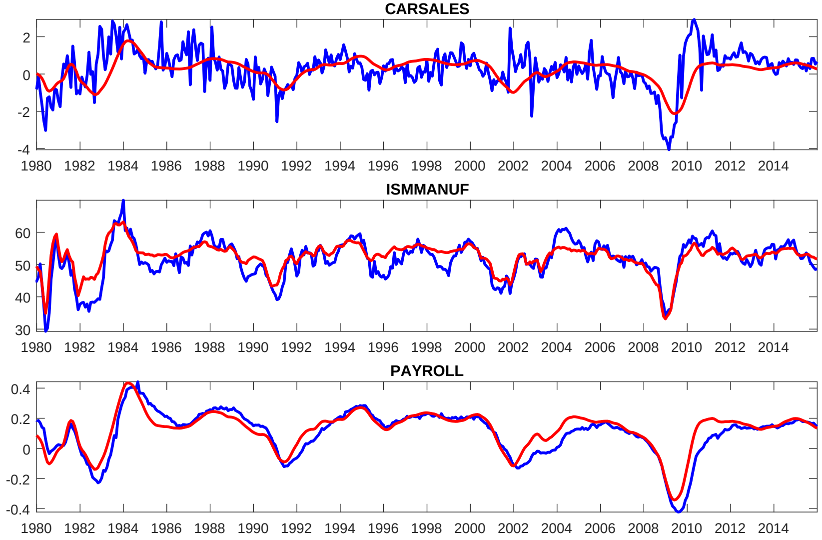
$$(I - \Phi(L))\mathbf{f}_t = \sigma_{\varepsilon_t}\boldsymbol{\varepsilon}_t, \tag{12}$$

$$(1 - \rho_i(L))u_{i,t} = \sigma_{\eta_{i,t}}\eta_{i,t}, \quad i = 1, \ldots, n \tag{13}$$

where the time-varying parameters will be specified as a random walk processes. TVP processes

THE MODEL

WHY ALLOW FOR HETEROGENEOUS DYNAMICS?



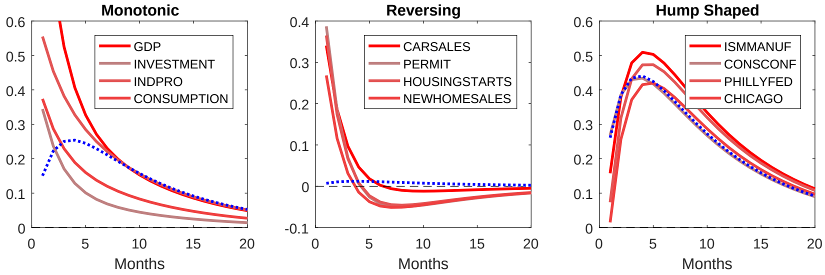
$$\Delta(\mathbf{y}_t) = \mathbf{c}_t + \mathbf{\Lambda}(\mathbf{L})\mathbf{f}_t + \mathbf{u}_t, \tag{14}$$

where $\mathbf{\Lambda}(\mathbf{L})$ contains the loadings on the contemporaneous and lagged common factors.

- Camacho and Perez-Quiros (2010) first noticed that survey data was better aligned with a distributed lag of GDP.
- D'Agostino et al. (2015) show that adding lags improves performance in the context of a small model.

THE MODEL

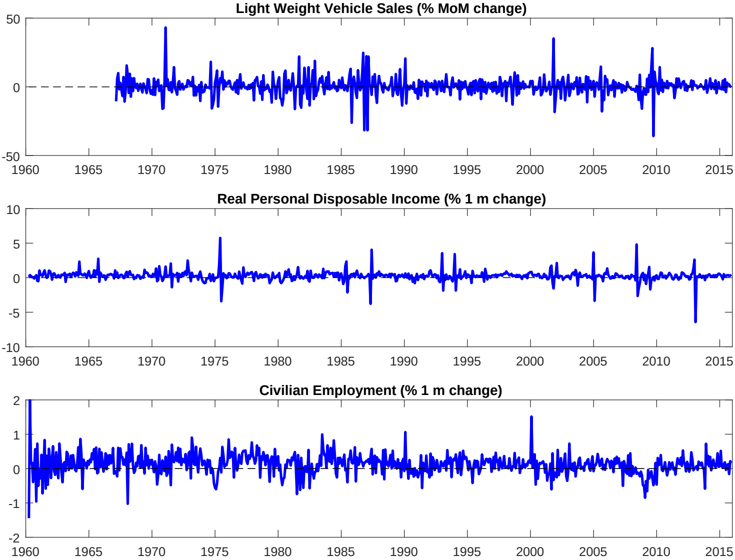
WHAT DO THE HETEROGENEOUS DYNAMICS ACHIEVE?



- Substantial heterogeneity in IRFs of observables to innovations in the cyclical factor

THE MODEL

WHY MODEL FAT TAILS?



$$\Delta(\mathbf{y}_t - \mathbf{o}_t) = \mathbf{c}_t + \boldsymbol{\Lambda}(\mathbf{L})\mathbf{f}_t + \mathbf{u}_t, \tag{15}$$

where the elements of $\mathbf{o}_t$ follow t-distributions:

$$o_{i,t} \overset{iid}{\sim} t_{\nu_i}(0, \omega_{o,i}^2), \qquad i = 1, \ldots, n \tag{16}$$

THE MODEL

SPECIFICATION OF OUTLIERS

The laws of motion of the various components are specified as

$$(I - \Phi(L))\mathbf{f}_t = \sigma_{\varepsilon_t}\boldsymbol{\varepsilon}_t, \tag{17}$$

$$(1 - \rho_i(L))u_{i,t} = \sigma_{\eta_{i,t}}\eta_{i,t}, \quad i = 1, \ldots, n \tag{18}$$

$$\eta_{i,t} \overset{iid}{\sim} N(0,1), \quad i = 1, \ldots, n \tag{19}$$

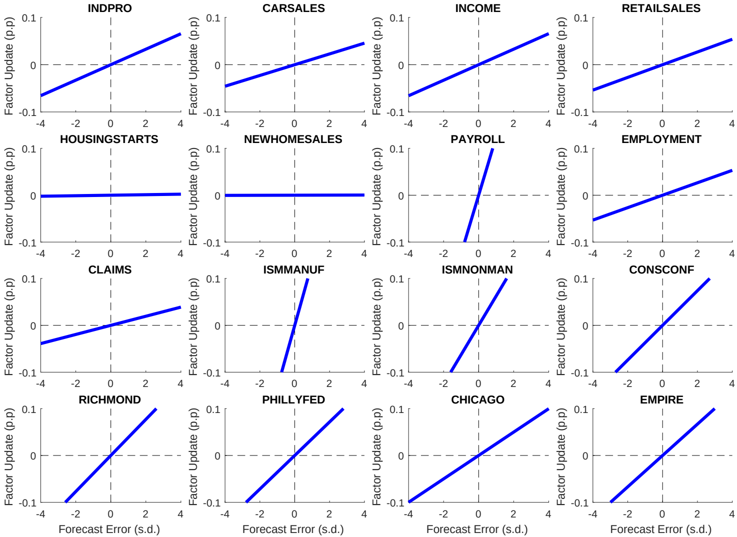
$$\boldsymbol{\varepsilon_t} \overset{iid}{\sim} N(\mathbf{0}, \mathbf{I}) \tag{20}$$

$$o_{i,t} \overset{iid}{\sim} t_{\nu_i}(0, \omega_{o,i}^2), \quad i = 1, \ldots, n \tag{21}$$

The degrees of freedom of the t-distributions, ν_i, are estimated jointly with the other parameters of the model.

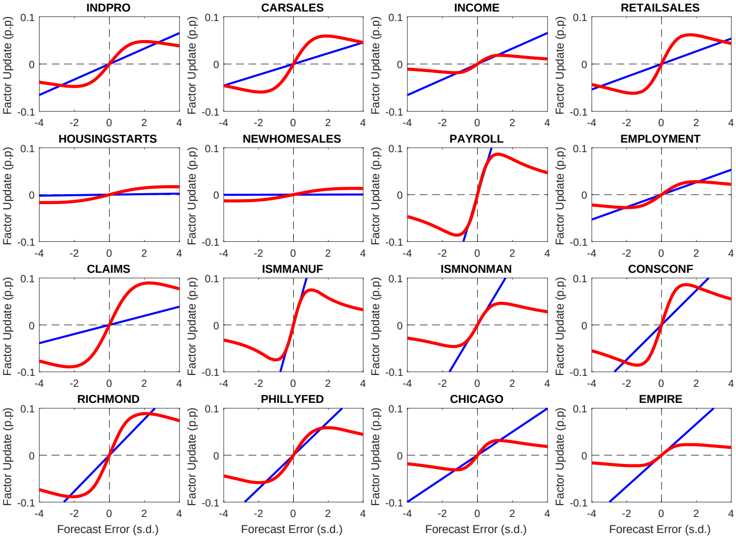
THE MODEL

NEWS DECOMPOSITIONS



THE MODEL

WHAT DO THE FAT TAILS ACHIEVE?



News decomposition details

ESTIMATION

ESTIMATION

DATA SETS

- For each country, we construct a data set comprising quarterly and monthly time series.
- We use both hard and soft indicators and the choice is guided by timeliness and coincidence with GDP. We use only indicators of real economic activity, excluding prices and financial variables.
- In each economic category we include series at the highest level of aggregation.
- For the US case, for example, this results in a panel of 28 series. For the UK we use 18 series.

ESTIMATION

MODEL SETTINGS AND PRIORS

- Our methods are Bayesian
- We use conservative priors that shrink the model towards the benchmark
- This has the appeal that we can let the data speak about to what extent the additional components are required

More details

ESTIMATION

OVERVIEW OF ALGORITHM

- Mixed frequency: Model is specified at monthly frequency. Observed growth rates of quarterly variables are related to the unobserved monthly growth rate using a weighted mean (see Mariano and Murasawa, 2003)

- We use a hierarchical implementation of a Gibbs Sampler algorithm (Moench, Ng, and Potter, 2013) which iterates between a small DFM on the outlier adjusted data and the univariate measurement equations. This leads to large computational gains due to parallelisation of this step.

- SVs are sampled following Kim et al. (1998), the Student-t component is sampled following Jacquier et al. (2004).

- Vectorized implementation of the Kalman filter

REAL-TIME OUT OF SAMPLE EVALUATION

- We construct a real-time data base for the US and other G7 countries: Germany, France, Italy, Canada, UK, and Japan
- For each vintage, sample start is Jan 1960, appending missing observations to any series which starts after that date
- Sources: (1) ALFRED, (2) OECD Original Release and Revisions Data
- Use appropriate deflators for nominal-only vintages
- Splice data for series with methodological changes
- Apply seasonal adjustment in real time for survey data

- The model is fully re-estimated every time new data is released/revised.
- The out of sample exercise starts in January 2000 and ends in December 2015. For the US, on average there is a data release on 15 different dates every month. This means 2744 vintages of data.
- Thanks to efficient implementation of the code, it takes just 20 min to run 8000 iterations of the Gibbs sampler on a single computer. But this would mean 5 months of computations for just one country!
- Made feasible by using Amazon Web Services cloud computing platform.

SELECTED EVALUATION RESULTS

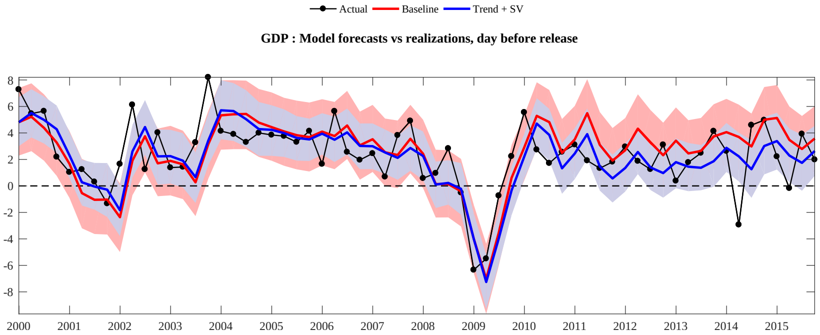
EVALUATION RESULTS

WHAT WE SHOW

- In the following slides, we compare four models
  1. Baseline DFM
  2. Trend + SV
  3. Trend + SV + heterogeneous dynamics
  4. Trend + SV + heterogeneous dynamics + fat tails
- We will consider the following metrics
  1. Point forecasts: Root mean squared error (RMSE) and mean absolute error (MAE)
  2. Density forecasts: Continuous rank probability score (CRPS) and log score
- Results are shown for US, UK, France GDP (third estimate)

EVALUATION RESULTS

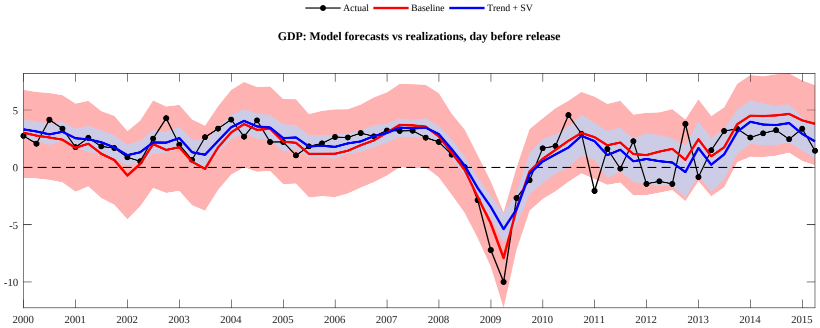
FORECASTS VS. ACTUAL OVER TIME (US)



- The addition of the long run trend eliminates the upward bias in GDP forecasts after the crisis...

EVALUATION RESULTS

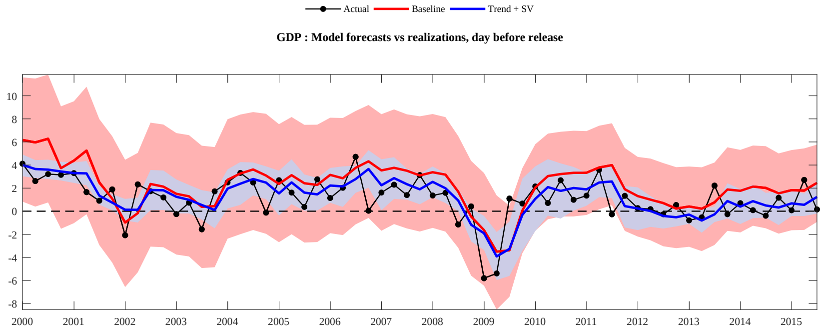
FORECASTS VS. ACTUAL OVER TIME (UK)



- Stochastic Volatility makes a **HUGE** difference for density forecasting.

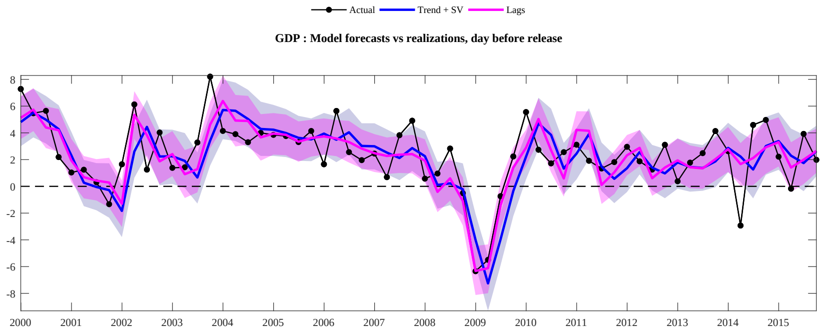
EVALUATION RESULTS

FORECASTS VS. ACTUAL OVER TIME (FRANCE)



EVALUATION RESULTS

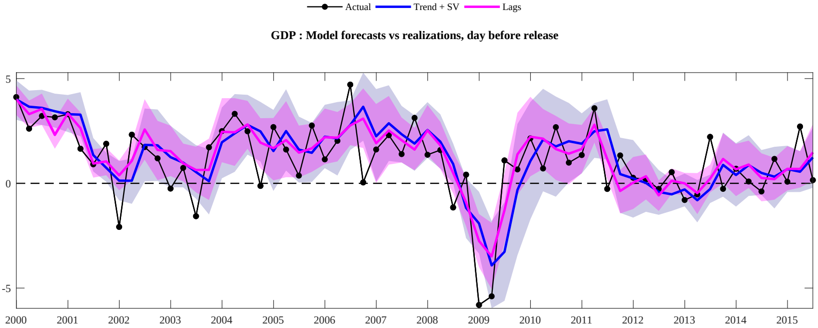
FORECASTS VS. ACTUAL OVER TIME (US)



- Heterogeneous dynamics capture recoveries more accurately

EVALUATION RESULTS

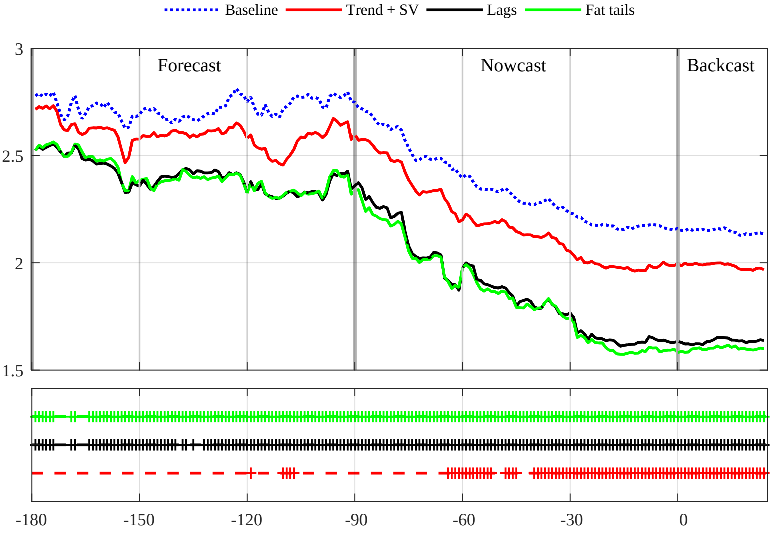
FORECASTS VS. ACTUAL OVER TIME (FRANCE)



- Heterogeneous dynamics capture recoveries more accurately

RESULTS: POINT FORECASTING (USA)

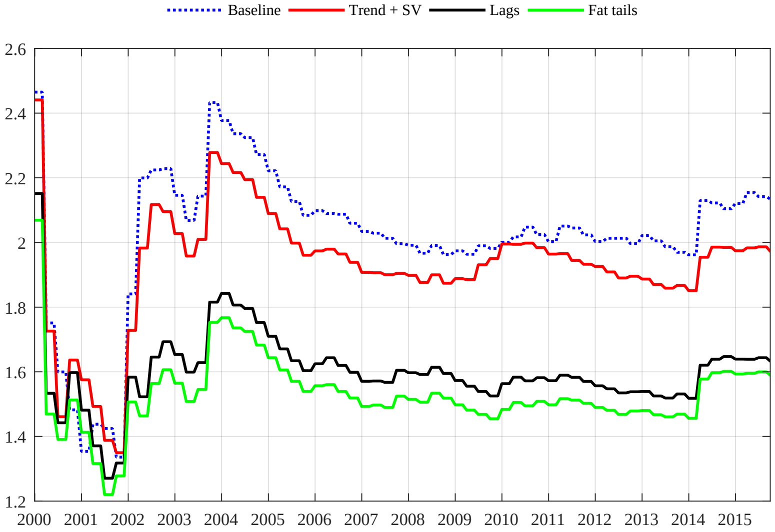
GDP: RMSE ACROSS HORIZONS



Note: Results with MAE very similar.

RESULTS: POINT FORECASTING (USA)

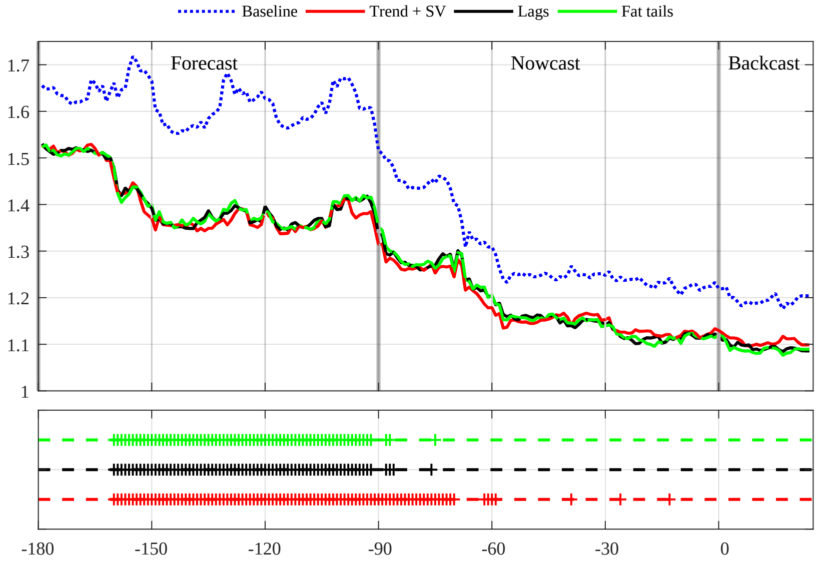
GDP: RMSE OVER TIME



Note: Results with MAE very similar.

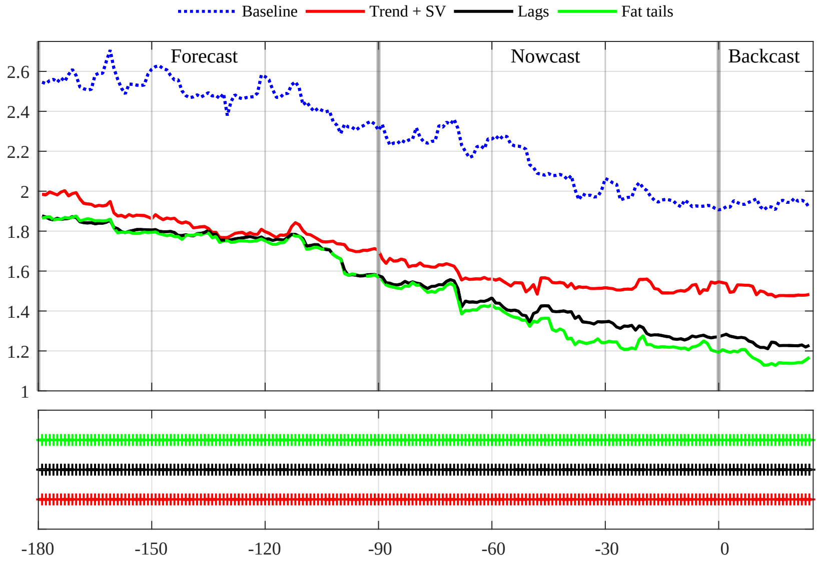
RESULTS: POINT FORECASTING (UK)

GDP: MAE ACROSS HORIZONS



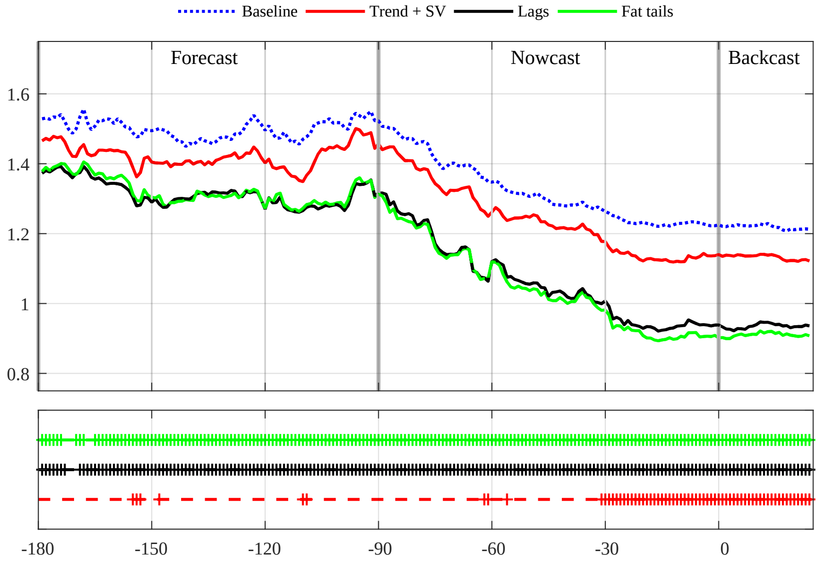
RESULTS: POINT FORECASTING (FRANCE)

GDP: RMSE ACROSS HORIZONS



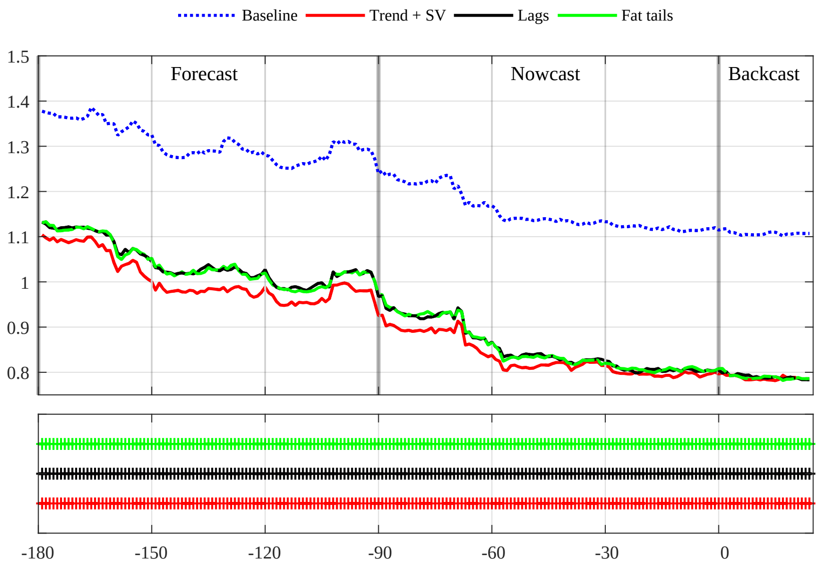
RESULTS: DENSITY FORECASTING (USA)

GDP: CRPS ACROSS HORIZONS



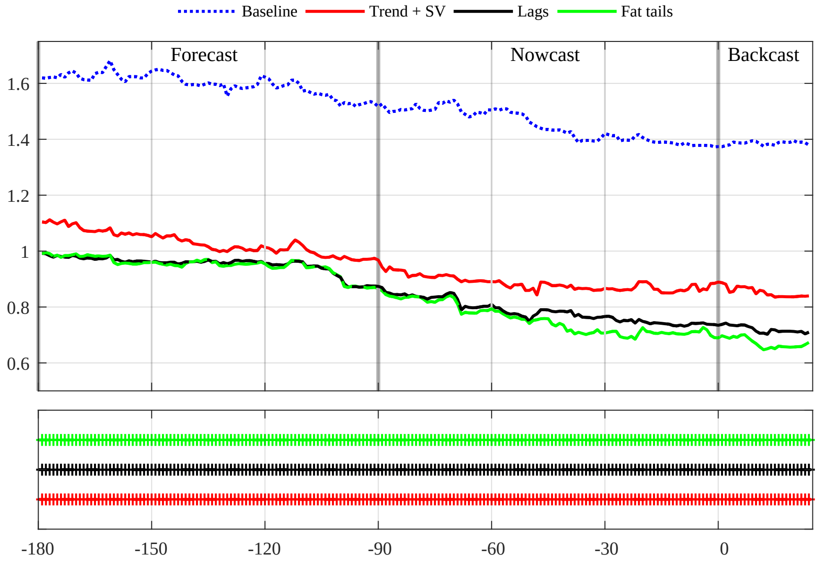
RESULTS: DENSITY FORECASTING (UK)

GDP: CRPS ACROSS HORIZONS



RESULTS: DENSITY FORECASTING (FRANCE)

GDP: CRPS ACROSS HORIZONS



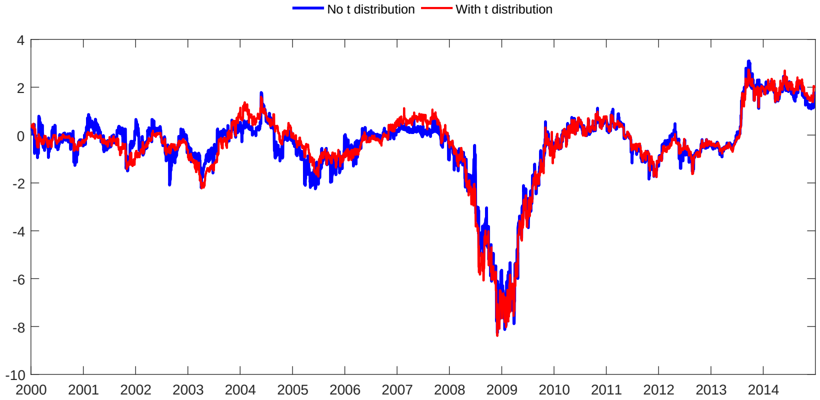
RESULTS

FORECASTS OF MONTHLY INDICATORS (30 DAYS BEFORE RELEASE)

	RMSE				LogScore				CRPS			
	M0	M1	M2	M3	M0	M1	M2	M3	M0	M1	M2	M3
INDPRO	0.54	1	0.99	0.99	-0.85	-0.27	-0.15	0.06***	0.3	1	0.99	0.98
NEWORDERS	2.98	1	0.98***	1	-2.73	0.19***	0.21***	0.15***	1.82	0.92***	0.9***	0.93***
CARSALES	7.13	1	1	1	-3.54	-0.28	0.16	0.24**	3.73	1	1.01	0.99
INCOME	0.83	1	1	1	-2.04	0.2	1*	-0.36	0.37	0.98	0.97	0.93***
RETAILSALES	0.98	1	0.99	0.98	-2.09	-2.56	-2.23	0.9	0.5	0.94***	0.94***	0.92***
EXPORTS	2.48	0.99	0.99	0.99	-2.63	0.25***	0.25***	0.28***	1.6	0.88***	0.89***	0.88***
IMPORTS	2.57	1	1.01	1.02	-2.64	0.22***	0.2***	0.24***	1.63	0.89***	0.91***	0.9***
PERMIT	5.89	1	1.01	1.01	-3.2	-0.01	-0.01	-0.01	3.32	1	1.01	1.01
HOUSINGSTARTS	8.18	1	1	1	-3.52	0.03	0.02	0.01	4.58	0.99	1	1
NEWHOMESALES	8.38	1	1.01	1.01	-3.63	0.05	0.05	0.08	4.62	1.01	1.01	1.01
PAYROLL	0.12	0.95***	0.88***	0.83***	0.64	0.23***	0.26***	0.26***	0.07	0.89***	0.84***	0.8***
EMPLOYMENT	0.26	1	0.99*	0.99*	-0.06	-0.14	-0.05	-0.02	0.14	1	0.99	0.99

RESULTS: DAILY TRACKING OF ECONOMIC ACTIVITY

THE T DISTRIBUTION LEADS MORE STABLE FACTOR



CONCLUSION

CONCLUSION

- We propose a bayesian DFM, which incorporates:
    1. Low-frequency variation in the mean and variance
    2. Heterogeneous responses to common shocks
    3. Outlier observations and fat tails

- The real-time nowcasting performance is substantially improved across a variety of metrics

- Overall, we provide a thorough assessment of novel model features for the nowcasting process across many countries and variables, and demonstrate how they contribute to improving point and density nowcasts in real time.

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APPENDIX SLIDES

Dynamic vs. Static Factors

An alternative benchmark?

- A dynamic factor model (with 1 lag and 1 factor) can be always rewritten as a static factor model (with 2 static factors, with a rank restriction on the variance of the transition equation).
- So the question is: How close to rank deficient is the static factor representation?
- To answer this question we look at the relative size of the eigenvalues of the variance in the transition equation of the (unrestricted) static factor representation of the model (a) using real data and (b) from data simulated from a ($s=1$, $r=1$) dynamic factor model (with parameters chosen so as to be in line with the estimation of our model).

DYNAMIC VS. STATIC FACTORS

AN ALTERNATIVE BENCHMARK?

- Two static factors:

$$\begin{bmatrix} F_t^1 \\ F_t^2 \end{bmatrix} = \begin{bmatrix} \phi_{11} & \phi_{12} \\ \phi_{21} & \phi_{22} \end{bmatrix} \begin{bmatrix} F_{t-1}^1 \\ F_{t-1}^2 \end{bmatrix} + \begin{bmatrix} \epsilon_{1,t} \\ \epsilon_{2,t} \end{bmatrix},$$

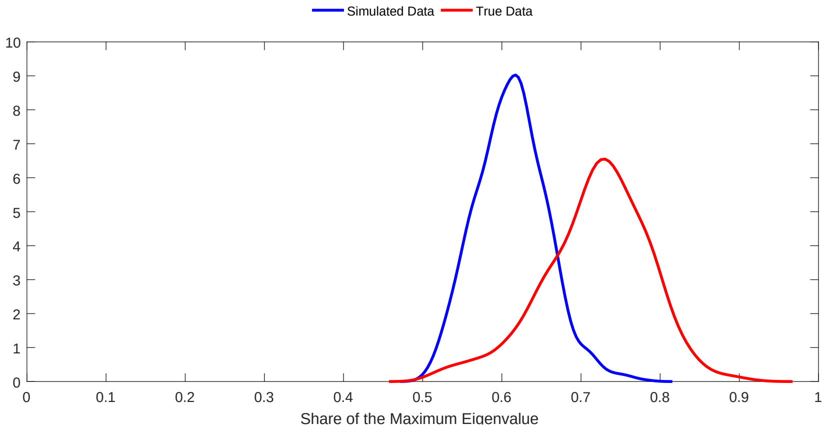
- One Dynamic factor:

$$\begin{bmatrix} f_t \\ f_{t-1} \end{bmatrix} = \begin{bmatrix} \phi_{11} & \phi_{12} \\ 1 & 0 \end{bmatrix} \begin{bmatrix} f_{t-1} \\ f_{t-2} \end{bmatrix} + \begin{bmatrix} 1 \\ 0 \end{bmatrix} \eta_t,$$

- The latter specification implies 2 static factors representation, with a reduced rank covariance matrix restriction on the shocks ϵ_t
- A static factor model can always be rotated into a dynamic factor provided that the rank restriction is satisfied.

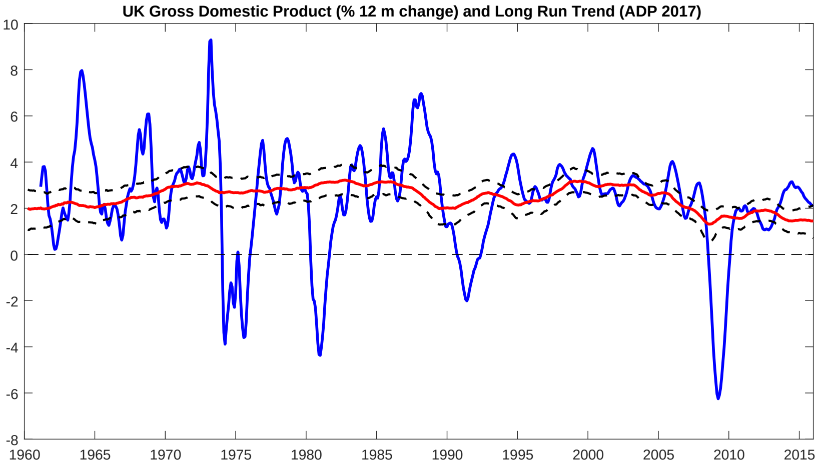
WHICH SPECIFICATION IS PREFERRED BY THE DATA?

EVIDENCE THAT SINGLE DYNAMIC FACTOR IS PREFERRED



THE MODEL

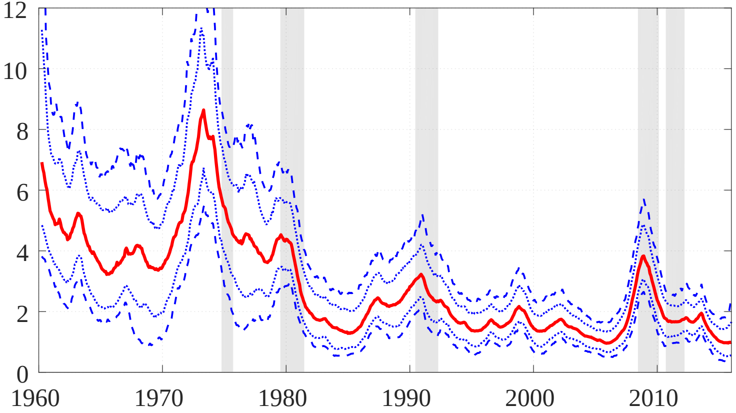
WHY EXPLICITLY MODEL LOW FREQUENCY VARIATION? THE UK CASE



Back to main

THE MODEL

WHY MODEL CHANGES IN VOLATILITY? THE UK CASE



Back to main

The model's time-varying parameters are specified to follow driftless random walks:

$$
\begin{aligned}
a_{j,t} &= a_{j,t-1} + v_{a_{j,t}}, & v_{a_{j,t}} &\overset{iid}{\sim} N(0, \omega_{a,j}^2) \quad j = 1, \ldots, r \\
\log \sigma_{\varepsilon_t} &= \log \sigma_{\varepsilon_{t-1}} + v_{\varepsilon,t}, & v_{\varepsilon,t} &\overset{iid}{\sim} N(0, \omega_{\varepsilon}^2) \\
\log \sigma_{\eta_{i,t}} &= \log \sigma_{\eta_{i,t-1}} + v_{\eta_{i,t}}, & v_{\eta_{i,t}} &\overset{iid}{\sim} N(0, \omega_{\eta,i}^2) \quad i = 1, \ldots, n
\end{aligned}
$$

Back to main slides

Banbura and Modugno (2014) show in a Gaussian model that the impact of a new release on the nowcasts can be written as a linear function of the *news*:

$$E(y_{k,tk}|\Omega_2) - E(y_{k,tk}|\Omega_1) = \mathbf{w_j}\left(y_{j,tj} - E(y_{j,tj}|\Omega)\right)$$

$$\mathbf{w_j} = \frac{\Lambda_k E\left((f_{t_k} - f_{t_k|\Omega})(f_{t_j} - f_{t_j\Omega})\right)\Lambda_j'}{\Lambda_j E\left((f_{t_j} - f_{t_j|\Omega})(f_{t_j} - f_{t_j\Omega})\right)\Lambda_j' + \sigma^2_{\eta_{j,tj}}}$$

Back to main slides

We show that with the Student-t distribution the weights are no longer linear, but depend on the value of the forecast error itself:

$$E(y_{k,tk}|\Omega_2) - E(y_{k,tk}|\Omega_1) = \mathbf{w_j}(y_{j,tj})\,(y_{j,tj} - E(y_{j,tj}|\Omega))$$

$$\mathbf{w_j}(y_{j,tj}) = \frac{\Lambda_k E\Big((f_{t_k} - f_{t_k|\Omega})(f_{t_j} - f_{t_j\Omega})\Big)\Lambda_j'}{\Lambda_j E\Big((f_{t_j} - f_{t_j|\Omega})(f_{t_j} - f_{t_j\Omega})\Big)\Lambda_j' + \sigma^2_{\eta_{j,tj}}\delta_{j,tj}}$$

$$\delta_{j,tj} = (((y_{j,tj} - E(y_{j,tj}|\Omega))^2/\sigma^2_{\eta_{j,tj}} + v_{o,j})/(v_{o,i} + 1)$$

Large errors are discounted as outlier observations containing less information.

Back to main slides

ESTIMATION

DETAILS ON MODEL SETTINGS AND PRIORS (1/2)

- Number of lags in polynomials $\mathbf{\Lambda}(\mathbf{L})$, $\phi(L)$, and $\rho(L)$: Set to $m = 1$, $p = 2$, and $q = 2$
- "Minnesota"-style priors applied to coefficients in $\mathbf{\Lambda}(L)$, $\phi(L)$ and $\rho_i(L)$.
- Variance on priors set to $\frac{\tau}{h^2}$, where τ governs tightness of prior, and h ranges over lag numbers $1 : p$, $1 : q$, $1 : m + 1$.
- Following D'Agostino et al. (2015), we set $\tau = 0.2$, a value which is standard in the Bayesian VAR literature.
- Shrink ω_a^2, ω_ε^2 and $\omega_{\eta,i}^2$ towards zero (standard DFM). For ω_a^2 set IG prior with one d.f. and scale 1e-3. For ω_ϵ^2 and $\omega_{\eta,i}^2$ set IG prior with one d.f. and scale 1e-4 (see Primiceri, 2005).

Back to main

ESTIMATION

DETAILS ON MODEL SETTINGS AND PRIORS (2/2)

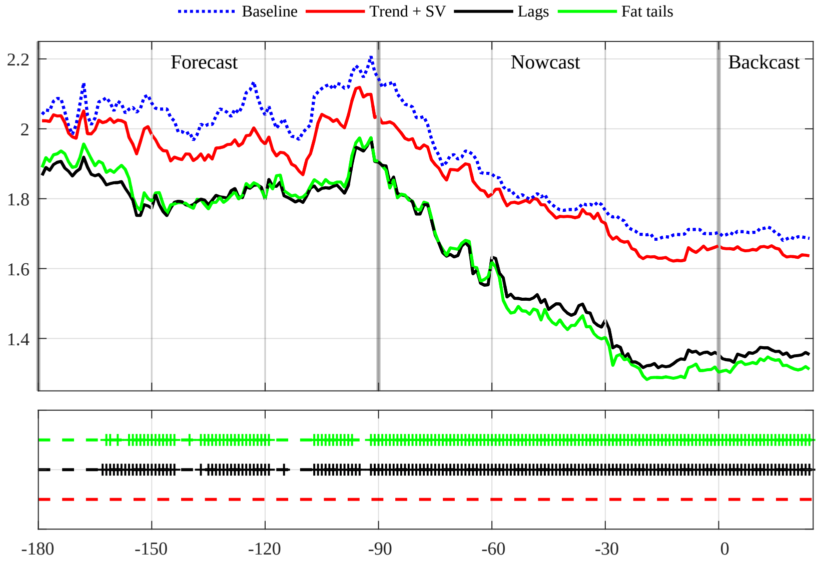
- For AR coefficients of factor dynamics, $\phi(L)$, prior mean is set to 0.9 for first lag, and zero in subsequent lags. Reflects a belief that factor captures highly persistent but stationary business cycle process.
- For factor loadings, $\mathbf{\Lambda}(L)$, prior mean is set to 1 for first lag, and zero in subsequent lags. Shrinks model towards factor being the cross-sectional average, see D'Agostino et al. (2015).
- For AR coefficients of idiosyncratic components, $\rho_i(L)$ prior is set to zero for all lags, shrinking model towards no serial correlation in $u_{i,t}$.

Back to main

ADDITIONAL EVALUATION RESULTS FOR USA, UK AND FRANCE

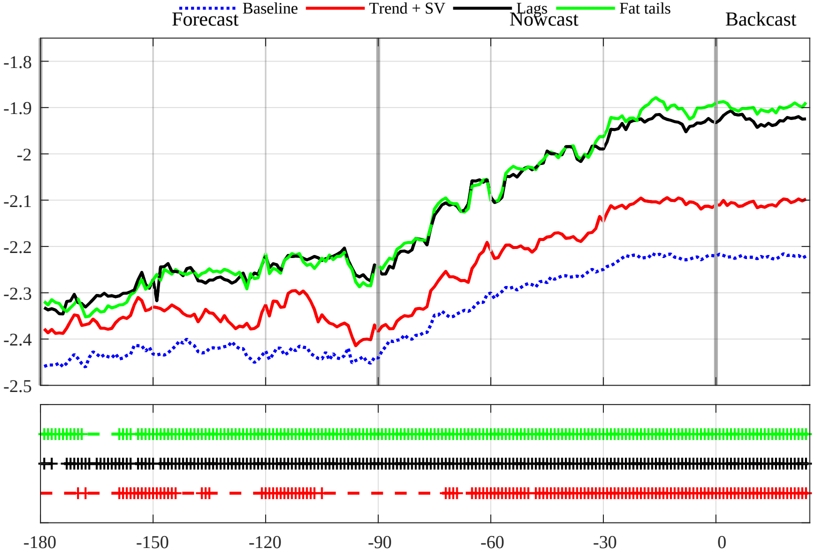
RESULTS: POINT FORECASTING (USA)

GDP: MAE ACROSS HORIZONS



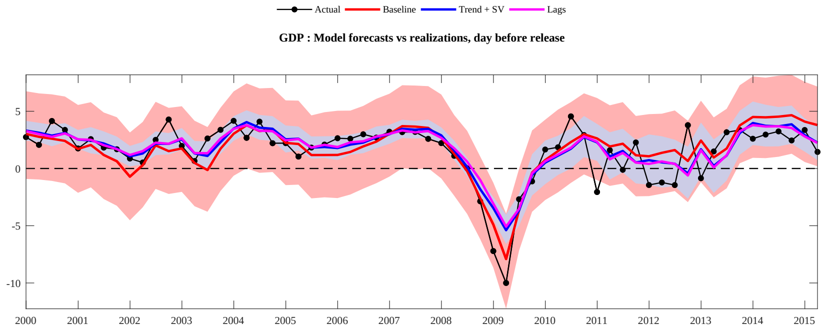
RESULTS: POINT FORECASTING (USA)

GDP: LOG SCORE ACROSS HORIZONS



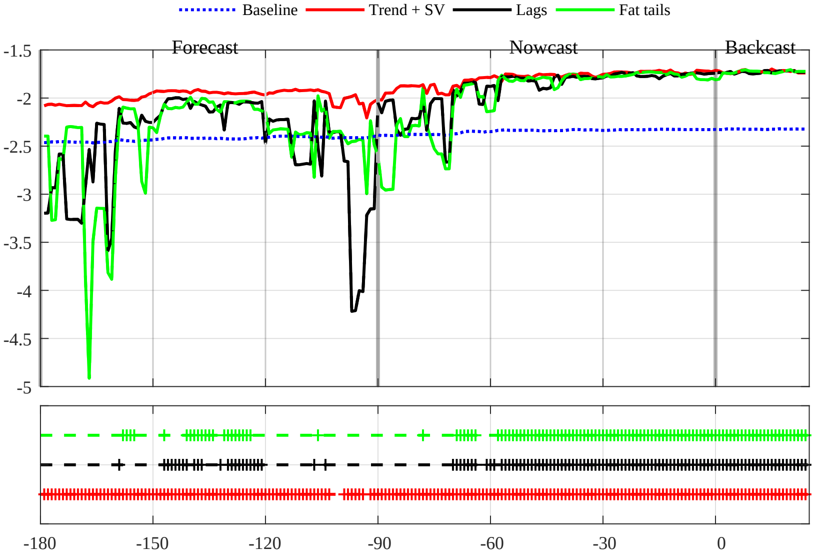
EVALUATION RESULTS

FORECASTS VS. ACTUAL OVER TIME (UK)



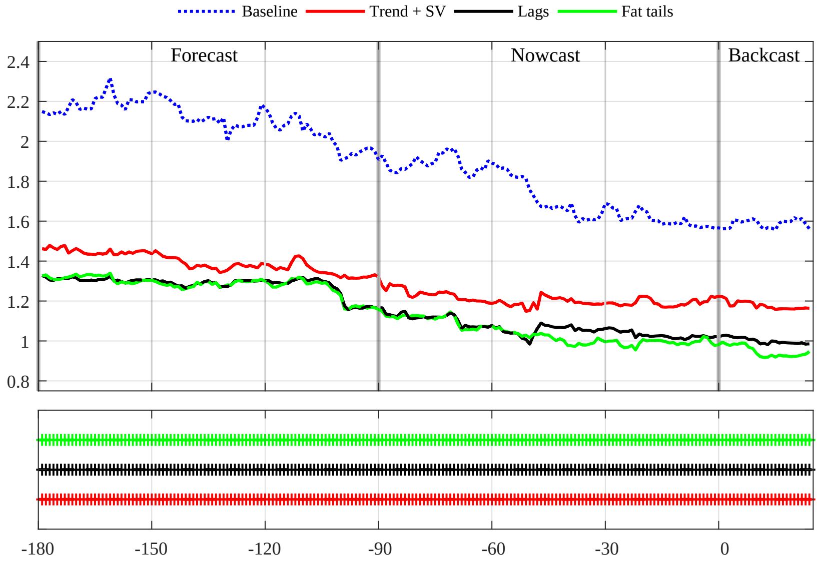
RESULTS: DENSITY FORECASTING (UK)

GDP: LOG SCORE ACROSS HORIZONS



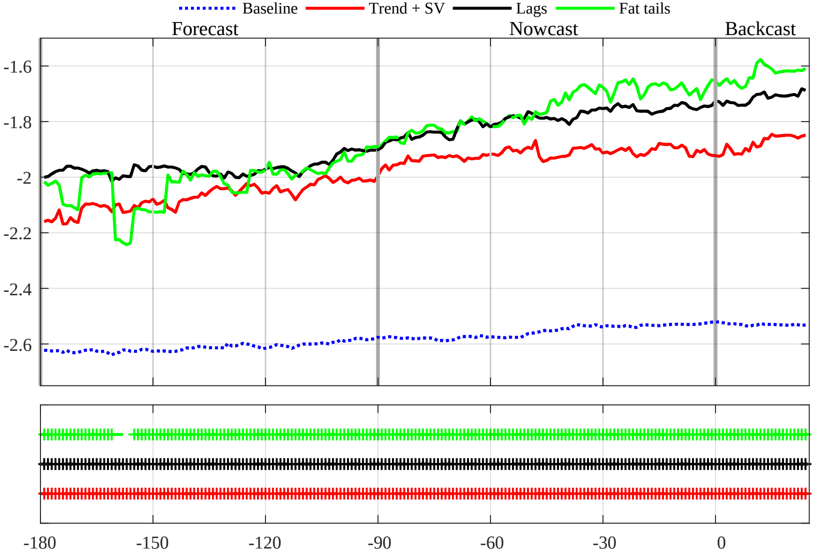
RESULTS: POINT FORECASTING (FRANCE)

GDP: MAE ACROSS HORIZONS



RESULTS: DENSITY FORECASTING (FRANCE)

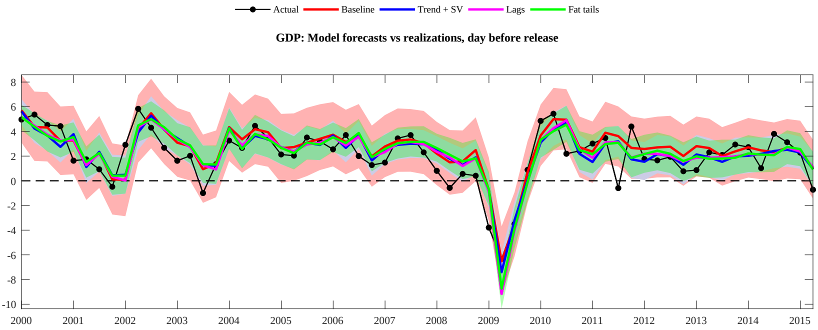
GDP: LOG SCORE ACROSS HORIZONS



EVALUATION RESULTS FOR OTHER COUNTRIES

RESULTS

FORECASTS VS. ACTUAL OVER TIME (CANADA)

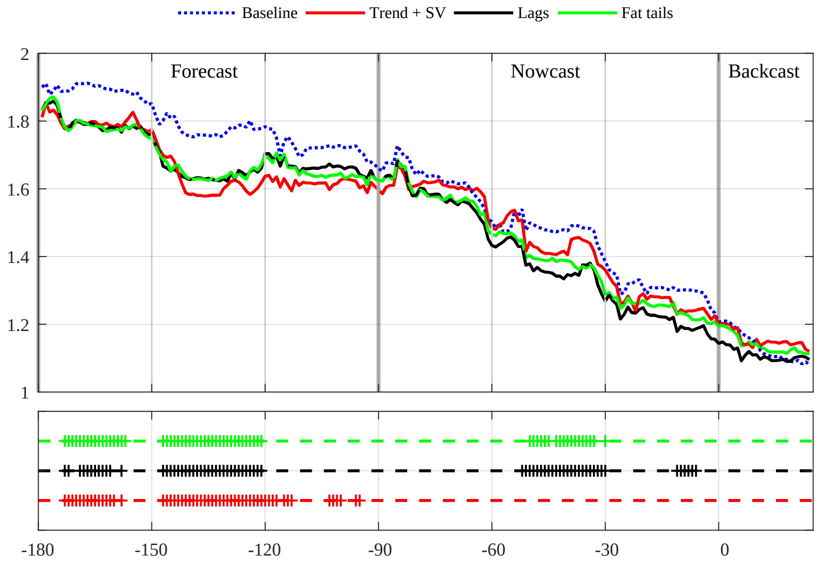


RESULTS: POINT FORECASTING (CANADA)

GDP: RMSE ACROSS HORIZONS

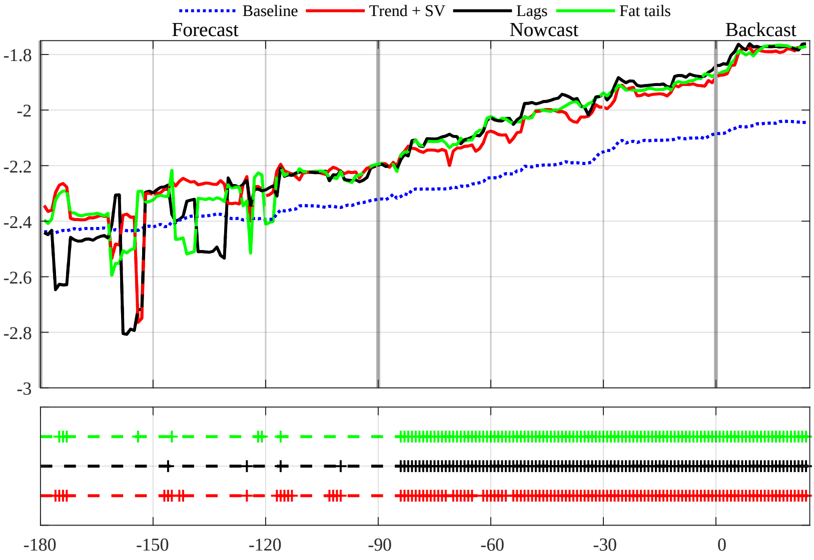
RESULTS: POINT FORECASTING (CANADA)

GDP: MAE ACROSS HORIZONS



RESULTS: DENSITY FORECASTING (CANADA)

GDP: LOG SCORE ACROSS HORIZONS

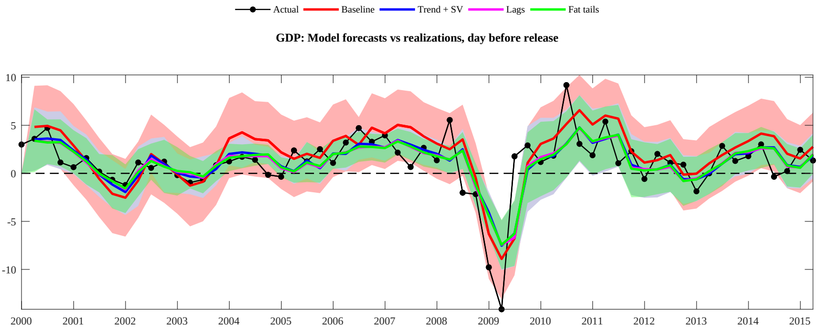


RESULTS: POINT FORECASTING (CANADA)

GDP: CRPS ACROSS HORIZONS

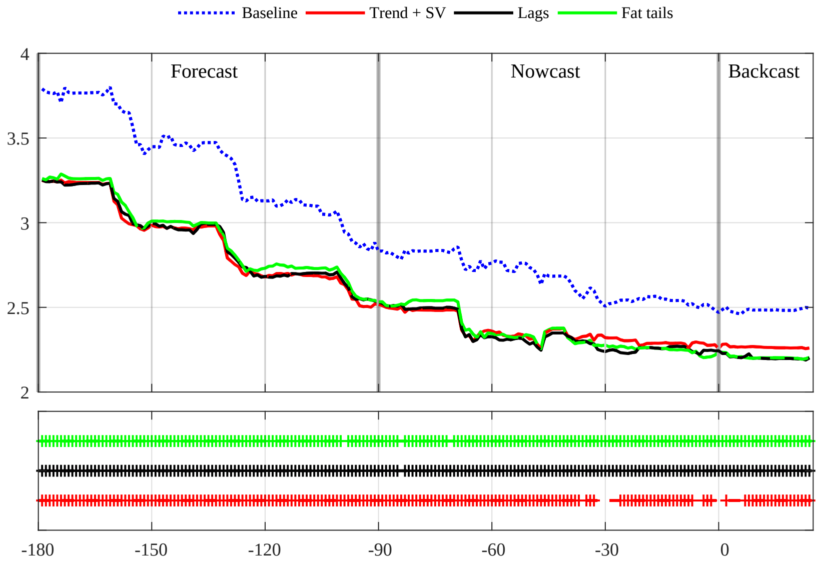
EVALUATION RESULTS

FORECASTS VS. ACTUAL OVER TIME (GERMANY)



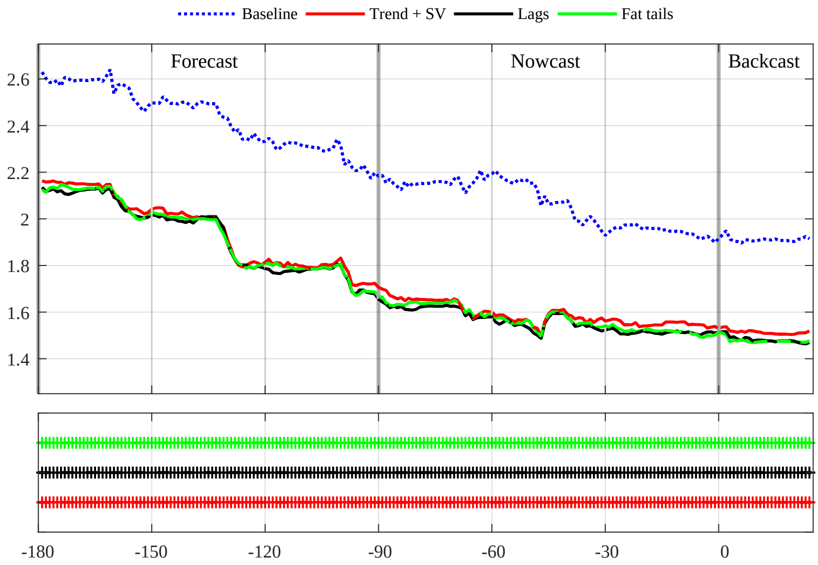
RESULTS: POINT FORECASTING (GERMANY)

GDP: RMSE ACROSS HORIZONS



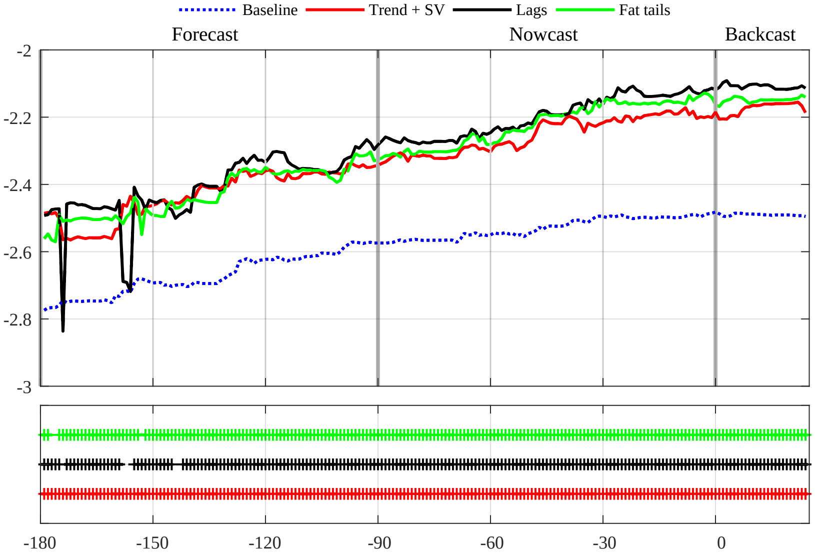
RESULTS: POINT FORECASTING (GERMANY)

GDP: MAE ACROSS HORIZONS



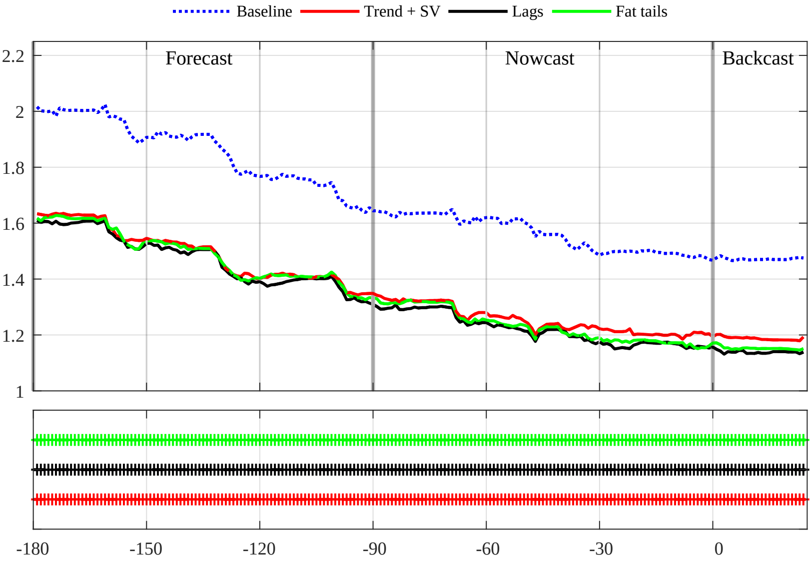
RESULTS: DENSITY FORECASTING (GERMANY)

GDP: LOG SCORE ACROSS HORIZONS



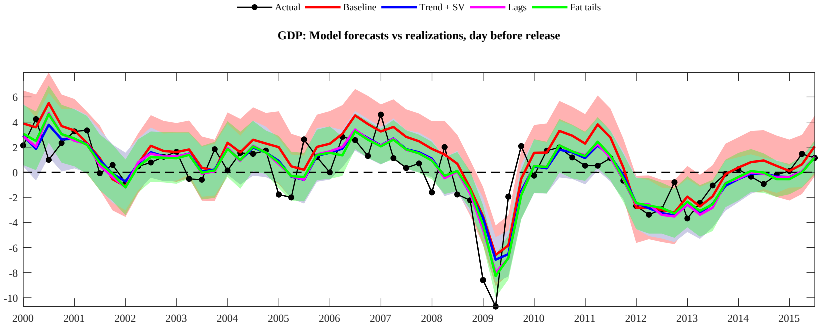
RESULTS: DENSITY FORECASTING (GERMANY)

GDP: CRPS ACROSS HORIZONS



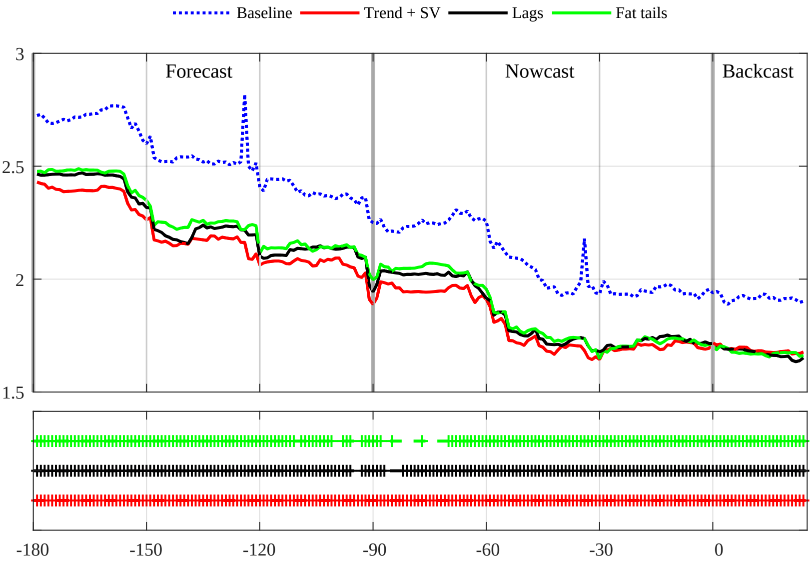
EVALUATION RESULTS

FORECASTS VS. ACTUAL OVER TIME (ITALY)



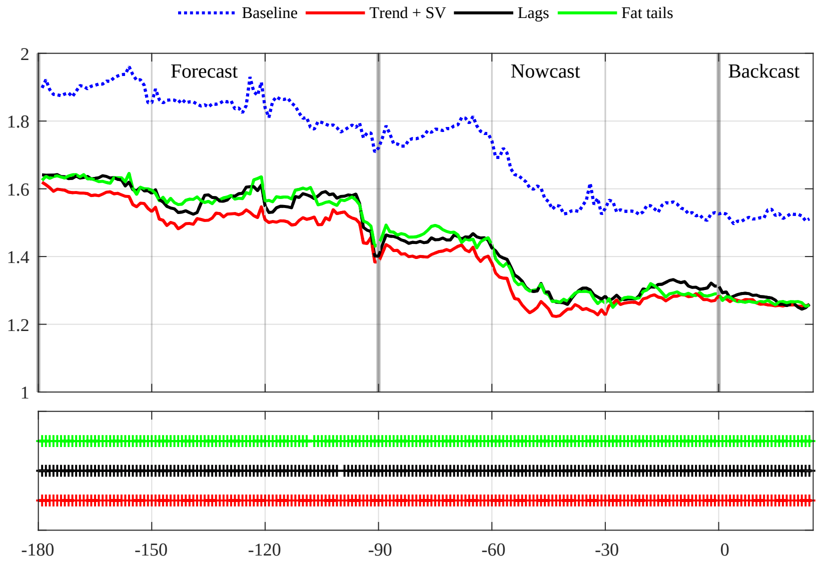
RESULTS: POINT FORECASTING (ITALY)

GDP: RMSE ACROSS HORIZONS



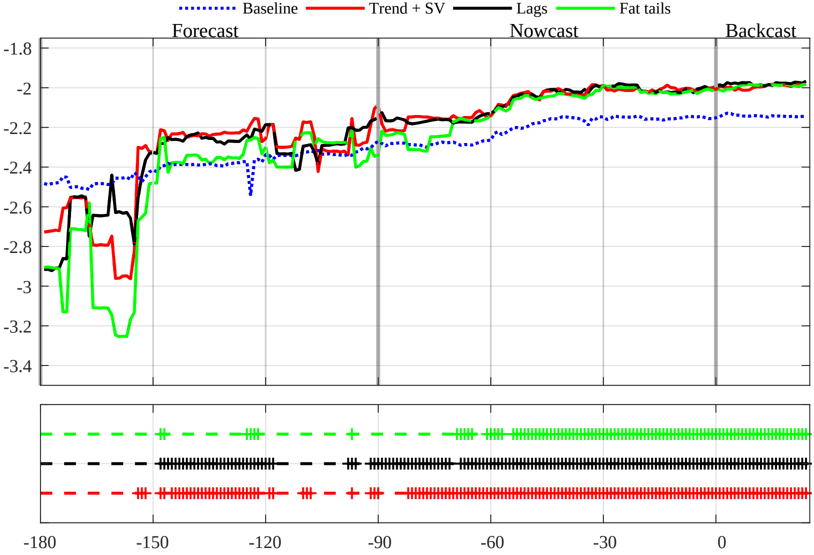
RESULTS: POINT FORECASTING (ITALY)

GDP: MAE ACROSS HORIZONS



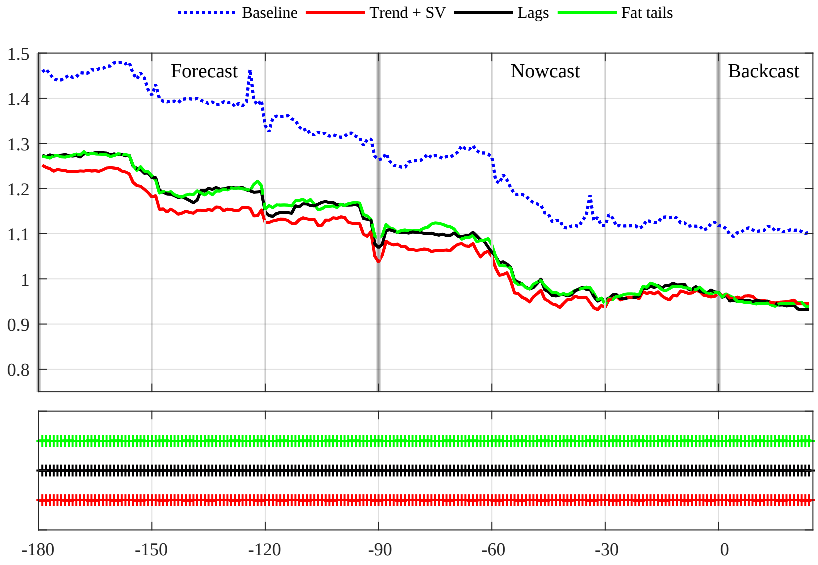
RESULTS: DENSITY FORECASTING (ITALY)

GDP: LOG SCORE ACROSS HORIZONS



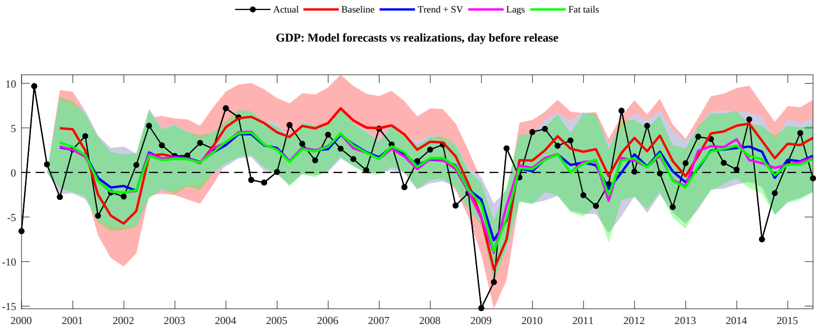
RESULTS: DENSITY FORECASTING (ITALY)

GDP: CRPS ACROSS HORIZONS



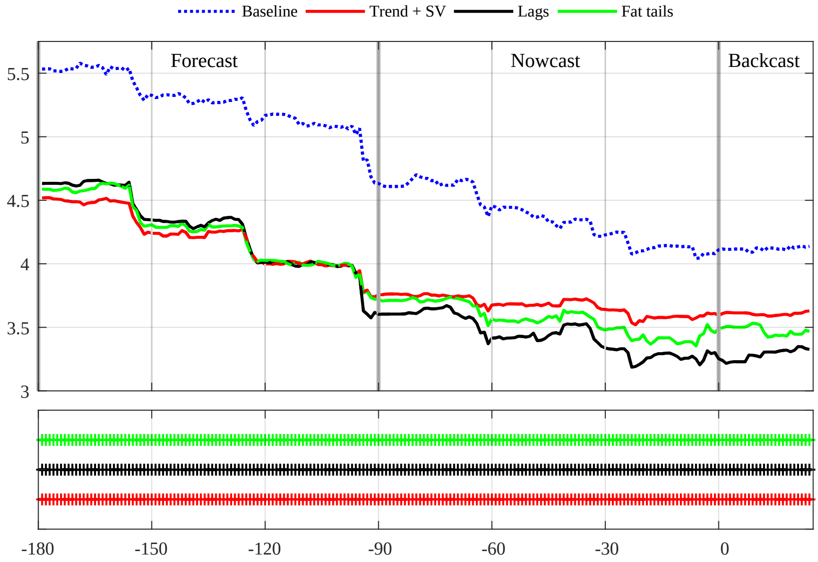
EVALUATION RESULTS

FORECASTS VS. ACTUAL OVER TIME (JAPAN)



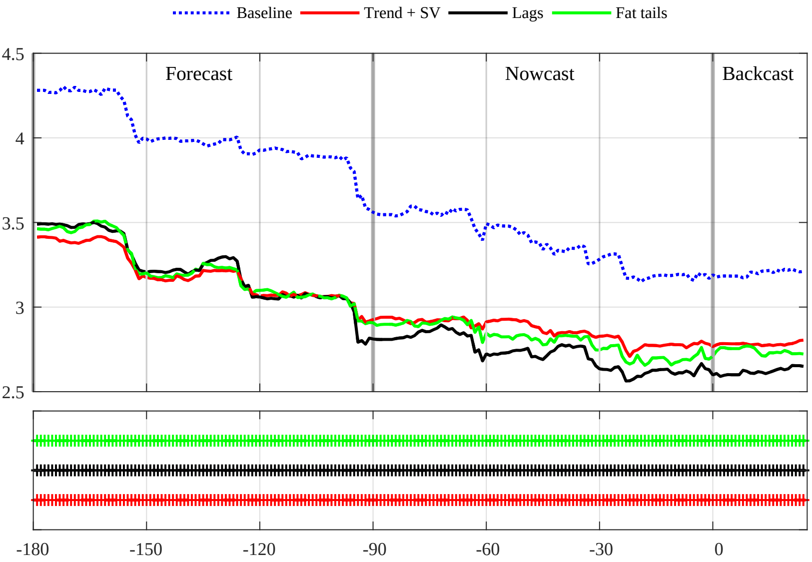
RESULTS: POINT FORECASTING (JAPAN)

GDP: RMSE ACROSS HORIZONS



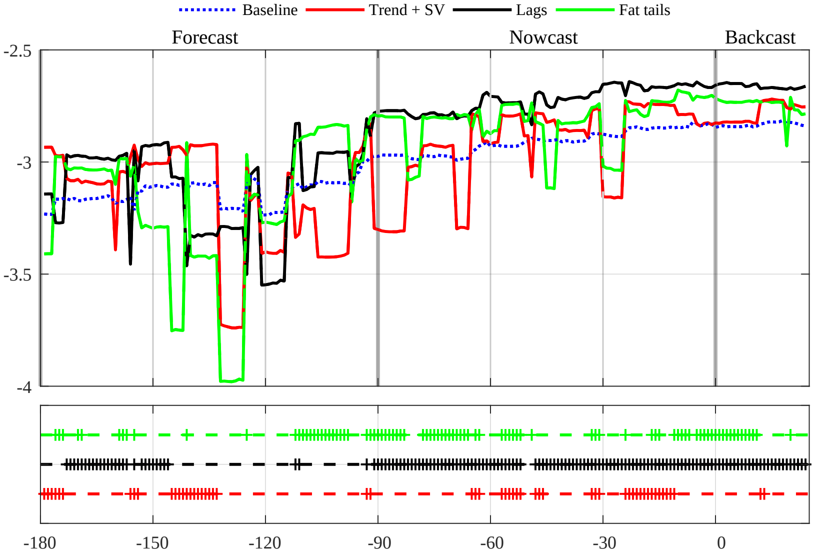
RESULTS: POINT FORECASTING (JAPAN)

GDP: MAE ACROSS HORIZONS



RESULTS: DENSITY FORECASTING (JAPAN)

GDP: LOG SCORE ACROSS HORIZONS



RESULTS: DENSITY FORECASTING (JAPAN)

GDP: CRPS ACROSS HORIZONS