Capturing Macroeconomic Tail Risks with Bayesian Vector Autoregressions

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Introduction

How do we measure (negative) tail risks to macroeconomic outcomes?

- Rapidly growing lit focused on GDP growth and quantile regression: Adrian, Boyarchenko, and Giannone (2019, ABG), Adrian, et al. (2018), Giglio, Kelly, and Pruitt (2016)
  - Focus on risks associated with poor financial conditions

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  - Focus on risks associated with poor financial conditions
- Some work considers risks to unemployment (e.g., Galbraith and van Norden 2019, Kiley 2018) or inflation
- Some work considers other methods, such as copula
- Other work drills deeper to better understand tail risks: Loria, Matthes, and Zhang (2019) examine drivers of left tail

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Interest in tail risks reflects a perception of asymmetries in distributions of outcomes

- Precedents: Markov switching and threshold models, plus literature on asymmetries in unemployment

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- Some recent research has focused on evidence of skewness in GDP growth: Kozeniauskas, Orlik, and Veldkamp (2018), Orlik and Veldkamp (2015), Jensen, et al. (2020)
- Monetary policymakers have commonly treated forecast distributions as being potentially asymmetric, at some points in time

Introduction

Important distinction: asymmetries in conditional vs. unconditional distributions

- ABG and others sometime refer explicitly to conditional: recessions associated with left-skewed distributions
- But one pattern that has been emphasized — downside risk varying more than upside — could occur with predictive distributions that are symmetric

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- ABG and others sometime refer explicitly to conditional: recessions associated with left-skewed distributions
- But one pattern that has been emphasized — downside risk varying more than upside — could occur with predictive distributions that are symmetric
- Need simultaneous mean and variance shifts
- Simple example: shift from N(0,1) to N(-2,4) $\Rightarrow$ 95% quantile edges down from 1.65 to 1.29, whereas 5% quantile drops from -1.65 to -5.29.

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We examine the ability of BVARs with stochastic volatility (SV) to capture tail risks in macroeconomic forecast distributions and outcomes

- BVARs have a known track record and can be used for a range of forecasting purposes
- BVAR-SV models commonly improve on the point and density forecast accuracy of their homoskedastic counterparts

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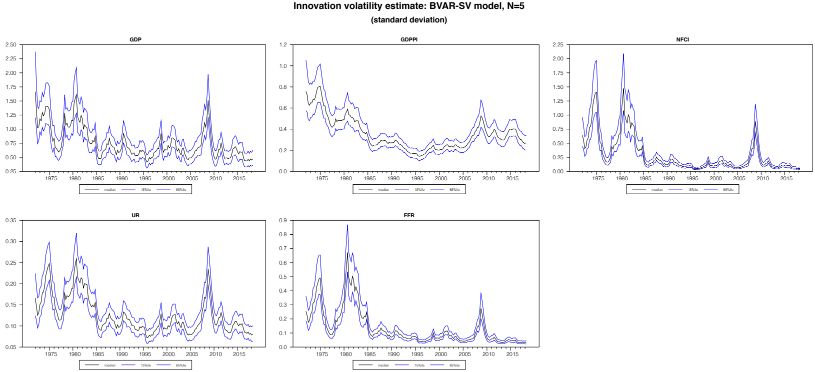
- BVAR-SV models commonly improve on the point and density forecast accuracy of their homoskedastic counterparts

BVAR-SV models have the potential to capture time-varying tail risks

- Due to simultaneous shifts in conditional means and variances
- Even though conditional distributions are symmetric (1-step, not necessarily multi-step)

Introduction



Introduction

Our models:

- Include 4 primary macroeconomic indicators and the NFCI indicator of financial conditions
- Focus on risks to GDP growth
- Include conventional BVAR-SV and a BVAR with a generalized factor structure to volatility in which the common factor is a function of past financial conditions
- Robustness checks:
  - Models with 2 and 15 variables
  - Models replacing NFCI with an indicator of financial volatility
  - Forecasting unemployment instead of GDP growth

Introduction

We provide more formal evaluations of asymmetries and risk forecasts than has much of the recent literature

- Formal tests of skewness in the data, BVAR residuals, and forecast errors
- Formal scoring of quantile and expected shortfall forecasts
  - Conventional quantile scoring function
  - More recent joint scoring function for the quantile and its associated expected shortfall
- BVAR-SV vs. ABG-style quantile regression

Introduction

Related contemporaneous paper: Caldara, Scotti, and Zhong (2019)

- Our focus is more on forecasting with VARs like those common in the literature, including formal scoring comparisons
- They focus more on using a bivariate VAR with an explicit correlation in shocks to levels and volatilities to produce time-varying asymmetries in conditional predictive distributions

Introduction

Main findings

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- QR-based approaches can come with some challenges in macro data samples: quantile crossing and coefficient variability

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- Formal statistical evidence of skewness in output growth is generally weak
- QR-based approaches can come with some challenges in macro data samples: quantile crossing and coefficient variability
- BVAR-SV models are able to capture time variation in output tail risks — with downside risks more variable than upside risks — like that emphasized in ABG
    - SV crucial
- BVAR-SV and BVAR-GFSV models score about as well as QR for downside tail risks

Outline

1. Models

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2. Data

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3. Forecast Metrics

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4. Empirical Results

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4. Empirical Results
5. Conclusions

Models: BVAR-SV model

$$
\begin{aligned}
y_t &= \sum_{i=1}^{p} \Pi_i y_{t-i} + v_t \\
v_t &= A^{-1}\Lambda_t^{0.5}\epsilon_t, \;\; \epsilon_t \sim N(0, I_n), \;\; \Lambda_t \equiv \text{diag}(\lambda_{1,t}, \ldots, \lambda_{n,t}) \\
\ln(\lambda_{i,t}) &= \gamma_{0,i} + \gamma_{1,i}\ln(\lambda_{i,t-1}) + \nu_{i,t}, \;\; i = 1, \ldots, n \\
\nu_t &\equiv (\nu_{1,t}, \nu_{2,t}, \ldots, \nu_{n,t})' \sim \; N(0, \Phi)
\end{aligned}
$$

- Λ_t contains the time-varying variances of conditionally Gaussian shocks
- A is uni-triangular
- Reduced-form VCV is $\text{var}(v_t) \equiv \Sigma_t = A^{-1}\Lambda_t A^{-1\prime}$

Models: BVAR-GFSV model

Incorporates a factor structure of volatility in a VAR-SV (CCM 2016, 2017) and links the volatility factor to the lagged NFCI

- Allows a link of poor financial conditions to elevated macroeconomic uncertainty and volatility, capturing the basic idea of ABG
- Each variable's log vol. follows a linear factor model with a common uncertainty factor $\ln m_t$ and an idiosyncratic component $\ln h_{i,t}$
- Generalizes a much simpler model of a robustness check in ABG

$$\begin{aligned}
y_t &= \sum_{i=1}^{p} \Pi_i y_{t-i} + A^{-1} \Lambda_t^{0.5} \epsilon_t \\
\ln \lambda_{i,t} &= \beta_{m,i} \ln m_t + \ln h_{i,t}, \;\; i = 1, \ldots, n \\
\ln m_t &= \sum_{i=1}^{p_m} \delta_{m,i} \ln m_{t-i} + \delta_f \mathrm{NFCI}_{t-1} + u_{m,t}, \;\; u_{m,t} \sim iid \;\; N(0, \phi_m) \\
\ln h_{i,t} &= \gamma_{i,0} + \gamma_{i,1} \ln h_{i,t-1} + e_{i,t}, \;\; i = 1, \ldots, n
\end{aligned}$$

Models: Priors and Estimation

SV Priors:

- VAR coefficients Π: Normal, with Minnesota-style prior, means of 0
- A, row by row: Normal, prior mean of 0 and variance $10 \cdot I$
- SV process: Normal, with $\gamma_{i,1}$ having mean of 0.9 and st. dev. of 0.2
- Φ: IW with mean of $0.03 \cdot I$ and 10 df

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Estimation:

- BVAR-SV estimated with a Gibbs sampler
    - GFSV's volatility factor is sampled with a particle Gibbs step
- We use 5000 retained draws from the posterior predictive distribution

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Symmetry?

- 1-step ahead predictive distributions are symmetric
- Multi-step predictive distributions don't have to be symmetric but are, empirically speaking

Models: Quantile Regression

Step 1 of 2: Conventional QR estimation

$$y_{t+h}^{(h)} = x_t'\beta + \epsilon_{t+h}$$

$$\hat{\beta} = \underset{\beta}{\operatorname{argmin}} \sum_{t=1}^{T-h} \left(\tau \cdot \mathbf{1}_{(y_{t+h}^{(h)} \geq x_t'\beta)} |y_{t+h}^{(h)} - x_t'\beta| + (1-\tau) \cdot \mathbf{1}_{(y_{t+h}^{(h)} < x_t'\beta)} |y_{t+h}^{(h)} - x_t'\beta| \right)$$

- h = forecast horizon of either 1 or 4 quarters
- $y_t = 400 \Delta \ln \text{GDP}_t, \;\; y_{t+h}^{(h)} \equiv h^{-1} \sum_{i=1}^{h} y_{t+i}$
- x_t includes a constant, y_t, and NFCI_t
- Model estimated for quantiles of τ = 0.05, 0.25, 0.75, 0.95, and 0.5.

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Step 2: Smooth the estimated quantile function by fitting a skewed-*t* distribution

- Fit to quantiles of $\tau = 0.05, 0.25, 0.75, 0.9$
- Use fitted distribution for computing expected shortfall, etc.

Data

VARs include 5 variables: GDP growth, unemployment rate, inflation (GDP deflator), federal funds rate, NFCI

- Results similar with 2 and 15 variables
- Alternative financial measure and longer sample: turbulence measure of volatility from Giglio, Kelly, and Pruitt (2016)

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We consider both in-sample and real-time, out-of-sample forecasts of GDP growth (and unemployment in a robustness check)

- We abstract from the real-time aspect of the NFCI
- In real-time evaluation, actuals = 1st release available in RTDSM

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Samples:

- Estimation with NFCI uses data starting in 1971, ending in 2018
- Estimation with turbulence uses data starting in 1959, ending in 2011
- Real time forecasts start in 1985 with NFCI and 1972 with turbulence

Forecast Metrics

We consider both in-sample and OOS forecasts for small samples of bad outcomes and comparability to ABG

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Basic checks: RMSEs of point forecasts and log scores of forecasts

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Tail risks to GDP growth evaluated at $\tau = 5\%$

- Results similar at $\tau = 10\%$

Forecast Metrics

5% quantile score

$$\mathrm{QS}_{t+h} = (y_{t+h} - Q_{\tau,t+h})(\tau - \mathbf{1}_{(y_{t+h} <= Q_{\tau,t+h})}),$$

where $Q_{\tau,t+h}$ = forecast quantile at quantile $\tau = 0.05$

- 5% quantile $\equiv$ value at risk (VaR)

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Expected shortfall (ES) and long-rise (LR)

- Shortfall = E(GDP growth in 5% tail)
- Long-rise = E(GDP growth in 95% tail)
- BVAR-SV: easily computed with draws from predictive distribution
- QR: Computed with complete skew-t density functions from smoothing step

Forecast Metrics

Joint VaR-ES score:

- VaR-ES can be jointly elicited, but ES by itself cannot (Fissler and Ziegel 2016)
- We use the joint score of Fissler, Ziegel, and Gneiting (2015)

$$
\begin{aligned}
S_{t+h} &= Q_{\tau,t+h} \cdot \left(\mathbf{1}_{(y_{t+h}<=Q_{\tau,t+h})} - \tau\right) - y_{t+h} \cdot \mathbf{1}_{(y_{t+h}<=Q_{\tau,t+h})} \\
&+ \frac{e^{\mathrm{ES}_{\tau,t+h}}}{1+e^{\mathrm{ES}_{\tau,t+h}}} \left(\mathrm{ES}_{\tau,t+h} - Q_{\tau,t+h} + \tau^{-1}\left(Q_{\tau,t+h} - y_{t+h}\right)\mathbf{1}_{(y_{t+h}<=Q_{\tau,t+h})}\right) \\
&\quad + \ln \frac{2}{1+e^{\mathrm{ES}_{\tau,t+h}}}
\end{aligned}
$$

Results: Roadmap

Note: BVAR-GFSV estimates generally very similar to BVAR-SV

Tests of skewness

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Practical challenges with QR in small samples

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Estimate of ES and LR: In-sample and out-of-sample forecasts

Formal assessment of forecast accuracy

Robustness checks

- Alternative measure of financial conditions: turbulence
- Alternative measure of economic activity: Δ unemployment rate

Results: Skewness

	skewness	Bai-Ng
Data, 1972-2018		
GDP growth	−0.364	−0.865
Unemployment	0.683	0.644
GDP inflation	1.402	1.995**
Fed funds rate	0.709	0.787
NFCI	1.979	2.016**

- Right column provides Bai and Ng (2005) time-series robust test statistic for skewness
- Raw data: skewness statistics are often large, but not necessarily statistically significant

Results: Skewness

	skewness	Bai-Ng
BVAR-SV resid., 1972-2018		
GDP growth	0.237	0.406
Unemployment	0.542	1.073
GDP inflation	0.196	0.589
Fed funds rate	1.422	0.644
NFCI	−0.186	−0.258
BVAR-SV resid./SV, 1972-2018		
GDP growth	0.129	0.664
Unemployment	0.326	2.783***
GDP inflation	0.119	0.956
Fed funds rate	−0.119	−0.754
NFCI	0.341	2.557**

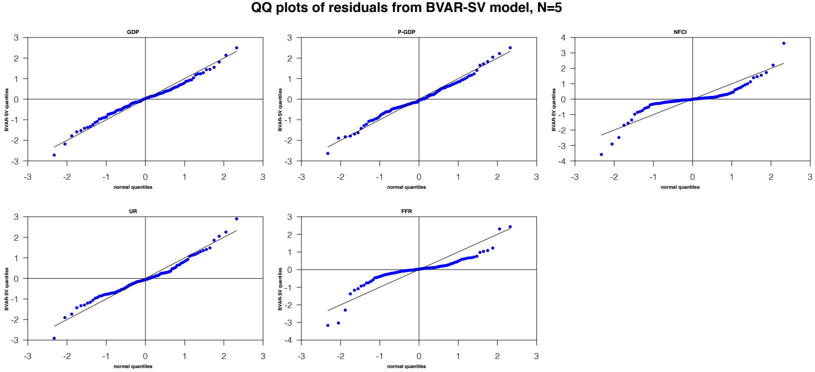
- BVAR-SV residuals: No evidence of skewness
- Normalized BVAR-SV residuals: Evidence of skewness increases some

Results: Skewness

	skewness	**Bai-Ng**
BVAR-SV forecast errors, h = 1Q, 1985-2018		
GDP growth	0.042	0.162
Unemployment	0.850	1.560
GDP inflation	-0.367	-1.839^{*}
Fed funds rate	-0.115	-0.260
NFCI	1.632	0.826

- OOS forecast errors: A little evidence of skewness

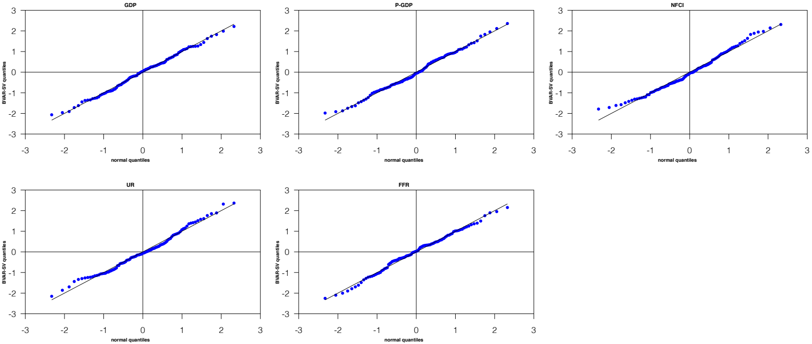
Results: Skewness



- BVAR-SV residuals: Notable departures from normality, esp. for NFCI and FFR

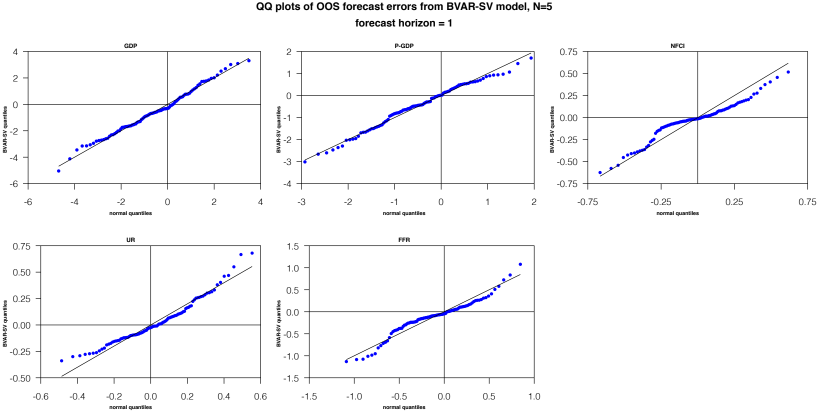
Results: Skewness

QQ plots of normalized residuals from BVAR-SV model, N=5



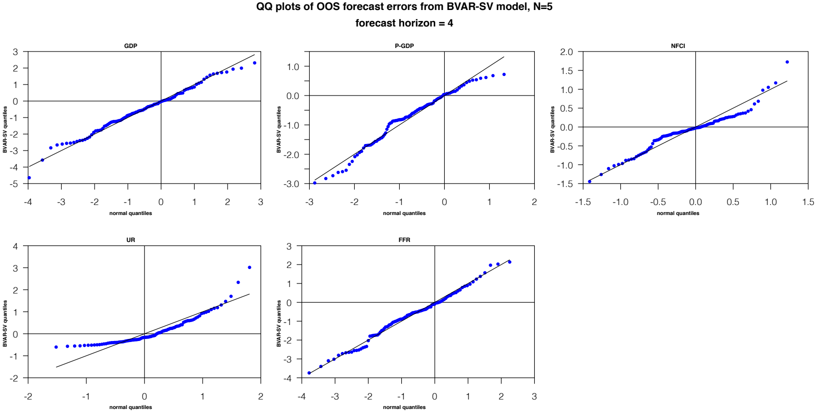
- Normalized BVAR-SV residuals: With normalization, departures from normality not so obvious

Results: Skewness



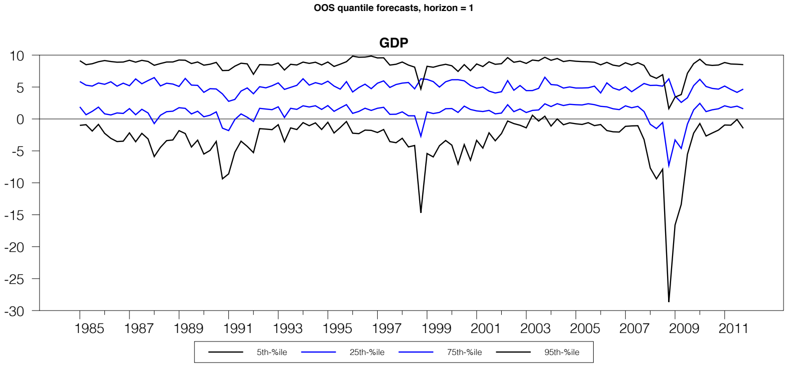
- OOS BVAR-SV forecast errors, 1-step: As in not-normalized residuals, there are notable departures from normality

Results: Skewness



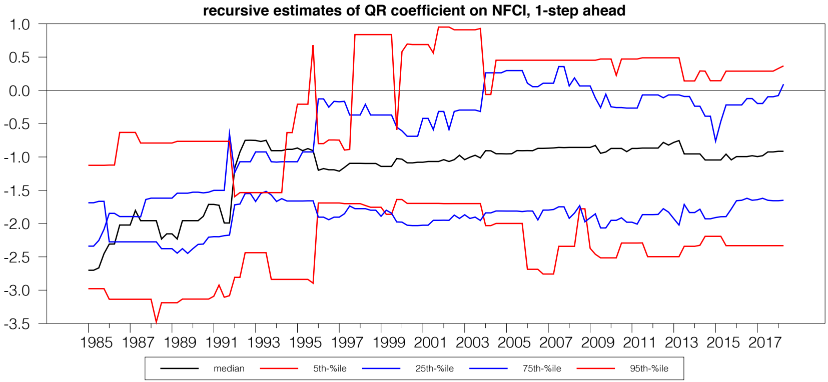
- OOS BVAR-SV forecast errors, 4-step: Again, there are notable departures from normality

Results: Empirical challenges with QR



- In OOS estimates for GDP growth using turbulence (1-step), the 75th and 95th quantiles cross in two periods

Results: Empirical challenges with QR



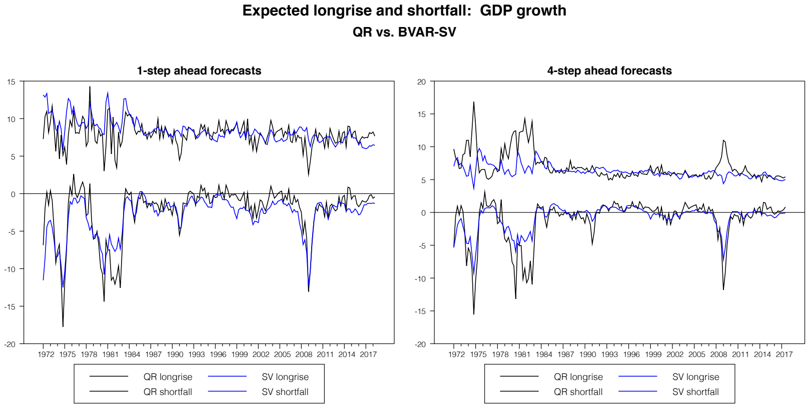
- In OOS estimates for GDP growth (1-step), the coefficient on NFCI_{t-1} can change sharply with the sample, esp. for the tail quantiles

Results: Empirical challenges with QR

Small samples: Common to use extremal quantile methods for bias correction and inference

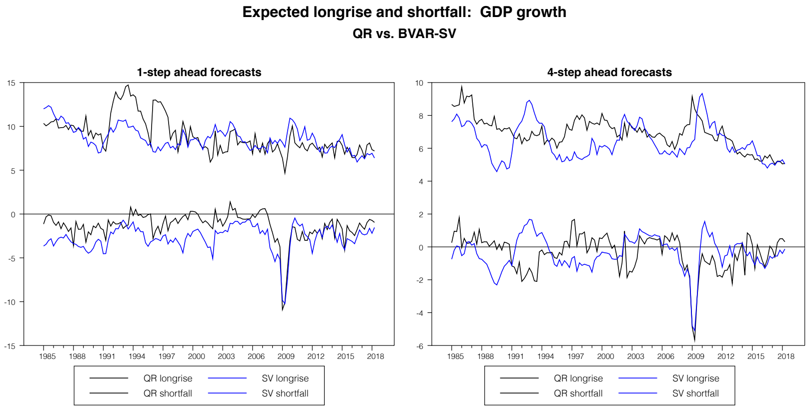
- Rule of thumb from Chernozhukov, Fernandez-Val, and Kaji (2017): extremal quantile methods should be used when $\tau T/k \leq 15$ to 20, where $\tau =$ quantile, $T =$ sample size, and $k = \#$ regressors.
- GDP-NFCI application: with $T = 160$, $\tau = 0.05$, and $k = 3$, $\tau T/k \approx 2.7$

Results: Predictive distributions



- In-sample forecast estimates display asymmetries highlighted by ABG: ES variability $>$ LR variability
- Pattern stronger at $h = 1$ than $h = 4$
- BVAR-SV comparable to QR, esp. at h=1

Results: Predictive distributions



- Asymmetries still present but a little weaker OOS than in-samplle
- QR-based estimates have some **upside** asymmetries in the 1990s
- OOS compared to IS: BVAR-SV estimates noisier; QR estimates less variable

Results: Predictive distributions

What drives the pattern in the BVAR estimates?

- Need SV to get conditional variance to move over time
- Need financial conditions

Results: Predictive distributions

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Monte Carlo experiments replicate variability of ES compared to LR

- Bivariate BVAR-GFSV based on GDP growth and NFCI
- BVAR-SV performance comparable to BVAR-GFSV

Results: Accuracy of in-sample forecasts of GDP growth

	BVAR-SV/QR			
	1985-2018		1985-2007	
	$h = 1Q$	$h = 4Q$	$h = 1Q$	$h = 4Q$
RMSE	0.943	0.962	0.994	1.023
Log score	0.044^{*}	0.031	0.004	−0.030
5% QS	0.982	1.081	1.031	1.100
5% VaR-ES	−0.073	−0.143	-0.151^{*}	−0.227
	BVAR-GFSV/QR			
RMSE	0.942	0.958	0.988	1.013
Log score	0.051^{**}	0.053	0.019	−0.010
5% QS	0.965	1.081	0.980	1.067
5% VaR-ES	−0.016	−0.073	−0.032	−0.112

- Conventional point and density forecasts: BVARs and QR broadly similar in accuracy
- Quantile score: Same
- VaR-ES score: Same, although GFSV sometimes better than SV and closer to QR performance

Results: Accuracy of out-of-sample forecasts of GDP growth

	BVAR-SV/QR			
	1985-2018		1985-2007	
	$h = 1Q$	$h = 4Q$	$h = 1Q$	$h = 4Q$
RMSE	0.875^{*}	0.873	0.867	0.819
Log score	0.062^{*}	0.146	0.065	0.162
5% QS	1.099	0.877	1.158	0.767
5% VaR-ES	-0.251^{*}	0.420	-0.355^{*}	0.591
	BVAR-GFSV/QR			
RMSE	0.874^{**}	0.872	0.860^{*}	0.821
Log score	0.111^{***}	0.176	0.122^{***}	0.186
5% QS	0.982	0.801	0.989	0.689
5% VaR-ES	-0.104	0.651	-0.135	0.782

- OOS: In conventional point and density forecasts, BVARs beat QR
- Quantile score: BVAR-GFSV as good as or better than QR, BVAR-SV a little more mixed
- VaR-ES score: BVAR-GFSV comparable to QR, BVAR-SV not quite as good as GFSV

Results: GDP growth forecast takeaways

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QR itself simple, but:

- 2nd step for smoothing adds complexity
- Need to estimate separate models for each quantile-horizon combination

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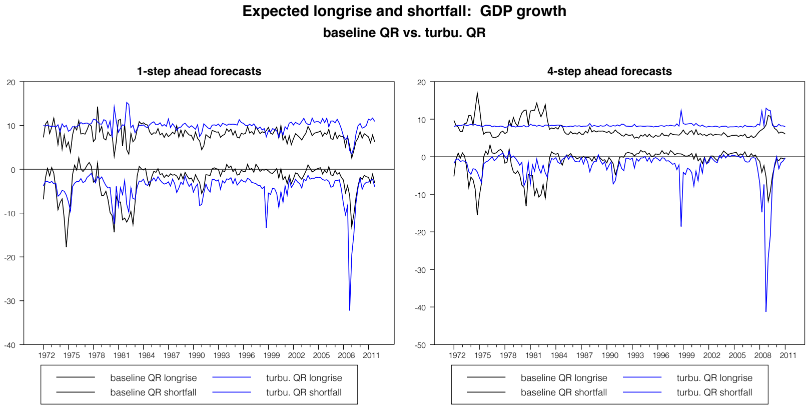
BVARs with time-varying volatility offer a viable alternative

- BVARs broadly useful for forecasting (point forecasts, scenario analysis, etc.)
- Single model can cover all variables, horizons, and quantiles of interest
- Need time-varying volatility to get shifts in conditional variances

Robustness results using turbulence: Predictive distributions



- QR: Replacing NFCI with turbulence greatly increases ES variability (even more so OOS)

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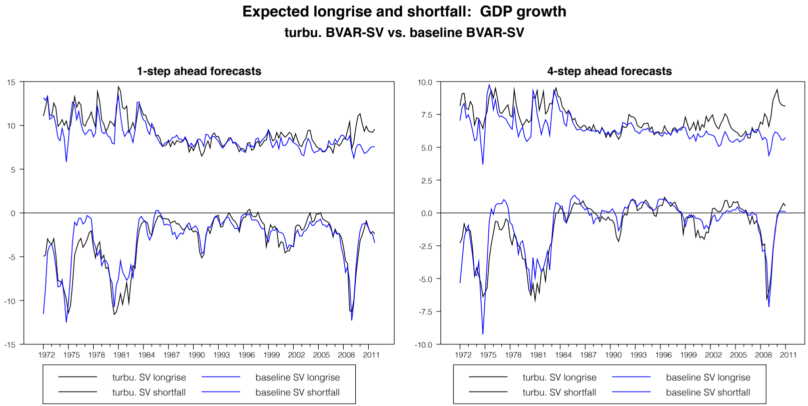
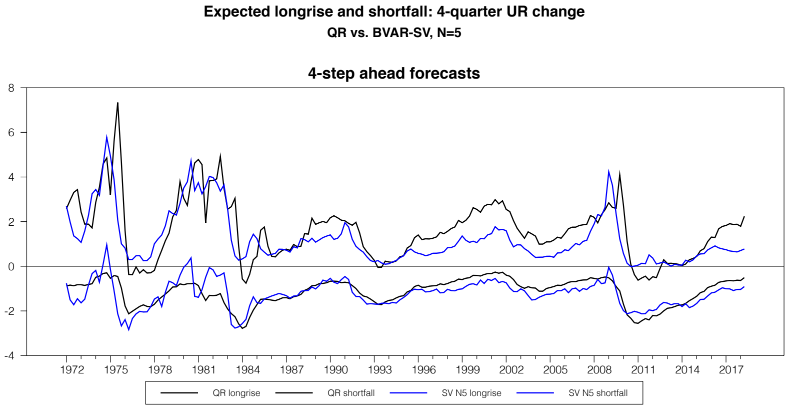


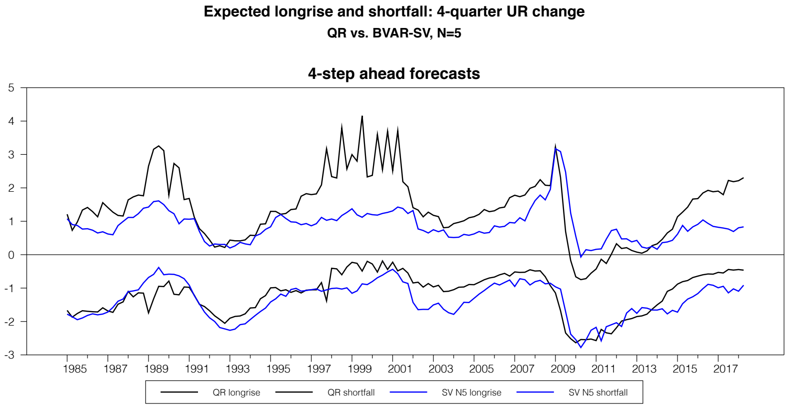
- BVAR-SV: Estimates similar with turbulence as compared to NFCI

Robustness results using unemployment: Predictive distributions



- In-sample estimates show considerable time variation in upside risk
- LR more variable than ES
- Contours of QR and BVAR-SV estimates are similar

Robustness results using unemployment: Predictive distributions



- Evidence of asymmetries in LR vs. ES is somewhat weaker out-of-sample
- Considerable choppiness of QR estimate in 1990s

Robustness results using unemployment: Accuracy of in-sample forecasts

	BVAR-SV/QR	
	1985-2018	1985-2007
5% QS	1.010	0.825
5% VaR-ES	0.060	0.092
	BVAR-GFSV/QR	
	1985-2018	1985-2007
5% QS	1.045	0.825
5% VaR-ES	0.050	0.097

- In-sample tail risk forecasts: SV and GFSV estimates about as accurate as QR

Robustness results using unemployment: Accuracy of out-of-sample forecasts

	BVAR-SV/QR	
	1985-2018	1985-2007
5% QS	1.092	1.125
5% VaR-ES	−0.014	−0.069
	BVAR-GFSV/QR	
	1985-2018	1985-2007
5% QS	1.096	1.121
5% VaR-ES	−0.039	−0.074

- Out-of-sample tail risk forecasts: SV and GFSV estimates about as accurate as QR

Conclusions

In general, a BVAR-SV model performs as well as quantile regression in measuring and forecasting tail risks to economic activity

- Key features for BVAR: time-varying volatility and inclusion of financial conditions
- Captures simultaneous shifts in conditional means and variances

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Key findings:

- Statistical evidence of skewness in output growth is generally weak
- QR-based approaches can come with some challenges in macro data samples: quantile crossing and coefficient variability
- BVAR-SV models are able to capture time variation in output tail risks — with downside risks more variable than upside risks — like that emphasized in ABG
- BVAR-SV scores as well as QR for downside tail risks