Forecasting Economic Activity with MF-BVARs

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1. **Incorporates a broad set of real-time real activity indicators**
2. **Benchmark performance against private sector forecasts**
3. **Explore role of model size and other specification choices**

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   - Outperforms Blue Chip 2-4 quarters out in RMSFE

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Main Takeaway: Medium-large MF-BVAR reliably forecasts real GDP in real-time, at both short and medium-run horizons

1. **Performs favorably against private sector forecasts**
   - Outperforms Blue Chip 2-4 quarters out in RMSFE
2. **Specification choices matter**
   - **Large** set of real activity indicators valuable, especially in nowcasting
   - Considerable gains in levels vs. growth rates
   - Optimal shrinkage selection matters for nowcasting

Related Literature on Forecasting

Bayesian VARs: Doan et al. (1984), Litterman (1986), Bańbura et al. (2010), Carriero et al. (2012), Koop (2013), Carriero et al. (2015), Giannone et al. (2015)...

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MF-BVARs: McCracken et al. (2017), **Schorfheide and Song (SS, 2015)**

What's new here?

- Use large real-time dataset suitable for Central Bank forecasting
  - 17-23% RMSFE gains relative to them, primarily since Great Recession
- In-depth analysis of specification choices

Outline

1. Description of the model
   - Mixed-frequency state-space
   - Priors
   - Data and baseline
2. Real-time RMSFE comparisons
   - Blue Chip
   - Alternative specifications
   - Schorfheide and Song

Mixed-frequency state-space

Observables $y_t' = \left[\begin{array}{ccc} y_t^{q'} & , & y_t^{m'} \end{array} \right]$

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- y_t^q: quarterly (low) frequency

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Monthly variables: $x_t' = \left[\begin{array}{ccc} x_t^{q'} & , & x_t^{m'} \end{array} \right]$

- x_t^m : equals y_t^m, when available
- x_t^q: latent variables subject to temporal aggregation constraint

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- x_t^m : equals y_t^m, when available
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- follow VAR(p)

$$x_t = c + \Phi_1 x_{t-1} + ... + \Phi_p x_{t-p} + \epsilon_t; \quad \epsilon_t \sim i.i.d.\ N(0, \Sigma)$$

Priors and Shrinkage Hyperparameters

Prior for VAR Parameters $\theta = (c, \Phi_1, \ldots \Phi_p, \Sigma)$

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- rate of decay with lags
- sums of coefficients, or "own persistence"
- "co-persistence"

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2) Prior standard deviations, σ_0

Data driven priors

- Find hyperparameters and prior std to maximize Marginal Likelihood (ML)
$$(\lambda^*, \sigma_0^*) = argmax\ P(Y_{0:T}|\lambda, \sigma_0)$$
  - Giannone, Lenza, Primiceri (2015); Carriero, Clark and Marcelino (2015)

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  1. Analytical ML with interpolated data via bivariate BVARs to find grid
  2. Approximate correct ML (Modified Harmonic mean) over grid

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Inference with Gibbs sampler

Baseline MF-BVAR

- 37 variables in levels (logs or percent)
  - monthly (30): real activity
  - quarterly (7): GDP, BFI, RES, GOV, Inventories (INV), X, M

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- Evaluation sample: 2004:Q4 through 2016:Q1

  Run model mothly: 136 observations for out-of-sample evaluation

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Exp. Category	Description
PCE	**Personal Consumption Expenditures** Vehicle Sales Real Retail & Food Service Sales Real Manufacturers' New Orders Personal Savings Rate Real Personal Income Less Transfer Univ. of Michigan Consumer Expectations **Aggregate Weekly Hours Worked** Total Nonfarm Payroll Employment Civilian Employment **Civilian Unemployment Rate** Civilian Participation Rate Initial Claims Unemployment
BFI	**Industrial Production** Capacity Utilization

Exp. Category	Description
BFI (cont.)	Real Manufacturing & Trade Sales Real Manufacturers' New Orders ISM Manufacturing Index Philly Fed Manufacturing Business Outlook Real Private Nonresidential Construction
RES	Real Private Residential Construction Housing Starts Housing Permits
CIV	Real Manufacturing & Trade Inventories Total Business Inventory-Sales Ratio
GOV	Real Public Construction Spending Real Federal Outlays
NX	Real Exports of Goods Real Imports of Goods Trade Balance in Goods & Services

In Schorfheide and Song (2015)

Data: quarterly real NIPA

Gross Domestic Product

Fixed Investment (*)

Business Fixed Investment

Residential Investment

Government Expenditures & Investment

Exports of Goods & Services

Imports of Goods & Services

Nonfarm Inventories

In Schorfheide and Song (2015)

* We use BFI and RI instead

Forecast Evaluation

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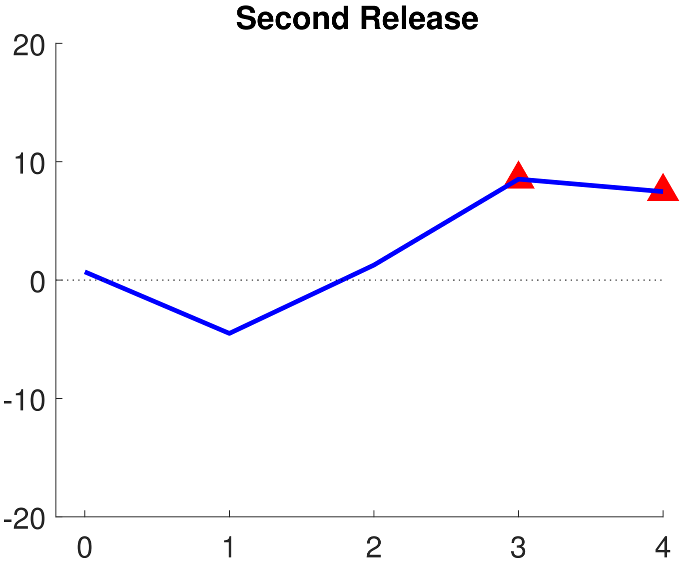
Diebold-Mariano/HLN for point forecasts

- Newey-West standard errors, lags equal to 25% sample (alternatives)

Real-time RMSFEG Comparisons

1. Blue Chip Consensus
2. Alternative specifications
3. Schorfheide and Song

1. Blue Chip Consensus: GDP growth RMSFEG gains



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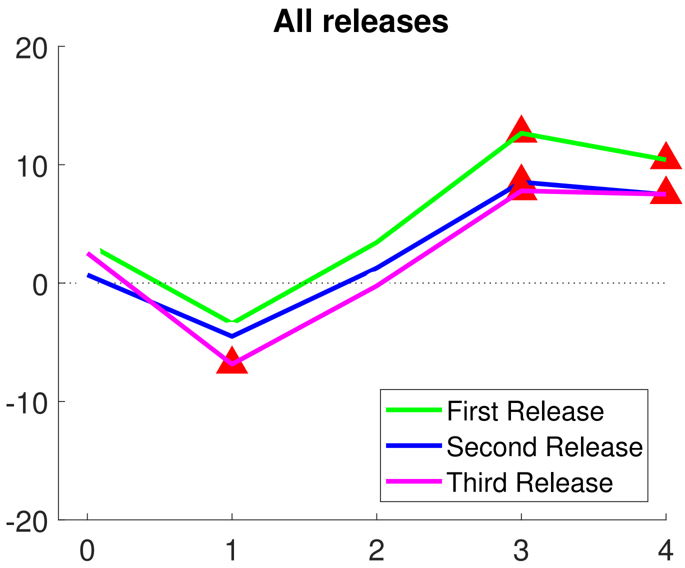

2. Alternative Specifications

- **Model Size**
  - smaller real models: sequentially add real activity indicators
    - grouped by NIPA expenditure component
  - also explore prices and financials (not today)
- **Levels vs. growth rates**
- **Data-driven vs. default hyperparameters**

2. Model Size: RMSFE Gains with Baseline

Model	SS Real
Number series	7
Horizon	
0	**21.3**
1	**14.8**
2	**17.4**
3	**17.3**
4	**12.3**

Bold: statistically significant

2. Model Size: RMSFE Gains with Baseline

Model	SS Real	+CONS
Number series	7	17
Horizon		
0	**21.3**	**13.0**
1	**14.8**	**7.3**
2	**17.4**	**8.2**
3	**17.3**	**12.0**
4	**12.3**	**11.8**

Bold: statistically significant

2. Model Size: RMSFE Gains with Baseline

Model	SS Real	+CONS	+BFI
Number series	7	17	23
Horizon			
0	**21.3**	**13.0**	**6.2**
1	**14.8**	**7.3**	6.4
2	**17.4**	**8.2**	**10.9**
3	**17.3**	**12.0**	**14.6**
4	**12.3**	**11.8**	**13.2**

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2. Model Size: RMSFE Gains with Baseline

Model	SS Real	+CONS	+BFI	+RES
Number series	7	17	23	27
Horizon				
0	**21.3**	**13.0**	**6.2**	**9.4**
1	**14.8**	**7.3**	6.4	2.3
2	**17.4**	**8.2**	**10.9**	**5.0**
3	**17.3**	**12.0**	**14.6**	**7.4**
4	**12.3**	**11.8**	**13.2**	**5.6**

Bold: statistically significant

2. Model Size: RMSFE Gains with Baseline

Model	SS Real	+CONS	+BFI	+RES	+CIV
Number series	7	17	23	27	30
Horizon					
0	**21.3**	**13.0**	**6.2**	**9.4**	**6.6**
1	**14.8**	**7.3**	6.4	2.3	1.2
2	**17.4**	**8.2**	**10.9**	**5.0**	2.4
3	**17.3**	**12.0**	**14.6**	**7.4**	**3.3**
4	**12.3**	**11.8**	**13.2**	**5.6**	0.5

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2. Model Size: RMSFE Gains with Baseline

Model	SS Real	+CONS	+BFI	+RES	+CIV	+GOV
Number series	7	17	23	27	30	32
Horizon						
0	**21.3**	**13.0**	**6.2**	**9.4**	**6.6**	**6.7**
1	**14.8**	**7.3**	6.4	2.3	1.2	0.8
2	**17.4**	**8.2**	**10.9**	**5.0**	2.4	2.4
3	**17.3**	**12.0**	**14.6**	**7.4**	**3.3**	3.0
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Model	SS Real	+CONS	+BFI	+RES	+CIV	+GOV
Number series	7	17	23	27	30	32
Horizon						
0	**21.3**	**13.0**	**6.2**	**9.4**	**6.6**	**6.7**
1	**14.8**	**7.3**	6.4	2.3	1.2	0.8
2	**17.4**	**8.2**	**10.9**	**5.0**	2.4	2.4
3	**17.3**	**12.0**	**14.6**	**7.4**	**3.3**	3.0
4	**12.3**	**11.8**	**13.2**	**5.6**	0.5	1.3

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2. Other specifications: RMSFE Gains with Baseline

- Growth Rates: **10-13** percent gains in levels, horizons 0 through 3, statistically significant

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- Default hyperparameters: **19** percent gain at nowcast from data-driven shrinkage, far less important at longer horizons
- Lag length: some deterioration in RMSFE with longer lags
- Rolling sample: somewhat better performance with recursive samples

3. Comparison to SS: RMSFE Gains with Baseline

Evaluation	*RT* 04m10-16m3
Horizon	
0	**23.5**
1	**19.5**
2	**23.8**
3	**22.5**
4	**17.4**

Bold: statistically significant

3. Comparison to SS: RMSFE Gains with Baseline

Evaluation	*RT* 04m10-16m3	*Pseudo* 98m10-07m11	*Pseudo* 07m12-16m3
Horizon			
0	**23.5**	3.5	**16.7**
1	**19.5**	7	**18.9**
2	**23.8**	5.8	**29.7**
3	**22.5**	2.4	**29.1**
4	**17.4**	**-4**	**27**

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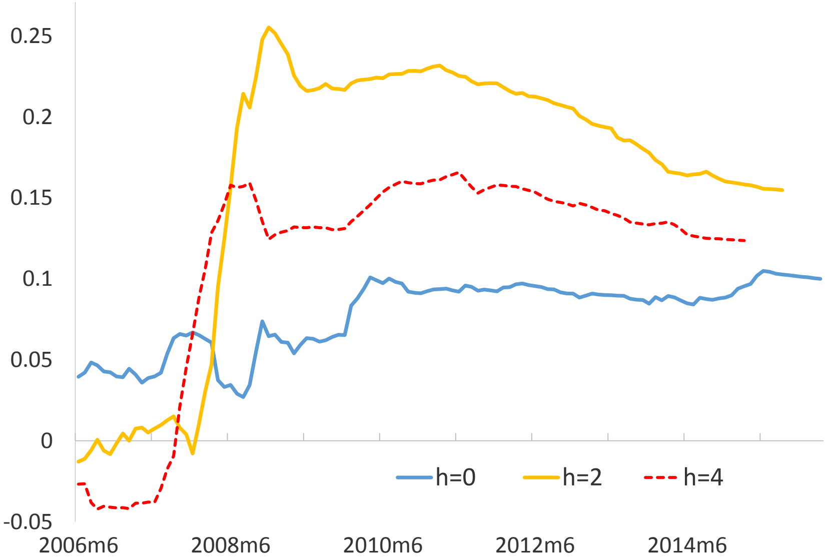
Conclusions

Medium-large MF-BVAR reliably forecasts real GDP growth in real-time, both at short and medium-run horizons

- Performs favorably against private sector forecasts
- Large set of real activity indicators valuable
- Big gains in levels vs. growth rates
- Massive gains relative to Schorfheide and Song, primarily since Great Recession

Average RMSFE Differences: SS less Baseline



2. Other specifications: RMSFE Gains with Baseline

Model	Growth Rates	Default Hyperparameters
Number series	37	37
Horizon		
0	**11.3**	**19.1**
1	**10.2**	- 1.6
2	**12.4**	- **2.3**
3	**12.6**	- 1.7
4	7.9	- 2.7

Bold: statistically significant