Financial Nowcasts and Their Usefulness in Macroeconomic Forecasting

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I Introduction

1. Renewed interest in financial variables for forecasting since the financial crisis
   - Stock and Watson (2003): mixed evidence
   - Recently: financial variables useful out-of-sample
   - E.g., Ghysels and Wright (2009); Espinoza, Fornari, Lombardi (2012); Faust, Gilchrist, Wright, and Zakrajšek (2012); Andreou, Ghysels, and Kourtellos (2013); Alessi, Ghysels, Onorante, Peach, and Potter (2014)

I Introduction

1. Renewed interest in financial variables for forecasting since the financial crisis
2. Growing interest in models featuring data at different frequencies
   - Nowcasting with dynamic factor models; e.g., Giannone, Reichlin, and Small (2008)
   - Mixed-frequency VARs
   - Mixed-data sampling (MIDAS)
   - Nowcasting and forecasting enhancements from capturing intraquarterly data

I Introduction

1. Renewed interest in financial variables for forecasting since the financial crisis
2. Growing interest in models featuring data at different frequencies
3. Importance of good nowcasts for multi-step forecasts in quarterly models
   - Faust and Wright (2013) for inflation
   - Del Negro and Schorfheide (2013), Schorfheide and Song (2015) for GDP growth

I Introduction

Suppose I have a quarterly model for forecasting and policy analysis that contains financial variables

- Real-world forecasts are usually made when some intraquarterly financial data are already available

1. Is there a benefit to conditioning on that intraquarterly data when making forecasts?
2. And if so, how to form the appropriate quarterly financial nowcasts?
3. How does this approach compare with mixed-frequency forecasting approaches?

I Introduction

Is there a benefit to conditioning on intraquarterly financial data when making forecasts?

- Generally yes, but with some caveats
- Helps to forecast conditional on multiple nowcasts

How to form the quarterly financial nowcasts?

- Average of available daily readings coupled with a daily random walk to complete the quarter

Forecast accuracy compared with mixed-frequency models?

- Generally quite competitive

II Models

Baseline: quarterly vector autoregressive models estimated using Bayesian methods

- 4 lags, Minnesota and sum-of-coefficient priors, etc.
- Well-documented forecasting properties
- E.g., Bańbura, Giannone, and Reichlin (2010); Koop (2013); Carriero, Clark, and Marcellino (2015)

II Models

Primary variables of interest: GDP, unemployment rate, CPI inflation, effective federal funds rate (policy rate)

- Treat the policy rate as a variable to forecast rather than a financial variable

Other variables of interest: consumption, total nonfarm payroll employment, productivity, core CPI inflation (excludes food and energy), employment cost index (a measure of labor compensation)

II Models

How to model financial variables?

- Rates as levels
  - BAA rate; 10-year Treasury rate; 3-month Treasury rate; S&P 500 index; broad trade-weighted dollar
- Rates as spreads
  - Credit/risk spread (BAA rate minus 10-year Treasury rate); term spread (10-year Treasury rate minus 3-month Treasury rate); S&P 500 index
- Financial factor from 58 financial variables (Andreou et al. 2013)

II Models

20 sets of results: 10 models and 2 evaluation periods

- Size: small-scale BVARs (4 variables of interest + financials) v. medium-scale BVARs (9 variables of interest + financials)
- Financial variables: (1) rate levels v. (2) rate spreads v. (3) financial factor
- Estimation period: 1959 onward v. 1985 onward (to account for potential break in VAR dynamics)
- Forecast evaluation period: 1994Q1-2015Q4 (includes financial crisis, Great Recession, aftermath) v. 1994Q1-2006Q4 (pre-crisis)

III Data

Goal: generate and evaluate out-of-sample forecasts based on real-time data

- Construct a real-time dataset from St. Louis Fed's ALFRED and Philadelphia Fed's RTDSM; very limited use of pseudo real-time data
- Financial variables are real-time by construction
- Quarterly financials = average for the quarter
- Current-vintage data as the "truth"
- Real-time macro data as of the survey date for the Survey of Professional Forecasters in each quarter

IV Conditional Forecasting with Financial Nowcasts

How to make conditional forecasts?

- Use “hard” conditioning in the Sims-Zha tradition; e.g., Waggoner and Zha (1999); Doan, Litterman, and Sims (1984)
- Omit uncertainty around that nowcast value in the current quarter

IV Conditional Forecasting with Financial Nowcasts

We examine relative MSEs for model *i*, variable *v*, horizon *h*:

$$\mu_{i,v,h} = \frac{MSE^{C}_{i,v,h}}{MSE^{U}_{i,v,h}}$$

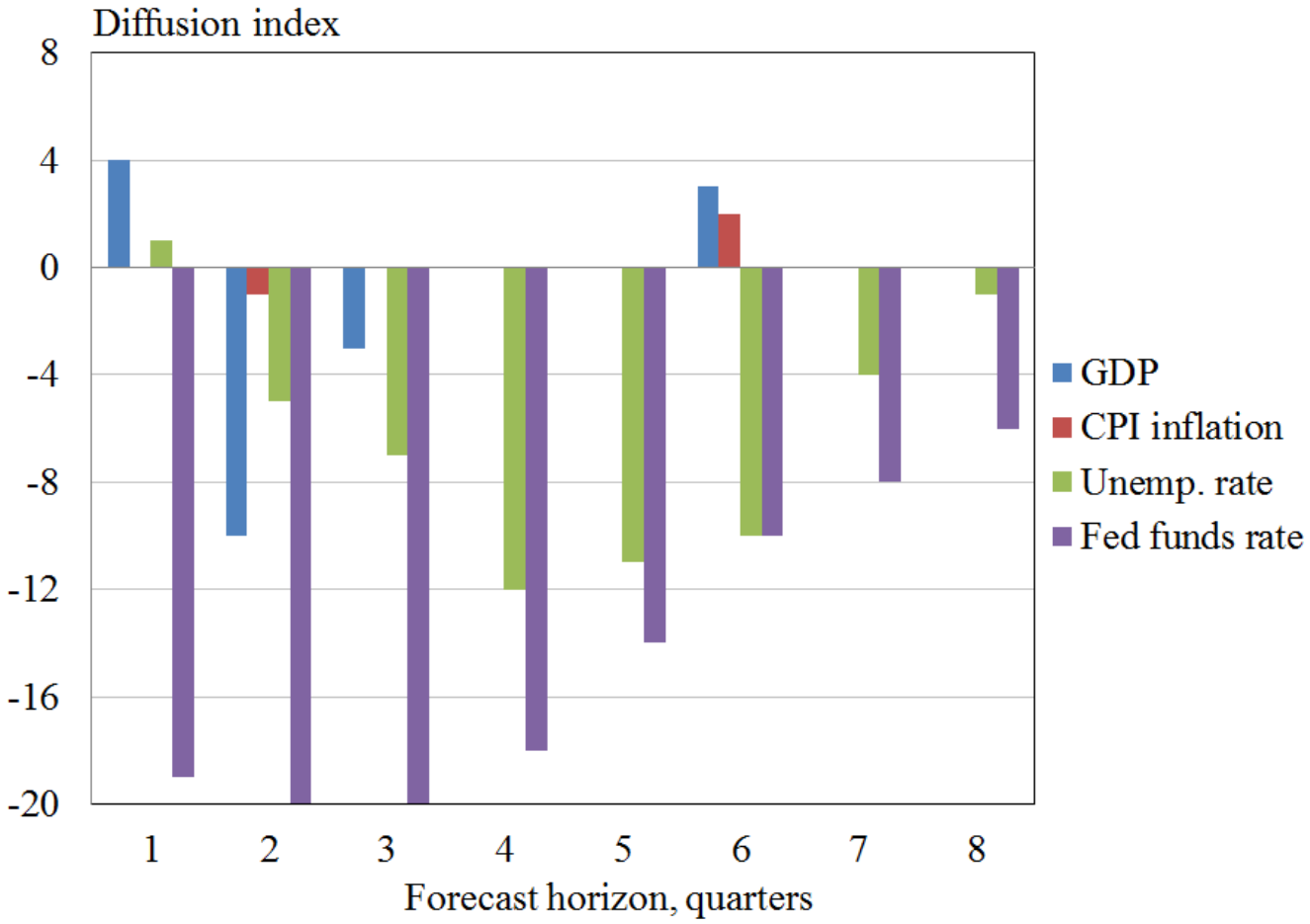
Summarize results by means of diffusion indexes

- $f_{i,v,h} = 1$ if $\mu_{i,v,h} \geq 1.1$
- $f_{i,v,h} = -1$ if $\mu_{i,v,h} \leq 0.9$
- (Diffusion index)$_{v,h} = \sum_i f_{i,v,h}$
- E.g., −20 implies notable improvements in forecast accuracy for conditional model across all specifications

IV Conditional Forecasting with Financial Nowcasts

1. Does conditioning on (only) the actual financial outcomes in a quarter improve forecast accuracy?
   - i.e., does knowledge of the financials help with forecast accuracy?

+3 months of financial data for nowcasts



Diffusion index = number of models with relative MSE≥1.1 minus the number of models with relative MSE≤0.9. Relative MSEs less than 1 favor the conditional forecast.

IV Conditional Forecasting with Financial Nowcasts

1. Does conditioning on (only) the actual financial outcomes in a quarter improve forecast accuracy?
   - In general, yes
   - Most notable improvements for unemployment rate, fed funds rate
   - But some caveats, especially for the one-step-ahead forecast/nowcast for GDP growth

IV Conditional Forecasting with Financial Nowcasts

1. Does conditioning on (only) the actual financial outcomes in a quarter improve forecast accuracy?
2. How to make financial variable nowcasts?

Nowcasting quarterly financial variables

RMSEs for nowcasts of quarterly financial variables, 1994Q1-2015Q4

	S&P 500	10-yr Treas.	3-mo Treas.	BAA yield	Exch. rate	Risk spread	Term spread
+1 month							
Average available + daily RW	2.510	**0.179**	**0.126**	**0.127**	**1.090**	0.117	**0.169**
MIDAS, daily data, beta (zero last lag)	2.972	0.185	0.135	0.144	1.216	0.128	0.177
MF-DFM (average of 24 models)	**2.473**	0.194	0.128	0.152	1.169	**0.114**	0.173
Average available	3.178	0.200	0.176	0.150	1.407	0.158	0.210

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Average available	3.178	0.200	0.176	0.150	1.407	0.158	0.210
+2 months							
Average available + daily RW	**0.886**	**0.056**	0.048	**0.049**	**0.393**	0.039	**0.066**
MIDAS, daily data, beta (zero last lag)	1.158	0.067	0.049	0.061	0.473	0.050	**0.066**
MF-DFM (average of 24 models)	0.983	0.066	**0.047**	0.057	0.430	**0.038**	0.074
Average available	1.442	0.107	0.087	0.077	0.662	0.082	0.105

IV Conditional Forecasting with Financial Nowcasts

1. Does conditioning on (only) the actual financial outcomes in a quarter improve forecast accuracy?
2. How to make financial variable nowcasts?
   - Easy to improve upon the average of the available data
   - Simple, powerful: average of available daily plus daily random walk to complete the quarter
   - Superior to survey nowcasts from SPF, Blue Chip

Relative RMSEs: Blue Chip Financial Forecasts v. Financial Variable Nowcasts

Financial variable nowcasts = average available + daily random walk, 2001Q1-2015Q4

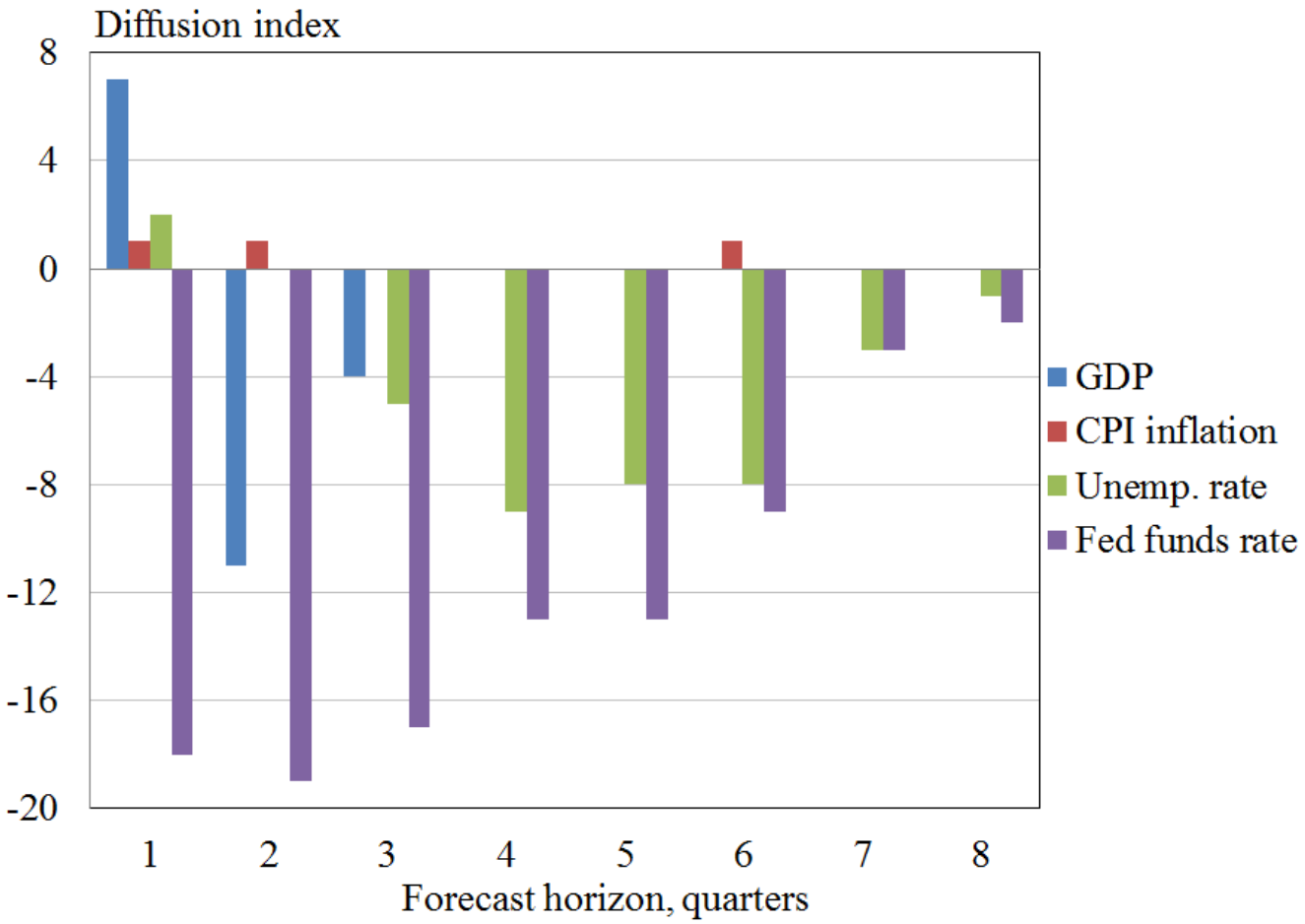
	10-yr Treas.	3-mo Treas.	BAA yield	Exch. rate	Risk spread	Term spread
Release date: 1st of month 1						
Relative RMSE: BCFF/model	1.27*	1.26	1.64**	1.90	1.79	1.16
Release date: 1st of month 2						
Relative RMSE: BCFF/model	1.26***	1.07	1.47***	1.56***	1.47*	1.27***
Release date: 1st of month 3						
Relative RMSE: BCFF/model	1.40***	1.52***	1.74***	3.25***	2.07***	1.32**

Statistical significance based on Diebold-Mariano test

IV Conditional Forecasting with Financial Nowcasts

1. Does conditioning on (only) the actual financial outcomes in a quarter improve forecast accuracy?
2. How to make financial variable nowcasts?
3. Does conditioning on financial variable nowcasts in a quarter improve forecast accuracy?

+1.5 months of financial data for nowcasts



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IV Conditional Forecasting with Financial Nowcasts

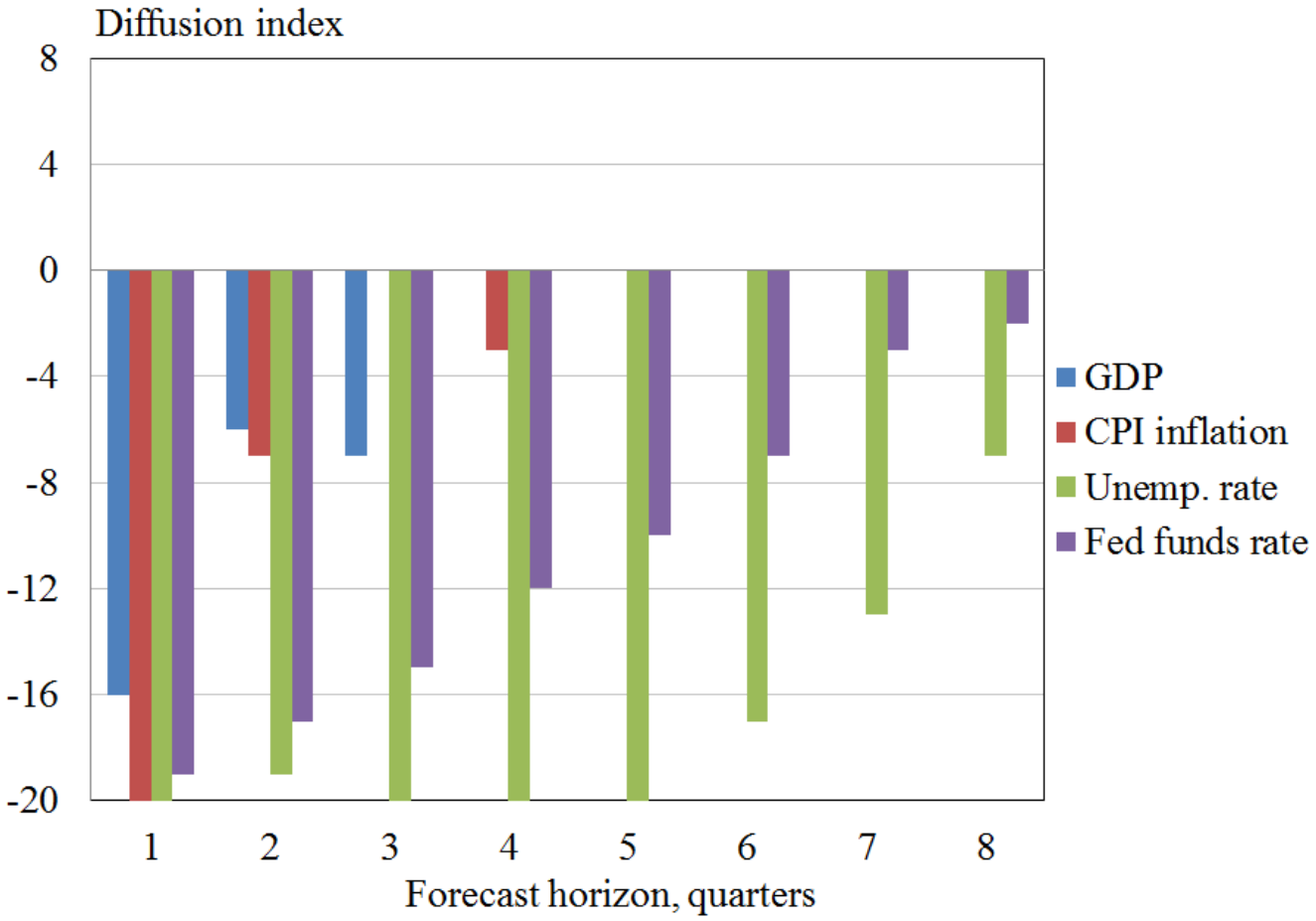
1. Does conditioning on (only) the actual financial outcomes in a quarter improve forecast accuracy?
2. How to make financial variable nowcasts?
3. Does conditioning on financial variable nowcasts in a quarter improve forecast accuracy?
   - Yes, in general
   - Some evidence of the weak contemporaneous relationship between financial variables and macro variables, some evidence of difficulties in nowcasting the former

V Conditional Forecasting with Financial Nowcasts and Other Nowcasts

Conditional forecasts made using financial nowcasts can sometimes *worsen* near-term forecast accuracy while improving forecast accuracy farther into the future

- How to fix this?
- Add nowcasts of other variables as additional conditions
- Augment financial nowcast conditions with nowcast conditions for GDP, unemployment, and CPI inflation from the SPF (e.g., at +1.5 months)

+1.5 months of financial data for nowcasts & other nowcasts



Diffusion index = number of models with relative MSE≥1.1 minus the number of models with relative MSE≤0.9. Relative MSEs less than 1 favor the conditional forecast.

V Conditional Forecasting with Financial Nowcasts and Other Nowcasts

Forecasting improvements are not just coming from the other nowcasts

Which nowcasts drive forecast improvements?

Share of forecasts that use financial & other nowcasts with lower RMSEs compared with forecasts using only other nowcasts, 1994Q1-2015Q4

Forecast horizon (quarters)	2	3	4	5	6	7	8
GDP growth	95	100	95	60	25	75	55
CPI inflation	50	45	65	75	40	70	80
Unemployment rate	30	60	80	80	80	75	80
Fed funds rate	100	100	100	85	90	85	90

Notes: All numbers are percentages. 100% = conditioning on both financial & other nowcasts always generates smaller RMSEs than conditioning on only other nowcasts; 0% = conditioning on only other nowcasts always generates smaller RMSEs than conditioning on both financial & other nowcasts

VI Horseraces with Mixed-Frequency Models

Compare with MIDAS models, similar in spirit to Schorfheide and Song (2015)

- Using either a conditioned quarterly BVAR model or a daily MIDAS model:
  - Bivariate regressions: one variable of interest and one financial variable; generate multi-step forecasts; repeat for other financial variables; average; compute RMSEs
  - Repeat for each variable of interest
- Estimated using data 1985 onward, recursive forecast evaluation 1994Q1-2015Q4

Conditional Forecasts from Quarterly BVARs v. MIDAS

Relative RMSEs: average of bivariate BVAR forecasts to average of bivariate MIDAS forecasts, 1994Q1-2015Q4

Forecast horizon (quarters)	1	2	3	4	5	6	7	8
+1 month								
GDP growth	1.00	0.94**	0.96	0.96	0.92**	0.94	0.97	0.95
CPI inflation	0.99	0.88	0.92*	0.88*	0.91*	0.95	0.91	0.88
Unemployment rate	1.06	1.02	1.00	1.02	1.06	1.08	1.08	1.08
Fed funds rate	1.10	0.95	0.98	1.00	1.02	1.04	1.06	1.07

Statistical significance based on Diebold-Mariano test

Conditional Forecasts from Quarterly BVARs v. MIDAS

Relative RMSEs: average of bivariate BVAR forecasts to average of bivariate MIDAS forecasts, 1994Q1-2015Q4

Forecast horizon (quarters)	1	2	3	4	5	6	7	8
+1 month								
GDP growth	1.00	0.94**	0.96	0.96	0.92**	0.94	0.97	0.95
CPI inflation	0.99	0.88	0.92*	0.88*	0.91*	0.95	0.91	0.88
Unemployment rate	1.06	1.02	1.00	1.02	1.06	1.08	1.08	1.08
Fed funds rate	1.10	0.95	0.98	1.00	1.02	1.04	1.06	1.07
+2 months								
GDP growth	1.04	0.93*	0.94	0.95	0.93*	0.96	0.95	0.95
CPI inflation	0.99	0.88*	0.92*	0.87**	0.91	0.94	0.91	0.88
Unemployment rate	1.09	1.03	1.00	1.02	1.05	1.07	1.08	1.08
Fed funds rate	1.14	0.97	0.97	1.00	1.02	1.04	1.06	1.07

Statistical significance based on Diebold-Mariano test

VI Horseraces with Mixed-Frequency Models

Forecast accuracy of quarterly BVARs using nowcasts of financial variables as conditions highly competitive with forecast accuracy from MIDAS models

VI Horseraces with Mixed-Frequency Models

Compare conditional forecasts from quarterly BVAR with MF-DFM

- Same variables in both models with real-time data as of SPF survey dates
  - 9 macro variables (MF-DFM: 5 quarterly, 4 monthly)
  - 3 financial variables: risk spread (BAA-10yr), term spread (10yr-3mo), S&P 500 index (MF-DFM: daily)
- Generate multi-step forecasts, compute RMSEs
- Estimated using data 1985 onward, recursive forecast evaluation 1994Q1-2015Q4

VI Horseraces with Mixed-Frequency Models

Conditional forecasts from quarterly BVAR made with:

- For daily data: financial nowcasts
- For monthly data: use data from the first month of the quarter to nowcast the unemployment rate, nonfarm payroll employment, CPI inflation, core CPI inflation

Conditional Forecasts from Quarterly BVAR v. MF-DFM

Relative RMSEs: quarterly BVAR forecasts to
MF-DFM forecasts, 1994Q1-2015Q4

Forecast horizon (quarters)	1	2	3	4	5	6	7	8
GDP growth	0.98	0.97	1.03	1.06	1.05	1.05	1.06	1.10
CPI inflation	1.11	0.92	0.98	0.93	0.96	0.95	0.93	0.95
Unemployment rate	0.97	0.79	0.77	0.78	0.80	0.82	0.83	0.85
Fed funds rate	0.66***	0.79	0.87	0.90	0.91	0.90	0.88	0.86

Statistical significance based on Diebold-Mariano test

VI Horseraces with Mixed-Frequency Models

Forecast accuracy of quarterly BVARs using nowcasts of financial variables and macro variables highly competitive with forecast accuracy from MF-DFMs that directly incorporate mixed-frequency data

VII Conclusion

Using nowcasts of financial variables in quarterly BVAR models can yield gains in multi-step forecasting accuracy

- Quarterly financial nowcasts: average of available daily data plus daily random walk highly accurate

Imposing additional nowcasts as conditions helps resolve problems with one-step-ahead forecasts… and improves multi-step forecast accuracy

Highly competitive with MIDAS models, MF-DFMs