

# Forecasting Regional and Industry-Level Variables: Challenges and Strategies

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Slides available at

<http://pages.slu.edu/faculty/rapachde/Research.htm>

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- Forecasting **regional** & **industry**-level variables important for
  - Policymakers at all levels of government
  - Private sector agents
  - Academics
- Exacerbates typical forecasting challenges
  - **Model uncertainty**
    - Plethora of potential predictors—global, national, regional, industry variables
    - Theoretical models usually highly stylized
  - **Structural instability**
    - Predictive ability can vary markedly over time
    - Difficult to anticipate structural changes

# Strategies with many potential predictors

- General (“kitchen sink”) model
  - Include all potential predictors in single model
- General-to-specific (GTS) modeling
  - Pre-test to remove “unimportant” predictors
- GTS with bootstrap aggregating (“bagging”)
  - Provides new learning sets for predictor selection
- Forecast combination
  - Weighted average of individual model forecasts
- Factor model
  - Regional/industry variable =  $f(\text{small \# of aggregate factors})$

- Over-reliance on one/small number of predictors is **risky**
- Incorporate information from large number of potential predictors to **diversify risk**
  - Similar to portfolio diversification (Timmermann, 2006)
  - Of course, **theory** should inform selection of potential predictors
- However, **over-parameterized** models usually perform very poorly
- So, we need to incorporate information **efficiently**, imposing various types of restrictions
- Strong relation to aggregate economy can warrant factor structure

# Kitchen sink model

- Consider  $N$  potential predictors, where  $N$  is “large”
- Let  $\Delta y_{k,t+h}^h = (1/h) \sum_{j=1}^h \Delta y_{k,t+j}$
- $\Delta y_{k,t} = y_{k,t} - y_{k,t-1}$
- $k$  denotes region/industry
- KS:  $\Delta y_{k,t+h}^h = a + b\Delta y_{k,t} + \sum_{i=1}^N c_i x_{i,t} + e_{k,t+h}^h$
- Drawbacks
  - In-sample **over-fitting**
  - Typically delivers very poor out-of-sample forecasts
  - Estimation may be infeasible if  $N$  is large relative to in-sample period
- Eg, kitchen sink model performs very poorly for forecasting U.S. equity premium (Goyal & Welch, 2008; Rapach et al., forthcoming)

- Pre-test general model
  - Use decision rule to remove extraneous (“unimportant”) predictors
    - Eg, drop predictors with  $|t\text{-statistic}| < 1.96$
    - More sophisticated rules/algorithms available
- Sometimes known as “LSE approach”
- Drawbacks
  - Relies on single historical realization (over-fitting in another guise)
  - Unstable decision rule

- Use **bootstrap** procedure to generate pseudo-samples
- For each pseudo-sample, apply decision rule to identify included predictors
- Forecast = average across bootstrapped pseudo-samples
- Bootstrap aggregating (Breiman, 1996)
  - Provides new learning sets
  - Reduces decision rule instability
  - Can improve forecasting performance

# Forecast combination

- Individual ARDL:  $\Delta y_{k,t+h}^h = a + b\Delta y_{k,t} + c_i x_{i,t} + e_{k,t+h}^h$ 
  - Individual model forecast based on predictor  $x_{i,t}$
- Combination forecast:  $\Delta \hat{y}_{k,t+h}^{h,c} = \sum_{i=1}^N w_i \Delta \hat{y}_{k,t+h}^{h,i}$ 
  - $\sum_{i=1}^N w_i = 1$
  - Weighted average of individual model forecasts
- Various combining methods available
  - Simple (eg,  $w_i = 1/N$ )
  - Weights based on recent forecasting performance
  - Relatively simple schemes typically work better (Timmermann, 2006)
- Reduces forecast variance (Rapach et al., forthcoming)
  - Type of shrinkage forecast
- Improves forecasting in presence of structural breaks (Hendry & Clements, 2004)
  - Difficult to estimate/predict timing of breaks

- Factor structure:  $\Delta y_{k,t} = \alpha_k + \beta_k f_t + \epsilon_{k,t}$
- $f_t$  = aggregate factor
- Think of CAPM, where  $\Delta y_{k,t}$  = stock  $k$  excess return,  $\alpha_k = 0$ ,  $f_t$  = market excess return
- Regional structure:  $\Delta \hat{y}_{k,t+h}^{h,f} = \hat{\alpha}_k + \hat{\beta}_k \Delta \hat{y}_{US,t+h}^h + \hat{\epsilon}_{k,t+h}^h$
- Model serial correlation in disturbance term (if it exists)

- Options for model estimation window
  - Recursive (ie, expanding)
  - Rolling
  - Fixed
- Can be optimal to use recursive window even in presence of breaks, due to familiar bias-efficiency trade-off (Pesaran & Timmermann, 2007; Clark & McCracken, forthcoming)
- Can combine forecasts from different estimation windows
- Can use different window schemes to estimate combining weights

# Forecasting U.S. state-level employment growth

- Research project with Jack Strauss
- Consider range of predictors
  - State-level variables: unemployment rate, labor force, real housing price, real income
  - National variables: unemployment claims, new consumer good orders, building permits, stock prices, oil price
  - Adjacent state employment growth (spillovers)
- Full sample: 1976:1–2009:2
- Forecast evaluation period: 1989:3–2009:3, 2-quarter horizon
  - 1990–1991 recession
  - Long 1990s expansion
  - 2001 recession/“jobless” recovery
  - Recent crisis
- AR benchmark

# Individual ARDL model results

Employment growth, 1989:3–2009:2 forecast evaluation period

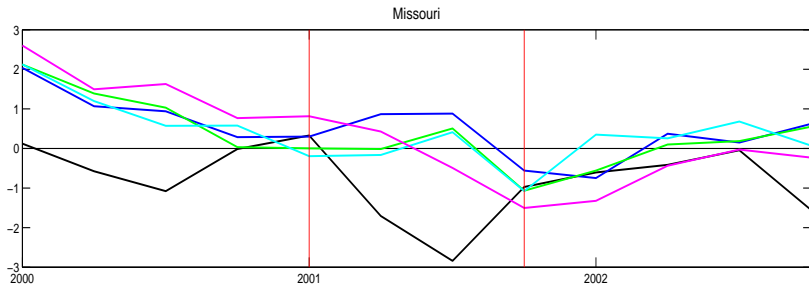
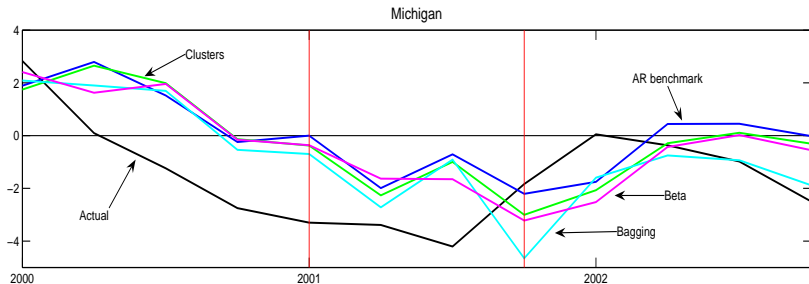
| Predictor     | US   | MI   | MO   | Avg. | # < 1 (%) | Min. | Max.  |
|---------------|------|------|------|------|-----------|------|-------|
| AR MSFE       | 1.15 | 3.57 | 2.35 | 3.36 | —         | 1.44 | 10.89 |
| State UNRATE  | 0.97 | 1.02 | 1.06 | 1.03 | 27 (54)   | 0.74 | 2.02  |
| State FORCE   | 0.98 | 0.86 | 1.05 | 1.25 | 15 (30)   | 0.86 | 8.57  |
| State HOUSING | 1.10 | 1.18 | 1.01 | 1.03 | 20 (40)   | 0.89 | 1.22  |
| State INCOME  | 1.02 | 1.20 | 1.06 | 1.15 | 11 (22)   | 0.94 | 6.06  |
| U.S. CLAIMS   | 0.87 | 0.91 | 0.76 | 0.90 | 43 (86)   | 0.70 | 1.90  |
| U.S. ORDERS   | 0.94 | 0.92 | 0.87 | 0.87 | 45 (90)   | 0.60 | 1.23  |
| U.S. PERMITS  | 0.97 | 1.00 | 0.94 | 1.05 | 26 (52)   | 0.71 | 3.69  |
| U.S. STOCK    | 0.71 | 0.85 | 0.84 | 0.87 | 45 (90)   | 0.55 | 1.03  |
| U.S. OIL      | 1.03 | 1.12 | 1.08 | 1.06 | 7 (14)    | 0.90 | 1.53  |
| ADJACENT      | —    | 1.05 | 0.96 | 1.02 | 25 (50)   | 0.69 | 3.30  |

# Other results

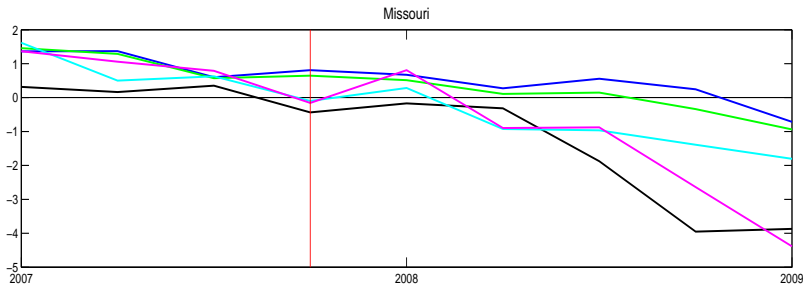
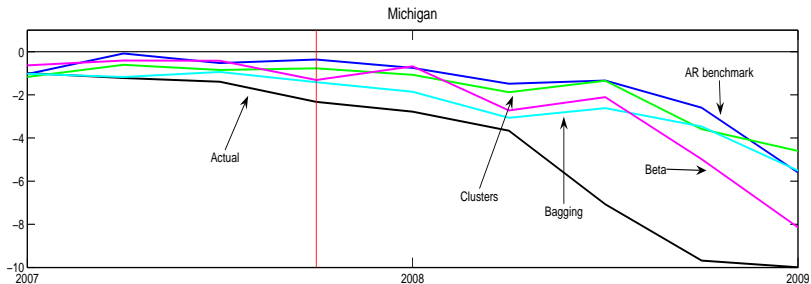
Employment growth, 1989:3–2009:2 forecast evaluation period

| Method         | US   | MI   | MO   | Avg. | # < 1 (%) | Min. | Max. |
|----------------|------|------|------|------|-----------|------|------|
| MEAN, state    | 0.95 | 0.98 | 0.94 | 0.96 | 43 (86)   | 0.81 | 1.39 |
| CLUSTER, state | 0.92 | 0.97 | 0.92 | 0.97 | 35 (70)   | 0.76 | 1.17 |
| MEAN, US       | 0.75 | 0.82 | 0.73 | 0.81 | 47 (94)   | 0.59 | 1.04 |
| CLUSTER, US    | 0.76 | 0.88 | 0.82 | 0.83 | 47 (94)   | 0.66 | 1.03 |
| MEAN, all      | 0.82 | 0.88 | 0.81 | 0.85 | 49 (98)   | 0.72 | 1.02 |
| CLUSTER, all   | 0.87 | 0.93 | 0.87 | 0.86 | 49 (98)   | 0.69 | 1.06 |
| GTS            | 1.26 | 1.20 | 1.10 | 1.09 | 25 (50)   | 0.69 | 2.42 |
| BAG            | 0.80 | 0.93 | 0.97 | 0.88 | 41 (82)   | 0.59 | 1.22 |
| CLUSTER-BAG    | 0.79 | 0.87 | 0.80 | 0.80 | 48 (96)   | 0.63 | 1.06 |
| BETA           | –    | 0.77 | 0.62 | 0.87 | 42 (84)   | 0.48 | 3.22 |
| CL.-BAG-BETA   | –    | 0.81 | 0.70 | 0.79 | 48 (96)   | 0.54 | 1.10 |

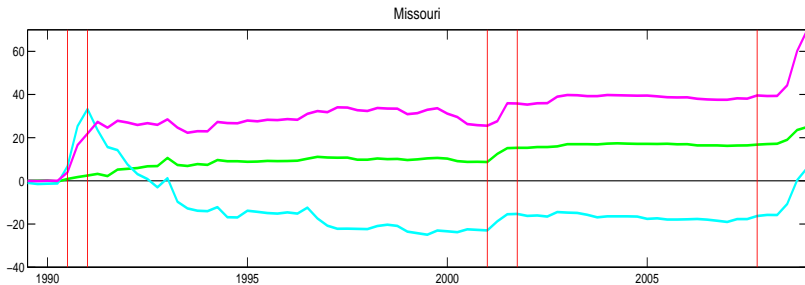
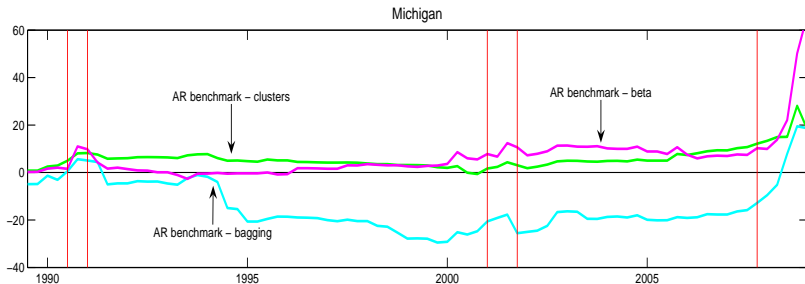
# Example forecasts, MI & MO, near 2001 recession



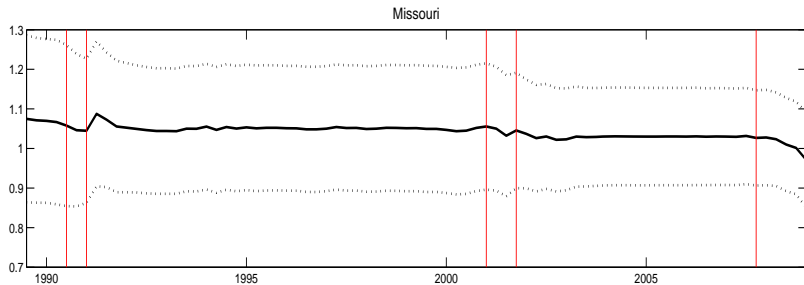
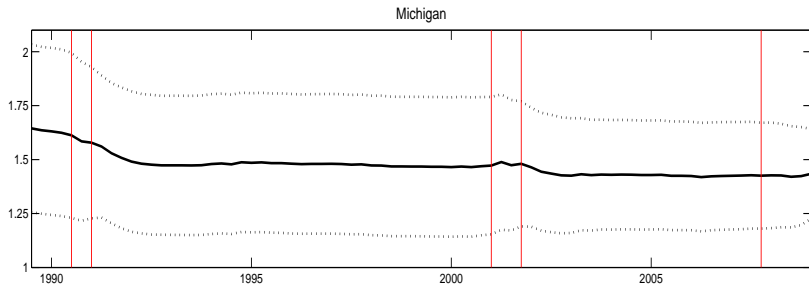
# Example forecasts, MI & MO, near recent crisis



# Difference in cumulative SFE, MI & MO



# Recursively estimated betas, MI & MO



- Rapach & Strauss (2009), “Differences in Housing Price Forecastability Across U.S. States,” *International Journal of Forecasting*
- Rapach et al. (2009), “How Predictable are Components of the Aggregate Market Portfolio?”

- Forecasting regional/industry-level variables can be more challenging than forecasting aggregates
  - Some idiosyncracies 'wash out' in aggregate
- Begin with seemingly naive time-series model, such as AR
  - Stringent benchmark—might be best you can do
- Use extensive backtesting
  - Goyal & Welch (2008) figure very helpful
- Consider combining across strategies