Large-Scale Dynamic Predictive Regressions

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Modelling with Big Data and Machine Learning:
Interpretability and Model Uncertainty

Set the Stage

A decision maker $\mathcal{D}$ wants to predict some quantity y based on a set of predictors $\boldsymbol{z}$.

A canonical approach is

$$y_t = \boldsymbol{\beta}' \boldsymbol{z}_{t-1} + \epsilon_t, \qquad \epsilon_t \sim \pi(0, \nu_t)$$

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Data-rich environments:

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Limitations of conventional approaches:

- OLS, MLE, Bayes with flat priors fail out-of-sample.
- Curse of dimensionality (over-fitting).

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Forecasting with many predictors:

Sparse Modeling (regularization/shrinkage)	**Dense Modeling (factor models)**

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Selection of few variables with the highest explanatory power

- E.g., Lasso, Elastic-Net, SSVS (spike-and-slab).

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- E.g., Lasso, Elastic-Net, SSVS (spike-and-slab).

Pros:

- Interpretability of the output.
- Parsimony.

Cons:

- Illusion of sparsity (see Giannone et al. 2018).
- Unstable over time.
- Could shrink variables that matter (for decision making).

Set the Stage

Forecasting with many predictors:

Dense Modeling
(factor models)

Few common components capture statistical features of a large set of predictors

- E.g., PCA/Factor Analysis.

Set the Stage

Forecasting with many predictors:

Pros:

- Widely used for predictions.
- Works well out-of-sample.

Cons:

- Lacks of interpretability (ex-post heuristics).
- Lacks of decision insight (un-supervised learning).

Dense Modeling (factor models)

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- E.g., PCA/Factor Analysis.

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(regularization/shrinkage)

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Both approaches mitigate over-fitting by reducing model complexity, i.e., reducing model's variance.

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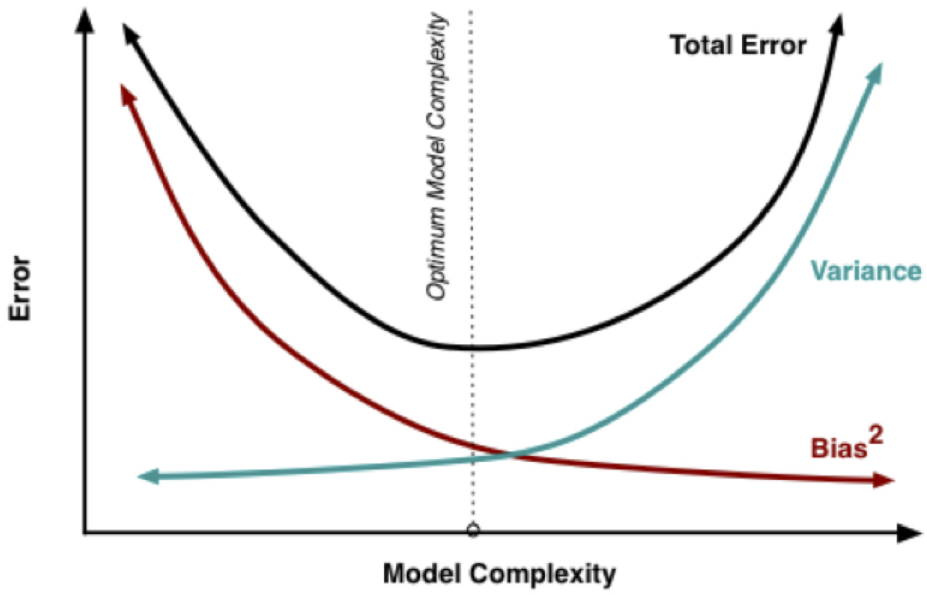
Balance bias-variance trade-off through cross-validation or using information criteria.



Set the Stage

What we do: we propose a large-scale predictive strategy:

- based on ensembling smaller models (aggreg. of weak/biased learners).

  Low variance and bias sequentially corrected.

- does not assume/impose sparsity (we retain all the data).
- keeps some economic interpretability (relative "weights" of predictors).

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Results: better out-of-sample predictability compared to conventional sparse/dense predictive strategies,

- Substantial economic gains when forecasting stock returns.
- Results are rationalized in simulation.

Outline

1. Modeling Framework
   - Decouple-Recouple Predictive Strategy.
2. Estimation (Markov Chain Monte Carlo)
3. Empirical Study
   - Forecasting U.S. inflation.
   - Forecasting stock returns across U.S. industries.
4. Simulation Study
5. Conclusion

Decoupling-Recoupling Predictive Strategy

$$y_t = \boldsymbol{\beta}_1' \boldsymbol{z}_{t-1,1} + ... + \boldsymbol{\beta}_j' \boldsymbol{z}_{t-1,j} + ... + \boldsymbol{\beta}_J' \boldsymbol{z}_{t-1,J} + \epsilon_t$$

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$$h_1(x_1) = p(y_{t+k}|\mathcal{A}_1) \qquad h_j(x_j) = p(y_{t+k}|\mathcal{A}_j) \qquad h_J(x_J) = p(y_{t+k}|\mathcal{A}_J)$$

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$$\hat{y}_{t+k}$$

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Issues :

- Predictions are biased and correlated.
- You may have your own prior $p(y)$.

Bayesian Predictive Synthesis

General result:

$$p(y|\mathcal{H}) = \int \alpha(y|\boldsymbol{x})h(\boldsymbol{x})d\boldsymbol{x} \qquad \text{where} \qquad h(\boldsymbol{x}) = \prod_{j=1}^{J} h_j\left(x_j\right)$$

Lindley (1983,1985), Genest and Schervish (1985), Crosse and West (1992), West (1991,1992)

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Latent Factors

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Synthesis Function
(Conditional Specification)

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! Necessary condition !

$$p(y) = \int \alpha(y|\boldsymbol{x}) m(\boldsymbol{x}) d\boldsymbol{x}$$

$$m(\boldsymbol{x}) = E\left[\prod_{j=1}^{J} h_j(x_j)\right]$$

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N.B: The functional form of $\alpha(y|\boldsymbol{x})$ is left unspecified by the theory.

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Dynamic Synthesis Function

We follow McAlinn and West (2018) and McAlinn et al. (2018) and assume

$$p(y_t|\boldsymbol{\Phi}_t, \mathcal{H}_t) = \int \alpha(y_t|\boldsymbol{x}_t, \boldsymbol{\Phi}_t) h_t(\boldsymbol{x}_t) d\boldsymbol{x}_t$$

$\boldsymbol{x}_t = (x_1, \ldots, x_J)'$ vector of latent states at time t

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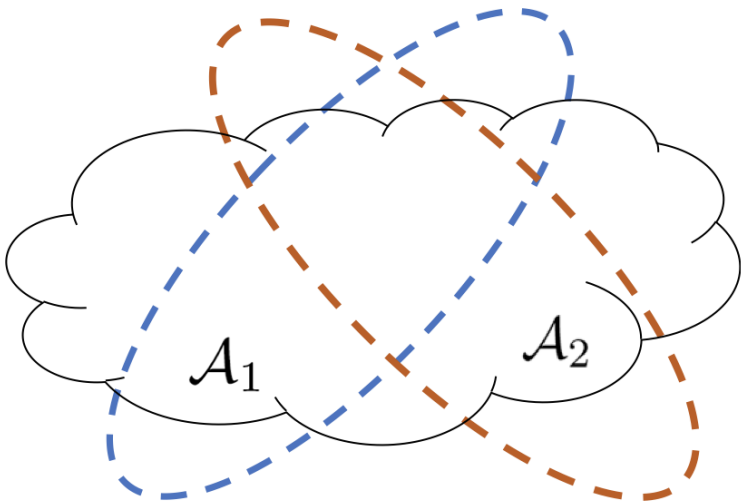
Dynamic Latent Factor Model

$\boldsymbol{x}_t = (x_1, \ldots, x_J)'$ vector of latent states at time t

$$y_t = \boldsymbol{F}_t' \boldsymbol{\theta}_t + \nu_t, \quad \nu_t \sim N(0, v_t),$$
$$\boldsymbol{\theta}_t = \boldsymbol{\theta}_{t-1} + \boldsymbol{\omega}_t, \quad \boldsymbol{\omega}_t \sim N(0, v_t \boldsymbol{W}_t),$$
$$\boldsymbol{\Phi}_t = (\boldsymbol{\theta}_t, v_t)$$
$$\boldsymbol{F}_t = (1, \boldsymbol{x}_t')' \quad \text{and} \quad \boldsymbol{\theta}_t = (\theta_{t0}, \theta_{t1}, ..., \theta_{tJ})'$$

Digression: Yet Another Model Combination?



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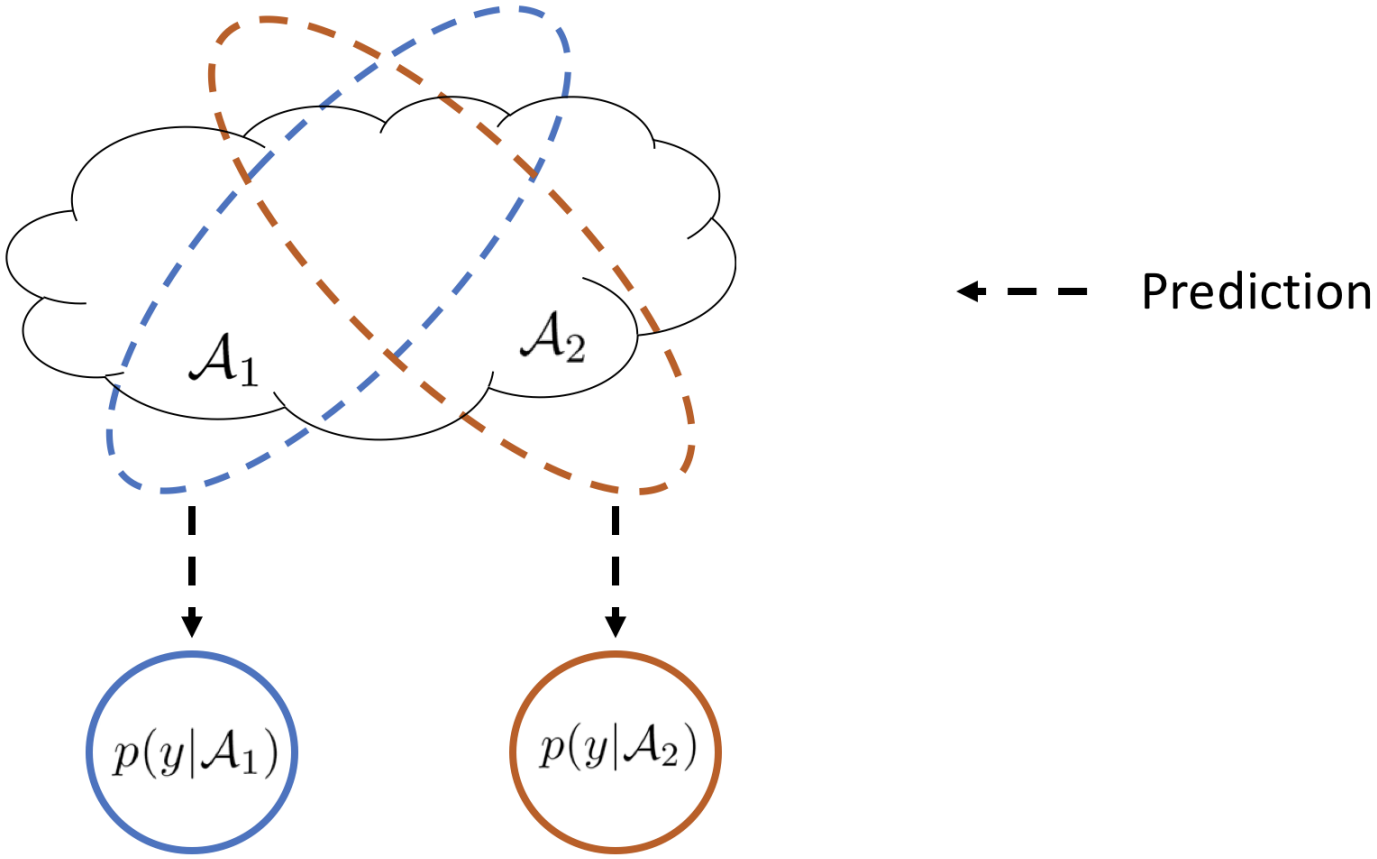

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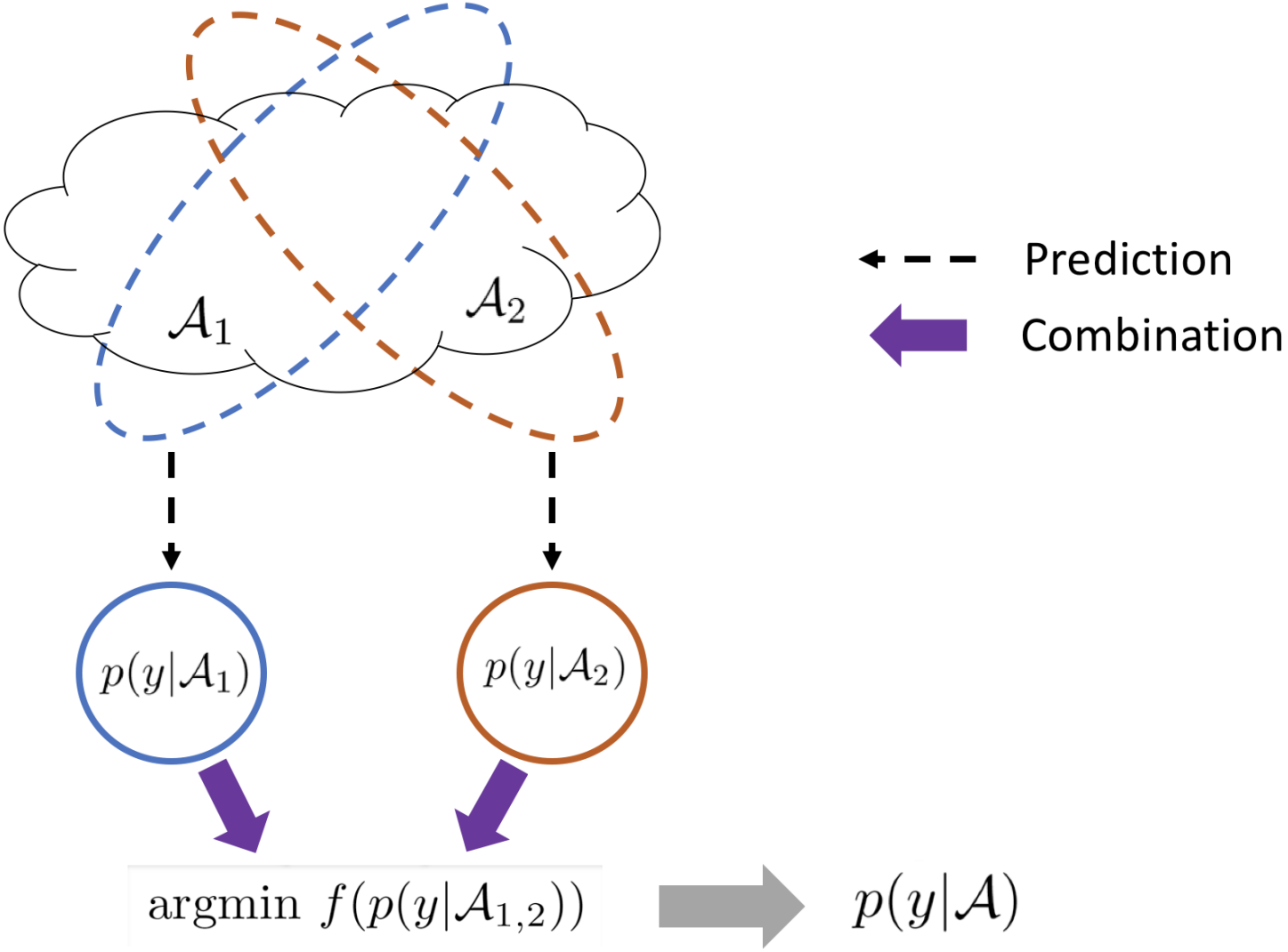

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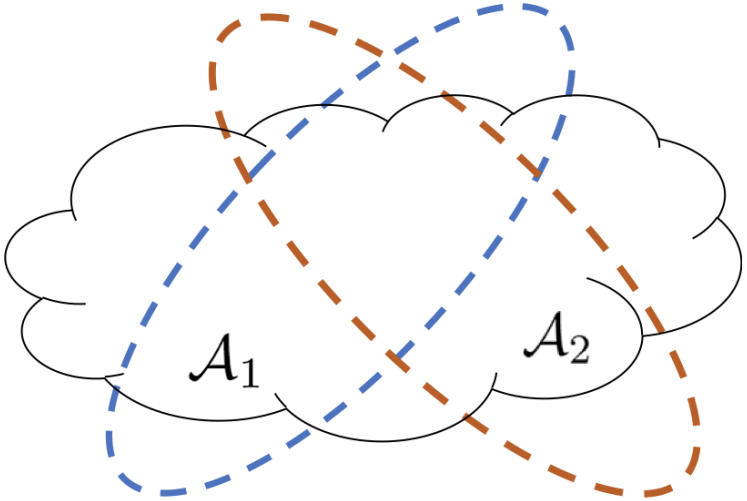

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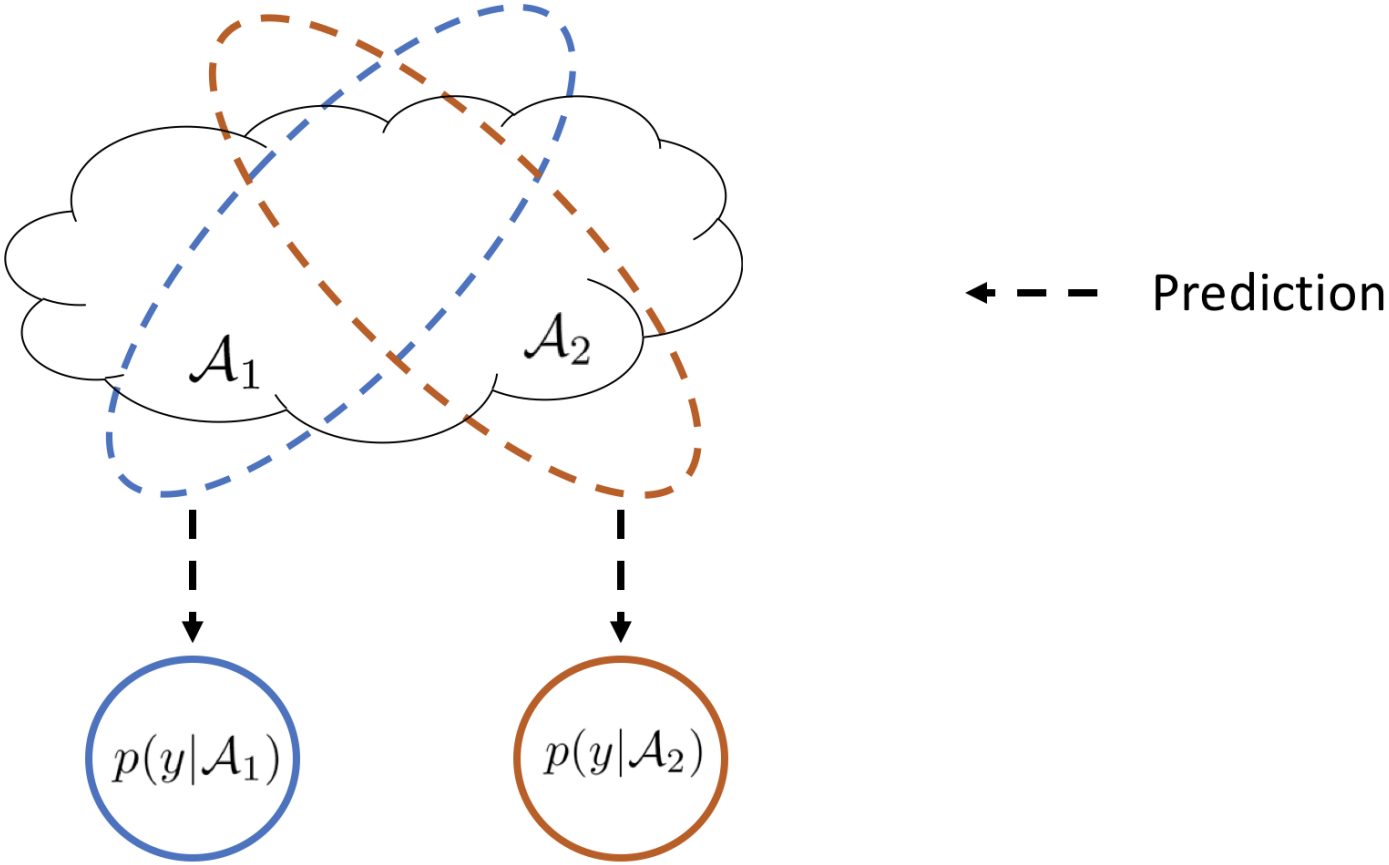

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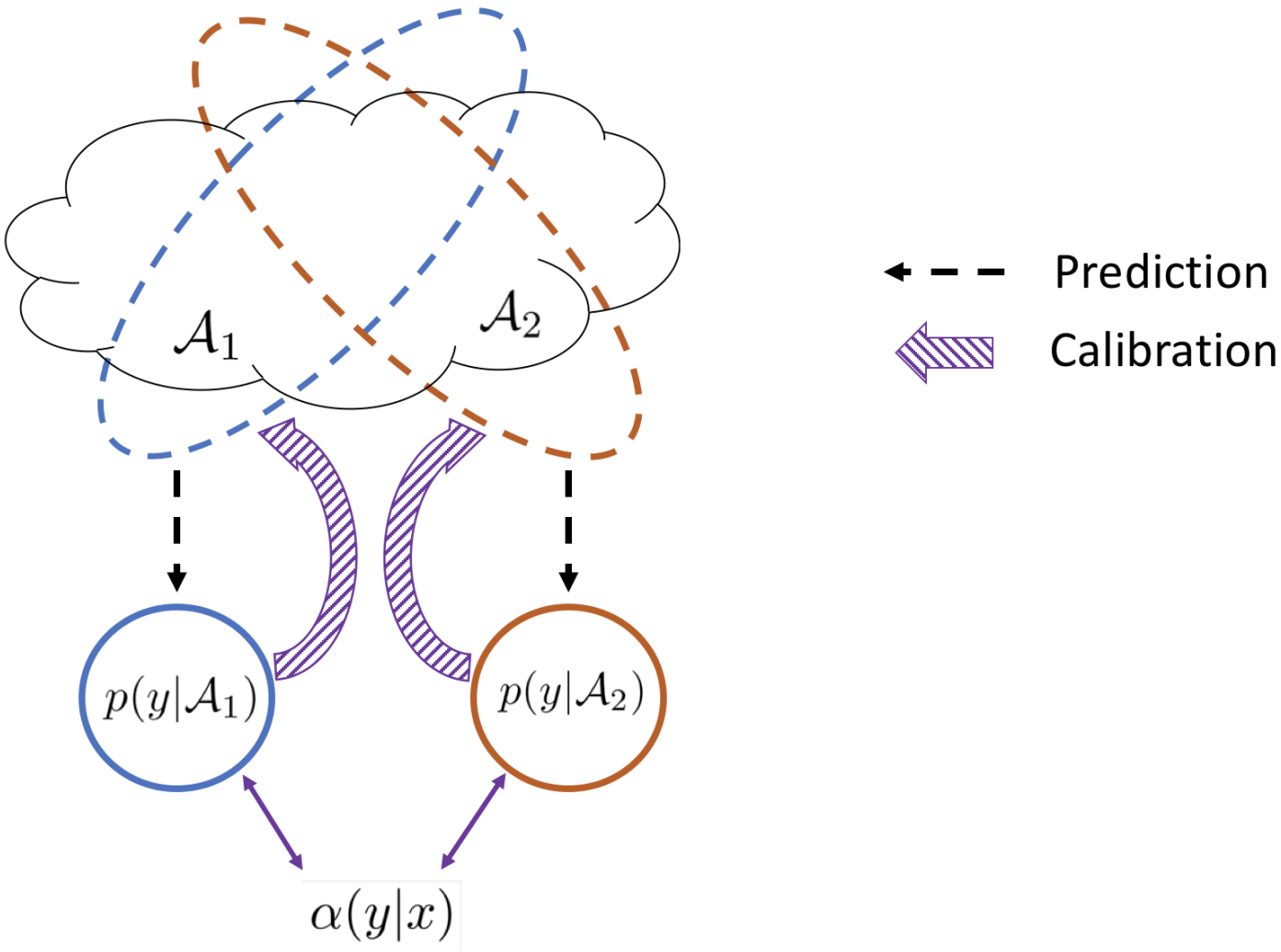

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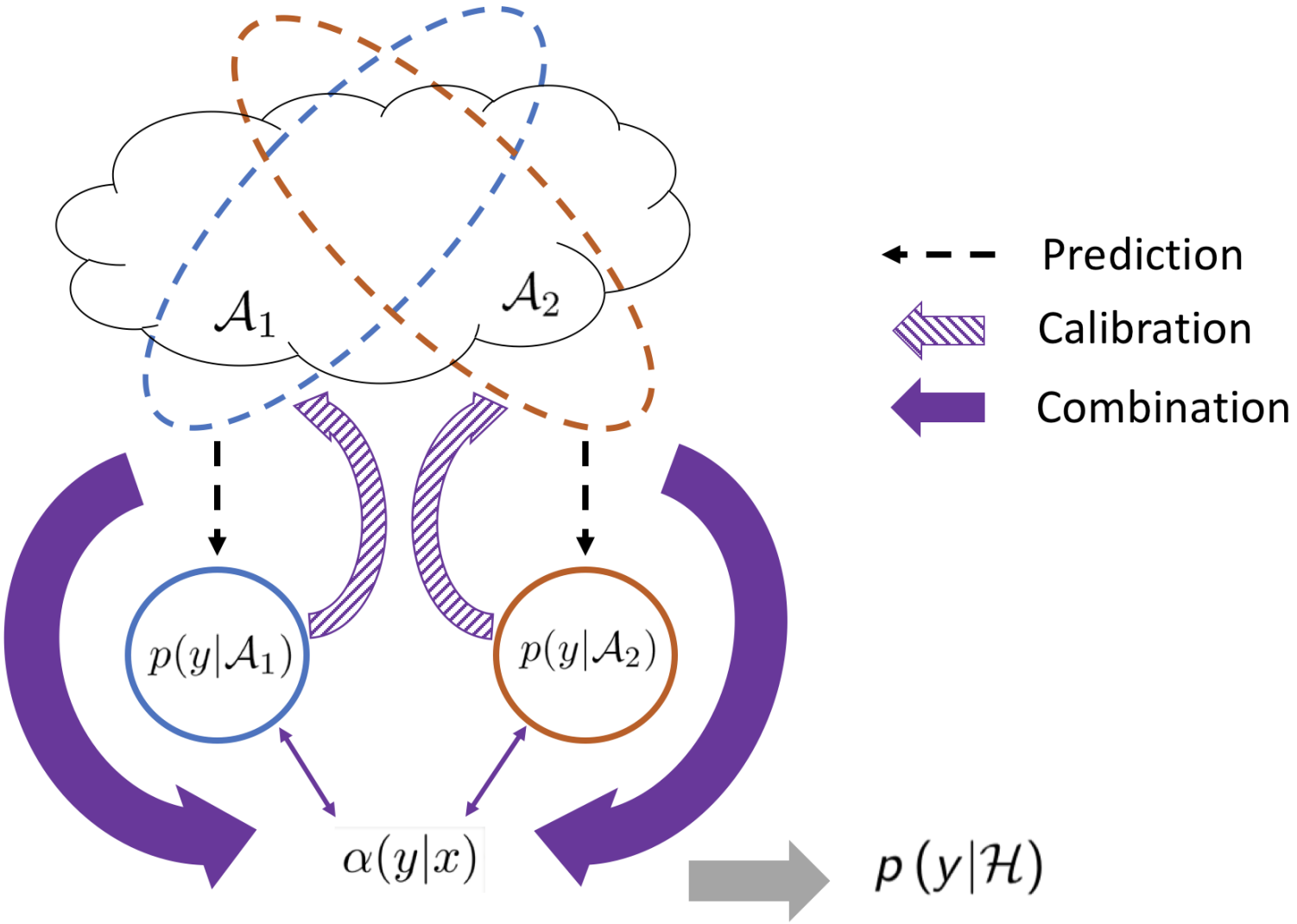

Estimation Strategy

Two-component block Gibbs sampler:

Block 1:
(bias and interdependencies)

Conditional on the "latent states" $\boldsymbol{x}_t$, the parameters $\boldsymbol{\theta}_t$, v_t and $\boldsymbol{W}_t$ are sampled from a Forward Filtering Backward Sampler (FFBS) algorithm.

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N.B: With $h_{tj}(x_{tj})$ Student-t density, we use a scale mixture of normals which allows for conjugate updating.

Empirical Study (Setting)

Two (regression-based) forecasting exercises:

- Forecasting U.S. inflation based on macroeconomic variables.
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Each $h_j(x_j) = p(y|\mathcal{A}_j)$ is generated by a TVP + SV for $j = 1, \ldots, J$.

$$y_t = \boldsymbol{\beta}_{tj}' \boldsymbol{z}_{tj} + \epsilon_{tj}, \quad \epsilon_{tj} \sim N(0, \nu_{tj}),$$
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Comparison based on the cumulative Log Predictive Density Ratios (LPDR),

$$\mathrm{LPDR}_t(k) = \sum_{i=1}^{t} \log\{p(y_{i+k}|y_{1:i}, \mathcal{M}_s)/p(y_{i+k}|y_{1:i}, \mathcal{M}_0)\},$$

where $\mathcal{M}_0$ is our strategy and $\mathcal{M}_s$ denotes the competitor.

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N.B: The J groups are selected based on their economic meaning.

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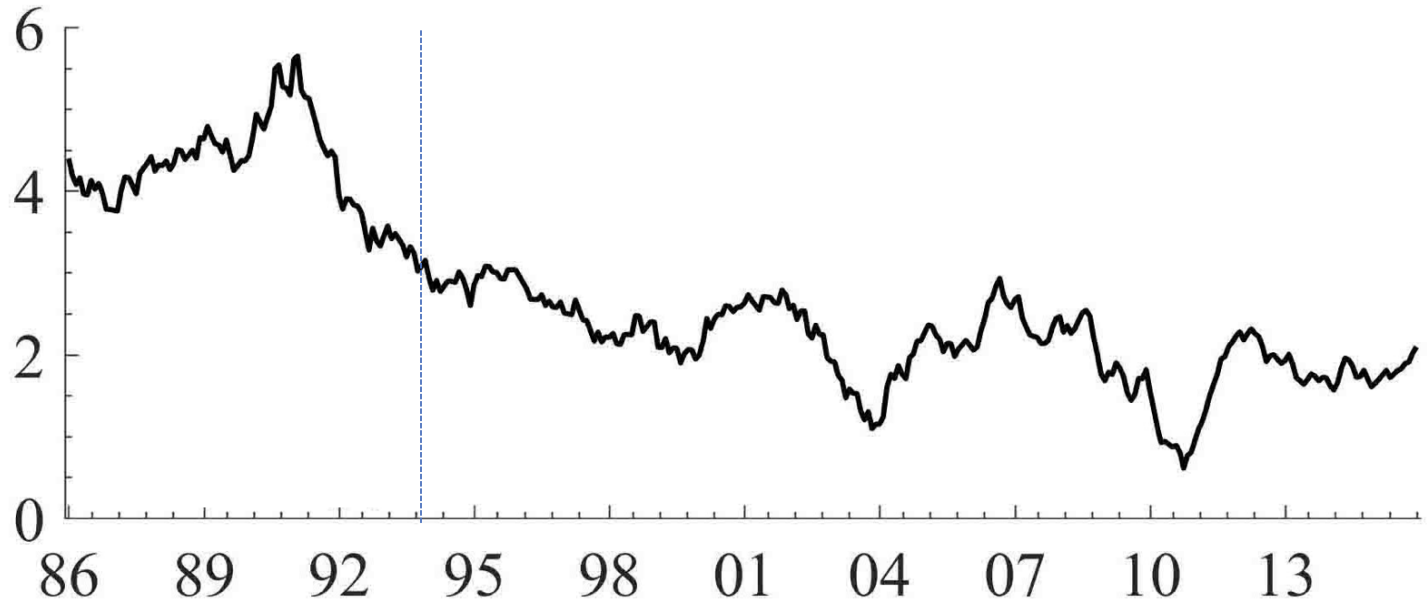
Timeline of the empirical application



Train subset models

Empirical Study (Setting)

Timeline of the empirical application

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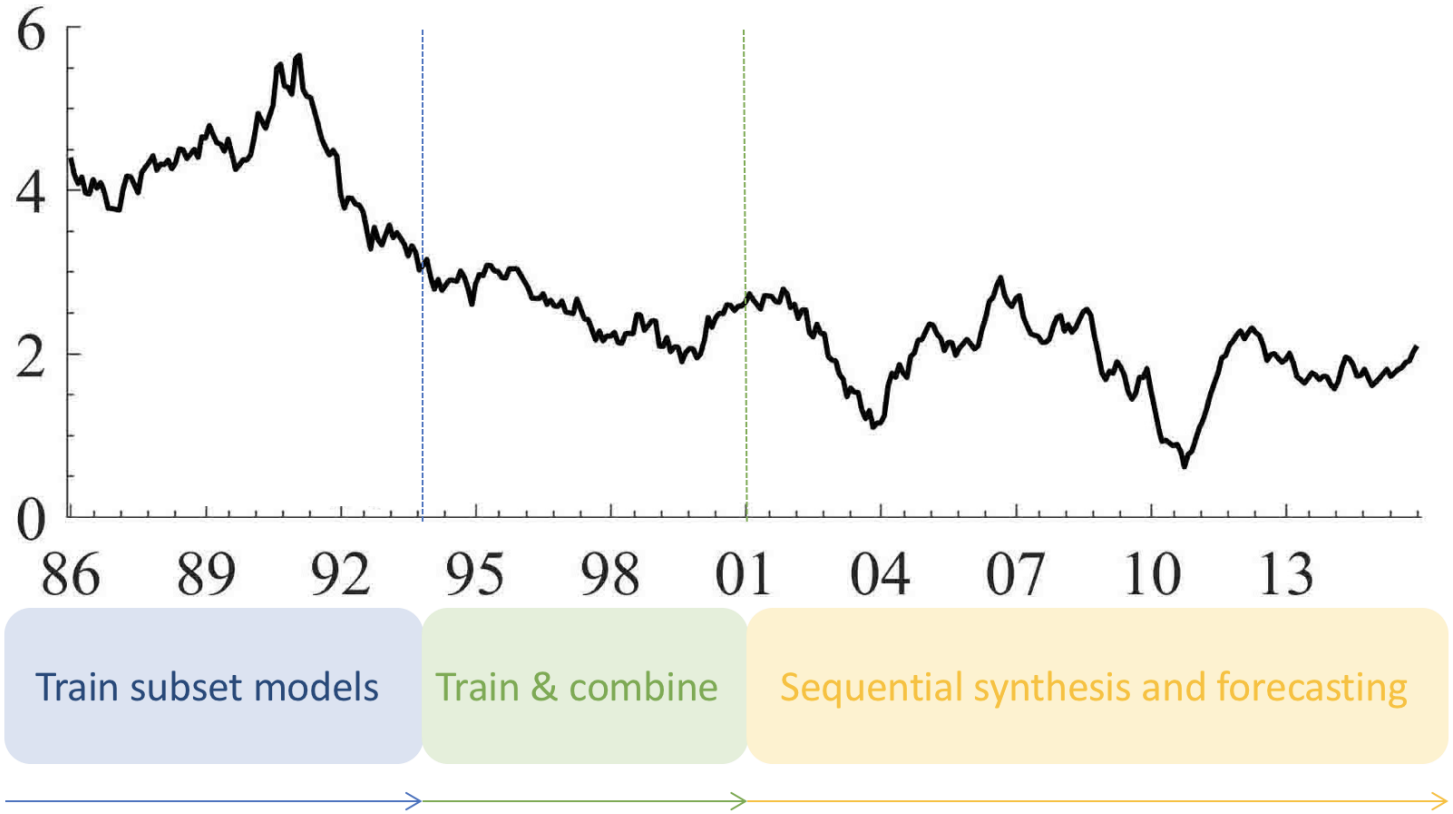

Empirical Study 1: Forecasting U.S. Inflation

Forecasting U.S. inflation using a large panel of macroeconomic variables (FRED-MD, $p = 128$)

- 1,3, and 12 months ahead

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$J = 8$ groups of predictors

- Output and income
- Labor market
- Consumption
- Inventories
- Money and credit
- Interest rates and FX
- Prices
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Compare against:

- Sequential BMA
- TVP factor model (k chosen by IC)
- Lasso (leave-one-out cross-validation)
- Linear pooling (equal-weight)
- Sub-group predictions

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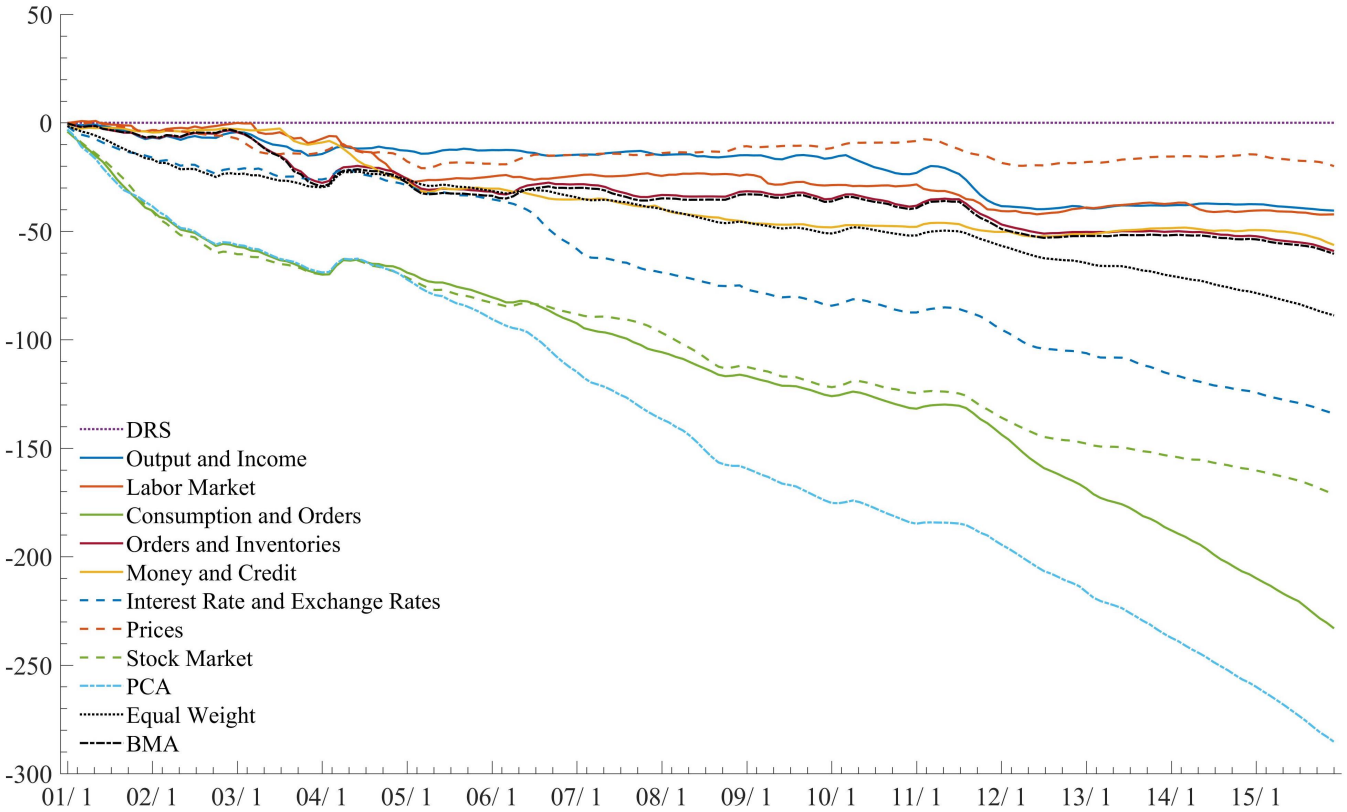
Empirical Study 1: Forecasting U.S. Inflation

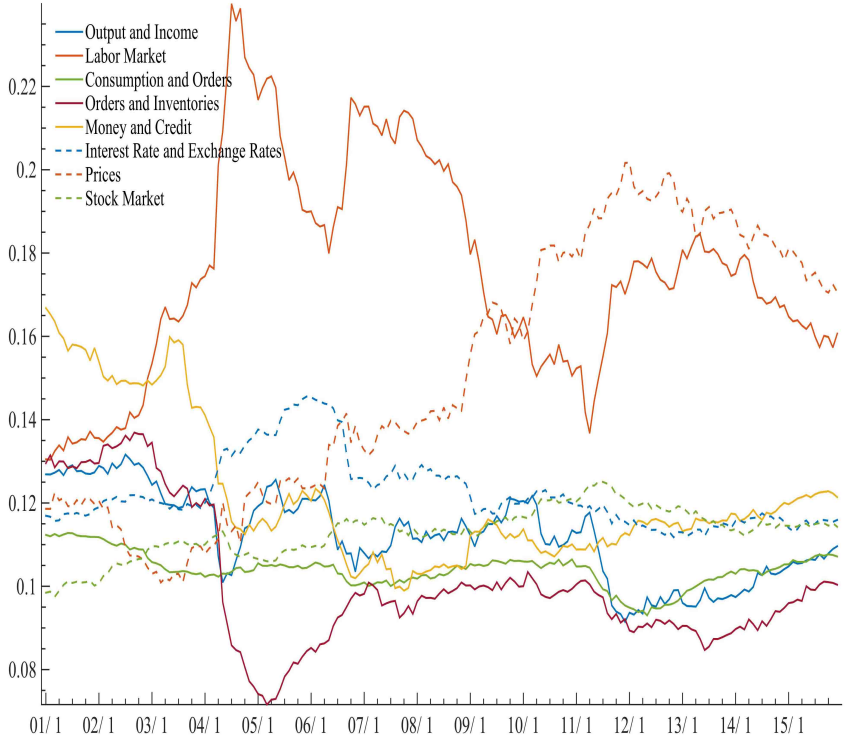
Figure: Out-of-sample log predictive density ratio



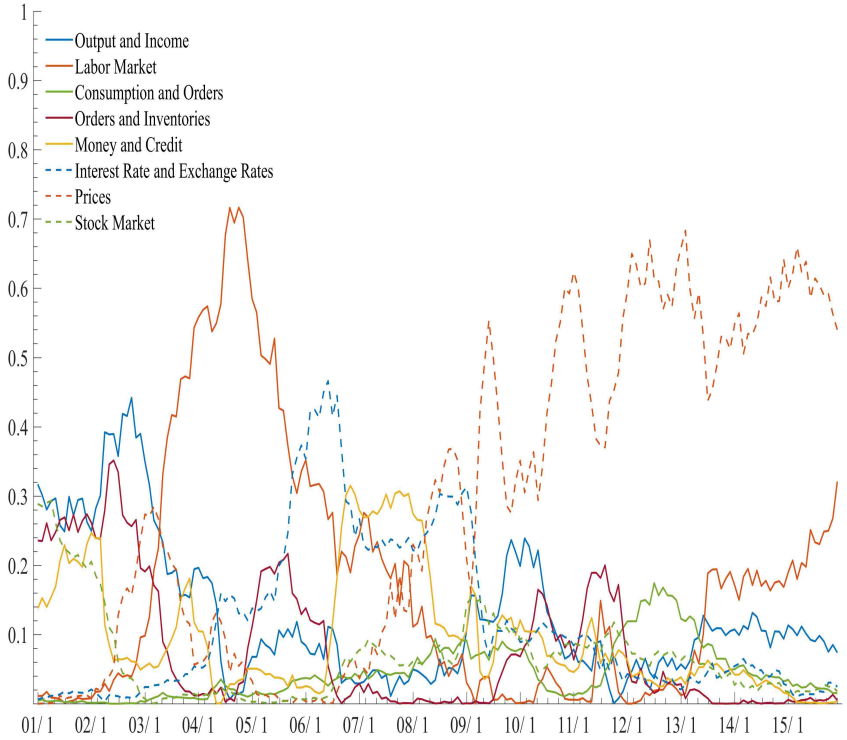
This figure shows the dynamics of the out-of-sample Log Predictive Density Ratio (LPDR) obtained for each competing specification. The sample period is 01:2001-12:2015, monthly. The objective function is the **one-step** ahead density forecast of annual inflation.

Empirical Study 1: Forecasting U.S. Inflation

Figure: Posterior means of **rescaled** interdependencies.



(a) 1-month ahead

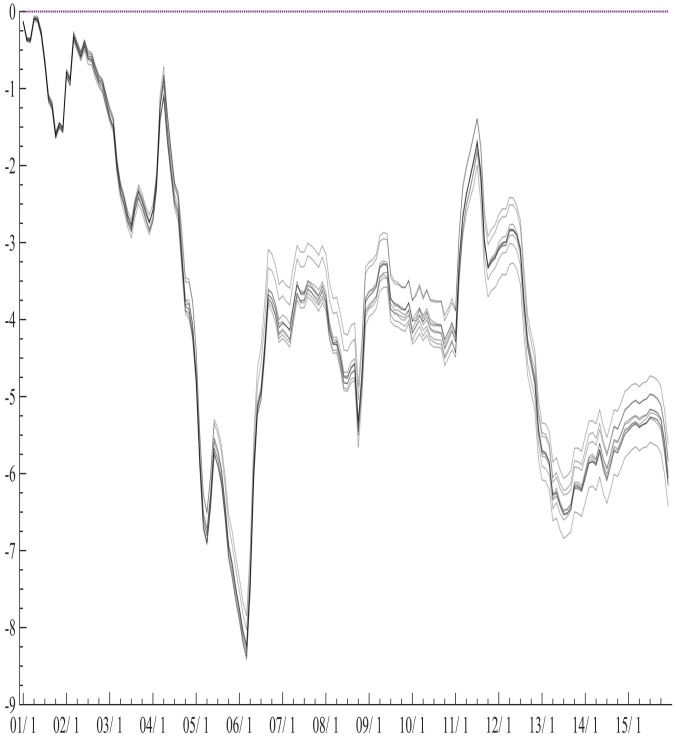


(b) 3-month ahead

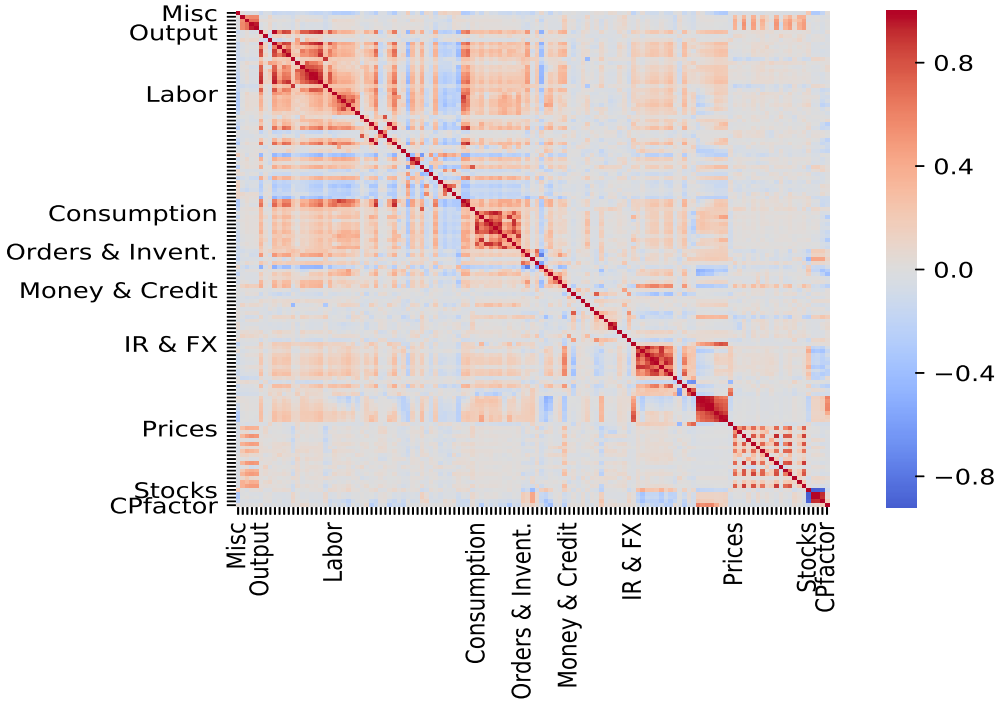
$$\tilde{\theta}_{jt} = \frac{\exp\left(\hat{\theta}_{jt}\right)}{\sum_{j=1}^{J} \exp\left(\hat{\theta}_{jt}\right)}, \quad j = 1, \ldots, J \qquad \text{s.t.} \quad \tilde{\theta}_{jt} \in (0,1), \quad \sum_{j=1}^{J} \tilde{\theta}_{jt} = 1.$$

Empirical Study 1: Forecasting U.S. Inflation

Figure: Qualitative vs. Random Paritioning



(a) LPDR Comparison



(b) Inputs Correlations

This figure shows a comparison between qualitative and random partitioning. Purple line is DRS using qualitative partitioning and black lines are DRS results using partitions chosen at random (computed over random partitions)

Empirical Study 2: Forecasting Industry Stock Returns

Forecast of the annual stock returns for different U.S. industries based on 63 pre-calculated financial ratios and 14 macroeconomic variables.

- 10 industries: Durbl, NonDurbl, Manuf, Energy, HiTech, Health, Shops, Telcm, Utils, Other.

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- Profitability
- Capitalization
- Financial Soundness
- Solvency
- Liquidity
- Efficiency
- Other
- Agg. Financials
- Macro

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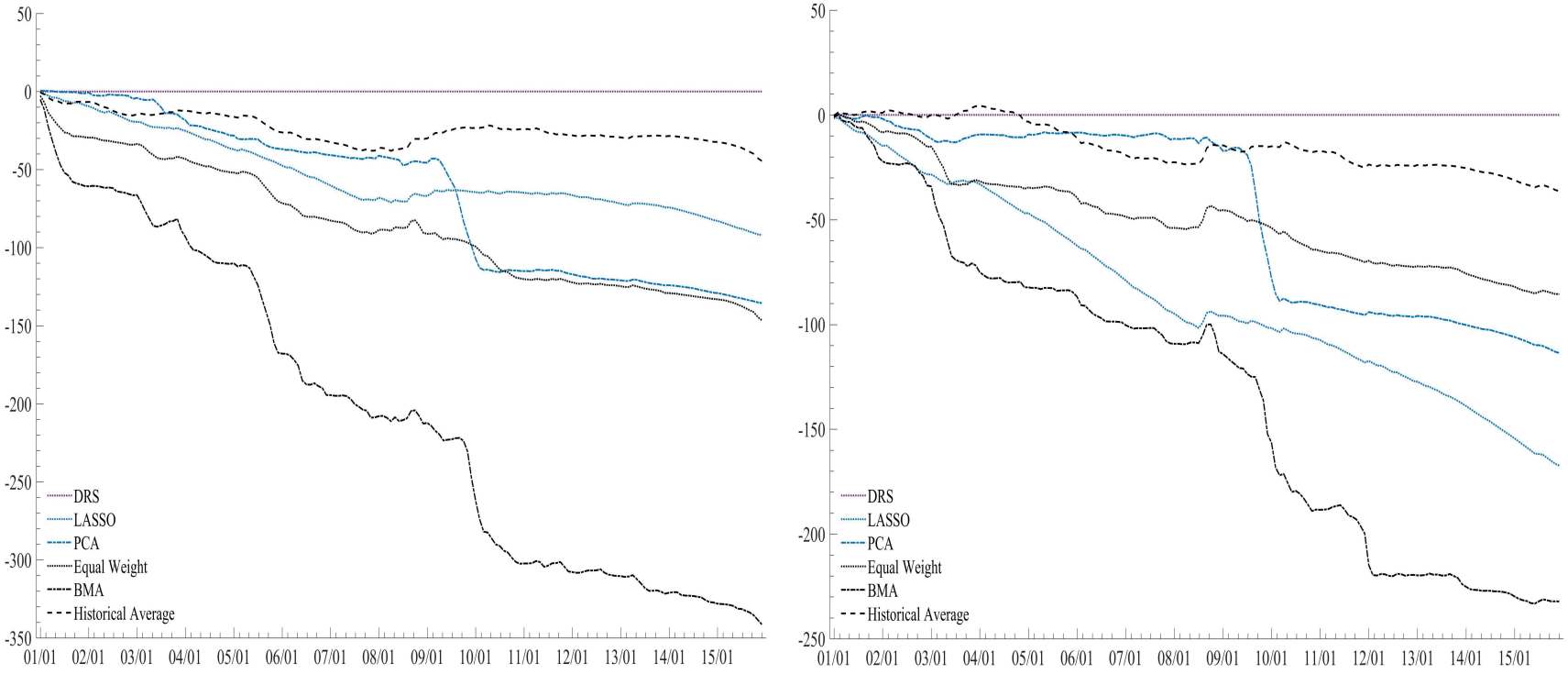
- Profitability
- Capitalization
- Financial Soundness
- Solvency
- Liquidity
- Efficiency
- Other
- Agg. Financials
- Macro

Empirical Study 2: Forecasting Industry Stock Returns

Figure: Out-of-sample log predictive density ratio

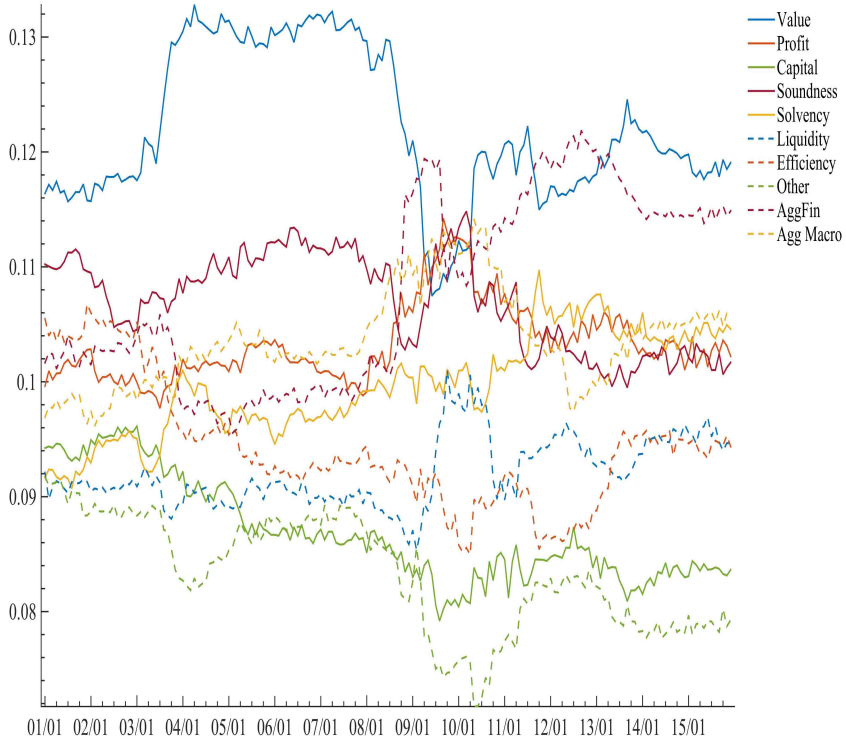


(a) Durable (b) Manufacturing

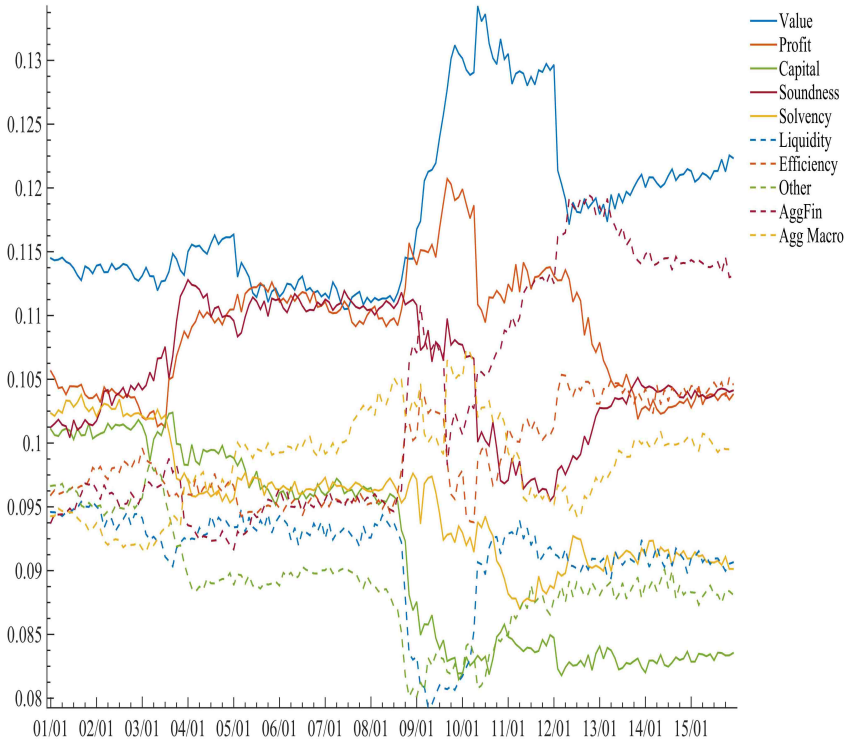
This figure shows the latent interdependencies across groups of predictive densities used in the recoupling step. Left panel the posterior mean estimates for Durable and right panel for the Manufacturing industry.

Empirical Study 2: Forecasting Industry Stock Returns

Figure: Posterior means of **rescaled** interdependencies.



(a) Durable



(b) Manufacturing

$$\tilde{\theta}_{jt} = \frac{\exp\left(\hat{\theta}_{jt}\right)}{\sum_{j=1}^{J} \exp\left(\hat{\theta}_{jt}\right)}, \quad j = 1, \ldots, J \qquad \text{s.t.} \quad \tilde{\theta}_{jt} \in (0,1), \quad \sum_{j=1}^{J} \tilde{\theta}_{jt} = 1.$$

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Empirical Study 2: Economic Significance

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N.B: Performance is evaluated based on Certainty Equivalent Returns (CERs).

$$CER_{i\tau} = \left[\frac{\hat{U}_{\tau,i}}{\hat{U}_{\tau}} \right]^{\frac{1}{1-\gamma}} - 1,$$

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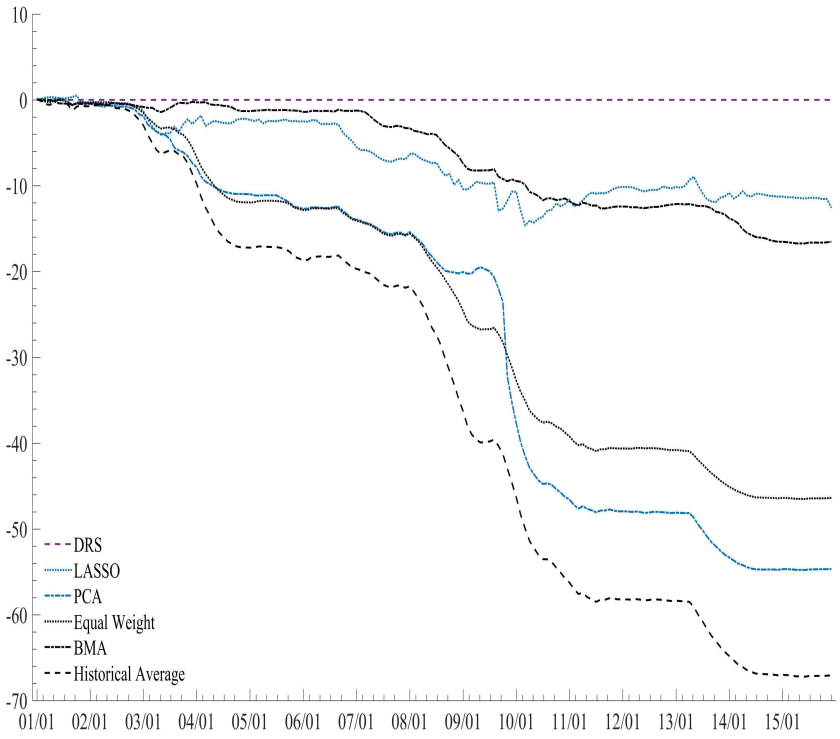
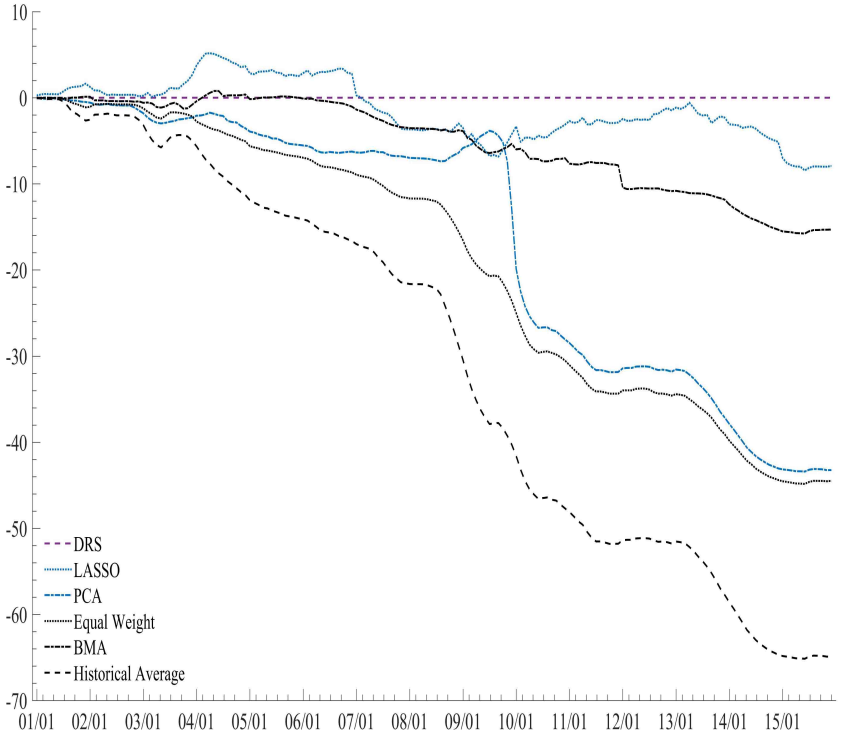
Empirical Study 2: Economic Significance

$$CCER_{it} = \sum_{\tau=1}^{t} \log\left(1 + CER_{i\tau}\right)$$



(c) Durable



(d) Manufacturing

Figure: OOS cumulative CER for an unconstrained investor

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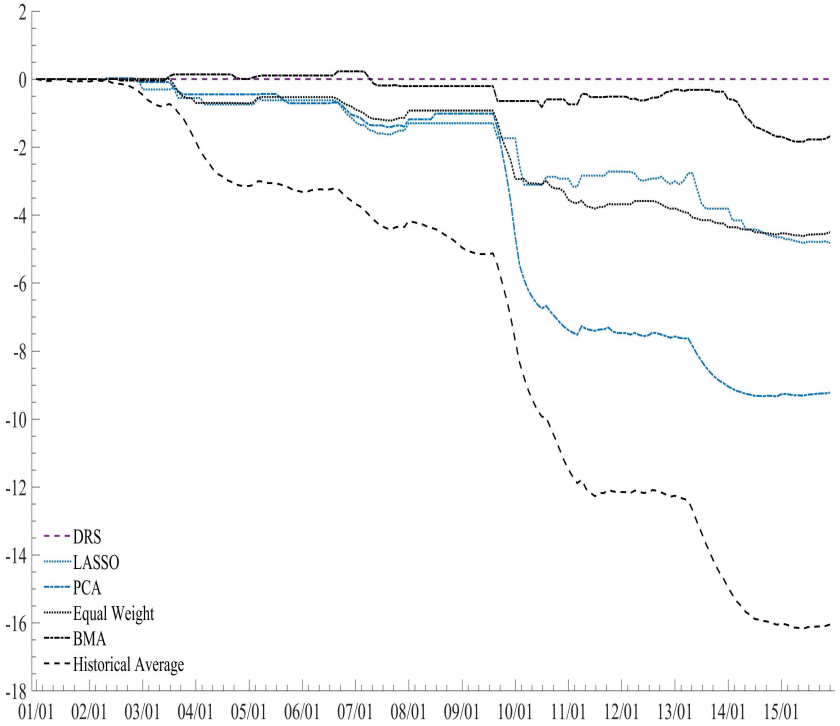
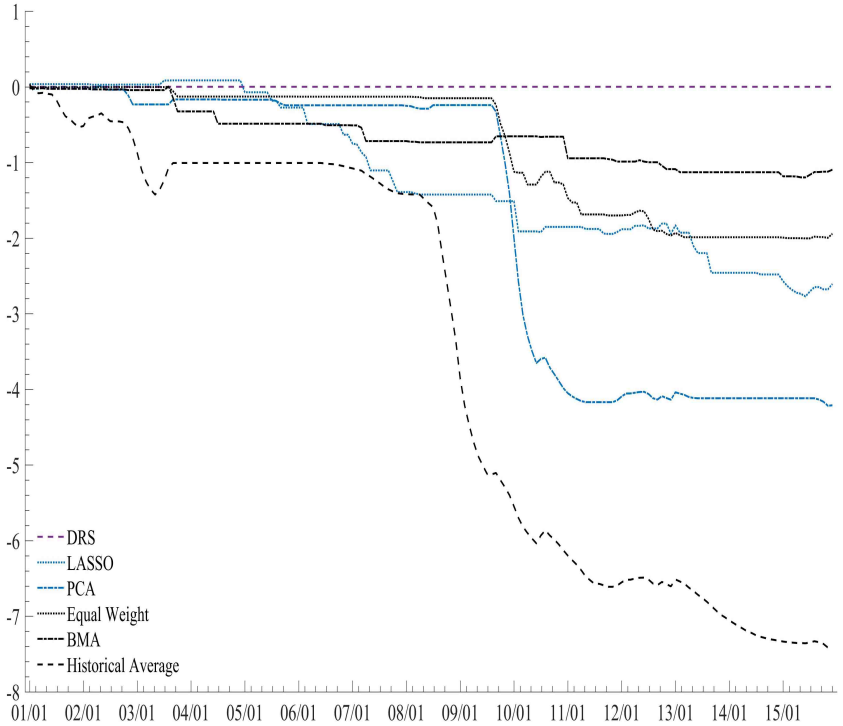


(a) Durable



(b) Manufacturing

Figure: OOS cumulative CER for an constrained investor

Simulation Study

We consider a simple – yet relevant – simulation study to illustrate the properties of our model.

Data are simulated from

$$y = -2z_1 + 3z_2 + 5z_3 + \epsilon, \quad \epsilon \sim N(0, 0.01),$$

$$z_1 = \frac{1}{3}z_3 + \nu_1, \quad \nu_1 \sim N\left(0, \frac{2}{3}\right),$$

$$z_2 = \frac{1}{5}z_3 + \nu_2, \quad \nu_2 \sim N\left(0, \frac{4}{5}\right),$$

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Setting:

- z_3 is omitted
- We assume $\neq$ sub-sampling and procedures.

Results:

- In small samples DRS improves w.r.t other methods by $\approx 60\%$.
- In long samples gains are smaller but persistent.

Conclusions

We propose a decouple-recouple strategy (DRS) for dynamic predictive regressions with a (relatively) large number of covariates.

Application to macro and finance:

- DRS outperforms typical competitors both statistically and economically.

Open issues/next steps:

- Can we group better the predictors?
- Hierarchical structure for larger dimensions?
- More sophisticated benchmarks?