

Forecasting Horse Races and “Belief Distortions”: A Hierarchical Bayesian VAR Study with Sentiment Signals

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1. Research Question and Motivation

Recent literature on Diagnostic Expectations (DE) suggests that economic agents overreact to news, whereas information rigidity models predict underreaction. This project investigates two precise questions:

- 1. Does expanding the information set of a hierarchical BVAR to include forward-looking financial prices and consumer sentiment reduce Root Mean Squared Forecast Error (RMSFE) relative to smaller baselines?*
- 2. Whether adding sentiment changes the Coibion-Gorodnichenko (CG) error-revision coefficient in a direction consistent with diagnostic overreaction.*

2. Data

I use monthly U.S. macroeconomic series from the FRED-MD database, covering the period **1985M1–2019M12**. The sample ends in 2019 to avoid COVID-19 outliers that would require complex volatility modeling beyond the scope of this term paper. To ensure consistent evaluation, variables are estimated in log-levels (to preserve cointegration) but evaluated in growth rates. The analysis compares three nested information sets:

- **Small Model (Baseline):** Industrial Production (INDPRO), Consumer Price Index (CPIAUCSL), Unemployment Rate (UNRATE), and Federal Funds Rate (FEDFUNDS).
- **Medium Model (Financial Extension):** Adds the 10-Year Treasury Yield (GS10) and S&P 500 Index (S&P500) to capture forward-looking financial cycles.
- **Full Model (Sentiment Extension):** Adds the University of Michigan Consumer Sentiment Index (UMCSENT) to test the marginal predictive power of “soft” data.

3. Econometric Framework

The core methodology relies on a reduced-form VAR estimated with a Minnesota-style Normal-Inverse-Wishart prior.

1. **Hierarchical BVAR:** Let y_t be the vector of endogenous variables. We estimate three nested BVAR systems with $p = 12$ lags:

$$y_t^{Small, Medium, Full} = c + \sum_{\ell=1}^p B_{\ell} y_{t-\ell} + u_t, \quad u_t \sim \mathcal{N}(0, \Sigma) \quad (1)$$

across three distinct information sets. Shrinkage is selected endogenously by treating λ as a hyperparameter with a hyperprior and choosing it by marginal likelihood. We compute RMSFE for $h = 1, 3, 12$ and report RMSFE ratios relative to the benchmark, together with Diebold-Mariano tests for pairwise comparisons. Benchmarks are a random-walk-type forecast and an AR(1) forecast defined on the same evaluation transforms used for the BVAR outputs.

2. **Identification of “Behavioral” Bias:** Let z_{t+h} denote the realized growth rate of a target variable ($z \in \{\text{INDPRO}, \text{CPI}\}$) at horizon h . Let $\hat{z}_{t+h|t}^{(m)}$ denote the forecast generated by Model $m \in \{\text{Small}, \text{Med}, \text{Full}\}$ at time t . To test the efficiency of the algorithmic forecasts, I estimate the following regression linking ex-post forecast errors to forecast revisions:

$$(z_{t+h} - \hat{z}_{t+h|t}^{(m)}) = \alpha_h + \beta_h (\hat{z}_{t+h|t}^{(m)} - \hat{z}_{t+h|t-1}^{(m)}) + \varepsilon_{t+h} \quad (2)$$

where the term in the first parenthesis represents the forecast error and the term in the second parenthesis represents the forecast revision. Since the forecast horizon h creates overlapping observations, inference on β_h relies on Newey-West HAC standard errors.

4. Interpretation and Expected Results

First, We verify whether the Hierarchical BVAR outperforms AR(1) benchmarks. The key test is whether the *Full Model* lowers RMSFE for real activity variables at short horizons ($h = 1, 3$) (and at long horizons $h = 12$). Then, by comparing β_h across the three nested models, we can isolate the marginal effect of sentiment. The key empirical object is the change in β_h when adding sentiment (Medium-Finance vs Medium-Finance+Sentiment), which might connect to diagnostic expectations.