Forecasting Industrial Production and Inflation: A Static Factor Model Analysis Across Different Periods

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01/06/2024

1 Introduction

This paper investigates the forecasting performance of static factor models compared to autoregressive models (ARMA) on Industrial Production (IP) and inflation using US economic data across three historical periods: the full sample (1960–2024), the Great Moderation (1985–2007), and the COVID-19 era (2019–2024).

2 Methodology

2.1 Data Transformation

Data were sourced from FRED-MD and made stationary via logarithmic differencing:

$$y_t^* = \log(y_t) - \log(y_{t-1}).$$

Outliers were identified by median-based rules and replaced with missing values, then imputed. All series were standardized: $\tilde{X}_{i,t} = (X_{i,t} - \bar{X}_i)/s_i$.

2.2 Static Factor Model

We employ the approximate static factor model:

$$X_t = \Lambda F_t + e_t,$$

where:

- X_t is an N-vector of observed, standardized variables at time t.
- F_t is an r-vector of static factors.
- Λ is an $N \times r$ loading matrix.
- e_t is an N-vector of idiosyncratic errors, assumed weakly correlated across i.

Factors and loadings were estimated by Principal Component Analysis (PCA), solving:

$$\min_{\Lambda,F} \frac{1}{NT} \sum_{t=1}^{T} ||X_t - \Lambda F_t||^2,$$

subject to normalization $F'F/T = I_r$. Missing values were handled via an Expectation-Maximization (EM) algorithm, iterating between: (1) PCA-based imputation of X_t given current loadings; (2) re-estimation of (Λ, F) by PCA on imputed data, until convergence.

The number of factors r is chosen by Bai and Ng's information criterion:

$$IC(r) = \ln\left(\frac{V(r)}{NT}\right) + r\,\hat{\sigma}^2\,\frac{N+T}{NT}\ln\left(\frac{NT}{N+T}\right),$$

where $V(r)$ is the sum of squared PCA residuals and $\hat{\sigma}^2$ their variance.

2.3 Forecasting via Local Projections

Forecasts of y_{t+h} use static factors in a local projection (LP) framework:

$$y_{t+h} = \alpha_h + \sum_{i=1}^{p} \beta_{h,i}\, y_{t-i+1} + \sum_{j=0}^{r} \gamma_{h,j}\, F_{t-j} + \varepsilon_{t+h}.$$

Lags p and r are selected by minimizing the Bayesian Information Criterion (BIC). Forecast accuracy is evaluated by out-of-sample Mean Squared Error (MSE):

$$MSE = \frac{1}{H} \sum_{h=1}^{H} (y_{t+h} - \hat{y}_{t+h})^2,$$

and BIC: $BIC = n \ln(MSE) + m \ln(n)$.

3 Results

For the full sample, ARMA(0,0) outperforms the static factor model in forecasting IP ($\text{MSE}_{ARMA} = 1.76 \times 10^{-4}$ vs. $\text{MSE}_F = 2.24 \times 10^{-4}$). During the Great Moderation, factor-based forecasts align with established literature, where factors capture common real shocks. In the COVID-19 era, factor models excel at forecasting inflation (optimal $p = r = 0$, $\text{MSE}_F = 1.30 \times 10^{-5}$), reflecting the importance of nominal co-movements in turbulent periods.

4 Discussion

Static factors summarize common variation across many macro series. Their superior performance during COVID-19 suggests that large, synchronous nominal shocks dominate inflation dynamics, which static factors capture more effectively than univariate ARMA. By contrast, in calm periods, simple persistence suffices for IP forecasting.

5 Conclusion

The appropriateness of forecasting models depends on economic regimes. Static factor models offer powerful tools when widespread shocks synchronize variables (e.g., pandemic inflation), whereas ARMA may be adequate in stable environments (e.g., full-sample IP). Policymakers should tailor forecasting approaches: use factor-augmented models when systemic shocks are likely, and simpler univariate approaches otherwise. Future work could test regime-switching factor structures to adapt endogenously to changing economic conditions.

References

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