

Do Real-Time Macro Regimes Improve Industry Return Forecasts?

Evidence from a Conditional Six-Factor Model

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Abstract

This study examines whether conditioning a standard U.S. equity six-factor model on a predetermined, real-time labor-market stress regime improves out-of-sample forecasts of industry excess returns. The analysis uses 49 value-weighted U.S. industry portfolios and combines the Fama-French five factors with momentum. NORMAL and STRESS states are defined using SAHMREALTIME, with the state for return month t based on the Sahm observation from $t - 2$. An expanding-window evaluation from January 1990 through June 2026 produces 21,413 industry-month forecasts. In sample, 11 of 49 industries exhibit state-dependent FF6 exposures after Benjamini-Hochberg FDR control at 5 percent, SMB shows the clearest state-dependent premium, and conditional pricing errors are lower. Real-time forecast accuracy does not improve. Relative to unconditional FF6, OOS R^2 is -0.312 percent, mean Rank IC is approximately 0.004, and the Clark-West test yields a one-sided p-value of 0.398. In this setting, empirically detectable state dependence does not generate a reliable real-time one-month forecasting advantage.

1. Introduction

Factor exposures and expected returns can vary with economic conditions, creating a natural role for conditioning information in asset-pricing models (Fama and French 1989; Ferson and Harvey 1991; Ferson and Harvey 1999). For forecasting purposes, the relevant standard is more demanding than identifying such variation retrospectively. The macroeconomic state must be observable when the forecast is formed, its relationship with returns must be estimated from information available at that date, and conditioning on the state must improve subsequent predictions relative to an unconditional benchmark. These requirements distinguish historical evidence of state dependence from information that can be used in a real-time forecasting exercise.

Existing research provides a basis for expecting time variation in both expected returns and factor relationships. Fama and French (1989) document variation in expected stock and bond returns across business conditions, and Ferson and Harvey (1991) show that economic risk premia vary through time. Conditional asset-pricing work further demonstrates that conditioning information can affect estimated exposures and cross-sectional return relationships (Ferson and Harvey 1999). The empirical specification used here starts from the Fama and French five-factor model (Fama and French 2015) and adds momentum, following the extensive evidence on momentum in stock returns and its incorporation into factor models (Jegadeesh and Titman 1993; Carhart 1997). A separate methodological issue concerns the information set used to identify economic conditions. Real-time macroeconomic data can differ materially from revised historical information, making vintage and release timing relevant for genuine forecast evaluation (Croushore and Stark 2001).

This paper asks whether conditioning a standard U.S. equity six-factor model on a predetermined, real-time labor-market stress regime improves out-of-sample forecasts of U.S. industry-portfolio excess returns relative to an otherwise identical unconditional six-factor model. The test assets are 49 value-weighted U.S. industry portfolios. The factor specification combines the Fama and French five factors with momentum and is referred to as FF6. Macroeconomic conditions are measured using the Federal Reserve Bank of St. Louis SAHMREALTIME series (Federal Reserve Bank of St. Louis n.d.-a). Each return month is classified as NORMAL or STRESS using the Sahm observation from two months earlier. This timing convention reflects the information available before the return month begins and prevents the state definition from using unemployment information released during that month.

The conditional model allows all six industry factor exposures to differ between NORMAL and STRESS. Forecast performance is evaluated through an expanding-window exercise beginning in January 1990. Each

forecast uses parameter estimates and factor-premium estimates based only on observations available through the preceding month. The resulting evaluation contains 437 forecast months and 21,413 industry-month predictions. Conditional FF6 is compared with an unconditional FF6 specification estimated on the same information set and with a historical-mean forecast.

The in-sample evidence shows clear state dependence in parts of the factor structure. Twenty-two of the 49 industries reject state-invariant FF6 exposures at the raw 5 percent level, and 11 remain significant after Benjamini-Hochberg false discovery rate control at 5 percent. Factor premia also vary across states, although the strongest evidence is concentrated in SMB. Its average monthly premium increases from -0.11 percent in NORMAL to 0.84 percent in STRESS. State-specific exposures and factor premia also produce smaller in-sample pricing errors than unconditional FF6.

These relationships do not translate into superior real-time forecasts. Relative to unconditional FF6, the conditional specification produces an OOS R^2 of -0.312 percent. Its mean monthly Rank IC is approximately 0.004, and the Clark-West comparison yields a one-sided p -value of 0.398. The conditional model therefore provides no statistically or economically meaningful improvement in aggregate next-month forecast accuracy. The portfolio exercise produces a related distinction. The conditional Top-10 strategy earns a higher raw CAGR than the analogous unconditional portfolio, yet its factor-adjusted performance does not indicate abnormal returns. Its annualized FF6 alpha is negative and statistically insignificant.

The study applies a strict real-time information constraint to a transparent conditional factor framework and evaluates several layers of evidence within the same design. The analysis compares state-dependent factor exposures, model-implied state-specific returns, and expanding-window forecasts constructed from historically available information. The main empirical finding is the gap between descriptive state dependence and implementable forecastability. Macroeconomic stress helps organize variation in industry factor exposures. In the real-time OOS design, the estimated relationships do not provide a reliable next-month forecasting advantage.

The remainder of the paper develops the data and empirical design before presenting in-sample evidence, OOS forecast results, portfolio implications, and robustness tests. The final discussion interprets the difference between retrospective state dependence and real-time predictive performance.

2. Data and Macro-State Construction

The primary test assets are the 49 value-weighted U.S. industry portfolios from the Kenneth R. French Data Library (French n.d.-a). This universe provides a broad and economically interpretable cross-section for testing whether factor exposures vary with macroeconomic conditions. Monthly factor data are obtained from the same source. The baseline specification combines the Fama/French five factors, MKT-RF, SMB, HML, RMW, and CMA, with the monthly momentum factor, MOM (French n.d.-b; French n.d.-c; Fama and French 2015). Throughout the paper, this six-factor specification is referred to as FF6. Industry excess returns are constructed by subtracting the monthly French risk-free rate from each industry's total return (French n.d.-b).

The primary sample requires a balanced cross-section containing all 49 industries in every included month. The balanced financial panel begins in July 1969, which is the first month in which all 49 value-weighted industry portfolios are simultaneously available in the source data. The sample start is therefore fixed by the availability of the complete test-asset universe. After alignment with the macroeconomic state variable, the final master dataset contains 683 usable monthly observations from July 1969 through June 2026. Table 1 summarizes the sample construction and regime frequencies.

Table 1. Sample and Macro-State Summary

Metric	Value
Sample period	1969-07 to 2026-06
Usable months	683
NORMAL months	524
STRESS months	159
STRESS share	23.3%
Mean NORMAL spell length	37.4 months
Mean STRESS spell length	13.2 months
$P(\text{NORMAL} \rightarrow \text{NORMAL})$	0.977
$P(\text{STRESS} \rightarrow \text{STRESS})$	0.925

Notes: The primary sample contains the balanced 49-industry panel after alignment with the predetermined Sahm state. December 2025 is absent because the October 2025 Sahm observation required by the study's $t - 2$ timing convention is unavailable.

Macroeconomic conditions are measured using **SAHMREALTIME** from the Federal Reserve Bank of St. Louis. The indicator tracks deterioration in U.S. labor-market conditions using the three-month moving average of the unemployment rate relative to its minimum over the preceding 12 months (Federal Reserve Bank of St. Louis n.d.-a). The standard Sahm threshold is 0.50 percentage points (Federal Reserve Bank of St. Louis n.d.-a; Sahm 2019). The real-time version of the series is appropriate for the study because the forecasting exercise requires macroeconomic information that was available when each forecast could have been formed (Federal Reserve Bank of St. Louis n.d.-a).

The timing convention assigns the state for return month t using the **SAHMREALTIME** observation from $t - 2$. Forecasts for month t are assumed to be formed at the end of month $t - 1$. At that point, the unemployment release covering month $t - 1$ is not yet available because it is published during month t (U.S. Bureau of Labor Statistics 2026). The Sahm observation for $t - 2$ is therefore the latest monthly reading that can be used without incorporating information released during the return month. This timing rule ensures that the regime assigned to month t is predetermined with respect to the month- t return.

A month is classified as **STRESS** when the relevant $t - 2$ **SAHMREALTIME** observation is at least 0.50. All remaining months are classified as **NORMAL**. The primary specification applies the published threshold directly and does not impose additional smoothing, minimum spell lengths, or data-dependent threshold selection. The resulting sample contains 524 **NORMAL** months and 159 **STRESS** months, corresponding to approximately 76.7 percent and 23.3 percent of usable observations, respectively. December 2025 is excluded because the October 2025 Sahm observation required by the $t - 2$ timing rule is unavailable (U.S. Bureau of Labor Statistics n.d.).

Figure 1 compares the predetermined Sahm signal with NBER recession dates. The NBER Business Cycle Dating Committee identifies U.S. business-cycle peaks and troughs retrospectively (National Bureau of Economic Research n.d.). In this study, NBER dates serve only as a descriptive reference for evaluating how the real-time labor-market stress measure relates to subsequently dated business-cycle downturns. They do not enter the construction of the **NORMAL** and **STRESS** states and are not used in the primary forecasting exercise.



Figure 1. Real-Time Sahm Indicator and NBER Recessions

3. Empirical Methodology

3.1 Unconditional and Conditional Factor Models

For each industry i , the unconditional FF6 specification relates monthly excess returns to contemporaneous factor realizations:

$$r_{i,t} = \alpha_i + \beta_i' \mathbf{F}_t + \varepsilon_{i,t}. \quad (1)$$

Here, $r_{i,t}$ denotes the excess return of industry i in month t , α_i is the regression intercept, $\mathbf{F}_t$ is the six-element vector containing MKT-RF, SMB, HML, RMW, CMA, and MOM, β_i is the corresponding vector of factor loadings, and $\varepsilon_{i,t}$ is the residual.

The conditional specification interacts the factor vector with the predetermined macro state:

$$r_{i,t} = \alpha_i + \delta_i D_t + \beta_i' \mathbf{F}_t + \gamma_i' (D_t \mathbf{F}_t) + \varepsilon_{i,t}. \quad (2)$$

where D_t equals one in STRESS months and zero in NORMAL months. The coefficient δ_i measures the change in the regression intercept associated with the STRESS state. The vector γ_i measures how the industry's six factor loadings change between NORMAL and STRESS.

The implied factor exposures are

$$\beta_{i,N} = \beta_i \quad (3)$$

in NORMAL months and

$$\beta_{i,S} = \beta_i + \gamma_i \quad (4)$$

in STRESS months. The interaction formulation estimates both states jointly and permits direct tests of whether factor exposures differ across states.

3.2 Inference and State-Dependent Factor Premia

Both factor models are estimated by ordinary least squares. Statistical inference uses Newey-West heteroskedasticity and autocorrelation consistent covariance estimates with six monthly lags in the primary specification (Newey and West 1987).

For each industry, state dependence in factor exposures is evaluated using the joint Wald hypothesis

$$H_0 : \gamma_i = \mathbf{0}. \quad (5)$$

Rejection indicates that the six-dimensional factor-loading vector differs across NORMAL and STRESS for that industry. Since the hypothesis is tested separately for 49 industries, the resulting p -values are adjusted using the Benjamini-Hochberg false discovery rate procedure at the 5 percent level (Benjamini and Hochberg 1995). The joint test focuses inference on changes in the complete six-factor exposure vector.

Factor premia are estimated separately by macro state. For each factor j , the regression

$$F_{j,t} = a_j + b_j D_t + u_{j,t} \quad (6)$$

is estimated with HAC inference. The implied average factor premium in NORMAL is

$$\lambda_j^N = a_j, \quad (7)$$

and the corresponding STRESS premium is

$$\lambda_j^S = a_j + b_j. \quad (8)$$

The coefficient b_j measures the difference in the average premium between STRESS and NORMAL.

3.3 Model-Implied Expected Returns and In-Sample Pricing Errors

State-specific expected industry excess returns are constructed strictly from estimated factor exposures and factor premia:

$$\mu_{i,s} = \beta'_{i,s} \lambda_s, \quad (9)$$

where s denotes NORMAL or STRESS. Neither state-specific regression intercept enters this measure. The intercept is α_i in NORMAL and $\alpha_i + \delta_i$ in STRESS. These terms remain part of the estimated return regressions and can be interpreted diagnostically as intercept or pricing-error components, but they are not included as expected-return or forecast components.

The in-sample pricing exercise compares each industry's realized average excess return within a state with the return implied by its estimated factor exposures and factor premia. Conditional pricing errors use state-specific betas and state-specific factor premia. The unconditional benchmark uses unconditional FF6 exposures and unconditional factor premia against the same state-specific realized return targets. Root mean squared error and mean absolute error summarize pricing errors across industries and states.

These measures evaluate state-specific in-sample fit. Out-of-sample predictive performance is evaluated separately using forecasts formed from historically available information.

3.4 Real-Time Out-of-Sample Forecast Design

The primary forecasting exercise begins in January 1990 and uses an expanding estimation window. The first forecast is based on observations from July 1969 through December 1989, giving 246 initial training observations, including 76 STRESS months.

For every forecast month t , all model parameters are estimated using observations through $t - 1$. The macro state assigned to month t uses the Sahm observation from $t - 2$, following the information timing established in Section 2. Factor premia are re-estimated within every expanding training sample. Full-sample factor means, future factor observations, and future industry returns do not enter forecast construction.

The conditional forecast uses the factor-loading vector associated with the predetermined state for month t together with the corresponding factor-premium vector estimated from the available training sample. The unconditional FF6 forecast uses unconditional betas and unconditional factor premia estimated through the same training endpoint. A third benchmark forecasts each industry's excess return using its historical mean through $t - 1$.

Forecasts are generated before realized month- t industry returns are attached to the evaluation dataset. The estimation window then expands by one month, and the models and factor premia are re-estimated for the next forecast. The final OOS sample contains 437 forecast months and 21,413 industry-month forecasts. The design therefore tests whether conditioning on the predetermined macro state improves forecasts that could have been formed using information available at each forecast date.

3.5 Forecast Evaluation and Portfolio Exercise

Forecast accuracy is evaluated using pooled root mean squared error and mean absolute error across industry-month observations. For benchmark b , OOS R^2 is defined as

$$R_{OS,b}^2 = 1 - \frac{\sum_{i,t} (r_{i,t} - \hat{r}_{i,t}^C)^2}{\sum_{i,t} (r_{i,t} - \hat{r}_{i,t}^b)^2}. \quad (10)$$

where b denotes either unconditional FF6 or the historical-mean benchmark. A positive value indicates lower total squared forecast error for the conditional model.

Cross-sectional ranking ability is evaluated each month using the Spearman rank correlation between conditional expected-return forecasts and realized industry excess returns. The time-series mean of this Rank IC is evaluated using HAC inference.

Because unconditional FF6 is nested within the conditional specification, the formal forecast comparison also uses the Clark-West adjustment (Clark and West 2007). For each forecast month,

$$CW_t = MSE_t^U - \left[MSE_t^C - \frac{1}{N} \sum_i \left(\hat{r}_{i,t}^C - \hat{r}_{i,t}^U \right)^2 \right]. \quad (11)$$

The adjustment accounts for estimation noise introduced by the additional parameters of the nested conditional model. The mean CW_t is evaluated using a one-sided HAC test of whether the conditional specification improves predictive accuracy.

The portfolio exercise provides a secondary assessment of the economic implications of the forecasts. Each month, industries are ranked by predicted excess return, and the ten highest-ranked industries are held in an equal-weight, long-only portfolio. Portfolio weights are formed before month- t returns are observed. Identical portfolios are constructed from conditional FF6, unconditional FF6, and historical-mean forecasts.

The primary transaction-cost assumption is 10 basis points applied to the fraction of the portfolio traded each month. Zero and 25 basis points are retained as sensitivity cases. The market benchmark is constructed as MKT-RF plus the French risk-free rate. Performance evaluation includes CAGR, annualized volatility, Sharpe ratios calculated from portfolio excess returns, maximum drawdown, active return, tracking error, information ratio, and turnover. Portfolio FF6 alpha is estimated from a six-factor time-series regression with HAC covariance estimation using six monthly lags.

4. In-Sample Evidence

The unconditional FF6 model provides a meaningful baseline description of monthly industry excess returns. Across the 49 industry portfolios, the average time-series R^2 is 0.6068, or approximately 0.607. The subsequent conditional analysis therefore evaluates state dependence relative to a model that already explains a substantial share of industry return variation.

The joint Wald tests provide clear evidence that factor exposures are not constant across the predetermined macro states for a subset of industries. At the conventional 5 percent level, 22 of the 49 industries reject the null hypothesis $H_0 : \gamma_i = \mathbf{0}$. After controlling the false discovery rate across all 49 industry-level tests using the Benjamini-Hochberg procedure at 5 percent, 11 industries remain significant. Figure 2 summarizes the distribution of these results across the industry universe. The evidence indicates that the complete FF6 exposure vector differs between NORMAL and STRESS for a non-trivial share of industries. Detailed industry-level test statistics are reported in Appendix Table A1.

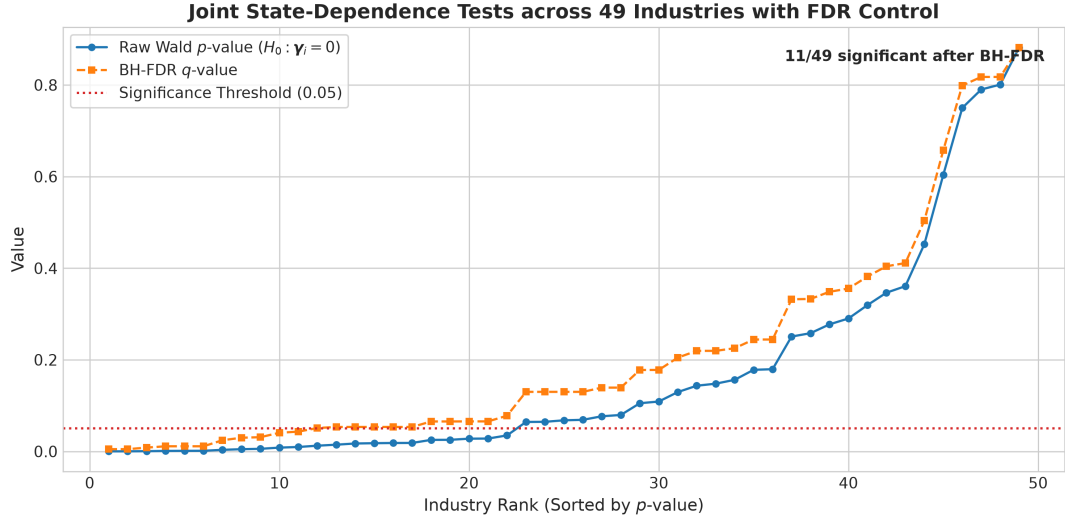


Figure 2. State-Dependence Significance Across Industries

Table 2 examines whether average factor premia also differ across macro states. The market excess return averages 0.57 percent per month in NORMAL and 0.76 percent in STRESS, a difference of 0.19 percentage points with $p = 0.712$. The largest and most precisely estimated difference occurs for SMB. Its average premium increases from -0.11 percent per month in NORMAL to 0.84 percent in STRESS. The resulting difference of 0.94 percentage points per month has a t -statistic of 3.41 and a p -value of 0.001.

Table 2. Factor Premia by Macro State

Factor	NORMAL	STRESS	Difference	HAC t	p -value
MKT-RF	0.57%	0.76%	0.19 pp	0.37	0.712
SMB	-0.11%	0.84%	0.94 pp	3.41	0.001
HML	0.23%	0.46%	0.22 pp	0.67	0.500
RMW	0.22%	0.42%	0.20 pp	0.92	0.356
CMA	0.21%	0.46%	0.25 pp	1.28	0.202
MOM	0.74%	0.17%	-0.57 pp	-1.08	0.279

Notes: NORMAL and STRESS columns report mean monthly factor returns. Difference is STRESS minus NORMAL in percentage points per month. HAC inference uses six monthly lags.

The remaining factor-premium differences are smaller or estimated less precisely. HML increases by 0.22 percentage points between NORMAL and STRESS, with $p = 0.500$. RMW increases by 0.20 percentage points, with $p = 0.356$, and CMA by 0.25 percentage points, with $p = 0.202$. MOM declines from 0.74 percent per month in NORMAL to 0.17 percent in STRESS, corresponding to a difference of -0.57 percentage points, with $p = 0.279$. SMB is therefore the only factor for which the primary specification provides strong statistical evidence of a state-dependent premium.

The state-dependent specification also produces smaller in-sample pricing errors. Across the pooled set of industry-state observations, conditional pricing-error RMSE is 0.393 percent, compared with 0.479 percent for unconditional FF6. Conditional MAE is 0.290 percent, compared with 0.377 percent for the unconditional model. The conditional specification also records lower RMSE and MAE within both NORMAL and STRESS. These results show that state-specific factor exposures and factor premia describe state-specific average industry returns more closely within the estimation sample.

The in-sample evidence therefore establishes statistically detectable state variation in parts of the factor structure, especially in industry exposures and the SMB premium. The next question is whether estimates of these relationships, formed only from information available at each historical forecast date, improve

real-time out-of-sample return predictions.

5. Out-of-Sample Forecast Evaluation

The real-time out-of-sample exercise spans January 1990 through June 2026. It contains 437 forecast months across 49 industries, producing 21,413 industry-month forecasts. Table 3 reports forecast accuracy for the conditional FF6 specification, unconditional FF6, and the historical-mean benchmark.

Table 3. Real-Time Out-of-Sample Forecast Performance

<i>Panel A: Forecast errors</i>		
Model	RMSE	MAE
Conditional FF6	6.7521%	4.9287%
Unconditional FF6	6.7416%	4.9158%
Historical mean	6.7425%	4.9179%
<i>Panel B: Relative forecast and ranking diagnostics</i>		
Metric	Value	
R^2_{OS} vs. unconditional FF6	-0.312%	
R^2_{OS} vs. historical mean	-0.286%	
Months conditional beats unconditional	48.05%	
Mean Rank IC	0.00431	
Median Rank IC	-0.00173	
Positive Rank IC months	49.43%	
Rank IC HAC t	0.410	
Rank IC two-sided p	0.682	
Clark-West HAC t	0.259	
Clark-West one-sided p	0.398	

Notes: OOS period is January 1990 through June 2026, comprising 437 months and 21,413 industry-month forecasts. RMSE and MAE are pooled across industry-month observations. Rank IC is the monthly cross-sectional Spearman correlation. Clark-West inference uses the monthly cross-sectional adjusted loss series and HAC lag 6.

The conditional model produces an RMSE of 6.7521 percent and an MAE of 4.9287 percent. Unconditional FF6 records an RMSE of 6.7416 percent and an MAE of 4.9158 percent. The historical-mean benchmark produces an RMSE of 6.7425 percent and an MAE of 4.9179 percent. The conditional FF6 specification therefore does not improve real-time OOS forecast accuracy relative to unconditional FF6. The differences in forecast errors are quantitatively small, but both RMSE and MAE favor the unconditional model. The historical mean also produces slightly lower forecast errors than the conditional specification.

The corresponding OOS R^2 measures reinforce this comparison. Relative to unconditional FF6,

$$R^2_{OS,U} = -0.312\%.$$

Relative to the historical-mean benchmark,

$$R^2_{OS,HM} = -0.286\%.$$

Both values are negative, indicating that the conditional model generates slightly larger total squared forecast errors than the respective benchmarks over the OOS sample. The monthly comparison leads to the same conclusion. Conditional FF6 has a lower cross-sectional mean squared error than unconditional FF6 in approximately 48.05 percent of forecast months. Improvements in monthly forecast loss therefore occur with roughly the same frequency as deteriorations and do not accumulate into superior aggregate accuracy.

The cross-sectional ranking evidence is similarly weak. The mean monthly Spearman Rank IC between conditional expected-return forecasts and subsequently realized industry excess returns is 0.00431, with a median of -0.00174. Rank IC is positive in 49.43 percent of forecast months. The HAC t -statistic for the mean is 0.410, corresponding to a two-sided p -value of 0.682. The average ranking association is consequently close to zero, economically small, and statistically insignificant. The conditional forecasts provide little evidence of improved ability to rank industries by their subsequent monthly returns.

The nested-model comparison yields the same empirical conclusion. The Clark-West test, which adjusts the comparison for the additional estimated parameters in the conditional specification, produces a t -statistic of 0.259 and a one-sided p -value of 0.398. The test therefore does not provide evidence that conditioning FF6 on the predetermined macro state improves predictive accuracy relative to unconditional FF6.

Figure 3 shows the cumulative difference in squared forecast errors between the conditional and unconditional specifications over the OOS period. Relative forecast performance varies through time, and the cumulative series moves in both directions over the sample. By the end of the evaluation period, the cumulative comparison favors unconditional FF6. The figure is consistent with the aggregate RMSE and OOS R^2 results and shows how relative forecast performance accumulates over the evaluation period.

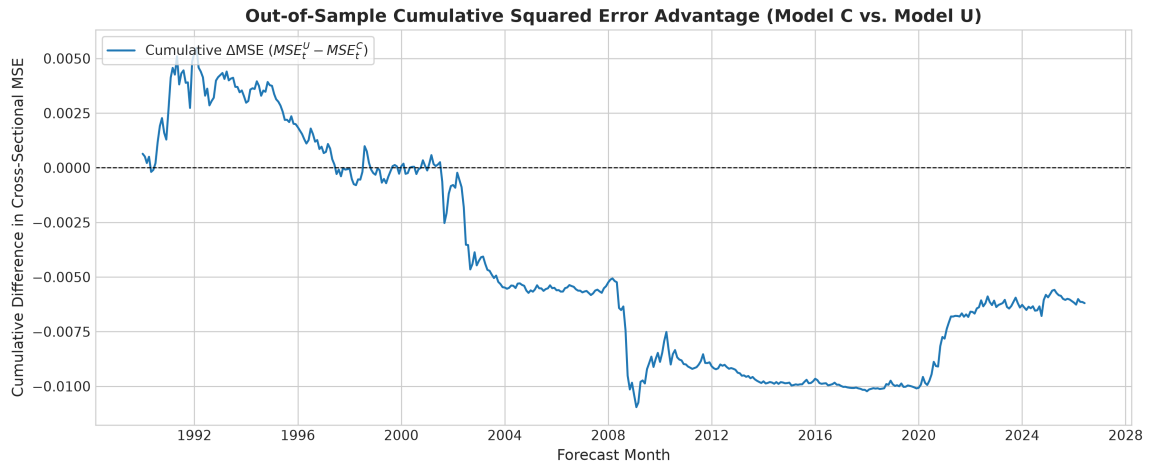


Figure 3. Cumulative OOS Squared-Error Difference

The OOS evidence provides a clear answer to the paper's primary forecasting question. Section 4 documents state-dependent factor exposures for a subset of industries and a statistically significant shift in the SMB premium. Applying those relationships in an expanding real-time forecasting exercise does not improve next-month industry-return predictions. Forecast errors are slightly larger for conditional FF6, cross-sectional ranking performance is close to zero, and the Clark-West test does not indicate superior conditional predictive accuracy.

6. Portfolio Implications

The portfolio exercise translates each forecasting rule into a simple monthly ranking strategy. Conditional FF6, unconditional FF6, and the historical-mean benchmark each form an equal-weight portfolio of the ten industries with the highest predicted excess returns. Table 4 reports performance under the primary transaction-cost assumption of 10 basis points, and Figure 4 plots cumulative wealth for the resulting strategies together with the broad market benchmark.

Table 4. Out-of-Sample Portfolio Performance, 10 bps

<i>Panel A: Absolute performance</i>						
Strategy	CAGR	Volatility	Sharpe	Max drawdown		
Conditional FF6	12.14%	18.04%	0.580	-52.58%		
Unconditional FF6	10.90%	18.78%	0.505	-57.57%		
Historical mean	10.30%	15.18%	0.548	-50.01%		
Market benchmark	11.05%	15.24%	0.591	-50.31%		
<i>Panel B: Active and factor-adjusted performance</i>						
Strategy	Active return	Tracking error	IR	FF6 alpha	Alpha t	Alpha p
Conditional FF6	1.46%	10.56%	0.138	-1.55%	-1.16	0.247
Unconditional FF6	0.49%	10.73%	0.046	-2.49%	-1.85	0.064
Historical mean	-0.69%	6.29%	-0.110	-1.86%	-1.87	0.062

Notes: The 10 bps transaction cost applies to the traded fraction of the three forecast-based portfolios. The market benchmark is MKT-RF plus RF and is not charged portfolio rebalancing costs. Sharpe ratios use portfolio excess returns. FF6 alpha is annualized; alpha inference uses HAC lag 6.

The conditional Top-10 portfolio earns a CAGR of 12.14 percent with annualized volatility of 18.04 percent and a Sharpe ratio of 0.580. Its maximum drawdown is -52.58 percent. Relative to the market, the strategy generates an annualized active return of 1.46 percent with tracking error of 10.56 percent, producing an information ratio of 0.138. The unconditional Top-10 portfolio records a CAGR of approximately 10.90 percent and a Sharpe ratio of 0.505, while the historical-mean portfolio earns approximately 10.30 percent with a Sharpe ratio of 0.548. The market benchmark has a CAGR of 11.05 percent and a Sharpe ratio of 0.591.

Regime conditioning therefore changes the portfolio rankings in a way that raises raw performance relative to the analogous unconditional and historical-mean strategies. The conditional portfolio also has a higher CAGR than the market benchmark. Its Sharpe ratio remains slightly below the market Sharpe, and the 10.56 percent tracking error indicates substantial variation in active performance. The resulting information ratio of 0.138 is correspondingly low.

The factor-adjusted results provide no evidence of abnormal performance. The conditional portfolio has an annualized FF6 alpha of -1.55 percent, with a t -statistic of -1.16 and a p -value of 0.247. The negative point estimate provides no indication of positive abnormal performance after controlling for the portfolio's six-factor exposures. The estimate is statistically insignificant and therefore does not provide evidence of reliably negative abnormal performance either.

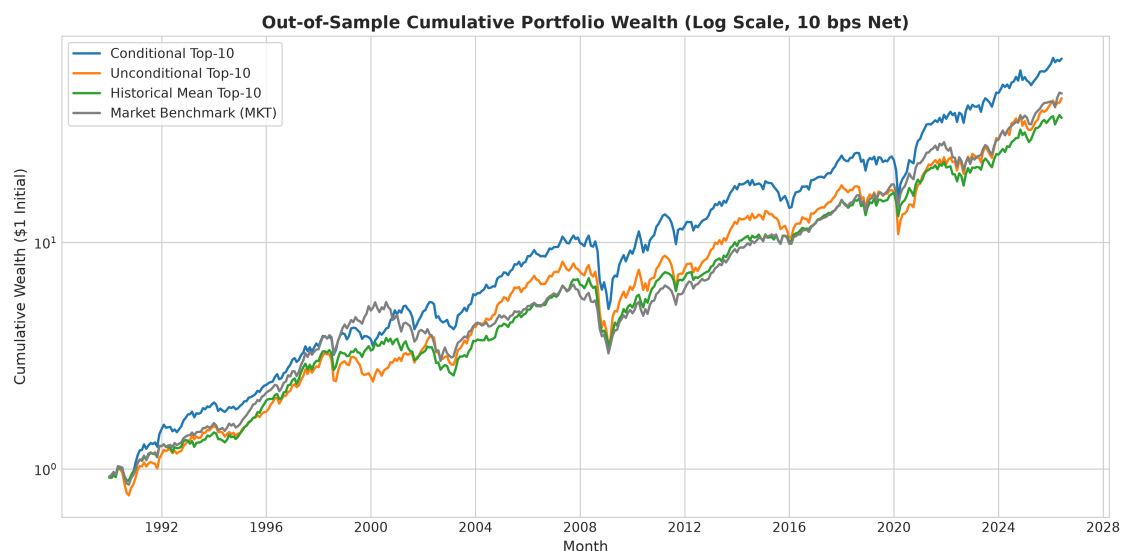
**Figure 4.** Cumulative Portfolio Wealth, 10 bps

Figure 4 summarizes the cumulative wealth paths under the primary 10 basis point cost assumption and illustrates the long-run differences generated by the three ranking rules. Transaction-cost assumptions of 0 and 25 basis points are examined as sensitivity cases in Appendix Table A3 and do not change the qualitative interpretation of the portfolio comparison.

7. Robustness

Table 5 summarizes the pre-specified robustness exercises. The primary OOS conclusion remains unchanged under alternative factor specifications, estimation windows, and industry classifications. Removing momentum and estimating FF5 produces a conditional RMSE of 6.7494 percent, compared with 6.7404 percent for unconditional FF5 and 6.7425 percent for the historical mean. The corresponding $R^2_{OS,U}$ is -0.266 percent, and the Clark-West test gives $t = 0.295$ with a one-sided p -value of 0.384. Removing MOM therefore does not improve conditional OOS performance.

Table 5. Robustness of the Out-of-Sample Result

Panel A: Real-time OOS robustness							
Specification	Months	Forecasts	RMSE C	RMSE U	$R^2_{OS,U}$	CW t	CW p
FF5	437	21,413	6.7494%	6.7404%	-0.266%	0.295	0.384
20-year rolling window	437	21,413	6.7669%	6.7446%	-0.660%	-0.026	0.510
30 industries	437	13,110	6.5220%	6.5136%	-0.258%	0.300	0.382
Continuous Sahm	437	21,413	6.7482%	6.7416%	-0.196%	1.463	0.072
Panel B: In-sample and retrospective state-dependence robustness							
Specification	Observations	BH-FDR significant		Status			
Primary Sahm, HAC6	683	11/49		Primary in-sample inference			
HAC12	683	17/49		Longer HAC lag			
CFNAI	683	29/49		Retrospective / revised state			
NBER	683	18/49		Retrospective state			
Panel C: Portfolio cost sensitivity							
0, 10, and 25 bps	Nine forecast-portfolio cost specifications; detailed results in Appendix Table A3.						

Notes: RMSE values are monthly percentage returns. CW p is one-sided. Panel B reports industry-level joint loading tests after BH-FDR control at 5 percent. CFNAI and NBER rows are not real-time OOS forecast tests.

Using a 20-year rolling estimation window produces similar evidence. All 437 forecast months satisfy the required training-sample and STRESS-observation thresholds. Conditional RMSE is 6.7669 percent, compared with 6.7446 percent for the unconditional benchmark, yielding $R^2_{OS,U} = -0.660$ percent. The Clark-West statistic is -0.026 with $p = 0.510$. A shorter and more adaptive estimation history therefore does not improve the conditional forecasts. The result also survives a change in the test-asset universe. Using 30 value-weighted industry portfolios generates 13,110 forecasts, with conditional and unconditional RMSEs of 6.5220 and 6.5136 percent. The resulting $R^2_{OS,U}$ is -0.258 percent, and the Clark-West test gives $p = 0.382$.

The continuous Sahm specification produces the closest result to formal OOS evidence. Conditional RMSE is 6.7482 percent, compared with 6.7416 percent for unconditional FF6, and $R^2_{OS,U}$ remains negative at -0.196 percent. The Clark-West statistic increases to 1.463, with a one-sided p -value of 0.072. The one-sided p -value of 0.072 provides suggestive evidence under a 10 percent threshold, although it does not meet the conventional 5 percent level. Continuous macro stress therefore contains mildly suggestive information under the nested-model adjustment. Raw forecast errors remain higher for the conditional model, so this evidence does not overturn the primary OOS conclusion.

Additional robustness tests examine in-sample inference and alternative macro classifications. Under the primary Sahm specification with HAC lag 6, 11 of 49 industries remain significant after BH-FDR correction. Increasing the HAC lag to 12 raises the count to 17, indicating that the evidence of state-dependent exposures is not eliminated by the longer covariance adjustment. The CFNAI specification (Federal Reserve Bank of St. Louis n.d.-b) identifies 29 of 49 industries as FDR-significant across 683 observations. The NBER specification identifies 18 of 49. CFNAI is treated as a retrospective or revised state classification in this

setting (Federal Reserve Bank of Chicago n.d.), and the NBER classification is ex post by construction (National Bureau of Economic Research n.d.). Their stronger in-sample significance therefore describes state dependence under alternative macro classifications and does not constitute a historical real-time forecasting test comparable to the predetermined Sahm specification.

Finally, transaction-cost sensitivities at 0 and 25 basis points leave the qualitative portfolio interpretation unchanged relative to the primary 10 basis point specification. Detailed cost results are reported in Appendix Table A3.

The robustness evidence reinforces the primary forecasting result across factor specification, estimation window, and industry universe. Continuous Sahm provides only marginal evidence under the Clark-West adjustment, while retrospective macro classifications reveal stronger state dependence in sample.

8. Discussion and Limitations

The empirical results reveal a clear distinction between state dependence and real-time forecastability. In sample, a subset of industries exhibits statistically detectable changes in FF6 exposures between NORMAL and STRESS, and SMB shows a significant difference in its average premium across the two states. The real-time OOS exercise does not translate these relationships into lower aggregate forecast errors. The main robustness specifications preserve this conclusion across alternative factor sets, estimation windows, and industry classifications.

Parameter estimation offers one plausible explanation for this pattern. The conditional specification estimates additional coefficients for state-dependent intercepts and factor exposures and also requires state-specific factor-premium estimates. These quantities are estimated from fewer effective observations than their unconditional counterparts. STRESS accounts for 159 of the 683 observations in the full sample, and the available STRESS history is more limited in the earlier expanding estimation windows. Genuine differences between states can therefore coexist with substantial uncertainty in the estimates used for a one-month-ahead forecast. The results do not isolate estimation uncertainty as the cause of the OOS outcome, but the structure of the forecasting problem makes it a relevant interpretation.

The retrospective-state robustness results reinforce the distinction between describing historical variation and producing implementable forecasts. Revised CFNAI classifications (Federal Reserve Bank of Chicago n.d.) identify state-dependent exposures for a larger number of industries, and NBER recession dates (National Bureau of Economic Research n.d.) also produce stronger in-sample evidence than the primary real-time Sahm specification. These classifications organize historical observations using information or dating conventions that are not equivalent to the information set available at each historical forecast date. Real-time forecasting requires the macro state to be observable before the return month and requires the relationship between that state and returns to be estimated entirely from prior data. The broader real-time macroeconomic literature similarly emphasizes that revised historical series can differ from the information actually available to forecasters (Croushore and Stark 2001).

State representation also matters. The primary 0.50 Sahm threshold creates a transparent and predetermined distinction between NORMAL and STRESS. The binary classification necessarily compresses variation in the intensity of labor-market deterioration. The continuous Sahm robustness produces the strongest Clark-West evidence among the OOS alternatives, with a one-sided p -value of 0.072. Its raw RMSE remains above the unconditional benchmark and its OOS R^2 remains negative. This result provides limited evidence that the magnitude of macroeconomic stress may contain information that is lost in the binary classification, without establishing robust forecast improvement.

The timing and horizon of the forecasting exercise impose an additional requirement. SAHMREALTIME is derived from publicly released labor-market information (Federal Reserve Bank of St. Louis n.d.-a; U.S. Bureau of Labor Statistics 2026). By the time that information can be incorporated into the predetermined state, financial prices may already reflect a substantial part of its implications. The analysis does not directly test this mechanism. It remains a plausible reason why a macro variable can organize historical factor exposures without generating useful next-month cross-sectional return forecasts. The conclusions are also specific to a one-month forecast horizon. State-dependent exposures can persist even when they offer little predictive content for returns over that particular interval.

The portfolio results are consistent with this broader interpretation. Conditional forecasts alter industry rankings enough to produce a higher raw CAGR than the analogous unconditional Top-10 strategy. The market retains a slightly higher Sharpe ratio, tracking error is substantial, the information ratio is low, and the conditional portfolio's FF6 alpha is negative and statistically insignificant. The ranking changes therefore have economic consequences for portfolio composition and raw returns. They do not establish robust factor-adjusted abnormal performance.

The scope of these conclusions reflects several design choices. The primary state measures one dimension of macroeconomic conditions through labor-market stress. Its binary form compresses a continuous signal, and STRESS observations are less frequent than NORMAL observations. The test assets are industry portfolios, so the results do not automatically extend to individual stocks or other asset classes. The Top-10 exercise is intentionally simple and omits portfolio optimization, capacity, taxes, and detailed trading frictions beyond transaction costs. CFNAI and NBER serve as retrospective robustness classifications and cannot be interpreted as deployable historical forecasting signals.

The main implication is therefore specific and empirically grounded: Macroeconomic regimes can help describe changes in factor exposures and selected factor premia. In this setting, those relationships do not generate a reliable next-month forecasting advantage when evaluated with real-time information.

9. Conclusion

This paper examines whether conditioning a standard FF6 model on a predetermined real-time labor-market stress regime improves out-of-sample forecasts of U.S. industry excess returns. The evidence shows clear state dependence in parts of the factor structure. A subset of industries exhibits statistically significant changes in FF6 exposures across NORMAL and STRESS, SMB shows the strongest state-dependent factor-premium difference, and the conditional specification produces smaller in-sample pricing errors.

These relationships do not translate into improved real-time forecast accuracy. Relative to unconditional FF6, the conditional model produces an OOS R^2 of -0.312 percent. Cross-sectional Rank IC is close to zero, and the Clark-West test does not provide evidence of superior predictive accuracy for the conditional specification. The portfolio exercise shows that regime conditioning changes industry rankings and produces different raw return paths. The resulting performance does not establish positive factor-adjusted abnormal returns.

The main forecasting conclusion is robust to alternative factor specifications, estimation windows, and industry classifications. A continuous Sahm specification produces the strongest Clark-West evidence among the OOS robustness checks, yet raw forecast errors remain higher and OOS R^2 remains negative.

The empirical implication is therefore specific. Macroeconomic state dependence can be present in factor exposures and premia without producing a reliable one-month-ahead forecasting advantage when the state and all model parameters must be estimated using information available in real time.

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A. Appendix

A.1 Detailed State Dependence

Table A1. Industry-Level Tests of State-Dependent FF6 Exposures

Industry	δ_i	$p(\delta_i)$	Wald $\gamma = 0$	Raw p	BH-FDR q	Reject
Agric	-0.910%	0.047	9.49	0.1479	0.2196	No
Food	0.311%	0.259	8.92	0.1782	0.2443	No
Soda	0.121%	0.804	9.58	0.1434	0.2196	No
Beer	-0.071%	0.836	5.74	0.4524	0.5038	No
Smoke	0.029%	0.944	11.74	0.0679	0.1301	No
Toys	1.263%	0.011	10.50	0.1052	0.1778	No
Fun	-0.287%	0.614	26.23	0.0002	0.0049	Yes
Books	0.160%	0.651	9.32	0.1563	0.2253	No
Hshld	0.354%	0.230	24.05	0.0005	0.0084	Yes
Clths	0.928%	0.005	22.23	0.0011	0.0112	Yes
Hlth	-0.158%	0.812	9.89	0.1296	0.2048	No
MedEq	0.528%	0.088	21.84	0.0013	0.0112	Yes
Drugs	0.028%	0.939	14.17	0.0278	0.0656	No
Chems	0.320%	0.283	17.28	0.0083	0.0407	Yes
Rubbr	-0.255%	0.427	15.82	0.0147	0.0534	No
Txtls	0.013%	0.979	7.50	0.2774	0.3485	No
BldMt	-0.542%	0.088	8.90	0.1795	0.2443	No
Cnstr	-1.198%	0.003	21.69	0.0014	0.0112	Yes
Steel	-0.929%	0.046	3.15	0.7902	0.8176	No
FabPr	-0.356%	0.641	19.43	0.0035	0.0245	Yes
Mach	-0.734%	0.032	7.34	0.2903	0.3556	No
ElcEq	-0.130%	0.684	11.90	0.0643	0.1301	No
Autos	0.065%	0.907	14.14	0.0281	0.0656	No
Aero	-0.339%	0.400	6.59	0.3608	0.4111	No
Ships	-0.971%	0.016	6.73	0.3465	0.4043	No
Guns	-0.473%	0.232	11.40	0.0768	0.1393	No
Gold	-0.990%	0.348	16.89	0.0097	0.0433	Yes
Mines	0.073%	0.918	15.31	0.0180	0.0534	No
Coal	0.243%	0.804	18.22	0.0057	0.0311	Yes
Oil	-0.456%	0.320	26.80	0.0002	0.0049	Yes
Util	-0.023%	0.936	18.61	0.0049	0.0299	Yes
Telecm	-0.118%	0.711	7.02	0.3194	0.3817	No
PerSv	0.611%	0.135	14.43	0.0252	0.0654	No
BusSv	0.135%	0.451	15.23	0.0185	0.0534	No
Hardw	-0.101%	0.834	16.24	0.0125	0.0511	No
Softw	-0.219%	0.724	11.30	0.0796	0.1393	No
Chips	-0.343%	0.352	11.88	0.0647	0.1301	No
LabEq	-0.224%	0.519	7.83	0.2508	0.3321	No
Paper	-0.196%	0.487	7.74	0.2581	0.3329	No
Boxes	0.306%	0.352	2.38	0.8818	0.8818	No
Trans	0.570%	0.029	15.41	0.0173	0.0534	No
Whlsl	0.105%	0.760	11.70	0.0690	0.1301	No
Rtail	0.573%	0.082	15.25	0.0184	0.0534	No
Meals	0.641%	0.099	14.41	0.0254	0.0654	No
Banks	0.443%	0.199	3.06	0.8009	0.8176	No
Insur	0.086%	0.826	3.45	0.7500	0.7989	No
RIEst	-0.306%	0.525	4.54	0.6040	0.6576	No
Fin	0.503%	0.122	13.56	0.0350	0.0779	No
Other	-0.619%	0.230	10.40	0.1089	0.1779	No

Notes: δ_i is the STRESS intercept shift and is reported in percentage points per month. The primary industry-level test is the joint Wald test $H_0 : \gamma_i = \mathbf{0}$ using HAC lag 6. BH-FDR q values control the false discovery rate across the 49 joint tests at 5 percent.

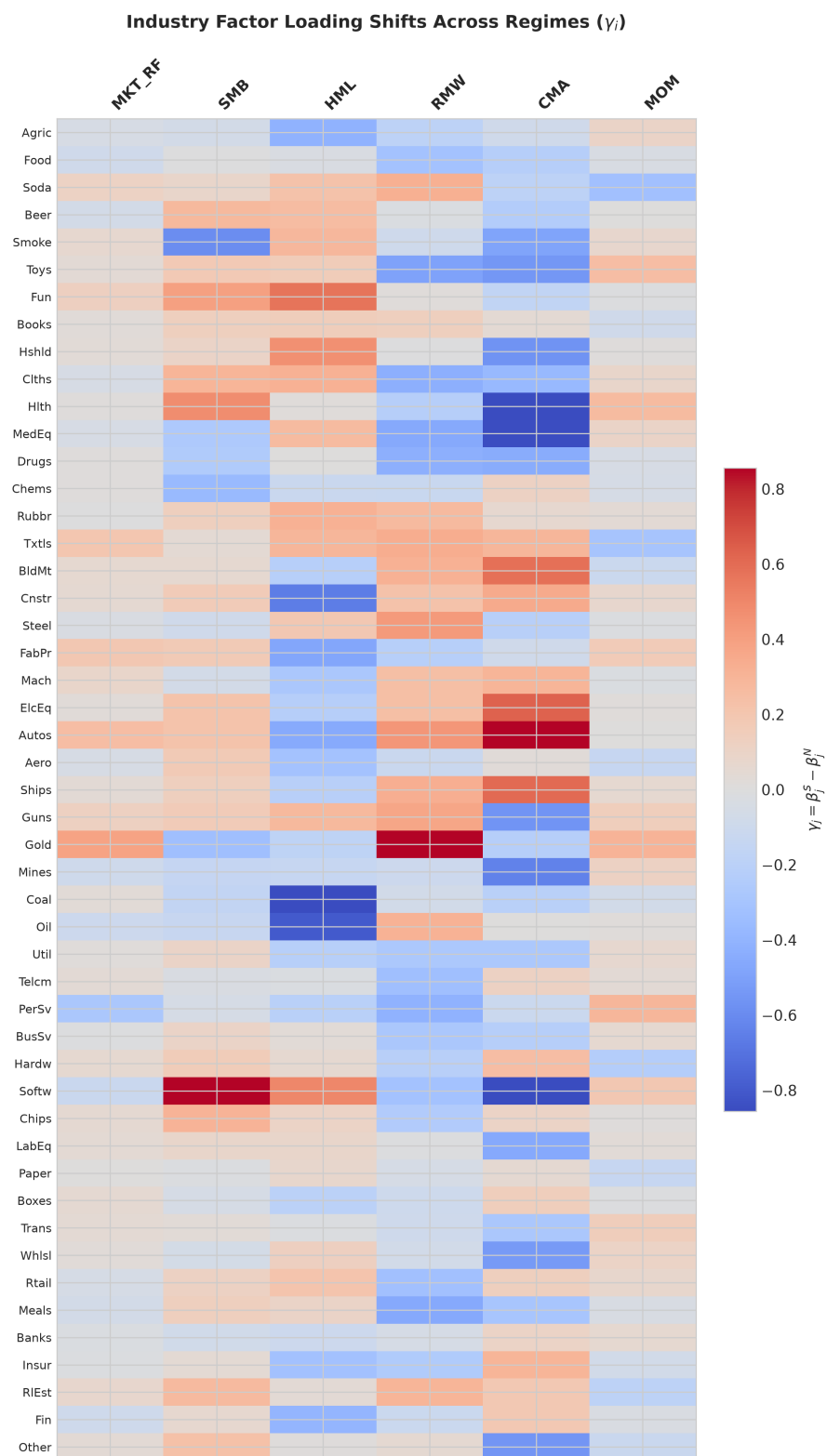


Figure A1. State-Dependent Changes in Industry Factor Loadings

A.2 Supplementary In-Sample Evidence

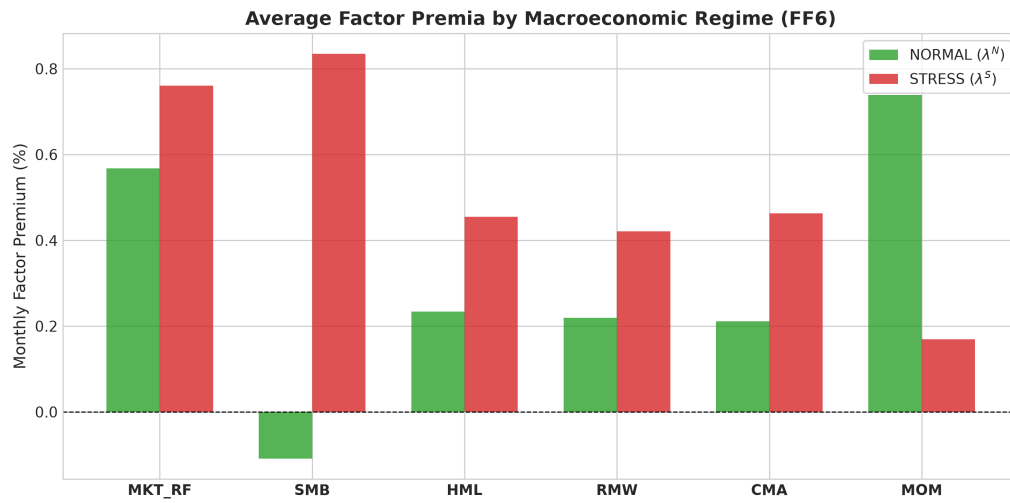


Figure A2. Factor Premia by Macro State

Table A2. In-Sample Pricing Errors by Macro State

Regime	Cells	RMSE U	RMSE C	Δ RMSE	MAE U	MAE C	Δ MAE
NORMAL	49	0.394%	0.289%	-0.105 pp	0.311%	0.227%	-0.084 pp
STRESS	49	0.550%	0.474%	-0.076 pp	0.443%	0.353%	-0.090 pp
POOLED	98	0.479%	0.393%	-0.086 pp	0.377%	0.290%	-0.087 pp

Notes: U and C denote unconditional and conditional FF6. Differences are conditional minus unconditional in percentage points. Negative values indicate smaller pricing errors for the conditional specification.

A.3 OOS Ranking Diagnostic

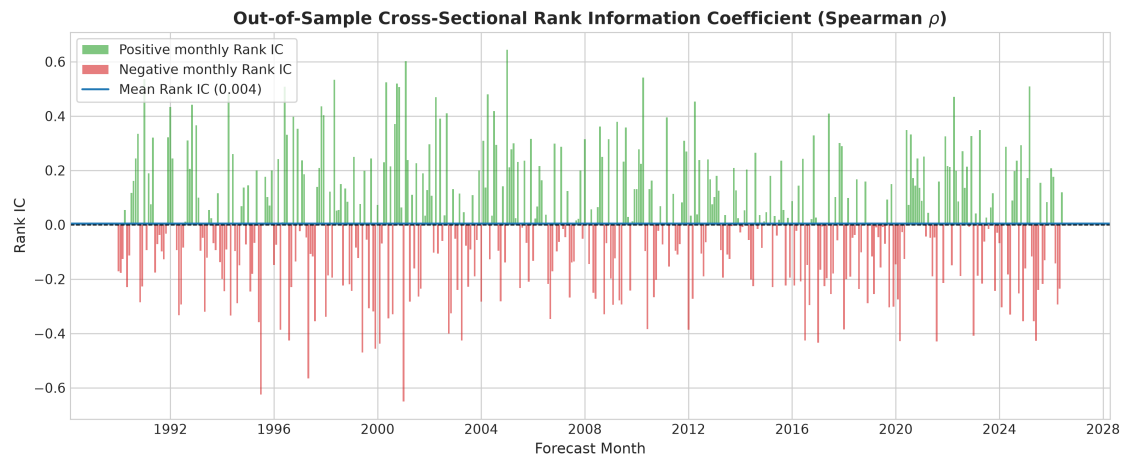


Figure A3. Monthly Cross-Sectional Rank IC

A.4 Portfolio Transaction-Cost Sensitivity

Table A3. Portfolio Performance at 0, 10, and 25 bps

Strategy	Cost	CAGR	Vol.	Sharpe	Max DD	Active	TE	IR	Ann. turnover	FF6 alpha	Alpha t	Alpha p
Conditional	0	12.28%	18.04%	0.587	-52.50%	1.59%	10.56%	0.151	64.53%	-1.42%	-1.06	0.289
Conditional	10	12.14%	18.04%	0.580	-52.58%	1.46%	10.56%	0.138	64.53%	-1.55%	-1.16	0.247
Conditional	25	11.92%	18.05%	0.569	-52.70%	1.27%	10.56%	0.120	64.53%	-1.75%	-1.30	0.192
Unconditional	0	10.95%	18.78%	0.507	-57.56%	0.53%	10.73%	0.050	19.77%	-2.45%	-1.82	0.069
Unconditional	10	10.90%	18.78%	0.505	-57.57%	0.49%	10.73%	0.046	19.77%	-2.49%	-1.85	0.064
Unconditional	25	10.84%	18.77%	0.502	-57.58%	0.43%	10.73%	0.040	19.77%	-2.55%	-1.89	0.058
Historical mean	0	10.40%	15.18%	0.554	-50.00%	-0.60%	6.29%	-0.096	44.76%	-1.77%	-1.77	0.076
Historical mean	10	10.30%	15.18%	0.548	-50.01%	-0.69%	6.29%	-0.110	44.76%	-1.86%	-1.87	0.062
Historical mean	25	10.15%	15.19%	0.539	-50.03%	-0.83%	6.28%	-0.132	44.76%	-2.00%	-2.01	0.045

Notes: Cost is in basis points and is applied to the traded fraction each month. Active return and tracking error are measured relative to the market benchmark. FF6 alpha is annualized and uses HAC lag 6 for inference. The market benchmark is unchanged across cost cases and is reported in main-text Table 4.

A.5 Detailed Robustness Inference

Table A4. Industry-Level State-Dependence Robustness

Industry	Primary Sahm	HAC12	CFNAI	NBER
Aero	0.4111	0.3886	0.0001	0.4182
Agric	0.2196	0.2434	0.0019	0.0042
Autos	0.0656	0.1153	0.3051	0.0514
Banks	0.8176	0.7983	0.5103	0.9624
Beer	0.5038	0.5338	0.0456	0.0133
BldMt	0.2443	0.2767	0.0002	0.0864
Books	0.2253	0.1288	0.0782	0.7125
Boxes	0.8818	0.8913	0.3051	0.1948
BusSv	0.0534	0.0415	0.0199	0.1307
Chems	0.0407	0.0297	0.0944	0.0098
Chips	0.1301	0.0714	0.1781	0.3043
Clths	0.0112	0.0025	0.0164	0.0018
Cnstr	0.0112	0.0065	0.0000	0.5741
Coal	0.0311	0.0146	0.1058	0.4178
Drugs	0.0656	0.0311	0.1074	0.2337
ElcEq	0.1301	0.1211	0.0023	0.2799
FabPr	0.0245	0.0071	0.0236	0.1703
Fin	0.0779	0.1153	0.0000	0.0047
Food	0.2443	0.2776	0.0018	0.0549
Fun	0.0049	0.0071	0.0000	0.0638
Gold	0.0433	0.0487	0.0649	0.0352
Guns	0.1393	0.1179	0.0199	0.0819
Hardw	0.0511	0.0487	0.6022	0.2917
Hlth	0.2048	0.2631	0.1869	0.6482
Hshld	0.0084	0.0061	0.0000	0.1384
Insur	0.7989	0.7983	0.0031	0.5260
LabEq	0.3321	0.3121	0.1058	0.0241
Mach	0.3556	0.3568	0.0002	0.0038
Meals	0.0654	0.0780	0.0456	0.0249
MedEq	0.0112	0.0071	0.2020	0.0124
Mines	0.0534	0.0728	0.0000	0.0047
Oil	0.0049	0.0025	0.0000	0.0047
Other	0.1779	0.1595	0.4322	0.2267
Paper	0.3329	0.2776	0.0058	0.1426
PerSv	0.0654	0.1153	0.0000	0.7198
REst	0.6576	0.7108	0.0000	0.0432
Rtail	0.0534	0.0487	0.0000	0.5816
Rubbr	0.0534	0.0204	0.0024	0.0262
Ships	0.4043	0.3121	0.0000	0.0461
Smoke	0.1301	0.1179	0.1869	0.0241
Soda	0.2196	0.2631	0.0000	0.1384
Softw	0.1393	0.1595	0.3509	0.2775
Steel	0.8176	0.7156	0.0065	0.3401
Telcm	0.3817	0.3939	0.0742	0.2267
Toys	0.1778	0.1710	0.0000	0.0316
Trans	0.0534	0.0481	0.6991	0.5685
Txtls	0.3485	0.3121	0.0020	0.1539
Util	0.0299	0.0237	0.1473	0.0047
Whlsl	0.1301	0.1179	0.0814	0.5460

Notes: Entries are BH-FDR q values for the industry-level joint test of state-dependent factor exposures. Bold entries reject at the 5 percent FDR level. Primary Sahm uses HAC lag 6; HAC12 changes only the covariance lag. CFNAI and NBER are retrospective or revised state classifications and are not real-time OOS forecast tests. The CFNAI specification contains 683 observations and 29 FDR-significant industries.

A.6 Data and Timing Documentation

Table A5. Data Sources, Coverage, and Information Timing

Dataset	Source	Raw coverage	Role	Timing / use in study
49 Industry Portfolios (VW)	Kenneth R. French Data Library	1926-07 to 2026-06	Primary test assets	Balanced 49-industry sample begins 1969-07.
Fama/French 5 Factors	Kenneth R. French Data Library	1963-07 to 2026-06	MKT-RF, SMB, HML, RMW, CMA	Monthly factors; forecast-window premia use observations through $t - 1$.
Momentum Factor (MOM)	Kenneth R. French Data Library	1927-01 to 2026-06	Sixth factor in FF6	Monthly factor; forecast-window premia use observations through $t - 1$.
SAHMLEALTIME	FRED, Federal Reserve Bank of St. Louis	1959-12 to 2026-07	Primary macro state	This study assigns return month t the Sahm observation from $t - 2$; threshold 0.50.
CFNAIMA3	Federal Reserve Bank of Chicago / FRED	1967-05 to 2026-06	Retrospective robustness state	Exact two-calendar-month lag; the revised full-sample series is used only for retrospective robustness and is not treated as a real-time OOS signal.
USRECM	NBER dates via FRED (Federal Reserve Bank of St. Louis n.d.-c)	1854-12 to 2026-07	Descriptive and retrospective robustness	Used for descriptive validation and ex-post robustness only; never constructs the primary forecast state.

Notes: Raw coverage comes from the final validation outputs. The primary processed sample contains 683 usable months from July 1969 through June 2026. The $t - 2$ Sahm assignment is this study's information-timing convention.