Geneva Graduate Institute (IHEID)

Topics in Econometrics

Term Paper

The Incremental Predictive Power of Consumer Sentiment in Macroeconomic Forecasting

Evidence from a Hierarchical Bayesian VAR and Forecast-Revision Diagnostics

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Abstract

Does consumer sentiment add predictive content for inflation and real activity once standard macro aggregates and financial prices are already included? I answer this question with a transparent horse race across nested information sets in a hierarchical Bayesian VAR, paired with a revision-based diagnostic of forecast updating following Coibion and Gorodnichenko (2015).

The information sets are nested by construction: *Small* contains standard macro aggregates, *Medium* adds a small set of financial prices, and *Full* further adds survey-based consumer sentiment (see Section 2 and `INTERNAL_MAPPING.md` for the exact series mapping). The point-forecast evidence shows that richer information sets can improve accuracy, but sentiment's incremental contribution to forecast accuracy is limited once financial variables are already in the information set (Table 1; Figure 1). The revision diagnostic, by contrast, indicates systematic patterns in forecast updating, and the information set can shift these patterns even when point accuracy changes little (Table 2). Because the competing specifications are nested, I treat standard equal-accuracy tests as suggestive and use nested-model-robust adjustments as a robustness check (Clark & McCracken, 2001; Clark & West, 2007) (Appendix Table 3). Throughout, revision-regression coefficients are interpreted as a diagnostic of internal consistency in a regularized forecasting system (and can partly reflect prior-induced conservatism), not as structural evidence about economic agents.

Keywords: Bayesian VAR; hierarchical shrinkage; forecasting; consumer sentiment; forecast revisions.

1 Introduction

This paper studies a practical forecasting question: does consumer sentiment add incremental predictive content for inflation and real activity once conventional macro aggregates and financial prices are already included? I organize the answer around two objects that matter to forecasting practice: *forecast accuracy* (how close point forecasts are to realizations) and *forecast discipline* (whether the forecasting system revises in an internally coherent way, rather than exhibiting systematic updating patterns).

Contributions and headline evidence.

- **Design: nested information sets in a hierarchical BVAR.** I run a horse race across nested information sets within a hierarchical Bayesian VAR that updates regularization strength within a hyperprior family rather than fixing it by hand (Bańbura, Giannone, & Reichlin, 2010; Giannone, Lenza, & Primiceri, 2015; Kuschnig & Vashold, 2021).

- **Accuracy versus discipline.** Sentiment's incremental contribution to point-forecast accuracy is limited once financial variables are included (Table 1; Figure 1), consistent with information overlap between sentiment and forward-looking prices (Bram & Ludvigson, 1998; Ludvigson, 2004). At the same time, a revision-based diagnostic following Coibion and Gorodnichenko (2015) shows systematic updating patterns, and the information set can shift these patterns even when point accuracy moves little (Table 2).

- **Revision diagnostics as model diagnostics.** Applied to model-implied forecasts, the Coibion and Gorodnichenko (2015) regression is an updating diagnostic for a *regularized* forecasting system: its coefficients summarize internal error–revision consistency and can partly reflect prior-induced conservatism rather than economic agents' behavior.

- **Inference discipline under nesting.** Because the specifications are nested, standard equal-accuracy tests can be distorted; I therefore emphasize magnitudes and stability and use nested-robust adjustments as robustness checks (Clark & McCracken, 2001; Clark & West, 2007) (Appendix Table 3).

Related literature. First, the revision diagnostic connects to work that uses forecast revisions to study expectation updating (Coibion & Gorodnichenko, 2015); here, it is applied as a diagnostic for a model-based forecasting system rather than a structural claim about beliefs. Second, evidence on whether confidence or sentiment contains incremental forecasting information is mixed once other indicators are included, motivating a conditional horse race (Bram & Ludvigson, 1998; Carroll, Fuhrer, & Wilcox, 1994; Ludvigson, 2004). Third, the inflation-forecasting literature emphasizes that parsimonious benchmarks are often competitive and that forecasting relationships can shift, which motivates cautious interpretation of incremental gains (Atkeson & Ohanian, 2001; Stock & Watson, 2007). Fourth, hierarchical BVAR shrinkage provides a disciplined way to compare information sets of different dimensions without ad hoc tuning (Bańbura et al., 2010; Giannone et al., 2015; Kuschnig & Vashold, 2021).

Roadmap. Section 2 describes the nested information sets and the evaluation setup. Section 3 presents the forecasting system, the role of hierarchical shrinkage, and the accuracy and revision diagnostics. Section 4 reports the evidence, and Section 5 concludes.

Empirical focus. The empirical goal is descriptive: quantify the incremental predictive content of sentiment conditional on macro aggregates and financial prices, and summarize forecast-updating patterns using the revision diagnostic. I avoid structural interpretations of revision-regression coefficients and treat formal comparisons under nesting cautiously.

2 Data

The dataset combines macro aggregates, a small set of widely used financial prices, and a survey-based measure of consumer sentiment. The information sets are nested to isolate incremental information content:

- **Small: macro aggregates.** Prices, real activity, labor-market slack, and the policy stance.
- **Medium: macro aggregates + financial prices.** Small plus a long-term interest rate, a broad equity price index, and an oil price series.
- **Full: macro aggregates + financial prices + sentiment.** Medium plus consumer sentiment.

The comparison between Medium and Full therefore targets whether sentiment contributes beyond information already summarized in market prices.

Following standard BVAR practice, the model is estimated in levels or log-levels (Giannone et al., 2015; Sims, 1980). Forecasts are evaluated on a common growth-rate scale constructed from model-implied level forecasts, using the same transformation as the code pipeline. The output-to-manuscript mapping is audited in `INTERNAL_MAPPING.md`.

3 Empirical design

3.1 Forecasting system and nested information sets

For each information set, I estimate a reduced-form VAR forecasting system and only change the information set. This isolates the incremental role of forward-looking prices and sentiment within a common estimation and prediction rule. The forecasting system is

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

where y_t collects the variables in the information set. Because adding variables increases parameter uncertainty even when predictive content is present, I regularize the system with Minnesota-style shrinkage and learn the overall tightness from the data using the hierarchical prior-selection approach of Giannone et al. (2015), as implemented in Kuschnig and Vashold (2021). Importantly, shrinkage is interpreted as statistical regularization of the forecasting system rather than as a proxy for economic frictions.

3.2 Pseudo out-of-sample evaluation

I evaluate performance in a recursive pseudo out-of-sample design with expanding estimation windows. At each forecast origin, the system is re-estimated using all data available up to that origin and then produces point forecasts at the horizons reported in the main accuracy table. This recursion mirrors a real-time workflow while remaining descriptive because it uses revised data rather than real-time vintages.

3.3 Forecast accuracy and nested-model inference

Forecast accuracy is summarized by RMSFE on the common evaluation scale described in Section 2. For target i and horizon h,

$$\mathrm{RMSFE}_{i,h} = \left(P^{-1} \sum_{t \in \mathcal{T}} (y_{i,t+h} - \hat{y}_{i,t+h|t})^2 \right)^{1/2}.$$

I report RMSFEs (Table 1) and relative RMSFEs versus a parsimonious benchmark (Figure 1). Because the information sets are nested, standard equal-accuracy tests can have nonstandard behavior (Clark & McCracken, 2001); I therefore emphasize magnitudes and stability and report a nested-model-robust adjustment as a robustness check (Clark & West, 2007) (Appendix Table 3).

3.4 Forecast discipline: revision-based diagnostic

To assess whether forecast updates are systematically related to subsequent forecast errors, I use the error-on-revision regression framework of Coibion and Gorodnichenko (2015) applied to model-implied forecasts:

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

where $r^{(m)}_{t,h}$ is the revision to the forecast for the same target date made one period apart. In this paper, the regression is used as a diagnostic of the forecasting system's updating rule: it measures whether revisions are followed by predictable errors, indicating systematic patterns in updating. Because the forecasts are produced under shrinkage, such patterns can partly reflect prior-induced conservatism, misspecification, or instability rather than an economic mechanism.

4 Results

This section reports the core evidence through two complementary lenses: forecast *accuracy* and forecast *discipline*. Accuracy evaluates whether sentiment improves point forecasts once macro aggregates and financial prices are already in the information set. Discipline evaluates whether the information set changes systematic patterns in forecast updates, using the revision-based diagnostic in Section 3.

Main takeaways.

- **Accuracy: limited marginal value of sentiment conditional on prices.** Adding financial prices can improve point forecasts relative to the macro-only system, but the incremental contribution of sentiment beyond prices is limited (Table 1; Figure 1).
- **Discipline: information sets can change updating patterns.** The revision diagnostic shows systematic updating patterns, and the information set can shift these patterns even when point accuracy changes little (Table 2).
- **Nested comparisons: interpret tests cautiously.** Because the specifications are nested, I emphasize magnitudes and stability and use nested-model-robust adjustments as a robustness check (Appendix Table 3).

4.1 Forecast accuracy

Table 1 reports RMSFEs by information set, and Figure 1 summarizes the same comparison in relative terms versus a parsimonious benchmark. *Notes:* The model

Table 1: Root Mean Squared Forecast Errors

model	variable	h1	h3	h12
Small	CPI	3.468	2.643	1.305
Small	INDPRO	7.649	5.558	4.998
Medium	CPI	2.982	2.500	1.349
Medium	INDPRO	7.315	4.966	4.371
Full	CPI	3.128	2.538	1.330
Full	INDPRO	7.424	5.087	4.387

labels correspond to nested information sets defined in Section 2. Small includes macro aggregates; Medium adds a small set of financial prices; Full further adds consumer sentiment. All evaluation-scale and pseudo out-of-sample implementation details follow the audited pipeline summarized in `INTERNAL_MAPPING.md`.

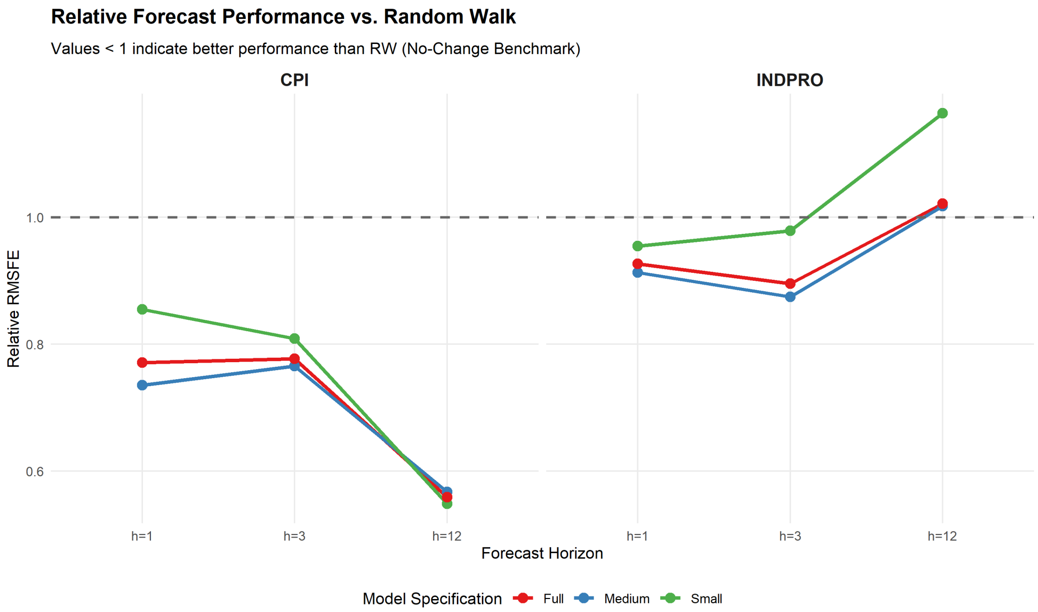

Figure 1: Relative forecast accuracy versus a parsimonious benchmark

Notes: The figure reports RMSFEs for each information set relative to a parsimonious benchmark, using the same evaluation scale as Table 1. See `INTERNAL_MAPPING.md` for source files.

4.2 Forecast discipline: revision-based diagnostic

Table 2 reports error-on-revision coefficients from the Coibion and Gorodnichenko (2015) diagnostic applied to model-implied forecasts. Interpreted as a diagnostic of the forecasting system, the coefficients summarize whether revisions are followed by predictable errors, indicating systematic updating patterns. *Notes:* The regression follows Coibion and Gorodnichenko (2015) but is applied to model-implied forecasts, so coefficients are interpreted as a diagnostic of internal error–revision consistency in a regularized forecasting system, not as structural evidence about belief formation. Sign patterns can reflect regularization, misspecification, or instability, so the paper emphasizes qualitative shifts across information sets rather than a behavioral mechanism.

Table 2: Coibion–Gorodnichenko Regression Results

term	estimate	std.error	statistic	p.value
Small CPI h=1	2.2608	1.1942	1.8931	0.0597
Small CPI h=3	0.6917	0.7987	0.8661	0.3874
Small CPI h=12	-0.5178	0.3213	-1.6115	0.1086
Small INDPRO h=1	0.7184	0.5612	1.2801	0.2019
Small INDPRO h=3	0.8923	0.4816	1.8528	0.0653
Small INDPRO h=12	0.1449	0.4423	0.3276	0.7436
Medium CPI h=1	0.7086	0.2840	2.4951	0.0134
Medium CPI h=3	0.5602	0.3204	1.7485	0.0818
Medium CPI h=12	-0.0841	0.2065	-0.4073	0.6842
Medium INDPRO h=1	0.2663	0.4916	0.5416	0.5886
Medium INDPRO h=3	0.5983	0.3637	1.6449	0.1015
Medium INDPRO h=12	0.3184	0.5292	0.6017	0.5480
Full CPI h=1	0.9257	0.3188	2.9040	0.0041
Full CPI h=3	0.6894	0.3729	1.8488	0.0659
Full CPI h=12	-0.0272	0.2111	-0.1291	0.8974
Full INDPRO h=1	0.1078	0.3465	0.3110	0.7561
Full INDPRO h=3	0.1889	0.3630	0.5204	0.6033
Full INDPRO h=12	0.2237	0.4925	0.4543	0.6501

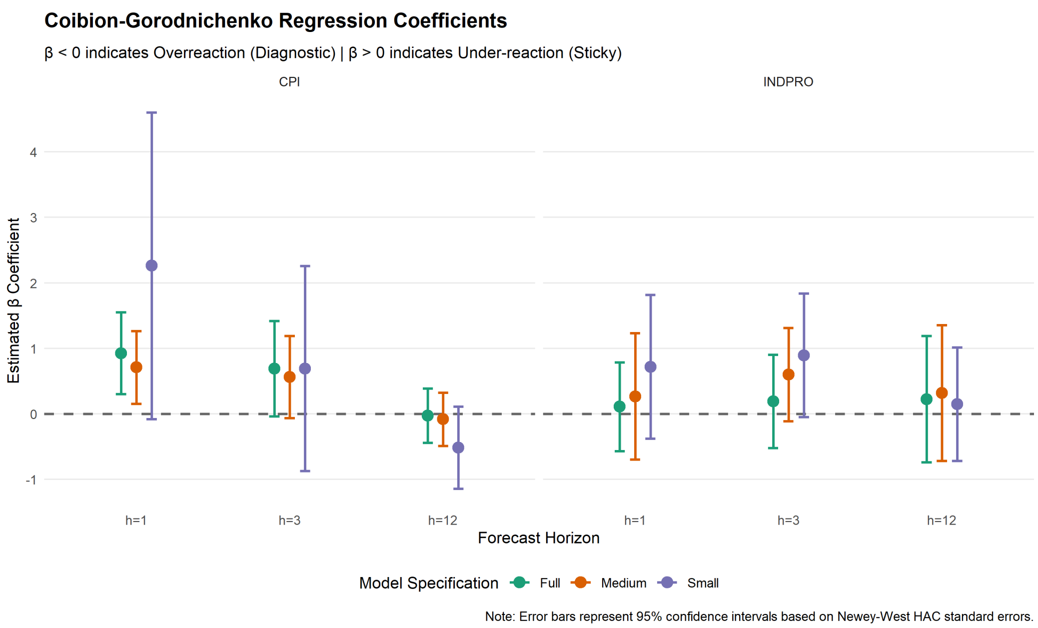

Figure 2: Revision diagnostic coefficients across information sets

Notes: Estimated coefficients from the revision diagnostic. Coefficients summarize internal error–revision consistency in the model-based forecasting system. See `INTERNAL_MAPPING.md` for source files.

4.3 Regularization and model stability

Figure 3 reports the time path of the learned shrinkage tightness parameter. The key message is methodological: hierarchical regularization adapts the forecasting system's effective complexity as information sets expand and as the data environment changes, which helps make horse-race comparisons less sensitive to ad hoc tuning choices.

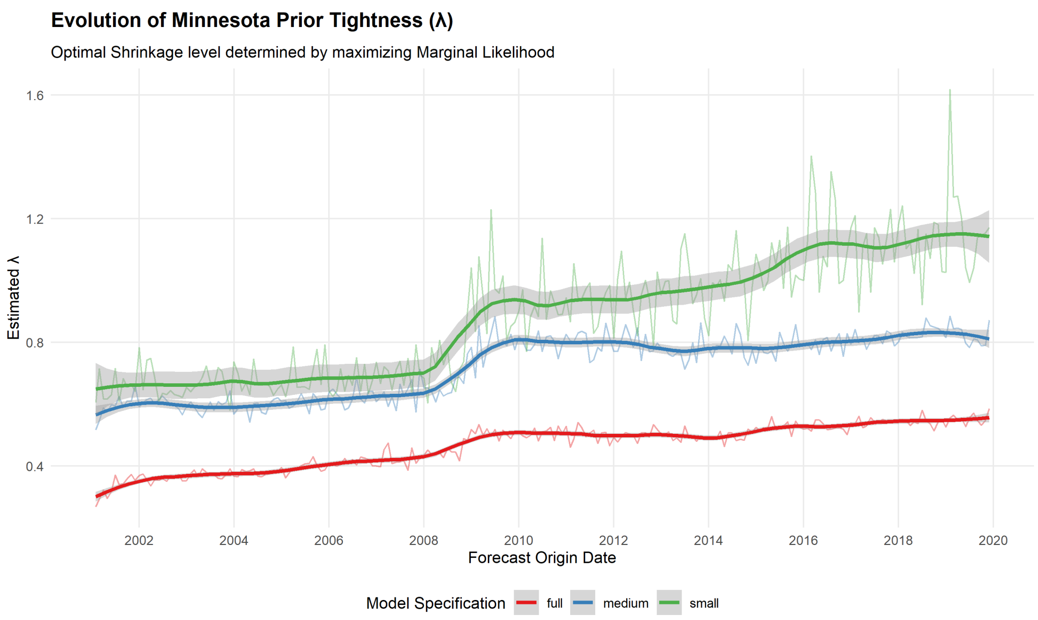

Figure 3: Evolution of learned shrinkage tightness

Notes: The figure plots posterior means of λ at each recursive forecast origin for each model specification. See `INTERNAL_MAPPING.md` for source files.

4.4 Economic interpretation and limitations

Taken together, the results support a single storyline. Financial prices can add incremental predictive content for point forecasts beyond the macro-only information set, while sentiment contributes limited incremental accuracy once prices are included (Table 1). For the revision diagnostic, the evidence indicates systematic updating patterns in model-implied forecasts and suggests that these patterns can shift across information sets (Table 2). Interpreting these shifts requires discipline: the regression is non-structural and the coefficients can be influenced by shrinkage, misspecification, or instability rather than an economic mechanism.

5 Conclusion

I study whether sentiment adds incremental predictive content in a hierarchical BVAR once standard macro aggregates and financial prices are already included. The results suggest a two-part pattern: sentiment has limited incremental value for point-forecast accuracy conditional on prices (Table 1), consistent with information overlap where forward-looking asset prices may already incorporate signals also present in sentiment indices (Section **??**). The revision diagnostic indicates that information sets may shift systematic patterns in forecast updating (Table 2), though these estimates are imprecise. When applied to model-implied forecasts from a regularized BVAR, revision-regression coefficients reflect the forecasting system's statistical updating rule under hierarchical shrinkage and can partly reflect prior-induced conservatism, not economic agents' beliefs or information processing. Because the specifications are nested and the exercise is descriptive, I emphasize magnitudes and stability over sharp statistical dominance claims and report nested-robust adjustments as robustness checks (Appendix Table 3).

This comparison provides no causal identification: sentiment's limited incremental RMSFE may reflect information aggregation by market participants, model misspecification, or unstable forecasting relationships. Future work priorities include real-time data vintages to address revision bias, alternative sentiment measures to test proxy sensitivity, and density forecast evaluation to assess whether sentiment contributes to uncertainty quantification even when point RMSFE gains are limited.

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A Additional figures and robustness

Nested-model forecast accuracy: Clark–West tests. Table 3 reports Clark–West MSPE-adjusted tests for nested model comparisons (Small vs. Medium; Medium vs. Full). This robustness addresses the nonstandard behavior of standard equal-accuracy tests under nesting.

Table 3: Clark–West (2007) MSPE-Adjusted Tests for Nested Models

Smaller	Larger	variable	horizon	t-stat	p-value	N	NW lag
Small	Medium	CPI	$h = 1$	3.312***	0.001	227.000	1.000
Small	Medium	CPI	$h = 3$	2.405***	0.008	225.000	3.000
Small	Medium	CPI	$h = 12$	-0.063	0.525	216.000	12.000
Small	Medium	INDPRO	$h = 1$	3.211***	0.001	227.000	1.000
Small	Medium	INDPRO	$h = 3$	2.387***	0.009	225.000	3.000
Small	Medium	INDPRO	$h = 12$	2.452***	0.008	216.000	12.000
Medium	Full	CPI	$h = 1$	-1.146	0.874	227.000	1.000
Medium	Full	CPI	$h = 3$	-0.325	0.627	225.000	3.000
Medium	Full	CPI	$h = 12$	0.742	0.230	216.000	12.000
Medium	Full	INDPRO	$h = 1$	0.107	0.458	227.000	1.000
Medium	Full	INDPRO	$h = 3$	0.057	0.477	225.000	3.000
Medium	Full	INDPRO	$h = 12$	0.253	0.400	216.000	12.000

footnotesize*Notes:* The Clark–West test adjusts mean squared prediction error comparisons to account for nested model structures (Clark & West, 2007). Under the null hypothesis that the smaller (nested) model is adequate, the test statistic has a standard normal distribution. Because specifications are nested and forecasting relationships may be unstable, results are interpreted as suggestive rather than definitive. Source file: see `INTERNAL_MAPPING.md`.

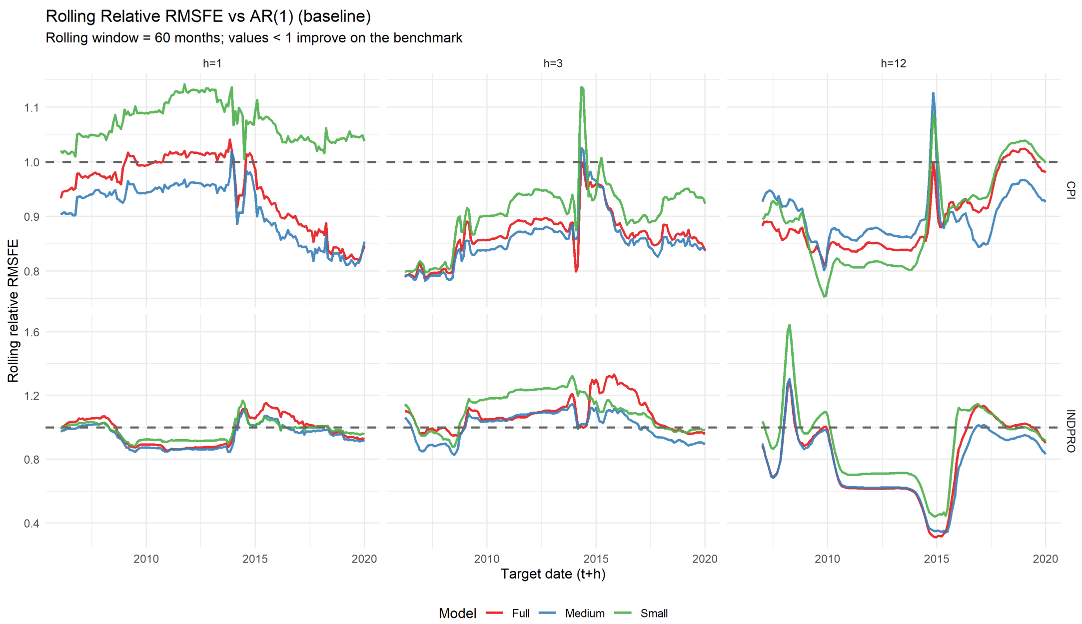


Figure 4: Rolling relative RMSFE versus an autoregressive benchmark

Notes: Rolling-window relative RMSFEs. Lower values indicate smaller forecast errors relative to the benchmark. See `INTERNAL_MAPPING.md` for source files.

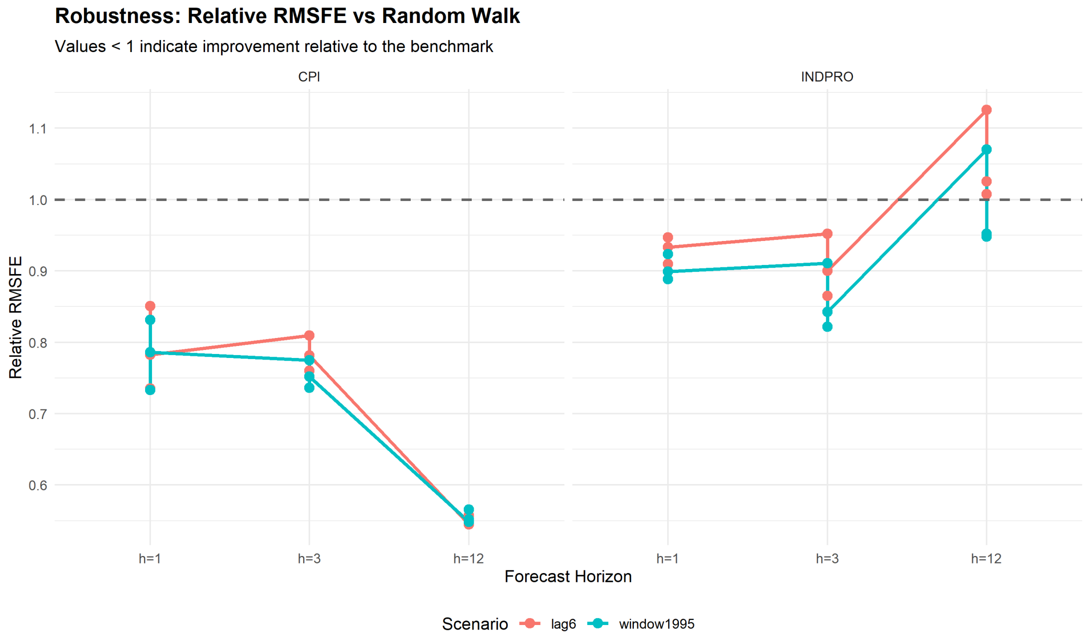


Figure 5: Robustness: relative RMSFE versus no-change benchmark

Notes: Relative RMSFEs under alternative implementation choices, benchmarked to the same reference forecast. See `INTERNAL_MAPPING.md` for source files.

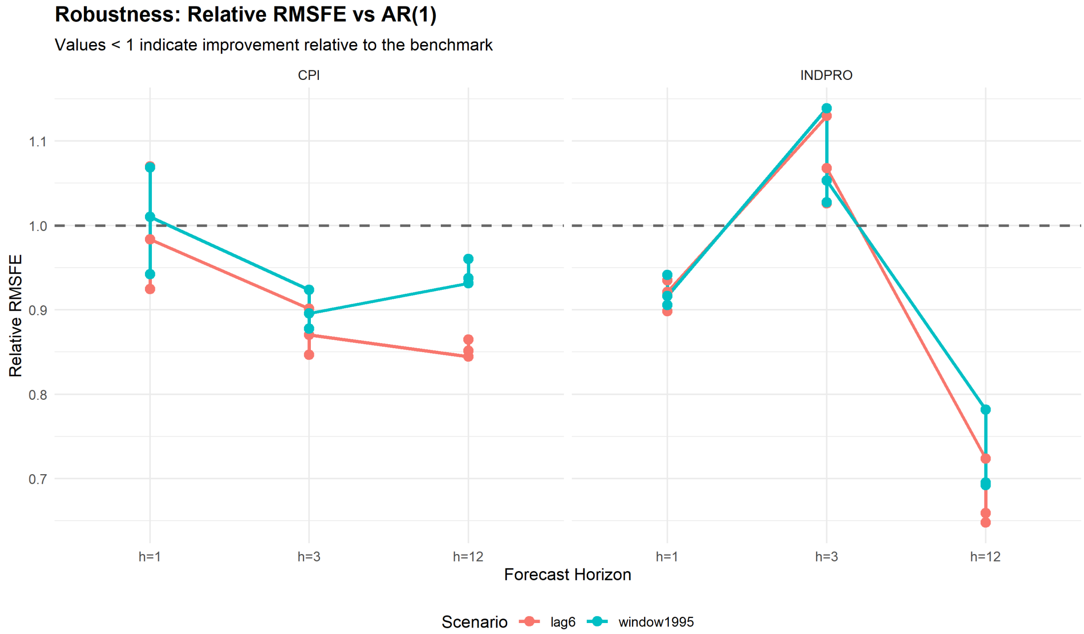
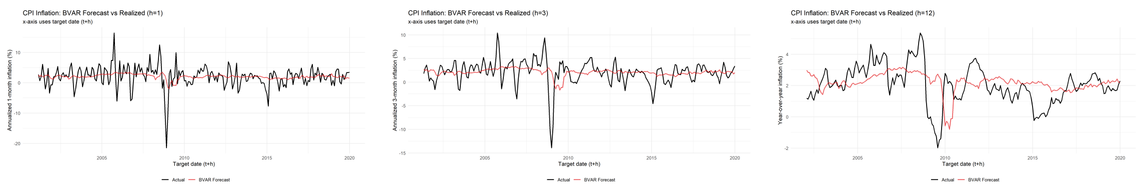


Figure 6: Robustness: relative RMSFE versus an autoregressive benchmark.

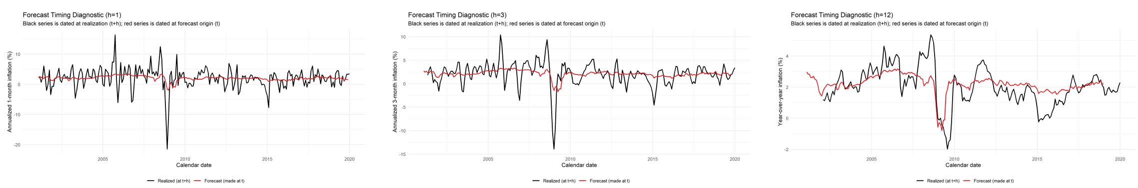
Notes: Relative RMSFEs under an alternative implementation choice, benchmarked to the autoregressive reference forecast. See `INTERNAL_MAPPING.md` for source files.



(a) Short horizon (b) Intermediate horizon (c) Long horizon

Figure 7: CPI inflation: forecast versus realized (multiple horizons).

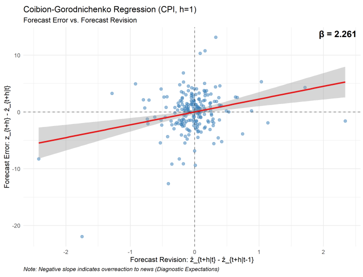
Notes: Each panel plots the model-implied predictive mean and the realized target on the evaluation scale. See `INTERNAL_MAPPING.md` for source files.



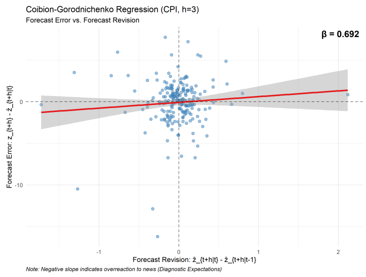
(a) Short horizon (b) Intermediate horizon (c) Long horizon

Figure 8: Forecast timing diagnostic (multiple horizons).

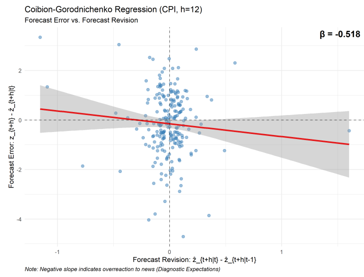
Notes: Realizations are dated at the target date; forecasts are dated at the origin date. See `INTERNAL_MAPPING.md` for source files.



(a) Short horizon



(b) Intermediate horizon



(c) Long horizon

Figure 9: Revision diagnostic scatter (multiple horizons)

Notes: Scatter of forecast errors against forecast revisions for CPI inflation in the baseline design. The fitted line corresponds to the Coibion and Gorodnichenko (2015) regression. See `INTERNAL_MAPPING.md` for source files.