# Online Appendix to

# *Harnessing Machine Learning for Real-Time Inflation Nowcasting*


Richard Schnorrenberger
*Kiel University*

Aishameriane Schmidt
*Erasmus Universiteit Rotterdam, Tinbergen Institute and De Nederlandsche Bank*

Guilherme Valle Moura
*Federal University of Santa Catarina*



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## Contents

# A Mixed-frequency framework in matrix form

For expositional simplicity, let us reduce the general multiple-predictors specification (1) to the single generic high-frequency predictor $x_t^{(w)}$ and neglect both the low-frequency predictors and seasonal dummies. From there, assume the latest data release for the target variable is associated with a given month $t$. Based on the high-frequency information set available up to the nowcast point, say $t+1-h$, and pre-sample information $\{\pi_0, x_0^{(w)}, x_{0-1/4}^{(w)}, \ldots, x_{0-p/4}^{(w)}\}$, one can construct the nowcast for $\pi_{t+1}$ at horizon $h = j/w$, with $j \in \{0, 1, 2, 3\}$, by using the following matrix representation for model estimation:

$$\begin{bmatrix} \pi_1 \\ \pi_2 \\ \vdots \\ \pi_t \end{bmatrix} = \begin{bmatrix} 1 & \pi_0 & x_{1-h}^{(w)} & x_{1-h-\frac{1}{4}}^{(w)} & x_{1-h-\frac{2}{4}}^{(w)} & \cdots & x_{1-h-\frac{p}{4}}^{(w)} \\ 1 & \pi_1 & x_{2-h}^{(w)} & x_{2-h-\frac{1}{4}}^{(w)} & x_{2-h-\frac{2}{4}}^{(w)} & \cdots & x_{2-h-\frac{p}{4}}^{(w)} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ 1 & \pi_{t-1} & \underbrace{x_{t-h}^{(w)}}_{\text{nowcast day } (nd)} & \underbrace{x_{t-h-\frac{1}{4}}^{(w)}}_{nd-\frac{1}{4}} & \underbrace{x_{t-h-\frac{2}{4}}^{(w)}}_{nd-\frac{2}{4}} & \cdots & \underbrace{x_{t-h-\frac{p}{4}}^{(w)}}_{nd-\frac{p}{4}} \end{bmatrix} \begin{bmatrix} c \\ \rho_1 \\ \beta_1 \\ \beta_2 \\ \beta_3 \\ \vdots \\ \beta_{p+1} \end{bmatrix} + \begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \vdots \\ \varepsilon_t \end{bmatrix} \quad \text{(A1)}$$

For example, suppose we stand at day 15 of December and we want to construct the nowcast for $\pi_{\text{Dec}}$ assuming a general high-frequency lag order $p$. In this case, the forecast horizon is $h = 2/4$ and we estimate the model using monthly data until November and weekly data until 15 November. To account for the lags $p$, the last high-frequency observations in (A1) will respectively be associated with 15 November, 8 November, 31 October, 22 October, 15 October, and so on up to the corresponding lag-length $p$. From there, the nowcast for $\pi_{\text{Dec}}$ is constructed using the estimated coefficients and all the low- and high-frequency information available until 15 December.

Ultimately, note that (A1) makes explicit that the general prediction model is still written at the monthly frequency but accounting for the $w$ high-frequency time increments within each common period $t$. The nowcast for the inflation rate at periods $t+1, \ldots, T$ can then be updated regularly using the high-frequency data increments that become available after $t$ and well before official releases of the target inflation rate.

# B Supplementary results

**Table B1:** RMSE: absolute values

| Horizon | SPF | | Shrinkage-based methods | | | | Tree-based methods | | | | Naive Models | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Median | Top 5 | LASSO | Ridge | Enet | sg-LASSO | RF | LLF | BART | LASSO-LLF | AR | RW |
| day 8 | 0,251 | 0,235** | 0,215*** | 0,222** | 0,218** | 0,239 | 0,257 | 0,285 | 0,247 | 0,241 | 0,341 | 0,460 |
| day 15 | 0,196 | 0,199 | 0,184 | 0,189 | 0,185 | 0,201 | 0,233 | 0,214 | 0,218 | 0,206 | 0,341 | 0,378 |
| day 22 | 0,143 | 0,136** | 0,128** | 0,135 | 0,128** | 0,164 | 0,191 | 0,155 | 0,173 | 0,132 | 0,341 | 0,378 |
| End-of-month | 0,119 | 0,115 | 0,110* | 0,117 | 0,110* | 0,113 | 0,167 | 0,142 | 0,154 | 0,145 | 0,341 | 0,378 |

Notes: The table reports the RMSE for each competing model. The models are described in Table 2. The AR column denotes a prediction from an autoregressive model or order 1 and the RW column denotes a random walk prediction. Results for the Diebold and Mariano (1995) test in the event of outperformance relative to the median of the SPF predictions benchmark are indicated by the symbols * (1% level), ** (5% level) and *** (10% level).

**Figure B1:** CUMSFE: tree-based methods versus the SPF benchmark

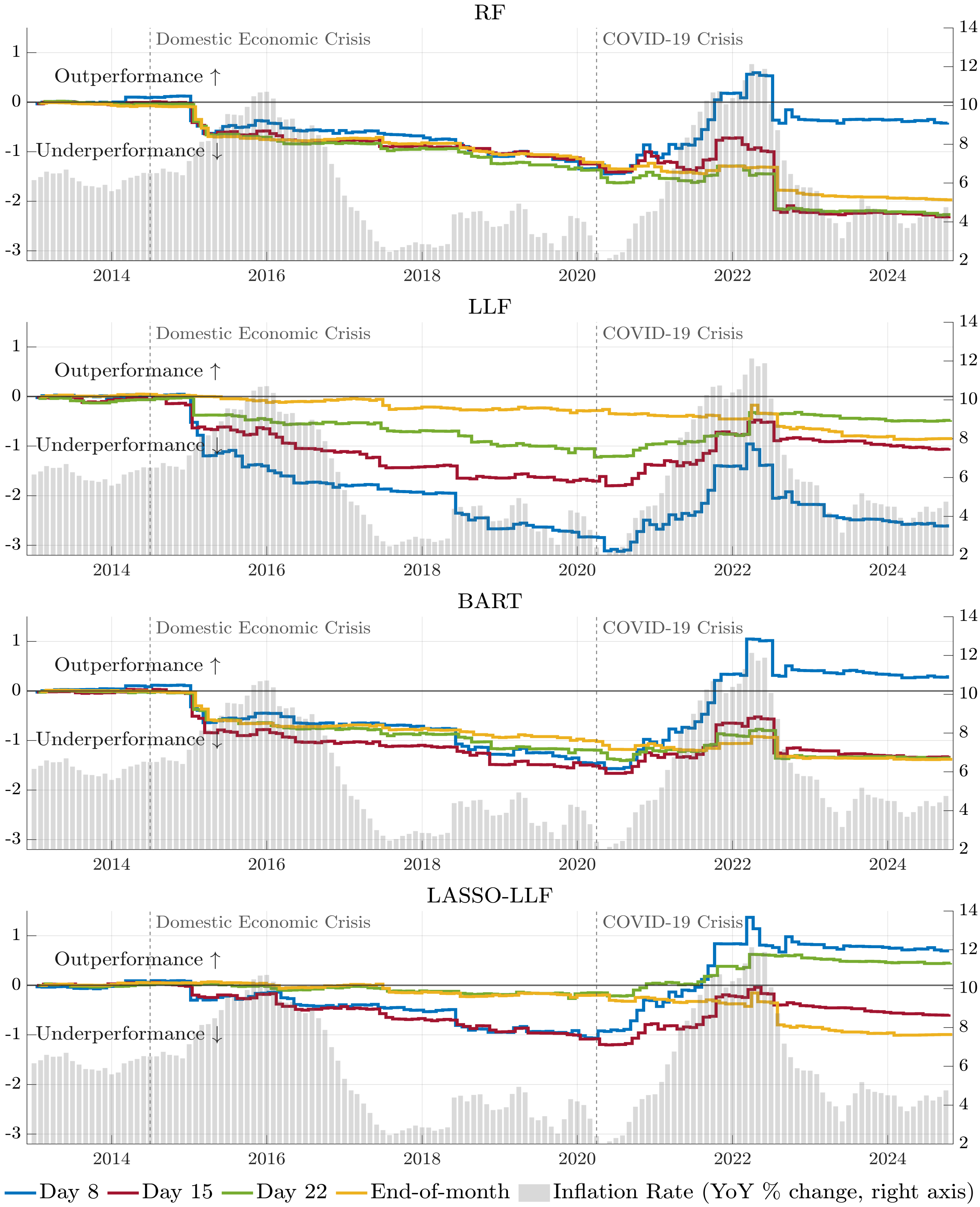
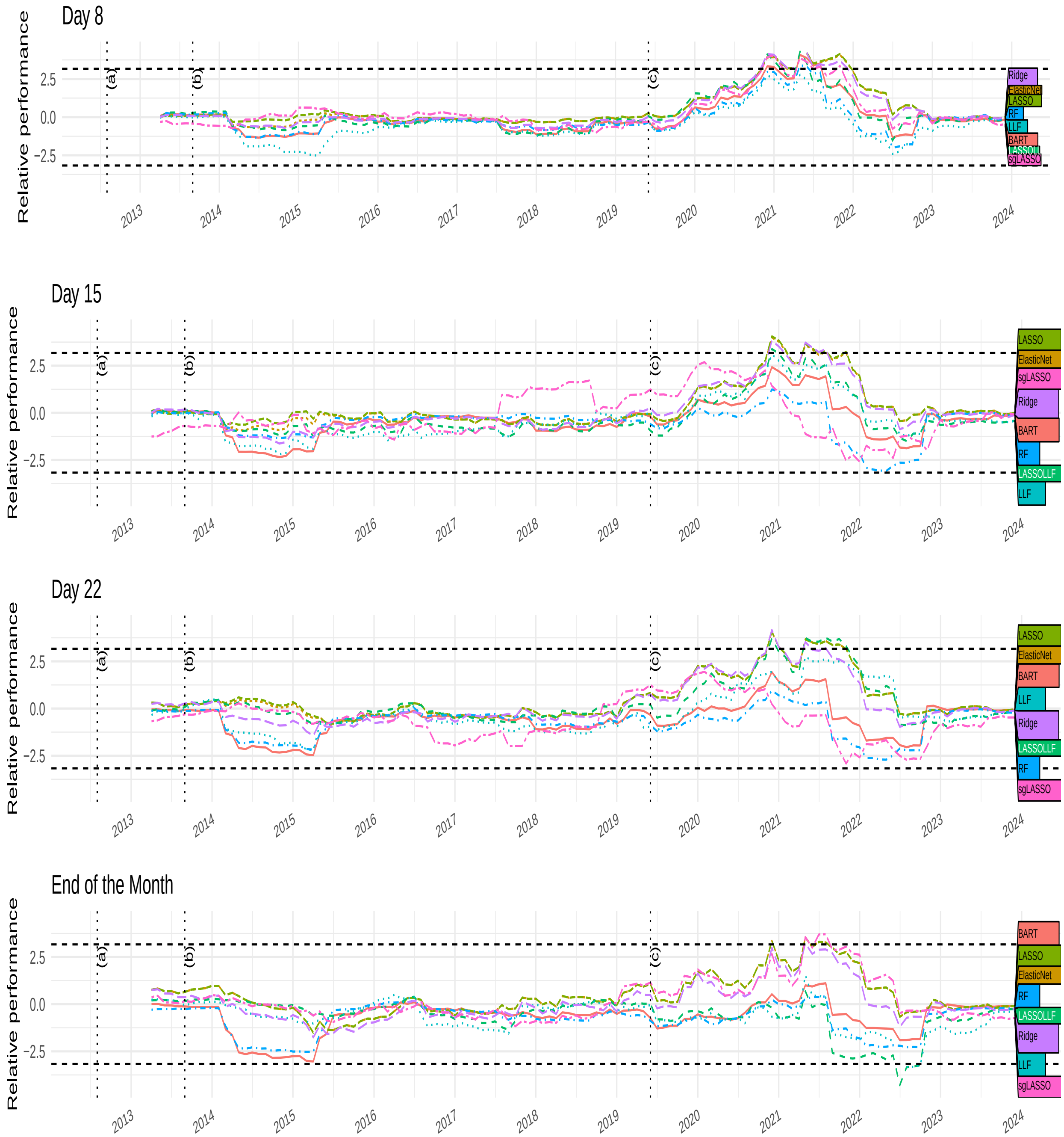
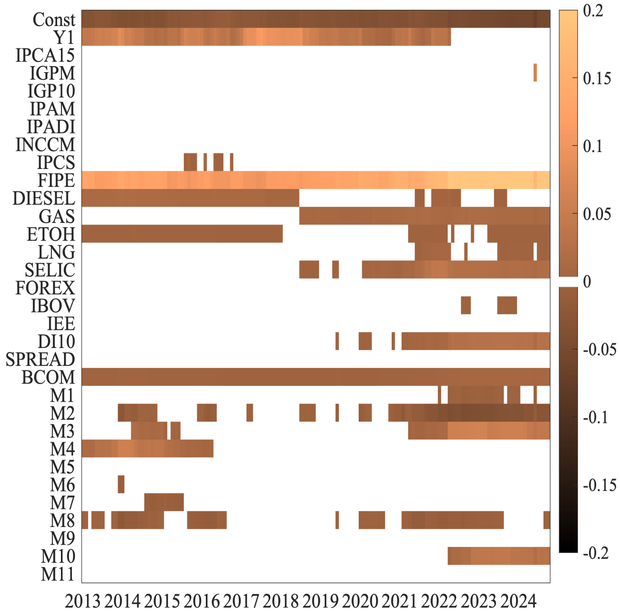


**Figure B2:** Fluctuation test: ML competing models versus the SPF benchmark

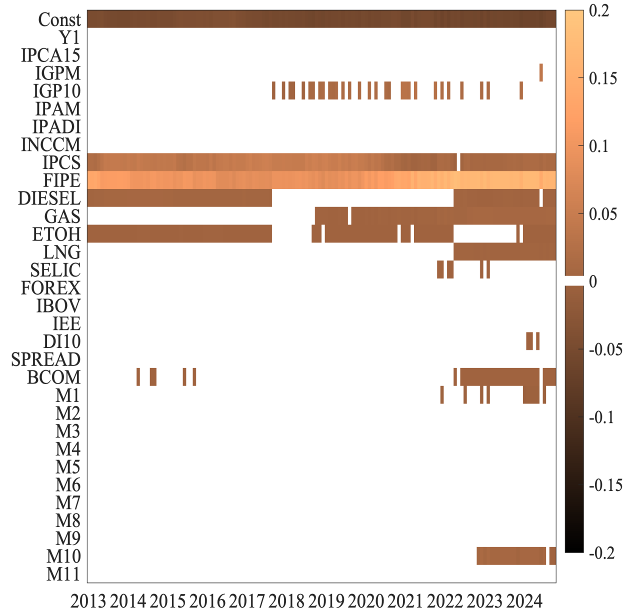



Notes: This Figure reports the fluctuation test from Giacomini and Rossi (2010) based on the squared loss differential between a machine learning method and SPF nowcasts. Areas between the horizontal dashed lines correspond to the 90% confidence interval of the two-sided statistical test. We used as window parameters of the test $\mu = 0.1$ and five for the number of lags in the variance of the DM test.

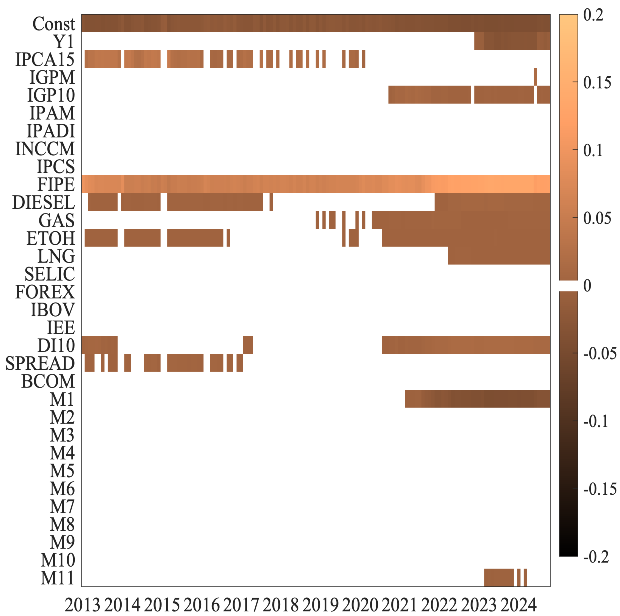
**Figure B3:** Heatmap of coefficient estimates using LASSO on the SPF nowcasting errors



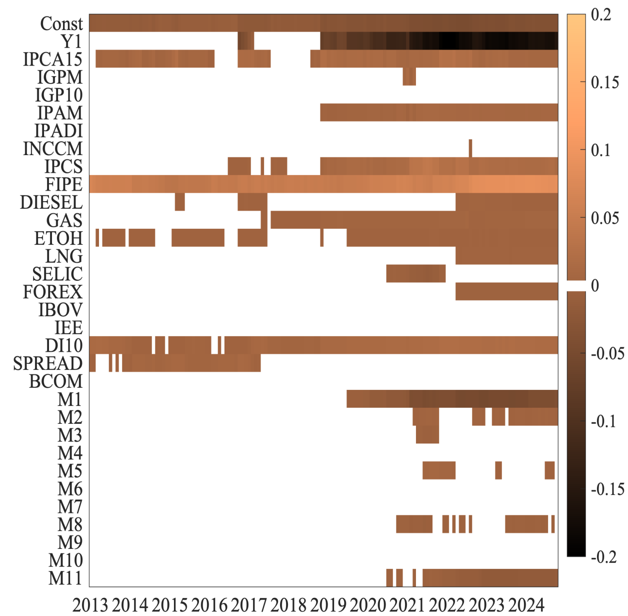

**(a)** Day 8




**(b)** Day 15




**(c)** Day 22




**(d)** End-of-month

Notes: This Figure depicts heatmaps of LASSO-fitted coefficients using SPF nowcasting errors as the dependent variable. Empty cells represent a coefficient estimate equal to zero, and thus a predictor that has not been selected at the estimation round $t$ in the evaluation period.