Referee Report for

Weekly Inflation Forecasting: A Two-Step Machine Learning Methodology

Major comments

- The paper compares forecast models using weekly data, but a key concern is the missed opportunity to utilize daily data directly in the forecasting models. By leveraging daily data, the comparisons might have been more insightful, potentially yielding even more accurate weekly forecasts. This aspect warrants further exploration to enhance the methodology.
- The paper's explanation of the two-step methodology, particularly regarding estimation and projection windows, is somewhat unclear, making it challenging to follow the precise steps of the forecasting process. More clarity in the presentation of these technical details would help readers better understand and evaluate the robustness of the approach.
- The methodology holds promise for weekly inflation forecasting, but the paper could benefit from clearer exposition and more comprehensive demonstrations. Improving the statistical evaluation of model performance and considering daily data comparisons could significantly bolster the paper's impact.
- The paper could discuss endogeneity issues and consider incorporating a more diverse set of economic and financial indicators to enhance the model's predictive power.
- It is not clear if the analysis is an in-sample or out-of-sample of the models at a monthly frequency, if the latter, what is the out-of-sample forecast period? One-month-ahead forecast as mentioned for only one model? Please clarify before introducing empirical analysis.
- The analysis overlooks intra-month seasonal patterns, such as paydays and weekends.
- The document assumes that (i) the monthly average of daily observations equals the inflation accumulated over 30 days, and (ii) the weekly average of daily observations matches the inflation accumulated over 7 days. While not necessarily incorrect, this assumption raises concerns related to the previous point. Using sums of daily observations might be more appropriate than relying on averages.
- There exists a large literature on interpolation that could offer crucial insights and enhance this study. For example, methodologies exist that impose constraints to ensure that the sum of weekly inflations (unobserved) aligns with the monthly inflation (observed).
- It's important to exercise caution when using variables in levels, particularly when normalizing (z-score) variables with a unit root. This could explain why the autoregressive term in Lasso is so significant.
- The document does not specify how cross-validation was conducted. In a time series context, independent k-fold validation isn't feasible. The document seems to neglect this aspect and omits an adequate description.
- Dimensionality reduction (from 500 to 86 variables) is performed using simple correlations. Why not allow the algorithms to handle this process, either as an initial step before forecasting or by jointly selecting and forecasting

Minor comments

- How does the model performance compare when applied to different periods or under varying economic conditions, such as high inflation or economic shocks? Additional sensitivity analyses could strengthen the model's robustness.
- The paper could have a roadmap at the end of the introduction.
- Testing the proposed model with data from other developing countries could help validate its applicability and robustness. Exploring the impact of unexpected global events, such as the pandemic, on inflation rates could add another dimension to the study.