BARCELONA SCHOOL OF ECONOMICS SUMMER FORUM 2023

INFLATION NOWCASTING IN PERSISTENTLY HIGH INFLATION ENVIRONMENTS

Aisha's website

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OUR QUESTIONS

Can we predict the current month inflation better than professional forecasters?
Do macro-financial variables carry relevant predictive information beyond market inflation expectations?
Which class of models will make better forecasts: shrinkage or tree based algorithms?

Brazil has the unique characteristic of having several non-official consumer price indices, which closely mimic the behavior of official inflation index (IPCA). Due to different release dates, they might contain information relevant for predicing the IPCA.

DATA

We built a dataset with 20 daily, weekly and monthly indicators from Jan/03 to Dec/22 (240 months). Oos forecast period starts in 2013.

- 7 Non-official CPIs [weekly & montly]
- 8 Financial variables [daily]
- 4 Fuel prices [weekly]
- 1 Median SPF FOCUS survey [daily]

The variables are not seasonally adjusted and transformed into month-on-month (MoM) % change; the only exceptions are the interest rates series (SELIC, DI10 and SPREAD) which are transformed into monthly changes. MoM transformations for high-frequency variables consider the same reference week or day from the preceding month. We add seasonal dummies in the regressors' matrix.

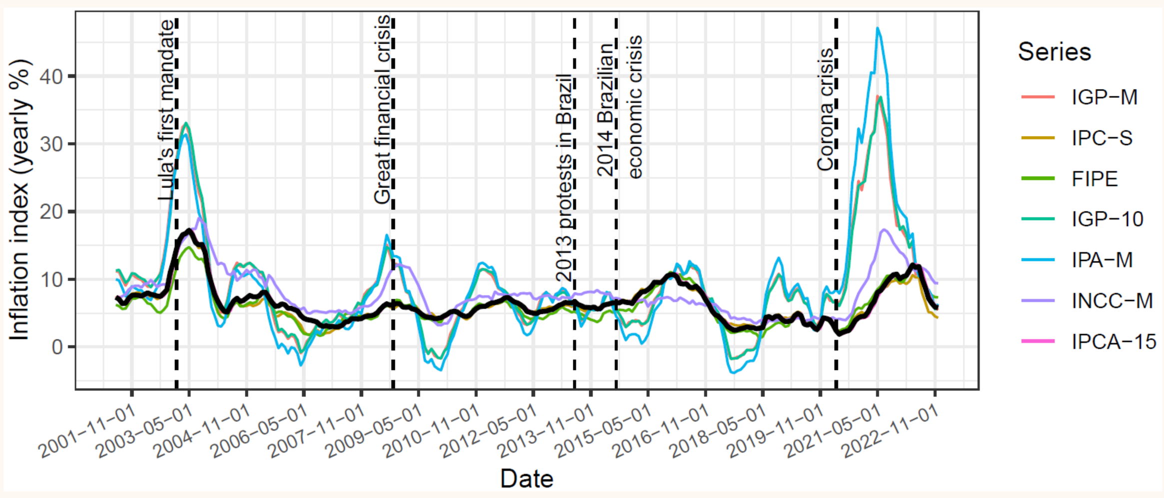

Fig 1 -Monthly Brazilian consumer price index (IPCA) from Jun 2001 to Dec 2022 in black, non-official CPIs in other colors. All lines correspond to different inflation indexes. IPCA-15, IGP-M, IGP-10, IPA-M and INCC-M are released monthly while IPC-S and FIPE are weekly indicators.

NOWCASTING SETUP

We use machine learning methods within an unrestricted MIDAS structure, where high-frequency data correspond to the latest information available at days 8, 15, 22 and end-of-month.

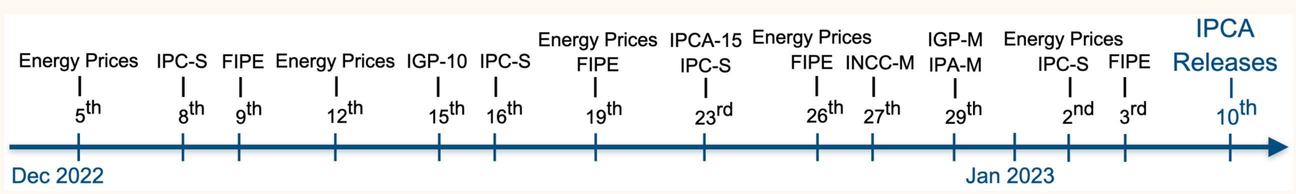

Fig 2 – Timeline of data releases for price indicators in the reference period of December 2022.

COMPARED MODELS

SHRINKAGE

LASSO[1]
Elastic Net[1]
Ridge[1]
Sparse group LASSO[1] (sg LASSO)

TREES

Random Forest[1]
Generalized Ranfom Forest[2]
Local Linear Forest[2]
Bayesian Additive Regression Trees[3]

Benchmarks: AR(p), RW and the median of the SPF. For RF we cross validate mtry. For GRF and LLF, we cross validate sample fraction, mtry, min node size, honesty related parameters. For LASSO and Ridge we cross validade λ, the penalty parameter and for EN we also cross validate the mixing parameter α. (1) denotes time-slice cross-validation; (2) denotes cross-validation; (3) was estimated using the standard priors from Chipman et al (2010).

RESULTS AND DISCUSSION

Tab 1 – RMSE for each competing model relative to SPF forecasts in the out-of-sample period.

Horizon	SPF	AR	RW	RF	GRF	LLF	LASSO	EN	Ridge	BART	sgLASSO
day 8	1	1,33	1,81	1,05	1,09	1,07	0,95	0,95	0,95	1,02	0,92
day 15	1	1,72	1,90	1,21	1,26	1,25	0,98	0,98	1,03	1,17	0,96
day 22	1	2,35	2,59	1,39	1,53	1,50	0,94	0,94	0,99	1,34	0,99
end-of-month	1	2,84	3,13	1,55	1,77	1,79	0,95	0,95	1,03	1,48	0,99

Fig 3 -Cumulative sum of loss differentials (CUMSFE) of the sg-LASSO nowcasts versus the survey of professional forecasters (SPF, median) on days 8, 15, 22 and end-of-month. The gray shaded areas correspond to rising inflation periods. The CUMSFE is given by $CUMSFE_{t_0,t_1} = \sum_{t=t_0}^{t_1} e_{t,M_1}^2 - e_{t,M_2}^2$ for a benchmark model M_1 (SPF) verus the sg-LASSO (M_2). A positive value indicates that sg-LASSO outperforms the SPF from t_0 to t_1 (and vice-versa for negative values).

Shrinkage methods on average outperform SPF and tree based methods – and performance is better at the firs two weeks of the month. sg-LASSO has lower forecasting error in the first half of the month; LASSO performs better at the end of the month.

When comparing loss differentials (Fig 3), sg-LASSO greatly outperforms SPF forecasts, in particular at the first week of the month. Overall SPF predictions underestimated inflation surge, and the model was able to capture trends in the data.

VARIABLE CONTRIBUTIONS

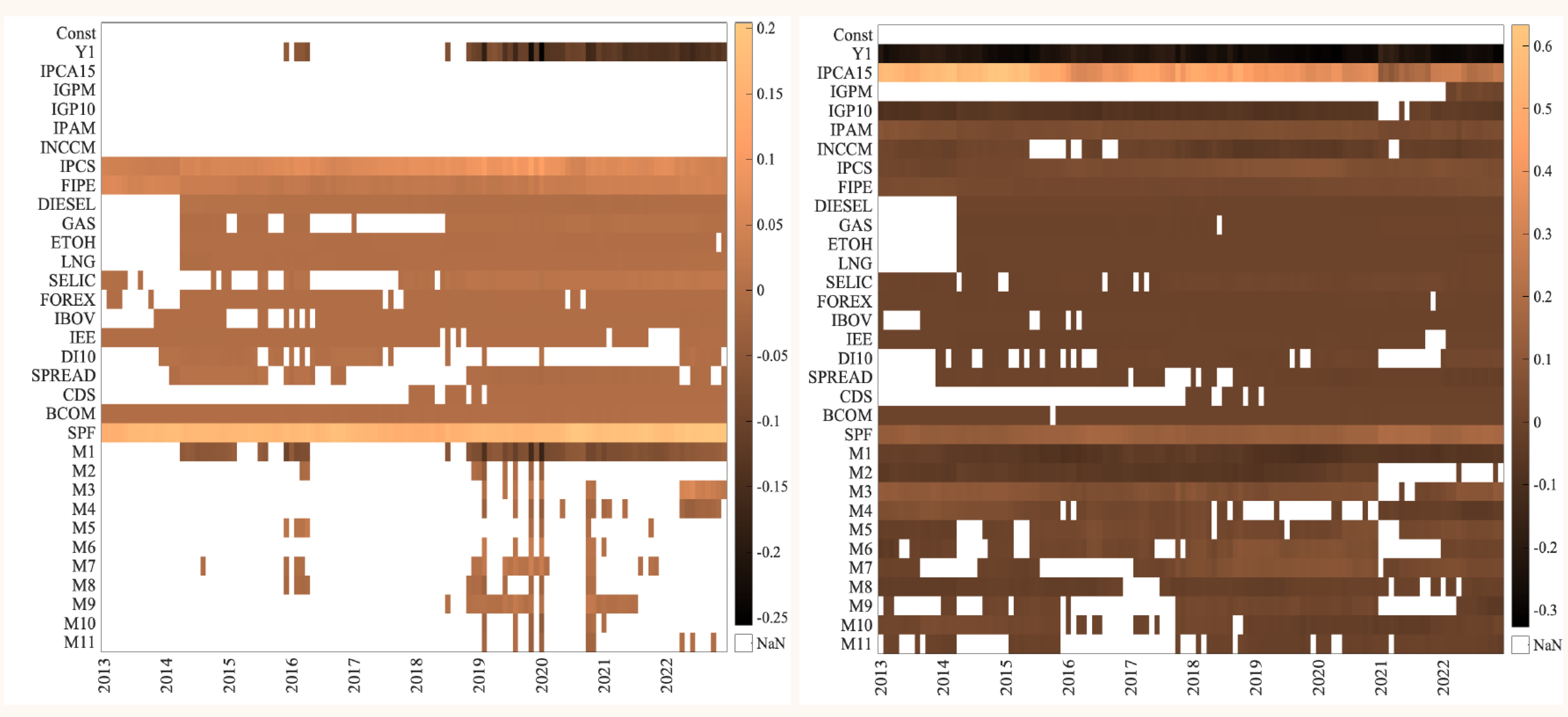

Fig 4 – Heatmap of coefficient estimates at week 1 (Left) and end of the month (Right) using one of the best performing methods: sg-LASSO (L = 0). Empty cells represent a coefficient estimate equal to zero, and thereby a predictor that has not been selected for a given period t in the evaluation period. M1, ..., M11 are seasonal dummies. Y1 is the lagged IPCA.

sg-LASSO prompts a fairly sparse structure at early month horizons while a denser structure prevailing at late month horizons stems from a higher data availability of low-frequency price indicators.
SPF inflation expectations, high-frequency price indicators, and the lagged IPCA are the most relevant variables at the first weeks. At the end of the month, the IPCA-15 is very relevant for the model.