Blockwise Boosted Inflation - Non-linear demand and supply determinants of inflation using machine learning

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Motivation

- Disentangling the source behind an inflation surge is crucial for the assessment of **inflation persistence** and monetary policy trade-offs.
- Typically challenges around identifying:
    1. **the role of demand and supply**
    2. **non-linearities**

- Use machine learning (ML) methods to **capture non-linearities**
- ML often subject to a "**black box**" critique
- We propose an interpretable boosted tree model with **economic intuition**:
    - structured into Phillips curve type **blocks** to linearly separate **different components** driving inflation
    - disentangling supply- and demand-like contributions via **monotonic constraints** on the direction of association between predictors and inflation

Existing literature

Inflation supply & demand drivers

- Decomposition using disaggregated prices and quantities: Shapiro et al. (2022); Firat and Hao (2023),
- DFMs, SVARs with sign restrictions: Eickmeier and Hofmann (2022); Kabaca and Tuzcuoglu (2023); Banbura et al. (2023); Ha et al. (2024); Giannone and Primiceri (2024).

Non-linearities or amplification mechanisms in inflation

- due to inflation expectations, supply constraints, and non-linear Phillips curve slope: Hazell et al. (2022); Cerrato and Gitti (2022); Benigno and Eggertsson (2023); Gitti (2024); Ascari and Haber (2022); Harding et al. (2023); Di Giovanni et al. (2023).

Inflation forecasting using machine learning

- Medeiros et al. (2021); Lenza et al. (2023) (among others)

Machine learning literature

- Monotonic constraints (Cano et al., 2019; Martens et al., 2011)
- Additive models that sum non-linear signals of predictors (Lou et al., 2012; Agarwal et al., 2021)

Neural network for inflation with Phillips curve components (Goulet Coulombe, 2022)

Main findings

1. Block structure and monotonic constraints **help separate demand and supply drivers**
2. Non-linearities in all blocks in recent episode.
    - demand: non-linear Phillips curve association with unemployment and v/u ratio
    - supply: non-linear effects from global supply chain pressures
3. Competitive out-of-sample forecast performance.

The Blockwise Boosted Tree Inflation Model

Boosted Tree method - no economic structure yet

$$\pi_{t+h} = F(X_{t-p}) = \sum f_i(X_{t-p}) + \epsilon_t$$

- π_{t+h}; $h = 1$ - one month ahead monthly inflation rate
- X_{t-p}; $p \in 0, 1, 2$; - large set of monthly indicators at period t and two lags
- $f_i(\cdot)$ - decision trees

- Sum predictions of decision trees to form overall prediction.
- **Decision trees are fit sequentially**. Fit trees between the input variable and inflation. Each tree learns from errors of previous trees.

Blockwise Boosted Inflation Model (BBIM) with Phillips curve components

Inspired by Phillips curve framework:

$$\pi_{t+h} = \rho\pi_{t-p} + \beta E_{t-p}(\pi_{t+h}) + \lambda g_{t-p} + \phi cost\_push^{*}_{t-p} + \epsilon_t$$

Our specification:

$$\pi_{t+h} = Trend_{t-p} + Supply_{t-p} + Demand_{t-p} + \epsilon_t$$

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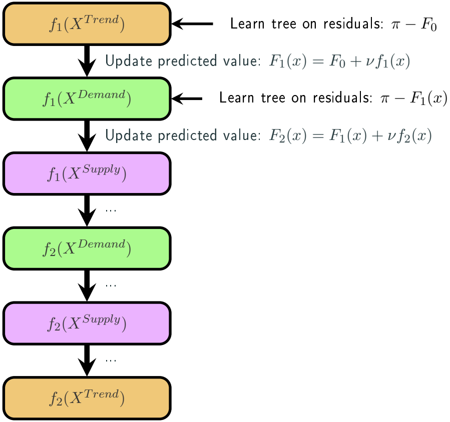
Block-wise boosted tree model:

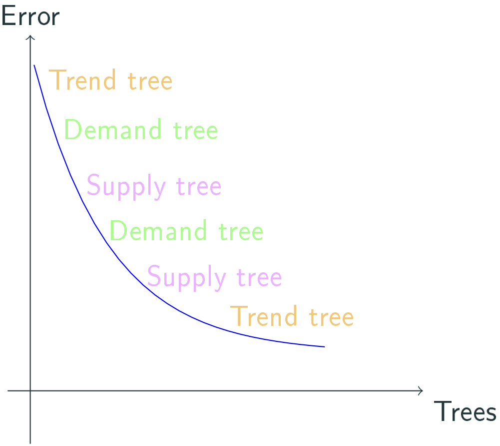
$$\pi_{t+h} = \sum_{i=1}^{M} f_i^{Trend}(X_{t-p}^{Trend}) + \sum_{i=1}^{M} f_i^{Demand}(X_{t-p}^{Demand}) + \sum_{i=1}^{M} f_i^{Supply}(X_{t-p}^{Supply}) + ... + \epsilon_t$$

- Blocks based on **different groups of indicators**: expectations, wages, activity, supply indicators.
- Non-linear decisions trees **within blocks**
- Blocks conditionally linear with respect to each other.

Training the blocks conditionally on each other – step-wise learning algorithm

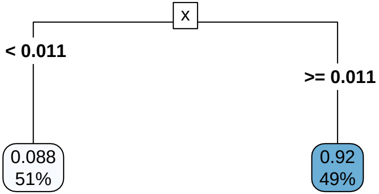
- Initialise boosting model F with target inflation: $F_0 = 2$
- Fit trees f to residuals of previous trees $r_{im} = \pi - F_{j-1}$
- Update model with learning rate $\nu = 0.02$: $F_j(x) = F_{j-1}(X) + \nu f_m(X_i^k)$

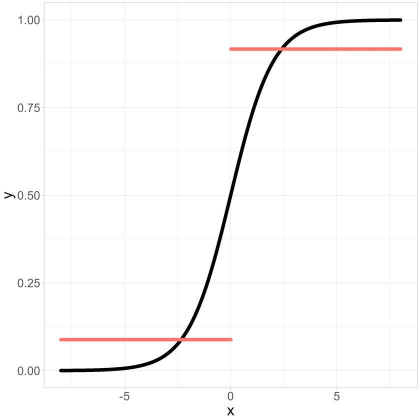




Inside the blocks – Illustration of decision trees

Fitting an arbitrary non-linear function with a decision tree, in this case, $Y = \frac{1}{1+\exp(-X)}$





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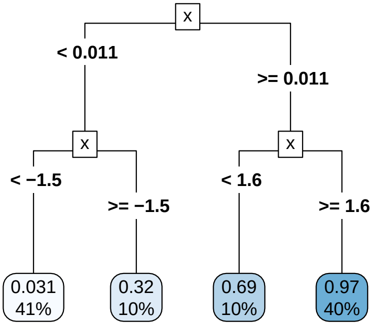
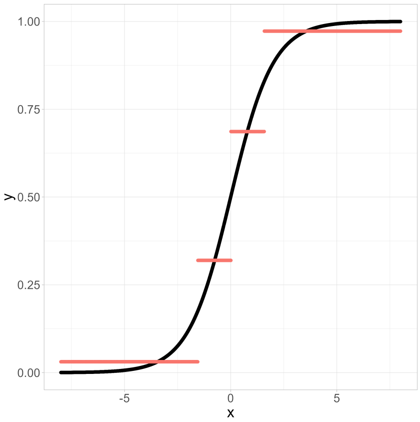
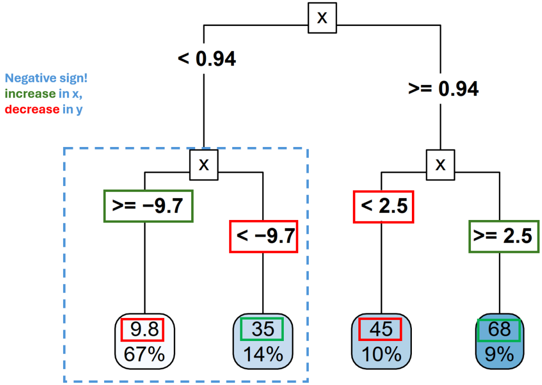
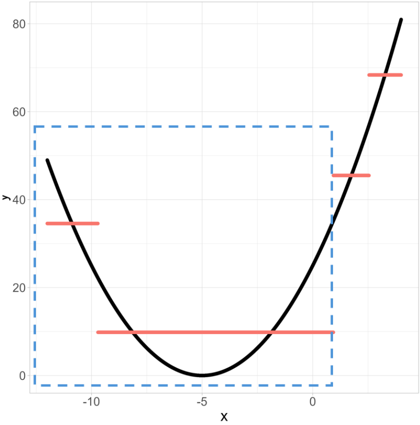




Separating demand-type and supply-type associations: monotonic constraints on tree splits

The bottom-left split violates restriction of a positive association and is discarded.

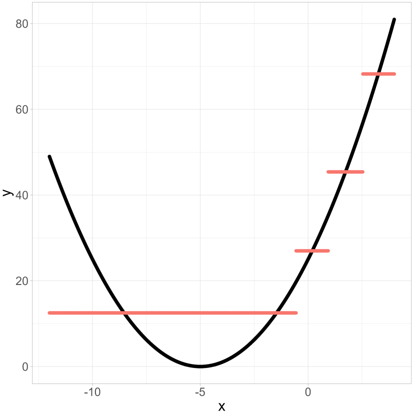




Separating demand-type and supply-type associations: monotonic constraints on tree splits

Functional form constrained to be **monotonically increasing**

- Splits that violate restrictions (when $x_1 < x_2$, then $\hat{y}_1 \leq \hat{y}_2$) cannot be used
- Tree algorithm finds alternative splits or does not split
- Implemented in standard packages



Model blocks and groups of indicators: monotonic constraints

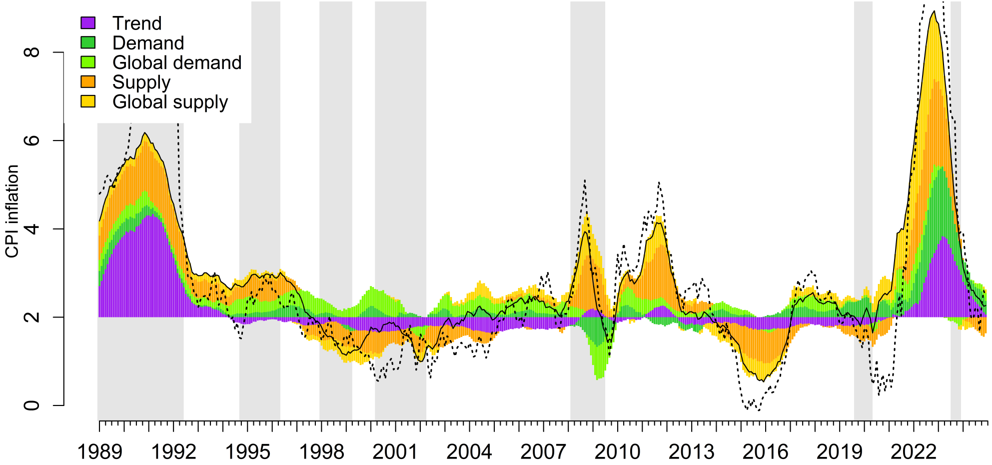
GROUP	INDICATORS	DEMAND	SUPPLY
Expectations, services inflation, wage growth	time indicator, 1-y ahead household infl. expectations, 5-y ahead financial market expectations, regular wage growth, services inflation, sub-components by sector		
Global activity	global PMI; US, EA: industrial production: US, EA: imports	+	−
	global activity shock, oil consumption demand shock (Baumeister and Hamilton, 2019)	+	
UK activity	industrial production, index of services; exports, imports, PMIs: services, manufacturing, construction; retail sales; consumer sentiment, quarterly (interpolated): consumption, investment	+	−
	Labour market: v/u ratio, employment,	+	−
	Labour market: unemployment rate	−	+
Global supply & costs	commodity prices: energy, non-energy, metals, food, agriculture		+
	global supply chain pressures: GSCPI (Fed), SCI (BoE)		+
	US PPI, EA PPI		+
	oil supply news shock (Känzig, 2021), global oil supply shock (Baumeister and Hamilton, 2019)		+
UK supply & costs	CPI components: goods, food, electricity, gas;		+
	PPIs: input, output, gas, electricity; UK spot gas price		+

Empirical set-up

- Cross-validation (CV) estimation over whole sample period: **1988–2024**
  - Consistent model learned on all time periods, to derive decomposition of inflation
  - Repeated CV (10x) to obtain stable estimates and estimate model stability.
  - Missing values imputed with median values (alt.: EM algorithm).
- Out-of-sample forecasting
  - forecast performance against other models: AR(2), random forest, Lasso
  - Initial training window 1988–1999, then expanding window forecasts. Retrain every quarter. Not accounting for data release calendar or revisions for now.
- Use Shapley values (Lundberg and Lee, 2017) to derive contributions from individual indicators to prediction & show functional forms learnt ▸ Shapley values

Results

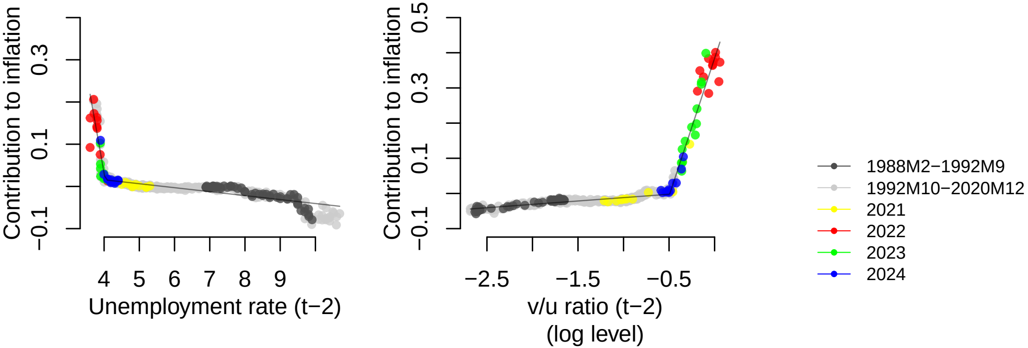
UK CPI inflation decomposition, 1989-2024



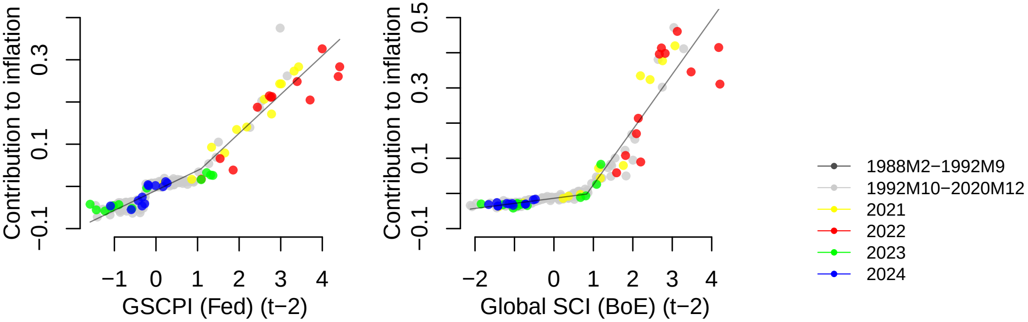
▸ Mean importance of indicators

▸ Decomp. with financial & MP components

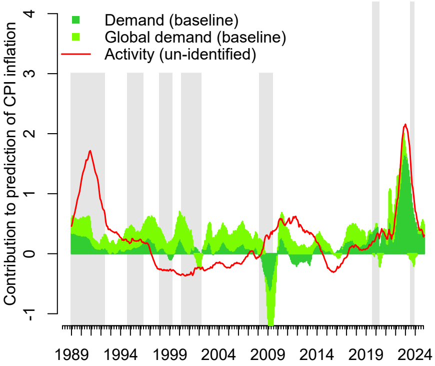
Domestic demand - functional forms: kinked Phillips curve in UE and tightness (V/U ratio), less evidence for non-linearity in other activity measures

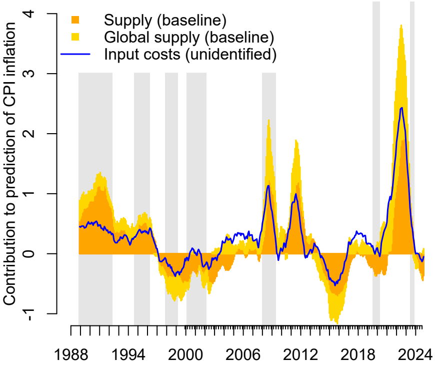


Supply: non-linear association with supply chain pressures, food, goods price inflation



Role of monotonic constraints: un-identified model with activity and input costs components, no monotonic constraints





Activity contribution does not capture relevant demand fluctuations.

Supply contribution under-estimated recently.

Results: Forecasting performance

Model performs competitively in out-of-sample forecasting

	Complete sample	2000–2019	2020–2024
AR2	1.00 (N/A)	1.00 (N/A)	1.00 (N/A)
Random forest	0.89*** (0.00)	0.90*** (0.00)	0.86** (0.01)
Lasso regression	0.87*** (0.00)	0.88*** (0.00)	0.82*** (0.01)
BBIM	0.87*** (0.00)	0.90*** (0.00)	0.79*** (0.00)
Unrestricted boosting model	0.86*** (0.00)	0.89*** (0.00)	0.80*** (0.00)

Notes: Mean absolute error relative to mean absolute error of AR(2). In parentheses: p-value of Diebold-Mariano test. ***, **, * indicate significance at 1%, 5%, or 10%. Sample period up to 2000–2024M12.

▸ Performance at different horizons ▸ Comparing components in cross-validation and forecasting

Takeways

- We propose a novel block-wise machine learning approach as a tool for economically interpretable analysis & detection of non-linearities.
- **Inflation decomposition**: block structure and restrictions on decision trees help separate demand and supply drivers.
- **Recent UK inflation episode**:
  - surge initially explained by supply, to lesser extent demand
  - non-linearities mattered, but have by now un-wound
  - short-term expectations added inflation persistence, but long-term expectations effects remained weak

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