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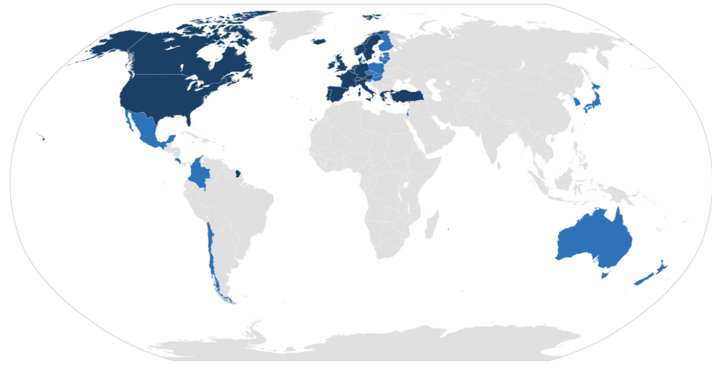

P2 Methods/ Data

Assessing the changing role of food price predictors – Evidence from OECD countries

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Background & Motivation

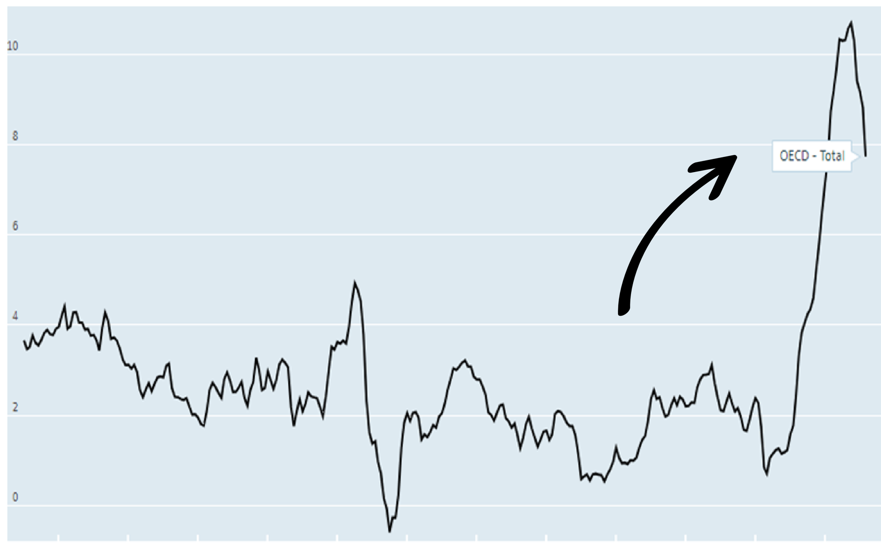

Figure 1: Annual growth rate of food CPI (OECD countries)

- Heterogeneities in rising food prices between countries
- Food prices are linked to the costs of living
- Food insecurity is on the rise in member & non-member countries
- OCED: accountable for ¾ of global trade, major importers and exporters of food and agr. commodities

Research Objectives

Detection of country clusters through time series clustering

Identification of cluster-specific food price predictors

Assessment of the marginal contribution of relevant features over time

Data

- Monthly food CPI data of OECD member countries: January 1999 – March 2023 (extracted from OECD.Stat)

Features for food price prediction:

❖ Imports & exports in goods (% change)
❖ BCI & CCI (base = 100)
❖ Energy prices (growth rate p. a.)
❖ Long-& short-term interest rates (% p.a.)
❖ Exchange rate (nat. currency/ US dollar)
❖ Industrial production (2015 = 100)
❖ Broad & narrow money 2015 = 100)
❖ Investments in R&D (GFCF)
❖ Share prices (2015 = 100)
❖ GDP growth (% change)
❖ Private consumption (current prices)
❖ Weather (temp. Change)

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Methodology

A combination of supervised and unsupervised machine learning (ML)

STEP 1:
Dynamic Time Warping (DTW) = algorithm that minimizes the cost of alignment between time series

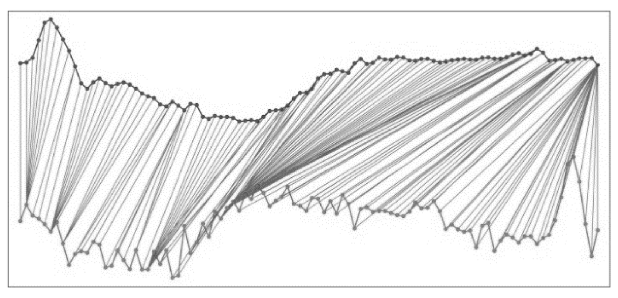


Figure 2: Dynamic Time Warping algorithm

STEP 2:
Long-Short Term Memory Neural Network (LSTM) = Sequential data analysis accounting for long-term dependencies and non-linear relationships

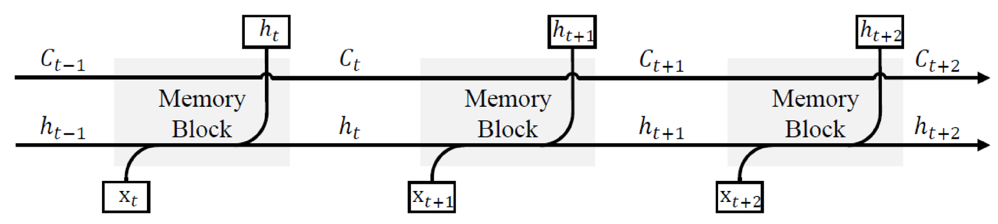


Figure 3: Linked memory blocks of an LSTM neural network

Results

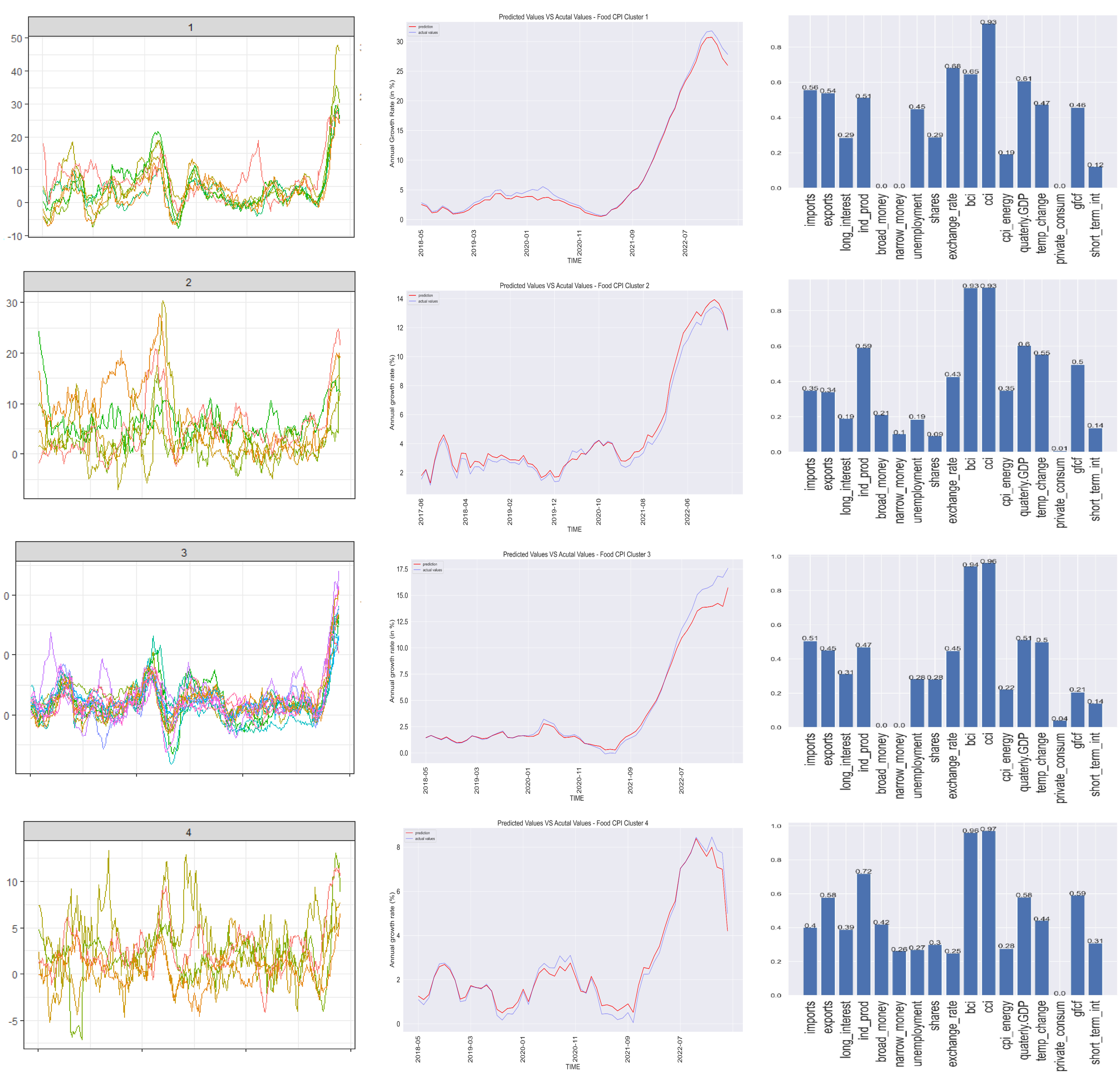
Cluster members	Food CPI time series	Prediction vs. actual values	Features´ Shapley Values

Colombia, Czechia, Estonia, Hungary, Lithuania, Latvia, Slovakia

Chile, Costa Rica, Greece, Island, Israel, Mexico

*Austria, Belgium, Germany, Denmark, Spain, Finland, France, UK **

Canada, Switzerland, Japan, Korea, Norway



** also Ireland, Italy, Luxemburg, Netherlands, Poland, Portugal, Sweden, USA*

Figure 4: Cluster Summary Results

Conclusion & Policy Implications

Long-term food price trends are cluster-specific and do not follow an uniform pattern → heterogenous food price inflation between clusters and over time

Food prices between clusters have a different set of predictors → no unique set of food price predictors → prompt & precise identification of predictors necessary to address food price surges

The marginal contribution of drivers changes over time → transient, non-linear/-static character of food price predictors → 'one-size fits all' policies appear not optimal