Measuring geographical and population coverage in CPI internet price collection

An application with groceries web scraping in Italy

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Meeting of the Group of Experts on Consumer Price Indices

[1] The views expressed herein are those of the authors and do not necessarily represent the views of the Bank of Italy and/or the Eurosystem.

Agenda

Coverage and CPI

- Modernization of CPI process to reduce biases and errors (Smith, 2021)
- Geographical dimension is key to assess CPI soundness (Berry et al., 2019)
- Prices may vary widely across space (Aten, 1996; Biggeri et al., 2017; Montero et al., 2020; Rao, 2001)

However:

- No consensus on the optimal degree of spatial disaggregation (Diewert, 2021)
- Limited attention devoted so far to CPI coverage in the literature (Diewert, 2021; Guerreiro et al., 2022; Hawkes and Piotrowski, 2003)

Objective

Our aim: propose a coverage metric for CPI data collection

- Represent geographical and population coverage
- Enable comparisons between areas of different extensions and population
- Enable weighted aggregations for the coverage metric

In addition:

- Demonstrate impact on CPI soundness when coverage experiences an abrupt change

Assumptions

The growth of e-shopping is generating both competing and complementing dynamics, with an impact on shopping travel pattern, e.g. duration, distance, (Shi et al., 2019; Le et al., 2022) and in-store landscape (Maat and Konings, 2018; Shah et al., 2021)

- Consumers are willing to travel for a limited time when doing purchases.
- Maximum acceptable travel time may vary according to frequency and magnitude of purchases.
- E-commerce shops have limited delivery range on certain categories of goods, in particular groceries.
- Consumer prices differ across geographical areas

→ Validity of price information in a certain location decays with travel distance

Fuzzy Coverage Index - Membership function

Geospatial fuzzy index (Zadeh, 1977; Zimmermann, 2011) to represent CPI data collection coverage. The Fuzzy set theory does not require the identification of a clear cut-off line thus taking into account the problem of imprecision.

Linear specification

$$lc(x) = max(1 - \frac{x}{D}, 0) \tag{1}$$

Inverse sigmoid specification

$$c(x) = 1 - \frac{1}{1 + e^{-k(x - \frac{D}{2})}} \tag{2}$$

Fuzzy Coverage Index - Aggregation

Unweighted aggregation

$$C_{mun} = \frac{\sum_{i=1}^{n} c_i}{n} \tag{3}$$

Population-weighted aggregation

$$C_{pop} = \frac{\sum_{i=1}^{n} c_i * pop_i}{\sum_{i=1}^{n} pop_i} \tag{4}$$

Spatio-temporal Price Indices

Time-interaction-Region Product Dummy (TiRPD) model (Aizcorbe and Aten, 2004)
➔ Ability to derive spatial and temporal parities in a single equation.

$$lnP_{ijt} = \sum_{i=1}^{N} \beta_i D_{ijt} + \sum_{t=1}^{T} \sum_{j=1}^{M} \delta_{jt} R_{ij} T_{jt} + \eta_{ijt} \tag{5}$$

The TiCPD provides the same answers as separate CPD or TPD models, with the advantage that it normalizes the relationships on a single region and time period.

Abrupt change indicator

Bayesian Estimator of Abrupt change, Seasonal change, and Trend (BEAST) (Zhao et al., 2019)

- Decomposition of time series into multiple trend and season signals
- Probability for each of the time series point to be an abrupt change point

Beast model:

$$y_i = T(t_i; \Theta_t) + \varepsilon_i \tag{6}$$

Trend change points are implicitly encoded in Θ_t.
Trend component in each segment:

$$T(t) = a_j + b_j t \text{ for } \tau_j \leq t < \tau_{j+1}, j = 0, ..., m \tag{7}$$

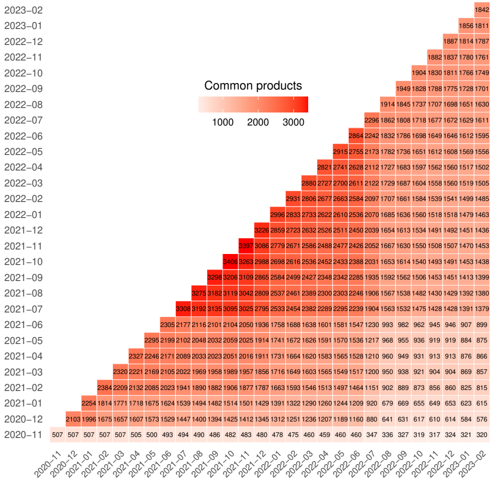
Grocery prices web scraping

- November 2020 to February 2023
- 23 online supermarket chains
- 616 outlets with GPS coordinates
- 19 Italian regions

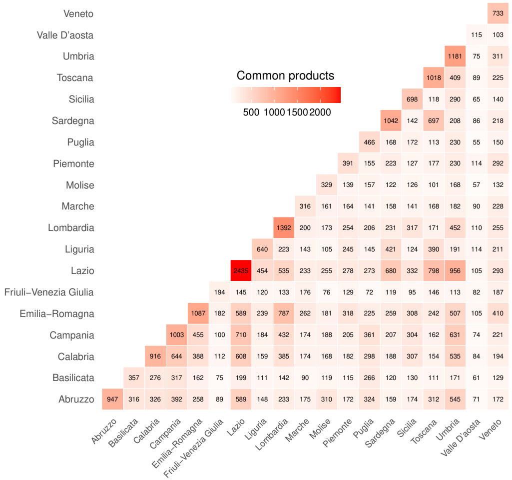
Coffee category (ECOICOP code 01.2.1.1)

- Average Italian household monthly expenditure: 11.91 EUR
- HICP weight: from 0.38% in 2020 to 0.43% in 2023
- 5338 unique products (2056 identified with GTINs)
- 1221755 total observations

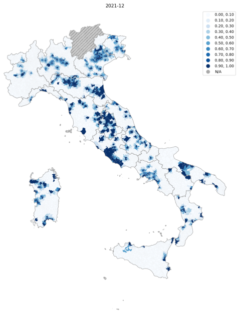
Common products across time

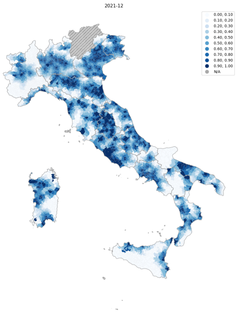


Common products across regions

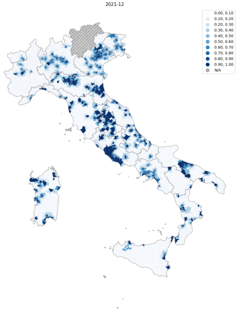


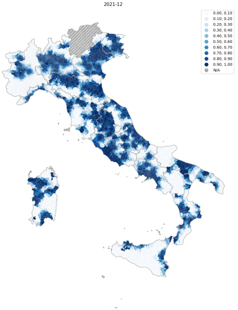
Coverage - Linear function at selected distance values





Coverage - Inverse sigmoid function at selected distance values





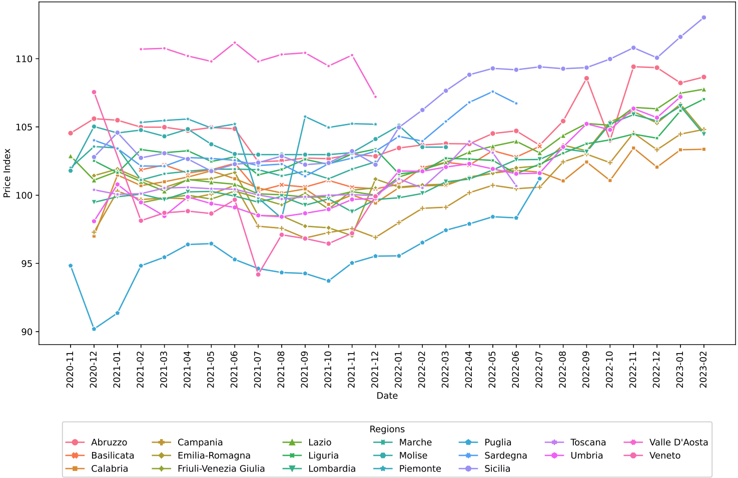
Coverage index stability

Spearman Rank correlation between pairs of indices with different D parameters and weighting methods:

- D parameters: 20 mins, 30 mins, 40 mins, 50 mins
- Correlation always positive and significant
- Correlation always > 0.86 within the same weighting method (municipalities or population)

→ **Proposed coverage index is stable regardless of the parameters or specification chosen.**

TiRPD indices



Coverage and TiRPD abrupt changes correlation

Region	Correlation	p-value
Abruzzo	0.359	*(0.061)*
Basilicata	0.399	*(0.101)*
Calabria	0.142	*(0.481)*
Campania	0.735	*(0.000)*
Emilia-Romagna	0.010	*(0.961)*
Friuli-Venezia Giulia	1.000	*(0.000)*
Lazio	-0.078	*(0.695)*
Liguria	0.410	*(0.034)*
Lombardia	-0.048	*(0.813)*
Marche	0.815	*(0.000)*
Molise	0.993	*(0.000)*
Piemonte	0.994	*(0.000)*
Puglia	0.300	*(0.186)*
Sardegna	-0.047	*(0.848)*
Sicilia	-0.033	*(0.868)*
Toscana	0.954	*(0.000)*
Umbria	0.554	*(0.003)*
Valle d'Aosta	0.999	*(0.000)*
Veneto	0.919	*(0.000)*

→ Significant correlation between abrupt changes in coverage and TiPRD indices.

Conclusions

- Abrupt changes in price data collection coverage can have significant impact on the CPI
- Coverage can provide relevant insights on the CPI quality
- National Statistical Institutes should consider calculating and publishing coverage metrics as complementary information for their CPI statistics.

Thank you for your attention

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