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NOWCASTING THE ITALIAN CONSUMER PRICE INDEX USING ONLINE PRICES AND MACHINE LEARNING

by Luca Bacco†, Tiziana Laureti§, Juri Marcucci*, Luigi Palumbo*,
Daniele Sasso† and Luca Vollero†

Abstract

Timely and accurate forecasts of the Consumer Price Index (CPI), an essential economic indicator measuring consumer prices over time, are crucial for central banks. Traditional forecasting models often struggle to incorporate real-time data and to adapt to rapid changes in the economic environment, leading to potential inaccuracies in short-term forecasts.
In this paper, we explore the potential of using online food price data obtained from 20 supermarkets across several major cities of a well-known chain in Italy, from December 2020 to March 2023. Our objective is exploring the feasibility and accuracy of forecasting the CPI for specific food categories using real-time, web-scraped data, particularly in periods of high macroeconomic uncertainty like those following the COVID-19 pandemic and the onset of the war in Ukraine. Our analysis demonstrates the potential of real-time web-scraped data for predicting official CPIs and offers valuable insights for researchers and practitioners interested in this specific approach. Specifically, our results suggest that web-based price data can complement traditional statistical sources, providing more granular and timely indicators that are especially useful during periods of economic volatility.

JEL Classification: C22, C53, E31, E37.

Keywords: consumer price index, inflation, COICOP, nowcasting, web scraping, ISTAT.

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1. Introduction[1]

The Consumer Price Index (CPI) is a critical economic indicator that measures prices over time for a basket of goods and services, serving as a key metric for assessing inflation and cost-of-living changes [1]. Its forecasts are key for economic agents and policy makers. However, traditional forecasting models may struggle to incorporate real-time data and adapt to sudden market changes, leading to potential inaccuracies in short-term forecasts, particularly in the aftermath of significant events like the COVID-19 pandemic or the onset of the war in Ukraine. This aspect is particularly relevant for economic actors such as households, firms, and financial institutions, whose expectations and decisions are influenced by central bank policies [2, 3], since inflation is a key policy target for a central bank [4].

At the same time, digitalization has increased the availability of new data sources characterized by high volumes, high velocity and great variety (Big Data). These new data sources have been recently used for producing and forecasting official statistics [5], particularly via web scraping. Following recent work [6, 7, 8], this study employs real-time online prices to forecast the CPIs for specific food macro-categories.

In particular, we collected data from 20 online facilities across several main cities in Italy from December 2020 to March 2023[2] focusing on COICOP5[3] products (as reported in Appendix A) under the COICOP4 categories of fruits, vegetables, and meat. In this context, prediction is particularly challenging, as more granular categories are usually more volatile than aggregates [9]. Moreover, fresh food prices are generally more volatile than other COICOP categories [10].

Focusing on the impact of the prediction horizons, varying within the set of 15, 30, and 45 days, we show the potential of this approach by comparing our results with the official CPI categories provided by the Italian National Statistical Institute (ISTAT). In particular, we aim to assess both the accuracy of the scraped data in approximating the actual CPI values and the performance of models trained on these data to forecast the CPI.

The rest of the paper is organized as follows. Section 2 reviews the relevant literature on the use of online prices and web scraping for CPI forecasting. Section 3 describes the

[1]We would like to thank Laura Bartiloro, Francesco Corsello, Alberto Felettigh and Fabrizio Venditti for their useful comments. The views and ideas expressed herein are those of the authors and do not necessarily reflect those of the Bank of Italy or the Eurosystem. All remaining errors are our own.
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[2]We had to stop in March 2023 because one of the main grocery retailers changed its website structure, making it impossible to continue web scraping as before.

[3]COICOP stands for ‘Classification of Individual Consumption According to Purpose’. It is an international standard developed by the United Nations to categorize household consumption expenditures by function or purpose — such as food, housing, transport, and health. COICOP is widely used in consumer price indices and national accounts to ensure comparability of consumption data across countries.

data sources, product classification procedures, and forecasting methodology, including the use of the Prophet model and the computation of consumer price indexes. Section 4 presents the main results and discusses the accuracy of the forecasts under different experimental conditions. Section 5 concludes with a summary of the key findings and outlines possible directions for future research.

2. Related Work

The literature has widely debated the use of online prices as representative of overall market prices. The prevailing view is that online prices closely mirror offline prices [11]. After the COVID-19 pandemic, several economic sectors, such as electronics have witnessed increasing sales, both to consumers and businesses, across most EU countries [12], indicating long-term structural changes [13]. Official price statistics have also adapted to the growing share of e-commerce in household consumption budgets, and researchers have advocated for the wider use of online prices in producing official CPIs [14]. The rapid expansion of the online marketplace has significantly transformed consumer purchasing behaviors, making digital price data increasingly relevant for economic analysis.

The MIT's Billion Prices Project [15] (BPP thereafter), by Alberto Cavallo and Roberto Rigobon, is one of the pioneering examples in price statistics leveraging those new tools, collecting prices from hundreds of online retailers on a daily basis from more than eighty countries and offering daily CPI indexes for selected countries and time frames since 2008.[4] However, BPP and similar early projects, such as the work by Cavallo [16], were mostly exploratory and faced challenges related to coverage, representativeness, and the need for continuous updating. At the time, the technological infrastructure for large-scale, automated data collection was not as advanced as it is today, limiting the ability of such projects to maintain long-term continuity. Moreover, some of these initiatives were discontinued, as they would have required ongoing methodological adaptations to remain relevant. The COVID-19 pandemic further complicated the landscape, introducing significant discontinuities in pricing behaviors and reinforcing the need for robust, real-time monitoring tools, particularly due to the difficulties faced by traditional data collection methods, such as in-person surveys, which were disrupted by lockdowns and restrictions.

Several National Statistical Institutes (NSIs) around the world have actively researched the use of web-scraped data and other automated data sources—such as transaction or scanner data—for their official CPI production, potentially supplementing or replacing manually collected price quotes [17, 18, 19]. These institutes include the US Bureau of Labor Statistics [20], the UK Office for National Statistics [21], Statistics New Zealand [22], Statistics Norway [17], Statistics Netherlands [23, 24], ISTAT [18], and Romania National Statistical Institute [25]. Some of these experiments have already transitioned into

[4] Data available at http://www.thebillionpricesproject.com/datasets/.

production, significantly transforming NSI data collection methods by increasing sample sizes and reducing response burdens.

In terms of forecasting, there is a growing body of literature validating the use of online prices for producing accurate forecasts of official statistics [26], anticipating official data releases [27]. In Poland, the Central Bank has been using web scraping data since 2009 to create short-term forecasts for food inflation [7, 8]. The increasing sophistication of web-scraping methodologies, combined with machine learning advancements, has further enhanced the predictive power of such approaches, making them valuable tools for economic monitoring and policymaking.

3. Data and Methods

3.1. Data

While in several European countries, such as France and the United Kingdom, online grocery retailers have achieved significant market penetration and established national-level pricing [28], for Italy we see substantial regional price differences, as also highlighted by previous literature [29, 30]. In line with the exploratory nature of our study, we base our analysis on daily grocery prices from 20 online shops in different Italian cities and regions, all belonging to the same national retail chain. We collected data daily over two years, from December 2020 to March 2023 (available at `https://doi.org/10.5281/zenodo.14927602` [31]).[5]

Web-scraped prices are collected from each online store using the "pick up" option for purchase delivery. In this way, the price information is linked to the geographical position, and we can ensure the parity between online prices and those applied in physical shops.

Each online supermarket is located with GPS coordinates and placed in a specific municipality. The provinces covered in our data collection routines are Bergamo, Caserta, Catanzaro, Cosenza, Cremona, Crotone, Frosinone, Latina, Lecco, Milano, Napoli, Palermo, Parma, Perugia, Reggio Calabria, Reggio Emilia, Rieti, Roma, Salerno, and Sondrio. As shown in Figure 1, these provinces are spread across the Italian territory, and their total population amounts to about 20 million people, which is equal to one-third of the total Italian population.

The official monthly CPIs provided by ISTAT for fresh products sold by weight[6] are based on local surveys, performed during the first 21 days of each month, across 80 Italian cities [32] to capture data from traditional small retailers and modern distribution channels, e.g., mass retailers. Scanner data, which are collected from modern distribution

[5]Since the source website had a dynamic architecture, we leveraged the API, which provides data to its front-end to access product and price information. This enabled us to minimize the load on the source website, as well as our requirements in terms of the infrastructure needed to perform the data acquisition.

[6]For instance, fruits, vegetables, or meat which are not pre-packaged in standardized units.

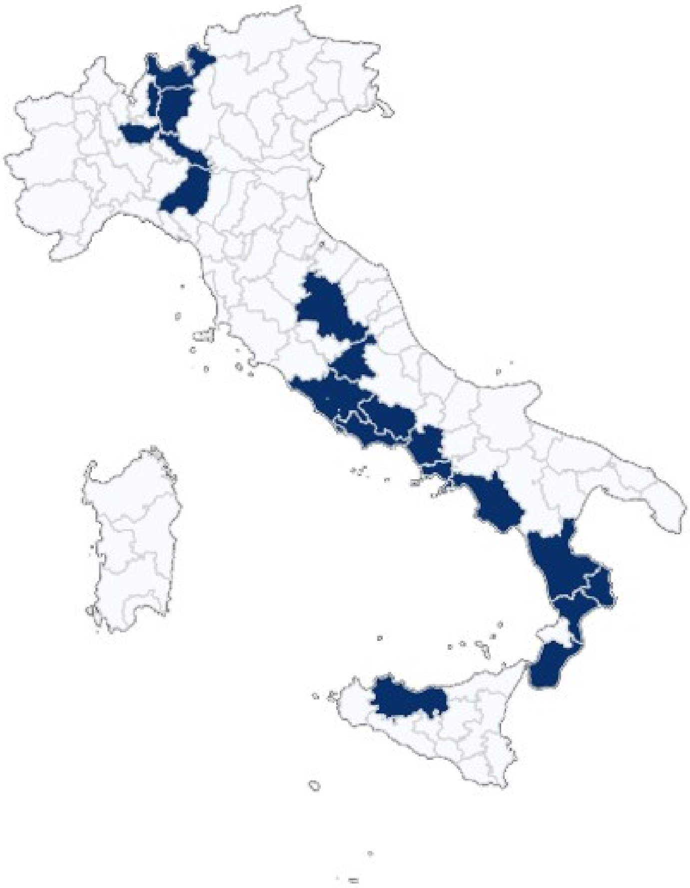

Figure 1: Map of the provinces covered during the data collection routine.

outlets providing prices and quantities sold for each product, are not used to track prices across those specific categories because the barcodes used to identify products sold by weights are not standardized across retailers.

Starting in 2022, ISTAT began incorporating food delivery services into the CPI by collecting prices through centralized web scraping across 12 municipalities. The data are based on a standardized basket, consisting of a predefined meal with beverages, sourced from the websites of major food delivery platforms.

3.2. COICOP5 Categories

The COICOP nomenclature is a hierarchical classification system used to categorize consumer expenditures, which is essential for economic analysis and statistical reporting, as it allows for a detailed understanding of consumption patterns and expenditure behaviours. At its most detailed level, at the five-digit level, i.e., COICOP5, it provides a granular categorization of goods and services. Each product is assigned to a specific category based on its characteristics and intended use, facilitating a structured data analysis and comparison approach.

This study focuses on a specific range of food products, particularly those related to fruits, vegetables, and meats. However, retailers usually do not map each of their products to these (detailed) categories, and the data we collected through web scraping do not present this information. Consequently, we need to label each of the collected products into its specific COICOP5 category.

This categorization forms the foundation of our subsequent analysis, allowing us to tailor our models to each product category's specific characteristics and improve our forecasts' reliability. We first manually labeled approximately half of the dataset with the help of domain experts, who assigned each product to its corresponding COICOP5 category based on product descriptions. Then, we built a set of rules, leveraging regular expressions (patterns used to match and manipulate text) and the domain knowledge, i.e., familiarity with retail terminology, product naming conventions, and classification criteria relevant to food items.

For each of the obtained sets of products (i.e., for each COICOP5 category), we built subsets that included only the k products that were mostly represented during the period taken into account. We employed k extracted from the set of values $\{10, 20, 30, 50, 100\}$. The reason behind this setup is to analyze, with respect to the data representation, whether including more items would result in improved performances or more noisy data, as focusing on a smaller set of representative items can help improve the nowcasting accuracy by reducing the noise [7].

Figure 2 shows the number of unique products per COICOP5 category within the macro-categories of fruits, vegetables, and meats. Here, a "unique product" refers to a distinct commercial item identified during the scraping process—such as different brands, packaging sizes, or variants of the same food (e.g., organic vs. non-organic bananas, or pre-packaged vs. loose items).

A significant observation from the figure is the substantial imbalance across different product categories. Fruit and meat categories are represented more extensively than vegetables, with some categories (such as bananas or poultry) including dozens of product variants. This imbalance reflects the greater commercial variety typically offered by retailers in those segments and has implications for the representativeness and noise levels of the data used in forecasting.

To mitigate the impact of this imbalance, we selected subsets of the top-k most frequently available products per COICOP5 category (with $k \in \{10, 20, 30, 50, 100\}$) for training and evaluation.

3.3. Forecasting Prices

To compute the CPI for each product in each category, we forecast the price index at specific prediction horizons of 15, 30, and 45 days. For instance, to forecast product prices at the end of March, we utilize observed nominal prices available up to mid-March (15 days), the beginning of March (30 days), and mid-February (45 days). The forecasting model training uses data on product prices from December 2020 up to the forecasting

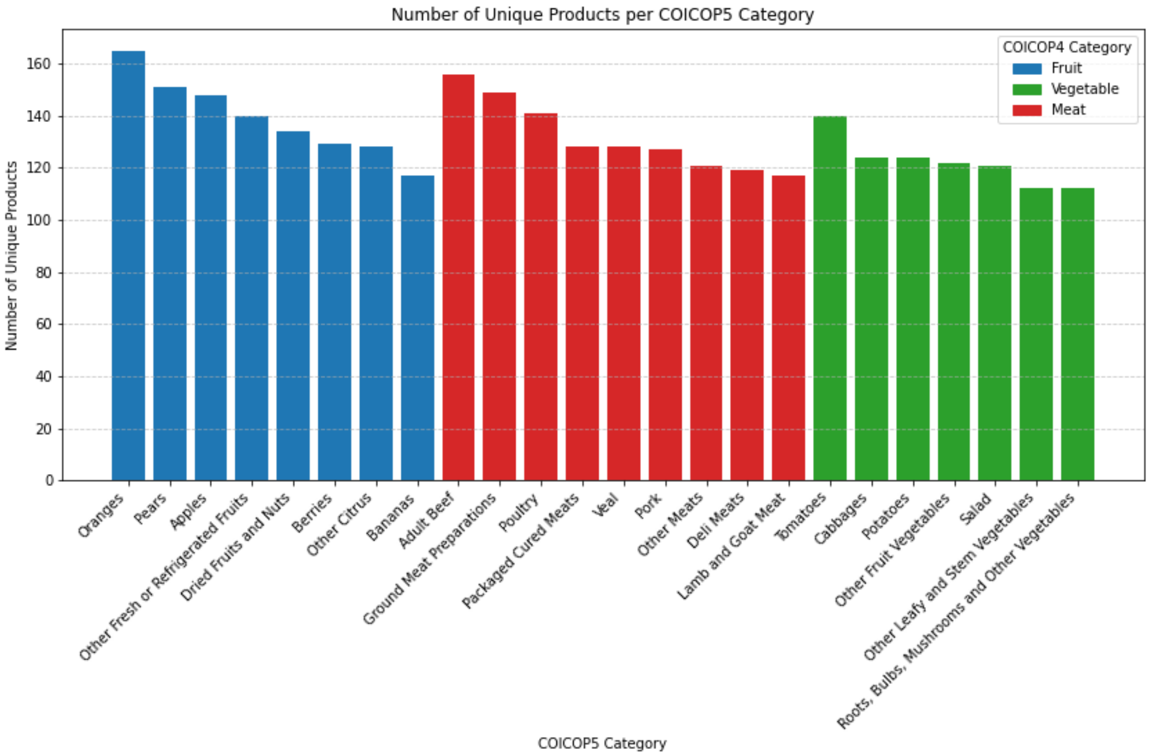

Figure 2: Number of unique products per COICOP5 category within the fruits (blue), vegetables (green), and meat (red) macro-categories. A "unique product" is defined as a distinct commercial item, potentially differing by brand, packaging, weight, or labeling.

date cutoff (i.e., the test data).

3.3.1. Predictive Model

We employ the Prophet framework developed by Facebook (Meta) researchers [33]. Prophet has been successfully employed in academic works, especially with high-frequency (such as weekly or daily) data [34, 35], with recent applications including energy demand [36], medical services demand [37], wholesale food prices [38], retail sales [39, 40, 41], and financial time series [42, 43, 44, 45]. Prophet belongs to the family of decomposable time series models [46], allowing for the isolation of non-linear trends (e.g., yearly, monthly, weekly, and daily seasonality) and holidays' effects. Different from other alternatives like TBATS[7] [47], Prophet can handle different holiday schemes without any *a priori* analysis. The advantages of a Prophet model over traditional time series methods like an AR(I)MA model [33] are i) a flexible specification of multiple concurrent seasonalities; ii) allowing for measurement at irregular intervals without the need for missing data interpolation, and iii) a straightforward interpretability of the results. Also, from a computational perspective, Prophet is fast to fit datasets of considerable size, thus allowing for rapid exploration of different model specifications.

[7]TBATS is the acronym for Trigonometric, Box-Cox transform, ARMA errors, Trend and Seasonal components.

The general representation for the time series $y(t)$ in Prophet is the following:

$$y(t) = g(t) + s(t) + h(t) + \epsilon_t \quad (1)$$

Where $y(t)$ is the target variable we want to forecast, $g(t)$ is a non-linear saturating trend function that models non-periodic changes in the time series, $s(t)$ represents all periodical (i.e. seasonal) changes, $h(t)$ is the effect of holidays, which can also occur at irregular schedules, and ϵ_t is the error term, representing variations not captured by the model. Prophet automatically identifies trend change points according to a set of tunable hyper-parameters. This specification is similar to a generalized additive model (GAM) [48].

3.3.2. Hyper-Parameters' Search

The hyperparameter tuning process is crucial for enhancing the performance of forecasting models. In this study, we utilized the Prophet model and conducted an extensive hyperparameter search to identify the optimal parameters for each product. The hyper-parameters considered were *changepoint prior scale*, ranging from 0.01 to 0.2, and *changepoint range*, ranging from 0.75 to 0.99, both with steps of 0.05. The changepoint prior scale controls the flexibility of the trend in the time series. A smaller value makes the trend less flexible (smoother), while a larger value allows for more abrupt changes. The changepoint range defines the proportion of the time series data in which changepoints are allowed to be placed. It ranges from 0 to 1, where 1 means changepoints can be placed throughout the entire time series, and a smaller value restricts changepoints to an earlier segment of the data. Using these ranges, all possible combinations of hyper-parameters were generated.

For each product, we fit a Prophet model for each hyper-parameter combination and evaluate the model using cross-validation. The cross-validation was conducted with a horizon of 15 days, and the Root Mean Squared Error (RMSE) was calculated for each set of hyper-parameters. The combination yielding the lowest RMSE was selected as the optimal set.

The hyper-parameter search process involved several key steps. Initially, the data for each product was prepared and aggregated. Subsequently, the top products with the most data points were identified. We trained the Prophet model on the product data for these selected products, performing cross-validation and computing performance metrics. The hyper-parameters with the minimum RMSE were determined and stored for future use.

This systematic approach ensures that the forecasting models are tailored to the specific characteristics of each product's data, thereby improving the accuracy and reliability of the forecasts. The identified optimal hyper-parameters were applied in subsequent optimization and forecasting stages, ensuring the models were fine-tuned for optimal performance.

3.4. Computing the Consumer Price Index

ISTAT's official CPI calculations employ fixed expenditure weights, typically based on the previous year's household spending shares. However, in this study, detailed sales or expenditure data for the specific products collected via web scraping are not available, making it impossible to reconstruct consistent weights at the COICOP5 level. Consequently, we adopt unweighted index methods, which are commonly used to compute elementary price indexes when quantity or spending data are missing. The usual procedures start from calculating an average monthly price for every product sampled [49] and then calculating the arithmetic or geometric mean of homogeneous products in each month. For specific cases, such as clothing, Statistics Netherlands proposed a stratification method to classify products and compute intermediate elementary aggregates [50]. We employ two computational methods to handle this issue and compute the CPIs for each COICOP5 category among the 24 we consider here. Following the specifications used by [51], the first one is an unweighted Time-Product Dummy (TPD) method:

$$lnP_{it} = \sum_{i=1}^{N} a_i D_i + \sum_{t=1}^{T} \gamma_t T_t + \mu_{it} \tag{2}$$

where, for each category, lnP_{it} is the log of the price of product i at time period t, D_i and T_t are the dummy variables for product i and time t, respectively, and a_i and γ_t their associated coefficients. The changes in the CPI between two periods can be obtained by comparing the time dummies γ_t coefficients. Mathematically, the change in CPI from period t_0 to period t can be calculated as:

$$\Delta \mathrm{CPI}_{t_0,t} = (\exp^{\gamma_t} - \exp^{\gamma_{t_0}}) * 100\% \tag{3}$$

By assuming that the base period t_0 has a coefficient $\gamma_{t_0} = 0$ (which is often the case in these dummy regressions), then the change in the price index for period t will simply be $(\exp^{\gamma_t} - 1) * 100\%$. In practice, the γ_t coefficients represent the logarithm of the relative price changes compared to the base period. By converting from the logarithm, we can obtain the percentage change in prices. For example, if $\gamma_t = 0.02$, it means there has been a change of $(e^{0.02} - 1) * 100\% \approx 2\%$ in prices compared to the base period.

This method allows for the calculation of price index changes without the need for weights, using only the information on prices and time dummies. A second method employs a weighted variant of the TPD method:

$$lnP_{it} = \sum_{i=1}^{N} a_i D_i + \sum_{t=1}^{T} \gamma_t T_t + \mu_{it} \tag{4}$$

where each observation of product i is associated with a weight w_i, which reflects the relative contribution of that product to the overall price dynamics of its COICOP5 category. These weights are not based on actual expenditure shares—since that information is unavailable—but are instead optimized to improve the alignment between the model-generated category-level CPI and the official CPI published by ISTAT for that same category.[8]

The weights are estimated by minimizing the mean absolute error (MAE) between the constructed CPI—derived from the weighted combination of forecasted product prices—and the official CPI for the corresponding COICOP5 category, over a training period preceding the forecast horizon.

We use the TNC (Truncated Newton Conjugate Gradient) [52, 53] method to optimize the weights, which supports simple variable bounds and is effective for large-scale problems with smooth functions. The optimization process involves formulating an objective function that calculates the sum of absolute differences between the official CPI and the computed CPI, considering the weights assigned to each product. The TNC algorithm is then employed to minimize this objective function, ensuring that the computed CPI closely aligns with the official CPI by adjusting the weights appropriately. This method effectively handles constraints and is scalable for large datasets, providing accurate economic indicators for each COICOP5 category. The data in this process spans multiple months, starting from December 2020, with the specific cutoffs for the forecasts from March 2021 to August 2021, to balance the need for data with the necessity of capturing sufficient seasonal variation. December 2020 provides a suitable starting point, as it marks the beginning of comprehensive data collection for our purposes, ensuring that our model captures the full range of economic activities and product price changes influenced by seasonal and market trends. The monthly forecasts are generated using a function that processes individual product prices, fits a Prophet model to the prior data, and predicts average prices for the specified periods.

3.4.1. Evaluation

To evaluate our approach, we compute two metrics: the *concordance* and the *mean absolute error* (MAE). The former refers to the agreement in sign between the official CPIs and the computed ones. The latter, instead, refers to the distance (in modulus) between them. In particular, apart from the aggregated error between the predicted and the official CPI indices, we distinguish between two kinds of errors: the prediction error (MAE_p) and the tracking error (MAE_t). The *prediction error* measures how much our

[8] For example, within the COICOP5 category *bananas*, the model forecasts the monthly price index using a set of individual banana products scraped from various online stores. The weights w_i are adjusted to minimize the error between the aggregated index built from those individual products and the official ISTAT index for *bananas*.

predicted index (CPI_p) aligns with the target metric, i.e., the index built by using the ground truth prices (CPI_{gt}). Instead, the *tracking error* quantifies how much the target metric aligns with the official CPI (CPI_o).

This distinction is crucial for a comprehensive evaluation of our pipeline. The prediction error reflects the forecasting performance of the model trained on web-scraped data, whereas the tracking error captures how well the web-scraped data, even before modeling, reproduce the dynamics of the official index. By decoupling these sources of error, we can separately assess the reliability of the data source and the effectiveness of the modeling process—an essential step for validating the feasibility of using scraped prices as a proxy or complement for official statistics. Mathematically, we compute the two errors as follows,

$$\begin{cases} MAE_p(CPI_p, CPI_{gt}) = \frac{1}{T}\sum_{t=1}^{T}|CPI_{p,t} - CPI_{gt,t}| \\ MAE_t(CPI_{gt}, CPI_o) = \frac{1}{T}\sum_{t=1}^{T}|CPI_{gt,t} - CPI_{o,t}| \end{cases} \tag{5}$$

where T is the number of the test data samples. Similarly, we distinguish two concordance metrics:

$$\begin{cases} C_p(CPI_p, CPI_{gt}) = \frac{1}{T}\sum_{t=1}^{T}[CPI_{p,t} * CPI_{gt,t} > 0] \\ C_t(CPI_{gt}, CPI_o) = \frac{1}{T}\sum_{t=1}^{T}[CPI_{gt,t} * CPI_{o,t} > 0] \end{cases} \tag{6}$$

4. Results and Discussion

In this section, we present the results of our analysis, focusing initially on the COICOP categorization and subsequently on the performance metrics of our predictive models.

Performance Metrics. Table 1 presents the aggregated errors in terms of MAE across different forecasting horizons and varying numbers of products for each category, averaged across all categories. The results are reported as absolute differences in month-on-month CPI variations, expressed in percentage, with their standard deviations calculated by bootstrapping. Additionally, Table 2 and Table 3 show the performance in terms of prediction and tracking errors and concordances, respectively, also averaged across all categories. For a more detailed analysis, Appendix A provides results for individual COICOP5 categories, as well as the magnitudes of the official CPIs. We also compared the results for the COICOP4 macro-categories (fruits, vegetables, and meat). Figure 3 and Figure 4 present the aggregated MAE, and the prediction and tracking MAE, respectively, for models developed with and without weights.

# prod.	45 days		30 days		15 days	
	No W	W	No W	W	No W	W
10	2.98 ± 1.94	3.08 ± 2.23	2.55 ± 1.66	2.73 ± 1.86	2.59 ± 1.92	2.59 ± 1.92
20	2.99 ± 1.97	2.91 ± 2.07	2.48 ± 1.73	2.49 ± 1.83	2.84 ± 3.36	2.84 ± 3.36
30	2.95 ± 1.97	2.83 ± 2.05	2.43 ± 1.72	2.41 ± 1.82	2.72 ± 3.24	2.73 ± 3.24
50	2.99 ± 2.39	3.26 ± 3.17	2.48 ± 2.04	2.89 ± 3.35	2.47 ± 2.24	2.46 ± 2.23
100	3.09 ± 2.42	3.13 ± 2.56	2.50 ± 2.07	2.58 ± 2.24	2.41 ± 1.98	2.40 ± 1.98

Table 1: Aggregated errors in terms of MAE for different numbers of products (first column), reported as absolute deviations in month-on-month CPI variations, expressed in percentage, averaged across all categories. Errors, along with their standard deviation across the 24 COICOP5 categories considered, are presented for two scenarios: computing the CPI with or without weights (*W* or *No W*, respectively). Results are shown for different forecasting horizons (45, 30, and 15 days).

# prod.	Prediction error						Tracking error	
	45 days		30 days		15 days			
	No W	W	No W	W	No W	W	No W	W
10	2.66 ± 1.51	2.75 ± 1.93	2.25 ± 1.38	2.31 ± 1.62	1.36 ± 1.08	1.36 ± 1.08	2.72 ± 2.06	2.73 ± 2.06
20	3.05 ± 2.92	2.83 ± 3.18	2.58 ± 2.83	2.46 ± 3.05	1.31 ± 0.96	1.31 ± 0.96	3.06 ± 3.28	3.24 ± 3.24
30	2.96 ± 2.92	2.94 ± 3.14	2.48 ± 2.85	2.50 ± 2.97	1.37 ± 0.81	1.37 ± 0.81	2.89 ± 3.18	2.89 ± 3.18
50	2.79 ± 2.46	3.11 ± 3.49	2.34 ± 2.18	2.74 ± 3.91	1.92 ± 2.41	1.92 ± 2.41	2.46 ± 1.96	2.47 ± 1.96
100	2.67 ± 1.82	2.76 ± 2.00	2.16 ± 1.48	2.25 ± 1.67	1.67 ± 1.34	1.67 ± 1.34	2.19 ± 1.49	2.18 ± 1.49

Table 2: Prediction and tracking errors in terms of MAE for different numbers of products (first column), reported as absolute deviations in CPI variations, expressed in percentage. Errors, along with their standard deviation across the 24 COICOP5 categories considered, are presented for two scenarios: computing the CPI with or without weights (*W* or *No W*, respectively). Prediction errors are shown for different forecasting horizons (45, 30, and 15 days).

# prod.	Prediction concordance						Tracking concordance	
	45 days		30 days		15 days			
	No W	W	No W	W	No W	W	No W	W
10	0.51 ± 0.13	0.52 ± 0.14	0.56 ± 0.14	0.56 ± 0.14	0.72 ± 0.17	0.72 ± 0.17	0.57 ± 0.13	0.57 ± 0.13
20	0.51 ± 0.12	0.54 ± 0.14	0.58 ± 0.12	0.58 ± 0.11	0.71 ± 0.12	0.71 ± 0.12	0.60 ± 0.14	0.60 ± 0.14
30	0.51 ± 0.14	0.49 ± 0.18	0.59 ± 0.11	0.58 ± 0.11	0.72 ± 0.09	0.72 ± 0.09	0.61 ± 0.13	0.61 ± 0.13
50	0.53 ± 0.14	0.49 ± 0.13	0.56 ± 0.15	0.55 ± 0.15	0.69 ± 0.13	0.69 ± 0.13	0.64 ± 0.15	0.64 ± 0.15
100	0.54 ± 0.12	0.53 ± 0.13	0.55 ± 0.11	0.56 ± 0.12	0.69 ± 0.14	0.69 ± 0.13	0.66 ± 0.14	0.66 ± 0.14

Table 3: Prediction and tracking concordances for different numbers of products (first column), averaged across all categories. Concordances, shown with their standard deviation across the 24 COICOP5 considered categories, are reported for two scenarios: computing the CPI with or without weights (*W* or *No W*, respectively). The prediction error is reported over different forecasting horizons (45, 30, and 15 days).

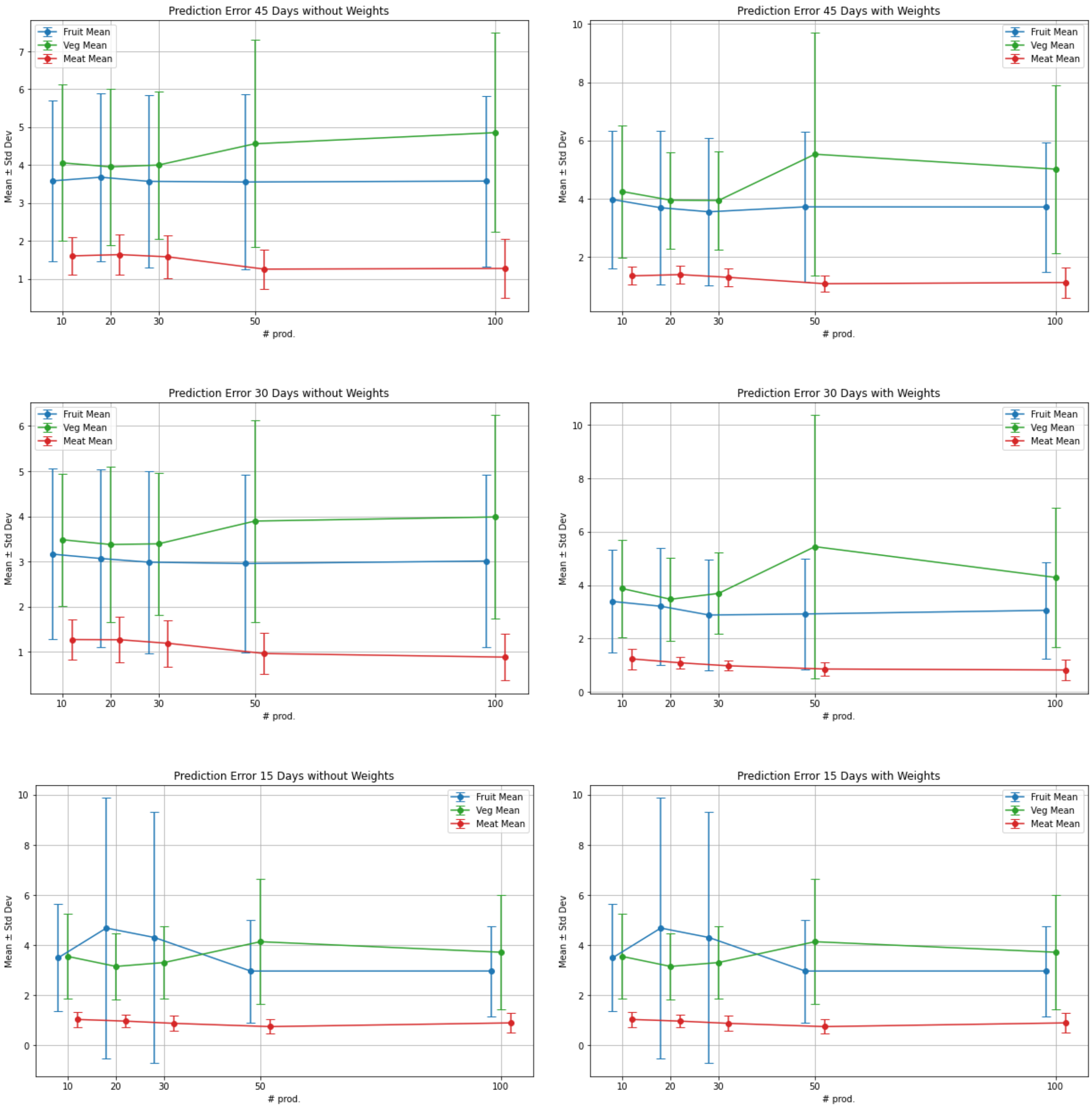

Figure 3: Aggregated errors in terms of MAE for different quantities of products belonging to COICOP4 categories of fruit, vegetable, and meat, computed without and with weights.

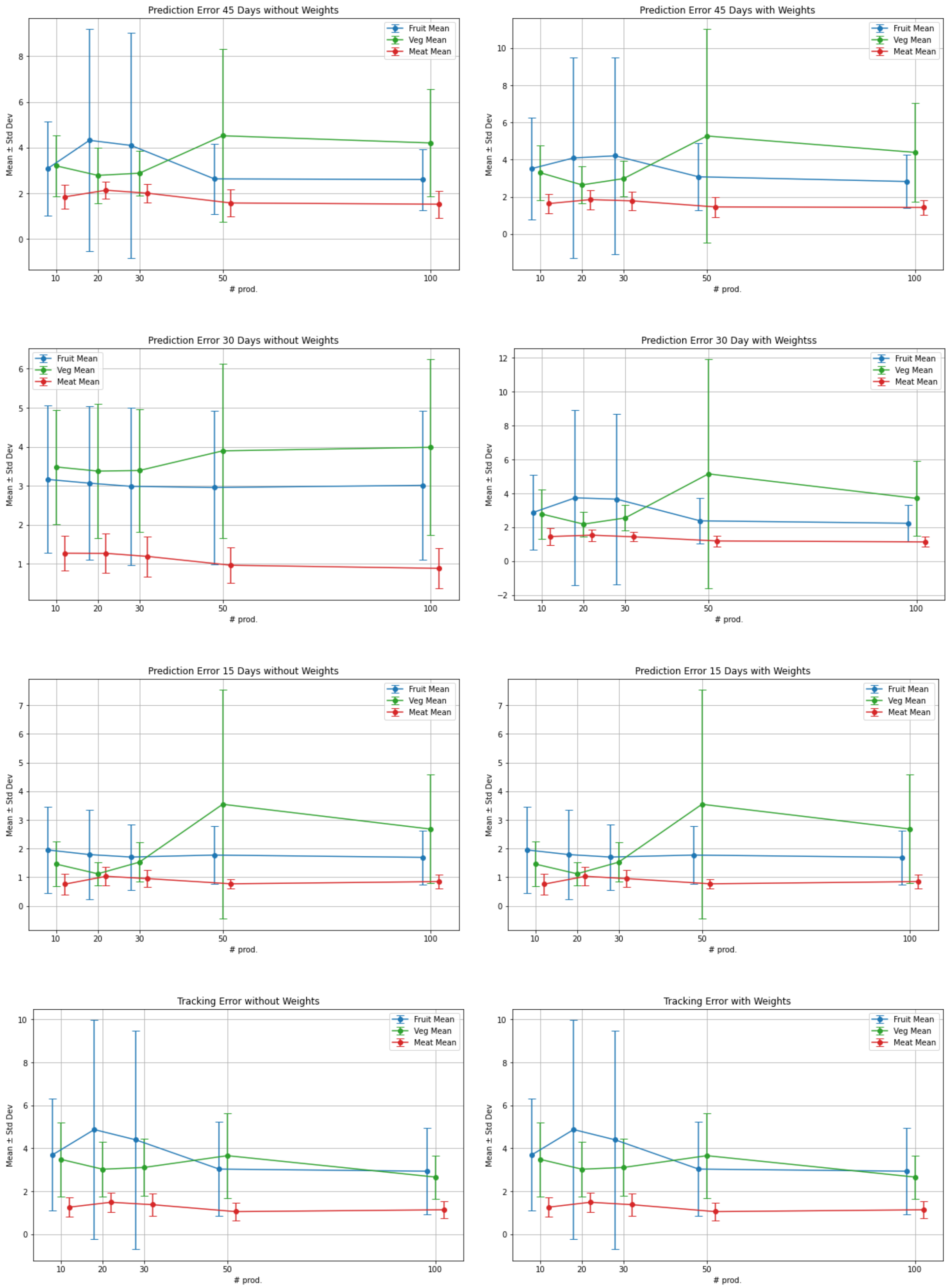

Figure 4: Prediction and tracking errors in terms of MAE for different quantities of products belonging to COICOP4 categories of fruit, vegetable, and meat, computed without and with weights.

The main findings from these evaluations are summarized below:

- *Impact of the prediction horizon:* As expected, forecast errors tend to decrease and prediction concordance improves as the forecasting horizon shortens.
- *Impact of the number of products:* Increasing the number of products used to compute the prediction and tracking metrics does not always lead to better performance. This can be attributed to the inclusion of noisy data [7], due to imperfect product categorization and the presence of infrequently observed items during the analysis period. Additionally, using a smaller set of frequently observed products offers a computational advantage: since each product requires an independent time series forecast (e.g., fitting a Prophet model), reducing the number of items proportionally lowers the overall computational cost for training and forecasting, particularly important when performing hyperparameter tuning across multiple horizons and categories.
- *Differences between prediction and tracking metrics:* Tracking metrics generally yielded worse results than prediction metrics, especially at shorter horizons and when fewer products were included in the analysis.
- *Effectiveness of weighting:* The use of weighting did not consistently improve performance. In most cases, the unweighted approach performed equally well or even better. However, we observed slight improvements in prediction metrics when weights were applied in experiments involving only 20 products. This suggests potential for future research aimed at refining and optimizing weighting strategies.
- *COICOP4 aggregation:*
  - *Error mitigation through aggregation:* As expected, aggregating forecasts at the COICOP4 level tends to reduce the impact of individual product-level discrepancies, resulting in more stable and accurate predictions. This effect is largely due to the smoothing of noise from underrepresented or highly volatile product categories.
  - *Seasonal stability of meat products:* The COICOP4 category for meat consistently exhibited lower forecast errors and standard deviations compared to fruits and vegetables. This reflects the relative price stability of meat, which is less affected by seasonal factors. In contrast, fruits and vegetables display substantial seasonal variation in both availability and prices, as evidenced by their higher standard deviations.

5. Conclusions

This study investigated the potential use of web-scraped data and machine learning techniques for forecasting subcomponents of the CPI, with a focus on food categories—specifically fruits, vegetables, and meats—sourced from a major supermarket chain in Italy.

The results, based on the application of machine learning models, particularly the Prophet framework, suggest that real-time web-scraped data offers a promising avenue for improving the timeliness and accuracy of CPI forecasts.

Among the product categories analyzed, meat prices consistently exhibited lower prediction errors and standard deviations than fruits and vegetables, likely reflecting their reduced sensitivity to seasonal fluctuations.

Our findings also underscore the importance of product selection in predictive accuracy. While increasing the number of products may intuitively seem beneficial, it can introduce noise due to non-representative or infrequently observed items. A balanced strategy that selects a limited but optimal number of representative products–those frequently observed and reliably categorized–proves more effective and computationally efficient.

Moreover, aggregating forecasts at the COICOP4 level, rather than the more granular COICOP5, helps mitigate the influence of product-level volatility. This higher-level aggregation smooths idiosyncratic noise and leads to more robust and stable predictions.

It is worth emphasizing that data collection took place during a period of elevated macroeconomic uncertainty—marked by the aftermath of the COVID-19 pandemic and the onset of the war in Ukraine. This context reinforces the importance of timely indicators, such as those derived from online data, in supporting economc analysis during rapidly evolving conditions.

Further research should explore the optimization of weighting schemes, potentially by tailoring weights to specific product categories or forecasting horizons. Future work could also investigate the use of advanced natural language processing (NLP) techniques to improve automated product categorization and data quality. Expanding the range of data sources-across different retailers, cities, and product types-would enhance generalizability and robustness of CPI forecasting models.

Although the present analysis is limited to 24 COICOP5 food categories from 20 locations, all sourced from a single retailer, the results demonstrate the feasibility of a scalable forecasting methodology. Nonetheless, nationwide implementation would require significant IT infrastructure to support continuous web scraping, data processing, classification, and quality assurance at scale. Moreover, legal and ethical constraints, heterogeneity in website structures, and representativity challenges would also need to be addressed.

In this light, we view our contribution as a step toward the development of hybrid systems that complement-rather than replace-traditional CPI measurement frameworks.

CRediT authorship contribution statement

Daniele Sasso: Software, Validation, Formal analysis, Investigation, Data Curation, Writing - Original draft, Visualization; **Luca Bacco:** Methodology, Software, Formal analysis, Investigation, Supervision, Writing - Original draft, Visualization; **Luigi Palumbo:** Conceptualization, Methodology, Software, Formal analysis, Data Curation, Writing - Original draft; **Juri Marcucci:** Conceptualization, Writing - Review & Editing, Visualization; **Luca Vollero:** Conceptualization, Resources, Writing - Review & Editing, Supervision, Project administration, Funding Acquisition; **Tiziana Laureti:** Conceptualization, Resources, Writing - Review & Editing, Supervision, Project administration, Funding Acquisition.

Data Availability

Data employed in this work are available at https://doi.org/10.5281/zenodo.14927602 [31].

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Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work the authors used ChatGPT in order to enhance the readability of the manuscript, based on text originally written by the authors. After using this tool/service, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

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Appendix A. Additional Material

COICOP4	COICOP5	Prediction error 45 Days No W	45 Days W	30 Days No W	30 Days W	15 Days No W	15 Days W	Tracking error No W	Tracking error W	CPI_o
Fruit	Dried Fruits and Nuts	0.81 ± 0.37	0.81 ± 0.48	0.65 ± 0.26	0.57 ± 0.22	0.29 ± 0.07	0.29 ± 0.07	0.74 ± 0.34	0.74 ± 0.34	0.80 ± 0.58
	Other Fresh or Refrigerated Fruits	3.71 ± 0.68	4.22 ± 1.26	3.00 ± 0.74	3.17 ± 1.06	2.17 ± 0.83	2.17 ± 0.83	4.21 ± 1.04	4.21 ± 1.04	1.50 ± 5.14
	Apples	1.48 ± 0.46	1.53 ± 0.59	1.39 ± 0.45	1.57 ± 0.56	1.04 ± 0.52	1.04 ± 0.52	1.55 ± 0.46	1.55 ± 0.46	0.10 ± 1.18
	Other Citrus	4.47 ± 0.75	4.33 ± 1.12	3.67 ± 0.73	3.61 ± 0.93	2.83 ± 0.72	2.83 ± 0.72	3.43 ± 0.73	3.43 ± 0.73	0.40 ± 4.49
	Oranges	8.30 ± 6.61	8.868 ± 6.99	7.56 ± 6.80	7.94 ± 7.15	2.70 ± 0.79	2.70 ± 0.79	9.44 ± 5.72	9.44 ± 5.72	1.70 ± 8.39
	Berries	5.05 ± 0.87	5.752 ± 1.56	4.57 ± 0.86	4.76 ± 1.14	3.38 ± 0.36	3.38 ± 0.36	7.55 ± 0.93	7.55 ± 0.93	1.30 ± 5.61
	Pears	1.78 ± 0.80	1.85 ± 1.02	1.28 ± 0.59	1.32 ± 0.70	1.20 ± 0.59	1.20 ± 0.59	2.25 ± 0.16	2.25 ± 0.16	0.80 ± 3.89
	Bananas	1.20 ± 0.11	1.03 ± 0.15	1.05 ± 0.10	0.87 ± 0.20	0.67 ± 0.09	0.67 ± 0.09	1.12 ± 0.14	1.12 ± 0.14	0.70 ± 0.84
Vegetables	Roots, Bulbs, Mushrooms and Other Veg.	1.80 ± 0.58	2.02 ± 0.80	1.77 ± 0.43	2.04 ± 0.59	0.90 ± 0.28	0.90 ± 0.28	2.92 ± 0.33	2.92 ± 0.332	0.70 ± 3.46
	Salad	3.54 ± 0.92	3.79 ± 1.26	2.75 ± 0.88	2.94 ± 0.99	1.98 ± 1.07	1.98 ± 1.07	3.24 ± 0.25	3.24 ± 0.25	1.60 ± 3.99
	Tomatoes	6.22 ± 3.43	7.31 ± 5.90	5.34 ± 3.22	7.46 ± 7.25	4.55 ± 4.39	4.55 ± 4.39	4.19 ± 1.85	4.19 ± 1.85	1.90 ± 6.01
	Other Fruit Vegetables	5.55 ± 1.69	5.51 ± 2.16	4.44 ± 1.49	4.48 ± 1.62	2.79 ± 2.16	2.79 ± 2.16	4.65 ± 1.08	4.65 ± 1.08	2.40 ± 7.86
	Other Leafy and Stem Vegetables	2.66 ± 0.85	2.79 ± 0.69	2.01 ± 0.47	2.16 ± 0.40	1.51 ± 0.35	1.51 ± 0.35	1.77 ± 0.26	1.77 ± 0.26	0.50 ± 2.36
	Potatoes	1.70 ± 0.14	1.63 ± 0.13	1.24 ± 0.30	1.17 ± 0.22	0.87 ± 0.10	0.87 ± 0.10	1.24 ± 0.14	1.24 ± 0.14	1.20 ± 0.99
	Cabbages	3.17 ± 0.80	2.99 ± 0.96	2.83 ± 0.71	2.66 ± 0.80	1.87 ± 0.82	1.87 ± 0.82	4.32 ± 0.35	4.32 ± 0.35	1.10 ± 6.00
Meat	Pork	1.52 ± 0.44	1.49 ± 0.38	1.18 ± 0.46	1.13 ± 0.42	0.81 ± 0.27	0.81 ± 0.27	0.99 ± 0.25	0.99 ± 0.25	0.60 ± 0.43
	Adult Beef	1.75 ± 0.42	1.69 ± 0.42	1.28 ± 0.47	1.30 ± 0.47	0.72 ± 0.14	0.72 ± 0.14	1.02 ± 0.25	1.02 ± 0.25	0.70 ± 0.30
	Poultry	2.58 ± 0.20	2.48 ± 0.27	1.58 ± 0.11	1.62 ± 0.12	0.77 ± 0.10	0.77 ± 0.10	1.41 ± 0.19	1.41 ± 0.19	1.10 ± 1.01
	Ground Meat Preparations	1.74 ± 0.47	1.62 ± 0.39	1.45 ± 0.31	1.35 ± 0.30	0.77 ± 0.32	0.77 ± 0.32	1.04 ± 0.38	1.04 ± 0.38	0.70 ± 0.35
	Packaged Cured Meats	1.95 ± 0.60	1.81 ± 0.43	1.94 ± 0.51	1.81 ± 0.36	1.41 ± 0.36	1.41 ± 0.36	2.02 ± 0.51	2.02 ± 0.51	0.80 ± 0.85
	Veal	1.49 ± 0.42	1.56 ± 0.42	1.31 ± 0.38	1.34 ± 0.31	0.89 ± 0.33	0.89 ± 0.33	1.00 ± 0.33	1.00 ± 0.33	0.40 ± 0.25
	Deli Meats	1.43 ± 0.53	0.99 ± 0.14	1.16 ± 0.40	0.94 ± 0.18	0.77 ± 0.09	0.77 ± 0.09	1.09 ± 0.13	1.09 ± 0.13	0.40 ± 0.20
	Lamb and Goat Meat	2.11 ± 0.64	1.28 ± 0.40	1.88 ± 0.45	1.25 ± 0.28	0.96 ± 0.13	0.96 ± 0.13	1.83 ± 0.19	1.83 ± 0.19	0.70 ± 0.61
	Other Meats	1.81 ± 0.16	1.79 ± 0.18	1.34 ± 0.11	1.39 ± 0.16	0.76 ± 0.12	0.76 ± 0.12	0.99 ± 0.17	0.99 ± 0.17	0.70 ± 0.48

Table A.4: The table presents prediction and tracking errors expressed in terms of MAE for all the considered COICOP5 categories, averaged across different product sample sizes (10, 20, 30, 50, 100) over periods of 45 days, 30 days, and 15 days. The prediction errors are reported with or without weights (W and No W, respectively). The official CPI (CPI_o) is reported in the final column to provide an indication of the magnitude.

COICOP4	COICOP5	Aggregated error 45 Days No W	45 Days W	30 Days No W	30 Days W	15 Days No W	15 Days W	CPI_o
Fruit	Dried Fruits and Nuts	0.65 ± 0.02	0.71 ± 0.16	0.62 ± 0.01	0.76 ± 0.30	0.73 ± 0.30	0.73 ± 0.30	0.80 ± 0.58
	Other Fresh or Refrigerated Fruits	4.19 ± 0.44	4.44 ± 1.00	3.24 ± 0.60	3.44 ± 1.10	4.09 ± 0.76	4.09 ± 0.76	1.50 ± 5.14
	Apples	1.53 ± 0.21	1.63 ± 0.74	1.32 ± 0.20	1.37 ± 0.73	1.30 ± 0.64	1.30 ± 0.64	0.10 ± 1.18
	Other Citrus	5.58 ± 0.34	5.22 ± 0.32	4.59 ± 0.21	4.45 ± 0.33	4.49 ± 0.62	4.49 ± 0.62	0.40 ± 4.49
	Oranges	6.49 ± 0.26	7.30 ± 0.71	5.59 ± 0.20	5.98 ± 0.56	9.88 ± 5.82	9.88 ± 5.82	1.70 ± 8.39
	Berries	5.63 ± 0.42	6.07 ± 0.46	5.13 ± 0.38	5.01 ± 0.36	5.48 ± 0.39	5.48 ± 0.39	1.30 ± 5.61
	Pears	3.25 ± 0.30	3.22 ± 0.67	2.72 ± 0.28	2.75 ± 0.29	2.44 ± 0.20	2.44 ± 0.20	0.80 ± 3.89
	Bananas	1.43 ± 0.16	1.29 ± 0.09	1.08 ± 0.16	1.00 ± 0.12	1.06 ± 0.09	1.06 ± 0.09	0.70 ± 0.84
Vegetables	Roots, Bulbs, Mushrooms and Other Veg.	2.75 ± 0.07	2.95 ± 0.04	2.96 ± 0.32	3.42 ± 0.36	2.80 ± 0.14	2.80 ± 0.14	0.70 ± 3.46
	Salad	3.81 ± 0.53	4.02 ± 0.91	2.93 ± 0.46	3.27 ± 0.51	3.29 ± 0.38	3.29 ± 0.38	1.60 ± 3.99
	Tomatoes	6.61 ± 0.51	7.59 ± 3.35	5.42 ± 0.24	7.78 ± 4.45	5.29 ± 1.50	5.29 ± 1.50	1.90 ± 6.01
	Other Fruit Vegetables	7.93 ± 1.32	7.99 ± 1.52	6.38 ± 1.37	6.78 ± 1.31	6.21 ± 1.27	6.21 ± 1.27	2.40 ± 7.86
	Other Leafy and Stem Vegetables	2.74 ± 0.61	2.92 ± 0.45	2.12 ± 0.22	2.30 ± 0.14	1.97 ± 0.20	1.97 ± 0.20	0.50 ± 2.36
	Potatoes	1.64 ± 0.07	1.71 ± 0.22	1.31 ± 0.10	1.34 ± 0.11	1.19 ± 0.10	1.19 ± 0.10	1.20 ± 0.99
	Cabbages	4.53 ± 0.29	4.61 ± 0.30	4.27 ± 0.20	4.21 ± 0.31	4.23 ± 0.18	4.23 ± 0.18	1.10 ± 6.00
Meat	Pork	1.21 ± 0.34	1.15 ± 0.24	0.94 ± 0.33	0.88 ± 0.24	0.88 ± 0.16	0.88 ± 0.16	0.60 ± 0.43
	Adult Beef	1.18 ± 0.32	1.13 ± 0.37	0.82 ± 0.29	0.82 ± 0.30	0.67 ± 0.18	0.67 ± 0.18	0.70 ± 0.30
	Poultry	1.80 ± 0.27	1.67 ± 0.29	0.95 ± 0.27	0.97 ± 0.32	0.99 ± 0.11	0.99 ± 0.11	1.10 ± 1.01
	Ground Meat Preparations	1.33 ± 0.41	1.24 ± 0.26	1.21 ± 0.50	1.15 ± 0.53	1.12 ± 0.50	1.12 ± 0.50	0.70 ± 0.35
	Packaged Cured Meats	1.76 ± 0.32	1.62 ± 0.21	1.48 ± 0.22	1.29 ± 0.11	1.32 ± 0.13	1.32 ± 0.13	0.80 ± 0.85
	Veal	0.77 ± 0.19	1.00 ± 0.27	0.62 ± 0.21	0.91 ± 0.37	0.68 ± 0.16	0.68 ± 0.16	0.40 ± 0.25
	Deli Meats	1.50 ± 0.69	0.90 ± 0.19	1.08 ± 0.48	0.73 ± 0.14	0.63 ± 0.08	0.63 ± 0.08	0.40 ± 0.20
	Lamb and Goat Meat	2.38 ± 0.69	1.46 ± 0.47	1.95 ± 0.50	1.22 ± 0.20	1.16 ± 0.02	1.16 ± 0.02	0.70 ± 0.61
	Other Meats	1.30 ± 0.10	1.17 ± 0.18	0.99 ± 0.14	1.03 ± 0.26	0.67 ± 0.20	0.67 ± 0.20	0.70 ± 0.48

Table A.5: The table presents aggregate errors expressed in terms of MAE for all the considered COICOP5 categories, averaged across different product sample sizes (10, 20, 30, 50, 100) over periods of 45 days, 30 days, and 15 days. The errors are reported with or without weights (W and No W, respectively). The official CPI (CPI_o) is reported in the final column to provide an indication of the magnitude.

COICOP4	COICOP5	Prediction concordance						Tracking concordance	
		45 Days		30 Days		15 Days			
		No W	W	No W	W	No W	W	No W	W
Fruit	Dried Fruits and Nuts	0.47 ± 0.06	0.51 ± 0.06	0.53 ± 0.06	0.54 ± 0.06	0.71 ± 0.10	0.71 ± 0.10	0.57 ± 0.09	0.57 ± 0.09
	Other Fresh or Refrigerated Fruits	0.53 ± 0.13	0.51 ± 0.12	0.50 ± 0.13	0.53 ± 0.16	0.58 ± 0.14	0.58 ± 0.14	0.62 ± 0.11	0.62 ± 0.11
	Apples	0.60 ± 0.13	0.51 ± 0.11	0.59 ± 0.15	0.55 ± 0.08	0.72 ± 0.12	0.72 ± 0.12	0.59 ± 0.08	0.59 ± 0.08
	Other Citrus	0.58 ± 0.13	0.49 ± 0.19	0.50 ± 0.19	0.49 ± 0.15	0.60 ± 0.15	0.60 ± 0.15	0.70 ± 0.05	0.70 ± 0.05
	Oranges	0.48 ± 0.08	0.44 ± 0.09	0.40 ± 0.13	0.40 ± 0.09	0.53 ± 0.08	0.53 ± 0.08	0.61 ± 0.09	0.61 ± 0.09
	Berries	0.51 ± 0.05	0.48 ± 0.12	0.53 ± 0.06	0.57 ± 0.10	0.69 ± 0.14	0.69 ± 0.14	0.37 ± 0.08	0.37 ± 0.08
	Pears	0.49 ± 0.11	0.53 ± 0.11	0.64 ± 0.11	0.61 ± 0.11	0.71 ± 0.07	0.71 ± 0.07	0.57 ± 0.18	0.57 ± 0.18
	Bananas	0.63 ± 0.08	0.60 ± 0.07	0.62 ± 0.06	0.63 ± 0.06	0.74 ± 0.09	0.74 ± 0.09	0.69 ± 0.12	0.69 ± 0.12
Vegetables	Roots, Bulbs, Mushrooms and Other Veg.	0.42 ± 0.13	0.34 ± 0.11	0.51 ± 0.14	0.50 ± 0.04	0.64 ± 0.14	0.64 ± 0.14	0.58 ± 0.17	0.58 ± 0.17
	Salad	0.52 ± 0.09	0.49 ± 0.11	0.69 ± 0.10	0.67 ± 0.09	0.73 ± 0.10	0.73 ± 0.10	0.79 ± 0.05	0.79 ± 0.05
	Tomatoes	0.42 ± 0.08	0.40 ± 0.13	0.50 ± 0.08	0.43 ± 0.07	0.73 ± 0.17	0.73 ± 0.17	0.76 ± 0.08	0.76 ± 0.08
	Other Fruit Vegetables	0.34 ± 0.11	0.33 ± 0.09	0.48 ± 0.18	0.44 ± 0.09	0.63 ± 0.23	0.63 ± 0.23	0.73 ± 0.15	0.73 ± 0.15
	Other Leafy and Stem Vegetables	0.41 ± 0.08	0.46 ± 0.10	0.52 ± 0.09	0.49 ± 0.14	0.69 ± 0.09	0.69 ± 0.09	0.59 ± 0.08	0.59 ± 0.08
	Potatoes	0.50 ± 0.09	0.51 ± 0.06	0.61 ± 0.10	0.60 ± 0.16	0.78 ± 0.09	0.78 ± 0.09	0.69 ± 0.12	0.69 ± 0.12
	Cabbages	0.47 ± 0.12	0.52 ± 0.11	0.46 ± 0.13	0.52 ± 0.12	0.71 ± 0.15	0.71 ± 0.15	0.51 ± 0.15	0.51 ± 0.15
Meat	Pork	0.49 ± 0.13	0.44 ± 0.16	0.55 ± 0.11	0.56 ± 0.12	0.62 ± 0.09	0.62 ± 0.09	0.59 ± 0.13	0.59 ± 0.13
	Adult Beef	0.41 ± 0.12	0.50 ± 0.13	0.58 ± 0.05	0.58 ± 0.06	0.84 ± 0.07	0.84 ± 0.07	0.69 ± 0.12	0.69 ± 0.12
	Poultry	0.61 ± 0.13	0.53 ± 0.06	0.63 ± 0.12	0.59 ± 0.08	0.77 ± 0.07	0.77 ± 0.07	0.64 ± 0.05	0.64 ± 0.05
	Ground Meat Preparations	0.53 ± 0.12	0.52 ± 0.15	0.66 ± 0.06	0.61 ± 0.07	0.68 ± 0.06	0.68 ± 0.06	0.70 ± 0.09	0.70 ± 0.09
	Packaged Cured Meats	0.72 ± 0.04	0.72 ± 0.09	0.68 ± 0.09	0.64 ± 0.09	0.78 ± 0.09	0.78 ± 0.09	0.41 ± 0.09	0.41 ± 0.09
	Veal	0.57 ± 0.05	0.55 ± 0.03	0.55 ± 0.09	0.58 ± 0.14	0.71 ± 0.12	0.71 ± 0.12	0.61 ± 0.14	0.61 ± 0.14
	Deli Meats	0.69 ± 0.05	0.72 ± 0.10	0.71 ± 0.10	0.75 ± 0.05	0.81 ± 0.12	0.81 ± 0.12	0.55 ± 0.05	0.55 ± 0.05
	Lamb and Goat Meat	0.61 ± 0.07	0.77 ± 0.05	0.59 ± 0.08	0.70 ± 0.08	0.77 ± 0.07	0.77 ± 0.07	0.51 ± 0.03	0.51 ± 0.03
	Other Meats	0.42 ± 0.11	0.43 ± 0.09	0.61 ± 0.12	0.58 ± 0.13	0.76 ± 0.09	0.76 ± 0.09	0.72 ± 0.07	0.72 ± 0.07

Table A.6: The table presents prediction and tracking concordances for all the considered COICOP5 categories, averaged across different product sample sizes (10, 20, 30, 50, 100) over periods of 45 days, 30 days, and 15 days. The errors are reported with or without weights (W and No W, respectively).