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Improving disaggregated short-term food inflation forecasts with webscraped data

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ABSTRACT

Recent studies suggest that webscraped price data can enhance the timeliness and accuracy of inflation nowcasts. In a forecasting competition against univariate time series benchmarks, we evaluate nowcasts and short-horizon forecasts using daily price quotes for Austria. Our findings indicate that webscraped data deliver accurate nowcasts several weeks earlier than official releases, because they enable the production of reliable estimates early in the reference month. Additionally, we demonstrate that nowcasts remain robust to structural breaks in food price dynamics. To our knowledge, this study is the first to examine whether webscraped nowcasts can improve disaggregated short-term forecasts up to one quarter ahead. Although direct forecasts at higher levels of aggregation are slightly more accurate, indirect forecasts derived from disaggregated data provide superior insights into the underlying dynamics of sub-components. These findings have implications for policymakers aiming to develop an effective system for real-time monitoring of inflation dynamics at a granular level.

1. Introduction

Prices of food and beverages are a critical yet highly volatile component of inflation, rendering them notoriously challenging to forecast. In the euro area, food and non-alcoholic beverages accounted for 15.5% of the consumption basket weights used for the Harmonised Index of Consumer Prices (HICP) compilation in 2025. Due to its large weight, even minor errors in forecasting food inflation can significantly distort overall HICP nowcasts. Beyond their substantial share in consumption expenditure, food prices are particularly salient for private households' inflation perceptions and expectations, as recent empirical evidence demonstrates (see e.g. Bonciani et al., 2024; Kučerová et al., 2024). This may be attributable to the disproportionate weight households assign to food purchases relative to official consumption statistics (Anesti et al., 2024) or the high frequency of food item purchases (D'Acunto et al., 2021). Consequently, food price inflation not only affects headline inflation directly, but its impact is amplified through its effect on the inflation expectations of households. Hence, properly understanding, interpreting, and projecting the price dynamics of these volatile food components in official inflation rates is crucial for central banks and other institutions alike.

Fig. 1 illustrates the evolution of HICP inflation rates for *Food and non-alcoholic beverages* in the euro area and Austria since 2000. The figure highlights the recent

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surge in inflation alongside further key features of inflation time series, such as time-varying trends, structural breaks, and seasonal behavior. Dashed lines denote selected macroeconomic events: the onset of the global food crisis in September 2006, the collapse of Lehman Brothers in September 2008, the ECB's introduction of negative interest rates in June 2014, the Russian invasion of Ukraine in February 2022, and the peak of the ECB's monetary policy interest rate hiking cycle in response to inflationary pressures in September 2023. Year-on-year inflation rates for the HICP aggregate of *Food and non-alcoholic beverages* peaked at 17.0% in January 2023 in Austria and at 17.5% in March 2023 in the euro area, markedly exceeding peak headline inflation rates of 11.6% and 10.6% in Austria and the euro area, respectively. In general, food price inflation in Austria closely tracks the corresponding aggregate for the euro area. This pattern is particularly evident in the post-2020 inflationary episode, characterized by macroeconomic shocks and supply-side constraints. Fig. 1 also illustrates the impact of a methodological change: at the beginning of 2021, the adoption of scanner data for price collection in the category of *Food and non-alcoholic beverages* introduced a structural break in Austria's food price inflation, which temporarily turned negative. Because Covid-19-related measures limited the availability of in-store collected prices in 2021, Statistics Austria supplemented the index compilation with online and scanner data. Beginning in January 2022, Statistics Austria has relied exclusively on scanner data to collect prices of *Food and non-alcoholic beverages*. Although less pronounced, both time series display seasonality in month-on-month developments, with average monthly inflation rates in Austria approximately 0.1 percentage points higher in the fourth quarter than in the first quarter.[1]

In response to the challenges of forecasting food price inflation, researchers and institutions have increasingly turned to alternative data sources. Since the inception of MIT's Billion Prices project (see Cavallo & Rigobon, 2016), a growing body of research has demonstrated that webscraped data provide timely and granular price information that is valuable for inflation nowcasting. Evidence suggests, for example, that food inflation nowcasts based on webscraped data outperform univariate benchmark models that have historically proven difficult to beat (see Macias et al., 2023; Soybilgen et al., 2023), and that webscraped price data can yield forecasts that are competitive with those from professional surveys (see Aparicio & Bertolotto, 2020). These findings are discussed in more detail in Section 2. Consequently, policymakers and official institutions have shown increasing interest in leveraging this data source. For instance, webscraped data play a prominent role in the ESCB's Price-setting Microdata Analysis Network (PRISMA) research network, which leverages detailed microdata to study firms' price-setting behavior and inflation dynamics.[2]

We contribute to this literature by developing a nowcasting and forecasting framework specifically applied to the European Classification of Individual Consumption according to Purpose (ECOICOP) division 01: *Food and non-alcoholic beverages* for Austria. To this end, we have created and maintained a database of webscraped price data from Austrian online retailers since 2020. With these data, we construct price indices that are consistent with the official methodological guidelines of Eurostat and Statistics Austria. This enables us to nowcast month-on-month inflation rates and to generate forecasts extending up to three months ahead. Our analysis is conducted at the most disaggregated level used in the computation of HICP inflation rates. Methodologically, the framework incorporates advanced time series and machine learning models, explores direct versus indirect aggregation strategies, and leverages mixed-frequency data sampling with unrestricted linear lag polynomials (UMIDAS) to assess the benefits of higher-frequency inputs.

Our research examines whether disaggregated nowcasts provide superior or at least comparable predictive accuracy. One of our contributions to the literature is the inclusion of an array of advanced time series and machine learning models as benchmarks for webscraping-based nowcasts. In addition, we provide a detailed assessment of forecasting accuracy at the granular level of elementary indices. Furthermore, we investigate whether predictive accuracy remains on par with time series models when aggregating webscraping-based nowcasts up to higher COICOP index positions. Therefore, we compare the direct time series forecasts of aggregated indices with indirect forecasts obtained by aggregating forecasts from the most disaggregated product categories. This provides the benefit that forecasts of indices at higher levels can be decomposed into specific sub-components that drive the results.

Moreover, recent literature suggests that superior forecast performance can be achieved by exploiting the higher frequency of available data rather than relying solely on monthly averages of high-frequency price data (see e.g. Beck et al., 2023; Modugno, 2013). We provide an analysis of the nowcast performance of webscraped data using an unrestricted mixed-data sampling (UMIDAS) regression model and find that employing indices calculated on a higher frequency than monthly can significantly improve forecasting accuracy.

Furthermore, to the best of our knowledge, this paper is the first to propose incorporating webscraped data to enhance time-series-based short-term forecasts of disaggregated inflation rates. For this purpose, we leverage the webscraped nowcast as the basis for the first month of a conditional three-month forecast. We find that this approach improves predictability at a highly disaggregated level, and this result is consistent across various COICOP categories, particularly for those with higher weights in the HICP.

In summary, our analysis shows that incorporating webscraped data significantly enhances the accuracy of nowcasting food price inflation and improves the predictive performance of short-term inflation forecasts in a volatile economic environment. The use of webscraped

[1] A seasonal-trend decomposition using loess (STL), as in Cleveland et al. (1990), also indicates pronounced monthly seasonality of comparable magnitude.

[2] For further information on PRISMA, see https://www.ecb.europa.eu/pub/research-networks/html/researcher_prisma.de.html.

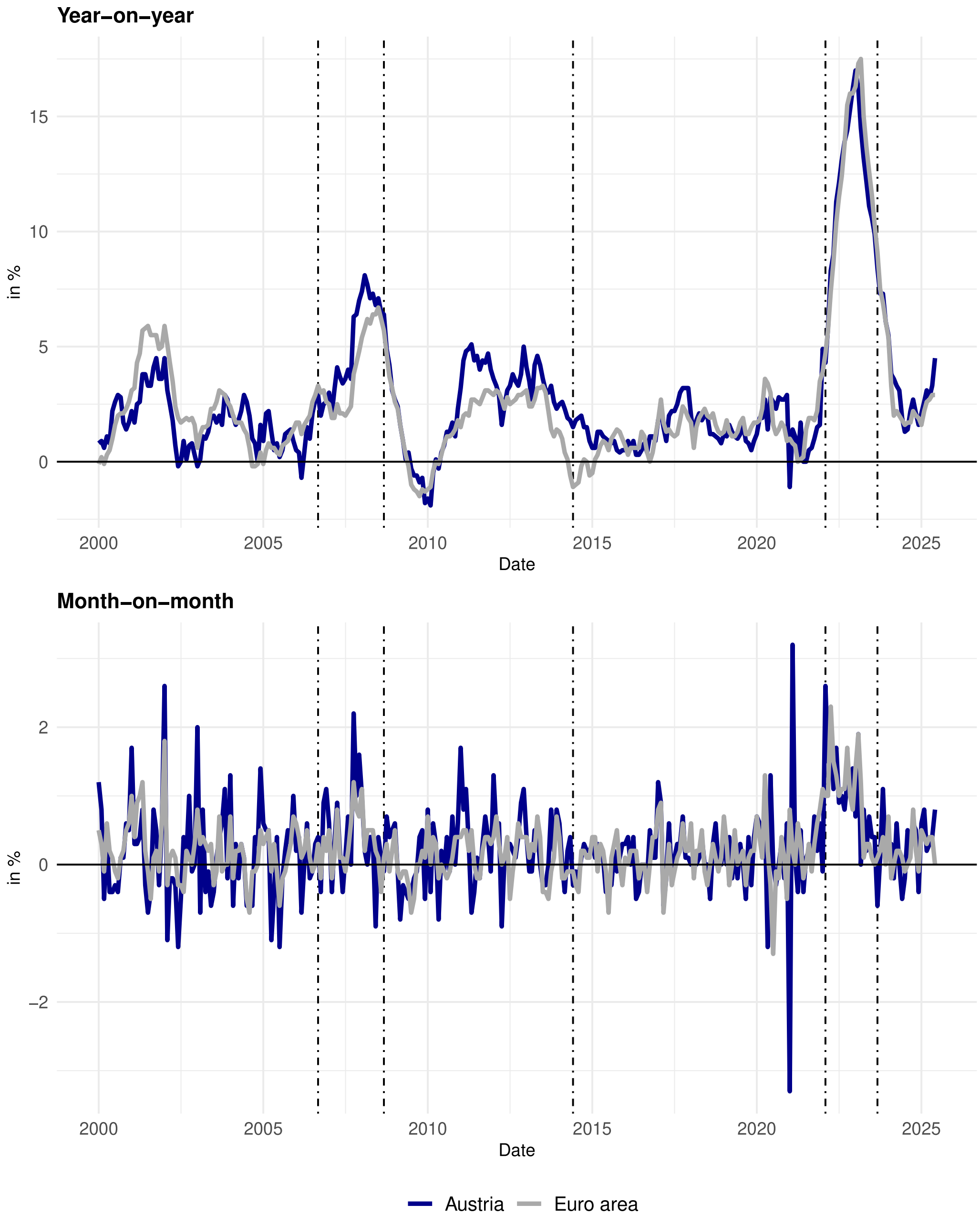

Fig. 1. Food price inflation. Note: Fig. 1 displays HICP inflation rates for the aggregate *Food and non-alcoholic beverages* (ECOICOP 01) for Austria and the euro area from January 2000 to June 2025. The dashed lines correspond to the start of the global food crisis in September 2006, the collapse of Lehman Brothers in September 2008, the introduction of the ECB's negative interest rate policy in June 2014, the Russian invasion of Ukraine in February 2022, and the peak of the ECB's monetary policy hiking cycle in September 2023.
Source: Eurostat.

data increases predictability at a highly disaggregated level and yields consistent results across various COICOP categories. Notably, this improvement materializes within several months, whereas traditional forecasting methods typically require several years of historical input data. Furthermore, our comparison reveals that while advanced time series models can match the performance of traditional approaches, they often involve tradeoffs in computational efficiency. Not least, we find that employing higher-frequency data as opposed to averaging across daily observed online prices can substantially improve the model fit. In particular, we are able to replicate a finding for scanner data by Beck et al. (2023), who use a MIDAS model and find that data collected during the first weeks of a given month can provide competitive nowcasts of monthly inflation rates.

The rest of the paper is organized as follows: Section 2 reviews the related literature. Section 3 describes the official inflation data and briefly explains the calculation of online price indices. Section 4 outlines the setup of a nowcasting and short-term forecasting competition. Section 5 presents the results of the analysis. Section 6 contains sensitivity analyses followed by the conclusion in Section 7.

2. Related literature

The macroeconomic analysis of inflation and the price-setting process has recently benefited from the availability of high-frequency price data, which have become more accessible thanks to dedicated data collection efforts. The structured collection of these data began with the Billion Prices project (Cavallo & Rigobon, 2016).[3] These data permit the analysis of moments of distributions of price changes and other statistics at the micro-level (Gautier et al., 2023). Furthermore, they improve our understanding of inflation by enabling us to observe the frequency and size of price changes and help us understand its micro-foundations in macroeconomic models, such as in the case of the menu costs model of price setting (Gautier et al., 2023; Carrera de Souza, 2022). Given a sufficient quantity and quality of micro-price data, it has been shown that they can provide timely high-frequency information on aggregate inflation dynamics and may improve nowcasting models of inflation rates.

Besides advances in data collection, selecting appropriate models for forecasting inflation is crucial. It has been a consensus in this literature that it is quite difficult for inflation forecasts to improve on simple univariate models or expert judgment (Faust & Wright, 2013). While the wider adoption of machine learning models has challenged this consensus (Joseph et al., 2024; Medeiros et al., 2021; Paranhos, 2025; Sengupta et al., 2025), these models largely depend on the inclusion of a large number of exogenous variables. Notable exceptions include Barkan et al. (2023) and Nason and Palasciano (2025), who focus on explaining the internal time series patterns of inflation rates. Another key point raised by Faust and Wright (2013) is the potential of nowcasts to improve forecasts. Cavallo and Rigobon (2016) show that indices constructed using online micro-prices can effectively track the movements of consumer price indices (CPIs) in the United States and Australia over the period from 2008 to 2016 and 2015, respectively. These indices strongly anticipate movements in public CPI data over both long and short time horizons, as shown by an illustrative example of online price movements around the Lehman Brothers bankruptcy on 15 September 2008. While these indices do not necessarily capture the price level well, they effectively track the dynamics of CPI inflation in several countries. Using estimates of impulse response functions, the authors show that webscraped data are informative for CPI dynamics and yield results that are not statistically significantly different from ex post realized CPI inflation at one- to eight-month horizons.

In a similar vein, Aparicio and Bertolotto (2020) forecast one-, two-, and three-month-ahead headline CPI inflation rates for several countries based on data from PriceStats. They compare various models with an equal-weighted average of forecasts as the benchmark specification. Their findings suggest that online price data closely track CPI data, and that the inclusion of such data into the proposed models significantly improves forecasts.

Macias et al. (2023) is the research closest to our own. They use data collected by Narodowy Bank Polski (NBP), which adopted webscraping price data on a weekly basis in 2009 and expanded to daily webscraping in 2018. They nowcast inflation rates for *Food and non-alcoholic beverages* alongside the elementary indices in this category and the sub-aggregates, comparing their nowcasts to various univariate models, as well as the judgmental forecast of the NBP. They show that the incorporation of webscraped data significantly improves the accuracy of nowcasts. In particular, for the aggregate *Food and non-alcoholic beverages*, even the direct use of price changes derived from online data reduces forecast errors by about 29% compared to their benchmark SARMA model. In addition, the inclusion of online data as an exogenous variable can lead to an even greater improvement in forecast accuracy in time series models. Macias et al. (2023) emphasize that the benefits of incorporating webscraped data into forecasting models can become evident within just a few months, particularly for aggregate inflation rates. Additionally, Macias et al. (2023) highlight the critical importance of the proper classification of products into HICP product groups when utilizing webscraped data for nowcasting purposes. Ensuring that the data used in the models are correctly classified into the product groups used in the calculation of inflation rates is crucial because it ensures that the data used in the nowcasting models accurately reflect the prices of specific food categories. This attention to classification leads to more reliable nowcasts and ultimately strengthens the validity of the forecasts. Szafranek et al. (2025) also use data from the Narodowy Bank Polski (NBP) E-CPI project to compare model-based approaches with the model-free nowcast obtained directly from webscraped prices. While model-based approaches that incorporate online prices slightly outperform the real-time online nowcast during relatively stable periods, the model-free nowcast proves superior in times of heightened uncertainty (e.g. Covid-19 or geopolitical shocks), when the performance of the model-based approaches deteriorates sharply. The authors argue that traditional models relying on historical patterns fail to capture exceptional peaks and troughs when inflation dynamics become irregular.

Our paper is also closely related to Soybilgen et al. (2023), who collected daily food price data from Turkish retailers and produced 132 indices on the most granular product category for which Turkstat publishes price indices. These subindices were then aggregated into a food price index. They concluded that the online data could nowcast both food and headline inflation rates with a considerable time advantage over official inflation data releases.

Given that the share of food purchases conducted online remains relatively limited, the value of online

[3] The Billion Prices project (or its commercial spinoff, PriceStats) does not provide price data of food items in Austria.

prices for forecasting food inflation crucially depends on the extent to which they mirror offline prices. However, the empirical literature regarding this comparison is still sparse. Cavallo (2017) reports that, on average, online and offline prices are identical in 72% of cases. This share varies considerably across countries, ranging from 42% in Brazil to 91% in Canada, with Germany – arguably the most comparable country to Austria – showing a match rate of 74%. Price concordance also varies across sectors, amounting to 52% for food. However, even when online and offline food prices diverge, the average absolute difference is modest, at around 3%.

An important contribution to the nowcasting of food inflation is also provided by Beck et al. (2023). While the authors do not use webscraped price data, but rather weekly household scanner data, their work is relevant to our paper due to their focus on highly disaggregated levels for nowcasting. For this purpose, they utilize a mixed-frequency data sampling (MIDAS) model combined with machine learning techniques. Their findings demonstrate that the use of household scanner data can enhance inflation nowcasts already within the first week of each month. Another related work is Harchaoui and Janssen (2018), who apply MIDAS models to U.S. data from the Billion Prices project and demonstrate that incorporating daily data enhances the precision of inflation forecasts. However, while their analysis, like ours, relies on webscraped price data, it focuses exclusively on headline inflation without examining the forecasts of disaggregated components.

In this study, we follow the literature that utilizes webscraped data to forecast official inflation rates (Aparicio & Bertolotto, 2020; Cavallo & Rigobon, 2016) and concentrate on the temporal dynamics of month-on-month changes within individual time series by not considering exogenous variables. Specifically, we extend the nowcasting of food inflation using webscraped data (Macias et al., 2023; Soybilgen et al., 2023; Szafranek et al., 2025) to short-term forecasts and enhance the benchmark models by adopting several flexible univariate time series models. Furthermore, to our knowledge, this paper is the first to provide a granular comparison of direct versus indirect forecasts at different levels of aggregation of the Harmonised Index of Consumer Prices (HICP). We also contribute to the literature of disaggregated food inflation nowcasting that examines the impact of incorporating higher-frequency data into a MIDAS framework (see Beck et al., 2023).

3. Official inflation data and online price indices

We use official month-on-month HICP inflation data from Statistics Austria alongside internal webscraped price data from Oesterreichische Nationalbank (OeNB) on ECOICOP category 01: *Food and non-alcoholic beverages*.

3.1. Indices calculated by statistics Austria

For the official inflation data, we use official index series compiled by Statistics Austria. The agency collects price information through both in-store and scanner data collection methods. Results for the previous month are published from the 15th to the 24th of each month.[4] Hence, webscraped data provide a head start of three to six weeks regarding the availability of timely price data, as exemplified in Fig. 2.[5] The HICP flash estimate at the beginning of the month is only available for headline inflation and the first level of categories. In our case, more detailed indices below the ECOICOP category 01: *Food and non-alcoholic beverages* can be proxied by nowcasts based on webscraped data or by time series models. A further decomposition of the flash estimate is crucial in order to identify the factors driving aggregate inflation dynamics.

3.2. Calculation of elementary indices based on webscraped data

The development of webscraping algorithms at OeNB started in the spring of 2020 within the scope of the ESCB PRISMA research network.[6] While webscraping can be rapidly implemented, maintaining the infrastructure, managing product classification into ECOICOP categories, and processing the data require significant resources in a production environment. Given the high benefits for economic analysis and research at OeNB, we continue to run a webscraping framework for Austrian online retailers. For this purpose, we collect daily data from 15 Austrian retailers, of which seven contribute to *Food and non-alcoholic beverages*, with 150,000 unique products overall and 20,000 unique classified products as of December 2024. The collected data include prices and supplementary product information (e.g. product name, product description, and shop internal categorization). Table 1 presents descriptive statistics of the webscraped data. In addition to summarizing the dataset, it is important to consider the relationship between online and offline prices. For the brick-and-mortar stores in our dataset, the prices are generally identical to those listed online because the online ordering system also functions as a price information system for in-store purchases. Notable exceptions include discounts on perishable goods at the end of the day. One retailer explicitly mentions product group discounts as an exception, while one delivery service states that it does not pass on discounts to consumers.

We compute monthly Laspeyres-type index time series of elementary indices following Statistik Austria (2022)

[4] For a timetable of HICP flash estimates and first releases in 2025, see https://www.statistik.at/fileadmin/pages/214/Pubtermine2025_EN.pdf.

[5] In official price statistics, it is becoming increasingly common to supplement traditional data collected in-store with scanner data, as implemented by Statistics Austria in January 2022 for the sub-aggregate *Food and beverages*. Moreover, webscraped data are employed in selected product groups that exhibit strong seasonal patterns (e.g. apparel). Consequently, webscraping not only provides timely microdata but also delivers information that is increasingly relevant in the compilation of official price indices. The broader adoption of these methods justifies the establishment of a continuously maintained webscraped price database to support more accurate inflation forecasting by central banks.

[6] The ECB continues to maintain its Daily Price Dataset (DPD) of webscraped data, but focuses on the larger euro area countries. The collection of Austrian data is therefore only supported by the OeNB.

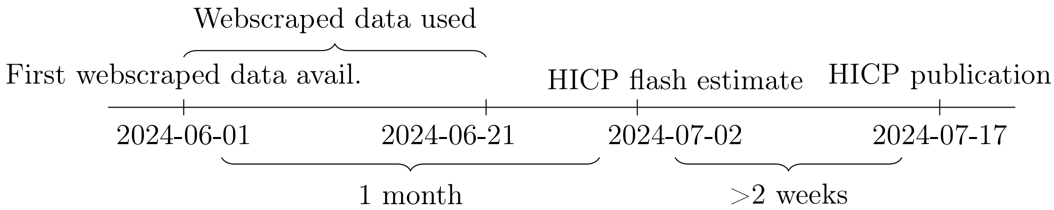

Fig. 2. Exemplary timeline of HICP data availability and publication. Note: Webscraped data are collected daily by OeNB and are available in real time throughout the month, starting from the beginning of the month. HICP flash estimates by Statistics Austria at higher levels of aggregation are made available at the end of the month or the beginning of the next month. Detailed indices are published in the third week of the following month.

Table 1
Summary statistics of product data by store.

Store	Overall	Classified		
	Products	Products	Prices	Mean No. Days
Store 1	20,030	4,838	4,540,577	1031
Store 2	47,591	838	659,491	851
Store 3	32,219	4,947	3,126,050	690
Store 4	3,547	750	205,902	359
Store 5	38,137	6,603	6,851,413	1142
Store 6	1,709	325	159,671	537
Store 7	5,622	751	250,597	378
All Stores	148,855	19,052	15,793,701	912

Note: Table 1 presents summary statistics for product data across different stores. The first column shows the total number of products per store. The remaining columns provide data on the number of classified products, the total number of observed prices, and the average number of days products were available.

by compiling the multilateral Gini, Eltetö and Köves, and Szulc (GEKS) indices with 13-month windows that adhere to the methodological guidelines of Eurostat (2022) as laid out in Appendix A in detail.[7] We choose a Jevons index as the underlying bilateral index. To avoid revisions of GEKS-Jevons indices, we employ a rolling window approach (movement splicing) as recommended by Eurostat (2024). The resulting index is therefore referred to as rolling window GEKS-Jevons (RWGEKS), constructed using movement splicing.[8] A detailed description of index compilation, splicing, aggregation, and chaining following the official methodology is provided in Appendix A.

3.3. Classification of products and aggregation to higher ECOICOP levels

To achieve a competitive forecast, an accurate and granular mapping of our webscraped products to the consumption basket defined by Statistics Austria (see Appendix B.4) is crucial. To compile prices and calculate the HICP, national statistical offices in the European Union divide the basket of goods according to the ECOICOP (European Classification of Individual Consumption according to Purpose) system (see Eurostat, 2024). This system is hierarchically structured into divisions (two-digit level, e.g. 01: *Food and non-alcoholic beverages*), groups (three-digit level, e.g. 01.1: *Food*), classes (four-digit level, e.g. 01.1.1: *Bread and cereals*), and sub-classes (five-digit level, e.g. 01.1.1.3: *Bread*). This common classification is referred to as a Level I classification.[9]

More granular divisions of the consumption basket are referred to as Level II. In Austria, the most detailed level at which Statistics Austria publishes indices is known as *Indexpositionen* (index positions). For instance, within the ECOICOP sub-class 01.1.1.3: *Bread*, the *Indexpositionen* include specific types of bread such as rye bread, wholemeal bread, and white bread. The elementary indices published at this level are also referred to as *Bundesmesszahlen*.[10] Items at this level may be added or discontinued in response to changing national consumption patterns. However, from 2020 to 2024, the only change within the *Food and non-alcoholic beverages* division in Austria was the introduction of two additional items in 2024. Since these items were only available for a short time span, we could not take them into account in the presented analyses.

[7] To address data issues and outliers, we perform basic integrity checks, such as ensuring that posted prices are greater than zero. Furthermore, we exclude products if their price z-scores exceed five in the distribution of price changes pertaining to the elementary index category. We refrain from using absolute thresholds for identifying erroneous price changes because legitimate significant price increases can materialize, for instance, when a discount period occurs.

[8] The authors of Statistik Austria (2022) employ the GEKS method with the Törnqvist index for food scanner data, as quantities are observed in conjunction with prices. A Jevons index is appropriate in the case of webscraped data, because we do not collect any data on quantities, which are essential in the compilation of Törnqvist indices. Index time series based on different splicing methods are generally very close to each other.

[9] We henceforth denote a generic index time series by its respective ECOICOP code in conjunction with its full name e.g. 008440: *Berries*.

[10] *Bundesmesszahlen* (elementary indices) are subject to revisions, typically available the following month. We do not consider the revised data for several reasons: one-month-ahead forecasts need to be produced in a timely manner and can only rely on initially reported data. In the subsample of 130 *Bundesmesszahlen*, there were revisions for 737 out of 13,970 data points, of which only 238 were larger than 1%. Revisions from 2017 were excluded due to unreliable information.

We use a bottom-up approach to classify products into their respective ECOICOP categories. That means product items are classified at the lowest level of *Indexpositionen* (elementary indices). We conduct product classification by applying regular expressions (regex) to product names and, when available, to supplementary information, such as product descriptions and store-specific product categories. Though designing this automated procedure of defining character strings that uniquely map to the most granular HICP index positions is potentially labor-intensive, it ensures a consistent and accurate classification of all relevant products in our sample. Unlike machine learning-based approaches, using regex provides transparency, replicability, and full control over the classification process, which is crucial for official statistics and price index construction. For a discussion of the importance of product classification when using webscraped data to nowcast inflation, see Macias et al. (2023). However, this approach also implies that a significant proportion of products remain uncategorized, as shown in Table 1.

For simplicity, we refer to this *Indexposition* level as COICOP-6 or level 6, and to the index as the *elementary index* throughout the text. Similarly, we use COICOP-2 (level 2) to COICOP-5 (level 5) to denote aggregated HICP categories.

The aggregation of elementary indices to higher COICOP levels requires appropriate weights and the application of the correct methodology on the national level. A detailed description of index compilation, aggregation, and chaining can be found in Appendix A.3, whereas Appendix B provides more information on data collection and product classification. Appendix C.1 presents time series plots of monthly and annual inflation rates, comparing official indices with those constructed from webscraped data.

4. Setting up a nowcasting and short-term forecasting competition

4.1. Scope of the framework

Our primary objective is to evaluate whether the monthly rate of change in webscraped price indices can effectively nowcast the official monthly rates for the COICOP division 01: *Food and non-alcoholic beverages* and the subcategories at all HICP index positions below.[11] Therefore, we select several simple and advanced time series models to benchmark and compare forecasting accuracy.

In addition to the nowcast, we provide three-month-ahead forecasts combining webscraped indices and time series models. The forecast conditions on the webscraped nowcast for the next month ahead, and then applies time series models to predict the official index series for the subsequent two months.

First, we perform the nowcasts and forecasts at the most disaggregated level, known as the elementary indices. Statistics Austria compiles this most granular level of disaggregated index positions pertaining to Level II HICP aggregates, which we refer to as level 6 indices (analogously to levels 2 to 5 pertaining to ECOICOP aggregates at Level I). We repeat this exercise for higher aggregation levels (up to COICOP level 2). To obtain time series forecasts for these higher-level HICP aggregates, we apply two approaches:

(1) **Indirect forecasts**: Time series models are estimated on elementary index series (level 6) and aggregated using the weights provided by the statistical office; see Appendix A.3.
(2) **Direct forecasts**: Time series models are directly estimated on aggregate official index series at levels 2 to 5 published by Eurostat.

We use data from Statistics Austria for the elementary indices starting in January 2014, as indices at this most granular level are not available prior to this date. We compute nowcasts and three-month-ahead forecasts from January 2021 through December 2024. Model estimation follows an expanding window approach. In the typical case, when official data are available well before webscraped data, the initial estimation window extends up to the month immediately preceding the first webscraping observation, ensuring that the first forecasts align with the earliest webscraped data. If instead the official data only become available after webscraped data, the initial window begins 13 months afterwards to ensure sufficient historical data before constructing forecasts.

4.2. Time series models

We evaluate out-of-sample forecast accuracy using a range of time series models. In addition to traditional benchmarks like the random walk or SARIMA models, we employ more advanced and flexible time series models like Prophet, Neuralprophet, or ETS and Theta.

We denote by y_t a discrete time series which is observed at $t = 1, 2, \dots T$. In our case, this will be the monthly rate of change of a specific index series for a given level of COICOP-aggregate or elementary index position.[12]

[11] We compile price indices using webscraped data and use them directly to estimate month-on-month inflation rates, denoted as 'nowcasts'. In contrast to Macias et al. (2023) who employ a SARIMAX model, where webscraping enters as exogenous variable, and to Soybilgen et al. (2023) who apply bridge equations, our approach is model-free in the econometric sense. Nevertheless, we fully adopt the methodology of Eurostat and Statistics Austria in compiling price indices. This enables us to nowcast price developments even with only a few months of available webscraped data. Throughout the text, model-based forecasts of month-on-month inflation in the next month are denoted as 'one-month-ahead forecasts' and forecasts for month-on-month inflation one quarter ahead are denoted as 'three-month-ahead forecasts'.

[12] Model specification needs to be done in a fully automated way that does not involve human intervention or expert judgment. Nixtla's `StatsForecast` (Garza et al., 2022) provides statistical and econometric models. This open-source Python library has approximately 4K GitHub stars and is highly performance-optimized, which makes it most suitable to predict thousands of time series in a distributed setting. We use the built-in automatic forecasting tools for ARIMA, ETS, Theta, and CES. These routines select parameters based on an information criterion. For Prophet and Neuralprophet, we use the corresponding Python packages.

Seasonal random walk (RW-S)

We begin with an adjusted random walk model that incorporates a seasonal component (hereafter also referred to as the naive model). In the first step, we de-seasonalize the time series of monthly inflation rates y_t employing seasonal-trend decomposition using loess (STL, see Cleveland et al., 1990) such that we arrive at a decomposition of month-on-month inflation rates y_t into an additive sum of an estimated seasonal s_t and de-seasonalized component y_t^{SA}:

$$y_{t-1} = y_{t-1}^{SA} + s_{t-1}. \tag{1}$$

The last value of the seasonally adjusted series y_{t-1}^{SA} is used as the forecast for y_t^{SA}, the de-seasonalized component one month ahead[13]:

$$y_t^{SA} = y_{t-1}^{SA} + \epsilon_t, \tag{2}$$

where ϵ_t is white noise. The seasonal effect for each forecast horizon is estimated using the historical average seasonal component for the corresponding calendar month. Then, the final forecast for y_t is the sum of the de-seasonalized random walk component y_{t-1}^{SA} and seasonal component for the corresponding calendar month t, denoted as $s_{t|t-1}$ and estimated using data up until $t-1$:

$$y_t = y_{t-1}^{SA} + s_{t|t-1}. \tag{3}$$

Random walk based on Atkeson and Ohanian (AO-S)

The simple forecast model is an adaptation of the seasonal random walk model described above, employed by Macias et al. (2023), who adapted the random walk model of Atkeson and Ohanian (2001).[14] Instead of applying the random walk model to the seasonally adjusted time series y_t^{SA}, we forecast y_t^{SA} using the moving average of its past 12 monthly values, so that

$$y_t = \frac{1}{12}\sum_{j=1}^{12} y_{t-j}^{SA} + s_{t|t-1}, \tag{4}$$

with $s_{t|t-1}$ also estimated by STL.

SARIMA

We select the best seasonal autoregressive integrated moving average SARIMA(p, d, q)(P, D, Q, m) model based on Akaike's information criterion (AIC):

$$y_t = \alpha + \sum_{i=1}^{p} \phi_i y_{t-i} + \sum_{j=1}^{q} \theta_j \epsilon_{t-j} + \sum_{k=1}^{P} \Phi_k y_{t-mk} + \sum_{l=1}^{Q} \Theta_l \epsilon_{t-ml} + \epsilon_t, \tag{5}$$

where α is a constant, p is the number of non-seasonal autoregressive terms, q is the number of non-seasonal lagged forecast errors (moving average terms), P is the number of seasonal autoregressive terms, Q is the number of seasonal lagged forecast errors (seasonal moving average terms), and m is the number of observations per year. Here, y_t denotes a stationary series $\Delta^d \Delta_m^D \tilde{y}_t$, obtained by non-seasonal differencing of order d and seasonal differencing of order D of a potentially integrated time series $\tilde{y}_t$. We consider $p, q \leq 5$, and $P, Q \leq 2$. The orders of differencing d and D are determined by testing for stationarity. The parameter $m = 12$, due to the monthly frequency of time series.

Autoregressive model (AR(1))

We also consider a simple autoregressive model:

$$y_t = \alpha + \beta y_{t-1} + \epsilon_t. \tag{6}$$

Lunsford and West (LW-S)

This model is a special case of the AR(1) model. Initially developed by Lunsford and West (2019) for long time series of low-frequency data and applied by e.g. Borio et al. (2022) and Graf (2024) for high-frequency data, it uses a simple heuristic where the current de-seasonalized monthly value y_t^{SA} is regressed on its first lag and an intercept:

$$y_t^{SA} = \alpha + \beta y_{t-1}^{SA} + \epsilon_t, \tag{7}$$

where α is the intercept, β is the autoregressive coefficient, and ϵ_t is the error term. If large outliers are detected (i.e. $|y_{t-1}^{SA}| > 25$), the value of y_{t-1}^{SA} is replaced by its lagged value, y_{t-2}^{SA}. The autoregressive coefficient estimate β is capped at 0.9 to ensure stationarity, and the intercept α is re-estimated in case the cap is binding.[15]

As in the RW-S model, the forecast of the full series is obtained by summing the forecasted seasonally adjusted component and the inferred trend and seasonal components:

$$y_t = \alpha + \beta y_{t-1}^{SA} + s_{t|t-1}, \tag{8}$$

with $s_{t|t-1}$ likewise estimated by STL.

Prophet

Prophet (see Taylor & Letham, 2018) is an additive, decomposable time series model given by

$$y_t = T(t) + S(t) + H(t) + \epsilon_t, \tag{9}$$

where $T(t)$ is a trend function, $S(t)$ denotes seasonalities, $H(t)$ is used to include irregular changes such as holidays, and ϵ_t is the error term. Prophet has gained popularity in recent years because it is very easy to use in an automated forecasting setting. However, there is

[13] The estimation employs STL as implemented by `statsmodels` using Python based on Cleveland et al. (1990). While STL permits us to retrieve an estimated trend component of the underlying time series, we refrain from de-trending the month-on-month inflation rates and only de-seasonalize the time series. We employ STL using weights, including an outer loop for outlier correction in the estimation routine. The parameters of the loess smoothing routine are set as the default values implemented in STL.

[14] We are grateful to a referee for drawing our attention to this model.

[15] To ensure consistency with the AR(1) model, we use the `StatsForecast` implementation of `SARIMA` with a fixed coefficient. It optimizes the conditional sum of squares to find starting values and then uses maximum likelihood estimation.

some evidence that AutoARIMA is faster and more accurate (see Russel, 2022). Therefore, we are interested in evaluating how Prophet performs compared to our web-scraped data. We use Prophet with its default settings: a linear trend with automatic change point detection, seasonalities enabled, and no holiday effects.

Neuralprophet

Neuralprophet (see Triebe et al., 2021) is an extension of Prophet that incorporates local context through autoregression and covariate modules. These modules can be set up as either traditional linear regression models or neural networks, allowing it to handle more complex patterns than Prophet. The model is formulated with the additional components as follows:

$$y_t = T(t) + S(t) + H(t) + F(t) + A(t) + L(t) + \epsilon_t, \tag{10}$$

where $T(t)$ represents the trend, $S(t)$ seasonal effects, and $H(t)$ event and holiday effects, and where ϵ_t is the error term, similar to Prophet. In addition, $F(t)$ denotes regression effects for future-known exogenous variables, $A(t)$ denotes autoregression effects based on past observations, and $L(t)$ accounts for regression effects for lagged observations of exogenous variables. As with Prophet, we do not include any holiday effects. Furthermore, no exogenous variables are present in our setting. The learning rate is set to 0.01; weekly and daily seasonalities are disabled, and we include 12 lagged observations.

Theta

The Theta model, introduced by Assimakopoulos and Nikolopoulos (2000), is defined as the solution to

$$\Delta^2 Z_t(\theta) = \theta \Delta^2 y_t \quad \text{for } t = 3, \dots, T, \tag{11}$$

where $y_1, \dots, y_T$ represent the original time series (non-seasonal or de-seasonalized), and Δ^2 is the second difference operator. The initial values Z_1 and Z_2 are obtained by minimizing the sum of squared deviations $\sum_{t=1}^{T}[y_t - Z_t(\theta)]^2$. An analytical solution to this minimization problem is given by

$$Z_t(\theta) = \theta y_t + (1-\theta)(A_T + B_T t) \quad \text{for } t = 1, \dots, T, \tag{12}$$

where

$$A_T = \frac{1}{T}\sum_{t=1}^{T} y_t - \frac{T+1}{2} B_T, \tag{13}$$

and

$$B_T = \frac{6}{T^2-1}\left(\frac{2}{T}\sum_{t=1}^{T} t y_t - \frac{T+1}{T}\sum_{t=1}^{T} y_t\right). \tag{14}$$

Here, A_T and B_T correspond to the intercept and slope from regressing y_t on time t. Fiorucci et al. (2016) propose a dynamic optimized Theta method which is available in the AutoTheta method by Garza et al. (2022).[16] The Theta model performs well in time series exhibiting changing trend behavior. It was top-ranked in the M3 competition (Makridakis & Hibon, 2000), and it was included as a model benchmark in the M4 competition (Makridakis et al., 2020).

Error–trend–seasonality (ETS)

Hyndman et al. (2008) developed a state-space formulation:

$$y_t = w(\mathbf{x}_{t-1}) + r(\mathbf{x}_{t-1})\epsilon_t, \tag{15}$$

$$\mathbf{x}_t = f(\mathbf{x}_{t-1}) + g(\mathbf{x}_{t-1})\epsilon_t, \tag{16}$$

encompassing multiple exponential smoothing variations.

The state vector is given by $\mathbf{x}_t = (\ell_t, b_t, s_t, s_{t-1}, \dots, s_{t-m+1})$, where ℓ_t denotes the level component, b_t represents the trend component, $s_t, s_{t-1}, \dots, s_{t-m+1}$ are the seasonal components with seasonal period m, and ϵ_t is a Gaussian white noise process with variance σ^2 and $\mu_t = w(\mathbf{x}_{t-1})$. For additive errors models $r(\mathbf{x}_{t-1}) = 1$, and for multiplicative errors models $r(\mathbf{x}_{t-1}) = \mu_t$. The AutoETS function by Garza et al. (2022) selects the best model using the AIC.

Complex exponential smoothing (CES)

Unlike simple exponential smoothing, which applies a fixed exponential decay of the weights, complex exponential smoothing (Svetunkov et al., 2022) allows for flexible weight patterns, including oscillating or harmonic patterns. The CES equation is derived by extending the simple exponential smoothing framework into the complex plane:

$$\begin{aligned}\hat{y}_t + i\hat{e}_t &= (\alpha_0 + i\alpha_1)(y_{t-1} + ie_{t-1}) \\ &\quad + (1 - \alpha_0 + i - i\alpha_1)(\hat{y}_{t-1} + i\hat{e}_{t-1}),\end{aligned} \tag{17}$$

where $\hat{y}_t$ and $\hat{e}_t$ are the estimated value and estimated error term at time t, i represents the imaginary unit with $i^2 = -1$, α_0 and α_1 are the real and imaginary components of the complex smoothing parameter, and y_{t-1} and e_{t-1} are the actual observation and error term at time $t-1$, respectively. The AutoCES function by Garza et al. (2022) selects the best model using the AIC. The types of models included are simple CES, as well as models with simple, partial, or full seasonality. The CES model provides the additional flexibility of benchmark models, as it does not require strictly defining trend or seasonal parameters and accommodates stationary as well as non-stationary data, which may prove particularly advantageous in periods characterized by potential structural breaks in food price inflation.

5. Nowcast and forecast results

In this section, we present results for both the nowcasts and the short-term forecasts for COICOP levels 2 to 6. For details on index compilation, aggregation, and chaining, see Appendix A. Detailed results are provided in Appendix C.2 and Appendix C.3. The indices that constitute the nowcast and enter the models are calculated as described in Section 3 and in Appendix A.

We primarily rely on the root mean squared error (RMSE) to evaluate the accuracy of our out-of-sample forecasts employing a squared loss function. We focus on

[16] From a user perspective, the optimal Theta models are very simple to implement with AutoTheta, because the interface is similar to AutoARIMA by Garza et al. (2022).

the RMSE as the baseline measure, due to its non-linear transformation of forecast errors; i.e. large forecast errors are more heavily penalized. Under the assumption that forecast errors are approximately normally distributed, the RMSE can be interpreted as an estimate of the forecast error standard deviation across models:

$$\mathrm{RMSE} = \sqrt{\frac{1}{T}\sum_{t=1}^{T}(y_{t+h} - \hat{y}_{t+h})^2}, \tag{18}$$

where y_{t+h} is the actual value h periods ahead, and $\hat{y}_{t+h}$ is the predicted value for T out-of-sample comparisons.[17] Furthermore, we employ the mean error (ME) as a measure of out-of-sample forecast accuracy:

$$\mathrm{ME} = \frac{1}{T}\sum_{t=1}^{T}(y_{t+h} - \hat{y}_{t+h}). \tag{19}$$

Building on the models introduced above, we created two variants of equally weighted ensembles: one incorporating webscraping nowcasts, and one disregarding them. We observe that the majority of naive forecast models yield significantly lower predictive accuracy than the other models. We therefore decided to exclude them from the ensembles. In the following results, we present an ensemble of all time series models and another ensemble that additionally includes webscraping.[18]

To formally assess differences in out-of-sample forecast accuracy, as measured by the RMSE, we implement the two-sided test by Diebold and Mariano (1995), incorporating the small-sample correction proposed by Harvey et al. (1997). For the three-step-ahead forecast, the long-run variance estimator is based on Bartlett weights.

5.1. Nowcasts

We begin the discussion of the results with an evaluation of the performance of webscraping indices as a way to nowcast the inflation rates of elementary indices compared to the one-month-ahead forecasts of the various univariate time series models outlined in Section 4.2, above.

5.1.1. Elementary indices

A simple way to aggregate the predictive accuracy of the 130 elementary indices is to rank them by forecast metrics and determine the frequency with which each model attains first ranks across index positions. Fig. 3 shows that for 47 elementary index categories, the webscraping-based nowcasts exhibit the lowest RMSE. RW-S never ranks first and is therefore not included in this figure. The ensemble with webscraping achieves 37 first ranks.

For each index series, we provide detailed results in Table C.11 in Appendix C.2.1. There, we report the RMSE in levels for the webscraping-based nowcast in the first column, while other columns present ratios of the time series models' RMSEs relative to that of webscraping (i.e. the first column). As suggested by the high number of first ranks of webscraping indices, many of the RMSE ratios are above one, indicating the higher predictive accuracy of the webscraping nowcasts. For several indices, webscraping also achieves significantly different predictive accuracy according to a Diebold and Mariano (1995) test.

Another way to convey predictive accuracy across elementary indices (level 6) is by using a heatmap of RMSE values of the different models. Fig. 4 presents this approach, showing a heatmap of RMSEs across all elementary index positions and model specifications. Overall, the webscraping nowcast performs comparably well across most elementary index positions. For a handful of items—primarily those subject to seasonal pricing and seasonal unavailability, such as fruits (008400: *Strawberries*, 008440: *Berries*, 008600: *Pears*, and 008900: *Grapes*) and vegetables (010600: *Cucumbers* and 010700: *Cauliflower*)—all models consistently show low predictive accuracy. Notably, the webscraping nowcast performs comparably to model-based forecasts even for these index positions.

Likewise, Fig. 5 presents the heatmap of RMSEs across index positions on the more aggregated COICOP level 5. The favorable performance of webscraping nowcasts on level 6 directly carries over to level 5 RMSEs. Again, index positions where webscraping fares relatively unfavorably are those where model-based one-month-ahead forecasts exhibit large forecast errors as well. The notable cluster of high RMSEs in the lower-left corner of Fig. 4 pertains to products subject to seasonalities in the level 5 aggregate 01161: *Fresh or chilled fruit*, defined as seasonal items by Statistics Austria.[19]

Additionally, Fig. 6 plots the difference in RMSEs between webscraping and the ensemble without webscraping plotted against the standard deviation of month-on-month inflation rates of each elementary index position, and shows that these seasonal items exhibit a relatively high standard deviation while not indicating the worse performance of webscraping. While 008400: *Strawberries*, 008200: *Tangerines*, and 005400: *Fresh fish* constitute (seasonal) product categories where webscraping underperforms, webscraping achieves superior forecast performance in seasonal product categories such as 009000: *Musk melons/cantaloupes*, 008900: *Grapes*, or 009200: *Bananas*. This pattern also holds for other elementary index positions with highly volatile inflation rates, indicating that the webscraping nowcast does not perform systematically worse in seasonal product groups and index positions with relatively volatile inflation rates. In the case of specialty meats such as 002500: *Veal cutlet* and 003800: *Pork sirloin*, the underperformance of webscraping is explained by insufficient coverage in online prices. Specifically, our sample only provides nine and five

[17] Some authors employ the term 'root mean squared forecast error' (RMSFE) and utilize the RMSE to denote the in-sample fit on the training data. As our paper assesses the precision of the out-of-sample forecasts, all the displayed error metrics are derived from forecasts.

[18] We recognize that the composition of the ensembles could be further optimized by tuning the weights, and we believe this is worth exploring in practical applications. In this study, our primary focus is to demonstrate the added value of webscraping and to develop a parsimonious method for combining forecasts from multiple models.

[19] See European Commission Eurostat (2025). Harmonised Index of Consumer Prices (HICP) Compliance Monitoring Report Austria.

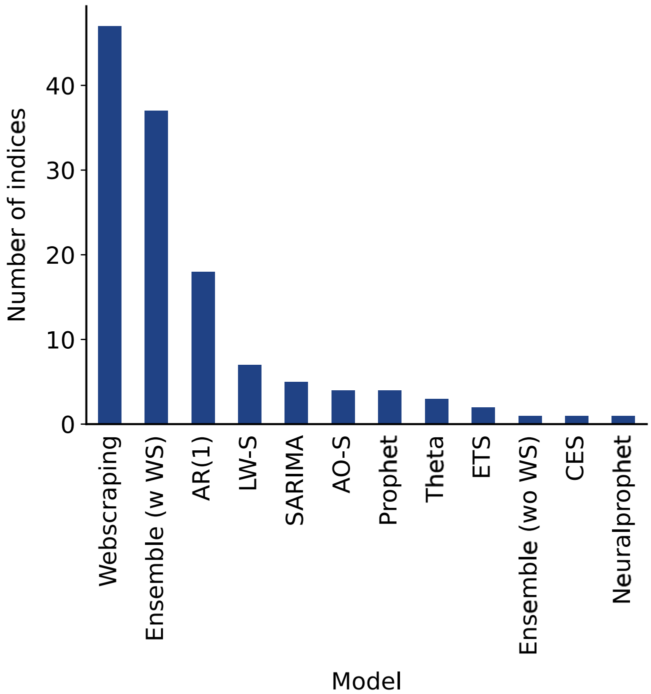

Fig. 3. Number of first ranks per model across elementary indices (level 6). Note: Fig. 3 shows the number of first ranks per model for one-month-ahead forecasts of the elementary indices at level 6.

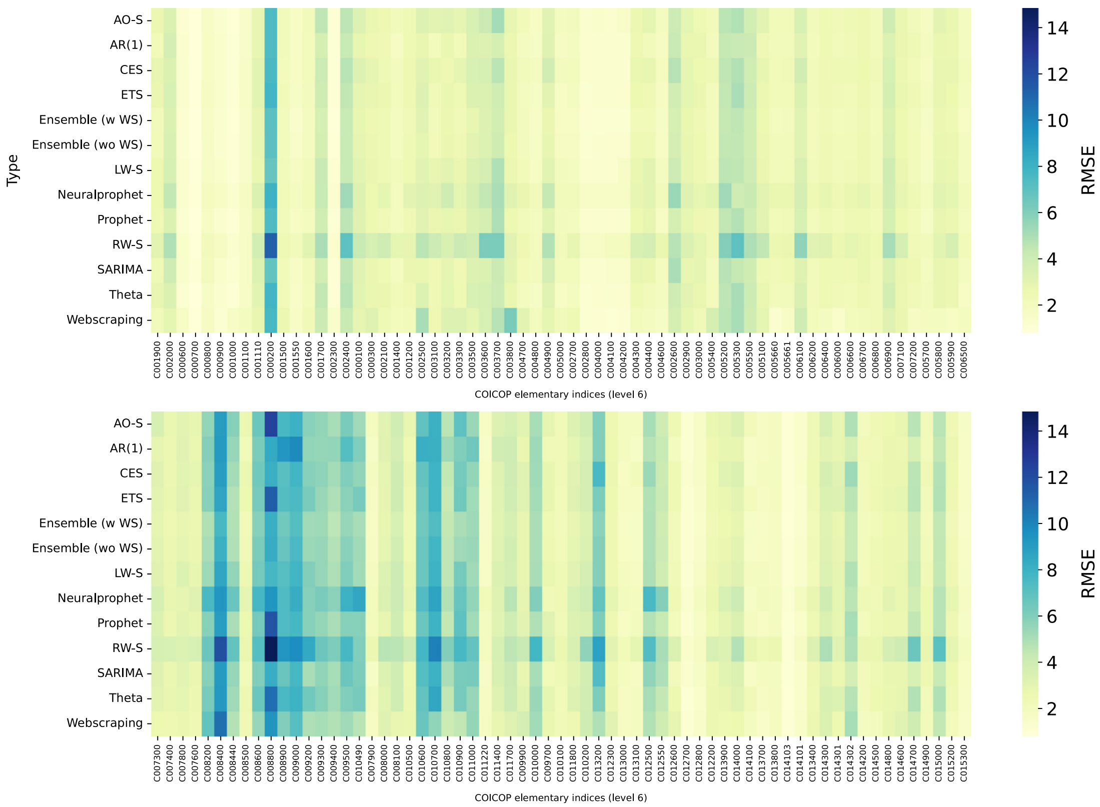

Fig. 4. Heatmap of RMSEs for elementary indices (level 6). Note: Fig. 4 shows the RMSE per model for one-month-ahead forecasts of the elementary indices at level 6.

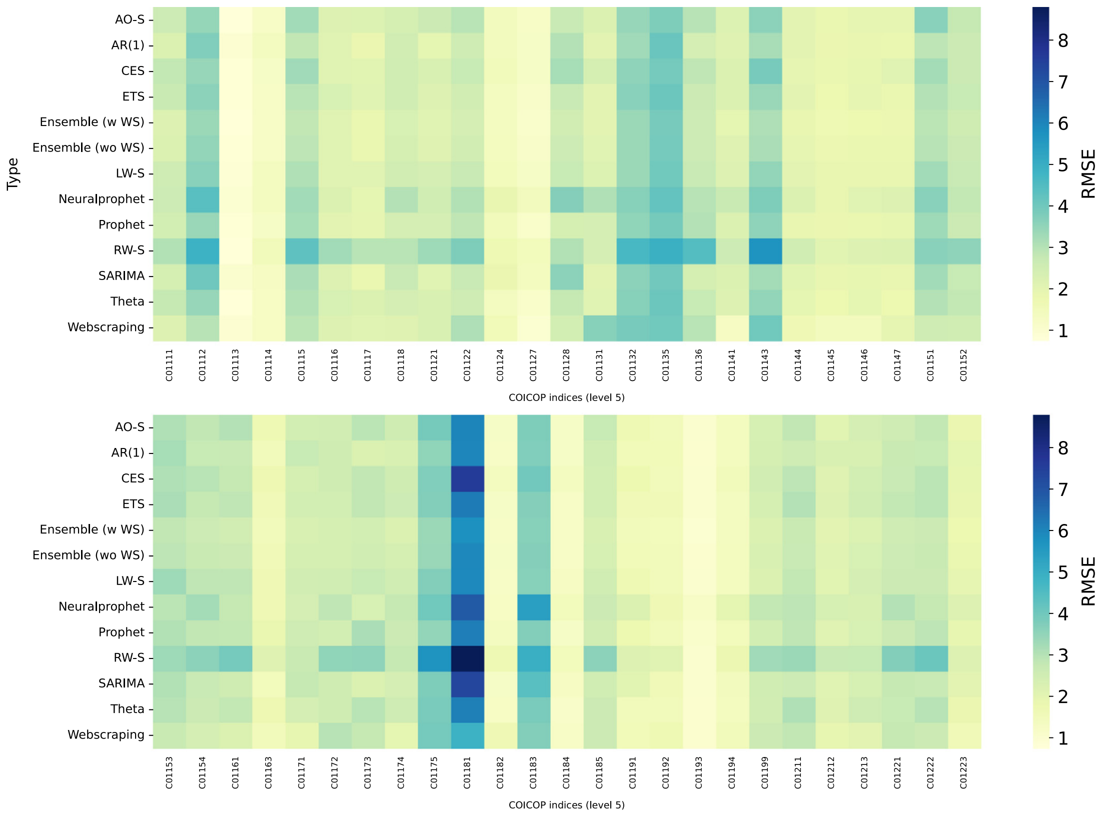

Fig. 5. Heatmap of RMSEs for elementary indices (level 5). Note: Fig. 5 shows the RMSE per model for one-month-ahead forecasts of the indices at level 5.

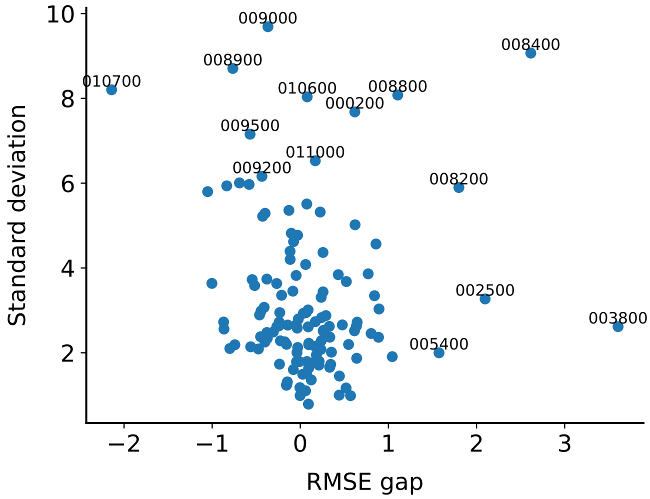

Fig. 6. RMSE gaps for elementary indices (level 6). Note: Fig. 6 displays the RMSE gaps between webscraping and the ensemble (wo WS) for the elementary indices (level 6), plotted against the standard deviation of each elementary index series in the out-of-sample forecast window.

product items in these categories, materially affecting the representativeness of our prudent sample, as shown in Appendix B.4.

Taken together, the above results show that webscraping nowcasts outperform model-based one-month-ahead inflation forecasts in terms of RMSEs for more than one-third of all elementary index positions. Moreover, the inclusion of webscraping into equally weighted ensemble forecasts based on time series models improves forecast accuracy markedly, as shown in Fig. 3. In addition, webscraping nowcasts perform as well as model-based forecasts in index positions covering items that are subject to seasonal pricing, seasonal unavailability, or high price volatility in general. The following section provides

Table 2
Indirect one-step-ahead forecasts of indices at levels 2–4.

COICOP	Text	Web-scraping	RW-S	AO-S	SARIMA	AR(1)	LW-S	ETS	Prophet	Neural-prophet	CES	Theta	Ensemble (w WS)	Ensemble (wo WS)
01	FOOD AND NON-ALCOHOLIC BEVERAGES	0.853	1.350*	1.144*	1.270	1.161	1.206*	1.125	1.168*	1.220	1.176*	1.108*	1.066	1.113
011	Food	0.893	1.322*	1.135	1.216	1.127	1.177	1.112	1.154	1.192	1.160*	1.100	1.053	1.095
0111	Bread and cereals	0.858	1.132	0.984	1.165	1.136	1.143	1.027	1.046	1.108	1.045	1.008	0.967	1.017
0112	Meat	1.271	1.392*	1.163	1.344	1.170	1.144	1.087	1.091	1.365	1.183	1.085	1.037	1.088
0113	Fish	1.938	1.173	0.935	0.915	0.864	0.935	0.895	0.952	1.052	0.943	0.901	0.865	0.888
0114	Milk, cheese and eggs	1.079	1.466***	1.426**	1.467*	1.421*	1.407	1.356*	1.404*	1.481**	1.408*	1.389**	1.290	1.373*
0115	Oil and fats	1.592	1.479***	1.329**	1.206*	1.105	1.247**	1.130	1.239**	1.320**	1.220**	1.105	1.096	1.127
0116	Fruit	1.844	1.784*	1.386	1.177	1.236	1.307	1.303	1.287	1.277	1.261	1.294	1.140	1.210
0117	Vegetables	1.537	1.281**	1.178*	1.295**	1.268**	1.203*	1.208*	1.308*	1.133	1.196**	1.176**	1.124	1.167*
0118	Sugar, jam, honey, chocolate and confectionery	1.700	1.254	0.963	1.131	0.968	0.962	0.942	0.995	1.261*	1.089	0.974	0.942	0.957
0119	Food products n.e.c.	1.048	1.064	0.864	1.007	0.853	0.909	0.839	0.893	1.092	0.885	0.799*	0.811*	0.834
012	Non-alcoholic beverages	1.394	1.540***	1.161*	1.261	1.177	1.168	1.205**	1.187**	1.251	1.222**	1.204**	1.102	1.142
0121	Coffee, tea and cocoa	2.313	1.245	1.046	0.982	0.981	1.049	1.125*	1.058	1.097	1.086	1.139**	0.994	1.018
0122	Mineral waters, soft drinks, fruit and vegetables juices	1.612	1.575***	1.110	1.188	1.159	1.102	1.192*	1.132	1.204	1.153	1.168*	1.061	1.093

Note: Table 2 presents the root mean squared errors of one-step-ahead forecasts of the indices. The first column contains the RMSE in levels for the webscraping-based nowcast, and the other columns contain ratios of the time series models' RMSEs relative to the first column. The stars indicate different levels of significance of a Diebold and Mariano (1995) test for equal predictive accuracy: * significant at the 10% level ($p < 0.10$), ** significant at the 5% level ($p < 0.05$), and *** significant at the 1% level ($p < 0.01$). The Harvey et al. (1997) (HNL) correction for small samples is used.

Table 3
Direct one-step-ahead forecasts of indices at levels 2–4.

COICOP	Text	Web-scraping	RW-S	AO-S	SARIMA	AR(1)	LW-S	ETS	Prophet	Neural-prophet	CES	Theta	Ensemble (w WS)	Ensemble (wo WS)
01	FOOD AND NON-ALCOHOLIC BEVERAGES	0.853	1.683	1.215**	1.137*	1.201**	1.271**	1.262**	1.258**	1.215*	1.146	1.227**	1.122	1.169*
011	Food	0.893	1.664	1.224**	1.141	1.191**	1.267**	1.249**	1.256**	1.221*	1.140	1.229**	1.121	1.166*
0111	Bread and cereals	0.858	1.324	1.008	0.965	1.100	1.072	1.012	1.089	0.973	1.016	1.009	0.963	0.994
0112	Meat	1.271	1.651*	1.152	1.160	1.137	1.136	1.101	1.097	1.199	1.085	1.094	1.047	1.096
0113	Fish	1.938	1.126	0.896	0.876	0.872	0.898	0.891	0.898	0.934	0.891	0.902	0.859	0.879
0114	Milk, cheese and eggs	1.079	1.752***	1.410**	1.362*	1.426*	1.400*	1.381**	1.393*	1.366**	1.375**	1.387**	1.281*	1.351*
0115	Oil and fats	1.592	1.456***	1.244**	1.159**	1.143	1.165*	1.144**	1.181**	1.221**	1.170**	1.149**	1.103	1.128*
0116	Fruit	1.844	1.561***	1.393**	0.867	1.001	1.352**	0.922	1.475***	1.026	0.972	1.557***	1.022	1.052
0117	Vegetables	1.537	1.763***	1.644***	1.652***	1.389**	1.664***	1.319*	1.734***	1.462***	1.389***	1.766***	1.311***	1.389***
0118	Sugar, jam, honey, chocolate and confectionery	1.700	1.362	0.985	1.005	0.964	0.981	0.978	0.971	0.993	0.966	0.993	0.939	0.952
0119	Food products n.e.c.	1.048	1.034	0.799*	0.906	0.862	0.869	0.855	0.837	0.888	0.833	0.792*	0.803*	0.828
012	Non-alcoholic beverages	1.394	1.701**	1.193**	1.106	1.194	1.221*	1.230**	1.211**	1.134	1.192**	1.206**	1.129	1.170
0121	Coffee, tea and cocoa	2.313	1.652*	1.085	1.032	1.045	1.064	1.089	1.071	1.001	1.048	1.185***	1.034	1.061
0122	Mineral waters, soft drinks, fruit and vegetables juices	1.612	1.542***	1.127	1.087	1.179	1.157	1.167*	1.128	1.082	1.123	1.138	1.082	1.115

Note: Table 3 presents the root mean squared errors of one-step-ahead forecasts of the indices. The first column contains the RMSE in levels for the webscraping-based nowcast, and the other columns contain ratios of the time series models' RMSEs relative to the first column. The stars indicate different levels of significance of a Diebold and Mariano (1995) test for equal predictive accuracy: * significant at the 10% level ($p < 0.10$), ** significant at the 5% level ($p < 0.05$), and *** significant at the 1% level ($p < 0.01$). The Harvey et al. (1997) (HNL) correction for small samples is used.

a more detailed investigation into out-of-sample forecast accuracy on a more granular level and is followed by an application of webscraped data in one-quarter-ahead forecasts.

5.1.2. Higher COICOP levels

Tables 2 and 3 compare the nowcasting performance of webscraping to that of other models across COICOP levels 2 to 4, for indirect and direct forecasts, respectively. The direct forecast denotes the model forecast based on the historical time series of the COICOP category in question, whereas the indirect forecast denotes forecasts on the level of elementary indices that are afterwards aggregated to the concerned COICOP category. Tables 4 and 5 show the corresponding mean error (ME).[20]

Level 2. Starting at the highest level of aggregation, i.e. at the level 2 category 01: *Food and non-alcoholic beverages*, webscraping outperforms all other models in both direct and indirect forecasts. In the case of indirect forecasts, the differences are significant for about half of the models, while for direct forecasts, webscraping does not significantly outperform RW-S, CES, and the ensemble incorporating webscraping. However, due to large variations in the standard deviation of loss differentials (i.e. the differences between two forecast error time series) employed in the Diebold–Mariano test, significance levels vary greatly across models. For instance, the direct one-month-ahead forecast errors of the SARIMA models are estimated to be significantly different from webscraped forecast errors at the 10% significance level, while the same comparison regarding the RW-S model shows no significant result. However, the RMSE ratio of the RW-S model exceeds that of the SARIMA model by a margin of more than 45%. This is due to the loss differential of the RW-S exhibiting a standard deviation roughly double that of the SARIMA model. Due to the penalization of high variation in loss differentials, the Diebold–Mariano test statistic is close to zero, yielding insignificant results despite large differences in RMSEs. This result carries over to lower level index positions as well, as can be seen, e.g. in the second row of Tables 2 and 3.

When using the mean error to assess bias, webscraping appears unbiased. Some time series models, particularly AR(1) and LW-S, tend to underestimate inflation rates by several tenths of a percentage point. This carries over to the ensembles, although the simple averaging mitigates this under- or overestimation present in their constituent models. In the case of indirect forecasts, webscraping nowcasts yield the lowest absolute mean error (ME) across all models and rank mid-range relative to direct forecasts.

[20] Since the webscraping nowcasts are always based on COICOP level 6 data, there are no genuine direct forecasts at higher aggregation levels. As a result, the RMSE and the ME values for the webscraping model are identical in both tables.

Table 4
Indirect one-step-ahead forecasts of indices at levels 2–4.

COICOP	Text	Web-scraping	RW-S	AO-S	SARIMA	AR(1)	LW-S	ETS	Prophet	Neural-prophet	CES	Theta	Ensemble (w WS)	Ensemble (wo WS)
01	FOOD AND NON-ALCOHOLIC BEVERAGES	−0.041	0.104	0.076	−0.329	−0.308	−0.302	−0.137	0.045	0.155	0.260	0.084	−0.091	−0.098
011	Food	−0.034	0.099	0.085	−0.304	−0.274	−0.272	−0.116	0.063	0.139	0.267	0.091	−0.072	−0.078
0111	Bread and cereals	−0.127	0.049	0.013	−0.277	−0.397	−0.364	−0.100	−0.040	0.085	0.170	0.016	−0.140	−0.142
0112	Meat	−0.007	0.047	0.056	−0.405	−0.338	−0.291	−0.196	0.020	0.015	0.420	0.067	−0.091	−0.103
0113	Fish	0.030	0.479	0.137	−0.282	−0.220	−0.217	−0.151	0.102	0.160	0.307	0.089	−0.043	−0.053
0114	Milk, cheese and eggs	−0.018	0.059	0.041	−0.239	−0.339	−0.272	−0.112	0.020	0.052	−0.001	0.052	−0.114	−0.127
0115	Oil and fats	−0.237	0.074	−0.082	−0.326	−0.552	−0.462	−0.085	−0.217	0.015	0.239	−0.056	−0.212	−0.208
0116	Fruit	0.050	0.168	0.192	0.056	0.259	−0.063	0.132	0.224	0.330	0.648	0.190	0.187	0.207
0117	Vegetables	−0.100	0.107	0.161	−0.538	−0.270	−0.296	−0.283	0.249	0.365	0.191	0.184	−0.108	−0.109
0118	Sugar, jam, honey, chocolate and confectionery	0.054	0.077	0.074	−0.477	−0.315	−0.326	−0.135	0.007	0.176	0.197	0.078	−0.115	−0.139
0119	Food products n.e.c.	0.056	0.054	0.072	−0.240	−0.249	−0.217	−0.129	0.015	0.163	0.056	0.072	−0.079	−0.099
012	Non-alcoholic beverages	−0.132	0.098	−0.028	−0.575	−0.625	−0.581	−0.349	−0.130	0.250	0.162	−0.003	−0.279	−0.300
0121	Coffee, tea and cocoa	−0.075	0.047	−0.102	−0.770	−0.608	−0.593	−0.417	−0.178	0.076	−0.313	−0.073	−0.378	−0.422
0122	Mineral waters, soft drinks, fruit and vegetables juices	−0.179	0.124	0.004	−0.466	−0.648	−0.585	−0.321	−0.113	0.341	0.408	0.025	−0.235	−0.243

Note: Table 4 presents the mean forecast errors of one-step-ahead forecasts of the indices.

Table 5
Direct one-step-ahead forecasts of indices at levels 2–4.

COICOP	Text	Web-scraping	RW-S	AO-S	SARIMA	AR(1)	LW-S	ETS	Prophet	Neural-prophet	CES	Theta	Ensemble (w WS)	Ensemble (wo WS)
01	FOOD AND NON-ALCOHOLIC BEVERAGES	−0.041	0.027	0.013	−0.142	−0.296	−0.310	−0.037	−0.218	0.008	−0.031	−0.009	−0.136	−0.149
011	Food	−0.034	−0.049	0.016	−0.131	−0.270	−0.302	−0.035	−0.211	0.020	−0.038	−0.006	−0.128	−0.142
0111	Bread and cereals	−0.127	0.017	−0.013	−0.113	−0.319	−0.245	−0.035	−0.254	−0.056	0.015	−0.033	−0.139	−0.141
0112	Meat	−0.007	−0.123	0.002	−0.254	−0.377	−0.345	−0.289	−0.168	−0.011	−0.133	0.004	−0.196	−0.223
0113	Fish	0.030	0.110	0.029	−0.254	−0.241	−0.260	−0.211	−0.070	0.101	0.042	0.014	−0.119	−0.140
0114	Milk, cheese and eggs	−0.018	−0.096	0.002	−0.217	−0.262	−0.231	−0.021	−0.183	−0.162	−0.052	−0.030	−0.127	−0.142
0115	Oil and fats	−0.237	0.028	−0.122	−0.348	−0.485	−0.427	−0.127	−0.436	−0.237	−0.270	−0.161	−0.311	−0.322
0116	Fruit	0.050	−0.041	−0.003	0.113	0.005	0.021	−0.071	−0.382	−0.002	−0.596	−0.055	−0.114	−0.138
0117	Vegetables	−0.100	0.081	0.116	−1.007	−0.188	−0.301	−0.190	−0.201	0.139	−1.018	0.067	−0.367	−0.405
0118	Sugar, jam, honey, chocolate and confectionery	0.054	0.051	0.026	−0.372	−0.354	−0.318	−0.286	−0.200	0.063	−0.208	−0.016	−0.213	−0.251
0119	Food products n.e.c.	0.056	−0.043	0.036	−0.279	−0.285	−0.261	−0.206	−0.202	−0.031	−0.061	0.023	−0.152	−0.182
012	Non-alcoholic beverages	−0.132	−0.034	−0.059	−0.338	−0.628	−0.567	−0.356	−0.306	−0.311	−0.202	−0.083	−0.326	−0.354
0121	Coffee, tea and cocoa	−0.075	−0.024	−0.105	−0.470	−0.538	−0.511	−0.462	−0.222	−0.245	−0.158	−0.160	−0.325	−0.360
0122	Mineral waters, soft drinks, fruit and vegetables juices	−0.179	−0.063	−0.027	−0.295	−0.706	−0.616	−0.331	−0.371	−0.255	−0.139	−0.042	−0.335	−0.357

Note: Table 5 presents the mean forecast errors of one-step-ahead forecasts of the indices.

Level 3. For COICOP level 3, covering the categories 011: *Food* and 012: *Non-alcoholic beverages*, webscraping again outperforms all time series models and ensembles in both direct and indirect forecasts. In the case of indirect forecasts, the differences are significant for about half of the models for 012: *Non-alcoholic beverages*, and significant for CES and RW-S for 011: *Food*. For direct forecasts, Diebold–Mariano tests indicate significant differences in predictive ability for about two-thirds of all models. Moreover, the improvements provided by webscraping are not significant for the RW-S, SARIMA, and CES models and the ensemble with webscraping for 011: *Food*, nor for the Neuralprophet, SARIMA, AR(1), and the ensemble models in the case of 012: *Non-alcoholic beverages*.

Regarding the bias of the nowcasts at COICOP level 3, webscraping nowcasts exhibit small negative errors for 011: *Food* and slightly more negative errors for 012: *Non-alcoholic beverages* on average. For indirect nowcasts, most models slightly overestimate 011: *Food* inflation, while the sign of MEs for 012: *Non-alcoholic beverages* vary across models, with some slightly underestimating and others slightly overestimating inflation rates on average. Overall, indirect nowcasts remain largely unbiased. For direct nowcasts, several models – AR(1), LW-S, and SARIMA – substantially underestimate in both cases, especially concerning 012: *Non-alcoholic beverages*. The biases of individual models are again proportionally reflected in the ensemble forecasts.

Level 4. Webscraping yields superior predictive ability in most categories for both indirect and direct forecasts and always outperforms RW-S. However, the differences between webscraping and time series models are not statistically significant in most cases; exceptions are 0114: *Milk, cheese and eggs*, 0117: *Vegetables*, and 0115: *Oil and fats*. However, time series models perform better than webscraping for 0113: *Fish*, 0118: *Sugar, jam, honey, chocolate, and confectionery*, and 0119: *Food products n.e.c.* The rather extensive scope of different products in the index position 0119: *Food products n.e.c.* makes product classification relatively coarse, possibly deteriorating the representativeness of the webscraped product sample in these categories. In essence, it may be the case that product classification by applying regular expressions on the product names is too rough and misclassifies products that are not part of the concerned index category, thereby deteriorating representativeness. For example, non-milk-based varieties of baby food products might be wrongly classified into 014101: *Baby food (milk)*, due to missing information on additional product features. However, differences in these index positions are generally insignificant, apart from the cases of the direct and indirect nowcasts of the Theta model and the ensemble incorporating webscraping and the direct forecast of the AO-S model in 0119: *Food products n.e.c.*

Regarding mean errors, webscraping yields mean errors close to zero in most categories, without systematic negative bias, and outperforms almost all models in indirect forecasts. Larger deviations mainly appear in 0115: *Oil and fats*, 0111: *Bread and cereals*, and 0122: *Mineral waters, soft drinks, and fruit and vegetable juices*. Regarding direct forecasts, mean errors are consistently low for the AO-S and Theta models. Across both direct and indirect nowcasts, AR(1), LW-S, and SARIMA, in particular, systematically underestimate many items. Ensemble forecasts reflect this underestimation but reduce their magnitude.

Level 5. For COICOP level 5, in the case of direct forecasts of the indices in the appendix in Table C.12, webscraping outperforms all time series models, including the ensemble with webscraping, in 19 of the 50 subcategories. The ensemble with webscraping performs better than webscraping alone in 30 categories. Other time series models, such as AR(1) and LW-S, outperform webscraping in 31 of the 50 categories. Webscraping performs poorly for categories such as 01131: *Fresh or chilled fish*, 01132: *Frozen fish*, 01133: *Dried, smoked, or salted fish and seafood*, and 01172: *Frozen vegetables other than potatoes and other tubers*.

Regarding the indirect forecasts for COICOP level 5 in the appendix in Table C.13, webscraping achieves superior predictive ability compared to all time series models for 17 out of 50 subcategories. 01124: *Poultry* shows a lower RMSE for autoregressive models and significant improvement upon the webscraping nowcast for both the ensemble with webscraping and the Theta models. In the subcategory 01131: *Fresh or chilled fish*, the ensemble with webscraping shows superior predictive ability, and webscraping performs worse than all other models. Likewise, webscraping does badly in the category of 01113: *Bread* where all but the SARIMA and the Neuralprophet models outperform webscraping—albeit insignificantly so, apart from the AO-S model. In the subcategory 01172: *Frozen vegetables other than potatoes and other tubers*, all models but the RW-S model outperform webscraping and all but the SARIMA and the Neuralprophet models show significant improvements.

The results shown in Tables 2 and 3 highlight that webscraping outperforms most direct and indirect forecasts by a wide margin in terms of RMSEs. Regarding time series models, the small performance difference between direct and indirect forecast metrics suggests that webscraping can improve upon nowcasts that are based on directly forecasting an aggregate time series and aggregating forecasts on the level of elementary indices alike. Because webscraping outperforms all models in both direct and indirect forecasts on the uppermost level of 01: *Food and non-alcoholic beverages* and because indirect forecasts allow for a decomposition of the nowcast into contributions from different levels of aggregation, which is infeasible in the case of direct model forecasts, we deem these results promising. This result carries over to most lower-level index positions, as shown in Tables 2 and 3 wherein webscraping again either outperforms all other models or does not perform significantly worse.

5.2. Three-month-ahead forecasts

While the existing literature for disaggregated forecasting with webscraped data (see e.g. Macias et al., 2023; Soybilgen et al., 2023) mainly compares the performance of nowcasts, we propose to complement multi-step-ahead forecasts with webscraping nowcasts. An analysis of multi-period inflation forecasts using webscraped data by PriceStats is provided by Aparicio and Bertolotto (2020), though only for headline inflation. On the other hand, Barkan et al. (2023) provide an analysis of disaggregated multi-period HICP inflation forecasts, but without using webscraped data. Hence, we add to the literature by evaluating multi-period-ahead forecasts, in particular three-month-ahead forecasts, on a disaggregated level using webscraped data.

In this section, models marked with an asterisk contain the webscraping nowcast for the one-month-ahead forecast. We again calculate equally weighted ensembles (excluding the random walk specifications) of all models with and without webscraping, as described above.

5.2.1. Elementary indices

We start with an analysis at the most disaggregated level of elementary indices. Table C.14 in the appendix presents the root mean squared errors of three-step-ahead forecasts of these indices. All columns contain ratios of RMSEs of the time series models with webscraping relative to the time series models without webscraping. Hence, ratios below one indicate a lower RMSE for the model that includes webscraping. Fig. 7 summarizes the percentage share of elementary index categories where webscraping improves the model. Depending on the chosen time series model the share of categories with an RMSE improvement varies between 62% and 90%. It is intuitive that a smaller proportion of categories shows lower RMSEs when an ensemble of time series models is used. Only five out of 130 categories are significantly different with a higher RMSE. Most of these elementary indices (e.g. nut cake, veal cut, and fresh fish) also displayed limited gains from webscraped nowcasts compared to one-step-ahead time series benchmarks.

The mean forecast errors for the elementary indices in Table C.24 in the appendix are generally close to zero, indicating limited systematic bias of our short-term forecasts. However, some time series models appear to persistently over- or underestimate specific categories. Including webscraped nowcasts does not seem to have a consistent effect on mean forecast errors. Similar patterns regarding the bias can be observed across higher-level COICOP aggregates.

Overall, we conclude that webscraping-based nowcasts provide a meaningful improvement to short-term forecasts at the most disaggregated level.

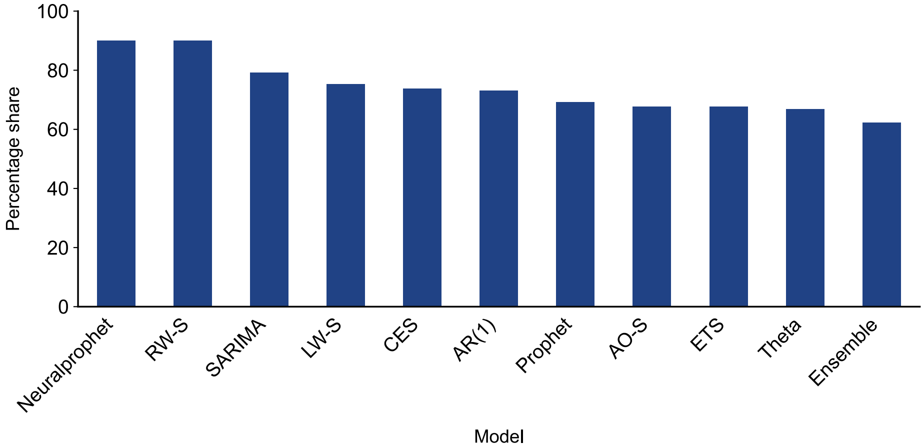

Fig. 7. Percentage share for elementary indices (level 6) where nowcasts improve three-month-ahead forecasts. Note: Fig. 7 shows the share of elementary indices at level 6, where webscraping-based nowcasts as one-month-ahead forecasts improve three-month-ahead forecasts.

Table 6
Indirect three-step-ahead forecasts of indices at levels 2–4.

COICOP	Text	RW-S	AO-S	SARIMA	AR(1)	LW-S	ETS	Prophet	Neural-prophet	CES	Theta	Ensemble
01	FOOD AND NON-ALCOHOLIC BEVERAGES	0.701*	0.818**	0.790**	0.777**	0.781**	0.817*	0.792**	0.783***	0.792**	0.833*	0.817*
011	Food	0.710*	0.820**	0.798*	0.784**	0.785*	0.820*	0.793**	0.786***	0.795**	0.831**	0.820*
0111	Bread and cereals	0.748*	0.814*	0.792**	0.777**	0.765**	0.811**	0.778***	0.769*	0.778**	0.819**	0.808**
0112	Meat	0.711*	0.844	0.847	0.808	0.824	0.814	0.829	0.830**	0.824**	0.815	0.844
0113	Fish	0.802	0.881	0.862**	0.882*	0.858*	0.912	0.926	0.857**	0.973	0.967	0.933
0114	Milk, cheese and eggs	0.631**	0.775**	0.773**	0.802**	0.798*	0.827**	0.777***	0.767**	0.808**	0.806**	0.803**
0115	Oil and fats	0.753*	0.859**	0.838**	0.922	0.905*	0.832**	0.892*	0.813**	0.889**	0.867**	0.903**
0116	Fruit	0.891	1.016	1.077	1.096	1.061	1.059	1.063	0.891	0.994	1.051	1.079
0117	Vegetables	0.810*	0.915	0.862**	0.875**	0.879***	0.900**	0.895*	0.874*	0.869*	0.870*	0.917*
0118	Sugar, jam, honey, chocolate and confectionery	0.441	0.898**	0.867	0.902	0.876*	0.915*	0.922**	0.817*	0.837**	0.927	0.920*
0119	Food products n.e.c.	0.783	0.907	0.820**	0.870	0.852*	0.915	0.886*	0.797***	0.930	1.000	0.909
012	Non-alcoholic beverages	0.702	0.918	0.832**	0.845*	0.850**	0.860*	0.859**	0.851**	0.850**	0.897	0.894
0121	Coffee, tea and cocoa	0.859	1.016	0.926	0.955	0.932	0.934	0.943	0.888*	0.947	0.971	0.977
0122	Mineral waters, soft drinks, fruit and vegetables juices	0.619**	0.912	0.838**	0.866	0.869*	0.851*	0.876*	0.854**	0.854**	0.871**	0.904

Note: Table 6 presents the root mean squared errors of three-step-ahead forecasts of the indices. All columns contain ratios of RMSEs of the time series models with webscraping relative to the time series models without webscraping. The stars indicate different levels of significance of a Diebold and Mariano (1995) test for equal predictive accuracy: * significant at the 10% level ($p < 0.10$), ** significant at the 5% level ($p < 0.05$), and *** significant at the 1% level ($p < 0.01$).

5.2.2. Higher COICOP levels

Next, we proceed in a similar manner as the previous section regarding the nowcast results. We compare direct and indirect three-month-ahead forecasts at the higher COICOP levels. Tables 6 and 7 display the results for the COICOP levels 2 to 4, while the results for level 5 are shown in the appendix in Table C.15 and Table C.16. The tables again report the RMSE ratios of three-month-ahead forecasts calculated by dividing the RMSE of forecasts that use webscraped data as the one-month-ahead forecast by the RMSE of solely model-based three-month-ahead forecasts. We also provide tables with mean forecast errors for assessing potential bias (see Table C.22 and Table C.23 in the appendix).

Level 2. Starting with the level 2 category 01: *Food and non-alcoholic beverages* for direct forecasts, using the webscraping-based nowcasts for a forecast horizon of one month improves the RMSE for all time series models, as indicated by RMSE ratios below unity. According to the Diebold–Mariano tests, the results are significantly different up to a 5% significance level, for all time series models except RW-S, SARIMA, ETS, and CES. Similarly, the indirect forecasts in Table 6 also show statistically significant differences in forecast accuracy and the ratios indicate improvements in all cases.

Turning to mean errors, indirect forecasts (see in the appendix in Table C.21) consistently underestimate the true values. Incorporating webscraping nowcasts has little effect on the overall underestimation. For direct forecasts, mean errors are heterogeneous across models. Incorporating webscraping for direct nowcasts (see Table C.20 in the appendix) reduces bias for RW-S, SARIMA, Prophet, Neuralprophet, AR(1), LW-S, ETS, and the ensemble model, while for other models, the effect is negligible. In the case of indirect forecasts, the inclusion of webscraping leads to small increases of bias in all models.

Level 3. A similar picture emerges when moving to COICOP level 3: forecasts become more accurate when webscraping-based nowcasts are included, and in most cases, the difference is statistically significant for direct and indirect forecasts alike. In the case of 011: *Food*, all improvements on one-quarter-ahead purely model-based forecasts are a significant difference in the case of indirect forecasts and for all but the RW-S and SARIMA models in the case of direct forecasts. When it comes to 012: *Non-alcoholic beverages*, the outperformance of models with webscraped data is significant at the 5% threshold for the SARIMA, LW-S, Prophet, Neuralprophet, and CES models, and significant at the 10% threshold for the AR(1) and

Table 7
Direct three-step-ahead forecasts of indices at levels 2–4.

COICOP	Text	RW-S	AO-S	SARIMA	AR(1)	LW-S	ETS	Prophet	Neural-prophet	CES	Theta	Ensemble
01	FOOD AND NON-ALCOHOLIC BEVERAGES	0.541	0.813**	0.829	0.775**	0.778**	0.792*	0.777**	0.808***	0.815*	0.791**	0.810*
011	Food	0.546	0.808**	0.834	0.774**	0.775**	0.808**	0.771**	0.804***	0.814*	0.784**	0.810*
0111	Bread and cereals	0.741	0.829*	0.942	0.784**	0.788**	0.887	0.779**	0.933	0.899	0.892	0.892
0112	Meat	0.526**	0.826	0.818	0.811	0.803	0.811	0.815	0.860	0.829	0.807	0.831
0113	Fish	0.803	0.909	0.880*	0.888*	0.888	0.907	0.912	0.876*	0.924	0.944	0.921
0114	Milk, cheese and eggs	0.632**	0.781**	0.870*	0.798**	0.799*	0.834**	0.802**	0.828**	0.827**	0.834**	0.843**
0115	Oil and fats	0.717	0.862**	0.920	0.911	0.924	0.886**	0.912	0.851**	0.896**	0.882**	0.922*
0116	Fruit	0.809*	0.878***	1.186	1.121*	0.865***	1.232*	0.879**	1.001	1.013	0.833***	1.010
0117	Vegetables	0.750**	0.754***	0.774***	0.800**	0.752***	0.822*	0.750***	0.834*	0.785***	0.728***	0.811***
0118	Sugar, jam, honey, chocolate and confectionery	0.441	0.912*	0.923	0.906	0.915	0.898*	0.896*	0.847**	0.906*	0.904**	0.926
0119	Food products n.e.c.	0.878	0.933	0.852*	0.856*	0.865**	0.877*	0.883*	0.867	0.931	0.995	0.910
012	Non-alcoholic beverages	0.526	0.893	0.888	0.851*	0.833**	0.841**	0.851**	0.917	0.858**	0.892	0.882*
0121	Coffee, tea and cocoa	0.545	0.985	0.979	0.943	0.932	0.949	0.968	1.017	0.976	0.945	0.988
0122	Mineral waters, soft drinks, fruit and vegetables juices	0.685**	0.905	0.877*	0.855*	0.842**	0.851*	0.867*	0.914	0.871*	0.887*	0.888

Note: Table 7 presents the root mean squared errors of three-step-ahead forecasts of the indices. All columns contain ratios of RMSEs of the time series models with webscraping relative to the time series models without webscraping. The stars indicate different levels of significance of a Diebold and Mariano (1995) test for equal predictive accuracy: * significant at the 10% level ($p < 0.10$), ** significant at the 5% level ($p < 0.05$), and *** significant at the 1% level ($p < 0.01$).

the ETS models in the case of indirect forecasts. When it comes to direct forecasts, significant results are obtained for the AR(1), LW-S, ETS, Prophet, CES, and ensemble models.

Level 4. Similarly, at COICOP level 4, direct forecasts benefit from the inclusion of webscraping-based nowcasts. Exceptions occur in 0116: *Fruit*, where SARIMA, AR(1), Neuralprophet, CES, ETS, and ensemble forecasts without webscraping are more accurate; and in 0121: *Coffee, tea, and cocoa* when using the Neuralprophet model. Regarding indirect forecasts, nearly all RMSE ratios are below one—again with 0116: *Fruit* and 0121: *Coffee, tea, and cocoa* as the only exceptions. This indicates improved predictive performance from the inclusion of webscraped data.

Level 5. The results at COICOP level 5 are also very promising for both direct (see Table C.15 in the appendix) and indirect (see Table C.16 in the appendix) forecasts. Only in some categories, models using webscraped data are outperformed and forecast errors differ significantly according to the Diebold–Mariano test. This is particularly evident in the case of 01131: *Fresh or chilled fish* and 01163: *Dried fruit and nuts* and for direct and indirect forecasts alike. When considering the results on level 6 (elementary indices), it becomes evident that the aggregate results on level 5 for 01131: *Fresh and chilled fish*, for example, are driven by the poor forecast accuracy of webscraping in the case of 005400: *Fresh fish*.

In summary, the analysis in Section 5.2 indicates that incorporating webscraped nowcasts for the first month can improve time-series-based indirect (aggregated) forecasts and direct forecasts at COICOP levels 2 to 5 for a three-month horizon. In other words, accurate webscraped nowcasts can be used to augment multi-step-ahead forecasts, and improvements are evident at higher and lower levels of aggregation.

6. Sensitivity analysis and higher-frequency data

We perform sensitivity analyses along two dimensions. First, we evaluate the potential impact of structural shifts in food price dynamics linked to the onset of Russia's invasion of Ukraine in February 2022. Second, we examine the impact of incorporating higher-frequency data into an unrestricted mixed-data sampling (UMIDAS) framework.

6.1. Possible structural breaks in food prices and external validity

As clearly illustrated in the introduction in Fig. 1, aggregate food price inflation increased sharply following the Covid-19 pandemic and the Russian invasion of Ukraine in February 2022. While global food commodity prices had already begun to rise in 2020, the invasion of Ukraine caused inflation to reach new heights, with wheat and maize prices particularly affected (see, for instance, European Central Bank, 2022).

Our webscraped data sample, which ranges from January 2021 to December 2024, covers a period of rising food inflation, with month-on-month rates peaking at 2.6% in February 2022.[21] Consequently, the advantages of webscraped data outlined above may not necessarily extend to more stable inflation regimes, when inflation rates lack a persistent upward trend and exhibit weaker correlations at the level of elementary indices. To assess the stability of forecast performance across inflation regimes, we compare the distributions of RMSEs from the out-of-sample one-month-ahead forecasts of elementary indices (level 6) before (see Table 8) and after the Russian invasion of Ukraine in February 2022 (see Table 9).

Despite the potential structural break in food price dynamics, the differences in mean and median RMSEs are negligible across the two samples, and the standard deviations of forecast errors do not change materially between the two periods.

Accordingly, both webscraping and model-based forecasts perform equally well in the relatively low-inflation period, with average month-on-month inflation rates for *Food and non-alcoholic beverages* of 0.38% from January 2021 to February 2022, and 0.59% from March 2022 to December 2024. These findings are encouraging, suggesting

21 This excludes the effects arising from the introduction of scanner and online data in the HICP compilation by Statistics Austria in January and February 2021, which were briefly discussed in Section 1.

Table 8
Forecast accuracy metrics for elementary indices (level 6).

Type	Mean	Median	SD	Min	Q1	Q3	Max	N
AO-S	3.43	3.03	1.87	0.65	2.08	4.21	9.81	130
AR(1)	3.24	2.61	2.09	0.43	1.94	3.93	12.84	130
CES	3.31	2.89	1.81	0.63	2.08	3.98	9.49	130
ETS	3.27	2.91	1.79	0.48	2.04	3.92	10.51	130
Ensemble (w WS)	3.04	2.72	1.65	0.46	1.90	3.81	8.76	130
Ensemble (wo WS)	3.10	2.69	1.70	0.49	1.94	3.77	9.03	130
LW-S	3.29	2.96	1.83	0.60	1.94	4.02	10.11	130
Neuralprophet	3.83	3.25	2.27	0.81	2.32	4.57	13.67	130
Prophet	3.32	2.99	1.83	0.69	2.05	3.95	9.87	130
RW-S	4.38	3.61	2.50	0.84	2.58	5.84	14.06	130
SARIMA	3.12	2.58	1.80	0.43	1.96	3.87	10.02	130
Theta	3.41	3.01	1.87	0.50	2.13	4.15	11.02	130
Webscraping	3.24	2.82	1.91	0.59	1.93	3.85	14.00	130

Note: Table 8 presents summary statistics for the RMSEs of the one-step-ahead forecasts of the elementary indices (level 6). The out-of-sample forecasts cover the period from January 2021 to February 2022, ending just before the outbreak of the Russia–Ukraine conflict.

Table 9
Forecast accuracy metrics for elementary indices (level 6).

Type	Mean	Median	SD	Min	Q1	Q3	Max	N
AO-S	3.14	2.58	2.00	0.78	1.98	3.68	14.09	130
AR(1)	3.06	2.45	1.87	0.81	1.93	3.42	10.28	130
CES	3.17	2.62	1.82	0.81	1.94	3.66	9.04	130
ETS	3.07	2.53	1.91	0.82	1.97	3.30	12.90	130
Ensemble (w WS)	2.81	2.29	1.65	0.73	1.82	3.07	9.17	130
Ensemble (wo WS)	2.92	2.36	1.70	0.76	1.89	3.16	9.23	130
LW-S	3.05	2.56	1.69	0.84	1.96	3.59	8.79	130
Neuralprophet	3.39	2.81	1.94	0.96	2.13	3.88	10.09	130
Prophet	3.08	2.50	1.92	0.75	1.92	3.41	13.35	130
RW-S	3.92	3.05	2.60	0.80	2.42	4.39	17.00	130
SARIMA	3.19	2.61	1.79	0.94	2.06	3.65	9.46	130
Theta	3.10	2.48	1.97	0.74	1.98	3.28	12.17	130
Webscraping	2.98	2.54	1.72	0.81	1.93	3.43	10.03	130

Note: Table 9 presents summary statistics for RMSEs of the one-step-ahead forecasts of the elementary indices (level 6). The out-of-sample forecasts cover the period from March 2022 to December 2024, starting shortly after the outbreak of the Russia–Ukraine conflict.

that the forecast accuracy of webscraped data is robust across different inflation regimes, consistent with evidence from Szafranek et al. (2025), who show that webscraped data remain highly effective even under heightened uncertainty.

6.2. Nowcasting with weekly indices in an unrestricted mixed-data sampling (UMIDAS) model

With higher-frequency data becoming more widely available to researchers, the question of how to effectively exploit such information to improve forecasts naturally arises (see Foroni & Marcellino, 2014; Ghysels et al., 2004). Modugno (2013), for instance, uses weekly and daily prices of raw materials and financial variables, showing that these help improve the forecast accuracy of U.S. headline inflation, particularly at short horizons (i.e. for nowcasting purposes). Recent empirical contributions in the field of inflation nowcasting have, for instance, employed scanner or webscraped data with weekly availability to improve upon inflation nowcasts that disregard this higher frequency dimension (see Beck et al., 2023).

In our now- and forecasting competition above, we aggregate the webscraped daily price time series to monthly price indices on the level of elementary indices in order to align as closely as possible with the official Eurostat and Statistics Austria methodology. Nevertheless, it is worthwhile to examine whether the higher-frequency data can enhance forecast accuracy. Therefore, we consider an unrestricted mixed data sampling (UMIDAS) model.

Instead of averaging product prices and aggregating to monthly indices, as is laid out in Appendix A.3, we compile weekly inflation rates $y_t^{(w)}$ where week w is part of the month–year period t for all HICP index positions considered above. Accordingly, we estimate the following UMIDAS model for month-on-month inflation rates:

$$y_t = \alpha + \sum_{w=1}^{4} \beta_w y_t^{(w)} + \sum_{p=1}^{3} \kappa_p y_{t-p} + \sum_{s=1}^{11} \gamma_s d_s + \varepsilon_t, \tag{20}$$

where $d_1, \ldots, d_{11}$ are monthly dummy variables (with January omitted as the baseline), and y_{t-p} denotes lags of the published HICP index position. Higher-frequency weekly inflation rates based on webscraping indices $y_t^{(w)}$ are constructed, as in Beck et al. (2023), such that week one covers days one to seven of a given month, week two covers days eight to 14, and so on.

While the limited size of our webscraped sample precludes a formal out-of-sample forecast evaluation, the in-sample exercise presented remains informative for two reasons. First, evidence from the inflation nowcasting literature using scanner data (see Beck et al., 2023) suggests that exploiting higher-frequency information can improve forecast accuracy, thereby motivating an investigation of our readily available webscraped price data. Second, we include weekly indices of webscraped prices as explanatory variables on the right-hand side of the above equation to assess whether price data from the first days of a given month already provide a competitive (in-sample) inflation nowcast.[22] To the best of our knowledge, this is the first study to implement a UMIDAS model at the highly granular level of elementary HICP indices and to provide supporting evidence that webscraped online price data collected at the onset of each month can already serve as a competitive food inflation nowcast.

Table C.25 and Table C.26 in the appendix report the in-sample OLS estimates of the UMIDAS models for the 130 elementary indices. The models exhibit a relatively strong in-sample fit, with an average R^2 of about 61% across index categories. The subsequent discussion focuses on identifying the explanatory variables that contribute most to model fit. Among the 130 estimated models, 75 include coefficients on the weekly indices that are statistically significant at the 1%, 5%, or 10% level. The first week of the month is particularly relevant in 50 models. In 36 cases, the first week and one or more subsequent weeks are significant, suggesting that the first half of the month tends to play a stronger role. In 28 categories, both the first and second weeks display statistically significant coefficients. It is noteworthy that only 18 models yield statistically significant coefficients for week four. These findings are consistent with evidence for German scanner data in Beck et al. (2023), who report that additional information obtained in the latter half of the month is of limited importance. This result also aligns with the practice of compiling the HICP by Statistics Austria, which primarily relies on scanner data from the first three weeks of each month.

Beck et al. (2023) also document that nowcasts improve particularly for unprocessed fruit and vegetables, dairy products, and fats. Consistent with this finding, we observe that Austrian webscraped data help to explain price variation in similar categories in a UMIDAS setting. These include most subcategories of COICOP-3 0114: *Milk, cheese, and eggs*, as well as 07300: *Butter* and 007800: *Olive oil*. Furthermore, several subcategories of COICOP-5 show significant improvements, in particular 01161: *Fresh or chilled fruit* and 01171: *Fresh or chilled vegetables other than potatoes and other tubers*.

The autoregressive (AR) lags included in the model capture part of the short-run persistence in month-on-month inflation rates. The autoregressive lag coefficients are significant in 50 of the 130 models. The first lag is significant in 30 models, and both the first lag and either the second or third AR lag are also relevant in five of these cases.

Similar to the time series models, seasonal effects are also present at the disaggregated level. In total, 93 of the 130 categories exhibit statistically significant seasonal components. For example, within the COICOP-5 category 01161: *Fresh or chilled fruit*, 11 out of 13 elementary indices show significant effects of the seasonal dummies. Likewise, in 01171: *Fresh or chilled vegetables other than potatoes and other tubers*, seven out of nine elementary indices display significant seasonal variation. Several processed food categories also reveal seasonal patterns, which might be linked to holiday-related consumption, such as increased purchases of chocolate products around Easter and Christmas (012500: *Milk chocolate*, 012550: *Chocolate box*, and 012600: *Chocolate bar*). Similarly, demand for 014800: *Mineral or table water* tends to rise in the summer months. At the same time, there are a few cases that may indicate potential overfitting, as nearly all seasonal dummies are highly significant—for instance, 000800: *White bread*, 000100: *Pizza, deep-frozen*, 005300: *Fish fingers, deep-frozen*, 005500: *Smoked salmon*, 014301: *Coffeepads and caps*.

Consistent with Beck et al. (2023), the UMIDAS approach provides evidence that higher-frequency data can improve forecast accuracy. When only a few years of webscraped data are available, nowcasts can be constructed using UMIDAS models or by incorporating the webscraped indices as exogenous regressors in a SARIMAX specification. However, these approaches sacrifice the long history of elementary indices, which extends much further back and is valuable for modeling time series patterns, such as persistence and seasonality. To address this tradeoff, we are currently pursuing a two-stage process. In Stage 1, we construct weekly and monthly indices based on webscraped data. In Stage 2, we generate short-term forecasts using these indices as nowcasts for the current month, which are available from the first week onward. This exploits the higher frequency of the current month while subsequently employing time series models that incorporate the longer monthly history of the elementary indices.

7. Conclusion

Food and beverage prices are an important and highly volatile component of inflation. A growing body of empirical evidence underscores their relevance for household inflation perceptions and the formation of these perceptions. Consequently, properly monitoring and forecasting their dynamics is of paramount importance for central banks and other policymaking institutions. Recent studies demonstrate that readily available online price data can

[22] With only about 50 monthly observations per elementary index time series, we must balance the inclusion of higher-frequency regressors against the risk of overparameterization, unless Bayesian estimation methods are employed.

provide an effective means of nowcasting food price inflation and can enhance purely model-based forecasts when such data are properly curated and classified according to the index positions used in official compilations. This motivated us to maintain a webscraping framework since 2020 for Austrian retailers at the Oesterreichische Nationalbank (OeNB) and to actively use the collected data for economic analysis and research.

Our study demonstrated that incorporating carefully constructed webscraping indices – by ensuring the quality of the classification of products at the most granular index level and applying official index calculation methodologies – significantly boosts the accuracy of monthly food inflation nowcasts and short-term forecasts for a three-month horizon. While direct forecasts at higher levels of aggregation produce slightly more accurate overall metrics, indirect forecasts derived from disaggregated data provide superior insights into the underlying dynamics of specific sub-components. The main advantage of indirect forecasting is that higher-level aggregates can be accurately broken down into their sub-components, helping forecasters to communicate exactly what is driving their forecast.

We extended the existing literature by being the first to integrate webscraped data into the time series-based short-term forecasts of disaggregated food inflation rates for Austria. Our findings reveal that webscraping not only reduces forecast uncertainty at a disaggregated level but also enhances predictability when aggregated to higher COICOP levels. Additionally, we observed that employing models beyond traditional ARIMA, such as advanced time series and machine learning models, can offer benefits, although they may involve tradeoffs in computational efficiency.

We conducted robustness analyses to evaluate the usefulness of webscraped data for volatile and seasonal HICP categories and tested whether the improvements persisted across different inflation regimes (before and after the Russian invasion of Ukraine). Although univariate time series model ensembles provide strong benchmarks, incorporating webscraped data further improves their accuracy. The higher frequency of such data can be exploited in mixed-data-sampling (MIDAS) models, where webscraped prices in the first weeks of a given month already yield competitive estimates of current inflation. However, reliable out-of-sample forecasts require a sufficiently long history of high-frequency observations. We therefore recommend a balanced strategy: use high-frequency data for monthly nowcasts and incorporate these into model-based forecasts extending up to one quarter ahead.

For practical inflation forecasting in central banks, this means that using state-of-the-art models and software from the machine learning community can help build reliable and automated real-time forecasting tools. Even without webscraped data available for all COICOP categories, our setup can easily incorporate forecasts based on expert judgment or exogenous regressors, thereby providing a flexible and robust framework. Moreover, our results show that nowcasts and short-term forecasts can be improved by compiling higher-frequency price indices based on webscraped data from online retailers. This approach is often more cost-effective than relying on scanner data. It can be applied to HICP categories for which online coverage is sufficiently comprehensive. These advances provide guidance for policymakers and practitioners seeking to develop effective systems for the real-time monitoring and forecasting of inflation dynamics at a granular level.

CRediT authorship contribution statement

Christian Beer: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Robert Ferstl:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Bernhard Graf:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Disclaimer

The views expressed in this paper do not necessarily reflect those of the Oesterreichische Nationalbank or the Eurosystem.

Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.ijforecast.2026.02.003. It contains Appendix A (index compilation), Appendix B (data collection and processing procedures), and Appendix C (detailed results).

Data and code availability

The replication code for the tables and figures is available at https://github.com/datarob/replication_prisma_stf.

References

Anesti, N., Esady, V., & Naylor, M. (2024). *Food prices matter most: Sensitive household inflation expectations*: *No. 2434*, Centre for Macroeconomics (CFM), Discussion Papers. URL: https://ideas.repec.org/p/cfm/wpaper/2434.html.

Aparicio, D., & Bertolotto, M. I. (2020). Forecasting inflation with online prices. *International Journal of Forecasting*, *36*, 232–247. http://dx.doi.org/10.1016/j.ijforecast.2019.04.018.

Assimakopoulos, V., & Nikolopoulos, K. (2000). The theta model: A decomposition approach to forecasting. *International Journal of Forecasting*, *16*, 521–530. http://dx.doi.org/10.1016/S0169-2070(00)00066-2.

Atkeson, A., & Ohanian, L. E. (2001). Are Phillips curves useful for forecasting inflation? *Federal Reserve Bank of Minneapolis Quarterly Review*, *25*, 2–11, Winter 2001.

Barkan, O., Benchimol, J., Caspi, I., Cohen, E., Hammer, A., & Koenigstein, N. (2023). Forecasting CPI inflation components with hierarchical recurrent neural networks. *International Journal of Forecasting*, *39*, 1145–1162. http://dx.doi.org/10.1016/j.ijforecast.2022.04.009.

Beck, G. W., Carstensen, K., Menz, J. O., Schnorrenberger, R., & Wieland, E. (2023). Nowcasting consumer price inflation using high-frequency scanner data: Evidence from Germany. http://dx.doi.org/10.2139/ssrn.4803810, Deutsche Bundesbank Discussion Paper No. 34.

Bonciani, D., Masolo, R., & Sarpietro, S. (2024). *How food prices shape inflation expectations and the monetary policy response*: *No. 135*, Milano: Università Cattolica del Sacro Cuore, Dipartimento di Economia e Finanza (DISCE), Working Paper. URL: https://hdl.handle.net/10419/306810.

Borio, C., Disyatat, P., Juselius, M., & Rungcharoenkitkul, P. (2022). Why so low for so long? A long-term view of real interest rates. *International Journal of Central Banking*, *18*, 47–87.

Cavallo, A. (2017). Are online and offline prices similar? Evidence from large multi-channel retailers. *American Economic Review*, *107*, 283–303. http://dx.doi.org/10.1257/aer.20160542.

Cavallo, A., & Rigobon, R. (2016). The billion prices project: Using online prices for measurement and research. *Journal of Economic Perspectives*, *30*, 151–178. http://dx.doi.org/10.1257/jep.30.2.151.

Cleveland, R. B., Cleveland, W. S., McRae, J. E., & Terpenning, I. (1990). STL: A seasonal-trend decomposition procedure based on Loess. *Journal of Official Statistics*, *6*, 3–73.

D'Acunto, F., Malmendier, U., Ospina-Tejeiro, J., & Weber, M. (2021). Exposure to grocery prices and inflation expectations. *Journal of Political Economy*, *129*, 1615–1639. http://dx.doi.org/10.1086/713192.

Diebold, F. X., & Mariano, R. S. (1995). Comparing predictive accuracy. *Journal of Business & Economic Statistics*, *13*, 253–263. http://dx.doi.org/10.1080/07350015.1995.10524599.

European Central Bank (2022). Economic bulletin: Issue 4, 2022. *ECB Economic Bulletin*, URL: https://www.ecb.europa.eu/pub/pdf/ecbu/eb202204.en.pdf.

Eurostat (2022). *Guide on multilateral methods in the harmonised index of consumer prices: 2022 edition*. Luxembourg: Publications Office of the European Union, http://dx.doi.org/10.2785/873932.

Eurostat (2024). Harmonised index of consumer prices (HICP) methodological manual – 2024 edition. *Eurostat Manual and Guidelines*, http://dx.doi.org/10.2785/055028.

Faust, J., & Wright, J. H. (2013). Chapter 1 – forecasting inflation. In G. Elliott, & A. Timmermann (Eds.), *Handbook of economic forecasting*: *Vol. 2*, (pp. 2–56). Elsevier.

Fiorucci, J. A., Pellegrini, T. R., Louzada, F., Petropoulos, F., & Koehler, A. B. (2016). Models for optimising the theta method and their relationship to state space models. *International Journal of Forecasting*, *32*, 1151–1161. http://dx.doi.org/10.1016/j.ijforecast.2016.02.005.

Foroni, C., & Marcellino, M. (2014). *Mixed frequency structural VARs*: *No. 2014/01*, Norges Bank, Working Paper. URL: https://ideas.repec.org/p/bno/worpap/2014_01.html.

Garza, F., Canseco, M. M., Challú, C., & Olivares, K. G. (2022). StatsForecast: Lightning fast forecasting with statistical and econometric models. PyCon Salt Lake City, Utah, US 2022. URL: https://github.com/Nixtla/statsforecast.

Gautier, E., Karadi, P., Conflitti, C., Fabo, B., Fadejeva, L., Fuss, C., Kosma, T., Jouvanceau, V., Martins, F., Menz, J. O., Messner, T., Petroulas, P., Roldan-Blanco, P., Rumler, F., Santoro, S., Wieland, E., & Zimmer, H. (2023). Price adjustment in the Euro area in the low-inflation period: Evidence from consumer and producer micro price data. In *Occasional Paper Series*: *No. 319*, European Central Bank.

Ghysels, E., Santa-Clara, P., & Valkanov, R. (2004). *The MIDAS touch: Mixed data sampling regression models*: *No. 2004s-20*, CIRANO, CIRANO Working Papers. URL: https://ideas.repec.org/p/cir/cirwor/2004s-20.html.

Graf, B. (2024). Inflation forecasting with the Lunsford-West model. *Internal OeNB Presentation*.

Harchaoui, T. M., & Janssen, R. V. (2018). How can big data enhance the timeliness of official statistics?: The case of the U.S. consumer price index. *International Journal of Forecasting*, *34*, 225–234. http://dx.doi.org/10.1016/j.ijforecast.2017.12.002.

Harvey, D., Leybourne, S., & Newbold, P. (1997). Testing the equality of prediction mean squared errors. *International Journal of Forecasting*, *13*, 281–291. http://dx.doi.org/10.1016/S0169-2070(96)00719-4.

Hyndman, R., Koehler, A., Ord, J., & Snyder, R. (2008). *Forecasting with exponential smoothing: The state space approach*. Springer Berlin Heidelberg.

Joseph, A., Potjagailo, G., Chakraborty, C., & Kapetanios, G. (2024). Forecasting UK inflation bottom up. *International Journal of Forecasting*, *40*, 1521–1538. http://dx.doi.org/10.1016/j.ijforecast.2024.01.001.

Kučerová, Z., Pakši, D., & Koňařík, V. (2024). Macroeconomic fundamentals and attention: What drives European consumers' inflation expectations? *Economic Systems*, *48*, Article 101153. http://dx.doi.org/10.1016/j.ecosys.2023.101153.

Lunsford, K. G., & West, K. D. (2019). Some evidence on secular drivers of US safe real rates. *American Economic Journal: Macroeconomics*, *11*, 113–139. http://dx.doi.org/10.1257/mac.20180005.

Macias, P., Stelmasiak, D., & Szafranek, K. (2023). Nowcasting food inflation with a massive amount of online prices. *International Journal of Forecasting*, *39*, 809–826. http://dx.doi.org/10.1016/j.ijforecast.2022.02.007.

Makridakis, S., & Hibon, M. (2000). The M3-competition: Results, conclusions and implications. *International Journal of Forecasting*, *16*, 451–476. http://dx.doi.org/10.1016/S0169-2070(00)00057-1.

Makridakis, S., Spiliotis, E., & Assimakopoulos, V. (2020). The M4 competition: 100,000 time series and 61 forecasting methods. *International Journal of Forecasting*, *36*, 54–74. http://dx.doi.org/10.1016/j.ijforecast.2019.04.014.

Medeiros, M. C., Vasconcelos, G. F. R., Veiga, Á., & Zilberman, E. (2021). Forecasting inflation in a data-rich environment: The benefits of machine learning methods. *Journal of Business & Economic Statistics*, *39*, 98–119. http://dx.doi.org/10.1080/07350015.2019.1637745.

Modugno, M. (2013). Now-casting inflation using high frequency data. *International Journal of Forecasting*, *29*, 664–675. http://dx.doi.org/10.1016/j.ijforecast.2012.12.003.

Nason, G. P., & Palasciano, H. A. (2025). Forecasting UK consumer price inflation with RaGNAR: Random generalised network autoregressive processes. *International Journal of Forecasting*, http://dx.doi.org/10.1016/j.ijforecast.2025.04.005.

Paranhos, L. (2025). Predicting inflation with recurrent neural networks. *International Journal of Forecasting*, http://dx.doi.org/10.1016/j.ijforecast.2024.07.010.

Russel, R. (2022). StatsForecast: ARIMA and Prophet adapter. https://github.com/Nixtla/statsforecast/tree/main/experiments/arima_prophet_adapter. (Accessed 3 September 2024).

Sengupta, S., Chakraborty, T., & Singh, S. K. (2025). Forecasting CPI inflation under economic policy and geopolitical uncertainties. *International Journal of Forecasting*, *41*, 953–981. http://dx.doi.org/10.1016/j.ijforecast.2024.08.005.

Carrera de Souza, T. (2022). Reassessing sticky price models through the lens of scraped price data. *Ensayos Económicos*, *1*, 66–108.

Soybilgen, B., Yazgan, M. E., & Kaya, H. (2023). Nowcasting Turkish food inflation using daily online prices. *Journal of Business Cycle Research*, *19*, 171–190. http://dx.doi.org/10.1007/s41549-023-00084-2.

Statistik Austria (2022). Standard-Dokumentation Metainformationen zum Verbraucherpreisindex und Harmonisierter Verbraucherpreisindex.

Svetunkov, I., Kourentzes, N., & Ord, J. K. (2022). Complex exponential smoothing. *Naval Research Logistics*, *69*, 1108–1123. http://dx.doi.org/10.1002/nav.22074.

Szafranek, K., Macias, P., Stelmasiak, D., & Błażejowska, A. (2025). Is big data a big help? Evidence from nowcasting food inflation during Covid-19 and wartime. *Journal of Forecasting*, *44*, 2346–2363. http://dx.doi.org/10.1002/for.70013.

Taylor, S. J., & Letham, B. (2018). Forecasting at scale. *The American Statistician*, *72*, 37–45. http://dx.doi.org/10.1080/00031305.2017.1380080.

Triebe, O., Hewamalage, H., Pilyugina, P., Laptev, N., Bergmeir, C., & Rajagopal, R. (2021). NeuralProphet: Explainable forecasting at scale. URL: https://arxiv.org/abs/2111.15397. arXiv:2111.15397.