Geneva, 2023, June 7-9

UNECE CPI Expert Group meeting

DEFINING PRODUCTS WITH TRANSACTION DATA: AGGREGATION METHODS AND ASSESSMENT OF THEIR IMPACT

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- Product definition and the relaunches problem
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- Results: GEKS Törnqvist on different stratifications
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Scanner data to estimate Italian inflation: the state of play

- Since 2018, Istat has been using scanner data for grocery products (excluding fresh food) to compile CPIs.
- In 2023, scanner data for 4,238 outlets (483 hypermarkets, 1,577 supermarkets, 588 discounts, 1,066 outlets with surface between 100 and 400 s.m. and 569 specialist drug). These outlets belong to the main 21 RTCs and cover the entire national territory (agreement with RTCs, and Nielsen cooperation)
- Starting from 2020, a dynamic approach has been adopted by considering all the matched GTINs in two consecutive months within each outlet and ECR4 market (representative of elementary aggregates).
- In the context of a dynamic approach, a procedure that manages the issue of relaunches has been implemented and used in the current production process, but the relaunches detected are a few.
- During the last three years, we carried out some empirical research on the use of multilateral methods (ML), whose results have been presented at the meetings of the dedicated Eurostat task force, at the UNECE expert group meetings and finally at the last Ottawa Group meeting.
- The idea is to introduce the ML method into the production of CPIs in the next future.

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Product definition and the relaunches problem

- Product specification has been recognized as a critical step that can strongly influence the performance of different methods for transaction data (Lamboray, 2022). While scanner data helps reducing lower-level substitution bias, other biases can appear because products are too tightly or too broadly defined.
- Tightly specified products may cause a bias as new and disappearing products in the two comparison periods are not considered in a matched price index (De Haan and Krisinich, 2014).
- Broadly specified products may cause a bias as the underlying transactions that make up the individual product may not be of the same quality, i.e. unit value bias (Dalen, 2017)

AIMS:

- This research work is aimed at testing in an experimental way the use of MARS (Chessa 2016, 2021) on Italian scanner data, to find a compromise between homogeneity and stability over time, looking also at the chance to better manage, through this way, the issue of relaunch.
- The GEKS-Törnqvist multilateral matched method is also applied to compile indices and to analyse the impact of different grouping of GTINs.

The MARS approach

- Several ways of partitioning a set of GTINs exist, each of which may have a different impact on product match and homogeneity and consequently on price changes.

- MARS combines a measure of product match:

$$\mu_t^K = \frac{\sum_{k \in K_{0,t}} q_t^K}{\sum_{i \in G_t} q_{i,t}}$$

and a measure of product homogeneity:

$$R_t^K = \frac{\sum_{k \in K} \ q_t^K \left(\bar{p}_t^K - \bar{p}_t \ \right)^2}{\sum_{i \in G_t} q_{i,t} \left(p_{i,t} - \bar{p}_t \ \right)^2}$$

Where $K_{0,t}$ is a set of products that are sold both in a fixed base month 0 (December of the previous year) and a second month t while G_t is the set of items sold in month t.

R squared and degree of product match are thus combined as follows to evaluate and rank item partitions

$$M_t^K = \mu_t^K R_t^K \qquad 0 \leq M_t^K \leq 1$$

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The case study for the experimental application of MARS

- Three product aggregates have been selected for the present exercise:
  - Rice; Chocolate; Products for the hygiene of the body.

- Data comes from the outlets of the province of Rome* and are referred to the period Dec-20: Apr-23.

- Transaction data are firstly aggregated by outlet type (hypermarkets, supermarket, discounts and specialist drug) across chains and location.

- The other dimensions, which are taken into account to define homogeneous groups of GTINs, are:
  - Brand; ECR markets; packaging volume (grams, centilitres).

* 127 outlets are included in the sample for year 2023: 57 supermarkets; 26 outlets with surface between 100 and 400 s.m.; 19 discounts; 9 hypermarkets; 16 specialist drug.

The case study for the experimental application of MARS

- Firstly, we tried to assess the impact of the different dimensions by testing if they significantly affect the price levels. To this aim, regression models were used:

$$\ln\left(p_i^t\right) = \alpha + \sum_k \beta_k x_{ki} + \sum_h \gamma_h y_{hi} + \sum_j \delta_j z_{ji} + \sum_s \eta_s v_{si} + \sum_t \theta_t w_t + u_i^t$$

Where p_i^t is the price of the reference i in period t and x, y, z, v, w are dummies for: brand; outlet type; market; packaging volume and time.

- As a second step, we consider different stratifications of GTINs, corresponding to different groups of products:

  S0) the narrowest defined groups of products. In this case, each group consists of a single GTIN per outlet type (the single item is identified by the combination of a GTIN and an outlet type).

Data description

S1) In the second case, strata (homogenous groups of items) are defined by market; brand and size: for each stratum, the price (quantity) is the unit value (total quantity) calculated considering all the GTINs of the same market, brand and packaging volume.

S2) the broadly defined groups of products, which correspond to stratification of GTINs according to market and packaging volume.

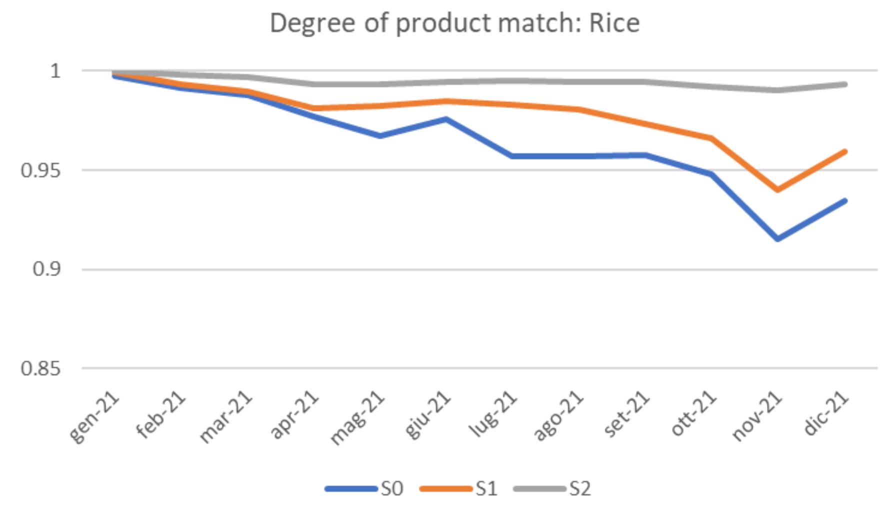
The table shows the number of markets, brands, different packaging volumes and GTINs for the three products explored in our exercise.

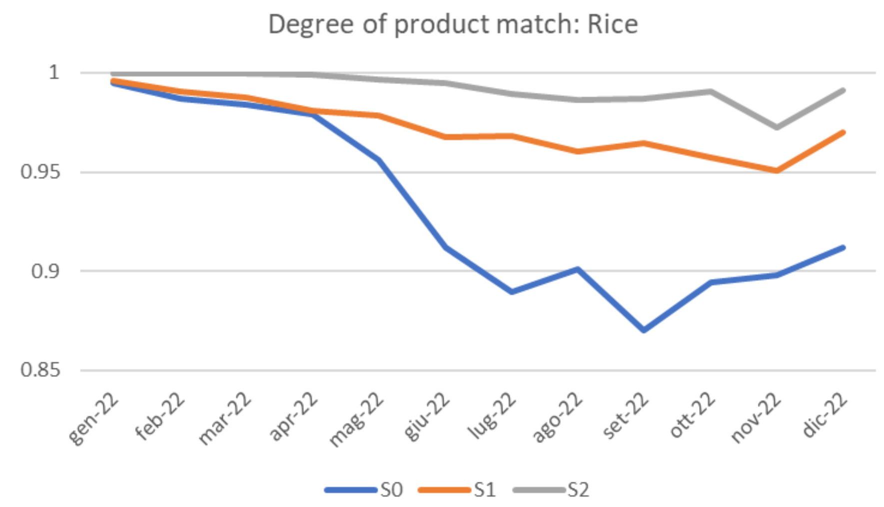
It also shows the number of strata that corresponds to the alternative definitions of product groups.

	Rice	Chocolate	Hygiene products
ECR markets	12	15	8
Brands	92	340	387
Packaging volums	16	192	65
GTINs*	397	1.347	2.253
GTINs per outlet type*	798	2.664	4.184
Strata S1*	604	1.588	1.688
Strata S2*	143	715	345

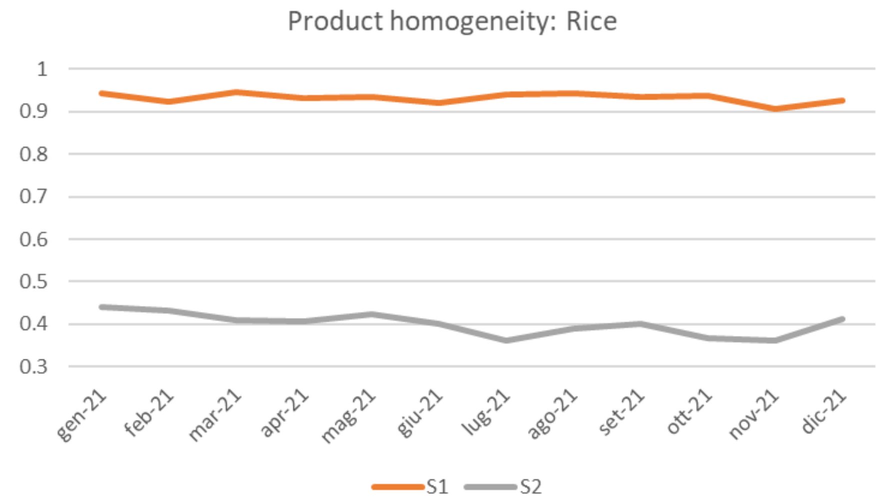
** average (Dec.2020-Apr.2023)*

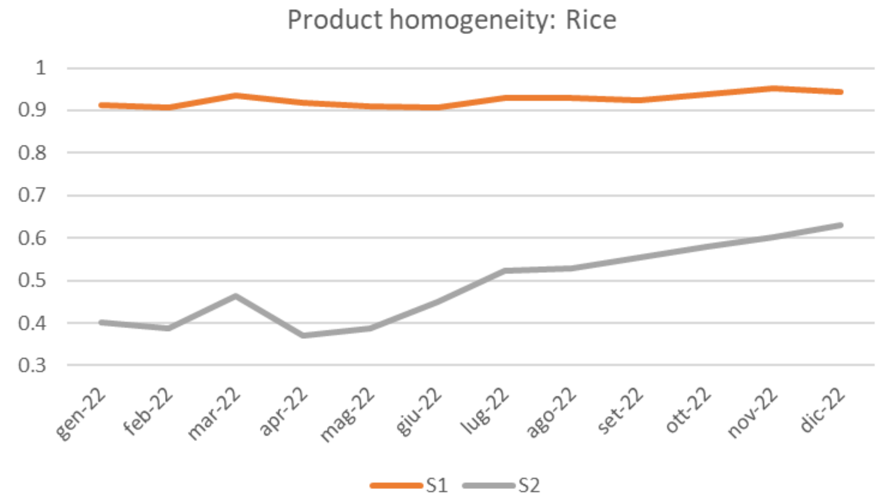
Results: Product match, product homogeneity and scores





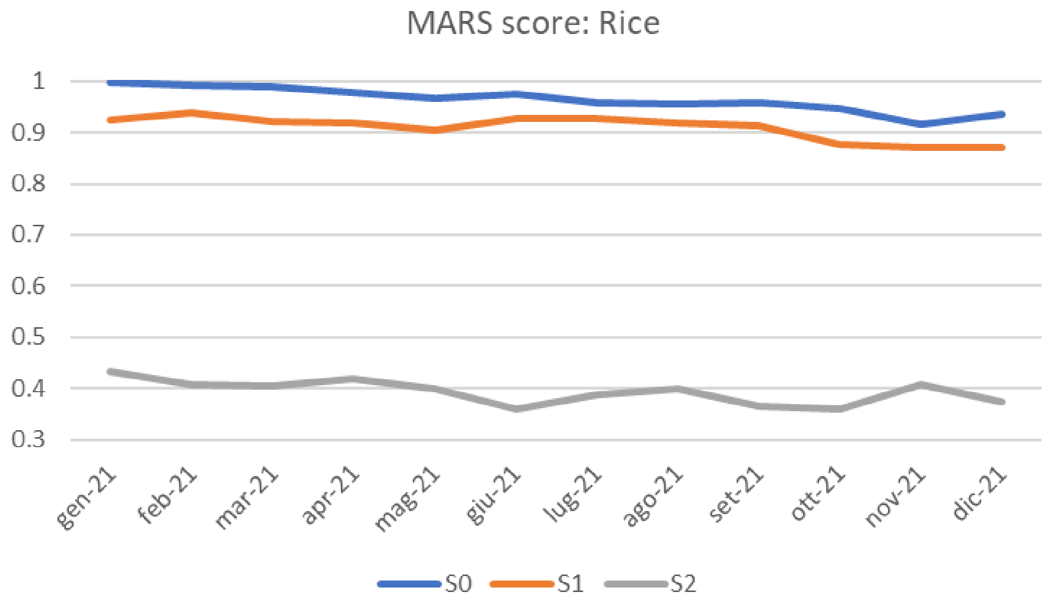
In 2021, the degrees of product match for options S0 and S1 are relatively close to each other. However, in 2022, the decline of the S0 line is significantly larger as compared to S1.

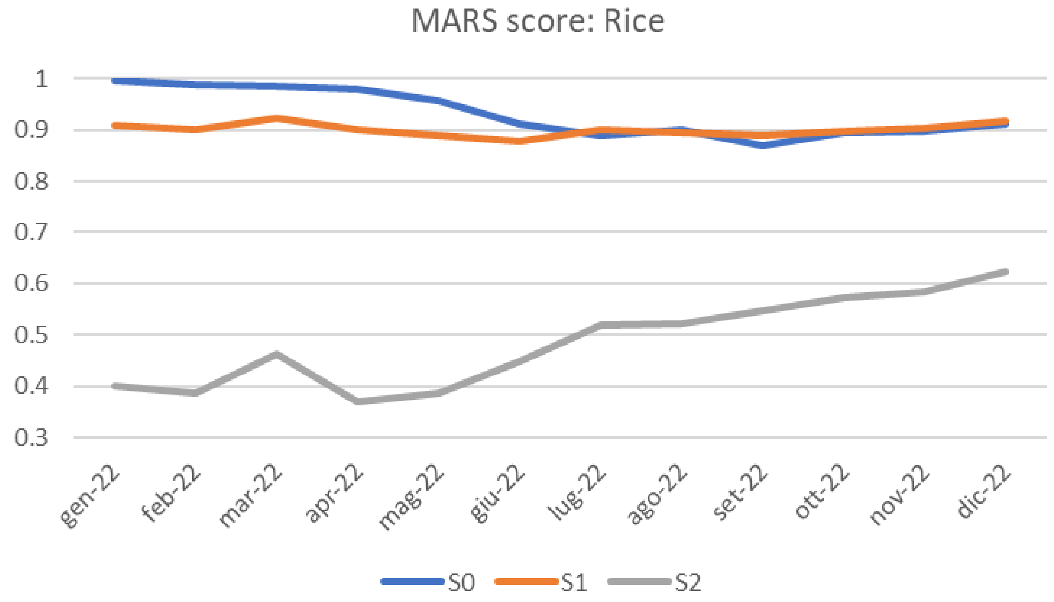




The broadest definition of product groups implies a sharp increase of the degree of heterogeneity

Results: Product match, product homogeneity and scores

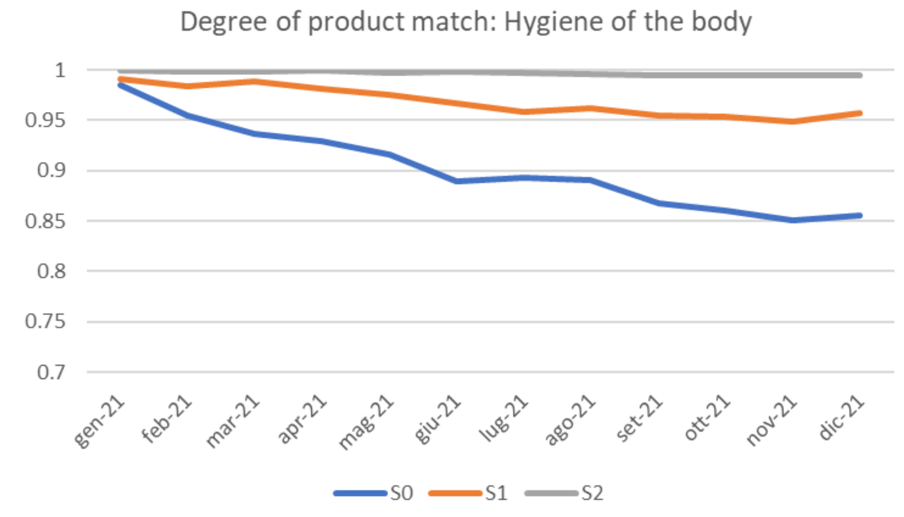


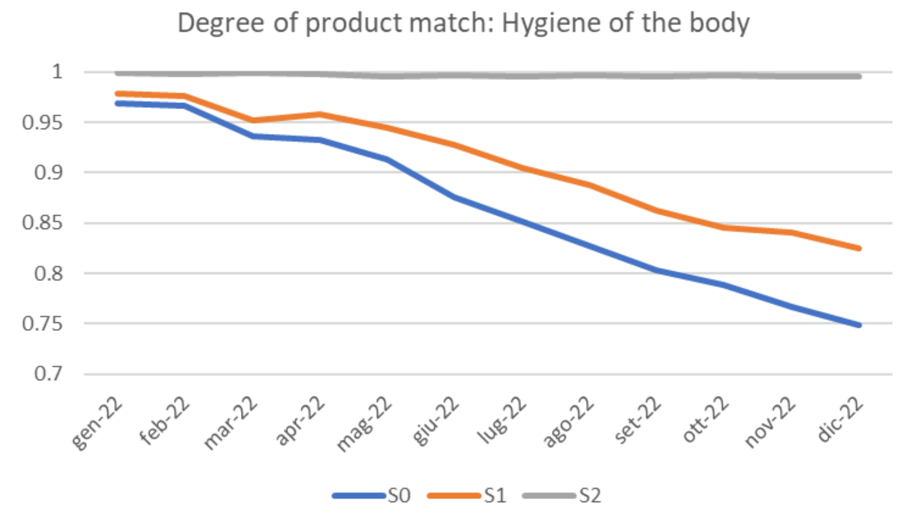


As a result, S0 seems to be the better option in 2021 but this is less evident as year 2022 is concerned.

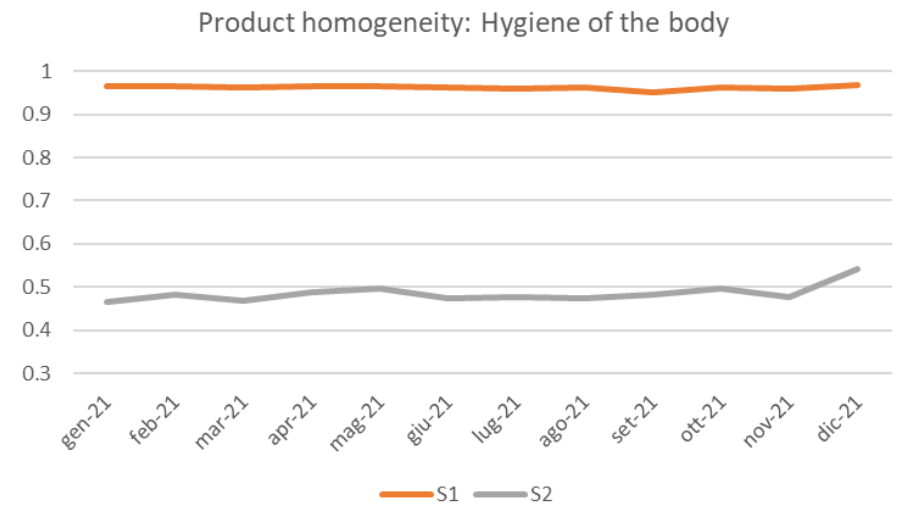
Over the two years, the score of S2 remains far below those of the other two options.

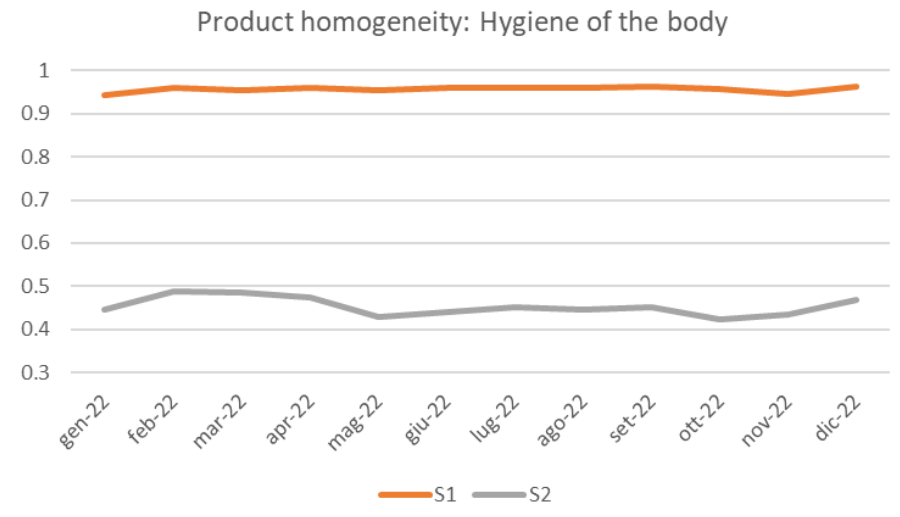
Results: Product match, product homogeneity and scores





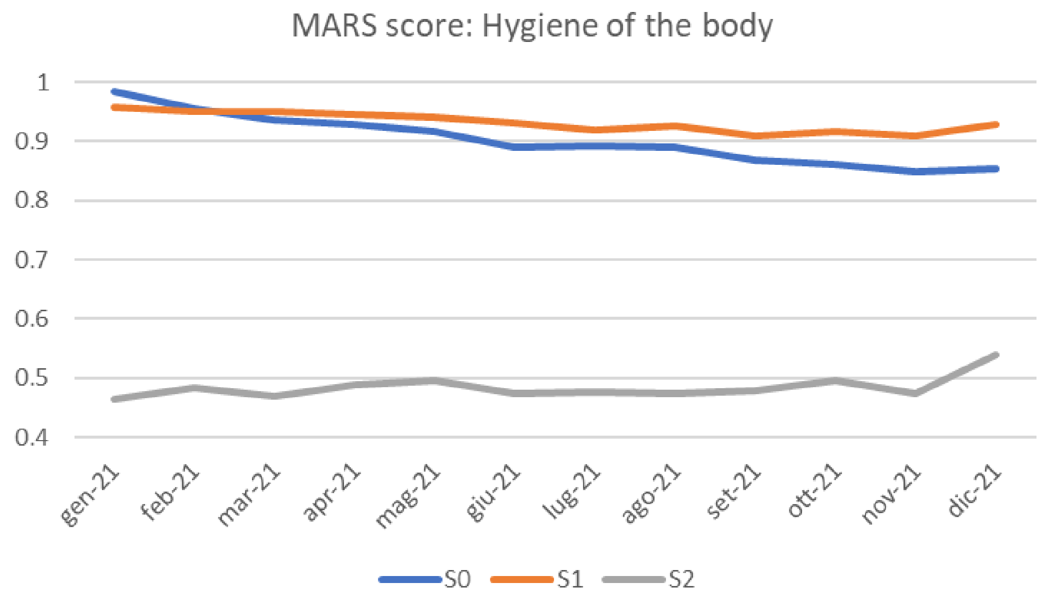
For personal hygiene products the degree of product match of S0 and S1 drops sharply (especially in 2022). Quite the opposite, product match of S2 is almost equal to 100% in both years.

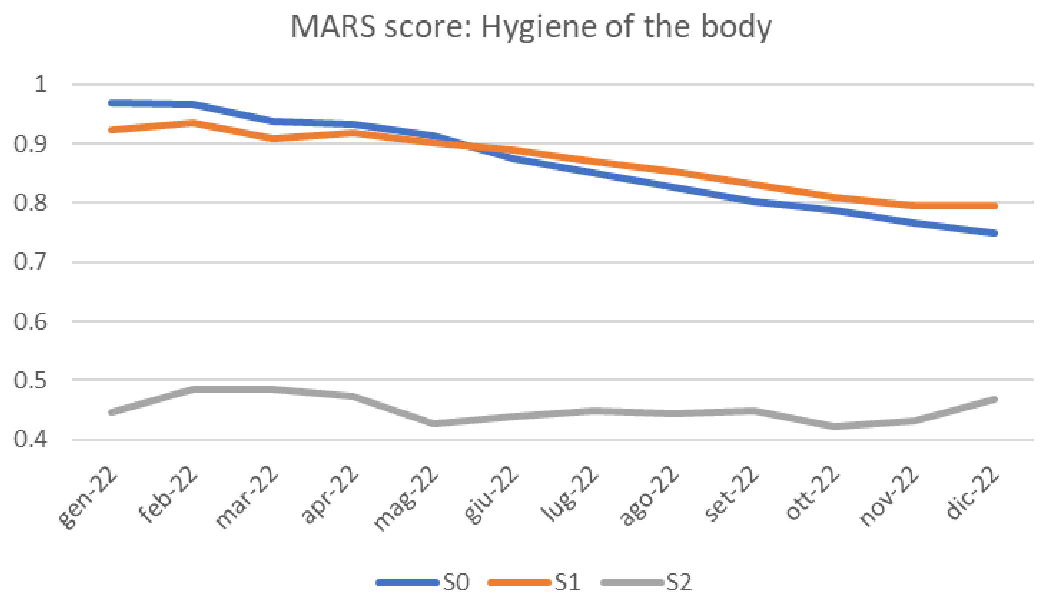




However, concerning S1, product homogeneity is almost equal to 100% in both years.

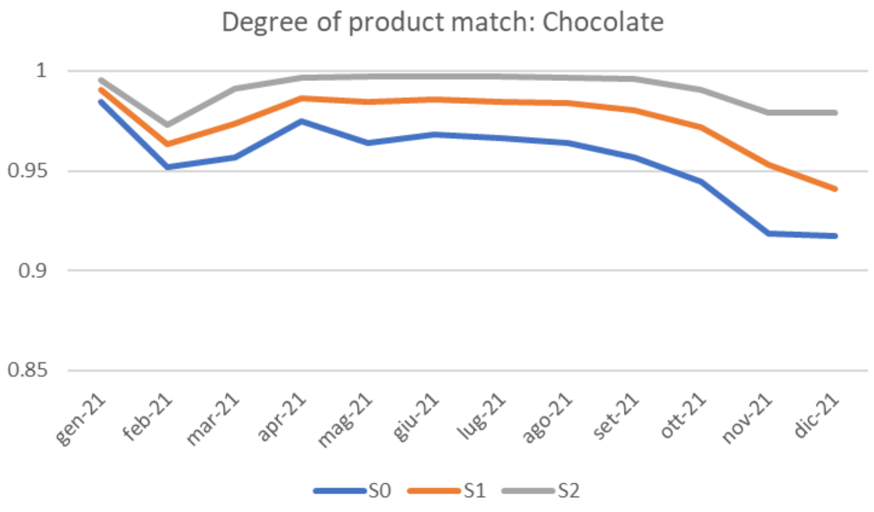
Results: Product match, product homogeneity and scores

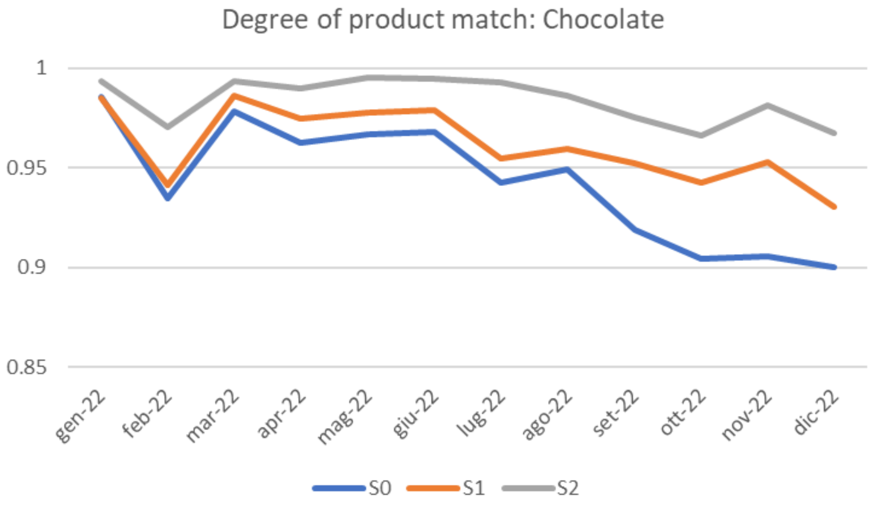


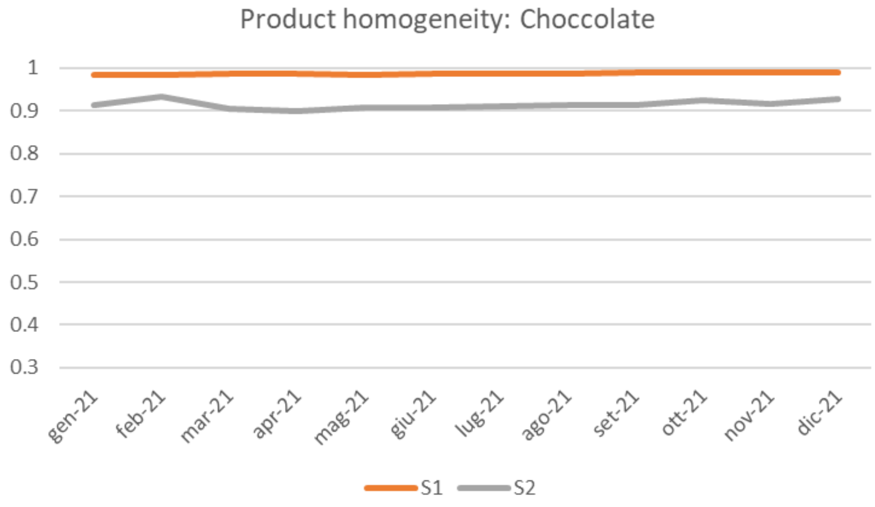


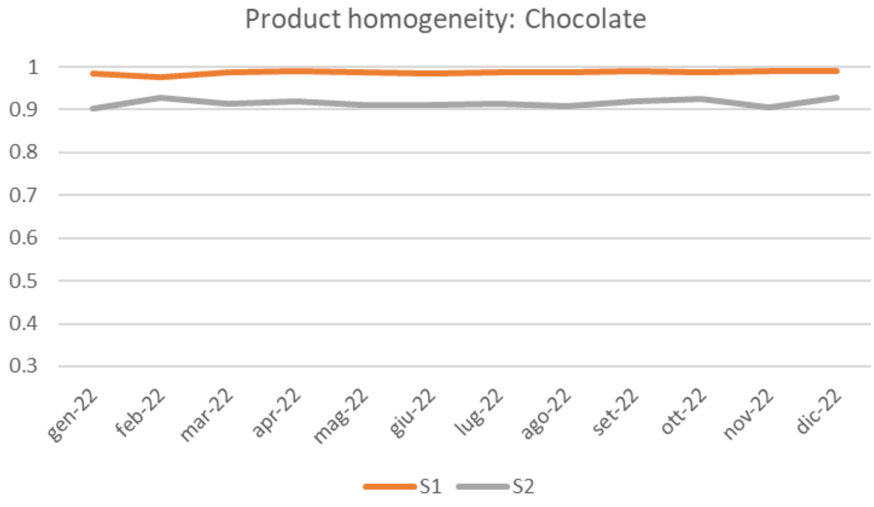
- In this case, the S1 option dominates the alternative stratifications.
- As for rice, the score of S2 remains far below those of the other two options.

Results: Product match, product homogeneity and scores



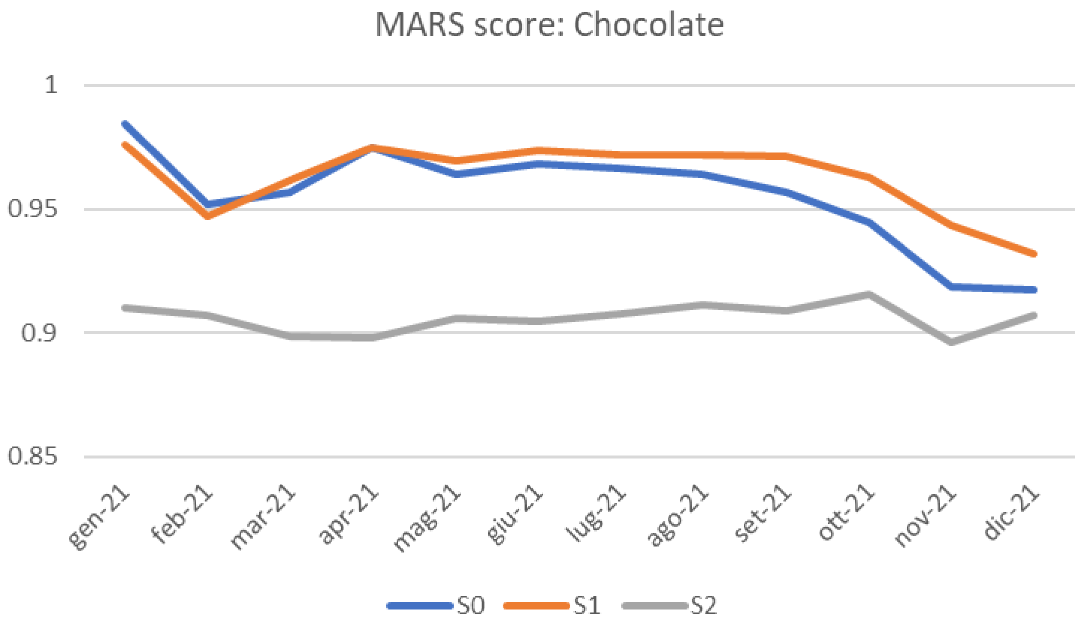


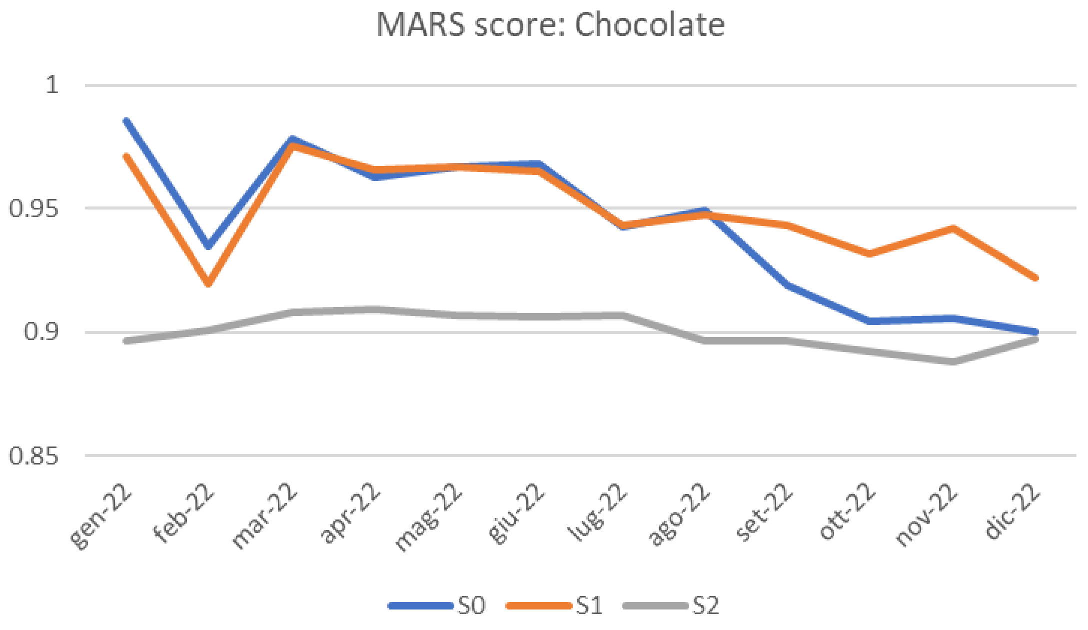




- Moving from S0 to S1, the increase of heterogeneity is very limited. Even option S2 exhibits quite a high degree of product homogeneity.
- In this case, the use of item clustering seems to have clear advantages: while reducing strongly the number of strata (groups) it keeps high level of homogeneity

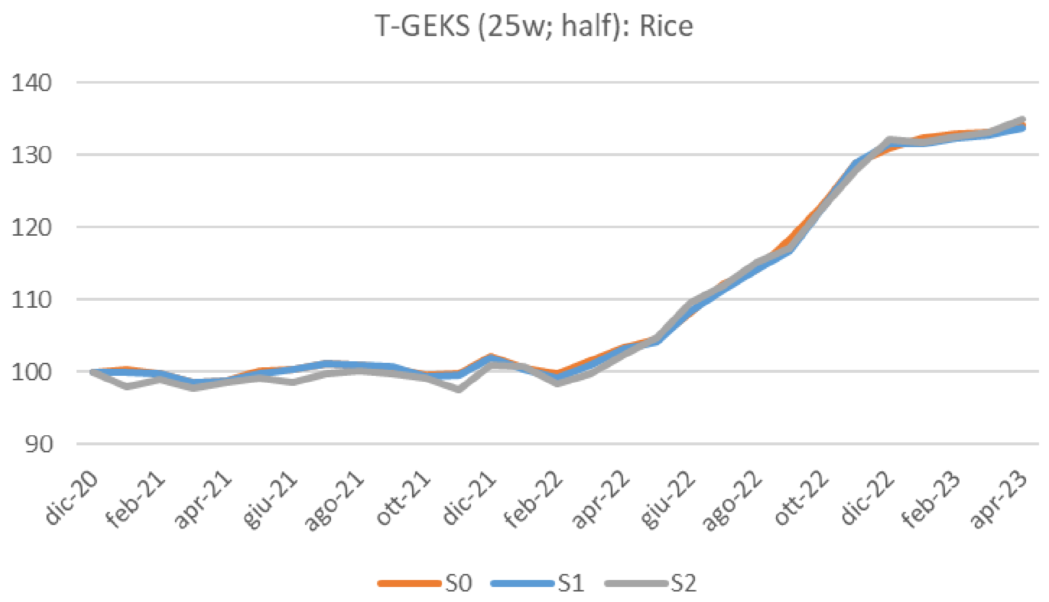
Results: Product match, product homogeneity and scores

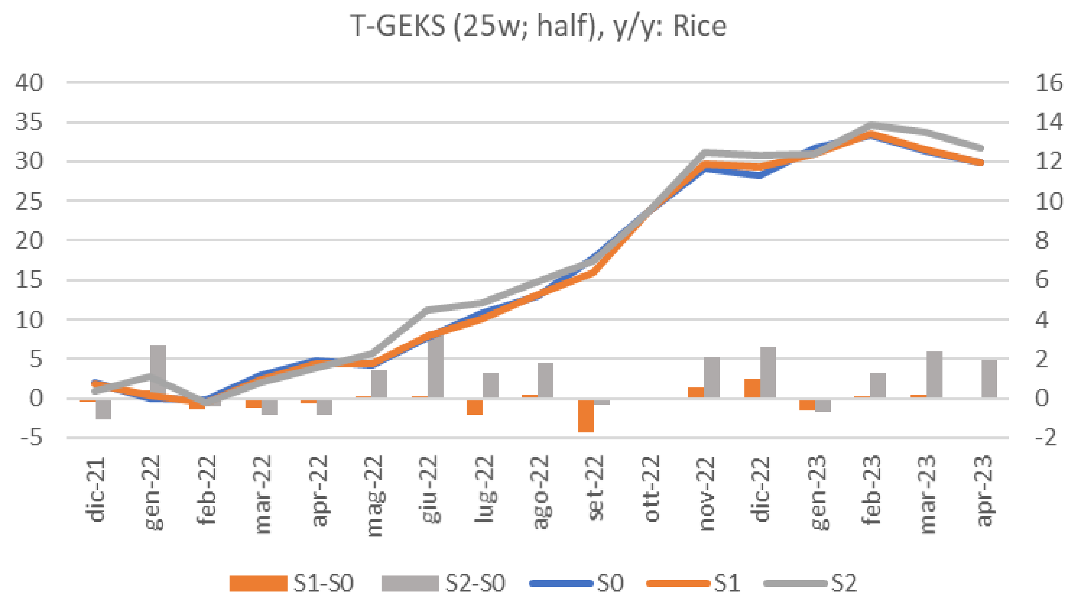




In the case of chocolate, the degree of homogeneity remains above 90%: for that reason, S2 MARS score is relatively close to S0 and S1.

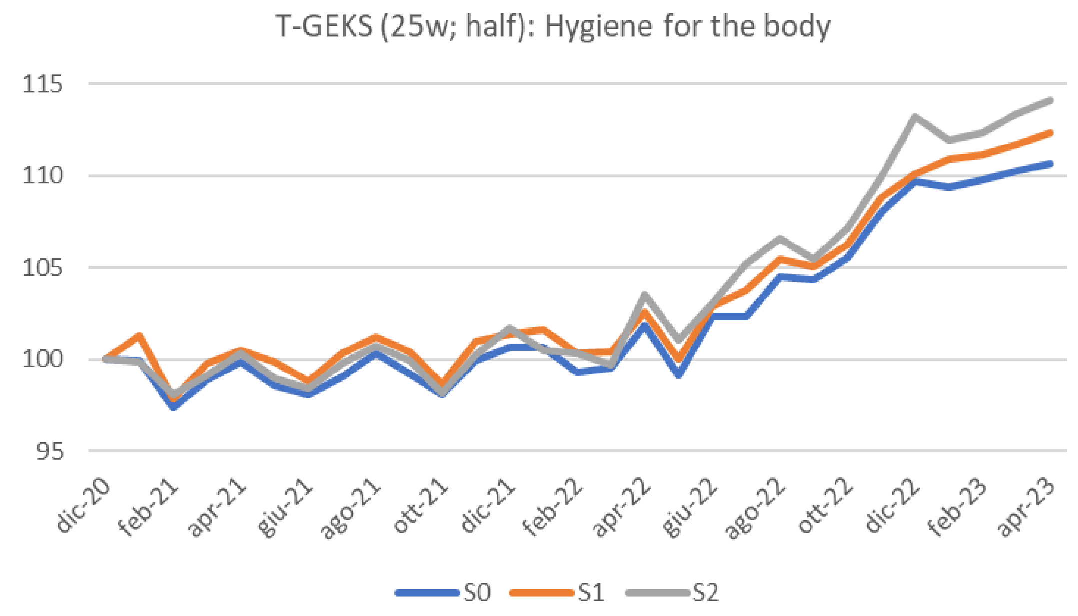
Results: GEKS Tornqvist on different stratifications

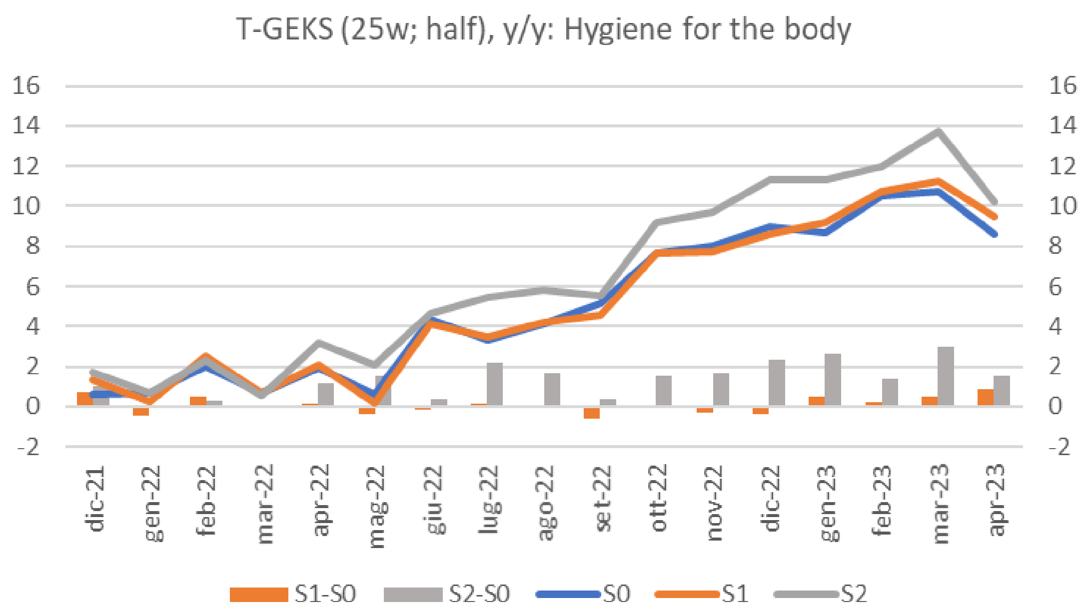




In the case of rice, the higher degree of heterogeneity in the case of S2 seems to produce an upward bias of the annual rates of change of the indices

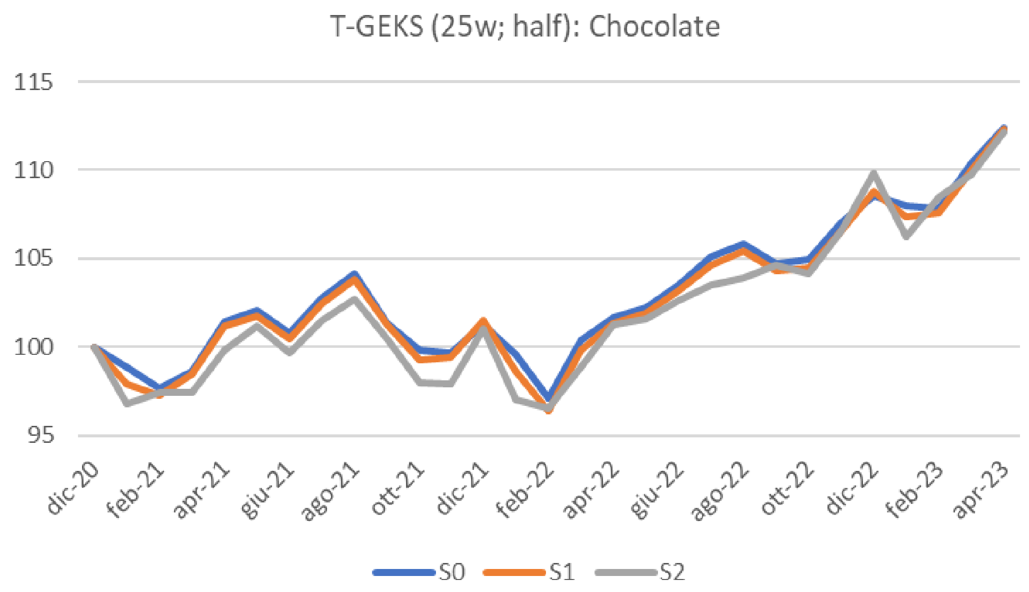
Results: GEKS Tornqvist on different stratifications

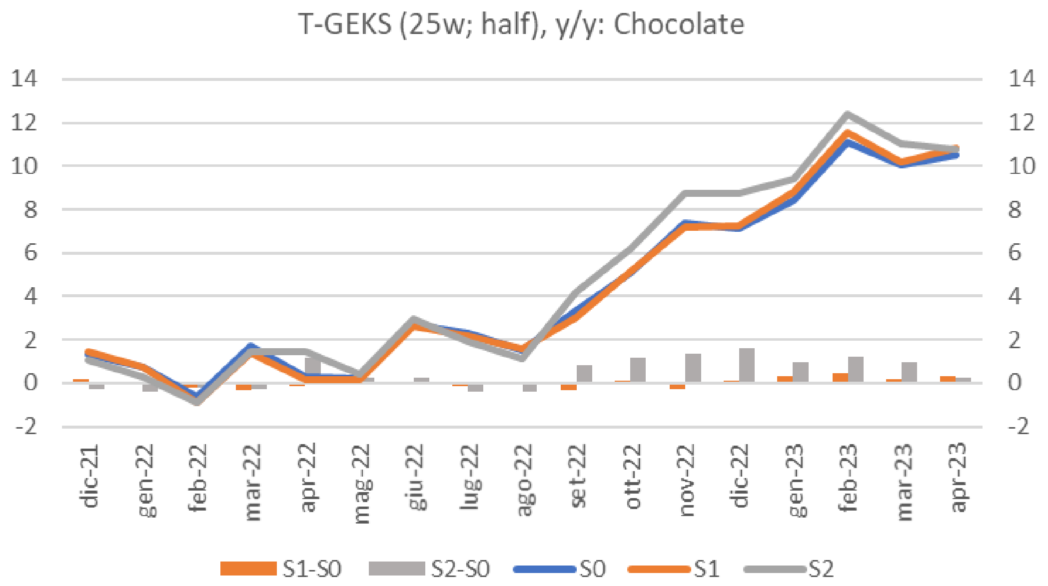




The same conclusion seems to hold for the personal hygiene products. The differences between the different stratification adopted S1, S2 and S0 are not negligible.

Results: GEKS Tornqvist on different stratifications





Even if, in the case of chocolate, S2 introduces an upward bias in the annual rates of change of the index, the differences are less pronounced.

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Conclusive remarks and perspectives

- The results confirm MARS to be a useful tools for finding a compromise between tightly, and broadly specified products avoiding the bias that can derive from these two extreme approaches in particular when there are new and disappearing products in the two comparison periods.

- If the variables to identify the homogeneous groups are correctly detected, match and homogeneity seem to be obtained. Maybe it could be considered the possibility to calculate M_t^K (the combination of R squared, and degree of product match) as a weighted product that gives a wider importance to the homogeneity side

- The variables to identify the homogeneous groups should be refined. In particular, beyond brand and ECR market (and outlet type), different classes of product size should be considered and not only the size of the products as is

- This refinement should help better manage the problems of relaunches related to grocery products and the issues related to shrinkflation, specifically when new packages are proposed, in parallel with the old ones surviving, weakening the capacity to detect the cases of relaunches

- These will be the main points of the next research Istat program in sight of the implementation of the multilateral methods for CPI compilation

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Thank you

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