

# Estimation of local Spatial Price Indices using scanner data: methods and experiments applied also for assessing poor-specific indices

Luigi Biggeri<sup>1</sup>, Monica Pratesi<sup>2</sup>

## Abstract

*This paper presents the organisation and the results of some experiments conducted to estimate Sub-National Spatial Price Indices (SN-SPIs) for the Italian provinces, by using scanner data on retail prices. The objective is twofold: to verify which are the appropriate methodological approaches to estimate SN-SPIs and whether it is possible to estimate poor-specific SN-SPIs, without knowing what prices the poor pay for the various products. Our proposal to abandon the approach of close like-to-like comparability of products results valid and the use of the data from the first quintile of price distributions of each product to estimate poor-specific SN-SPIs is surely interesting. Further research and experiments are needed, which should be conducted also by the National Statistical Institutes of other European countries.*

**Keywords:** Scanner data on retail purchases, sub-national Spatial Consumer Price Indices, poor-specific Spatial Consumer Price Indices, country product dummy model, GEKS method.

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1 University of Firenze and Camilo Dagum Centre on Advanced Statistics for the Equitable and Sustainable Development – ASESD, [luigi.biggeri@unifi.it](mailto:luigi.biggeri@unifi.it).

2 University of Pisa and Camilo Dagum Centre on Advanced Statistics for the Equitable and Sustainable Development – ASESD, [monica.pratesi@unipi.it](mailto:monica.pratesi@unipi.it).

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## 1. Introduction

This paper builds based on a scientific report prepared for the MAKSWELL Project<sup>3</sup>. It refers to the first part of the report moving forward from the results obtained for the estimation of Sub-National Spatial Consumer Price Indices (SN-SCPIs) for each Italian province, by using scanner data on retail prices<sup>4</sup>.

The objective is twofold: first, to verify which are the appropriate methodological approaches to estimate SN-SCPIs and, second, to verify whether it is possible to estimate poor-specific SN-SCPIs, without knowing what prices the poor pay for the various products, and if it is possible to track poor-specific consumption behaviour.

The availability of high-frequency scanner data is surely useful, in addition to traditional sources of price data, to compute the SN-SCPIs.

According to the experiments conducted by various National Statistical Institutes, particularly in Italy, the use of such data has certain advantages but also some limitations which will be summarised in Section 2.

In any case, for the computation and use of the SN-SCPIs, there are two main problems, which arise also by using scanner data, that need to be addressed and possibly solved (ICP-World Bank, 2021).

The first problem refers to the level of comparability of products among the different subnational areas to be achieved. The more tightly the products are defined, the more difficult it becomes to find products meeting the specifications in all the subnational areas. Therefore, to increase the number of comparable products that have to be also representative of each area, it can be appropriate to use loosening specifications of products (Biggeri and Rao, 2021, pag.19).

The second problem depends on the main use of the SN-SCPIs. To provide adequate information regarding the real incidence, nature, and extent of

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3 Deliverable 3.2 of MAKSWELL project. MAKSWELL project (MAKING Sustainable development and WELL-being frameworks work for policy analysis), funded by the European Union's Horizon 2020 Programme, proposes to extend and harmonise the indicators able to capture the main characteristics of the beyond-GDP approach suggesting a new framework that includes them in the evaluation of the public policies.

The authors of this deliverable are: Pratesi, M., C. Giusti, S. Marchetti, L. Biggeri, G. Bertarelli, F. Schirripa Spagnolo, T. Laureti, I. Benedetti, F. Polidoro, F. Di Leo, and M. Fedeli.

4 We have adequately modified the content of various sections especially for the comment of the results obtained and written a new section for the estimation of poor-specific spatial price indices.

economic poverty, it is necessary to use and therefore compute poor-specific SN-SCPIs (Biggeri and Rao, 2021, pp.13-14).

This paper presents the organisation and the results of some experiments conducted to address the issues and achieve the two objectives mentioned above.

The first experiment refers to the general computation of the SN-SCPIs conducted by using the same scanner database and elementary data but applying a different principle of product comparability. One is computed considering the comparison of like-to-like products for the different subnational areas (World Bank approach). The other considers the principle of comparability at the level of very detailed groups of products, by loosening the “tight” specification of the elementary products given that the products of each group satisfy the same consumer needs (that we called the ASESD approach, considering that the idea was born by ASESD Centre’s researchers<sup>5</sup>).

For the computation of poor-specific SN-SCPIs - that is to calculate SPIs closer to the prices paid by the poor - we conducted a second experiment by using price values of the first quintile of the price distribution of each product, assuming for the time being that the poor purchase the less expensive items of a product and that these have prices whose values are below the first quintile of the price distribution.

However, to corroborate this last assumption, it would be important to have some information on the consumption behaviour of poor households. To this aim, we report here some results of a specific tentative survey and analysis on where people in a condition of absolute poverty purchase some large consumption products. This information is collected by the Italian Households Expenditure Survey and the analyses have been conducted by researchers of the Unit of Price Statistics for the MAKSWELL project.

The paper is organised as follows. In Section 2, the database is presented,

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<sup>5</sup> The ASESDS is a Tuscan Universities Research Centre (also called Camilo Dagum Centre) on Advanced Statistics for the Equitable and Sustainable Development-ASESD, which has 61 members.

highlighting the advantages and the limitations of the scanner data on prices for the computation of the SN-SCPIs. In Section 3, the procedure, the methodology, and the main results of the estimation of the indexes obtained by using the World Bank and the ASED approaches are presented. As the results obtained by the two approaches are quite different, we propose, in Section 4, some explanation of the differences and an analysis of their internal consistency. In Section 5, the methodology and the results of the poor-specific SN-SCPIs computation are presented. Section 6 is dedicated to the main results of the analysis of the places where people in a condition of absolute poverty purchase some large consumption products. Final remarks and recommendations in Section 7 conclude the paper.

## **2. The available scanner database: advantages and limitations for the computation of Sub-National Spatial Consumer Price Indices**

The Italian National Institute of Statistics - Istat has over ten years of experience in the usage of the scanner data on retail prices for constructing both CPIs (Consumer Price Indices) and SN-SCPIs (Sub-National Spatial Consumer Prices Indices). Scanner data is the scanning of bar codes at checkout lines of retail stores.

Since 2014, Istat has been receiving the scanner data on the retail prices from the market research company ACNielsen which is authorised to do it by the chains of modern distribution in the framework of an agreement with the Association of Modern Distribution. ACNielsen provides Istat with scanner data every week by uploading the data files on a dedicated Istat web portal.

Recently, Istat has introduced the scanner data in the computation of the official CPIs, while until now the data have been used in the construction of the SN-SCPIs only in an experimental way (Laureti and Polidoro, 2021).

These data benefit from an impressive coverage of transactions along with information on sales, expenditure, quantities, and quality with very detailed information on characteristics of products sold (brand, size, and type of outlet) provided at barcode level or, more precisely, at the GTIN (Global Trade Item Number) code. The scanner data of the modern distribution provide millions of prices for thousands of products identified by the GTIN code. They predominantly refer to supermarkets and hypermarkets, especially for food, beverages, and personal and home care products. After a process of data cleaning and trimming outliers, the unit value price per item code can be computed by dividing the total turnover for that item by the total quantity sold.

In October 2018, an agreement between Istat and ASEDS-Dagum Centre was signed to implement the tasks of the MAKSWELL project, and, for this purpose, Istat provided the Centre with the scanner database referred to the years 2017 and 2018. The database is a random sample of approximately 1,800 outlets, hypermarkets (more than 500), and supermarkets (almost 1,300), and contains data concerning food and grocery products sold in the most important retail chains (95% of modern retail chain distribution that covers 55.4% of total retail trade distribution for this category of products). More specifically, scanner data are obtained from 1,781 outlets of the main 16

Retail Trade Chains (RTCs), thus covering the process of the entire national territory. Outlets have been stratified according to provinces (107), chain distribution (16), and outlet types (hypermarket, supermarket), for a total of more than 800 strata. Probabilities of selection were assigned to each outlet based on the corresponding turnover value. For each GTIN, prices were calculated taking into account turnover and quantities: the weekly unit value price is equal to the weekly turnover divided by weekly quantities. Monthly and annual unit value prices are calculated by the arithmetic mean of weekly prices weighted with quantities.

Many authors have contributed with papers and reports on how scanner data can improve price measurements, highlighting the advantages and some difficulties in using data that allow for the simultaneous collection of price and quantity information (for a review of the literature see Feenstra and Shapiro, 2003); Biggeri and Rao, 2021; Laureti and Polidoro, 2022). Taking also into account the results of the experiments and the many discussions among the members of ASES-Dagum Centre and the researchers of Istat's Price Statistics Unit, we can summarise here the various advantages and some limitations in using the scanner data for the computation of the SN-SCPIs.

The main advantage is that scanner data may help to overcome the issue of price data availability in the various areas involved in the comparisons by fulfilling the requirements of representativeness and comparability that emerge when compiling SCPIs. Due to the high territorial coverage which characterises scanner data, we can compare price levels among the various geographical areas within a country at a very detailed territorial level (provinces). In addition, it is worth noting that GTIN codes describe the products in detail and they are generally the same for each item at the national level. In this way, we can solve the issue of comparability. Since detailed information on turnover and quantities for each item code in every area is available, it is possible to account for the economic importance of each item in its market, thus fulfilling the representativeness requirement. Moreover, as different modern RTCs can sell products of different quality and offer additional services, information on the type of outlet and retail chain can be included in order to account for these quality characteristics that may influence the price of a product. Moreover, the availability of turnover weights (defined considering also sampling weights, when necessary) allows

to correctly include the corresponding representativeness of the products in terms of the total turnover of the group to which the products in question belong (Basic Headings, in the World Bank approach).

Other advantages of the use of scanner data are: (i) the reduction of measurement errors. By using the unit value for each GTIN as a price concept we can refer to a more accurate measure of an average transaction price than an isolated price quotation as in the case of traditional price data collection (see Diewert, 1995). (ii) The reduction of conceptual uncertainty. The GTIN unit value is a more representative price over the reference period than the usual price collected using traditional on-field surveys. These prices include temporary price promotions and reflect the actual price paid by consumers. Moreover, by aggregating over a year it is possible to smooth out the effect of price and quantity bouncing behaviour. Using scanner data, (iii) we add a time dimension to multilateral spatial price comparisons since detailed data are usually available at the point of sale and at the time of transaction. Another advantage (iv) is the use of itemised information contained in scanner data. When using the unit value approach, indeed, items must be tightly defined at a fine level of aggregation to maximise homogeneity and prevent quality differences from affecting the unit values. Finally, (v) it is obvious that using scanner data to carry out spatial comparisons will increase cost efficiency, since price data collection may be limited to traditional stores and shops, thus lowering data collection costs for the National Statistical Institutes.

However, some limitations should be taken into account in the context of this study and the computation of complete SN-SCPIs. The available scanner data: (i) do not cover all the retail chains of modern distribution (95%); (ii) cover all the 107 Italian Provinces in 2018, but the small size of some newly established provinces allows some estimations only for 103 out of 107 provinces and the rural areas are not completely covered; (iii) cannot be used for perishables and seasonal products such as vegetables, fruit and meat, and fresh fish, since these products are sold at price per quantity and generally are not pre-packaged with GTIN codes.

Moreover, we have to consider that, as already said, all the scanner data available cover about 10.5% in terms of the total expenditures of families for consumption (Istat, 2020). In addition, this share is not uniform across the Italian territory.

Therefore, it is evident that to estimate a complete system of SN-SCPIs it is necessary to build up a database that could allow the estimation of these indices related to the entire universe of household consumption.

Istat indeed collects consumer prices by using different data sources: territorial surveys at the outlets by non-probability samples, administrative data, and scanner data (selected by probability sampling). However, a strategy to use and integrate all the data sources is still missing, considering also the fact that the data come both from probability and non-probability samples, as already discussed in a paper presented at a Workshop on non-probability samples held at the University of Trier (Biggeri *et al.*, 2020). Istat is working on this line.



### **3. The estimation of Spatial Consumer Price Indices by using two different approaches**

The available and usable scanner data provided to the Dagum Centre refer mainly to food and grocery products concerning the categories and sub-classes of the ECOICOP - European Classification of Individual Consumption: they are 63 and the total number of products is 87,545. The annual price quotes are 2,032,574.

The sub-classes included in Food and non-alcoholic beverages are 46 (from sub-class 01.1.1.0 to sub-class 01.2.2.3.0). The sub-classes included in Alcoholic beverages are 7 and the sub-classes included in the other non-food categories are very few (only 10) and not enough to be representative of all the categories belonging to non-Food classes. Therefore, we decided to present our experiments only on the Food subclasses (which include also non-alcoholic beverages)

The analysis was conducted on the Italian provinces using the 2018 scanner database.

The two approaches apply different methods to satisfy the principle of product comparability. Methodologies, procedures, and results are presented in the next sub-sections.

#### **3.1 World Bank approach**

In this experiment, the principles and the construction procedure are quite similar to the one used in the ICP (International Comparison Programme) of the World Bank to compute the international PPPs (Purchasing Power Parities). In particular, the principle of comparability is applied in a very tight way by considering the comparisons of the like-to-like items (products) for the different sub-national areas (provinces, in our experiments). Under this approach, the lowest level of aggregation of the products is the so-called Basic Heading (BH) level, as defined by the World Bank (World Bank, 2013). Here we consider the 46 sub-classes belonging to the food category as BHs.

Within this approach, there is the risk that not all the products are available in all areas.

However, because the 2018 scanner dataset includes all the products identified by the corresponding GTIN, we can include in the comparisons also those products acquired by consumers with reduced quantities. The availability of turnover weights (defined considering also sampling weights) allows including the corresponding representativeness of these products correctly. For this reason, we provisionally call the computed SPIs as PPPs.

To improve the quality of price comparisons, defined by the strength of interconnections and overlaps in the priced items across different provinces, the following group of products was excluded since in these cases price data does not exhibit a spatial chain: whole milk, low-fat milk, olive oil, aged cheese, other cheese, lager beer, and frozen seafood.

As far as the methods for the PPPs computation are concerned, a two-step procedure is adopted (World Bank Group, 2015). In the first step, provincial PPPs are computed at the BH level using the Country Product Dummy (CPD) model by comparing price and quantity data referring to products sold in the various Italian provinces, while in the second step, we aggregate the results from the BH level comparisons to the higher level aggregate (Food category), using the GEKS procedure based on Fisher indices.

### *3.1.1 Aggregation method at BH level: BH PPPs*

As underlined above, scanner data bring detailed information about the characteristics of the elementary product and information about the turnover of that specific product, allowing the comparison of like-to-like products. Weights for each specific product are based on turnover for that product.

For each GTIN, weight is obtained by dividing the total weighted turnover by the weighted turnover for that product for each province.

Since product overlaps exhibit a chain structure, the weighted CPD method exhibits some aspects of spatial chaining and therefore we selected this method for computed provincial PPPs for product aggregates. Aiming at taking into account the economic importance (representativeness) of each product expressed by expenditure weights  $w_{ijr}$  based on turnover, we used a weighted CPD model. In this way, the representativeness requirement can be achieved by computed weighted spatial index numbers.

Let's assume that we are attempting to make a spatial comparison of prices between  $Mr$  provinces, with  $r = 1, 2, \dots, R$  Regions. In the first stage of aggregation of price data at the item level, which leads to price comparisons at the BH level,  $p_{ij}$  and  $q_{ij}$  represent the price and quantity of  $i$ -th item in  $j$ -th province  $i = 1, 2, \dots, N; j = 1, 2, \dots, Mr$ . To compute provincial PPPs, we used the CPD model according to the approach followed by the World Bank.

Besides accounting for quality variations in the cross-area price data, CPD is a regression-based econometric methodology that can be extended and generalised to provide a comprehensive framework for carrying out both international and intra-national analyses. The literature is still expanding and a recent paper by Rao and Hajargasht (2016) further developed the CPD-based stochastic approach through the use of modern econometric tools. This method suggests that price levels are estimated by regressing logarithms of prices on provinces for each province and product dummy variables; the model is given for each BH by:

$$\begin{aligned} \ln p_{ij} &= \ln PPP_j + \ln PPP_i + \ln \mu_{ijr} \\ &= \pi_j + \eta_i + v_{ijr} \\ \ln p_{ij} &= \sum_{j=1}^{Mr} \pi_j D^j + \sum_{i=1}^n \eta_i D^i + v_{ijr} \end{aligned} \quad (1)$$

where  $D^j$  is a provincial-dummy variable that takes value equal to 1 if the price observation is from the  $j$ -th province and 0 otherwise, and  $D^i$  is a commodity dummy variable that takes value equal to 1 if the price observation is for the  $i$ -th commodity and 0 otherwise and  $v_{ijr}$  are normally distributed errors with zero mean and constant variance  $\sigma^2$ . Parameters of this kind of model can be estimated once one of the parameters of the model is set at a specific value (Suits, 1984; Laureti and Rao, 2018). For example, if province 1 is taken as the reference or numerator province, then  $\pi_1$  is set at zero and the remaining parameters are estimated. To estimate the parameters of this model, we impose normalisation  $\sum_{i=1}^{Mr} \pi_i = 0$ , thus symmetrically treating all provinces. If  $\hat{\pi}_j = (1, 2, \dots, Mr)$  are estimated parameters, PPP for the province  $j$  in region  $r$  is given by  $PPP_j = e^{\hat{\pi}_j}$ . The CPD method-based price comparisons are transitive and base-invariant.

Aiming at taking into account the economic importance (representativeness) of each product, expressed by expenditure weights  $w_{ij}$  based on turnover, we

used a weighted CPD model, by running weighted least squares on the model (1). The weighted CPD is equivalent to applying ordinary least squares to the following model:

$$\sqrt{w_{ij}} \ln p_{ij} = \sum_{j=1}^{M_r} \pi_j \sqrt{w_{ij}} D^j + \sum_{i=1}^n \eta_i \sqrt{w_{ij}} D^i + \sqrt{w_{ijr}} v_{ijr} \quad (2)$$

The assumptions and procedures to obtain the weighted PPP<sub>j</sub> are those above explained.

### 3.1.2 Aggregation above BHs: Provincial PPPs for Food category

The next and final step for compiling provincial price comparisons is to aggregate the results from BH level comparisons to higher level aggregates. Let's assume that there are  $L$  basic headings ( $l = 1, \dots, L$ ) and  $e^r$  expenditure for  $i$ -th BH in province  $r$ . We decided to use the Fisher price index since it has a range of axiomatic and economic theoretic properties. The Fisher index is given by:

$$P_{rk}^{Fisher} = \sqrt{P_{rk}^{Laspeyres} \cdot P_{rk}^{Paasche}} \quad (3)$$

Where:

$$P_{rk}^{Laspeyres} = \frac{\sum_{l=1}^L p_l^k q_l^r}{\sum_{l=1}^L p_l^r q_l^r} = \sum s_i^r \left( \frac{p_l^k}{p_l^r} \right) \quad (4)$$

$$P_{rk}^{Paasche} = \frac{\sum_{l=1}^N \frac{p_l^k q_l^k}{p_l^r q_l^r}}{\sum_{l=1}^N \frac{p_l^r q_l^k}{p_l^r q_l^r}} = \left[ \sum_l s_l^k \left( \frac{p_l^k}{p_l^r} \right)^{-1} \right]^{-1} \quad (5)$$

with:

$$s_i^r = \frac{e_i^r}{\sum_{l=1}^L e_l^r} = \frac{p_l^r q_l^r}{\sum_{l=1}^L p_l^r q_l^r} \quad (6)$$

As the Fisher binary index in eq. 3 is not transitive, it is possible to use the GEKS method (World Bank, 2013) to generate transitive multilateral price comparisons across different regions. The resulting index is given by:

$$P_{rk}^{GEKS-FISHER} = \prod_{r=1}^R [P_{rs}^{Fisher} \cdot P_{sk}^{Fisher}]^{1/R} \quad (7)$$

The GEKS-Fisher-based formula is used in cross-country comparisons made within the ICP at the World Bank Group (2015) and the OECD-Eurostat comparisons. In order to obtain a set of  $R PPP_s$  that refer to the group of regions (Italy), we standardised the GEKS-Fisher-based PPPs (S-GEKS).

As these PPPs are now transitive, the ratios between the PPPs for each base are the same. To achieve a set of PPPs that has the group of countries as a base – thereby ensuring a neutral presentation - it is necessary to standardise the PPPs in the matrix. This is done by dividing each PPP by the geometric mean of the PPPs in its column.

### 3.1.3 Results

Following the methodology illustrated in sub-section 3.1.1, we first run a CPD model for each available BH and each province by using weighted turnover.

As expected – having considered identical products in the various provinces - the results obtained show that for many food products, frequently purchased (for example dry pasta and non-alcoholic beverages) there are very small differences in the level of prices among the various provinces. However, the variability of provincial PPPs is different for the different BHs, and in some cases, a certain or high variability emerges. See for example the descriptive statistics reported in Table 3.1 respectively for Coffee, Fresh Pasta, and Eggs BHs, and in Table 3.2 for Food category (Italy=100). The PPPs are reported in Figure 3.1 (a, b, c, d).

**Table 3.1 - Descriptive statistics based on provincial PPPs for Coffee, Fresh Pasta, and Eggs (Mean =100) - Year 2018**

	Coffee	Fresh Pasta	Eggs
Min	92.69	83.03	75.90
Max	107.24	112.14	114.55
CV	3.32	6.45	7.38

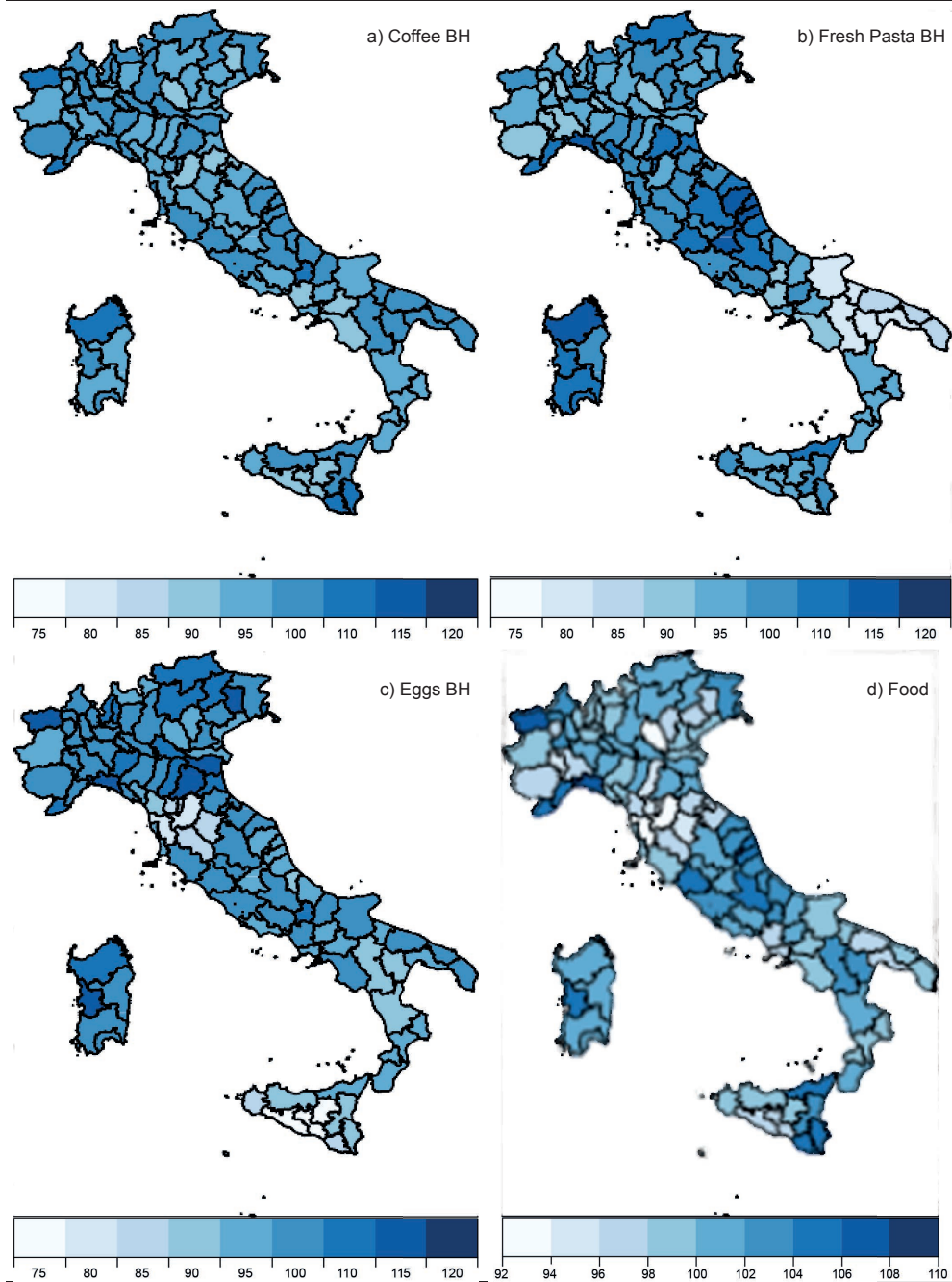
Source: Authors' processing on Istat scanner database

**Table 3.2 - Descriptive statistics based on provincial PPPs for Food (Mean =100) - Year 2018**

	Food
Min	92.47
Max	107.83
CV	3.00

Source: Authors' processing on Istat scanner database

Figure 3.1 - PPPs at provincial level for certain products and for Food (Italy=100) - Year 2018



Source: Source: Authors' processing on Istat scanner database

The North-South dualism is confirmed only for some BHs. As shown in Figure 3.1, a modest variability or near homogeneity is observed in PPPs for the Coffee BH; in this case, the coefficient of variation across Italian provinces is equal to 3.32%. In the case of Fresh Pasta, for which the coefficient of variation is equal to 6.45%, PPPs in the Northern provinces are generally higher than those in Southern Italy. The less expensive provinces are Matera (83.03), Potenza (83.31) located in the Basilicata region, and Foggia (83.67) located in Puglia, while the most expensive provinces are Genova (112.14) located in the Liguria region, Ascoli Piceno (111.06) and Fermo (111.02) located in Marche. Moreover, interesting results are provided for the Eggs BH, for which a high level of heterogeneity across Italian provinces is observed.

Using the results obtained in the first step, we computed the PPPs for the “Food” aggregate using as a weight the weighted turnover for each BH.

Descriptive statistics are reported in Table 3.2 and the PPPs for “Food” are reported in Figure 3.1d.

From Table 3.2 and Figure 3.4 we cannot observe a high level of price heterogeneity across Italian Provinces for food products. The most expensive provinces are Aosta and Genova (with PPPs equal to 107.83 and 107.5 respectively) located in Northern Italy, while the less expensive provinces are Firenze and Pisa (with PPPs equal to 92.47 and 93.57 respectively) located in Central Italy. This latter result is certainly not expected and maybe it could be partially explained by the prevalent presence of a specific retail chain, in those areas.

As already pointed out, there are various advantages to using scanner data to compute SPIs and PPPs. On the other hand, the like-to-like approach may have some limitations. To use strictly comparable products, indeed, some products may be excluded since they are produced and consumed at the local level. In our application, we had to exclude some BHs due to the insufficient overlap across provinces (*i.e.* whole milk, low-fat milk, olive oil, aged cheese, other cheese, lager beer, and frozen seafood). It is also worth noting that PPP results may be influenced by the characteristics of the modern retail trade which is not uniformly distributed across Italian territory in terms of types of retail chains and market share. In Table 3.3, although data are referred to the year 2016, it is clear that in some

Southern regions the share covered by the retail chains is lower than that observed in the North of Italy. In addition, consumer choice among the different distributional channels may be considered. In Southern regions, consumers tend to buy food products in open markets and traditional shops more frequently than consumers in Northern regions.

Moreover, we have to take into account the influence of the pricing policy adopted by the different commercial chains in the different areas of the country.



Table 3.3 - Scanner data: market shares (hypermarket and supermarket) (% values) – Year 2016

Retail Chains	Coop Italia	Conad Italia	Esselunga	Selex commerciale	Gruppo Auchan	Gruppo Carrefour Italia S.P.A.	Finiper	Gruppo V&Gé	Gruppo SUN S.C.A.R.L.	Agorà Network S.P.A.	Gruppo Aspiag S.P.A.	Bennet Sigma	Crai	Despar servizi	Total	
Piemonte	18.2	4.3	12.4	17.9	7.0	16.4	1.5	1.4	2.5	3.7	8.7	0.1	1.6		95.9	
North-West	-	22.3	-	8.6	-	45.1	-	-	-	-	-	-	-	-	76.0	
Liguria	42.2	17.0	3.9	4.8	0.7	8.8	1.5	3.2	2.6	13.5	2.7	1.3	0.3		99.8	
Lombardia	7.9	3.3	31.3	9.9	8.2	9.9	6.4	1.1	6.1	0.9	5.2	1.1	0.2	0.6	94.8	
Trentino-Alto Adige/Südtirol	18.0	13.8	-	-	-	-	-	-	34.4	0.6	32.4	-	-	-	99.1	
North-East	9.1	3.6	1.2	32.3	6.3	2.1	1.6	6.2	2.0	0.4	3.1	12.7	2.8	2.6	87.0	
Friuli-Venezia Giulia	21.3	7.7	-	9.4	1.1	4.2	2.9	1.2	-	8.0	29.9	4.0	2.6	2.1	94.3	
Emilia-Romagna	41.2	26.5	9.9	6.6	1.5	1.8	1.4	0.2	0.3	0.2	1.8	1.8	3.0	0.5	98.5	
Toscana	51.2	14.8	22.1	1.1	1.9	2.8	-	0.1	-	0.2	5.4	-	0.3	0.0	99.9	
Umbria	30.8	29.9	0.9	22.1	2.7	0.7	-	0.2	2.4	-	3.1	-	0.3	-	92.2	
Centre Marche	18.5	12.6	-	18.2	25.8	0.9	4.1	9.8	-	-	-	-	7.0	0.4	97.4	
Lazio	14.3	24.5	0.9	3.4	10.7	13.3	-	0.7	14.4	-	8.5	-	0.8	1.7	93.2	
Abruzzo	10.0	29.8	-	2.7	11.1	5.7	8.3	2.6	18.2	-	0.7	-	3.2	0.7	92.9	
Molise	-	30.9	-	23.4	-	1.6	-	5.7	27.6	-	-	-	6.4	0.9	96.6	
Campania	4.4	20.5	-	7.6	8.1	9.2	-	20.7	-	0.2	-	-	2.8	2.3	1.8	
South and Puglia	18.6	9.6	-	29.1	17.2	-	-	1.2	-	1.4	-	-	6.9	0.2	7.1	
Islands Basilicata	6.9	10.3	-	6.0	10.4	0.9	-	5.0	-	-	-	-	5.3	5.4	17.6	
Calabria	-	30.2	-	3.3	17.3	8.9	-	4.0	-	-	-	-	1.6	3.5	18.4	
Sicilia	6.3	19.5	-	4.4	20.1	1.5	-	19.8	-	-	-	-	1.1	7.5	6.2	
Sardegna	-	30.6	-	12.8	12.6	5.6	-	13.8	-	3.8	-	-	5.0	9.7	4.3	
<b>Italia</b>	<b>18.5</b>	<b>13.3</b>	<b>12.1</b>	<b>11.11</b>	<b>7.8</b>	<b>7.1</b>	<b>2.3</b>	<b>3.2</b>	<b>3.1</b>	<b>2.8</b>	<b>2.7</b>	<b>2.7</b>	<b>1.8</b>	<b>1.4</b>	<b>1.2</b>	<b>93.7</b>

Source: Authors' re-aggregation on the computation made by Istat's Price Unit on the scanner dataset

## 3.2 ASED Approach

### 3.2.1 Estimation of Spatial Consumer Price Indices by loosening the tight comparability of the products

This second experiment has been conducted by using a different innovative approach regarding the definition and satisfaction of the principle of comparability decided by the ASED Centre. The principle of comparability is applied at the level of each “Group of Products” of the ECOICOP classification, by loosening the “tight” specifications of the elementary products. The approach considers the unit value prices from the consumer side (or point of view). The hypothesis is that the elementary products (items) belonging to each group satisfy in any case the same consumer needs (and may give him the same utility), also if the brands, quality, *etc.* are different.

The comparison is therefore done by considering the average level of prices of the group of products purchased in the different areas (provinces), considering the basket of elementary products that the consumers of each area have really purchased<sup>6</sup>. Then the average level of prices of the different groups of products is aggregated to obtain the SPIs for each sub-national area. Therefore, these groups, and not the BHs, are the building blocks of the comparison, defined using 102 groups of the ECOICOP-8-digit classification.

In the first step, we computed  $\bar{p}_{kj}$  which is the weighted mean price for each group of products in ECOICOP-8-digit  $k$  and province  $j$ . Let  $r_{ikj}$  and  $q_{ikj}$  be respectively the annual turnover and the total quantity sold<sup>7</sup> of item  $i$  belonging to ECOICOP-8-digit  $k$  in province  $j$ . The unit price  $p_{ikj}$  is equal to<sup>8</sup>:

$$p_{ikj} = r_{ikj} / q_{ikj}$$

and its relative weights in terms of turnover are equal to:

$$w_{ikj} = r_{ikj} / \sum_{i=1}^{n_{kj}} r_{ikj}$$

6 The value of the average level of prices of the different provinces could be affected by the different typologies of families (number of components, age, *etc.*) in the provinces (Istat, 2009; Biggeri and Laureti, 2018). To obtain a more precise comparison among the different averages, it could be necessary to make some standardisation of the provincial averages. This is an issue that the unit of research will deepen in a near future.

7 Which are the expenditure and the quantity purchased by consumers.

8 Obviously, taking account of the different size of the items' package.

where  $n_{kj}$  is the number of items in the  $k$ -th group of products in the  $j$ -th province. Finally, the weighted mean price is:

$$\bar{p}_{kj} = \frac{1}{n_{kj}} \sum_{i=1}^{n_{kj}} p_{ikj} w_{ikj}$$

The second step is devoted to the aggregation of the average level of prices of the group of products (102) to estimate the provincial SPI. It should be noted that not all 102 product groups are present in all provinces. Therefore, to compute the SPI at the provincial level we use a Country Product Dummy model.

Under the CPD model approach the logarithm of  $p_{kj}$  is considered as a function  $SPI_{jj}$ , the spatial price index of the  $j$ -th province relative to the other provinces, of  $P_k$ , the “provincial” average price of the  $k$ -th group of commodities, and of a random error term:

$$\begin{aligned} \ln \bar{p}_{kj} &= \ln SPI_j + \ln P_k + \ln \mu_{kj} = \\ &= \pi_j + \eta_k + v_{kj} \\ \ln \bar{p}_{kj} &= \sum_{j=1}^{M_r} \pi_j D^j + \sum_{k=1}^n \eta_k D^k + v_{kj} \end{aligned} \quad (8)$$

where  $D^j$  is a provincial-dummy variable that takes value equal to 1 if the price observation is from  $j$ -th province and 0 otherwise; and  $D^k$  is a  $k$ -group of products dummy variable that takes value equal to 1 if the price observation is for  $k$ -th group and 0 otherwise, and  $v_{kj}$  are normally distributed with zero mean and constant variance  $\sigma^2$ .

Following the estimation procedures already illustrated in sub-section 3.1.1 and using a weighted CPD model, where the weight is the ratio between the total turnover of one group of products in one province and the total turnover of the province, we can estimate  $\hat{\pi}_j$  and then obtain the provincial Spatial Price Indices by  $SPI_j = e^{\hat{\pi}_j}$ .

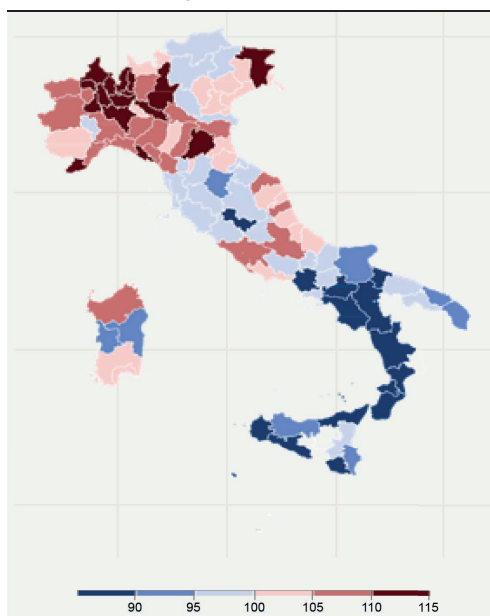
### 3.2.2 Results: the ASED SPIs for food

The estimates of the SPIs for Food obtained on the basis of model equation (8) present high variability or heterogeneity as shown by the descriptive statistics reported in Table 3.4 and by the SPIs reported in Figure 3.5.

**Table 3.4 - Descriptive statistics based on provincial SPIs for Food: ASED Approach (Italy=100) - Year 2018**

Food		
Min	70.73	Province: Agrigento
Max	113.38	Province: Como
CV	7.51	

**Figure 3.5 - SPIs for Food at Provincial level: ASED Approach (Italy=100) - Year 2018**



Source: Authors' processing on Istat scanner database

The results obtained are somehow expected. Indeed, provinces in the north of Italy show SPI values greater than 100, while provinces in the south show values smaller than 100. However, there are exceptions, *i.e.* provinces in the north-east Alps Mountains that show SPI below 100, even if they are close. Provinces in the centre of Italy have SPIs close to 100, with some evidence of SPI lower than 100 for provinces located in the Appennino mountains (middle of central Italy), and SPI greater than 100 for the provinces located at the seaside, both Adriatico (east), Ligure and Tirreno (west).

The lowest SPI is estimated for the province of Agrigento, in Sicily (south of Italy), while the highest is in the province of Como, in Lombardia region (north of Italy). The provinces with the highest SPI are all located in the north-west, but these are also over 100 for the city of Aquila (AQ) located in Abruzzo, a region in the south of Italy.

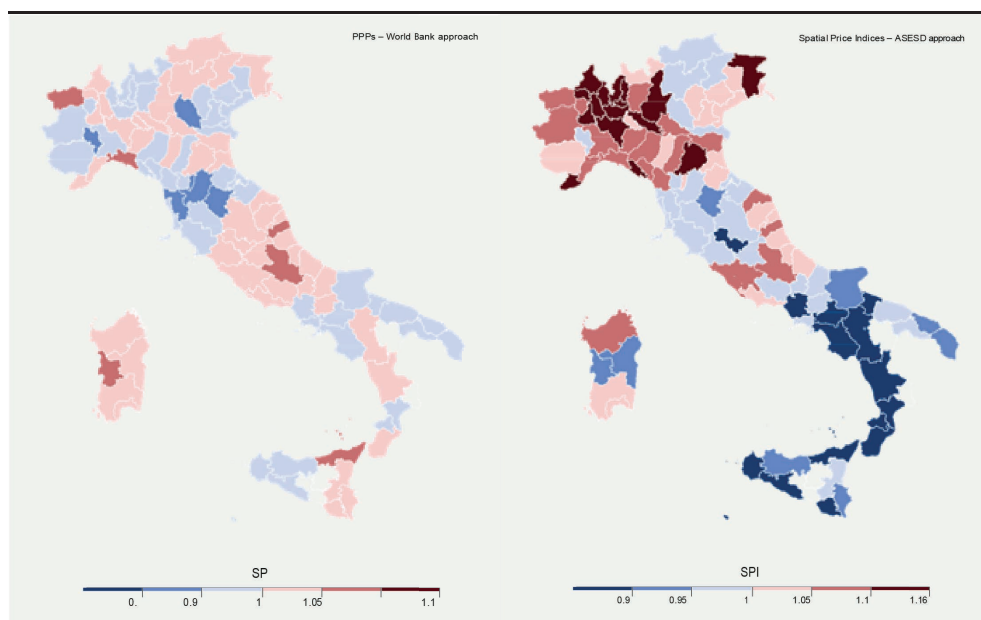
In conclusion, it must be observed that in many provinces the SPIs is around 100. In these cases the comparisons between the values of the different

provinces are quite uncertain. In fact, following Suits (1984) we derived the p-values for the rescaled  $\alpha_j$ , which are not reported here. However, setting an I type error equal to 0.1 we observed that for 43 provinces we can't reject the hypothesis  $\alpha_j = 0$ , which corresponds to SPI equal to 1 (in our case = 100).

#### 4. A general analysis of the results of the experiments to compute the PPPs and SPIs: some concluding remarks

The results obtained from the two experiments are undoubtedly interesting. Actually, the estimations of the PPPs (World Bank approach) and SPIs (according to the ASEDS approach) at the provincial level are quite different with different variability, as we can see from the different CV reported in Table 3.2 and 3.4 (respectively 3.00 and 7.51). The differences are easily appreciated by examining Figure 4.1 which reports the indices computed with the two approaches using the same scale.

**Figure 4.1 - PPPs and SPIs computed according to the World Bank and ASESD approaches - Year 2018**

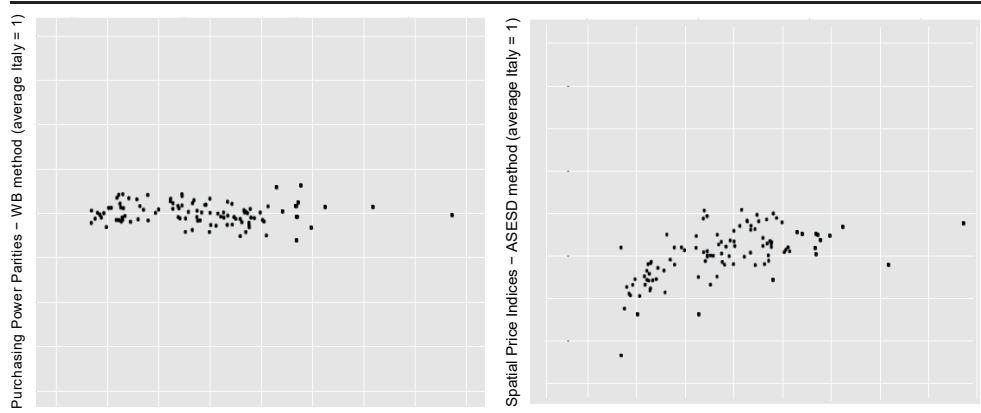


Source: Authors' processing on Istat scanner database

The results of the two experiments are therefore different, but we have to take into account that the followed procedures are different too. As suggested in the World Bank book (2013), when we compute the within-country PPPs one would expect some internal consistency. Price levels in poor areas should be generally lower than those in richer areas; they also show a similar pattern across the basic headings. To check this hypothesis, we have done

a comparison between the two computed indices and the value-added per capita by Italian province as reported in Figure 4.2. It is evident that the Indices computed with the ASES method satisfy in some way the previously mentioned consistency, while the PPPs do not satisfy it (in fact the correlation coefficients are about +0.60 for the first index and -0.10 for the second).

**Figure 4.2 - Scatterplot of the PPPs (World Bank approach) and SPIs (ASESD Method) vs. the value-added per capita in the Italian provinces - Year 2018**



Source: Authors' processing on Istat scanner database

As explained in the previous sub-sections, the two sets of SPIs values have been computed with different methodologies and with slightly different sets of data. The difference in the results most likely depends on the different methodologies used: the Word Bank approach is based on like-to-like product comparisons, and we expect that the range of the price for the same identical product cannot vary so highly in hypermarkets and supermarkets, although located in different areas of the Italian territory. The influence of the political prices of the different commercial chains should be analysed; to have a clearer picture of the reasons for the differences the analyses should be done at a disaggregated level. Unfortunately, a finer comparison at the Basic heading level is not possible at this moment, but we plan to better investigate it in the future. We will conduct further experiments to compute SPIs using other methods, for example, that used in the US: to make the products as comparable as possible, a hedonic regression was estimated, below the basic heading with class variables that include the product's characteristics, such as type, size, and brand (Aten, 2021).

In any case, the results already obtained are interesting and useful from a scientific and official statistics point of view. We recommend that the unit of research continues the experiments and that the same experiments are conducted also by the units of research in other European countries.



## 5. A tentative measure of poor-specific SPIs: SPIs for the first quintile of price distributions

To provide adequate information regarding the real incidence, nature, and extent of economic poverty, it became necessary to use and therefore compute poverty-related SN-SCPIs.

To compute poor-specific PPPs at the international level, Deaton (2006) and Deaton and Dupriez (2011), proposed to combine the average price levels with different specific baskets of goods and services for the poor, obtained by the BHS from 62 developing countries. This is an important step to calculate the global poverty lines. However, the method is not easily applicable to obtain adequate poor-specific spatial indices, especially at the sub-national level within a country. In fact, the consumer behaviour of poor households varies for quality of the commodities, channels of distribution, location of the markets, and above all the prices paid. So to compute the poor-specific SPIs, we have to use also the prices paid by the poor (Biggeri and Leoni, 2004; Giusti *et al.*, 2017)

Therefore, because we do not know the prices paid by the poor, for the computation of poor-specific SN-SCPIs following the ASED approach, we conducted a preliminary experiment by using data of the first quintile of the price distributions of each product, assuming for the time being that the poor purchase the cheapest items of each specific product. After all, the lowest prices are often also used for the measurement of Absolute Poverty (ABSPO) as it is done by Istat (2009)<sup>9</sup> and it is written in a report on ABSPO published by the Joint Research Centre of the European Commission (Menyhért *et al.*, 2021).

To obtain such SPIs by using the lowest prices, the model equation (8) is modified as follows:

$$\ln \bar{p}_{kj}^{\tau} = \ln SPI_j^{\tau} + \ln P_k^{\tau} + \ln \mu_{kj}^{\tau} \quad (9)$$

where  $\bar{p}_{kj}^{\tau}$  is the quantile of order  $\tau$  of the unit prices ( $p_{ijk}$ ) of items belonging to group  $k$  (ECOICOP-8-digit) and province  $j$ . The parameters of the model are estimated by regressing the logarithm of the quantile on province dummy variables and on a group of product dummy variables as done for model (8).

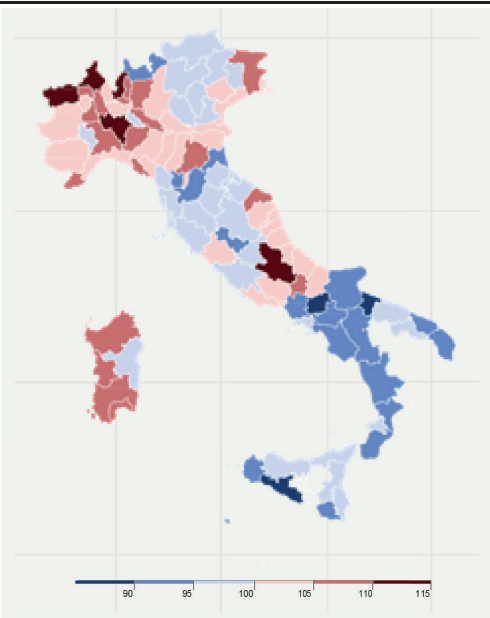
<sup>9</sup> Actually, for Italy Spatial Price Indices for poor families can be obtained by using the data on absolute poverty (Biggeri and Pratesi, 2018; Biggeri and Laureti, 2018).

For example, setting  $\tau = 0.2$  we have obtained the estimates of spatial price indices related to the lowest prices for each Italian province, which we denote as SPIs(Q0.2), for which we report the descriptive statistics in Table 5.1, showing the results in Figure 5.1.

**Table 5.1 - Descriptive statistics based on provincial SPIs (Q0.2) for Food: ASESD method (Italy=100) - Year 2018**

	Food	
Min	82.00	Province: Agrigento
Max	114.30	Province: Aosta
CV	6.10	

**Figure 5.1 - Spatial Price Indices SPIs Q0.2 at provincial level for Food: ASESD method (Italy=100) - Year 2018**



Source: Authors' processing on Istat scanner database

Looking at the results of the estimation of the SPIs(Q0.2), many provinces in the North-west and on the Adriatico seaside, excluding Puglia province, show a SPIs(Q0.2) greater than 100, while many provinces in the North-east, Centre and South of Italy show SPIs(Q0.2) near or smaller than 100. Sardegna provinces show SPIs(Q0.2) greater than 100, with the exception of Nuoro.

If we compare this tentative measure of poor-specific SPIs with the general SPIs computed (as mean) considering all the prices, we observe that the former indices present, as expected, smaller values and a little bit less variability than the latter (CV respectively 6.10 and 7.51), but the differences are not uniform at the territorial level within the country.

This tentative measure of poor-specific SPIs has provided some interesting information. However, we must keep in mind that the comparisons between the SPIs( $Q_{0,2}$ ) of different provinces and between SPIs( $Q_{0,2}$ ) and the general SPIs are really uncertain in various cases, as the computations of p-values show.

Therefore, to improve the validity of these price indices some information on the consumption behaviour of poor households should be collected. A tentative survey to give some insight on that has been carried out by Istat.

## **6 Where people in a condition of absolute poverty purchase some frequent consumption products**

As anticipated in Section 1, to obtain some information on the consumption behaviour of households, a first tentative survey and analysis were conducted by researchers of Istat. We present here a summary of the results. Since 2015, Istat has added a special section (a two-week diary) in the Household Expenditures Survey (HES) aimed at investigating the type of outlets where the households purchased a list of the 25 most frequently purchased products. The types of outlets listed are seven: traditional shops, open markets and street vendors, hard discounts, hypermarkets and supermarkets, department stores and outlet chains, farm or direct producers, and the Internet. After an experimental period, Istat researchers carried out an analysis of 2019 HES data, which produced the following results.

The results obtained from these preliminary analyses of 2019 HES data show some interesting differences between non-poor and absolutely poor households (identified by means of the poverty lines calculated and updated each year by Istat) in terms of choice of the type of outlet where purchasing a list of 25 large consumption products.

In particular, the purchase of some essential products such as bread, milk, and eggs is (relatively) more important for poor families. In general, the use of the traditional shop and open market is very similar for the poor and non-poor families; while the poor families made more frequent purchases in hard discounts and less in hypermarkets/supermarkets than the non-poor families.

In Table 6.1, we report in detail the types of outlets chosen by Italian families in absolute poverty who have made at least one purchase in the two weeks of observation. It is clear that the choice of the types of outlet is different for each kind of product.

This evidence is worth to be deepened also by breaking down the analysis at territorial level, overcoming the problem of a too small sample if we take into consideration only poor households. This line of research is aimed at improving the estimation of the actual prices paid by poor families in different Italian geographical areas by taking into account their different behaviour in the choice of the outlet where purchasing in particular large consumption products. The possible results obtained could enhance the spatial comparison of consumer prices by making reference to the poor part of the population.

**Table 6.1 - Types of products by types of outlets where Italian absolute poor households make purchases (% distribution) - Year 2019**

Products	Traditional shops	Open market and Street vendors	Hard discounts	Hypermarkets and supermarkets	Departments stores and outlet chains	Farms or direct producers	Internet	Total
Bread	41.5	1.7	19.1	37.6	0.1	0.0	0.0	<b>100.0</b>
Pasta	13.9	1.0	31.3	53.3	0.5	0.0	0.0	<b>100.0</b>
Biscuits, rusks, snacks	10.9	1.6	32.3	55.0	0.2	0.0	0.0	<b>100.0</b>
Fresh meat	30.2	1.3	23.9	43.9	0.3	0.3	0.0	<b>100.0</b>
Frozen meat	10.9	1.6	16.4	69.3	0.8	0.8	0.1	<b>100.0</b>
Cured meat	15.7	1.1	29.6	53.1	0.2	0.3	0.0	<b>100.0</b>
Fresh fish	41.8	13.6	14.0	30.3	0.0	0.3	0.0	<b>100.0</b>
Frozen fish	10.3	1.7	32.6	54.4	1.0	0.0	0.0	<b>100.0</b>
Milk	13.7	1.1	32.5	52.5	0.2	0.0	0.0	<b>100.0</b>
Cheeses	14.7	0.8	30.4	53.7	0.2	0.2	0.0	<b>100.0</b>
Yogurt	10.7	0.9	32.5	55.6	0.3	0.0	0.0	<b>100.0</b>
Eggs	14.3	2.4	32.6	49.7	0.2	0.7	0.0	<b>100.0</b>
Fresh fruit	25.1	10.8	24.9	38.8	0.1	0.2	0.0	<b>100.0</b>
Fresh vegetables, potatoes, and legumes	25.1	9.6	24.1	40.7	0.2	0.3	0.0	<b>100.0</b>
Dried or frozen vegetables, potatoes and legumes	10.3	5.0	30.6	53.4	0.4	0.4	0.0	<b>100.0</b>
Olive oil	8.5	1.3	33.2	55.4	0.3	1.4	0.0	<b>100.0</b>
Mineral water	11.5	0.7	29.1	58.1	0.4	0.1	0.0	<b>100.0</b>
Soft drinks	8.1	2.0	31.2	58.2	0.5	0.0	0.0	<b>100.0</b>
Wine	13.4	0.0	32.3	53.5	0.0	0.9	0.0	<b>100.0</b>
Coffee	10.1	1.1	31.4	56.5	0.1	0.3	0.5	<b>100.0</b>
Medicines	94.0	0.0	0.7	5.4	0.0	0.0	0.0	<b>100.0</b>
Personal hygiene products (soap, deodorant, baby diapers, etc.)	10.3	0.9	31.7	55.1	1.7	0.1	0.2	<b>100.0</b>
Cleaning products	12.8	2.3	31.1	51.7	2.1	0.0	0.0	<b>100.0</b>
Disposable items for the kitchen (napkins, dishes, etc.)	13.5	1.5	34.1	49.6	1.3	0.0	0.0	<b>100.0</b>
Toys and video games	27.2	9.1	17.3	34.4	11.9	0.0	0.0	<b>100.0</b>

Source: Authors' re-aggregation on the computation made by Istat's Price Unit on 2019 Istat HBS data

## 7. Concluding remarks

The goal of our work is twofold: first, to verify which are the appropriate methodological approaches to estimate the Sub-National Spatial consumer price Indices (SN-SCPIs) and second to verify whether it is possible to estimate poor-specific SN-SCPIs, without knowing what prices the poor pay for the various products and, consequently, if it is possible to track poor specific consumption behaviour.

To this end, two experiments have been conducted. The first experiment refers to the general computation of the SN-SCPIs by using the same scanner database and elementary data but applying a different principle of product comparability. One is computed considering the comparison of like-to-like products for the different subnational areas (World Bank approach). The other considers the principle of comparability at the level of very detailed groups of products, by loosening the “tight” specification of the elementary products given that the items products of each group satisfy the same consumer needs (that was called ASES approach). For the computation of poor-specific SN-SCPIs - that is to calculate SPIs closer to the prices paid by the poor, we conducted a preliminary experiment by using data of the first quintile of the price distributions of each product, assuming, for the time being, that the poor purchase the cheapest items of a product.

The results of the first experiment show that the provincial PPPs computed by using the World Bank approach present little variability among the different territorial areas; while the SPIs computed following the ASES approach show a much more pronounced variability. In any case, the proposal to loosen the “tight” comparability of the elementary products provides spatial price indices which look better than those obtained by applying the World Bank approach, because they are more consistent with the fact that price levels in poorer areas are generally lower than those in richer areas. The results will be further verified and analysed at a disaggregated level to have a clearer picture of the reasons for the differences. Moreover, further experiments will be conducted to compute SPIs using other methods, for example making the products as comparable as possible by estimating a hedonic regression, below the basic headings.

In addition, the tentative experiment to measure poor-specific SPIs provides some interesting information. If we compare the poor-specific SPIs with the

general SPIs considering all the prices, as expected, the former indices are a little smaller and present a little bit less variability than the latter, but the differences are not uniform at the territorial level within the country. Moreover, we have to keep in mind that their estimation is really uncertain in various cases, as the computations of p-values show. To improve the adequacy of the poor-specific SPIs it is necessary to know the consumption behaviour of poor households at the sub-national level (possibly at the provincial level) and their behaviour in order to choose cheaper products. The results of the survey and analysis conducted by Istat researchers provided important insights, but they are only at the national level. Therefore, it is necessary to break down the analysis at the territorial level, overcoming the problem of a too-small sample if we take into consideration only poor households. In this way, we could take into account their different behaviour in the choice of the outlet where they purchase products and the prices they pay.

Finally, we have to remember that by using only scanner data on retail prices of the outlet of modern distribution it is impossible to estimate a complete system of sub-national Spatial Consumer Price Indices. In fact, the purchases of products and services by consumers take place in various forms and in different types of outlets, as shown in Section 6.

Therefore, it is evident that to estimate a complete system of general SN-SCPIs it is necessary to build up a database that could allow the estimation of these indices related to the entire universe of household consumption.

Istat collects indeed consumer prices by using different sources: territorial surveys at the outlets by non-probability samples, use of administrative data, and use of scanner data (Big Data). Therefore, it is necessary to follow a strategy to use and integrate all the consumer price sources of data, considering also the fact that the issue has to be faced that the data come both from probability and non-probability samples. It is important to stress the need for further research and experiments in this field, also taking account of the recent studies and development presented at many Workshops and Webinars organised during the last months of the year 2021 and the first months of 2022 by the International Association of Survey Statisticians (IASS, 2022) and by the Survey Research Methods Section of the American Statistical Association.

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