List prices vs. bargain prices: which solution to estimate consumer price indices?[1]

Carlo De Gregorio[2]

Abstract

Alternative approaches to CPI surveys are here evaluated, in markets where final prices are based on some sort of price listing. Three types of surveys are compared: local surveys (LOC), with small samples and a local price collection; list price surveys (LIS), with huge samples and centralised collection; mixed surveys (MXD), in which LOC and LIS are jointly used. Based on a multiplicative pricing model, some conditions are derived to establish the relative efficiency of these approaches. The alternatives have also been tested on five different random populations. LIS surveys appear very efficient under very restrictive hypotheses on the regularity of discount policies. LOC surveys may be efficient only if the variability of list prices is reasonably low. MXD surveys appear the most promising solution if a correction parameter is introduced to account for the covariance between list prices and discount policies. MXD surveys appear better positioned for monitoring consumer market and the range of products available to the consumer.

Keywords: Consumer price index, Survey design, Sampling

Introduction

In some consumer markets the prices actually paid by customers are decided by retailers on the basis of some kind of official listing of prices[3]. This happens for instance in the case of new vehicles, package holidays, tourist services, pharmaceutical drugs, tobacco, ICT, housing: list prices affect with varying degrees a wide set consumer markets. Generally list prices may be regarded as a kind of rule for pricing policy, by means of which producers, institutions or retailers themselves influence the dynamics of actual bargain prices[4]. This conditioning usually does not imply a straight control: list prices may in fact generally diverge from transaction prices, especially if retailers have some margins to apply their own

---

[1] This paper has been prepared during a period of secondment at Eurostat, during which the author collaborated with the unit G6, in charge of the production of the HICP, and coordinated the works of a HICP Task Force on Sampling which stimulated the work on this subject. The author is obviously the only responsible for the views expressed in this paper, which do not necessarily reflect the views of Istat nor those of Eurostat.

[2] Senior researcher Istat, email: cadegreg@istat.it.

[3] We will use the term "list prices" to refer to what are also usually called "*the (manufacturer's) suggested retail price (MSRP or SRP), list price or recommended retail price (RRP)*". See Wikipedia, *Suggested retail price*. This source also specifies that a SRP is "*the price the manufacturer recommends that the retailer sell it for. The intention was to help to standardize prices among locations. While some stores always sell at, or below, the suggested retail price, others do so only when items are on sale or closeout*". We will use indifferently the terms "transaction price" or "bargain price" to mean the price effectively paid by the consumer.

[4] The connection between oligopoly or imperfect competition and the use of list prices is, for instance, mentioned by Sweezy (1939) in his milestone explanation of the concept of the "kinked demand curve". Sweezy notes moreover that "*(...) list prices become less trustworthy guides to real prices the longer bad times last*" (pag. 572). In completely different perspectives and contexts, but on the same subject, see, for example, Marn et al. (2003) and Thanassoulis (2005).

pricing and sales policy. Generally these margins imply the possibility to apply discounts to list prices: the latter can be thus interpreted as a sort of superior limit.

There are several market-specific ways to intend list prices, and it is not our intention to classify them here. In general, the markets where list prices are applied are usually characterised by some degree of oligopoly, at least at producer level, or by a regulatory framework: anyway, the intrinsic nature of pricing policies may differ to some extent from market to market. In the case of new cars, for instance, producers' list prices represent a medium term pricing policy tool. Effective prices diverge from list prices because of at least two distinct factors: the last minute discount policies decided by the producers are used to bring short term corrections to list prices; at the end of the chain, dealers apply their point-of-sale policies[5]. Some kinds of pharmaceutical drugs are sold at a retail price that discounts an official price[6]. In some countries, even tobacco can be priced by retailers on the basis of list prices, although more often this market is strictly constrained to official price lists. The case of package holidays looks very similar to the one of new cars: official list prices, published in the catalogues, are usually discounted for advance or last minute booking, with a pricing policy that reflects short term market related concerns by tour operators and travel agents. Other markets, where there is no distinction between producers and retailers, are also regulated by suggested list prices: this is the case, for example, of accommodation services and of many tourist services. Something different happens in the housing market, where the prices publicly asked for by the sellers play the same role as list prices[7].

In general, the use of list prices for CPI estimates is discouraged by standard practices, although it is tolerated in those cases where the collection of bargain prices is deemed too heavy. In general, when list and bargain prices coexist, in order to produce accurate estimates of price dynamics we have to face a trade off between alternative data collection techniques. List prices are in fact much easier to collect[8], they can be managed centrally and with more sophisticated sampling designs: but they may be not representative of transaction prices. The collection of bargain prices, on the other hand, implies a much higher burden, with the assistance of a local price collection network and a smaller sample size. This burden may happen to be very high: in the case of cars, for example, highly skilled price collectors are strongly needed (Eurostat, 2005).

These two approaches are generally conceived as mutually exclusive. In the case of new cars, for example, existing approaches can be divided in two broad classes: some use list prices and others collect actual bargain prices by means of local surveys. In both cases, large drawbacks can be identified. Even a good or almost-perfect measurement of the dynamics of list prices can be misleading, more probably in the short term. On the other side, the smaller samples used for the collection of bargain prices affects heavily the coverage of market segments and the management of the turnover in the product range.

This last point is having a growing importance. The regulatory framework of the HICP has explicitly introduced the concept of consumption segment, and has identified it as the

[5] There is an appreciable economic literature (mainly in the US) on the divergence between list and bargain prices in the market for new cars (Zettelmeyer et al., 2003;Goldberg, 1996; Jung, 1959). This literature mainly focuses on price discrimination. Retail policies are tailored on the various types of customers (e.g.: age, social conditions, sex) (Scott-Morton et al., 2003). They are also based on how much information the customer shows to have upon the market. For a similar approach, concerning the European car market, see Lutz (2004).

[6] This is for example the case of non prescription drugs in Italy.

[7] There is some literature on this subject: see for example Genesove at al. (2001), Knight et al. (1998), Horowitz (1992).

[8] They are very often available on the internet.

cornerstone in the definition of the population parameter in the estimation of the CPI (European Commission, 2007). This mere point has given a major role to the analysis of consumer markets in the estimates of a CPI. In this context the mixed approaches, which try to combine the price collection techniques, might be encouraged: nevertheless, at the moment they are not explicitly applied nor it seems that they have been systematically considered. Given this context, we address in particular the following questions: Can it be useful to split the sampling issue in two components, one aimed at estimating list prices dynamics and the other dedicated to the estimate of the dynamics of retailers' policies? Is it efficient to estimate a list price index by means of a centralised and almost exhaustive survey, and to estimate separately an average retailers' discount index by means of a much smaller local survey? Is it possible to obtain an unbiased estimate and a good gain in precision? At which conditions? And what about sample size? In other words, is it possible to exploit the large centralised samples – and the high quality of the available information on the behaviour of list prices - to support the information collected by means of smaller local surveys?

Quite obviously, the answer to these questions depends crucially on the behaviour of each component of the variability of final prices. In section 1 it is proposed a model to analyse this variability. In section 2 some conditions are derived in order to evaluate the relative efficiency of different approaches. In section 3 some sampling simulations are made on randomly generated populations. In section 4 some generalisations are examined. Finally, some conclusions are extracted from the results of this analysis.

1. Two stage pricing and variance decomposition

Let's assume that we are dealing with a market where transaction prices are based on suggested list prices. In particular, if we use the subscript *i* to identify each "model"[9] and the suffix *ij* to identify the single transaction involving model *i*, we could express the effective price p_{ij} of product *i* in transaction *ij* as:

$$p_{ij} = l_i r_{ij} \tag{1.1}$$

where *l* identifies the list price and *r* a multiplicative discount factor[10]. Each transaction price is thus viewed as a list price multiplied by a correction factor reflecting the pricing policy of the retailer. Suppose also that it is possible to have a one-to-one correspondence between each transactions in the base and its replication in the current period[11]. Using

[9] For explanatory purposes, the terms we use are implicitly referred to the car market, but they should be regarded as having more general validity. It is also implicitly assumed, in order not to complicate too much the formulas, that the models present in this market have all similar market shares (in value terms).

[10] We can easily assume that $r_{ij} \leq 1$, so that $p_{ij} \leq l_{ij}$, that is retail prices are discounted list prices. In other words, for each model *i* there exists one only list price in each moment and a plurality of product offers *ij*, each one characterised by an effective price. Alternative descriptions might be used to express the same concept, for example using an additive discount component: moreover, multiplicative factors can be readily translated in additive ones by means of logarithmic transformations.

[11] This is a major hypothesis, since it gives the possibility to simplify very much the computation of the index and the sample design. See Ribe (2000). It is equivalent to assume that no major change in the range of products available for consumption has taken place between the base and the current month: in other terms, there is no need to take account of replacements. See in section 4 some thoughts on the consequences connected to the relaxation of this hypothesis.

capital letters to express the corresponding indices we have[12]:

$$Y_{ij} = X_i D_{ij} \qquad (1.2)$$

where the suffix for the current month *m* and the reference month *0* are omitted[13], while $i=1, \ldots, Q$ and $j=1, \ldots, n_i$. Let $N = \sum_i n_i$ be the total number of transactions. Assume for simplicity that the true population average of the index *Y* is:

$$\overline{Y} = \frac{\sum Y_{ij}}{N} = E[Y] = E[X]E[D] + Cov(X,D) = \overline{X} * \overline{D} + \sigma_{XD} \qquad (1.3)^{14}.$$

With some algebra, and assuming that X and D are normally distributed, the variance of *Y* can be decomposed as follows:

$$\sigma_Y^2 = E\left[\left(Y - \overline{Y}\right)^2\right] = \overline{X}^2\sigma_D^2 + \overline{D}^2\sigma_X^2 + \sigma_X^2\sigma_D^2 + 2\overline{XD}\sigma_{XD} + \sigma_{XD}^2 =$$
$$\overline{X}^2\sigma_D^2 + \overline{D}^2\sigma_X^2 + \sigma_X^2\sigma_D^2 + 2\overline{XD}\sigma_D\sigma_X\rho_{XD} + \left[\sigma_D\sigma_X\rho_{XD}\right]^2 \qquad (1.4)^{15},$$

where ρ_{XD} is the correlation coefficient between the indices of list prices and of the discount policies. The last two terms of expression (1.4) depend on the linear relationship between list prices and discount policies.

If the index D_{ij} is constant for every couple *ij* then:

$$\sigma_Y^2 = \overline{D}^2\sigma_X^2 \qquad (1.5),$$

that is the variance of transaction price indices (*Y*) depends only on the variance of list price indices (*X*) while the index of the discount policy represents merely a scale factor. They coincide if no retail policy is applied (D_{ij}=1).

If *X* and *D* are only linearly independent, their covariance and correlation coefficient are both null and expression (1.4) can be simplified as follows:

$$\sigma_Y^2 = \overline{X}^2\sigma_D^2 + \overline{D}^2\sigma_X^2 + \sigma_X^2\sigma_D^2 \qquad (1.6).$$

---

[12] That is: $Y^m = \frac{p^m}{p^0}$, $X^m = \frac{l^m}{l^0}$, and $D^m = \frac{r^m}{r^0}$.

[13] According to the current annual chaining procedures, which nowadays characterises the HICP project, month 0 can be identified with the month of December of the preceding year. Due to annual chaining, and following Ribe (2000), the objects of CPI estimates (i.e.: the population parameters to be estimated) is the set of 12 monthly indices of the current year based December of the preceding year. This same approach has been followed in Istat centralised CPI surveys (Istat, 2007; De Gregorio, 2006; De Gregorio, Fatello et al., 2008; De Gregorio, Munzi et al., 2008).

[14] In order to have a value weighted Laspeyres index we should have included weights. We omit them in order not to complicate the notation: these results would not have change substantially if we had used weighted means of the indices or any other elementary aggregation technique (e.g.: Jevons, Dutot, etc.). The simplification that is adopted here is useful for a straightforward application of simple random sampling results.

[15] The general formula, with no restrictions on the distributions of X and D, is:

$$\sigma_Y^2 = \overline{X}^2\sigma_D^2 + \overline{D}^2\sigma_X^2 + \sigma_X^2\sigma_D^2 - 2\overline{XD}\sigma_D\sigma_X\rho_{XD} - \left[\sigma_D\sigma_X\rho_{XD}\right]^2 + \sigma_{X^2Y^2} \qquad (1.4.n).$$

2. Estimators and biases

A comparison can be made by observing the characteristics of the estimates obtained with three different types of surveys: local surveys (*LOC*), in which a sample of n_{loc} bargain prices is observed by means of a network of price collectors visiting a sample of outlets; centralised surveys of list prices (*LIS*), by means of which only list prices are collected, presumably centrally, with a sample size n_{lis} which it is reasonable to expect much larger than n_{loc} and eventually very near to be exhaustive[16]; mixed surveys (*MXD*), in which list and transaction prices are observed with independent *LIS* and *LOC* surveys and distinct sample sizes[17].

2.1 Local survey of bargain prices (LOC)

Examining the first case, let's assume that a simple random sample of transactions is drawn from the population Y_{ij}. Given formula (1.3), an estimate of the price index is

$$\bar{y}_{loc} = \frac{\sum y_{ij}}{n_{loc}} \tag{2.1.1}$$

where n_{loc} is the sample size, corresponding to a small sampling fraction. Obviously, this sample mean is an unbiased estimate of the population mean:

$$B_{loc} = E\left[\bar{y}_{loc} - \bar{Y}\right] = 0 \qquad (2.1.2)^{18}$$

The average square deviation (*S*) between the sample mean and the population mean coincides with the variance of the sample mean $V(\bar{y})$[19]:

$$S(\bar{y}_{loc}) = \sigma^2_{\bar{Y}} = \frac{\sigma^2_Y}{n_{loc}}(1 - f_{loc}) \tag{2.1.3}$$

where f is the sampling fraction ($f_{loc} = \frac{n_{loc}}{N}$) and σ^2_Y is defined in (1.4). The sampling fraction will be probably very close to zero, so that the preceding expression can be modified as follows:

$$S(\bar{y}_{loc}) = \frac{\sigma^2_Y}{n_{loc}} \tag{2.1.4}$$

[16] This type of survey is generally centralised, since it is more efficient to concentrate the know how and the information needed to perform it.

[17] From now on *LIS*, *LOC* and *MXD* will be used as shortcuts to identify each type of survey. Furthermore, capital letters (Y, D, X) will be used to indicate the population values, while small ones (y, d, x) will be correspondingly used for sample values.

[18] See Cochrane (1974), p. 22.

[19] See Cochrane (1974), p. 23.

2.2 Centralised survey of list prices (LIS)

List prices are generally collected with a centralised production process: the sample, and in particular its coverage, may be much larger if compared with *LOC* surveys and even nearly coincide with the entire population. An estimate of population mean is then obtained as follows:

$$\bar{y}_{lis} = \frac{\sum x_i}{n_{lis}} = \bar{x}_{lis} \quad (2.2.1).$$

The bias of this estimate is then derived by averaging the difference between sample and population mean (the latter being derived from (1.3)):

$$B_{lis} = E\left[\bar{y}_{lis} - \bar{Y}\right] = E\left[\bar{x}_{lis} - \overline{XD} - \sigma_{XD}\right] = \left(1 - \bar{D}\right)\bar{X} - \sigma_{XD} \quad (2.2.2).$$

The bias includes two effects. The first depends on the dynamic of the discount policy: if this policy varies on average (e.g.: an increase in the correction coefficient applied by retailers, that is $\bar{D} > 1$), then expression (2.2.1) will bring an underestimate of population mean since it is not able to account for this change of policy. The second is given by the covariance between X and D, which cannot be measured if only X is collected.

Based on (2.2.2), the average quadratic deviation from the population mean can be expressed as follows:

$$S\left(\bar{y}_{lis}\right) = \frac{\sigma_X^2}{n_{lis}}\left(1 - f_{lis}\right) + \left[\bar{X}\left(1 - \bar{D}\right) - \sigma_{XD}\right]^2 = \sigma_{\bar{x},lis}^2 + B_{lis}^2 \quad (2.2.3).$$

The first term of (2.2.3) corresponds to the variance of the sample mean of X. Since we expect a huge sample size, its value is very likely to be near to zero, especially because sampling fraction tends to unity. In this case the first term of the right hand side of expression (2.2.3) can be ignored. Hence:

$$S\left(\bar{y}_{lis}\right) \cong B_{lis}^2 \quad (2.2.4).$$

2.3 Mixed independent estimates of discount and list prices

Let's assume in this case that list prices are observed for the entire population while effective prices are observed on a local sample only, whose size is n_{mix}. Suppose moreover that the two surveys are run independently, so that by means of list prices we measure $\bar{X}$ while with the sample we obtain an estimate of $\bar{D}$. In this case:

$$\bar{y}_{mix} = \bar{X}\frac{\sum d_{ij}}{n_{mix}} = \bar{X} * \bar{d}_{mix} \quad (2.3.1).$$

The bias in this case is given by:

$$B_{mix} = E\left[\bar{y}_{mix} - \bar{Y}\right] = E\left[\bar{X} * \bar{d}_{mix} - \overline{XD} - Cov\left(X, D\right)\right] = -\sigma_{XD} \quad (2.3.2).$$

Comparing this result with B_{lis} (2.3.2), only one component of the bias is present: the one depending on the interaction between *X* and *D* and which cannot be measured by means of the estimator (2.2.1). In this case, the average quadratic distance of (2.3.1) from the population mean is:

$$S(\bar{y}_{mix}) = \frac{\sigma_D^2}{n_{mix}}(1 - f_{mix}) + \sigma_{XD}^2 = \bar{X}^2 \sigma_{\bar{d},mix}^2 + B_{mix}^2 \qquad (2.3.3).$$

2.4 Mixed covariance-corrected estimates of discount and list prices (MXD)

Given the results derived just above in (2.3.2) and (2.3.3), and in particular given the bias that affects the mixed estimates, it seems possible to introduce an estimate of the correction factor needed to bring that bias to zero. We introduce, more specifically, a correction on (2.3.1). Moreover, we differentiate from the case treated in paragraph 2.3 by considering the case in which a sample is used also to estimate the dynamics of list prices. As a consequence, two samples are used for this type of survey: a large sample of size n_{mxd}^{x} for list prices and a smaller sample whose size is n_{mxd}^{d} for bargain prices: the corresponding sampling fractions will be presumably strongly different. The two samples, the one used for list prices and that used for bargain prices, are independently drawn. By means of the first we estimate $\bar{X}$ while with the latter we estimate $\bar{d}$ and *Cov(xd)*. In particular:

$$\bar{y}_{mxd} = \bar{x}_{mxd} * \bar{d}_{mxd} + \sigma_{XD} \qquad (2.4.1)$$

Consequently:

$$B_{mxd} = 0 \qquad (2.4.2).$$

The variance of the sample mean is then:

$$S(\bar{y}_{mxd}) = \bar{X}^2 \sigma_{\bar{d},mxd}^2 + \bar{D}^2 \sigma_{\bar{x},mxd}^2 + E\left[(\sigma_{xy} - \sigma_{XY})^2\right] \qquad (2.4.3),$$

where the last term (the variance of the sampling covariance) can be assumed close to zero[20].

3. An evaluation of the different approaches to sampling

3.1 Comparing formulas

A comparison between *LOC* and *LIS* surveys can be performed by confronting expressions (2.1.4) and (2.2.4). If we assume the absence of linear relations between *X* and *D*, and if we consider $\sigma_{\bar{x},lis}^2$ very close to zero, we can derive that:

$$S(\bar{y}_{lis}) > S(\bar{y}_{loc}) \Leftrightarrow (1 - \bar{D}^2)\bar{X}^2 < \frac{\bar{X}^2 \sigma_D^2 + \bar{D}^2 \sigma_X^2}{n} \Leftrightarrow \frac{(1 - \bar{D}^2)}{\bar{D}^2} < C_D^2 + C_X^2 \qquad (3.1.1)$$

[20] This result derives from the fact that the samples used in *LIS* and *MXD* are independent.

where $C^2_{\bar{D}}$ and $C^2_{\bar{X}}$ are the squared coefficients of variation of the corresponding sample means. In other words, *LIS* surveys deliver better results as long as the variability of retail policies is below a threshold whose value depends directly on the variability of *X* and *D*. The higher they are, the higher will be that threshold, since the results of *LOC* surveys becomes increasingly volatile. If a linear relation exists between the two pricing components, its presence tends to make *LOC* surveys more preferable since the *LIS* bias is, as a consequence, relatively higher.

The comparison between *LOC* (or *LIS*) and *MXD* approaches is instead relatively trivial, since *MXD* uses more information. Quite clearly, larger gains of precision will be obtained with respect to *LOC* surveys if the variance of list price indices is relatively high.

We already know that with *LOC* surveys estimates are unbiased with a confidence interval that depends on the variance of the sampling means of X and D, and on the sampling size. This last is presumably kept small in absolute and relative terms by the high burden of price collection: the sampling fraction is presumably very close to zero. In the case of *LIS* surveys confidence intervals for the estimates of the dynamics of list prices will be very small, mainly because the sampling fraction will be close to unity. Moreover it is reasonable to expect a small variability in list prices and, consequently, more precise estimates for this component. These are biased estimates of effective price changes if retailers modify their pricing policy: the bias can also be eventually influenced by any covariance between their policy and the actual dynamics of list prices. Quite obviously, the more $\overline{D} \neq 1$ and/or $\rho_{XD} \neq 0$, the more *LIS* surveys are not a good solution. Finally, *MXD* surveys with covariance correction deliver unbiased estimators with lower confidence intervals with respect to local surveys. The highest gain in efficiency can be obtained if the variability of list prices is relatively high.

3.2 Some simulations with random populations

Other elements can be inductively derived from the results of some simulations: the three approaches to sampling have in fact been tested taking into account some different hypotheses concerning the nature of the target population.

In particular a set of artificial reference populations have been created starting from a benchmark random population (Simulation 1 in Table 1) defined as follows: (a) it is composed by 250 models in the market and about 12 thousands transactions referred to these models in the base and in the current month; (b) the list prices of the models are increased on average by 2.5% from month *0* (base) to month *m*: the rate of increase of the price of each model is uniformly distributed, between a minimum of 0 and a maximum of 5%; (c) retailers apply in each period and in each transaction an average 5% discount on the corresponding list price: for each transaction the rate of discount is uniformly distributed between a minimum of 0% and a maximum of 10%; (d) a set of 300 independent samples are drawn from this population: each run of sampling produces a sample for *LOC* survey, a sample for *LIS* survey, while the *MXD* is derived from the joint use of the first two samples; (e) in particular, the *LOC* survey is based on a random sample extracted with a sampling fraction of 1% of all transactions, while the *LIS* survey uses a sample that includes about 80% of the models.

Other four random populations are drawn from this same structure by simply changing the characteristics of the pricing policy, concerning namely the dynamics of the list prices and that of the discount policies. The objective is to simulate the performance of each type of survey in all such populations.

Table 1. - Distinguishing features of the random populations

Type of survey	Simulation 1	Simulation 2	Simulation 3	Simulation 4	Simulation 5
Maximum increase in list prices	5.0%	**20.0%**	5.0%	5.0%	5.0%
Distribution of discounts in the reference month	uniform	uniform	uniform	uniform	uniform
Distribution of discounts in the current month	uniform	uniform	uniform	**Correlated with X^2**	**constant within model and uniform between models**
Maximum discount rate in the current month	10.0%	10.0%	**5.0%**	10.0%	10.0%

Table 2 and Chart 1 show some results obtained from these simulations. Simulation 1 will show on average no correlation between *X* and *D* and a nearly zero dynamics of the discount policy (that is $\overline{D} \cong 1$). Since the *LIS* bias is negligible, this type of survey is expected to perform quite well. The resulting 2.53% increase in Y is determined by a 2.47% increase in list prices X and a 0.06% increase due to the average change in retail policies. Covariance and correlation are close to zero. The variability of the discount policy *D* is almost ten times larger than that of list prices *X*.

The estimates produced by the 300 *LIS* samples (see also Chart 1) - although they are slightly biased - present a very small range in the sample means: the range between 97.5th and the 2.5th percentile in the distribution of the sample means is 0.207. On the contrary, while the estimates obtained with *LOC* surveys are unbiased, their range is much larger than *LIS* survey's, by a factor of more than 7. The performance of *MXD* surveys looks better than the *LOC* ones, but anyway very close to it: in particular, *MXD* shows lower extreme values in the distribution of the population mean.

This picture changes slightly if the variability of *X* is increased. In the second simulation the variability of list prices is much higher than in simulation 1. As a consequence, *MXD* surveys perform now much better than *LOC* surveys. In fact, in this simulation the largest gains derive now from the better coverage of *X* variability that is offered by *LIS* surveys. The differences between the corresponding percentiles of the distribution of the sample estimates derived from *MXD* surveys appear then much reduced with respect to *LOC* surveys (nearly 25% less).

In simulation 3 the hypothesis of zero dynamics in the discount policy has been removed. In particular, with respect to simulation 1 it has been assumed that the maximum rate of discount decreases from 10% in the reference month to 5% in the current one: this implies an average increase in the prices applied by retailers. Discounts keep on being applied randomly: so covariance and correlation are still negligible. The index *Y* showed a 5.24% increase, determined by a 2.45% increase in *X* and a decrease of 2.72% in *D*. This change in retail policy implies a strong increase in the bias deriving from the exclusive use of list prices. In particular the estimate based on price lists makes an average error of more than 2.65% and presumably a much higher mean square error with respect to the other survey techniques. *LIS* survey, in fact, only records the increase in list prices, and cannot measure the fact that effective prices increase faster because the average rate of discount has also decreased.

Table 2. - Main sampling indicators, by type of survey and simulation

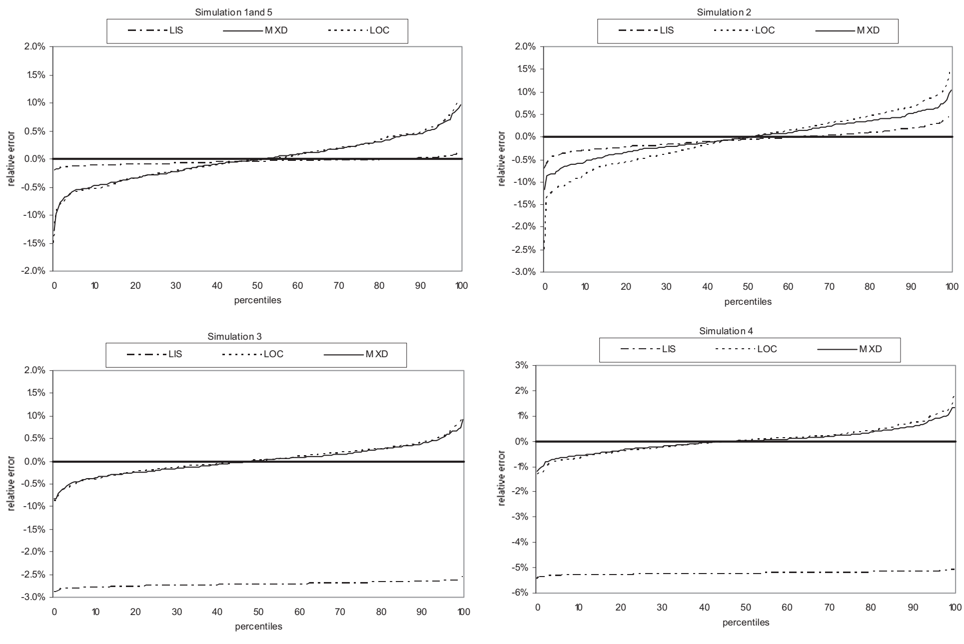
Type of survey	Bias (%)	95% interval of the mean	Mean(Y)	Mean(D)	Mean(X)	V(D)	V(X)	R^2	Sample size
				Simulation 1					
LIS	0.06	0.207	2.48%		2.48%		0.00021		9507
LOC		1.546	2.52%	0.05%	2.47%	0.00182	0.00021	-0.006	120
MXD		1.388	2.53%	0.05%	2.48%	0.00182	0.00021	-0.006	120
Population			2.53%	0.06%	2.47%	0.00185	0.00021	-0.011	11938
				Simulation 2					
LIS	0.07	0.749	9.63%		9.63%		0.00326		9465
LOC		2.172	9.65%	0.06%	9.58%	0.00180	0.00323	0.013	119
MXD		1.530	9.70%	0.06%	9.63%	0.00180	0.00326	0.013	119
Population			9.71%	0.07%	9.63%	0.00181	0.00327	0.002	11891
				Simulation 3					
LIS	2.65	0.193	2.46%		2.46%		0.00020		9622
LOC		1.310	5.26%	2.73%	2.46%	0.00118	0.00020	0.020	122
MXD		1.252	5.26%	2.73%	2.46%	0.00118	0.00020	0.020	122
Population			5.24%	2.72%	2.45%	0.00119	0.00020	0.015	12081
				Simulation 4					
LIS	4.89	0.216	2.50%		2.50%		0.00022		9964
LOC		2.167	7.89%	5.21%	2.50%	0.00293	0.00021	0.555	126
MXD		1.796	7.89%	5.21%	2.50%	0.00293	0.00022	0.551	126
Population			7.87%	5.18%	2.51%	0.00297	0.00022	0.562	12508
				Simulation 5					
LIS	-0.01	0.212	2.39%		2.39%		0.00021		9600
LOC		1.568	2.37%	-0.01%	2.38%	0.00191	0.00021	-0.046	120
MXD		1.419	2.38%	-0.01%	2.39%	0.00191	0.00021	-0.046	120
Population			2.37%	-0.01%	2.39%	0.00192	0.00021	-0.040	12065

Notes: (a) The interval is given by the difference between the 97.5th and 2.5th percentile of the distribution of the sample means.
(b) The means of Y, D and X have been expressed in terms of rates of change (between the reference and the current month) and not of index.
(c) The columns *V(...)* report the estimate of the variance of the variable between parentheses.

In simulation 4 some covariance between list prices and retail policies is introduced: in particular, it is assumed that discount corrections in the current period are correlated with the level of X^2. This implies that a change has taken place in the retail policy from the base and the current month (as it happened in simulation 3), and in particular that the effect of the correlation between list and retail policies must be taken into account. In particular, it has been assumed that maximum discount in period *0* is 10% and that in the current period the retail correction can be increased proportionally to the square of X: a random effect is also included. This correction implies a strong growth in the D index, that is a price increase stronger than the one registered by list prices. The table also shows a higher value for the correlation coefficient, which now surpasses 0.5. This effect mainly implies that the bias of *LIS* estimates is quite larger then in former simulations, while the comparative advantage of *LOC* and *MXD* remains substantially unaltered. *MXD* keeps on performing better as far as precision is concerned.

A last variant of simulation 1 can concern the case in which retail policies vary at model level. We assume that discount is uniformly distributed between 0 and 10% in period 0, while in the current period its pattern changes: it is fixed for each transaction involving a same model, and changes only from model to model according to as uniform distribution. In terms of consequences for the estimates, this case is very similar to that presented in simulation 1. In fact, whatever correlation between discount policies and any variable uncorrelated with X does not induce any bias in the estimates.

Chart 1. - Percentiles of the distribution of the relative error of the sample mean, by type of survey and simulation



4. Some generalisations

It seems that *MXD* surveys guarantee generally better performances, by allowing large improvements to the results of *LOC* surveys. *LIS* surveys are instead very weak since they need very strict hypotheses on retailers behaviour in order to be considered viable. As concerns *LOC* surveys, they need conditions of low variability of list prices to give appreciable results. Several hypotheses have been done anyway to reach these conclusions with some formalisation. It is worth the while to spend a few words on the consideration of possible generalisations of these results, trying in particular to draw some hints on the consequence of relaxing the hypothesis of one-to-one correspondence between the transactions of the reference and of the current month. Other aspects might interfere meaningfully with the production of such estimates, as for example the consideration of the desired time horizon of our estimates (monthly, quarterly or yearly indices) and the consideration of the possibility of adopting a more articulated sampling design. Furthermore, it must also be kept in due account the fact that many of the conditions that we have derived in sections 2 and 3 may be valid in a specific month but not in the generality of the twelve months

4.1 The correspondence between transactions

As summarised in expression (3.1.1), the comparative evaluation of the three survey methods (*LOC, LIS* and *MXD*) depends crucially on the relative variability of the indices of list prices and retail policies (*X* and *D*). In general, the advantages of adopting *LIS* surveys are higher the higher is *X* variability. If we consider the case of new cars, such results seem to imply that the CPI for cars ought to be estimated on the basis of a *LOC* survey, since list prices are very stable. But if we recognise that the variability of list prices depends not merely on the dynamics of the list price attached to each model but also on models' turnover than things might change a lot. The variability of list prices in presence of a high model turnover may increase strongly and may push in favour of the use of *LIS* surveys.

In the simulation described in section 3 only the first source has been considered. But the change in the product range may be very influential on *X* variability, independently of which quality adjustment technique is being implicitly or explicitly adopted. In fact the change in the product range impairs the one-to-one correspondence and this implies the necessity to operate replacements and to compare the prices of different models within a same segment. This source of higher variability of *X* implies relatively more advantages in the use of *LIS* surveys, especially in the *MXD* approach, while the defects of *LOC* surveys emerge more clearly. *LIS* surveys in fact give the possibility to exploit large samples and more articulated sample designs. It may guarantee, for example, a good segmentation through stratification: *LOC* surveys do not give this possibility. Surveying systematically list prices offers the possibility to deliver a better representation of the turnover of models and of the product range, and more generally guarantees a better picture of the consumer market, which may be difficult to obtain with the smaller sample size implied by *LOC* surveys[21].

[21] A better adaptation to HICP Regulation 1334 (see European Commission, 2007) and to the consumption segments approach is also guaranteed by LIS or MXD surveys.

4.2 Time horizon of the estimates

LIS surveys are clearly affected by a bias when retail policies change or when a linear correlation exists between these policies and the dynamics of list prices. This mere fact makes *LIS* surveys a weak short term price indicator. But what can we say about their longer term performance?

The answer to this question depends on the nature of retailer policies. Since it is difficult to imagine systematic trends (increasing or decreasing) in the behaviour of the index *D*, the issue is to know how it varies, how regular or cyclical is its behaviour, how it affects year-on-year price changes.

What we can expect is that a yearly average of the 12 monthly price indices may be less affected by changes in discount policies and by correlation with list prices. The choice of the survey technique depends then also on the target of our estimates: the choice to be made to make a good quarterly index may be quite different from the case in which the target is a monthly index. The longest the time horizon the less *LOC* surveys are useful.

There is a further complication: any regularity in the behaviour of prices, must be measured with an instrument – the price index – whose base is defined with reference to a single month (December t-1), at least in the HICP context. As a consequence, any weakness in the method that we apply may affect the base month and all the estimates referred to the current year. This problem is part of the categories of problems connected for example to seasonal products. If the month of December represents a particular month in the seasonal evolution of indices, it may happen that in this base month estimates error and confidence intervals are larger[22]. The use of *LIS* or *LOC* surveys may, for opposite reasons, suffer the same drawback, while *MXD* surveys represent a safer solution.

4.3 Sampling design

Discount policies may depend on short term producers' policies or on point of sale policies. There exists a huge literature on this subject[23]. As we have seen before (see simulation 5), should there exist any correlation between these policies and other variables different from list prices indices[24], these would not imply a bias on *LIS* estimates. Nevertheless, the existence of these correlations may be helpful while deciding the sample design to be adopted, since it may help to define an efficient stratification especially for *MXD* surveys.

In this type of approach, two distinct samples are drawn: a relatively small *LOC* sample and a huge *LIS* sample. The sample designs of these two surveys may be drafted in order to guarantee an efficient usage of formula (2.4.1) at stratum level. A deeper study of the behaviour of retailers can give the possibility to study an efficient stratification in order to pass rapidly from a *LIS* survey to a *MXD* survey. It could be useful to test which structural variables mainly influence bargaining. If these variables have to do with the characteristics of customers (and much of the literature stresses this point) then the use of local surveys looks less promising since the characteristics of price collectors may induce a bias.

[22] See De Gregorio, Munzi et al. (2007).

[23] From different perspectives, see for example Sweezy (1939) , Jung (1959) , Goldberg (1996), Zettelmayer (2003), Scott Morton (2003), Marn et al. (2003).

[24] Retailers' policies may be related, for example, to the customer, to point-of-sale strategies, to the kind of vehicle, to the brand, to the age of the model, etc.

4.4 Monthly estimates

The relative advantage of *LIS*, *LOC* and *MXD* surveys may not be constant during the whole year. We have implicitly adopted Martin Ribe's approach to CPI estimates and sampling design[25], in which the unchained index is used as the parameter to be estimated. In a HICP context, this means that the parameter is the population monthly index based on December of the previous year. In this theoretical context, the problem of sampling deals with the definition of at least 12 distinct sample designs, one for each month.

Also in the cases where no seasonal effect is present, indices' variability is generally not constant across months, and changes systematically the more we get far from the base month. In the case of list prices, their variability depends in fact crucially on the time horizon of the index. It is reasonable to assume that, for each model, list prices tend to vary not very frequently during the year. The more the current month is far from the base the higher the probability that the list price of a given model has changed and thus the higher might be the variability of X, especially if we consider the effects of replacements. Taking December year t-1 as the base month, there will be a huge diversity between the profile of X variability that is registered in January and in December year t. In January most of the units will probably show no price change and the variability will be very low although concentrated in a few models. In December the price changes which have taken place in the eleven months before will have cumulated and will affect reasonably most of the models in the population. These differences do not only imply the heterogeneity of the monthly patterns of variability: what may be different is also the distribution of the observations, which is probably very far from approximating well the normal or the log-normal distributions in the first months of the year.

[25] Ribe (2000).

Concluding remarks

Explicit formalisations of the sampling design to be adopted for CPI estimates are quite rare in specialised literature[26]. In the preceding sections we have proposed some formalisations based on probability sampling in the simplified context of one-to-one correspondence between transactions in the reference and in the current month. This in order to deliver a base for analysing a dichotomy which is quite frequent in price statistics and which can be expressed as follows: Is it better to use a centralised survey of list prices (that is, a survey made in the statistical office by collecting and storing official listings) or to opt for a local price collection of bargain prices? Is it better a huge sample of models and a collection of prices which are not the real ones, or a small sample of actual transactions?

One first suggestion is that the dichotomy between adopting *LIS* or *LOC* surveys appears to some extent a too simplistic way to face the issue of producing a reliable estimate of the CPI. The use of mixed surveys (*MXD*), where *LIS* and *LOC* surveys are both used each month, appears to be a more complete tool to estimate price indices in markets where list prices are part of the pricing policy. But, as we have seen in paragraph 2.4, in order to produce reliable estimates and to avoid any systematic bias, *MXD* estimates must include a covariance correction, to be estimated by means of local surveys (see expression (2.4.1)). The conditions by which *LIS* or *LOC* surveys become more efficient are very likely to be changing with months and with circumstances due to sudden changes in the variability of list prices and discount policies.

There are not only strictly technical reasons behind the superiority of *MXD* surveys: it is legitimate to expect that the relaxing of the strict hypotheses that we have adopted to simulate the sample design bring further elements in support to *MXD* solutions. The main advantage that they convey – which is proper, although to a minor extent, also of *LIS* surveys - lays in the possibility to offer a more complete monitoring of consumer markets, since they give the possibility to trace the main changes in the range of product available to consumers and, as a consequence, to manage more properly replacements. Under this point of perspective, it seems that *MXD* surveys comply in a more satisfying way with the recent trends in applied CPI theory, and in particular with new concepts such as the consumption segments, which have been introduced recently within the HICP project with the objective to pave the way for a proper definition of the population parameter and, as a consequence, for more coherent sampling designs[27].

LIS surveys are more frequently adopted, typically in the case of new cars. Nevertheless, the adoption of *LIS* surveys is in general risky, and in particular for short term estimates. In fact, very strict conditions have to be fulfilled in order to guarantee the production of unbiased estimates: these assumptions concern in particular the dynamics of retailers correction on list prices. *LOC* surveys loose their efficiency if list price variability is relatively high, that is if a medium term horizon (generally some months, often one year or more) is considered.

Market analysis, market-specific and country-specific evaluations should then be made concerning the components of price and price index variability, and to support the choice of

[26] The work of Ribe (2000) gives an important contribution on this subject and, although the solution is still incomplete, it paves the way for further improvements. The most tricky aspect has to do, in particular, with the definition of the reference population and, consequently, of the parameter to be estimated.

[27] European Comission (2007).

a method. Such analyses could in particular help to model the variability of discount policies in order to provide a framework for improving sampling designs and to set the *LOC* survey in the context of a *MXD* approach, and thus to reduce its burden.

Further efforts should also be dedicated to compare the alternative approaches to CPI surveys, by means of more complex sample designs, based on stratified or multi-stage samples. The comparative advantage of *MXD* solutions might in fact be further qualified and quantified.

References

Cochrane W.G. (1977), *Sampling techniques*. 3rd edition. John Wiley & sons, New York, p.428.

De Gregorio C. (2006), "Il nuovo impianto della rilevazione centralizzata del prezzo dei medicinali con obbligo di prescrizione", *Contributi Istat*, n.16.

De Gregorio C., Fatello S., Lo Conte R., Mosca S., Rossetti F. (2008), "Sampling design and treatment of products in Istat centralised CPI surveys". *Contributi Istat* n. 1.

De Gregorio C., Munzi C., Zavagnini P. (2008), "Problemi di stima, effetti stagionali e politiche di prezzo in alcuni servizi di alloggio complementari: alcune evidenze dalle rilevazioni centralizzate dei prezzi al consumo". *Contributi Istat* n. 6.

European Commission (2007), "Commission Regulation (EC) no 1334/2007 of 14 November 2007 amending Regulation (EC) No 1749/96 on initial implementing measures for Council Regulation (EC) No 2494/95 concerning Harmonised Indices of Consumer Prices". *Official Journal of the European Union*, 15 Nov., L296/22-26.

Eurostat (2005), "HICP standards for cars and other vehicles". *Paper by Eurostat and the Task Force "Implementation Group on Quality Adjustment and Sampling"*. HCPI 05/520 Rev.1 Final.

Genesove D., Mayer C., (2001), "Loss aversion and shelter behaviour: evidence from the housing market". *The Quarterly Journal of Economics* (Nov.), Vol.116, No. 4, 1233–1260

Goldberg P. K., (1996), "Dealer price discrimination in new car purchase: evidence from the consumer expenditure survey". *The Journal of Political Economy*, Vol. 104, Issue 3 (June), 622-654.

Horowitz J.L., (1992), "The role of the list price in housing markets: theory and an econometric model", *Journal of Applied Econometrics*, vol. 7, 115-12.

Istat (2007), *The characteristics of Istat CPI centralised surveys*. Mimeo, Istat.

Jung A.F., (1959), "Price variations among automobile dealers in Chicago, Illinois", *The Journal of Business*, Vol.32, No.4, 315-326.

Knight J.R., Sirmans C.F., Turnbull C.K., (1998), "List price information in residential appraisal and underwriting", *Journal of Real Estate Research*, Vol.15, Nos.1/2, 59-76.

Lutz M. (2004), "Pricing in Segmented Markets, Arbitrage Barriers, and the Law of One Price: Evidence from the European Car Market". *Review of International Economics*, 12(3), 456–475.

Marn M.V., Roegner E.V., Zawada C.C., (2003), "The power of pricing", *The McKinsey Quarterly*, No.1, 27-36.

Ribe M. (2000), "Price index, statistical inference and harmonisation". *Proceedings of the 4th International Conference on Methodological Issues in Official Statistics*. 12-13 October.

Scott Morton F., Zettelmeyer F., Silva-Risso J. (2003), "Consumer Information and Discrimination: Does the Internet Affect the Pricing of new cars for woman and minorities?" *Quantitative Marketing and Economics*, March, Vol.1, No.1, 65-92.

Sweezy P., (1939), "Demand under conditions of oligopoly", *The Journal of Political Economy*, Vol. 47 No.4 (Aug), pp.568-573.

Thanassoulis J., (2005), "List prices, bargaining and resultant productivity diffusion delay". *Discussion paper,* series n.220, Department of economics, Oxford university.

Zettelmeyer F., Scott Morton F., Silva-Risso J. (2003), "Inventory Fluctuations and Price Discrimination: The Determinants of Price Variation in Car Retailing", Yale School of Management, manuscript.