Variance screens for detecting collusion: an application to two cartel cases in Italy

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In this paper the effectiveness of variance screens in detecting collusion is tested on two Italian antitrust cases, dealing with collusion in motor fuel (gasoline and diesel) market and in the market of personal care and baby food products sold in pharmacies. In both cases the Italian Competition Authority found documental evidence of collusion. We found that the variance screen would have successfully detected collusion, consistently with antitrust investigations findings. Based on the specific features of time series analysed, several methodological remarks are made, concerning treatment of series displaying stability phases separated by jumps or instabilities, alternative explanations of price patterns and the kind of collusion detected.

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Variance screens for detecting collusion: an application to two cartel cases in Italy

Fabio Massimo Esposito – Massimo Ferrero[1]

Introduction

Detection of cartels based on empirical data has always been a difficult task for antitrust agencies. It needs a great amount of data on prices and costs to check if actual prices in a market are above the competitive level and why it is so. Data nevertheless are often unavailable or very costly and time-consuming to collect; moreover, the kind of data required to assess a conspiracy is of a very sensitive nature; finally, data on their own can tell several, often conflicting, stories. For this last reason data screening is only useful in preliminary stages of investigations engaged in by competition bodies to detect cartels: it allows to select the markets or the situations where the circumstances for a conspiracy are at work and the presence of a cartel is most likely, but proof of a price-raising agreement demands a lot more evidence than the simple one about price movements or parallelism.

In this paper we discuss one of the techniques of data screening, suggested in the economic literature to detect cartels. It is grounded on the analysis of the time volatility of market prices: we hypothesize that we would find lower price variance (and higher price mean) with cartels than in competitive markets. There is some justification in the economic literature to assume lower price variance where a conspiracy is at work (see section II). The test therefore consists in checking whether different time periods for a single market, or geographical areas for a single product (or group of homogeneous products), exhibit different patterns of price variance: periods or areas where lower variance is found are the most interesting for an in-depth investigation to detect the existence of a cartel[2].

This method has some positive features:

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[2] The method we consider is based on the analysis of changes across different time periods in the intertemporal variance of *market* price, or differences in the intertemporal variance of *market* price between various geographic areas, and not on the analysis of differences in the variance of *firm* prices, computed for various times or areas. Although the latter could be also a technique to detect conspiracies (the very purpose of price-fixing cartels is to make participant firms' prices uniform), it needs data more difficult to collect than the former.

- it is intuitive and easy to implement: it makes use only of (aggregate) prices data, and not also of costs data, more difficult to collect; it is grounded on computations of everyday use (variance of prices);
- it has theoretical and empirical basis;
- it would be effective even if firms known that competition agencies were adopting it to screen for cartels: notwithstanding the risk of detection, there would be low price variance all the same as a consequence of cartel members behaviour[3].

We test the effectiveness of the technique by applying it to two industries, namely the motor fuel (gasoline and diesel) market and the market of personal care and baby food products sold in pharmacies. In Italy, the Autorità Garante della Concorrenza e del Mercato (the Italian Competiton Authority, from now on AGCM) has in the past years detected conspiracies for both sectors[4], so they are well suited to check whether the conjecture of low price variance where cartels are at work is verified and it is enforceable by competition agencies in performing their duties. The results of our analysis confirm the hypothesis, but at the same time they highlight some problems that one could run into when enforcing it. We will discuss in detail these points.

The paper is organized as follows. We begin in section I by reviewing the arguments and facts suggested in the economic literature, both theoretical and empirical, to support the idea of low price variance during cartel periods. Section II discusses the analysis of price data and reports results about motor fuel market, and section III describes the application of the method to the personal care and baby food products market. Section IV concludes, with a discussion of the difficulties and open questions relevant to the operational cartel detection activity based on low price variance.

I. Review of the literature

There are both theoretical and empirical arguments that support the conjecture of low price variance due to collusive behaviour by firms.

Some theoretical models give the insight that cartel prices respond less to cost shocks because if prices moved in the same way as costs the conspiracy could be disrupted; indeed, every change in the price by a member of the cartel could be held as cheating, rousing a price cut by the other participants in an attempt to punish the alleged cheater, and in the longer term a price war. Athey, Bagwell and Sanchirico (2004), for example, assume an oligopolistic market where every firm knows the movements of its own costs, but not the changes of costs of the other firms; if prices are fixed by the cartel on a cost basis (each member reveals its costs to settle the cartel prices), so that

[3] See Abrantes-Metz, Froeb, Geweke and Taylor (2005).

[4] The judge has reversed the AGCM ruling about the fuel market conspiracy. Although it was not his main argument, the judge questioned the existence of a cartel, holding that institutional setting could force parallel behaviour without collusion.

quantities sold by each firm are the greater the lower are its costs, firms with higher costs will have an incentive to (overtly) cut their prices, declaring costs figures below the actual ones. In order to avoid this behaviour, or the exercise of expensive controls over participant firms cost movements, cartel prices could be fixed *una tantum*, at the beginning of the conspiracy life, and then strictly maintained across time by a punishment system that should be applied whenever a price change by the firms occurs.

Harrington and Chen (2004) develop a quite different model: the firms are aware that a cartel could be detected by price screening, therefore they fix cartel prices so as the probability of detection is minimized. Particularly firms' customers become suspicious with regard to the existence of a cartel where they see anomalous prices, that is where observed prices are very different from expected prices; the expectations are based on beliefs about prices changes based on their past history. The model shows that optimal cartel prices, after a transitional phase in which they rise irrespective of costs, enter into a stationary phase in which they are responsive to costs; they are nevertheless much less volatile than non-collusive prices, because costs changes are not fully passed through, so that customers are not made suspicious and detect the conspiracy.

Another reason for reduced price volatility is that cartels are usually at work where there are high entry barriers (either structural or caused by members' behaviour) or, where entry is possible, they try to make up for it co-opting newcomers into the agreement; price movements generally caused by new firms are therefore prevented.

If frequent demand shocks gave potentially rise to price changes, conspiracies could establish market information sharing systems to anticipate the shocks and to prevent their effects, so that also in these circumstances price volatility is reduced[5].

Finally, discounts given by firms to customers are a source of price movements: average discounts can fluctuate across time if they are linked to sold quantities, or to the achievement of turnover targets, and so on. By choosing to sell at list price, removing therefore all their systems of discount, cartel participants can reduce the price dispersion[6].

Some empirical works analyze the connection between collusion and price rigidity, showing that the latter rises in more concentrated markets. Abrantes-Metz, Froeb, Geweke and Taylor (2005) find that the prices of frozen fish sold to the Defense Personnel Support Center in Philadelphia, U.S., decreased on average by 16%, while their standard deviation decreased by 263%[7] after the collapse of a bid-rigging cartel.

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[5] There is a growing literature (both empirical and theoretical) showing that firms tend not to react to temporary price shocks. Reasons can be different: fear to be considered "unfair" when exploiting shocks, prices based on mark-ups an so on.

[6] For all these sources of price volatility see Connor (2004).

[7] Prices also became more responsive to cost changes.

Connor (2004) tells about a cartel in the U.S. for two products, for which he compares the price variances during the pre-cartel and the cartel periods: the coefficient of variation decreased by 32% for product A and by 20% for product B; the dispersion between single firms' prices also decreased.

Bolotova, Connor and Miller (2005) examine price patterns when the lysine and citric acid cartels were at work. These conspiracies were prosecuted both by the U.S. Department of Justice and by the European Commission[8]. The study refers to the U.S. market prices, showing that the lysine price increased by over 30% and its variance decreased during the cartel period; the citric acid price increased by over 13% when the conspiracy was at work, the variance also increased. The authors interpret this last result as a consequence of the especially long period of the citric acid cartel: it would be more difficult to enforce cartel discipline during longer period; another explanation for the result could be the shortage of data for non-collusive periods compared with the greater availability of observations for the cartel period[9].

II. The motor fuel market

Motor fuel markets suit very well to test the effectiveness of the cartel detection method based on price variance analysis. The products are quite homogeneous, so we can comfortably compare price patterns for multiple geographical markets because they refer to the same products.

The European Commission reports on its web site[10] data about average weekly prices for gasoline and diesel fuel, for the EU-15 member states, from 1994 to 2005. We can therefore compare, for both fuels, price volatility between Italy and the other markets, to assess whether if price variance for Italy, where a cartel was revealed, is lower than the other EU states' one.

The AGCM found in 2000 that all major oil companies in Italy created a cartel that was implemented through so-called "brand agreements" between the companies and their distribution networks. In Italy retail price is set by service stations, but the companies recommend a retail price to their network members. From February 1994 until 1999, the brand agreements fixed the purchasing price for service stations as recommended retail price minus a discount. The companies adopted a mechanism to set the purchasing price for service stations, which acted as a disincentive for the stations to diverge from the recommended price levels. As a result, the recommended price had all the characteristics of an imposed price. The brand agreements were in force also after the AGCM ruling, that is they worked over the whole period considered in our analysis.

[8] For the Commission decisions see OJ L 152, 07.06.2001, p. 24-72 (lysine case) and OJ L 239, 06.09.2002, p. 18-65 (citric acid case).
[9] For other cases see D. W. Carlton (1986, 1989).
[10] See http://europa.eu.int/comm/energy/oil/bulletin/time_series/index_en.htm.

We considered only the period from 1998 to 2005, because we deemed too long a 12-years period, from 1994 to 2005, to give meaningful results. Analysed prices were retail prices, net of tax.

A preliminary analysis of the data revealed that the price series are not stationary. If the series variance is not steady across time, a comparison between the variances to find which one is the lowest, or to assess whether one of them is lower than another one, is not meaningful. We therefore turned price levels into percentage changes, whose series are stationary.[11] This transformation allows a straight comparison of the variances, without having to weight them by the mean of the series (that is, computing the coefficient of variation).

Standard deviations of the price series from 1998 to 2005 for EU-15 markets are in Table 1.

Table 1: standard deviations of price series for EU-15 countries, 1998-2005

	Gasoline st. dev.	Diesel fuel st. dev.
Italy	0.018567	0.016542
Spain	0.020326	0.020191
Austria	0.02291	0.022108
United Kingdom	0.023984	0.02253
France	0.026601	0.025421
Greece	0.029489	0.032649
The Netherlands	0.031492	0.032356
Ireland	0.033019	0.033883
Luxembourg	0.03475	0.032872
Portugal	0.035147	0.022715
Sweden	0.036565	0.03529
Denmark	0.039514	0.040184
Germany	0.045113	0.042432
Finland	0.048913	0.038499
Belgium	0.05118	0.044052

Rows in the table are arranged by the standard deviation of the gasoline series. Italy’s standard deviations are the lowest both for gasoline and diesel fuel markets.

We compared price volatility across different markets in Europe separately for periods 1998-99 and 2004-05, because from 2000 on crude oil price became much more volatile, and this could produce a greater variability during the latter period also for retail fuel prices. The results are as follows:

[11] We note that if we assume a lower price volatility across time where cartels are at work, due to a greater tendency of firms to keep rigid prices, the same reduced variability should be observed for prices percentage changes.

Table 2: standard deviations of prices, subsamples 1998-1999 and 2000-2005

	Gasoline st. dev. 98-99	Diesel fuel st. dev. 98-99	Gasoline st. dev. 2000-05	Diesel fuel st. dev. 2000-05
Austria	0.018259	0.021012	0.024277	0.022491
Belgium	0.033415	0.03171	0.055861	0.047469
Denmark	0.021217	0.028509	0.043938	0.043373
Finland	0.04657	0.026538	0.049722	0.041729
France	0.016504	0.01909	0.029187	0.0272
Germany	0.036709	0.041671	0.047611	0.04274
Greece	0.018904	0.04051	0.032247	0.029658
Ireland	0.016557	0.014945	0.036898	0.038141
Italy	0.012503	0.014418	0.020181	0.017195
Luxembourg	0.023372	0.023334	0.03779	0.035492
Portugal	0.033877	0.016192	0.035591	0.024483
Spain	0.02009	0.025898	0.020434	0.017965
Sweden	0.024068	0.034933	0.039872	0.035444
The Netherlands	0.024435	0.025479	0.033528	0.034358
United Kingdom	0.025826	0.033463	0.023385	0.017543

As before, price volatility is the lowest for the Italian gasoline and diesel fuel markets, for both periods.

We analysed price variance also for shorter time periods, that is separately for each year from 1998 to 2005; tests about variance differences across yearly series showed indeed that price percentage changes variance is in many cases significantly different from year to year:

Table 3.1 – Standard deviation of the gasoline price percentage changes

	1998	1999	2000	2001	2002	2003	2004	2005
Austria	0.018	0.018	0.026	0.022	0.023	0.022	0.024	0.028
Belgium	0.023	0.040	0.053	0.062	0.051	0.051	0.051	0.068
Denmark	0.017	0.023	0.052	0.040	0.037	0.031	0.042	0.058
Finland	0.046	0.045	0.052	0.049	0.037	0.052	0.034	0.069
France	0.008	0.018	0.028	0.028	0.021	0.024	0.030	0.040
Germany	0.029	0.042	0.045	0.048	0.053	0.038	0.052	0.049
Greece	0.016	0.020	0.040	0.035	0.027	0.027	0.027	0.036
Ireland	0.006	0.022	0.032	0.055	0.037	0.020	0.026	0.042
Italy	0.008	0.013	0.020	0.018	0.013	0.016	0.014	0.033
Luxembourg	0.020	0.025	0.037	0.037	0.037	0.033	0.031	0.050
Portugal	0.009	0.046	0.040	0.015	0.067	0.020	0.020	0.024
Spain	0.019	0.019	0.014	0.023	0.021	0.019	0.020	0.023

Sweden	0.022	0.025	0.049	0.038	0.034	0.042	0.038	0.038
The Netherlands	0.020	0.027	0.043	0.034	0.028	0.028	0.029	0.037
United Kingdom	0.015	0.031	0.029	0.028	0.018	0.017	0.019	0.026

Table 3.2 – Standard deviation of the diesel fuel price percentage changes

	1998	1999	2000	2001	2002	2003	2004	2005
Austria	0.020	0.020	0.024	0.019	0.021	0.024	0.025	0.022
Belgium	0.019	0.039	0.046	0.040	0.042	0.061	0.046	0.049
Denmark	0.027	0.027	0.043	0.052	0.033	0.053	0.041	0.035
Finland	0.026	0.026	0.048	0.037	0.030	0.049	0.041	0.043
France	0.010	0.020	0.027	0.019	0.020	0.034	0.032	0.027
Germany	0.032	0.048	0.043	0.040	0.043	0.043	0.053	0.033
Greece	0.048	0.030	0.037	0.031	0.027	0.029	0.029	0.023
Ireland	0.010	0.018	0.017	0.075	0.026	0.027	0.026	0.024
Italy	0.008	0.016	0.016	0.011	0.013	0.018	0.011	0.026
Luxembourg	0.021	0.023	0.036	0.032	0.025	0.047	0.033	0.037
Portugal	0.013	0.018	0.036	0.005	0.024	0.031	0.019	0.020
Spain	0.020	0.030	0.016	0.012	0.018	0.022	0.018	0.017
Sweden	0.044	0.024	0.041	0.031	0.027	0.043	0.036	0.033
The Netherlands	0.021	0.028	0.038	0.034	0.026	0.039	0.041	0.027
United Kingdom	0.016	0.043	0.024	0.012	0.012	0.018	0.017	0.019

It turned out that prices volatility in the Italian gasoline market was the lowest in 1999 and during the period 2002-04, the second-last in 2000 and 2001, the third-last in 1998 and the fifth-last in 2005; the variability for the diesel fuel market was the lowest for the period 1998-2000 and in 2004, the second-last from 2001 to 2003 and the seventh-last in 2005. The analysis seems to suggest strong indications of collusion in Italian motor fuel markets from 1998 to 2004, but weaker in the last year.

A requisite step of the detection method proposed is the check about the average levels of prices, that is for our specific analysis whether price levels in Italy were higher than abroad. We could not indeed suppose that a cartel is at work in a market where price is lower than in other similar environments. We compared Italy prices with the prices of the Euro-area markets for the period 2002-04, avoiding in this way distortions that could be produced if we used prices expressed in different currencies. The average prices for both fuels (net of tax elements), for the whole period, are as follows[12]:

[12] We note that the non-stationarity of the price series does not prevent comparisons of their averages. The series exhibit an upward trend due largely to the rising path of the crude oil, so we can remove this long term element to get stationary series, by subtracting crude oil prices from retail fuel prices. Moreover, the cost element we subtract is the same for all the retail price series; this transformation of the data affects only the levels of the prices, producing a sort of margin (retail price minus oil price) series, whereas our average prices comparison is completely unaffected, because we have only to check their order.

Table 4: average prices, net of taxes

	Gasoline average prices (€/000 litres)	Diesel fuel average prices (€/000 litres)
Austria	332.4736538	330.0362821
Belgium	314.7028546	314.9476745
Finland	319.227590	331.1282029
France	275.3800946	285.4119434
Germany	297.9564103	305.1737179
Greece	345.2434295	312.9675321
Ireland	330.4492797	**351.8813212**
Italy	349.9708974	339.5115705
Luxembourg	334.8792949	317.6046795
Portugal	320.418141	320.821391
Spain	321.8628974	320.5284551
The Netherlands	**353.5786538**	332.1425320

Italy average prices are on the top of the Euro-area markets ranking: only The Netherlands for gasoline and Ireland for diesel fuel have average prices higher than Italian ones.

The analysis gives some hint that Italian motor fuel markets were the scene of a cartel of the major oil companies. The AGCM investigation confirmed it for the years until 1999; the conspiracy scenario seems nevertheless likely also for the period from 2000 on. We have to consider whether the higher average level and the lower variance values for Italian markets could be explained by reasons that have nothing to do with cartels. For example:

- ✓ distribution network costs in Italy are higher than in many other European states;
- ✓ the higher share of retail price in Italy attributable to tax elements, that makes less viable competitive strategies based on price cuts, because decreases of the consumer price imply more than proportional drops of the firms unit revenue[13];
- ✓ specific policies of hedge as to crude oil price fluctuations by companies operating on the Italian markets, that make retail prices less responsive in Italy to oil price changes than in other European states[14].

These market features confirm that the cartel detection method based on price variance is useful at most during the preliminary stage of an

[13] This happens because a large part of the taxation on fuels is a lump tax, not linked with the product price.

[14] This is an assumption that should be verified. It is credible if we consider that the market and possibly price leader in Italy, Eni, is much weaker abroad, where its competitors are price drivers; therefore, the assumption could be sound if Eni adopted hedge strategies different from its competitors' ones.

investigation; only an in-depth inquiry (like the AGCM's one in 1999-2000) allows to prove the existence of a conspiracy and to rule out that the observed price pattern can be explained by other, competitive, reasons.

III. Personal care and baby food products sold both in pharmacies and in supermarkets

In 2002 AGCM fined national, regional and provincial professional associations of pharmacies[15] and pharmacists for restraining competition in the sale of pharmaceuticals and of several personal care and baby food products through *(i)* forbidding any individual discounting policy, *(ii)* the definition and diffusion of recommended sale price lists, *(iii)* the creation of commissions in charge of monitoring prices in other distribution channels and of defining recommended price lists, *(iv)* the invitation to follow producers' listed prices, *(v)* limitations to advertising.

Specifically, AGCM fined:

- the national associations of pharmacists
- the regional associations of Emilia Romagna and Lombardy
- the provincial associations of Turin and Genoa, regional capitols of Piedmont and Liguria;
- most of the provincial associations of Lombardy;
- a minority of the provincial associations of Trentino Alto Adige, Veneto, Friuli, Emilia Romagna, Marche, Tuscany, Campania;
- three out of four provincial associations of Sardinia.

According to the result of the investigation, collusive behaviour was therefore strong in Northwestern Italy and Sardinia, significant in Emilia Romagna, scattered in Northeastern Italy and almost absent in the rest of Italy.

During the investigation AGCM acquired from AC Nielsen value and quantity data regarding regional sales of several personal care and baby food products in pharmacies and supermarkets, spanning from march 1999 to march 2001. These data have been used to test whether the use of a variance screen would have effectively detected possible collusive behaviour from pharmacies belonging to local associations fined by AGCM.

Data

AGCM bought from A.C. Nielsen data on volume and value sales of the *two* most representative brands of selected personal care and baby food

[15] Traditionally, pharmacies in Italy have sold many products different from prescription and over-the-counter drugs, always relating to health care and baby care, whose quality was somehow "certified" by the fact the pharmacy was run by a physician. Considered that currently OTC drugs are sold only in pharmacies, Italian pharmacies are halfway between a store selling only prescription drugs and a drugstore, although their core business is in prescription and OTC drugs.

products sold both in pharmacies and in supermarkets: antiseptics, deodorants, toothpastes, toothbrushes, feminine sanitary pads, personal hygiene soaps, baby cereals, baby food. The dataset included separate series for supermarkets and pharmacies; for each channel, there were sales data for all different packages and variants of brands included in the dataset, broken down by eight territorial areas[16], made of one or more administrative Italian regions. Volume was defined as "number of packages sold".

Supermarket data were weekly, while pharmacies data were monthly. Weekly data were converted to monthly data by summing weeks belonging to the same month; for weeks common to two months, volumes and values were attributed to months on the basis of the number of days of the week belonging to each month. Data on value and volume sales were used to compute average prices for 25 months.

Table 5 reports average values of the weight of brands included in dataset over pharmacies sales, the share of pharmacies in the sales of these brands and the ratio of sale prices of pharmacies to those of supermarkets (for product items sold in both channels).

Table 5: summary information on products in the dataset

	Share of brands in the dataset over total pharmacy sales of the product category	Share of pharmacies in the sales of brands in the dataset	Ratio of pharmacies price to supermarket prices (brands in the dataset, product items sold in both channels)
Antiseptics	1,70%	43,09%	1,38
Baby cereals	48,10%	43,03%	1,12
Baby food	36%	21,79%	1,12
Deodorants	33,60%	10,03%	1,38
Feminine pads	59,80%	4,64%	1,09
Personal hygiene soaps	2,30%	37,24%	1,61
Toothbrushes	20,90%	18,36%	1,11
Toothpaste	17,10%	9,93%	1,14

Coverage of some brands is very low, because of wide availability of unbranded products (antiseptics) and of differentiation of brands sold in each channel (Personal hygiene soaps).

Average prices of product categories considered were systematically lower in supermarkets than in pharmacies. Over time, price levels relative to supermarkets increased in three cases (antiseptics, soaps, deodorants), while for the other categories there was a tendency to reduction. Relative sales share of pharmacies was stable or declining for all products.

Price positioning of all product items was the same in all regions.

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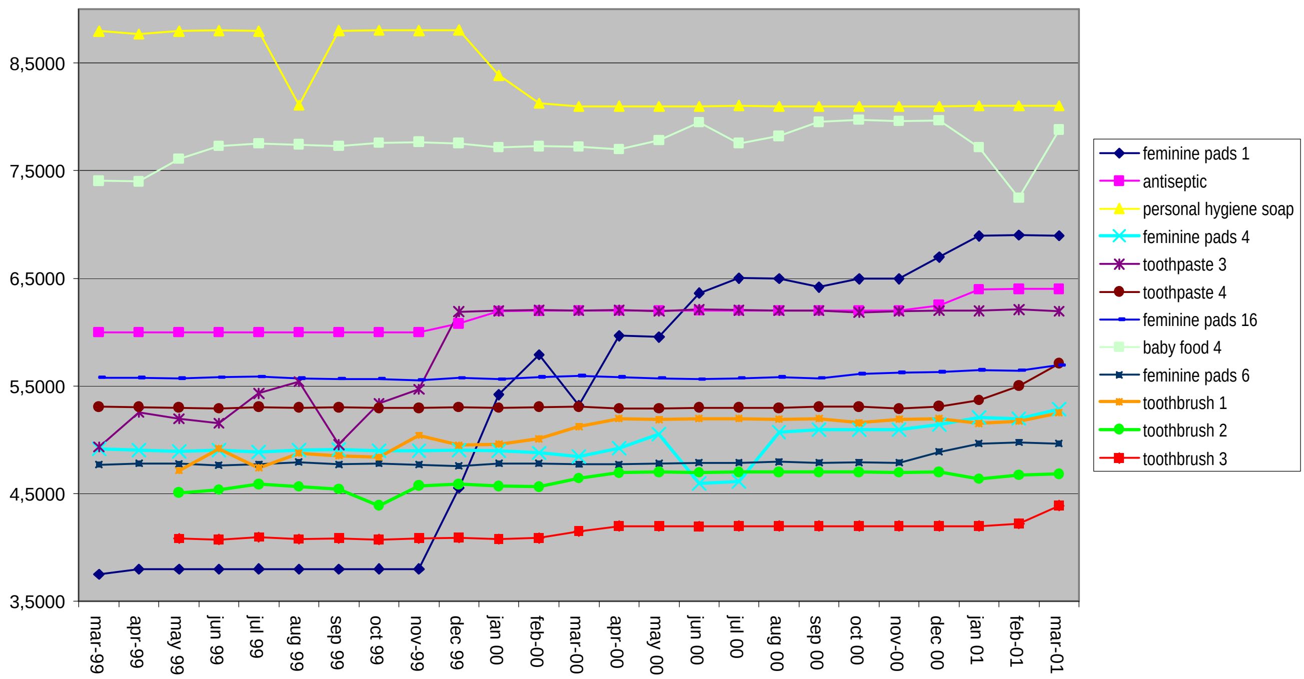
[16] North West (Valle d'Aosta, Piedmont, Liguria), Lombardy, North East (Trentino Alto Adige, Veneto, Friuli), Emilia Romagna, Center (Tuscany, Umbria, Marche), Lazio, Center South (Abruzzi, Campania, Puglia), South (Basilicata, Calabria, Sicily). Sardinia was not included in the data set.

From this dataset it was obtained a sample of 45 product items[17] sold in both channels, in all areas and with almost complete time series: 1 antiseptic, 6 deodorants, 4 toothpastes, 5 toothbrushes, 16 feminine sanitary pads, 1 personal hygiene soap, 7 baby cereals, 5 baby food product items.

Final sample included therefore 45 x 8 x 2 = 720 series, 25 months long each (except for toothbrushes, which began in may 1999 and were 23 months long).

Graph 1: Sample of typical pharmacies' series
(Emilia Romagna, thousands of italian liras)



Graph 1 shows the typical patterns of the pharmacies series. Many series are clearly not stationary. Several series includes periods of strong stability of price, even if the whole series moves through different price levels. Some of these series exhibit level jumps (e.g., personal hygiene soap, antiseptic), remaining stable before and after the jump; other series show a period of stability and then, after a jump to a new price level, become more variable (e.g. feminine pads 1); others, on the contrary, become more stable after jumping (e.g. toothpaste 3). Supermarkets prices exhibit smoother patterns, but there is no instance of flat patterns.

Such different patterns suggest that our sample contains products *(i)* featuring one or more short collusive phases separated, preceded or followed by periods of price variability (e.g. feminine pads 1, toothbrush 1, toothpaste

[17] By "product item" we mean a specific package/brand/product, e.g. Mentadent AZ toothpaste tartar control 75 ml tube.

3); *(ii)* featuring a series of periods of stability separated by jumps, belonging to the same collusive regime.

In this case, computing variances over the entire sample periods would not allow to catch possibly collusive behaviour.

Therefore, it was decided to compute variances over subsamples. It was assumed that a period of price stability of less than six months could not be safely considered the result of collusion, because of the time it takes coordination and implementation of a cartel. In addition, this is the minimum period over which a variance can be sensibly computed. On the basis of this assumption, for each series were identified twenty 6-months periods (months 1-6, 2-7, …, 20-25), and the variance screen analysis would be carried out over these 6-months periods, computing for each series the minimum variance over its subsamples.

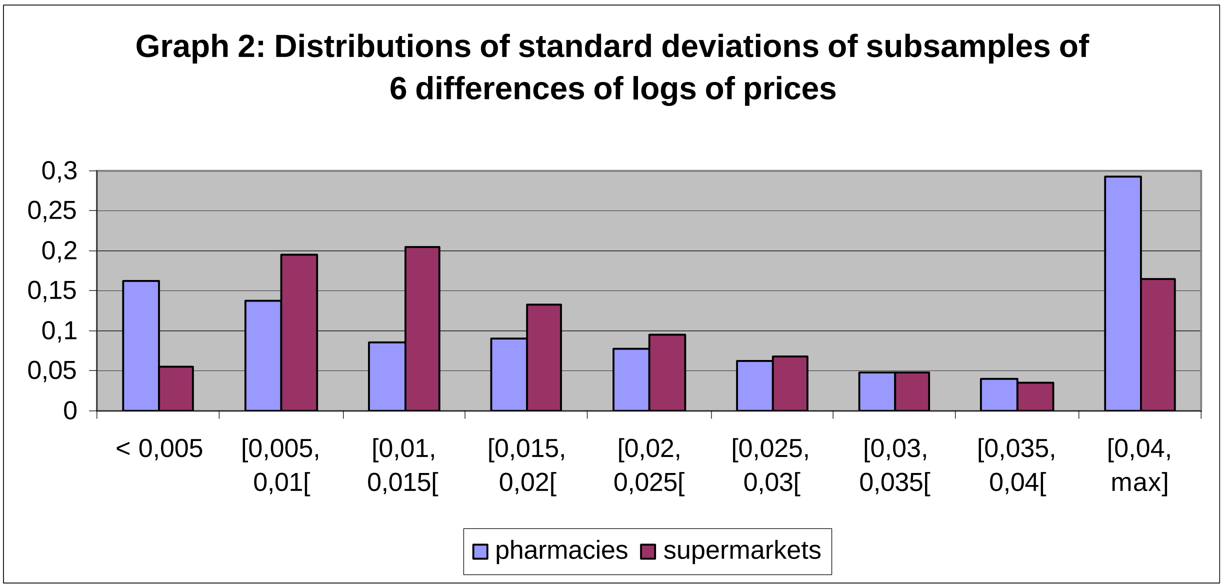
However, computation of variances over non-stationary series makes little sense. Therefore, it was decided to compute differences of logs of prices, in order to make series *(i)* as stationary as possible and *(ii)* comparable: differences of logs approximate rates of change, that are independent of unit of measure (unit prices are for a package).

Variance screen analysis has been therefore carried out over standard deviations computed on subsamples of six subsequent differences of logs of prices.

Benchmark choice

Choosing a benchmark required an answer to two questions: *(i)* are supermarkets variances an appropriate benchmark ? *(ii)* If so, which variance has to be chosen ?

Previous knowledge of supermarkets and pharmacies institutional features and competitive structure, and the results of the investigation, suggested to take as a natural benchmark the variance of supermarket price changes. The behaviour of prices and shares seemed to confirm this presumption.



Graph 2 shows the distributions of standard deviations of subsamples of differences of the logs of prices. Table 6 reports the main statistics.

Table 6: statistics of the distributions of standard deviations of subsamples

	N	Min	Median	Mean	Max	St. deviat.
Pharmacies	7182	0,000025	0,021394	0,036916	0,874525	0,051953
Supermarkets	7200	0,000941	0,016603	0,030304	0,764491	0,056058

Supermarkets subsamples distribution has a smaller range, included in the range of pharmacies subsamples distribution. Supermarkets' mean and median are lower than pharmacies', but there is a significant concentration (about 16%) of pharmacies standard deviations in the lowest class, about three times greater than the percentage of supermarket standard deviations in the same class.

The fact that on average supermarket prices were *less* variable than pharmacies' does not contradict the choice of supermarkets' as a benchmark. First, in order to have an effective benchmark, some of the series of the "likely collusive" industry must satisfy the benchmark (otherwise it would have no discriminatory power); the fact that the mean and the median of supermarkets are lower means that this is a conservative benchmark, in the sense that if there is some form of collusion among supermarkets, only pharmacies series displaying an even more collusive behaviour will be selected. Secondly, the high frequency, compared to supermarkets, of standard deviations in the lowest class implies a strong presumption of collusion for at least those subsamples.

Two possible variance benchmarks were identified: *(i)* the minimum of all supermarket subsamples standard deviations and *(ii)* the minimum variance across regions for a given product. The second one actually fared much better.

First benchmark: absolute minimum

In this case, the benchmark was the lowest standard deviation of subsamples of differences of logs of supermarket prices.

For each product item and each region, the minimum standard deviation of subsamples of differences of logs of pharmacies prices was computed. If such a minimum was lower than the benchmark, then the series was classified as "collusive", in the sense that it had at least one "collusive" episode.

The application of this criterion identified 47 "collusive" series, mostly belonging to Emilia Romagna and Lombardy (23,4% each); less represented were Northwest (14,9%), Centre (12,8%), Lazio and South (10,6%). None of the series belonged to Northeast (see Table 7).

Table 7: variance screen - benchmark based on the lowest standard deviation

	North West	Lombardy	North East	Emilia Romagna	Centre	Lazio	Centre South	South	n. possibly collusive series
feminine pads 1		X		X					**2**
feminine pads 2		X		X					**2**
feminine pads 3									**0**
feminine pads 4									**0**
feminine pads 5				X					**1**
feminine pads 6		X							**1**
feminine pads 7		X		X					**2**
feminine pads 8					X				**1**
feminine pads 9									**0**
feminine pads 10				X		X			**2**
feminine pads 11		X				X		X	**3**
feminine pads 12									**0**
feminine pads 13		X							**1**
feminine pads 14	X					X		X	**3**
feminine pads 15	X	X		X					**3**
feminine pads 16								X	**1**
baby cereals 1								X	**1**
baby cereals 2									**0**
baby cereals 3									**0**
baby cereals 4									**0**
baby cereals 5									**0**
baby cereals 6									**0**
baby cereals 7									**0**
toothpaste 1									**0**
toothpaste 2	X			X					**2**
toothpaste 3									**0**
toothpaste 4									**0**
deodorant 1									**0**
deodorant 2									**0**
deodorant 3									**0**
deodorant 4									**0**
deodorant 5									**0**
deodorant 6		X			X		X		**3**
antiseptic		X		X	X	X			**4**
pers. hyg. soap	X	X		X					**3**
baby food 1									**0**
baby food 2									**0**
baby food 3									**0**
baby food 4									**0**
baby food 5									**0**
toothbrush 1									**0**
toothbrush 2		X		X					**2**
toothbrush 3	X			X	X	X			**4**
toothbrush 4	X				X				**2**
toothbrush 5	X				X		X	X	**4**
	7	***11***	***0***	***11***	***6***	***5***	***2***	***5***	***47***

Strong indications of collusive behaviour for Emilia Romagna and Lombardy were broadly consistent with AGCM findings; however, the other regions were less differentiated than expected; in particular, a stronger evidence for Nortwest could be expected.

However, visual inspection revealed that several series showing typically “collusive” patterns – in particular series with jumps - were not selected.

Second benchmark: minimum by product

In this case, the benchmark is the lowest standard deviation of subsamples of differences of logs of supermarket prices *for a given product item* (across regions). As before, for each product item and each region, the minimum standard deviation of subsamples of differences of logs of pharmacies prices was computed; if such a minimum was below the lowest supermarkets standard deviation for the same product item, then that region was dubbed as (presumably) “collusive”.

There are therefore 45 benchmarks, one for each product item. Minimum variance is computed across regions: implicitly, it is assumed that heterogeneity across products is more important than that across regions; this seems reasonable, given the products analysed.

This second, weaker, benchmark was actually able to pick out *almost* all the “suspect” series that appeared to be left out by the first criterion. In several cases, the number of regional series considered “collusive” for a given product doubled (table 8). In some cases, however, it picked out also series dubiously collusive.

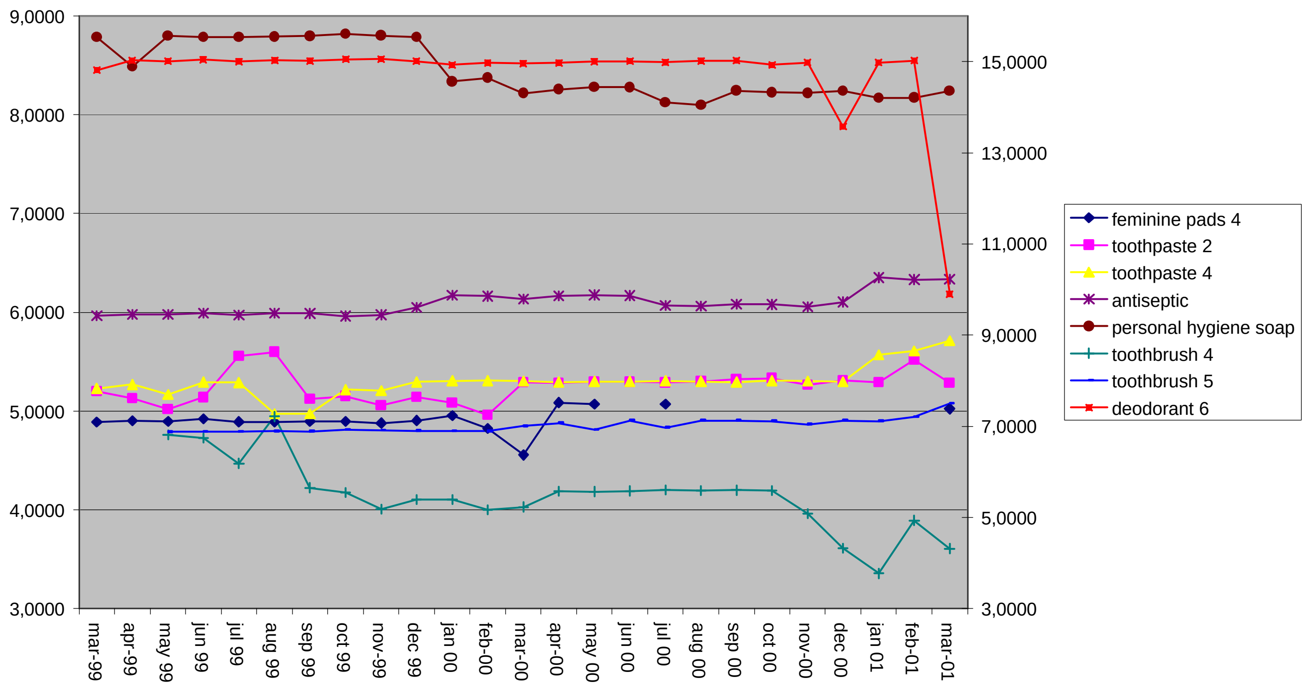
Table 8: variance screen - benchmark based on minimum standard deviation differentiated by product

	North West	Lombardy	North East	Emilia Romagna	Centre	Lazio	Centre South	South	n. possibly collusive series
feminine pads 1		X		X				XX	3
feminine pads 2		X		X					2
feminine pads 3									0
feminine pads 4	XX	XX	XX	XX	XX			XX	6
feminine pads 5				X					1
feminine pads 6		X							1
feminine pads 7		X		X			XX		3
feminine pads 8		XX		XX	X				3
feminine pads 9	XX	XX		XX					3
feminine pads 10	XX			X	XX	X			4
feminine pads 11	XX	X				X		X	4
feminine pads 12									0
feminine pads 13	XX	X		XX	XX			XX	5
feminine pads 14	X	XX		XX	XX	X		X	6
feminine pads 15	X	X		X	XX	XX			5
feminine pads 16		XX		XX	XX	XX		X	5
baby cereals 1								X	1
baby cereals 2									0
baby cereals 3									0
baby cereals 4									0
baby cereals 5									0
baby cereals 6									0
baby cereals 7									0
toothpaste 1		XX		XX					2
toothpaste 2	X	XX	XX	X					4
toothpaste 3	XX	XX		XX	XX			XX	5
toothpaste 4	XX		XX	XX	XX	XX			5
deodorant 1		X							1
deodorant 2									0
deodorant 3									0
deodorant 4		XX						XX	2
deodorant 5								XX	1
deodorant 6	XX	X	XX	XX	X		X	XX	7
antiseptic	XX	X	XX	X	X	X	XX	XX	8
pers. hyg. soap	X	X	XX	X	XX	XX			6
baby food 1									0
baby food 2									0
baby food 3		XX							1
baby food 4	XX			XX					2
baby food 5	XX								1
toothbrush 1	XX			XX					2
toothbrush 2		X		X					2
toothbrush 3	X			X	X	X			4
toothbrush 4	X	XX	XX	XX	X			XX	6
toothbrush 5	X		XX	XX	X		X	X	6
	19	*23*	*8*	*25*	*15*	*9*	*4*	*14*	*117*

X = picked also by the lowest variance benchmark; XX = picked only by differentiating minimum variance by product

To illustrate the kind of series left out by the first benchmark and caught by the second one it is interesting to look at the Northeast region, that has eight "collusive" series under the second benchmark and none under the first one.

Graph 3: North East - series not caught by absmin threshold (price levels, thousands of liras) (scale to the right for deodorant 6)

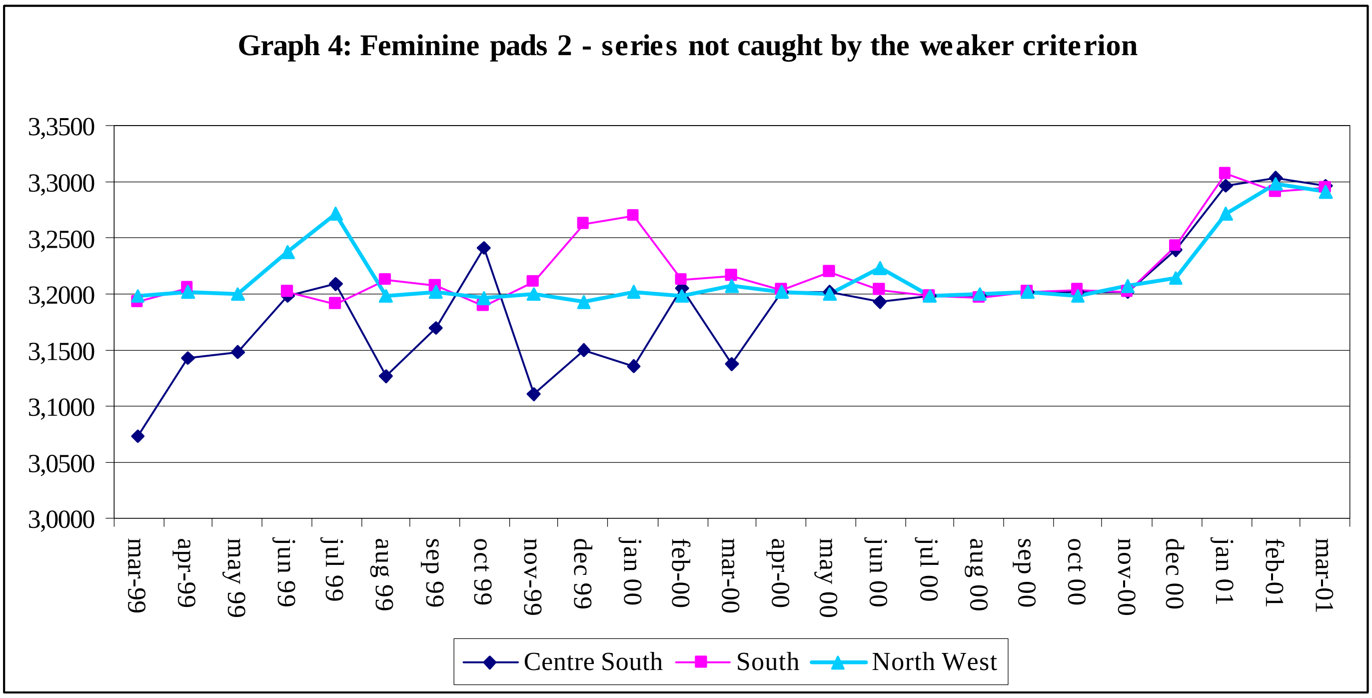


Graph 3 shows that the strong criterion did not catch an almost flat series (deodorant 6), a series with a jump downward separating two almost flat long periods (personal hygiene soap), a series containing two small jumps upward separating three almost flat periods (antiseptic), three series with long periods of stability (almost flat patterns) and one jump (toothpastes 2 and 4, feminine pads 4), a series with a long flat period (toothbrush 5) and a series with a short flat period (toothbrush 4).

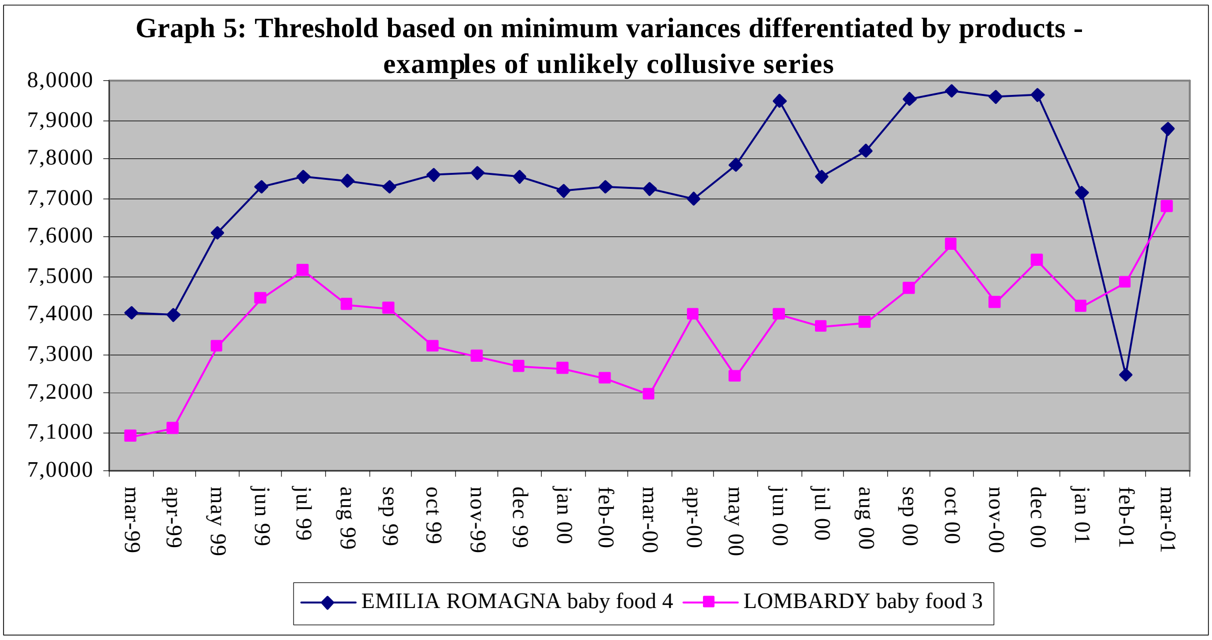
Almost flat sections are strong indicators of collusion: given that series come from the aggregation of the sales of many pharmacies, almost flat patterns require a nearly complete stability of individual prices and shares – unless one is willing to accept that almost flatness is just the result of aggregation of compensating individual patterns, an hypothesis that seems way too strong. All the more, series showing jumps from one flat period to another are very strong evidence of collusive behaviour. Therefore, the criterion of the lowest standard deviation in the sample, failing to identify several series with almost flat sections and with jumps from one flat section to another, was a very imperfect criterion.

One reason for his failure may be that only 2,7% of pharmacies subsample standard deviations are below the minimum of supermarket standard deviations, even if there is plenty of “small” pharmacies subsample standard deviations: almost 30% of them are below the first quartile of supermarket subsample standard deviations; so the first criterion is too strong, while the second, being based on minima differentiated by products, is able to pick more small pharmacies subsample standard deviations.

Some possible classification errors remained, however. Graph 4 depicts series for feminine pads 2. Series show a period of stability of 8-10 months between February and December 2000 (variation is less than 50 liras, i.e. less than 3 eurocents), and the Northwest series is almost flat for a year and a half. At least the Northwest series should have been considered "collusive".



Graph 5 depicts a possible opposite error. At least the Lombardy series should not have been caught.



The criterion based on minimum standard deviations differentiated by products shows a picture of possible collusive behaviour in Italian regions a bit different than that emerging from the application of the criterion based on the lowest supermarket variance.

Emilia Romagna and Lombardy remain the regions with the greater number of “possibly collusive” series (more than half of the region series are “possibly collusive”), but now North West region (which has the third greatest number of “possibly collusive” series) emerges more clearly as a region with worrying behaviours (42% of her series are “possibly collusive”).

More interestingly, now all regions show some evidence of possibly collusive behaviour: but while for Centre South, Lazio and North East regions this evidence is weak (no more than 20% of their series is “possibly collusive”) – consistently with AGCM findings – Centre and South regions appear in a more ambiguous position, with about one third of the series marked as “possibly collusive”.

IV. Concluding remarks

The examples discussed show that if a variance screen analysis had been run before these investigations, the analysis would have correctly identified competitive worries; it would have been helpful also in directing the investigations towards the analysis of possible alternative explanations of collusive patterns of prices. In the case of pharmacies, the analysis would have also widened the geographic scope of the investigation.

On the methodological side, the analysis carried out raises several interesting points:

(i) *significant standard deviations may occur even if there is collusion;* a series which is characterized by strong stability over two periods (with say zero variance) but has a jump between them (so that *there is a switch between two strictly collusive regimes*) will not display a zero variance, but a positive and possibly high standard deviation, that may easily pass the screen, notwithstanding being a clearly collusive situation; the same may happen in less extreme situations, as our analysis shows. Therefore, screens must be calibrated in order to catch all such situations; visual inspection and the choice of an appropriate benchmark are crucial. In our case, a screen based on minimum standard deviations differentiated by product has worked well. In general, one can think of several refinements of the selection method; the most promising one seems to be a two-step procedure, where in the first step one looks for the series exhibiting long periods of stability separated by jumps as candidate strong collusive series, and then the method outlined above is applied to the other series.

(ii) *menu costs can explain small standard deviations*: products representing a very small amount of sales can be priced by all sellers at the manufacturer list price and changed only as that one changes, in order to save on menu costs; therefore, unless there is additional evidence, very small standard deviations can be taken as evidence of sellers collusion only if each of the products they refer to represents a significant share of sellers total sales.

This point is particularly relevant in the pharmacies case. In general, collusion is more easily sustainable when colluding firms have a large share of the sales of products on which collusion is attempted. But what if colluding firms are multiproduct firms, and some of the products on which colluding firms have larger market shares are also a very small part of the assortment put on sale ? In the pharmacies case, the sample included product items with different pharmacies' share of sales; but even where this share was high, some product item represented a very small share of pharmacies sales in the product categories they belonged to, e.g. antiseptic and personal hygiene soap. For these very products, antiseptic and personal hygiene soap, collusive patterns emerged. For them, menu costs would be an attractive explanation. Unfortunately, data do not allow to shed light on this point, although the downward jump of personal hygiene soap series seem to follow closely a reduction of listed price[18].

As to product items where pharmacies had small shares, it was known that some associations advised to follow producers list prices. Using the list prices published every march by the *Informatore Farmaceutico* (an industry publication), it was possible to ascertain that list prices acted as focal points for some of the product items considered. In particular, long periods of stability for toothpastes, toothbrushes and some feminine pads were clearly linked to the stability of list prices. Pharmacies average share in these product categories is low, so we would not expect successful collusion here; on average, price differential with supermarkets is actually fairly low. A simpler explanation is possible: list prices allow to save on menu costs and guarantee pharmacists an handsome margin. However, brands in the dataset are an important part of pharmacies sales in those categories, in particular for feminine pads. Given that more stable patterns emerge with higher frequency in regions where pharmacists associations were more "active", it is possible to speculate that, at least in these regions, recommended list prices were used as focal points to avoid price wars among pharmacies, and so menu costs played a small role.

[18] Curiously, the price in 1999 is actually equal to the listed price for 2000, and the price in 2000 is equal to the listed price for 2001; the jump downward occurs when the new catalogue of listed prices becomes available. We do not have the 1999 listed price, so it is impossible to check if there is a constant percentage discount.

(iii) *variance screens based on prices may actually be a screen for price parallelism*: variance screens are applied to time series describing the aggregate behaviour of a group of firms; if the variance of the time series is found to be “low”, then the aggregate price does not change very much over time; this implies not only that firms’ prices do not move very much, but also that quantities sold by each firm do not move very much: otherwise, the aggregate price would change anyway and there would be variability over time even with stable prices (short of compensating movements). In this case, the screen is identifying some kind of parallel behaviour aiming to stabilize relative prices and market shares. This behaviour is easier to identify in markets where demand is stable (and so quantities sold by each firm change very little over a suitable time period, say a month), as in the case of motor fuels.

The extreme case of constancy of average prices over time characterizes the pharmacies case; here, unless one is willing to make the very strong assumption that individual sales do not change, it must be true that individual prices are not only constant, but also equal, as only in this case quantity variations do not affect prices; furthermore, when the series jumps and then remains stable at a new level, then all firms’ prices must jump. Therefore, in this case not only there is a parallel behaviour, but there is also a uniform price set by the firms; the variance screen in this case is actually a screen for a collusion over a given price. The cases discussed in this paper highlight therefore the ability of the variance screen to identify parallel behaviour linked to collusion over market shares and over a given price level.

(iv) *aggregation may matter*: one of the advantages of the variance screens is that they can be applied to aggregate data, which are usually easier to find in the screening phase, before a formal investigation is opened. However, aggregation of a large number of individual series may force, on purely statistical grounds, a lower variability of the aggregate series; this effect may partly explain the lower variance of supermarkets series (more supermarkets than pharmacies are sampled). In general, this effect may bias comparisons among industries and countries and the choice of the benchmark.

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