

THE IMPACT OF COLLUSION ON PRICE BEHAVIOR: EMPIRICAL RESULTS FROM TWO RECENT CASES

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Abstract

We used extensions of traditional ARCH and GARCH models to examine the difference in the behavior of the first two moments of price distribution during collusion and the absence of it using prices from two recently discovered conspiracies, citric acid and lysine. According to our results, citric acid conspiracy increased price by 9 cents per pound relative to pre-cartel and post-cartel periods. Lysine conspiracy managed to raise price by 25 cents per pound. In addition, the variance of prices during lysine conspiracy was lower than the variance of prices during pre-cartel and post-cartel periods as we expected. In opposite to expected, the variance of prices during citric acid conspiracy was higher relative to more competitive periods. Using the estimation result we predict that citric acid cartel imposed overcharge equal to 12 percent of the market price and lysine cartel imposed overcharge equal to 25 percent of the market price.

Key words: ARCH, cartel, citric acid, GARCH, lysine, overcharge, price, variance

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Introduction

During recent decades collusive behavior has been core interest of many theoretical and empirical studies in the areas of both economics and law. Changes in antitrust legislation of many countries created additional incentives for research analyzing overt collusive conduct. Considerable amount of theoretical studied concentrated on mathematical derivations of conditions characterizing collusive behavior under different assumptions. With time, more data became available from court records, uncovered cartels that had terminated earlier, and different public sources. Researchers in the rapidly developing area of empirical industrial organization used available data and new econometric techniques to study cartels behavior and test hypotheses formulated in the theoretical literature. Still there remain many determinants and effects of collusive behavior to be studied and analyzed.

Different empirical studies analyzed numerous aspects of collusive behavior such as price and output strategies, price wars, duration, stability, profitability, effectiveness, impact on the market and consumer behavior, etc. Our study belongs to the group of research investigating the impact of collusive conduct on the market price behavior. Our objective is to analyze using econometric technique the impact of collusion on the behavior of the first two moments of price distribution, the mean and the variance. We hypothesize that the behavior of the first two moments of price distribution under the assumption of a successful collusion is different during collusive and non-collusive periods. In particular, the mean price is higher and the variance of the price is lower during collusion in comparison with the period when there is no collusion. To test the hypotheses we use price data from the two recently discovered conspiracies, citric acid and lysine conspiracy, by employing an extension of traditional an autoregressive conditional heteroscedasticity (ARCH) model and generalized ARCH (GARCH) models.

The hypothesized changes in the first two moments of price distribution may indicate the presence of collusive behavior in certain situations. Proposed econometric procedure may be used in the screening process conducted by antitrust and competition authorities. In addition, it may be also used as an alternative to the econometric models commonly employed in court proceedings to quantify the effect of conspiracy on market price. An advantage of using the ARCH and the GARCH models is that they require minimum amount of data, at least price time-series for a cartelized product before, during and after hypothesized or known conspiracy.

Our paper is organized as follows. Theoretical background and hypotheses are presented in the next section followed by the section discussing empirical models. Next, data set description is presented and followed by the discussion of results and conclusion.

Theoretical Background and Hypotheses

Cartels, groups of independent companies binding themselves with an agreement on prices or quantities, are more likely to operate in heavily concentrated or oligopolistic markets. In most cases cartels are self-enforced agreements, and these may be legal or illegal. Assuming that the behavior of the firms acting in oligopolistic markets is profit maximizing, they have an incentive to collude in order to increase their joint level of profit (Stigler, 1961 and 1964). If their collusion is successful, the collusive firms may achieve a monopolistic level of profit if they manage to act as a multiplant monopolist¹. According to microeconomic theory, firms may achieve this goal by reducing output, which results in an increase in the market price. In practice, the firms may control output, or prices, or both. In terms of practical implementation the easiest strategy to use is price control (Stigler, 1961). The output control strategy may be easier to employ, but the actions would be too revealing to antitrust authorities.

As it turns out not all cartels pursue joint profit maximization by the means of direct price increase as the main strategy. Another strategy is to reduce the variance of prices by homogenizing firms' business practices as in the case of the Sugar Institute (Genesove and Mullin, 2001). A reduction in price variance could lead to an increase in the joint profits of colluding firms as well. Finally, colluding firms may implement a cost efficiency strategy as in the case of some Webb-Pomerene export cartels (Dick 1996a and 1996b).

In general, both legal and illegal cartels are self-enforced agreements². Success of collusive agreements depends on two major factors. These are ability of a cartel to enforce effectively its discipline and market environment the cartel operates in, i.e.

¹ The first order maximization condition outcomes are the same for a multiplant monopolist and for a cartel (proved in Besanko and Braeutigam, 2001).

² For example, Webb-Pomerene cartels were legal cartels. They operated under the umbrella of the Webb-Pomerene Export Trade Act, but were self-enforced agreements. Thus, they faced the same problems with the enforcement of cartel discipline as illegal cartels.

market supply and demand conditions. Failure to enforce a collusive agreement effectively, i.e. quickly detect deviators, punish them and prevent opportunistic behavior in the future, often leads to termination of a collusive agreement. Also, market conditions such as new entry, demand or supply shock may break already existing cartel. As it was shown in the theoretical and empirical literature, high demand shock creates incentives for cartel members to deviate from the established discipline (Porter (1983), Green and Porter (1984), Rotemberg and Saloner (1986), Ellison (1994)). This usually results either in a price war or termination of collusion accompanied by a decrease of market price towards more competitive level.

The opportunistic behavior of cartel members, also known as cheating in cartel literature, is a major problem in effective enforcement of cartel discipline. Deviators do not rigorously follow established price discipline and sell product for the lower price than it is required by collusive agreement. A deviator seeks to increase its individual profit. Also, buyers may provoke opportunistic behavior of the cartel's members. A large buyer searching for big discounts may increase an incentive to deviate. The search cost for discount for this buyer on the market with a few sellers is relatively low. An incentive to deviate always exists as long as it potentially guarantees an extra individual profit. Although, the deviators are also aware of the possible cost of their behavior, which is possible punishment in case if their actions become revealed to other members. This cost approximately equals to the probability of being detected by other members multiplied by the probability of being punished by them if they decide to do this, times the expected value of punishment. Other members may detect opportunistic behavior if their market shares start shrinking. They may decide not to punish because this could result in a decrease of the cartel profit. If they decide to punish, it usually comes in the form of price war, "tit-for-tat" strategy of other members, or termination of collusion. Given that

opportunistic behavior of cartel members is common, short-run individual benefits of deviators outweigh expected losses from it.

In summary, rigorously followed cartel discipline may result both in price increase and variance decrease. As firms start following the established price discipline, variance of prices tends to decrease in comparison with non-collusive period. It is more challenging to control the variance of prices, although it would generate additional profit for cartel. This is why collusion is more common on the homogeneous product markets, when it is easier for firms to monitor prices. But even in this case, heterogeneity of numerous contract conditions such as quantity discounts, delivery terms, interest, etc. introduce additional variability in prices. Also, the participants of collusive agreements may intentionally use contract conditions to deviate in order to obtain extra profit. Thus, different strategies of opportunistic behavior would always contribute additional variability in prices.

Our study analyzes two uncovered conspiracy that are known to be successful. Our first hypothesis relates to the mean price behavior. We expect that the mean price during collusion is higher than the mean price when there is no collusion. Price increase follows from the profit-maximization conditions on the concentrated markets. Our second hypothesis relates to the variance behavior. We expect that the variance of prices during collusion is lower than the variance of prices when there is no collusion under the assumption of a successful collusion, i.e. when most of the members in most of the time follow established price discipline and cartel may effectively address opportunistic behavior of its members. Our hypotheses are formulated under the assumption that there is no significant change in market environment of cartel operation that could introduce an additional shock to prices.

Empirical Model

To examine the behavior of the first two moments of price distribution, the mean and the variance, we employ econometric procedure that allows simultaneous analysis of the mean and the variance. In this section we discuss the AR(m), ARCH(m), and GARCH (m,r) models that we use in our analysis.

An autoregressive process of order m , denoted AR(m), for an observable variable Y in period t is represented as:

$$Y_t = c + \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + \dots + \phi_p Y_{t-m} + u_t \quad (1)$$

where u_t is a white noise:

$$E(u_t) = 0, \quad (2)$$

$$E(u_t u_s) = \sigma^2 \text{ for } t=s, \text{ and } 0 \text{ otherwise.} \quad (3)$$

Condition (3) implies that the unconditional variance of u_t is the constant σ^2 , and the conditional variances could change over time.

The square of u_t itself may follow an AR(m) process:

$$u_t^2 = \zeta + \alpha_1 u_{t-1}^2 + \alpha_2 u_{t-2}^2 + \dots + \alpha_m u_{t-m}^2 + w_t \quad (4)$$

where w_t is a new white noise process:

$$E(w_t) = 0 \quad (5)$$

$$E(w_t w_s) = \lambda^2 \text{ for } t=s, \text{ and } 0 \text{ otherwise.} \quad (6)$$

A white noise process u_t satisfying the variance equation (4) is described as an autoregressive conditional heteroscedastic process of order m , denoted as ARCH(m). Stationarity (regularity) condition requires $\zeta > 0$ and $\alpha_j \geq 0$ for all $j \leq m$. This class of models was introduced by Engle (1982). The ARCH(m) specification can be considered as an AR(m) process for u_t^2 (Hamilton, 1994).

Generalized ARCH (GARCH) type models are extensions of ARCH type models.

The GARCH(r,m) variance equation is represented by (7):

$$h_t = k + \delta_1 h_{t-1} + \delta_2 h_{t-2} + \dots + \delta_r h_{t-r} + \alpha_1 u_{t-1}^2 + \alpha_2 u_{t-2}^2 + \dots + \alpha_m u_{t-m}^2 + w_t \quad (7)$$

where $u_t = \sqrt{h_t} v_t$,

v_t is i.i.d with mean zero and unit variance.

Stationarity (regularity) condition requires $k > 0$, $\delta_i \geq 0$ for all $i \leq r$, $\alpha_j \geq 0$ for all $j \leq$

m, and $\sum_{t=1}^r \delta_t + \sum_{t=1}^m \alpha_t \leq 1$.

Calculation of the sequence of conditional variances $\{h_t\}$ for $t=1$ to $t=T$ requires their pre-sample values. Usually they are calculated as a sample average of the squared predicted residuals for each pre-sample observation in T sequence (Bollerslev (1996), Hamilton (1994)).

We estimate an extension of traditional ARCH(m) and GARCH(m,r) model to analyze the mean and the variance behavior in our study. To test whether the mean price and its variance during conspiracy differs from the mean price and the variance when there is no conspiracy, we introduce a conspiracy dummy variable in the models. It is incorporated both in the mean and the variance equations to control for the shift in their behavior between collusive and non-collusive regimes. The exact specification of each model is presented in the tables with the estimation results in the appendix.

Data and Descriptive Statistic Analysis

*Citric Acid*³. We use the citric acid prices reported by Connor (1998b, Appendix, Table 1). These are monthly U.S. contract citric acid prices for the period of February 1987 - April 1997 reported by Purchasing Magazine⁴. This price time-series was based on monthly surveys of up to 500 chemical purchasing agents and buyers of bulk purchases (truck or tanker-car loads), f.o.b., USP grade citric acid. Contract prices are prices of supply contracts in force for three months, or more (usually one year). For the purpose of this study we assume that July 1991 is the beginning date of the conspiracy and June 1995 is the ending date of the conspiracy⁵.

*Lysine*⁶. We use lysine prices reported by Connor (2000, Appendix, Table A2). We use average prices of lysine for the U.S. market available for the period of January 1990 to June 1996. These prices are obtained from the Exhibit C to Plaintiff's Interim Report No.1 (April 29, 1996 supplement), *In re Amino Acid Lysine* federal class-action suit; exhibits 61,63, 65, and 67 in *U.S. v. Michael Andreas et al.* For the purpose of our

³ Citric acid is a colorless, crystalline organic chemical, one of the carboxylic acids. It is present in almost all plants, especially citrus fruits, and in many animal tissues and fluids. It is used in many foods, confections, and soft drinks. Citric acid is widely used in industry as a water conditioner, cleaning polishing agent, and chemical intermediate.

⁴ Price diagrams are presented in the appendix.

⁵ Four companies pled guilty to fixing prices and output levels of citric acid in the United States, Archer Daniels Midland Co. (ADM), Bayer AG, Hoffmann-La Roche AG, and Jungbunzlauer AG. The last three are the Swiss companies. According to ADM's plea agreement the period of the conspiracy was vaguely identifies as "at least as early as January 1993" and ending June 1995. The terms of this plea agreement were negotiated with DOJ before filing with the Court in October 1996. Though, later (1997), when DOJ filed against three Swiss conspirators, the beginning date of the conspiracy was specified as July 1991. Connor (1998) points out that July 1991 is a more reasonable date for the beginning of the conspiracy. In addition, he argues that the conspiracy had the effects on the market far beyond June 1995. This is because the prices do not adjust to before- conspiracy quickly. For details on citric acid market and collusion see Connor (2001).

⁶ Lysine is an essential amino acid found in proteins. It is required for growth and bone development in children, assists in calcium absorption and maintaining the correct nitrogen balance in the body and maintaining lean body mass. Furthermore it is needed to produce antibodies, hormones, enzymes, collagen formation as well as repair of tissue. Lysine is produce from dextrose, a sugar made from corn. Lysine is an important food and feed ingredient. It is widely used as a feed component in hogs, poultry and fish production. Technological process of lysine production was discovered in Asia in 1960s.

study we assume the period of conspiracy as August 1992 - June 1995 excluding the four months of the collusion lapse in March-July 1993⁷.

Descriptive Statistic Analysis

Descriptive statistic analysis reveals some evidence of the presence of collusive behavior on both citric acid and lysine market (Table 1 and Table 2 respectively⁸). The mean cartel price for citric acid is 75.96 cents per pound. This price is higher than the mean pre-cartel and post-cartel prices, that are 65.35 and 72.91 cents per pound respectively. The mean cartel price for lysine during the 1st period of conspiracy is 90.13 cents per pound and during the 2nd, more effective period, is 110.30 cents per pound. The latter higher than pre-cartel and post-cartel lysine prices, that are approximately the same, 102.90 and 102.50 cents per pound respectively. Thus, in both cases we observe a noticeable increase in price during conspiracy relative to non-conspiracy periods.

The behavior of the variance of lysine price supports our expectation, i.e. it decreases during collusive period. While the variance of citric acid price exhibits opposite to the expected trend. In citric acid case, the variance during conspiracy is 25.66 and this is higher than the variance before or after conspiracy. In lysine case, the variance during the 2nd period of conspiracy is 73.04 and this is lower than the variance during pre-cartel, post-cartel and the first period of collusion. Actually the lowest variance we observe during lapse of lysine cartel in April – July 1993. This may be explained by the

⁷ Before ADM's entry in 1991, three Asian companies, Ajinomoto, Kyowa, and Sewon Group were the major producers of lysine in the world and the only firms sharing the US market. They admitted that employed price-fixing strategies. When ADM entered the market, world lysine prices dropped from \$1.30 to \$0.64 per pound. And the latter one was below the cost of production, that results in losses for all producers in the lysine market. In June 1992, ADM met with Asian companies representatives in Mexico City to discuss the condition of future global conspiracy. Increasing prices and sharing information on prices and volumes were discussed during this meeting. Asian companies reached agreement with the DOJ to plead guilty, pay fines, and cooperate in prosecuting ADM and its officers in August, 1996. ADM plead guilty and agreed to pay fine in October, 1996. Connor (2001) inclines to consider June 1992 to be the beginning date of lysine conspiracy and July 1995 to be the termination of conspiracy accounting for total of 36 months. August 1992 is considered to be the first month when conspiracy had an effect on the market. March – July 1993 is considered to be a period when conspiracy was not effective. Defendants' plea agreements adopted a shorter conspiracy period, November 1993-June 1995 (Connor, 2001a). For more details on lysine market and collusion see Connor (2000, 2001a and 2001b).

⁸ All tables are presented in appendix.

short duration of this lapse during which previous market price effect could have been strong. Another justification could be that prices observed during this period were almost on the same level as marginal cost and even lower. Thus, the conspirators had to prevent their decrease.

The unexpected behavior of the variance in citric acid case may be explained by the actual length of the conspiracy period under consideration as well as the length and conditions of pre-cartel and post-cartel periods. Citric acid conspiracy period in our analysis is longer than lysine conspiracy period, but pre-cartel period almost twice shorter⁹. Pre-cartel period introduces more variability to the prices than post-cartel periods. It happens because conspiracy market price effect stays on the market for a certain period of time after the conspiracy has been formally terminated. Also, the market price effect of conspiracy does not take place immediately after the first meeting of the conspirators and their decision to collude. There is a period that may last several months, or even a few years, when prices are growing until they reach the level on which they are going to be fixed. Certainly, the variance is lower in the sub-period of the conspiracy when prices have reached the level on which they are actually being fixed. Also, the implementation of the collusive agreement to what extent to raise the price, take different time depending on each particular conspiracy. Another problematic issues that may impact this unexpected variance behavior is cartel discipline and market conditions cartel operates in as we discussed earlier. So, under certain circumstances it may be expected that the variance of the price during conspiracy is higher than the variance of the price when there is no conspiracy. Also, it is known that lysine conspiracy was an effective one in terms of cartel discipline enforcement. Cartel participants followed their agreement approximately in 90 percent of all cases (Connor, 2001a).

⁹ The choice of the length of the pre-cartel and post-cartel periods is totally determined by the number of the available observations.

From descriptive statistic analysis we also can note additional features of price behavior that may indicate presence of collusion. In the case of citric acid, post-cartel price is kept on level close to cartel price and higher than pre-cartel price. Also, the variance during post-cartel period is very small. In the lysine case although the post-cartel price is approximately at the same level as pre-cartel price, the variance of the former is more than two times lower than the variance of the latter. This confirms the hypothesis that market price effect of conspiracy stays on the market for a certain period of time and does not disappear immediately (Connor, 1998). This happens because conspirators cannot control all market forces and the long-term contract provisions are in force. In addition expected antitrust indictment followed by civil suites may encourage conspirators to continue to influence prices but in more relax way¹⁰.

Results

Citric Acid. Using ARCH test we reject the null hypotheses of conditional homoscedasticity at p-value equal to 0.0000¹¹. The power of this test is the same if we repeat it for any model including from 1 to 15 lags. Also, we use modified Box-Pierce (Ljung-Box-Pierce) statistic to test for the presence of sample autocorrelation for the residuals and the square residuals (variances) obtained from the OLS regression¹². Q(1) for the model with the first lag only is 79.92 and has a p-value equal to 0.0000. Q(2)-Q(20) are statistically significant at the same level of significance. Therefore, we reject the null hypotheses of uncorrelated mean price changes. The same procedure applied to

¹⁰ Sproul (1993) analyzed the effect of antitrust prosecution on prices charged by firms indicted for price-fixing. Using the survey of 25 cases filed between 1973 and 1984 he found that prices increased by approximately 7 percent over the four years following an indictment.

¹¹ ARCH test is based on the Lagrange multiplier principle. LM statistic = $N \cdot R^2$, where N is the number of observations and R² is a goodness-of-fit statistics from the regression of the squared residuals on a constant and q lagged values of the squared residuals. This statistics has Chi-Square distributions with q degrees of freedom.

¹² Modified Box-Pierce (Ljung-Box-Pierce) statistic has Chi-Square distribution with the number of degrees of freedom equal to the number of the lags included in the model. Q(1) means that the statistic is calculated based on the model with one lag.

the squared residuals reveals similar results. Ljung-Box-Pierce statistics for the models including up to the first twenty lags are statistically significant at p-value equal to 0.0000. Thus, we reject the null hypothesis of the conditional homoscedasticity of the variances. This suggests that ARCH and GARCH models may be suitable for describing the error process. To choose the order of AR process for the ARCH and the GARCH mean equations we use Akaike (AIC) and Swartz (SC) information criteria¹³. We concentrate on the evaluation of these criteria for the models including up to the first four lags¹⁴. Both AIC and SC are minimized when one lagged variable is included in the analysis. Thus, we use AR(1) specification for the mean equation in the ARCH and the GARCH models.

Lysine. To investigate the autocorrelation structure of the lysine prices we use the same procedure as in the case of citric acid¹⁵. The outcomes of ARCH and Ljung-Box-Pierce test applied to the residual and squared residuals are similar to those of citric acid¹⁶. The statistics levels along with their significance levels are close in both cases. The final conclusion is that we reject the null hypotheses of uncorrelated price changes and conditional homoscedasticity for lysine prices as well. As for the AR process, AIC is minimized for the model with only one lag and SC is minimized for the model with two

¹³ We used Dickey-Fuller test to conduct a unit root test. We reject unit root if only ten lagged variables are included in the model. In this case test statistic is -2.6449 and critical value corresponding to 10 % significance level is -2.57. We fail to reject a unit root if we include 1 to 9 lags. In all these cases resulting test statistics is greater than the critical value. Failure to reject unit root may be explained by the following. First, our data set experiences two switching regimes from pre-cartel to cartel and from cartel to post-cartel. Structural shocks influencing the time-series data may be the reasons of the failure to reject the unit root (Perron, 1989). Second, our sample is relatively small. Unit root may be difficult to reject in small samples (Wooldridge, 2002).

¹⁴ Due to limited number of the observation available and econometric technique employed we can consider only limited amount of lagged variables to be able to estimate ARCH and GARCH models.

¹⁵ In contrast to citric acid case we reject a unit root when one or two lagged lysine prices are included in the model. For example, Dickey-Fuller statistic and augmented Dickey-Fuller statistic for the model with one lag are -3.6277 and -3.6027 while critical values of t-statistics are -2.57 and -3.13 respectively. When we include more lags we fail to reject unit root. The reasons here may be the same as those we discussed in citric acid case earlier.

¹⁶ In lysine case ARCH test LM statistic is statistically significant at alpha equal to 0.0000 for all models including up to 17 lags. Ljung-Box-Pierce statistic is statistically significant for Q(1)...Q(20) both in the case of the residuals and the squared residuals.

lags. Thus, both AR(1) and AR(2) are potential candidates. Therefore we consider both of them and discuss the model that performs best.

Maximum likelihood estimation results for the ARCH and the GARCH models are presented in Table 3 and Table 4 for citric acid case and in Table 5 and Table 6 for lysine case. We present the ARCH(1) and the GARCH(1,1) results. Estimation of higher order ARCH models showed that higher order lagged unconditional variances were not statistically significant and did not satisfy stationarity constraints. Similar tendency was observed when other than the GARCH(1,1) model specifications were estimated. In addition, we had numerical problems with estimation of the GARCH(2,2) and higher order GARCH. Thus, we present and discuss the estimation results for the ARCH(1) and the GARCH(1,1). In each product case we estimated three different specification of our model with different combinations of independent variables in the mean and the variance equations (see Tables 3-6).

Citric Acid. All estimated coefficients in the ARCH(1) models satisfy stationarity constraints. Model [1] is estimated as the ARCH(1) with lagged price and constant as explanatory variables. Lagged unconditional variance in the variance equation is positive as required by stationarity constraint and has a p-value of 0.3520. Incorporating in the mean equation of conspiracy dummy variable along with its interaction with the lagged price (Model [2]) shows that the estimated coefficients for these two variables have an acceptable p-value. The estimated coefficient for conspiracy dummy variable is 8.81 and has p-value equal to 0.1090. Interaction effect has a small magnitude and p-value equal to 0.1760. Given this specification of the mean equation, unconditional variance becomes more statistically significant than in Model [1], and has similar magnitude. Finally, we incorporated conspiracy dummy variable in the variance equation as well (Model [3]) to

control for the hypothesized shift in the variance induced by collusion. Thus, the estimation results of Model [3] are those we are going to discuss in greater details.

The estimated coefficient for the conspiracy dummy variable in the mean equation is 9.15 and has a p-value equal to 0.0880. The estimated coefficient for the interaction effect of conspiracy dummy variable and lagged price is -0.11 and has a p-value equal to 0.1450. Both estimated coefficients are statistically significant at acceptable probability of type one error. Thus, the mean price of citric acid during collusion is 9.04 cents per pound higher than the mean price during the period when there is no collusion, which is represented by pre-cartel and post-cartel periods. The estimated effect of conspiracy on the mean price is similar to the effect discussed earlier in the descriptive analysis section. The estimation results of the variance equation shows that unconditional variance has a p-value of 0.3130 only, which does not suggest a highly statistically significant impact of the past unconditional variances on the present unconditional variance. The positive direction effect of this coefficient suggests that the higher is unconditional variance yesterday, the higher is unconditional variance today and vice versa. The estimated coefficient for the conspiracy dummy variable in the variance equation is 1.49 and has a p-value equal to 0.1340. The positive effect of the conspiracy on the variance is not what we hypothesized. But this result is consistent with the variance analysis using descriptive statistic.

The estimation results for the mean equation in the GARCH(1,1) model are similar in magnitude and statistical significance to the estimation results for the mean equation in the ARCH(1) models. In the variance equation the estimated coefficient for conditional variance is negative. Lagged unconditional variance has a stronger statistical effect in the GARCH(1,1) model than in the ARCH(1) model. Its estimated coefficient is positive and has a p-value 0.0870. The estimated coefficient for the lagged conditional

variance is negative and has a p-value 0.0710. This suggests that the higher is the past conditional variance, the lower is the present conditional variance and vice versa. The estimated coefficient for the conspiracy dummy variable is positive, as in the ARCH(1) variance equation and is statistically significant at the probability of type one error equal to 0.2900 only. Thus, in the case of citric acid, the estimation results confirm the hypothesis that conspiracy results in the statistically significant price increase and they show different from the expected effect of the conspiracy on the variance behavior.

Lysine. To examine the impact of lysine conspiracy on price behavior we followed similar to the citric acid case estimation procedure. According to the estimation results, the ARCH(1) effect is stronger and the GARCH(1,1) is weaker in the case of lysine conspiracy than in the case of citric acid conspiracy. In the ARCH(1) case the estimated coefficient for the lagged unconditional variance is positive and statistically significant at 1 percent of probability of type one error in all three models. The estimated coefficient for the conspiracy dummy variable in the mean equation is 25.73 and has a p-value 0.0000. The estimated coefficient for the interaction effect between the conspiracy dummy variable and the lagged price is negative and has a p-value equal to 0.0000 as well. The ARCH(1) estimation results suggest that the lysine conspiracy induced the price increase by 25.52 cents per pound. In the variance equation the estimated coefficient for the conspiracy dummy variable is negative as expected, but it is statistically significant at the probability of type one error equal to 0.2190 only. The estimation results obtained using the GARCH(1,1) procedure show similar magnitude and direction effect of the estimated coefficients. According to the GARCH(1,1) estimation results the conspiracy effect on the market price was 24.59 cents per pound. The lagged unconditional variance is statistically significant at an acceptable level of the probability of type one error. Lagged conditional variance is not statistically significant at

an acceptable probability of type one error. In summary, in the case of lysine we find support to both hypotheses. The mean price was higher and the variance was lower during conspiracy periods relative to the periods when this conspiracy was not effective. We can use the estimation results to predict the overcharge rate imposed by cartels¹⁷. Predicted prices calculated using the fitted ARCH(1) and the GARCH(1,1) models serve as proxy for the price during collusion (*P collusion*). Benchmark price (*P benchmark*) is calculated as *P collusion* minus the estimated coefficient for conspiracy dummy variables in our models. In lysine case the ARCH(1) and the GARCH(1,1) predict *P collusion* equal to 101.52 and 101.50 cents per pound respectively. Predicted *P benchmark* for lysine market approximately equals to 76.00 and 76.91 cents per pound based on the ARCH and the GARCH model respectively. This results in overcharge rate equal to 25.14 percent, if the ARCH model is used, and 24.23 percent, if the GARCH model is used for prediction. In citric acid case predicted *P collusion* is equal to 75.96 and 75.90 cents per pound using the fitted ARCH(1) and the fitted GARCH(1,1) respectively. *P benchmark* implied by these models is equal to 66.92 and 67.00 cents per pound based on the ARCH and the GARCH model respectively. Thus, for citric acid market the overcharge rate is 11.90 percent, if the ARCH is used, and 11.73 percent, if the GARCH is employed for prediction. Our estimates fall in the range of overcharge estimates appeared in other studies examining these two conspiracies¹⁸.

¹⁷ Overcharge rate (in %) = [(*P collusion* – *P benchmark*)/*P collusion*]*100.

¹⁸ Survey of numerous studies estimated cartel overcharges is presented in Connor (2005, Table 2).

Conclusion

We used extensions of traditional ARCH and GARCH models to examine the difference in the behavior of the first two moments of price distribution, the mean and the variance, during collusion and the absence of it using prices from two recently discovered conspiracies, citric acid and lysine. We expect that successful collusion increases the mean price and decreases its variance relative to pre-cartel and post-cartel periods. Thus, the change in the price behavior confirmed by the changes in the first two moments of price distribution, the mean and the variance, may indicate the presence of collusive behavior on the market.

Examining lysine prices we find support to both the mean and the variance hypotheses. Citric acid prices support the mean price hypothesis and fail to support the variance hypothesis. Citric acid conspiracy resulted in statistically significant price increase approximately by 9 cents per pound relative to pre-cartel and post-cartel periods. Lysine conspiracy managed to raise the price by approximately 25 cents per pound relative to pre-cartel, post-cartel period and a sub-period of conspiracy when it was not effective. In addition, the variance of prices during lysine conspiracy was lower than the variance of prices during pre-cartel and post-cartel periods. In contrast, the variance of the citric acid prices during conspiracy was higher relative to pre-cartel and post-cartel period. There may be at least two explanations of the unexpected variance behavior. First, the length of the citric acid conspiracy is longer than the length of lysine conspiracy. Thus, it could be more difficult for cartel to supervise and enforce cartel discipline during longer period of time. Possible opportunistic behavior of cartel members could contribute to the variability in citric acid prices. In lysine case we know that this conspiracy was successful; cartel members followed the discipline in 90 percent of all cases. Second, data availability problem may have had an impact on the analysis outcome. The number of

available pre-cartel observations in citric acid case is almost half as much as the number available pre-cartel observations in lysine case and less than the number of observations available for cartel period. Thus, during conspiracy prices may appear to be more volatile.

We use the estimation results to calculate cartel overcharge as a percent of the market price. Citric acid cartel imposed overcharge equal to approximately 12 percent of the market price during collusion. Lysine cartel imposed overcharge approximately equal to 25 percent of the market price. Our estimates fall in the range of overcharge estimates calculated in other studies examining the same conspiracies.

The results of our study have implications for both antitrust policy and court decision-making dealing with illegal cartel conduct. In particular, the econometric technique employed can be used to test for the presence of collusive behavior on the markets where collusion is likely to take place. Thus, it may be used in the screening analysis conducted by antitrust authorities. It may be also used as an alternative to the econometric models commonly employed in court proceedings to quantify the effect of conspiracy on market price. An advantage of using the ARCH and the GARCH models is that they require minimum amount of data, at least price time-series for a cartelized product before, during and after hypothesized or known conspiracy.

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Appendix

Chart 1.

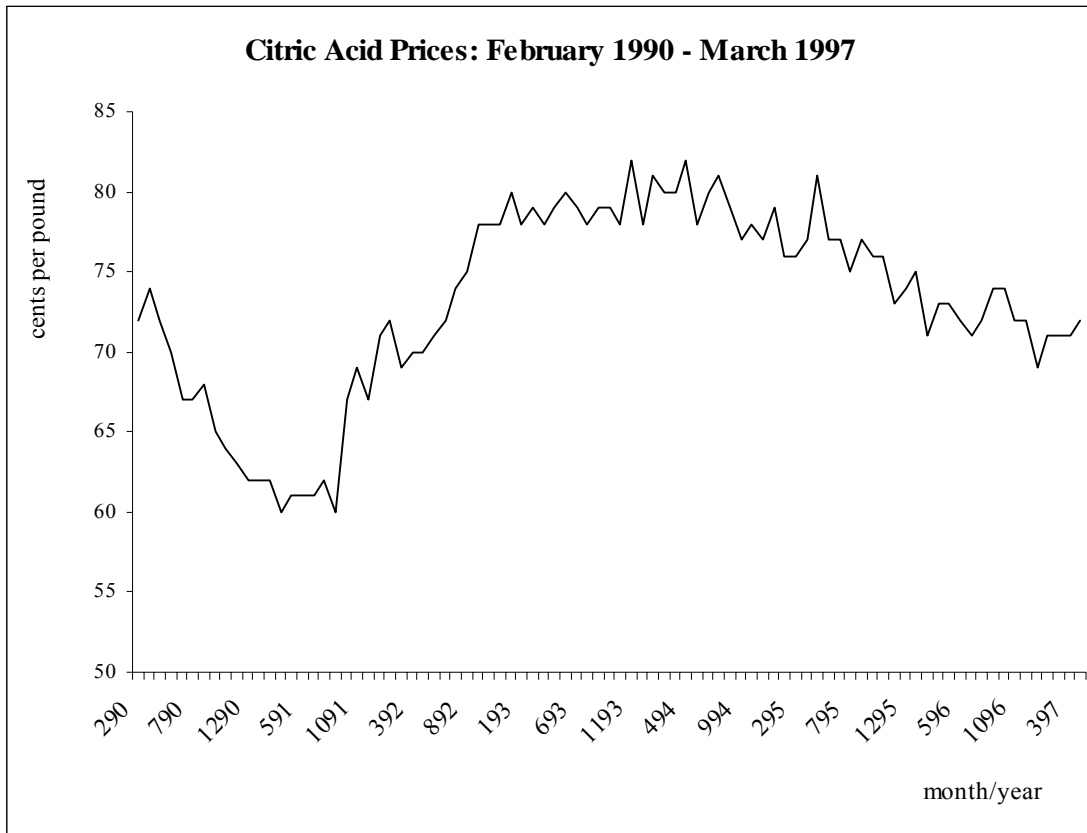


Chart 2.

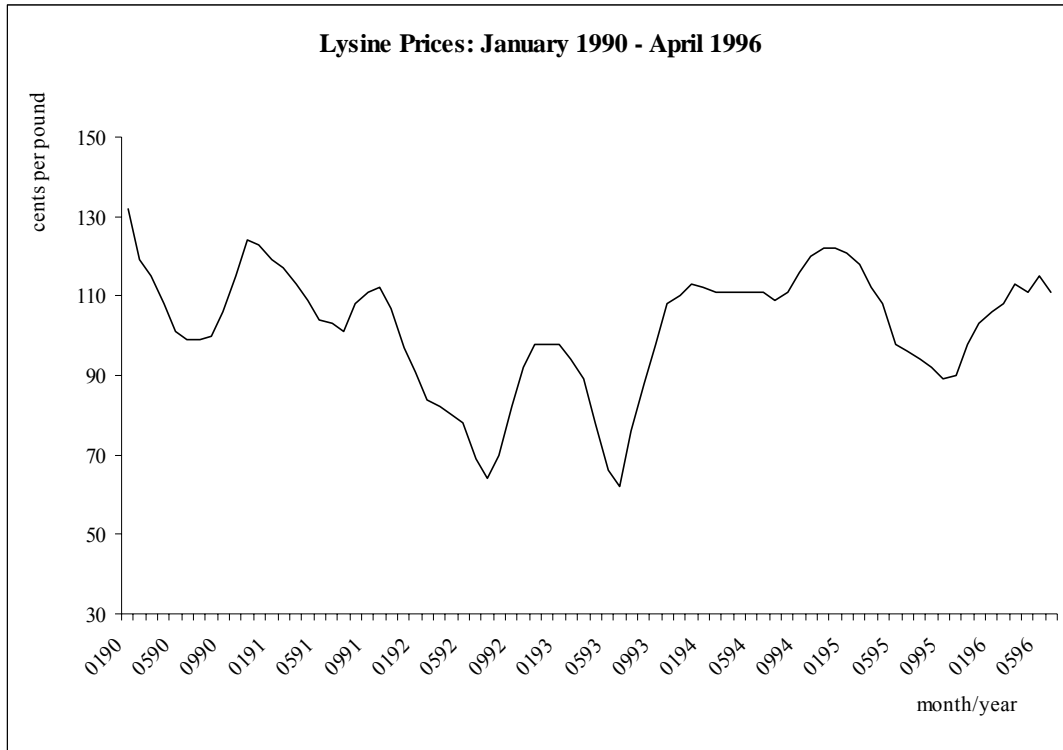


Table 1. Descriptive Statistics: Citric Acid Prices

| Period | N | Mean | Variance | Skewness | Kurtosis |
|--------------------|----------|-------------|-----------------|-----------------|-----------------|
| Pre-Cartel | | | | | |
| 02/90-6/91 | 17 | 65.35 | 20.24 | 0.65 | -0.92 |
| Cartel | | | | | |
| 07/91-06/95 | 48 | 75.96 | 25.66 | -1.41 | 1.62 |
| Post-Cartel | | | | | |
| 07/95-04/97 | 22 | 72.91 | 4.09 | 0.33 | -0.41 |
| Sample | | | | | |
| 02/90-04/97 | 87 | 73.11 | 35.22 | -0.66 | -0.44 |

Table 2. Descriptive Statistics: Lysine Prices

| Period | N | Mean | Variance | Skewness | Kurtosis |
|---------------------|----------|-------------|-----------------|-----------------|-----------------|
| Pre-Cartel | | | | | |
| 01/90-07/92 | 31 | 102.90 | 263.22 | -0.70 | 0.16 |
| 1st period | | | | | |
| 08/92-03/93 | 8 | 90.13 | 96.70 | -1.43 | 1.71 |
| Cartel lapse | | | | | |
| 04/93-07/93 | 4 | 70.50 | 59.67 | -0.17 | -4.41 |
| 2nd period | | | | | |
| 08/93-06/95 | 23 | 110.30 | 73.04 | -0.94 | 1.01 |
| Post-Cartel | | | | | |
| 07/95-06/96 | 12 | 102.50 | 90.45 | -0.22 | -1.66 |
| Sample | | | | | |
| 01/90-06/96 | 78 | 102.05 | 234.62 | -0.78 | 0.17 |

Table 3. Maximum Likelihood ARCH (1) Estimation Results: Citric Acid

| Estimated Coefficient | Model [1] | Model [2] | Model [3] |
|---|------------------|------------------|------------------|
| <i>Mean equation</i> | | | |
| <i>dependent variable: price</i> | | | |
| Intercept | 3.74 | 2.23 | 2.22 |
| st.error | 2.58 | 4.02 | 3.45 |
| p-value | 0.1480 | 0.5790 | 0.5200 |
| Lagged price (LP) | 0.95 | 0.96 | 0.96 |
| st.error | 0.04 | 0.06 | 0.05 |
| p-value | 0.0000 | 0.0000 | 0.0000 |
| Conspiracy dummy (DC) | | 8.81 | 9.15 |
| st.error | | 5.49 | 5.36 |
| p-value | | 0.1090 | 0.0880 |
| LP*DC | | -0.10 | -0.11 |
| st.error | | 0.08 | 0.07 |
| p-value | | 0.1760 | 0.1450 |
| <i>Variance equation</i> | | | |
| <i>dependent variable: unconditional variance</i> | | | |
| Intercept | 3.40 | 2.85 | 2.06 |
| st.error | 0.70 | 0.59 | 0.61 |
| p-value | 0.0000 | 0.0000 | 0.0010 |
| Lagged unconditional variance | 0.14 | 0.16 | 0.15 |
| st.error | 0.15 | 0.15 | 0.15 |
| p-value | 0.3520 | 0.2780 | 0.3130 |
| Conspiracy dummy | | | 1.49 |
| st.error | | | 0.99 |
| p-value | | | 0.1340 |
| LLF | -180.399 | -174.348 | -173.19 |

Table 4. Maximum Likelihood GARCH (1,1) Estimation Results: Citric Acid

| Estimated Coefficient | Model [1] | Model [2] | Model [3] |
|---|------------------|------------------|------------------|
| <i>Mean equation</i> | | | |
| <i>dependent variable: price</i> | | | |
| Intercept | 3.99 | 2.45 | 2.84 |
| st.error | 2.53 | 3.92 | 3.33 |
| p-value | 0.1150 | 0.5330 | 0.3940 |
| Lagged price (LP) | 0.95 | 0.96 | 0.95 |
| st.error | 0.03 | 0.06 | 0.05 |
| p-value | 0.0000 | 0.0000 | 0.0000 |
| Conspiracy dummy (DC) | | 8.58 | 9.00 |
| st.error | | 5.22 | 4.78 |
| p-value | | 0.1000 | 0.0600 |
| LP*DC | | -0.10 | -0.10 |
| st.error | | 0.07 | 0.07 |
| p-value | | 0.1670 | 0.1100 |
| <i>Variance equation</i> | | | |
| <i>dependent variable: conditional variance</i> | | | |
| Intercept | 6.11 | 4.82 | 3.33 |
| st.error | 2.57 | 1.60 | 1.18 |
| p-value | 0.0170 | 0.0030 | 0.0050 |
| Lagged unconditional variance | 0.09 | 0.15 | 0.23 |
| st.error | 0.10 | 0.11 | 0.13 |
| p-value | 0.3430 | 0.1850 | 0.0870 |
| Lagged conditional variance | -0.68 | -0.61 | -0.49 |
| st.error | 0.56 | 0.37 | 0.27 |
| p-value | 0.2250 | 0.0950 | 0.0710 |
| Conspiracy dummy | | | 1.27 |
| st.error | | | 1.20 |
| p-value | | | 0.2900 |
| LLF | -179.693 | -173.332 | -172.284 |

Table 5. Maximum Likelihood ARCH (1) Estimation Results: Lysine

| Estimated Coefficient | Model [1] | Model [2] | Model [3] |
|---|------------------|------------------|------------------|
| <i>Mean equation</i> | | | |
| <i>dependent variable: price</i> | | | |
| Intercept | 22.07 | -6.58 | -5.71 |
| st.error | 2.89 | 4.65 | 4.60 |
| p-value | 0.0000 | 0.1570 | 0.2150 |
| Lagged price (LP) | 0.80 | 1.05 | 1.04 |
| st.error | 0.03 | 0.04 | 0.04 |
| p-value | 0.0000 | 0.0000 | 0.0000 |
| Conspiracy dummy (DC) | | 27.24 | 25.73 |
| st.error | | 6.15 | 5.66 |
| p-value | | 0.0000 | 0.0000 |
| LP*DC | | -0.23 | -0.21 |
| st.error | | 0.06 | 0.05 |
| p-value | | 0.0000 | 0.0000 |
| <i>Variance equation</i> | | | |
| <i>dependent variable: unconditional variance</i> | | | |
| Intercept | 6.31 | 10.97 | 12.12 |
| st.error | 2.31 | 2.96 | 3.92 |
| p-value | 0.0060 | 0.0000 | 0.0020 |
| Lagged unconditional variance | 0.99 | 0.65 | 0.76 |
| St.error | 0.26 | 0.23 | 0.25 |
| p-value | 0.0000 | 0.0050 | 0.0020 |
| Conspiracy dummy | | | -5.82 |
| st.error | | | 4.74 |
| p-value | | | 0.2190 |
| LLF | -232.77 | -230.254 | -229.799 |

Table 6. Maximum Likelihood GARCH (1,1) Estimation Results: Lysine

| Estimated Coefficient | Model [1] | Model [2] | Model [3] |
|---|------------------|------------------|------------------|
| <i>Mean equation</i> | | | |
| <i>dependent variable: price</i> | | | |
| Intercept | 22.01 | -6.30 | -5.19 |
| st.error | 2.91 | 4.65 | 4.51 |
| p-value | 0.0000 | 0.1750 | 0.2500 |
| Lagged price (PL) | 0.80 | 1.05 | 1.04 |
| st.error | 0.03 | 0.04 | 0.04 |
| p-value | 0.0000 | 0.0000 | 0.0000 |
| Conspiracy dummy (DC) | | 26.88 | 24.79 |
| st.error | | 6.10 | 5.47 |
| p-value | | 0.0000 | 0.0000 |
| PL*DC | | -0.22 | -0.20 |
| st.error | | 0.06 | 0.05 |
| p-value | | 0.0000 | 0.0000 |
| <i>Variance equation</i> | | | |
| <i>dependent variable: conditional variance</i> | | | |
| Intercept | 6.26 | 11.55 | 13.10 |
| st.error | 2.62 | 4.15 | 5.01 |
| p-value | 0.0170 | 0.0050 | 0.0090 |
| Lagged unconditional variance | 0.99 | 0.66 | 0.79 |
| st.error | 0.28 | 0.24 | 0.25 |
| p-value | 0.0000 | 0.0060 | 0.0020 |
| Lagged conditional variance | 0.003 | -0.03 | -0.04 |
| st.error | 0.08 | 0.13 | 0.10 |
| p-value | 0.9670 | 0.8400 | 0.7200 |
| Conspiracy dummy | | | -6.66 |
| st.error | | | 4.95 |
| p-value | | | 0.1780 |
| LLF | -232.772 | -230.221 | -229.726 |