6 Detecting Cartels

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Cartels are among us. Their attempts to coordinate the prices they set and the quantities they produce are often effective. A recent comprehensive survey found the median increase in price attributable to collusion to be around 25 percent (Connor 2004). So cartels exist and are bad. When we find them, we ought to prosecute and penalize them. But how do we find them?

Broadly speaking, market collusion can be detected through structural or behavioral means. Structural methods of discovering cartels entail identifying markets with traits thought to be conducive to collusion. For example, it has been shown that structurally, cartel formation is more likely to exist where there are fewer firms, more homogeneous products, and more stable demand.[1] Grout and Sonderegger (2005, p. 15) is representative of this approach:

> . . . the fundamental background reduces to three core issues—product, volatility, and company criteria. The first core question is whether the industry has a homogeneous product or not. Cartels are far more likely if the product is fairly homogeneous between companies in the market. . . . Second, does the industry display volatile turnover over a sustained period of time?
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> Cartels are more likely if output and market conditions are normally stable. . . . Finally, are the leading players in the market large and relatively constant? If there are significant changes in the market shares or regular exits and entrants, then cartels are less likely.

One could imagine investigating industries who score high on these relevant traits with the hope of finding evidence of a cartel.

In contrast, uncovering cartel behavior through behavioral methods involves observing the means by which firms coordinate or the end result of that coordination. The means of coordination can be some form of direct communication, and many cartels have been detected by evidence of such communication. The evidence could come from a person party to the cartel or from an employee who stumbles across documents suggestive of collusion. For example, the monochloroacetic acid cartel was discovered because the management of Clariant, after acquiring the Hoechst chemicals business, found evidence of Hoechst being part of a cartel. They chose to come forward to the American and European antitrust authorities.[2] In the case of lysine, it was an employee of Archer Daniels Midland, engaged in the conspiracy, who came forward in exchange for immunity. With the employee acting as an FBI informant, cartel meetings were recorded on videotape for the FBI.[3] In both cases it was the means by which firms colluded that ultimately led to the cartel's discovery.

Alternatively, cartel behavior can be revealed by the market impact of the coordination of firms' prices or quantities, or other aspects of their market behavior. Buyers could become suspicious of parallel movements in prices or an inexplicable increase in prices. A sales representative for a colluding firm may become suspicious because she is instructed not to bid for the business of certain potential customers (as part of a customer allocation scheme) or not to offer reasonable price concessions when business might be lost to competitors. For example, the European Commission investigated the stainless steel industry (and found collusion) after buyers complained to the Commission about a sharp increase in prices.[4] Although we do not know the specifics of the complaints, the cartels in graphite electrodes[5] and thermal facsimile paper[6] were reportedly discovered also after buyer complaints.[7]

This chapter explores the role of *economists as detectives* and, more specifically, detection through the analysis of prices, market shares, and other economic data. The focus on the behavioral method is mainly due to its more apparent efficacy in uncovering collusion. To see the weakness to a structural approach, imagine the "ideal" market for collusion: two firms, homogeneous products, stable demand, no large buyers, excess capacity, and so forth. Even though such a market would surely be flagged by a structural investigative tool, my own prior belief is that a very high fraction of those markets are not cartelized. Based on what we know (admittedly from only discovered cartels), the frequency of collusion in most economies is rather low. Hence, given a low prior probability of collusion, the posterior probability—conditional on all those structural variables taking values conducive to collusion—is still probably quite low. In other words, I think the likelihood of false positives with a structural approach is quite high. By contrast, a behavioral approach will be shown to focus on potentially more informative measures so that one might imagine a lower rate of false positives. Of course, all this is speculative but it does serve to reveal my own prior beliefs.

Having cavalierly dismissed structural methods, let me immediately qualify that view as I have been told that the Dutch competition authority has deployed structural methods with some success including, for example, uncovering collusion in the shrimp industry. But then it has also been mentioned to me that the Dutch economy may be rife with cartels in which case the prior probability of collusion is far from being low.[8] If that is indeed the case then the posterior probability of a cartel being present, conditional on many of the right structural traits, may be high enough to make such an approach useful. However, most economies probably have a low rate of collusion in which case structural methods are much less likely to be efficacious.

This chapter will then explore how the analysis of economic data—prices, quantities, market shares, demand shifters, cost shifters, and the like—can allow us to discriminate between collusion and competition to identify the presence of a cartel. The process of detection involves a sequence of screening, verification, and prosecution. During the *screening* of markets, a kind of triage is used to identify industries worthy of close scrutiny. *Verification* then is necessary to systematically exclude competition as an explanation for observed behavior and gather evidence in support of collusion. Whereas screening may entail studying price patterns, verification requires controlling for demand and cost factors and any other variables necessary to distinguish between collusion and competition. The final task of *prosecution* comes when sufficient economic evidence is developed to persuade a court or some other administrative body that there has been violation of law. One may interpret this exercise as the same as verification though with a different set of standards. With respect to US case law, economic evidence is not typically sufficient to prove guilt; there must be some evidence of coordination.[9] The discussion of this chapter will be centered on the role of economic analysis in screening and verification.

The systematic search for illegal activity is a common practice. In identifying fraudulent tax returns, tax authorities—such as the US Internal Revenue Service—are proactive in developing models that flag certain returns as worthy of investigation. In their lookout for insider trading, securities authorities—such as the US Securities and Exchange Commission—ex post monitor volume leading up to a significant announcement. In tracking down fraud, credit card companies use statistical models to identify aberrations in spending patterns. As these cases attest, government agencies and private corporations actively search for illegal activity. However, there are really no analogous policies when it comes to illegal cartels. Although attempts are made over time, it is fair to say that economic analysis—as occurs in government, academe, or private consulting—has not been applied to the discovery of cartels. Economic analysis can be instrumental to the prosecutorial argument and essential in assessing damages, but as yet it has not been applied to detecting cartels. My objective is therefore to review the theoretical and empirical methods available for cartel detection and to show how economic analysis can assist in the task of identifying industries worthy of close inspection.

Section 6.1 reviews the four methods generally used in detecting collusion and the research that implements these methods. Section 6.2 focuses on collusive markers for price and market share based on discussions from the theoretical literature on collusive pricing. Section 6.3 explores how a cartel may be able to beat a test for collusion. Section 6.4 concludes by discussing the feasibility of a more aggressive screening policy by the antitrust authorities.

6.1 Empirical Methods for Detecting Cartels

It is important to be clear as to what it is we are searching for. The objective is not to identify industries with high price-cost margins but rather to uncover prosecutoriable cases of collusion. In terms of current antitrust practice this generally means explicit collusion—

where firms have engaged in direct communication and obvious coordination—rather than tacit collusion—where firms are able to coordinate through some mutual understanding and without the aid of direct communication. From both a legal and economic perspective, explicit collusion is conceived as a discrete event; firms are or are not explicitly colluding. Of course, the impact of collusion, whether explicit or tacit, on price and welfare can be of varying degrees, and the extent of collusion is certainly pertinent to the calculation of damages and the appropriate enforcement policy. What is different about the presence of a cartel is that firms are explicitly coordinating their behavior through illegal means of communication. Having drawn this distinction between explicit and tacit collusion, I am sorry to say, because of inadequacies in the underlying theory, my ensuing analysis will largely ignore this distinction. Nevertheless, it is important to know that this distinction exists, and that future research may move it to the front of our collective mind.

Verification of episodes of collusion is a data-intensive and time-intensive task that requires controlling for the many determinants of behavior. It can involve identifying a competitive benchmark and comparing the behavior of suspected colluders to it. It can involve estimating collusive and competitive models to see which better fits the data. It is not practical to engage in such an exercise except where there are already some suspicions, that is, some evidence that collusion is afoot in an industry.

It is the role of screening to identify candidates for verification. In most antitrust cases, screening doesn't occur through economic analysis but rather through such avenues as buyer complaints, upset competitors, and the corporate leniency program. Although economic analysis can serve a screening function, the "suspicious" behavior it identifies does not provide "conclusive" evidence of collusion. Economic analysis may establish that behavior is inconsistent with a class of competitive models but not that it is consistent with some collusive model. It may show that there has been a structural break in behavior but leave unaddressed whether it is due to the formation of a cartel or some other change. Like verification, screening can be intensive in terms of data, modeling, and estimation. When it is, it is then not a practical undertaking without other evidence that collusion may be present.

In this section, I review four empirical methods that have been used for detecting collusion. Match a clever economist with a suspected cartel and a unique method of detecting collusion may emerge. Indeed there are apt to be useful methods hidden in consultants' drawers or buried in court documents. In limiting this review to the published literature, four methods are reviewed for detecting collusion, and these methods are based on asking the following questions: (A) Is behavior inconsistent with competition? (B) Is there a structural break in behavior? (C) Does the behavior of suspected colluding firms differ from that of competitive firms? and (D) Does a collusive model fit the data better than a competitive model? Methods A and B are generally screening methods in that they do not call for evidence of collusion but rather evidence that doesn't sit well with competition. Methods C and D address contrasting competition and collusion as alternative explanations of firm behavior and thus serve verification purposes. A key difference between those two methods is that in method D the competitive benchmark is estimated using data from suspected colluding firms, whereas in method C it is done using data from unsuspected firms (or markets). These various methods are reviewed in sections 6.1.1 through 6.1.4. In section 6.1.5, I show why high price–cost margins are not an adequate screening device, and in section 6.1.6, I provide a critique of these four methods.[10]

6.1.1 Is Firm Behavior Inconsistent with Competition?

This approach is based on identifying properties of behavior that would always hold under competition—or at least for a wide class of competitive models—and to test whether they are present for a particular industry. The null hypothesis is competition and the empirical task is to accept or reject that hypothesis. Of course, rejection does not imply collusion, only that behavior is inconsistent with the specified class of competitive models. As I will show, this approach is complimentary to later ones that test for collusion in that together they can be used to identify which firms may be members of a cartel by determining whose behavior is inconsistent with competition. The properties analyzed could be how firms' prices are related—for example, are they correlated when they should be independent?—or how a firm's price responds to cost and demand shocks—for example, do prices fail to rise with cost?

Testing for consistency of behavior with a competitive model is conducted in Porter and Zona (1993, 1999) and Bajari and Ye (2003). I will focus on the latter paper and cover Porter and Zona (1993, 1999) in section 6.1.3.

Bajari and Ye (2003) The setting is a first-price sealed bid procurement auction in which the product or service is homogeneous and bidders costs are independent.[11] Bidder i's cost valuation has the cdf $F(c_i \mid z_i, \theta) : t[\underline{c}, \bar{c}] \to [0, 1]$, where θ is a vector of parameters common across bidders and z_i is a vector of publicly observed independent variables that, are unique to firm i but may be correlated across firms.

The competitive model is based on the unique equilibrium to the following game: Bidder i's expected profit from bidding b_i is

$$(b_i - c_i) \prod_{j \neq i} [1 - F_j(B_j^{-1}(b_i))],$$

which is the gain from winning, $b_i - c_i$, times the probability that bidder i wins, where $B_j(\cdot)$ is the bidding function of j. Competitive bids can then be correlated if one fails to control for z_i. However, controlling for them, costs and thereby bids are independent. Thus this is a (conditional) independent private values (IPV) setting.

The competitive model predicts that after controlling for publicly available information $(z_1, \ldots, z_N)$, firms' bids are independent (more specifically, the unexplained part of one firm's bid is independent of the unexplained part of another firm's bid). Second, firms' bids are exchangeable: a permutation of the publicly available information analogously permutes the bids. In other words, firms' bidding functions are identical. Note that these properties do not pertain to a single firm but rather collections of firms; the competitive theory is being used in terms of what it predicts about the relationship among firms' bids. For example, it is not being proposed to determine whether a firm's bid is increasing in the distance between its office and the project site (which would be natural as then transportation costs are higher) but rather whether firms' bids respond the same way to distance.

The implementation of this model involves estimating a pricing equation for each firm and then testing whether independence and exchangeability hold for various (perhaps all) subsets of firms. A test for independence determines whether the unexplained part of each firm's bid is independent. A test for exchangeability determines whether firms' estimated coefficients are the same.

Bajari and Ye (2003) use this approach in analyzing procurement auctions for seal coating (a highway maintenance process) in Minnesota, North Dakota, and South Dakota in 1994 to 1998. Their data set has 138 projects for which there are eleven main companies. These contracts are awarded through a sealed bid auction with the contract going to the lowest bidder. From the engineering estimates of the cost of each project, the dependent variable is the ratio of the bid of firm i on project t, $BID_{i,t}$, to the engineering cost estimate for project t, EST_t. The bid equation is

$$\frac{BID_{i,t}}{EST_t} = \beta_0 + \beta_{i1} LDIST_{I,t} + \beta_{i2} CAP_{i,t} + \beta_{i3} MAXP_{i,t} + \beta_{i4} LMDIST_{i,t} + \beta_{i5} CON_{i,t} + \epsilon_{i,t}.$$

$LDIST_{i,t}$ is a measure of the distance between firm i and project t, so cost (and thus a competitive firm's bid) can be expected to be increasing with distance. In procurement auctions, capacity is an important factor in that it can influence production cost—if cost is increasing as capacity tightens—but also opportunity cost as a project won today may prevent the firm from bidding on a potentially more lucrative project tomorrow. $CAP_{i,t}$ is utilized capacity of firm i at the time of project t, which is measured as the ratio of the firm's total winning contracts up to the time of auction t to the firm's total of winning contracts in the entire season. $CON_{i,t}$ is the proportion of work done (by dollar volume) by firm i in the state where project t is located and is intended to capture familiarity with local regulators and local material suppliers. Finally, $LMDIST_{i,t}$ measures the minimum distance among rivals and $MAXP_{i,t}$ is maximal free capacity among rivals. Both variables pertain to the competitiveness of firm i's environment in terms of its rivals' cost.

The estimated coefficients are found to be sensible; a firm's bid is increasing (and statistically significant) in the log of distance, used capacity, and minimum distance among rivals and is decreasing in concentration. The estimated coefficient on the maximal free capacity of rivals is not significantly different from zero.

To test for independence, the residuals are calculated for each firm's bid function, $\epsilon_{i,t}$. A test of independence between firms i and j involves testing the hypothesis that the coefficient of correlation for $\epsilon_{i,t}$ and $\epsilon_{j,t}$ is zero. Among the 23 pairs of 11 largest firms that have at least four bids in the same auction, the null hypothesis of independence cannot be rejected at the 5 percent level in all but four cases. However, of these four pairs, three of them only bid against each other at most two or three times a year which, it is argued, doesn't suggest they interact enough to make collusion worthwhile. This leaves firms 2 and 4 as the lone candidates for being a cartel.

Exchangeability means that the independent variables enter the firm's bid function in a symmetric way, so the hypothesis is $\beta_{ik} = \beta_{jk}$, $\forall i \neq j$, $\forall k$. They conduct a test for exchangeability among all 11 main firms—thus running a regression that pools all 11 firms—and also test it for each pair of main firms—pooling only those two firms. The null hypothesis is rejected at the 5 percent level only when all 11 main firms are pooled and when firms 2 and 5 are pooled.

In sum, the analysis reveals that all pairs of firms satisfy both the test of independence and exchangeability except for firms 2 and 4 and firms 2 and 5. This approach not only suggests that collusion may be present—as some firms act contrary to a competitive model—but also which firms may be colluding. Out of the eleven firms in their data, two candidate cartels are identified: firms 2 and 4 and firms 2 and 5. Given that there are many feasible cartels, this is a highly useful exercise and is complementary to later approaches to be reviewed.[12]

The next natural question is whether the observed departures from competition are consistent with some model of collusion. Consider a collusive model in which the identities of the cartel's members are common knowledge to the other bidders and the cartel bids optimally, using the lowest cost among the cartel members. Further suppose that colluding firms are submitting complementary bids that exceed the bid of the designated member. This could lead to a lack of independence if, for example, complementary bids are some multiple of the designated firm's bid. It could also lead to a failure of exchangeability. If two cartel members don't compete against each other, then this could mean that factors affecting the cost of one doesn't affect the bid of the other. This case will be discussed in greater depth later. A second question is whether firms could be colluding and still satisfy independence and exchangeability. The answer is clearly yes, and all they have to do is to proportionately scale their "competitive" bids. This is an important point to which I will return later.

6.1.2 Has There Been a Structural Break in Firm Behavior?

A second general approach to identifying collusion is to look for a structural break in firm behavior. This break could be associated with the formation of a cartel but also with its demise. In either case there ought to be a discrete change in the firm's pricing function. As opposed to the other methods described earlier, this method requires data before the time of suspected collusion. While it can be implemented without prior information as to what patterns are consistent with collusion, theory and past evidence on cartels would enhance its power by suggesting what properties to focus upon and what we ought to observe if indeed a cartel has formed. Has average price changed? Has the relationship between the firm's price and cost changed? Has the relationship among firms' prices changed? Has the variance of price and market share changed?[13] Of course, econometric evidence of structural change is far from conclusive evidence of collusion if this has not been distinguished from other sources of a break. It is then appropriate to think about this method as a screening device that is to be followed with verification methods (described later) if a structural break is found in the data.

The classical Chow test is a useful test for structural change *if* there is prior information as to when a cartel could have formed (or could have collapsed). However, if observation of, say, a price series is used to identify a possible break in market conduct, then the Chow test is inappropriate and can lead to spurious rejection of parameter stability. Thus, the prior information must not be the series for which one will be econometrically testing for a structural break.

Appropriate events for identifying a candidate breakpoint are those that either are conducive to cartel formation (i.e., make collusion easier or more profitable) or are observed along with cartel formation (e.g., allow the cartel to operate more effectively). It has been documented that trade associations are used as a cover for cartel meetings, and more to the point, trade associations have been created for that express purpose. For example, the Amino Acid Manufacturers International Association was formed by members of the lysine cartel (Connor 2001) and the Oklahoma Highway Department only started receiving identical bids at procurement auctions some time after the Asphalt Refiners Association was formed (Funderburk 1974). A test for a break in the relationship among firms' bids around the time of the creation of the association would be useful. Nevertheless, structural change can occur even if firms are not colluding. For example, the formation of an association can lead to enhanced correlation of firms' prices because it promotes the exchange of information that homogenizes firms' beliefs. It is not clear, however, that such homogenization will lead to higher average prices. It is then important to consider the various implications of a trade association and identify those effects unique to collusion.[14]

There are other events that can contribute to cartel formation and thus serve as candidate breakpoints. One should be concerned that there will be structural change even if the event does not trigger collusion. Exit or merger (particularly of a maverick firm) might allow a cartel to form, but an exit will change the noncollusive solution as well. Though average price is predicted to rise in response to an exit or a merger (whether or not a cartel forms), there may still be distinguishing effects of collusion. For example, cartel formation might predict more parallel behavior among firms, while noncollusion will have no such prediction. To properly address the question of collusion, one must deal with the endogeneity of the event toward understanding the factors behind it. For example, if a firm with an inferior technology exits and technology is more uniform among the remaining firms, then there might be more correlation among these firms' prices because of the greater homogeneity in their cost-generating processes. All this serves as a note of caution but need not rule out using these events as a date for which to test for structural change in firm behavior.

There are further events—such as entry—that provide candidate breakpoints for the collapse of a cartel. A case in point is the growing expansion of Chinese manufacturers in the market for vitamin C that eventually led to the collapse of the cartel in that market (Levenstein and Suslow 2001). While, even under noncollusion, a change in firms' prices can be expected in response to the expansion of new competitors, a discrete change in that pricing relationship does not occur *unless* it causes a cartel to dismantle itself.

Although it presumes there is already some suspicions about the presence of a cartel, one can test for structural change at the time at which suspected colluding firms become aware of a government price-fixing investigation or private litigation because such is likely to lead to a collapse of the cartel. Abrantes-Metz et al. (2006) use that type of event and find a significant decrease in the price variance. These cartel-destabilizing events could even occur in other (related) markets when firms take it as a signal that the authorities are going to investigate them as well. On this point Block, Nold, and Sidak (1981) find that a price-fixing case in the bread market for one city reduced the markups for bread in neighboring cities. While a comparison of prices before and after the launching of an investigation is often used to measure the impact of collusion on price,[15] it can be used to provide evidence of collusion as well.

Another method, but one that should be used cautiously, is to relate one feature to some other feature of the data serving to identify a possible breakpoint for structural change. For example, a plot of the average price series could establish a date at which price begins to follow a rising trend. That date could then be used as a breakpoint to test whether there is a break in, say, the correlation among firms' prices. However, care needs to be given to avoid a bias in looking for evidence of structural change. The result will very much depend on the class of noncollusive price-generating processes that is specified.

Even if there is not a candidate breakpoint, econometric methods exist for determining whether there is an unknown time at which structural change occurred. One approach goes back to Quandt (1960), who conducted a test for each possible breakpoint and then used the largest test statistic. The distribution theory for that test statistic has since been developed, beginning with Andrews (1993).[16] Once again, any evidence of structural change must be followed by an examination of the properties of the change and whether the change conforms with our understanding of collusive behavior.

A search for explicit collusion by identifying structural change can be confounded by a breakdown of tacit collusion. To see this, suppose that firms are currently tacitly colluding and a persistent demand shock hits that destabilizes the equilibrium. The sharp fall in demand could induce an abrupt shift to another equilibrium or a period of disequilibrium before a new equilibrium is reached. On this point, it is noteworthy that some cartels were preceded by abnormally low prices, such as the cartels in graphite electrodes (Levenstein and Suslow 2001) and citric acid (Connor 2001). One conjectured explanation is that firms were tacitly colluding but collusion fell apart on account of some shock. Failure to get the industry back to some tolerable level of prices through tacit means could have induced explicit collusion.[17]

6.1.3 Does the Behavior of Suspected Colluding Firms Differ from That of Competitive Firms?

Firms were suspected of colluding at procurement auctions of asphalt contracts by the Oklahoma Highway Department (OHD) over the span of 1954 to 1965 (Funderburk 1974). During the time of suspected collusion, bids were identical and, beginning in 1957, were constant at 10.25 cents a gallon. With identical bids, the OHD awarded the contract to the nearest firm to the job site in order to minimize the delivery costs incurred by the state, which, it was later argued, acted as a market allocation scheme. During the same time period, these suppliers made bids and won contracts in other states at an average price of only 6 cents a gallon, and furthermore the uniformity in bids in Oklahoma was not observed there. It was estimated that the maximum freight cost for these Oklahoma contracts was 2.48 cents a gallon, which meant that any of these firms could have won additional contracts with a price of 10.24 cents a gallon and, even if they absorbed freight costs, would receive a net price of 7.76 cents a gallon, exceeding the price of 6 cents that these same firms bid in other states.

The approach just described involves comparing the behavior of suspected colluders with some competitive benchmark. In the case of asphalt contracts, the benchmark is comparable markets in which firms are not thought to be colluding; specifically, among the distinct geographic markets for the same product or service, the firms are suspected of colluding in some but not all of these markets. Porter and Zona (1999) use the benchmark approach in examining collusion in school milk contracts. Alternatively, if there is prior information about the identities of the cartel members and the cartel is not all inclusive, a benchmark can be provided by the behavior of noncolluding firms. A third benchmark is when data show periods of suspected collusion but also of competition, such as before or after the suspected time of collusion. Data are more problematic from the time when collusion is thought to have temporarily broken down because a price war could be part of the collusion, and so need not be an appropriate competitive benchmark.[18]

The usual implementation of this concept is to estimate reduced-form price equations by regressing price on cost and demand shifters. After a price equation for (suspected) cartel members and a price equation for noncolluding firms are estimated, a test is conducted to determine whether the prices are statistically different. If they are statistically different, then prices of the noncolluding firms must be checked to see if they are consistent with those of a competitive model and if the colluding firms act in a manner consistent with some model of collusion.

Porter and Zona (1993) The setting is a first-price sealed bid procurement auction as in Bajari and Ye (2003). Bidding behavior is specified to satisfy a log-linear bidding rule, $\log(b_{it}) = \alpha_t + \beta X_{it} + \epsilon_{it}$, where i is the firm and t is the project, α_t is an auction-specific effect, and X_{it} is a vector of observable variables affecting cost and the probability of winning.

The data are from 116 auctions conducted by the New York State Department of Transportation (DOT) for highway construction contracts over the span of 1979 to 1985. There was prior information about who might be members of the bidding ring. One of the firms was previously convicted for rigging bids on a Long Island highway construction project and four other firms were listed as unindicted conspirators, all at auctions that took place prior to the data set. This prior information was used to identify a candidate cartel comprised of these five firms. As a reality check, the authors provide some evidence that, in the absence of collusion, the suspected firms would have competed, so that the set of auctions at which they would have participated significantly intersect. If that were not the case, then there was little reason for them to collude. The maintained hypothesis was that unsuspected firms were acting competitively.

Porter and Zona first consider whether the determination of firms' bid levels differ between cartel firms and competitive firms. For the bid equation the exogenous variables are (1) the backlog of a firm at the time of an auction as measured by the dollar value of contracts won but not yet completed, (2) the capacity of a firm as measured by the maximum backlog (capacity squared is included as well), (3) a firm's capacity utilization rate, which is backlog divided by capacity (and capacity utilization squared), and (4) a dummy variable for whether a firm's headquarters is on Long Island (which serves to measure geographic proximity to a job). The bid equation is estimated separately for competitive firms and cartel firms.

The estimated bid function for competitive firms is reasonable with all estimated coefficients being highly significant. A firm's bid is initially decreasing and then increasing in utilization and initially decreasing and then increasing in capacity. In contrast, the estimated bid function for cartel firms shows that their bids are not statistically significantly related to utilization and are initially increasing and then decreasing in capacity, contrary to that for competitive firms. To test for differences in these estimated coefficients, the bid equation is estimated using all bids. Under the null hypothesis that there is no collusion, the two subsamples—competitive firms and cartel firms—should have the same estimates as those using the entire sample. A Chow test allows that hypothesis to be rejected. The authors conclude that the estimated model fits the bids of competitive firms reasonably well and the bids of cartel firms are statistically different from those of competitive firms.

A more interesting test is conducted on the ranking of bids. In terms of a multinomial logit (MNL), the likelihood of the observed ranking of bids for auction t is

$$\Pr(b_{r_1 t} < \cdots < b_{r_{n_i} t}) = \prod_{i=1}^{n_t} \frac{e^{\beta Z_{r_i t}}}{\sum_{j=i}^{n_t} e^{\beta Z_{r_j t}}},$$

where r_m denotes the firm with the mth lowest bid, $Z_{r_m t}$ are exogenous variables, and n_t is the number of bidders at auction t. The crucial property of the MNL is that the model (if correctly specified) can be estimated from any subset of bids. For example, compare using the lowest bid,

$$\prod_{t=1}^{T} \frac{e^{\beta Z_{r_1 t}}}{\sum_{j=1}^{n_t} e^{\beta Z_{r_j t}}}, \tag{6.1}$$

and the remaining higher bids,

$$\prod_{t=1}^{T} \prod_{i=2}^{n_t} \frac{e^{\beta Z_{r_i t}}}{\sum_{j=i}^{n_t} e^{\beta Z_{r_j t}}}. \tag{6.2}$$

Porter and Zona estimate the model with all ranks, the lowest rank, and the higher ranks. The null hypothesis is that the estimated coefficients are the same and is tested using a likelihood ratio test. Based on the bids of competitive bidders, the null hypothesis cannot be rejected; the estimates of the lowest competitive bid and the higher competitive bids are not statistically different. However, when estimated with the bids of the suspected cartel members, the null hypothesis is soundly rejected.

With this distinguishing empirical property of suspected cartel members, the next task is to show that it is consistent with some model of collusion. Why would collusion result in the process determining the lowest bid differing from that of higher bids? Porter and Zona suggest the following collusive scheme: The cartel identifies a firm to submit the lowest bid with the other firms instructed to offer higher bids. The designated firm's bid will be driven by its cost and the desire to trade off the probability of winning and the surplus it receives if it wins, just as with competitive firms. In contrast, the phantom bids of the other cartel members are only required to be higher and thus need not be generated by an analogous process. Their bids are not set so as to maximize their expected payoff but rather only to give the appearance of competition. Such a collusive model could explain why there would be this disparity between the process generating the lowest cartel member's bid and that of the bids of the other cartel members.

As with the independence and exchangeability tests of Bajari and Ye (2003), testing whether the estimated coefficients for (6.1) and (6.2) are the same for suspected colluding firms is a test of competition and can be conducted without a competitive benchmark. Nevertheless, a rejection of this test can be more confidently concluded as due to collusion, rather than some other form of misspecification, if the test is not rejected for firms not suspected of colluding.

Porter and Zona (1999) A similar approach is taken in Porter and Zona (1999) in examining collusion at procurement auctions for school milk.[19] The market is a city school district that awards an annual contract for the supply of school milk. School districts conduct their auctions independently. The analysis focuses on the school districts in the Cincinnati area for which there were three defendants: Coors, Meyer, and Louis Trauth (two of them having confessed to rigging bids). Furthermore the defendants testified that the cartel used an incumbency scheme whereby if a cartel member had served a particular district in the previous year, then the other firms were to either not participate or submit high complementary bids.

The approach is similiar to that of the earlier study. A reduced form model of a firm's bid level is estimated, though, in this case, it is done simultaneously with a probit specification for whether a bid was submitted. The strategy is to determine whether there are systematic differences between the estimated bid equations for cartel members and competitive firms and, if so, whether these differences can be explained with a particular model of collusion.

The authors have detailed data on the characteristics of a contract which relate to cost—for example, the distance between the processing plant and the school district (*Distance*) and the size of the school district—and the competitive environment—for example, if a firm is the closest one to the district (and thus has a cost advantage over other bidders). Using data for all competitive firms plus a particular defendant, Porter and Zona regressed the bids on various factors (along with estimating the probability that a bid is submitted). This is done assuming the slope coefficients are the same for all firms and when the slope coefficients for the defendant are allowed to differ from those of the other firms. Both intercepts are allowed to differ. Under the null hypothesis the estimated coefficients should be the same for the two estimations, and this hypothesis is tested by a likelihood ratio test for each of the three suspected cartel members. It is worth noting that the test is not whether colluders bid more but rather whether their bids are determined differently from that of competitive firms. Higher bids could simply be due to drawing valuations from a different distribution.

For each of these three firms the null hypothesis is rejected at any conventional significance level, which means that suspected colluding firms' bids are determined by a different process than that of unsuspected firms. The unsuspected firms' bids respond in a manner consistent with the competitive model—for example, their bids are increasing in *Distance*, while the bids of two colluding firms are *decreasing* in *Distance* (all three colluding firms' bids are decreasing in distance relative to that of the other firms). The estimates for the bid submission equation show that bids are significantly lower in the distance ranges for which these firms are more likely to bid than competitive firms. This result is inconsistent with the competitive model as well. As cost is increasing in distance, a firm's bid should be increasing in distance. Furthermore, if there is a fixed cost to submitting a bid (or there is an opportunity cost to winning a contract), a firm should be more inclined to do so where it thinks it can win with a higher price–cost margin, which, controlling for cost factors, suggests that a firm's bid should be relatively *higher* where it is relatively more likely to bid.

Because unsuspected colluders are the competitive benchmark, it is clear that suspected colluders' bids have systematically departed from the behavior of competitive firms. Nevertheless, collusion is only one possible explanation for this departure. What is needed is a collusive model that predicts the direction of these departures. Before turning to that task, I discuss below what was learned from the estimates of the probability of a firm submitting a bid on a contract.

A reduced-form probit model was estimated in which the dependent variable takes the value 1 if a firm submitted a bid on a contract. Estimates for competitive firms are generally consistent with competition—for example, firms are less likely to submit a bid when *Distance* is longer. Relative to nondefendants' behavior, the three suspected colluders were much more likely to submit bids when *Distance* is 30 miles or less. Furthermore the decision to submit bids was found not to be independent across colluding firms, as ought to hold for the competitive model after controlling for all public information. By way of the estimated probit equation for competitive firms, the residual was calculated for each auction for each of the colluding firms. For each of the three pairs of these firms, the unexplained portion of each firm's submission decision was positively and significantly correlated. That the submission of bids was positively correlated across cartel members suggests parallel behavior. As additional evidence, the authors examined the residuals to the bid level equations and found that they were also positively correlated; a high bid by one of them makes it more likely that the others bid high.

Porter and Zona provide a collusive story to explain why bid levels and bid submissions depart from the competitive benchmark. That colluding firms' bids may not be increasing in distance makes sense if more distant school districts are not collusive. There are many firms and districts and, if indeed these firms are coordinating their behavior, it'll be effective only in those markets for which non-colluding firms are neither numerous nor have a significant cost advantage (e.g., situated as the closest processors). Firms then would be submitting higher bids in districts for which they have a distance advantage—so collusion works—whereas in more distant markets they would be forced by competition to submit lower bids (despite the higher transportation costs). As to the correlation in the submission of bids, this is consistent with complementary bidding that is intended to give the impression of competition. A cartel member who is not selected to win a contract (e.g., by the incumbency scheme) submits a higher bid than the incumbent to provide the appearance of competition. Ironically this correlation of the decision to submit a bid is interpreted as evidence of collusion!

6.1.4 Is Firm Behavior More Consistent with Collusion Than with Competition?

Now consider an approach that puts collusive and competitive models into a horse race to determine which better fits the data. The general strategy is to specify structural competitive and collusive models of firms' prices or bids and to estimate them using cost and demand shifters. There is evidence of collusion if a collusive model better fits the data. All the approaches reviewed here use functional forms and thus are subject to specification error. More recently attention has moved to less parametric methods for estimating oligopolistic behavior (at auctions), though they have not yet been applied to the issue of distinguishing collusion from competition.[20]

Porter (1983a) and Ellison (1994) There is another rationale for looking for structural breaks, which is that sharp changes in price—inexplicable in light of cost and demand shifts—are consistent with theories of collusive pricing under imperfect monitoring while not being easily reconcilable within a competitive theory. As originally established by Green and Porter (1984) for a context in which cartel members can only imperfectly monitor the behavior of each other, sustaining collusion may require periodic reversions to low prices as a form of punishment to induce compliance. In particular, a price war will ensue when the realized price is relatively low as such an event is suggestive of a firm having cheated and produced too much. The details of the theoretical argument are provided in section 6.2; here I describe the empirical test for distinguishing collusion from competition.

The focus is on the Joint Executive Committee, which was a cartel among railroads created to coordinate the rate charged for transporting grain from Chicago to the US East Coast. Existing in the late nineteenth century, the cartel is well documented as it preceded the establishment of the Sherman Act (and subsequent court cases) that made price-fixing illegal.

The empirical model being estimated in Porter (1983a) is a two-equation structural model that seeks to explain the determination of price and quantity using cost and demand shifters:

$$\log Q_t = \alpha_0 + \alpha_1 \log P_t + \alpha_2 LAKES_t + \epsilon_{1t}, \tag{6.3}$$

$$\log P_t = \beta_0 + \beta_1 \log Q_t + \beta_2 S_t + \beta_3 I_t + \epsilon_{2t}. \tag{6.4}$$

The demand equation (6.3) for rail services for grain relates the volume of grain shipped, Q_t, to the rate for rail services, P_t, and a demand shifter, $LAKES_t$, which takes the value 1 (0) when the Great Lakes is (not) open for shipping; the Great Lakes provide an alternative means of transportation so one expects $\alpha_2 < 0$. Equation (6.4) is referred to as a "supply relation" and is a re-arrangement of the profix-maximizing (first-order) condition defining the optimal supply of firms. S_t is an exogenous variable capturing changes in the composition of the cartel due to entry and acquisitions. The key variable here is I_t, which, according to the theory (and presuming $\beta_3 > 0$), takes the value 1 when firms are in the collusive phase (producing a relatively low quantity) and 0 when they are in the punishment phase (producing a relatively high quantity and engaging in a price war). I_t is unknown to the economist and is presumed to be determined by a stochastic process. The empirical model is then a switching regression in which the stochastic process governing I_t is estimated along with the other parameters, in particular, β_3, which measures the effect on price from a regime switch.

The test for collusion is based on the following comparison: The competitive model predicts there will be no regime switches, which means no systematic changes in price unrelated to movements in cost and demand functions. The collusive model, according to the theory of Green and Porter (1984), predicts that there will be regime switches, with firms moving between high prices and low prices (after controlling for cost and demand shifters). Furthermore the theory predicts that these switches will occur when there is a low (unobserved) demand shock. The shock will produce the low price that induces a temporary price war.

Central to testing this theory of collusion is the structure placed on the stochastic process determining I_t. Using only the feature of the theory that there are regime switches, Porter (1983a) assumes I_t is independently and identically distributed (iid) over time. The stochastic process is then defined by a single parameter, which is the probability of being in the collusive phase in a given period ($I_t = 1$). Porter finds evidence in support of the collusive model as six to eleven regime switches are identified. Furthermore price falls significantly—about 40 percent—when firms move to a price war.

Of course, the theory does not just say there are regime switches; they occur when there is evidence consistent with a firm having cheated. This more refined implication of the collusive theory is tested by Ellison (1994).[21] He actually enriches the structure placed on I_t in two ways. First, he assumes the regime—whether collusive or punishment—follows a Markov process so that the probability of being in a collusive phase tomorrow depends on the current phase, that is, whether firms are currently colluding or engaging in a price war. Second, this Markov process is allowed to depend on "triggers" that might, according to the logic of the theory, induce a shift to a price war. The intent of these triggers is to proxy for a firm receiving a "suspiciously high market share." For example, one variable measures the largest difference, among all firms, between a firm's realized quantity and a benchmark value (think of this as a firm's cartel quota). The prediction is that a higher value for these variables will make a switch from a collusive regime to a price war more likely.

Ellison (1994) finds persistence in regimes as the estimated probability of colluding tomorrow, given firms are colluding today, is very high at 0.975, while the probability of colluding tomorrow, given firms are currently engaged in a price war, is only 0.067. As to the estimated effects of the price war triggers, the evidence is more ambiguous, though some of the variables do make it more likely to transit from colluding to a price war. In sum, the evidence tends to support the Green-Porter model of collusion over standard noncollusive oligopolistic competition. From a cartel detection perspective, this approach provides a structure for looking for the regime switching that might occur when firms are colluding.[22]

Baldwin, Marshall, and Richard (1997) The task is to determine whether a cartel was operating at some or all of 108 oral ascending timber auctions in the Pacific Northwest over a span of 1975 to 1981. A class of competitive models is specified and includes the maintained hypothesis that once controlling for publicly observed variables, it is IPV. When a single unit is auctioned, competition results in the winning bid being the second highest valuation. However, the specified class of competitive models also allows multiple units to be auctioned. If there are m units to be auctioned (and $m < n$, where n is the number of bidders), then with each bidder bidding for at most one unit, the winning bid is the $m + 1$-order statistic over n valuations.

Collusion is modeled using the collusive auction model of Graham and Marshall (1987), which allows for side payments. There is at most one cartel (a maintained assumption) and it contains l members. The cartel elicits members' valuations prior to the auction and a cartel representative submits the highest valuation of the cartel members. For the case of a single unit, if the cartel fails to contain the two highest valuations, then the price paid by the winning bidder is, as usual, distributed as a second-order statistic. More generally, if the cartel includes those firms with the highest k values, then the price is distributed as a $k + 1$-order statistic. Thus under collusion the price is distributed as a mixture among these order statistics. Finally, Baldwin, Marshall, and Richard nest the two models by allowing for both the possibility of a bidding ring and multiple units to be auctioned off.

This class of models provides two possible reasons why bidding can be less aggressive—collusion (or a bigger cartel) and a larger supply is being auctioned off. The setup makes these two alternatives analogous in that both m and l are assumed to be unobserved and independent across auctions. The independence of the size of the cartel is a bit problematic, though the authors argue that it is plausible given the auctions are geographically dispersed and occur over several years. The functional forms for the probability distribution over m and l are identical and allowed to depend on various factors. Though the determination of m and l is reduced form, the bidding models are structural given m and l.

The independent variables influencing bidding behavior and the size of the cartel include the volume of timber offered for sale on a tract, the time over which the timber is required to be cut (i.e., the contract length), a measure of logging cost, and a measure of the quality of the timber. The probability of joining the coalition depends on the volume of timber and, so as to control for geographic proximity among bidders, a "bidder proximity dummy" takes the value 1 when the highest and second highest bidders are in the same county.

The models are estimated using maximum likelihood. By the log-likelihood criterion, the single-unit collusive model noticeably outperforms the single-unit competitive model.[23] This suggests that the competitive model is misspecified, but it could be for reasons other than that firms are actually colluding. Baldwin, Marshall, and Richard dismiss one likely alternative, which is that the assumption that the distribution on valuations is lognormal is incorrect. Performance of the nested models is not enhanced when multiple supply is added to collusion. The authors conclude that the best model—based on performance and parsimony—is the single-unit collusive model.

Banerji and Meenakshi (2004) Banerji and Meenakshi (2004) compare the performance of collusive and competitive models in examining oral ascending bid wheat auctions in India. Their prior information is that the three largest buyers (with a total market share of about 45 percent) may be colluding. The competitive model is IPV with asymmetric distributions; the three largest buyers are allowed to draw valuations from different distributions than that of the remaining buyers (all who are assumed to have the same distribution). Hence the winning bid for the competitive model is the second-order statistic over the valuations of three large buyers and the small buyers. Banerji and Meenakshi specify the collusive model to be one of bid rotation, whereby the three largest buyers randomly decide on the buyer to participate in a particular auction. The winning bid is then the second-order statistic over the valuations of one large buyer and the small buyers. It is assumed that the identity of the participating cartel member is determined prior to observing the specifics of the lot up for auction.

The data they have is for 421 auctions from two months in 1999. The data include some quality variables, the number of bidders who cast bids during the auction, the winning price, and the identity of winning bidder. They apply a structural model that incorporates a result from Athey and Haile (2004) to identify the latent distributions: identification only requires the second-order statistic and the identity of the winning bidder. The various criteria used in comparing the performance of the two models include the log-likelihood value and the mean sum of squared residuals. The collusive model fits the data better than the competitive model.

Bajari and Ye (2003) This study also compares structural models of collusion and competition to see which performs better. Recall that their initial tests identified two candidate cartels: firms 2 and 4 and firms 2 and 5. The three candidate models are then a competitive model (where there is no collusion), cartel 24 (where firms 2 and 4 collude and all other firms do not), and cartel 25 (where firms 2 and 5 collude and all other firms do not). Their approach is Bayesian as they calculate a posterior probability distribution over these three models based on the observed markups.

The first step is to specify a prior distribution over the three models; this is arbitrarily assumed to be the uniform distribution. The next step is estimating the likelihood of observing the actual markups given a particular model. Finally, Bayes's rule is used to derive a posterior set of beliefs on the set of models.

To execute this approach, one first needs a measure of actual markups. Specifying a structural model of bidding provides a first-order condition defining a firm's bid, which is a function of its cost and the distribution on other firms' bids. By estimating that distribution and using the observed bid, one can backout the firm's cost and get an estimate of the markup. The competitive model is specified to be the IPV model with asymmetric bidder valuation distributions. The cartel model is the competitive model but where the two colluding firms act as a single profit-maximizing bidder with cost equal to their minimum cost (thus presuming they can make side payments). This procedure is done for each of the three models to yield the observed markups.

The more challenging task is to estimate the likelihood of these markups for a particular model. Toward this end, structural cost parameter estimates are needed, and these are derived by eliciting a distribution on markups from industry experts. From this markup distribution, a random draw is made for each bidder for each auction. From the observed bid one can infer the latent cost. This latent cost is then regressed on the exogenous factors, which yields a set of estimates for the structural model. With these estimates and a model, the likelihood of a particular set of costs is calculated. Simulation methods are used to then calculate an expected likelihood based on an estimated prior distribution over costs and structural parameter values.

The predicted markup at the 50th percentile for the estimated distribution is 3.33 percent for the competitive model, 4.13 percent for cartel 24, and 4.47 percent for cartel 25. As the industry experts put it at 5 percent, the cartel models fit the median markup better. However, at the 99th percentile, the cartel models predict a markup vastly higher than the 15 percent predicted by the industry experts. Cartel 24 has it at 33.54 percent and cartel 25 at 58.26 percent, while the competitive model is much closer at 23.81 percent. Because of its poor performance in the tails, the posterior probability that the model is competitive is very close to one.

There are two methodological innovations worth noting. First, the use of industry experts to provide ancillary information is novel and potentially fruitful but there are concerns. Industry experts might be good at predicting median markups but—due to fewer observations—much less effective at extreme markups: recall that it was the poor fit between the experts and the cartel models on extreme markups that allowed the competitive model to be assigned such a high posterior probability. In addition there is a concern that if experts' beliefs are based on what they infer about cost from bids, their judgment depends on the model they are using. Did they presume competition? Or did they suspect collusion? If they presumed firms competed, then was the approach biased in favor of the competitive model?

Second, the Bayesian approach provides an alternative to having two discrete categories: "Yes, there is collusion" and "No, there isn't collusion." It does indeed seem more useful to potential plaintiffs and antitrust authorities to be able to assign some (well-defined) strength to the hypothesis of collusion in deciding whether to bring a case. One could also imagine having a more informed prior distribution on there being a cartel by using the empirical frequency of discovered cartels. Although there are sure to be many undiscovered cartels, this would at least provide a lower bound to the prior probability of there being a cartel.

6.1.5 The Pitfalls of Using a High Price–Cost Margin as a Screen for Collusion

Because the ultimate objective in forming a cartel is a high price–cost margin—defined as (Price − Marginal cost)/Price—it is natural to think about using a high price–cost margin as a screen for collusion. It can be directly measured if one has both good price and cost data. Although not many economists find themselves in that situation (especially with regards to cost data), there are indirect estimation methods; indeed many of the methods thus far reviewed do exactly that.[24] With information on price, quantity, and cost and demand shifters, an industry price–cost margin can then be estimated. So, why not then use a high price–cost margin as a screen for collusion?

The problem with this approach is that we know from past studies that there is considerable variation in price–cost margins across industries—it is not as if most industries have values consistent with the dominant models of competition—and that there are many industries with high price–cost margins for which there is no evidence or even suspicion about collusion. A high price–cost margin (properly measured) is evidence of *market power* and does not imply collusion. Other reasons for a high price–cost margin are greatly differentiated products, production technologies protected by patents and trade secrets, and high search costs for consumers. All these cases are much more ubiquitous than collusion. Many industries might have high price–cost margins, but my own prior belief is that only a precious few are cartelized.

It is also worth noting when a high price–cost margin is not a necessary implication of collusion. For example, consider an industry subject to Bertrand price competition so that the noncollusive price–cost margin hovers around zero. Collusion may then have the impact of raising the price–cost margin to a level, say, commensurate with Cournot quantity competition. A naïve economist unaware of the appropriate competitive benchmark may infer from the observed price–cost margin that a cartel is not present because the price–cost margin is consistent with *some* model of competition.

In light of this critique of the efficacy of using a high price–cost margin as a screen for collusion, let us review the relative advantages of some of the approaches I have recommended. Although a high price–cost margin should not necessarily raise suspicions about collusion, a sharp *increase* in the price–cost margin ought to. While one can easily rationalize a high price–cost margin without resorting to the presence of a cartel, notable changes in the price–cost margin are not so easily rationalized without it. Of course, big changes in demand and cost will suffice, but they ought to be observable (by virtue of their size) and thereby one can take account of them. Hence the method described in section

6.1.2—screening for abrupt changes in price (or price–cost margins)—is likely to be a more effective screen than looking for high price–cost margins.

In stating that some level of the price–cost margin is suggestive of collusion, one is inferring that it is high *relative* to some competitive benchmark. Without any further analysis, this competitive benchmark would have to be chosen arbitrarily by assuming the form of competition (e.g., price or quantity competition), the degree of product differentiation, the ease of consumer search, and so forth. When this was done in the past, it was typical to assume homogeneous products, zero search costs (and there are no other source of frictions that may create market power), and firms compete in quantities, all of which are quite arbitrary. An attractive feature of the method described in section 6.1.3 is that a competitive benchmark is identified for the market in question by examining comparable markets not suspected of collusion, comparable firms not suspected of colluding, or a time period for which the suspected firms are believed not to have been colluding. These benchmarks are superior to making an arbitrary selection of the noncollusive solution.

The arbitrariness of the competitive model does plague the method described in section 6.1.4 in that the economist must choose a lot of structure without much guidance from the data; this includes the competitive model that will be estimated and serve as the benchmark for the estimated collusive model. It is this structure, however, that allows testing for more informative and telling implications of collusion. One is not just requiring that a collusive model explain the level of prices better than a competitive model but also that it explain better how prices respond to cost and demand shifters. For example, the approach of Porter (1983a) doesn't try to find evidence of collusion by determining whether prices are, in some sense, high but rather whether the price-generating process is subject to regime switches that cannot be explained by cost and demand shifters. That is a more refined and informative implication of the collusive theory. It also has the virtue that it can detect the presence of a cartel even if price–cost margins are not, in some economywide sense, high.

6.1.6 Discussion

In summary, we reviewed four methods that can be used in connection with detecting collusion: (A) determining whether firm behavior is inconsistent with competition, (B) determining whether there is a structural break in firm behavior, (C) determining whether the behavior of suspected colluding firms differs from that of (presumed) competitive firms, and (D) determining whether a collusive model better fits the data than a competitive model.

In their least sophisticated forms, methods A and B provide no direct evidence in support of collusion. Rather, they seek to establish whether observed behavior has a difficult time being explained by competitive models. If a set of firms fails that test—their behavior is inconsistent with competition or there is an inexplicable change in behavior—it is necessary to turn to one of the other methods to assess whether collusion is the most natural explanation.

With regard to method A, the issue is whether the competitive model is misspecified, and if so, it could be due to there being collusion or to assumptions on cost and demand being wrong. Misspecification due to omitted variables is particularly a concern here. To confidently reject the competitive model in Bajari and Ye (2003) on the ground that firms' bids are not independent requires that one has not left out relevant variables that would result in firms' costs being correlated. Bajari and Ye stress this caveat and, for example, note that if two firms use the same subcontractor in calculating cost and the other firms do not, then the bids of those two firms will be positively correlated and thus violate independence without there being collusion. Although it is a tall order to confidently reject the null hypothesis of competition, one is less concerned if such a test is used only as a preliminary diagnostic tool.

Methods C and D allow a researcher to compare collusion and competition but in very different ways. Method C requires finding a competitive benchmark, either firms in the market who are not thought to be part of the suspected cartel, a comparable market (e.g., a different geographic market for the same product or service) that is thought to be competitive, or a time period during which the suspected firms were thought to have been competing. There must then be prior information as to which firms may be colluding, in which markets there may be collusion, and over what time there might have been collusion. This method is then inapplicable to an all-inclusive global cartel for which data are only available during the time of suspected collusion.

A general concern with method C has to do with the endogeneity of the competitive benchmark. For example, if the benchmark comes from firms who were not members of the cartel, why weren't they members? It is natural to suppose they are different in some way from the cartel members, so then the issue is whether the data one has are adequate to control for those differences. A model of endogenous cartel formation could shed light on how to handle such concerns. Furthermore there is a presumption that noncolluding firms will act the same in an industry with a cartel as they would without a cartel. Their conduct obviously depends on particular behavioral properties, since noncolluding firms will generally produce less when other firms are colluding but their quantities and prices will still be increasing in cost. Nevertheless, it would be interesting to more broadly explore which properties of firm behavior are robust to whether its competitors are (knowingly) colluding and whether it depends on the collusive scheme deployed.

When the competitive benchmark is based on data from comparable markets for which there is no prior information about collusion, one has to be concerned that collusion might simply be more effective there. For example, suppose firms are able to tacitly collude in market X but not in market Y. As a result firms may resort to explicit collusion in market Y, and as a result collusion is suspected there but not in market X. The "competitive" benchmark is then, unbeknown to the researcher, not so competitive after all. Failure to find higher prices in market Y would then be misleading. Indeed one could find lower prices in market Y. If the inability to tacitly collude in market Y is a reflection of the competitiveness of the industry, it is possible that the highest sustainable price is greater in market X where less competitiveness allows tacit collusion to work. That is, there are certain factors that determine whether firms tacitly or explicitly collude (ceteris paribus, firms prefer the former as they are not as much at risk of paying penalties), and these factors might also determine the collusive outcome. Explicit collusion may only occur where collusion is difficult, and thus collusive outcomes might be more competitive.[25] But even if the price level is not noticeably different in the two markets, behavior—say, in how price responds to cost and demand shifters—might still vary significantly because explicit collusion operates differently from tacit collusion. Unfortunately, theory provides little help here.

After finding there are differences between suspected colluding firms' behavior and some competitive benchmark, there are two follow-up issues. First, the difference could be due to, say, omitted variables and not due to market conduct. Second, any difference must be rationalized with some collusive model. The ultimate objective is not to show that behavior is inconsistent with competition but rather that it is most naturally explained by collusion. Certain collusive models provide predicted directions as to how collusion is apt to depart from competition. For example, Porter and Zona (1999) argue that collusion in markets geographically close to cartel members' plants, and competition in more distant markets would make a firm's bid less of an increasing function of distance and perhaps even a decreasing function of distance. Thus Porter and Zona took the observed empirical departure from the competitive benchmark and offered a collusive equilibrium to rationalize it. An issue is how much discretion a researcher has in terms of various collusive schemes. Providing ancillary evidence in support of a particular collusive scheme is highly useful.

By contrast, method D builds into it both competitive and collusive models. Thus one can offer criteria for comparing the performance of the two behavioral models. This method is also the most widely applicable in that it can be used even if there is no prior information as to collusion, the cartel is all-inclusive (all firms and all markets), and data are only available during the cartel regime. The major disadvantage is misspecification. In that structural models are being estimated, there is the usual enhanced concern of misspecification compared to the reduced form price equations of method C. For example, firm symmetry is a maintained hypothesis in Baldwin, Marshall, and Richard (1997), but it is quite possible for the collusive model to outperform because buyers have different distributions over valuations. Misspecification of cost and demand conditions may then cause the competitive model to underperform.

Misspecification is apt to be an even more serious concern for the collusive model. Although there is typically a limited number of competitive models and equilibria to them, there are many more collusive equilibria even for a single model; that is, there are many more equilibria for the repeated game than for the static game. Collusive solutions can differ in terms of bid rotation, territorial allocation, side payments, market share allocations, and so forth. On these grounds, one is more likely to erroneously reject the collusive model than the competitive model. Ancillary evidence as to how firms might be colluding can be useful here. For example, there is evidence that a Florida school milk cartel used side payments, and this suggests that market shares can fluctuate over time as contracts go to the most efficient, with the others receiving transfers as compensation. In contrast, there is no evidence of side payments for a Texas school milk cartel, which suggests that collusion requires stable market shares. In both cases Pesendorfer (2000) finds the data in his study to be consistent with these hypotheses. This reminds us how the collusive solutions can vary greatly but also how other evidence can help with the multiplicity problem.

Another source of bias can arise due to mislabeling firms, markets, and periods as being noncollusive when they actually are collusive, and vice versa. Incentives of cartel members to hide evidence is recognized by Porter and Zona (1993) in noting that some of their "competitive" firms could actually have been part of the cartel. They use past convictions to identify likely suspects—if they found it profitable to collude once, they may find it profitable again—but then this misses out on firms who previously avoided convictions or have since found it optimal to join the cartel. Similarly, lack of observed interaction among firms—such as not bidding on the same contracts—can lead one to conclude that these firms are not candidates for collusion when in fact their lack of interaction is due to collusion. The usual example is a collusive scheme in which a designated cartel member submits a bid and the others do not. There could then be a bias against certain firms being considered as candidate cartels.

6.2 Collusive Markers

For developing economic evidence of collusion, one needs to know what to look for—what behavioral patterns are indicative of collusion? An important line of work is then to provide collusive markers—behavior that distinguishes collusion from competition. These markers can be developed through theoretical models or by documenting the behavior of price-fixing cartels. In this section, I review what theory has to offer and, in some cases, provide examples of cartel exhibiting these markers. A more systematic and detailed summary of documented cartel behavioral patterns—along with experimental evidence—will have to await another paper.

Theory has a crucial role to play in providing collusive markers, and theory is essential if one pursues the empirical method of contrasting the behavior of suspected colluders with that of competitive firms. When one finds a difference, it is important to know whether the difference is consistent with some collusive story. If instead the empirical method of detection is to look for structural breaks—perhaps to identify the formation of a cartel—having collusive markers can indicate what kind of change in behavior to look for. Markers are particularly valuable from the perspective of screening, where one wants easily measured traits to suggest which industries might have a cartel.[26]

Before embarking on this review, I should add an important disclaimer that evidence supporting collusion need not imply evidence against competition. The ensuing work will derive distinguishing features of collusion and competition *for a particular class of models*. Even with evidence of collusion, there is always the possibility that there actually is no collusion and the problem is we've misspecified the noncollusive model. Similarly failure to find evidence of collusion may be due to misspecifying the collusive model; for example, we've focused on the wrong collusive equilibrium. At best, collusive markers can serve to screen industries to determine whether they are worthy of more intense investigation.

My discussion will focus on what theory has to say about patterns in prices and market shares and how it depends on whether firms are colluding. Theory offers insight into how collusion affects: (1) the relationship between firms' prices and demand movements, (2) the stability of price and market share, and (3) the relationship between firms' prices. A wide array of collusive models will be covered, and it is useful to identify five crucial dimensions along which they may differ. First, a collusive model can be static or dynamic. A static approach compares what Nash equilibrium yields and what is gotten from either exogenously imposing some collective preferences (e.g., joint profit maximization) or requiring adherence of individual firm behavior to the prescription of a cartel manager. A dynamic approach assumes an infinite horizon setting in which outcomes less competitive than static Nash equilibria are sustained using strategies that punish deviations from the collusive agreement. By the dynamic approach, collusion is often distinguished from competition when equilibrium conditions bind, which is the case when collusion is not so easy. Second, models differ in terms of the market institution, which is generally either posted price—which characterizes most retail markets—or an auction. Third, models differ in terms of whether the cartel is allowed to make side payments to each other. Indeed, implicit in assuming joint profit maximization is that transfers are allowed, for otherwise it is not clear why some firms would go along with such an objective. Fourth, a model may allow firms to send messages to each other prior to choosing price or quantity. Where this is pertinent is when firms have private information about their preferences, such as cost or, in the context of an auction, their valuation. One necessarily thinks of models with direct communication as being associated with explicit rather than tacit collusion. Fifth, most models assume firms are colluding without concern for being detected by the antitrust authorities. There are a few studies, however, for which detection may occur and firms are cognizant of how their behavior can influence detection, which then has implications for the price path.

The decision to focus on the unique implications of collusion for price and market share is largely due to the relative ease with which such data are available. There are clearly other identifying markers associated with collusion. For example, unit profit is uncorrelated with firm size under competition but is negatively correlated with firm size under collusion (Osborne and Pitchik 1987), noncollusive prices depend on whether nearby products are owned by rival firms though that is not true when firms collude and maximize joint profits (Bresnahan 1987), and there is greater excess capacity under collusion (Benoît and Krishna 1987; Davidson and Deneckere 1990). Finally, the theoretical literature on collusive pricing is rich in identifying industry traits that are conducive to collusion.[27] Thus the search for collusive markers can be supplemented with attention to certain industry traits. Research has found that collusion is easier to sustain or is more profitable when concentration is higher, orders are more frequent, firms are more symmetric (Compte, Jenny, and Ray 2002; Vasconcelos 2005), multi-market contact is greater (Bernheim and Whinston 1990), and cost is more volatile (Harrington and Chen 2006).

6.2.1 Predictions on Price

The basic logic whereby collusion is sustainable as an equilibrium in a repeated game model is predicated upon rewards and punishments.[28] A Nash equilibrium for the static game is one where each firm's behavior (which is typically a price, bid, or quantity) is optimal given the (correctly anticipated) behavior of other firms. Firms collude for the purpose of raising price above the static Nash equilibrium level so as to yield higher profits. This necessarily means that a firm's behavior doesn't maximize current profit; a firm's collusive quantity is below that which maximizes current profit or its collusive price exceeds that which maximizes current profit. As cheating on the collusive outcome raises current profit, firms can only be deterred from doing so if they experience a future loss. This future loss from cheating comes from an intensification of competition in response to cheating. Thus, if firms act collusively, then they continue colluding, but if a firm cheats, then firms revert to some low-profit punishment path. This may mean going to the static Nash equilibrium for some length of time or an outcome with even lower profits (perhaps pricing below cost) or an asymmetric equilibrium that is particularly detrimental to the firm that deviated (perhaps requiring that the firm produce very little). It follows that a firm that considers deviating from a collusive outcome realizes that it can raise current profit but lower its future profit stream. The equilibrium condition or incentive compatibility constraint (ICC) requires that the forgone future profit stream is at least as great as the gain in current from deviating. When the punishment is reversion to the noncollusive outcome for T periods, the ICC is

$$\sum_{\tau=1}^{T} \delta^{\tau}(\pi^{c} - \pi^{nc}) \geq \pi^{d} - \pi^{c},$$

where π^c, π^{nc}, and π^d are the collusive profit, noncollusive profit, and the (optimal) profit from deviating, respectively. $\delta \in (0,1)$ is the common discount factor across firms. In this simple case the model is stationary and the solution is symmetric. Deviation yields higher current profit of $\pi^d - \pi^c$ but lower future profit of $\pi^c - \pi^{nc}$ over the next T periods (with firms returning to the collusive outcome thereafter). Equilibrium requires that this condition hold so that abiding by the collusive agreement is optimal for all firms. Since

$\pi^c > \pi^{nc}$, this will hold when T is sufficiently high and δ is sufficiently close to one, so firms sufficiently value future profits.

To derive our first collusive marker, let us modify that setting to where the demand curve changes over time. Firms jointly observe the demand shock and then choose prices. At this point, demand could be independently and identically distributed (iid) over time or show some persistence or follow some cyclical pattern. Suppose that the demand shifts are well-behaved in that "higher demand" corresponds to the demand curve shifting out and both the monopoly price and the static Nash equilibrium price rising.[29] Hence the static Nash equilibrium price (which we are taking as the noncollusive benchmark) would follow movements in demand—price rises when demand increases—and thus price and quantity are positively correlated over time. These properties also hold under perfect collusion where (symmetric) firms charge the joint profit-maximizing price.

Thus far the relationship between the price path and demand movements is not distinguishable between competition and collusion. Now suppose that firms are not so patient and thus cannot perfectly collude; that is, firms achieve the collusive outcome that yields the highest profit subject to satisfying the ICCs. This necessarily implies that the ICCs bind, which will serve to produce some useful collusive markers.

The initial work on this class of models is Rotemberg and Saloner (1986) who considered (observable) iid demand shocks. Their result is that when ICCs bind, price is *lower* when demand is stronger and thus price and quantity are *negatively* correlated. As demand shocks are iid, the future loss from cheating is always the same, since the expected future forgone collusive profit is independent of the current demand realization. However, the current gain from cheating is higher when demand is stronger because, with the price fixed, the gain in sales from undercutting rival firms' price is greater. Since the incentive to cheat is then more powerful when demand is greater, cartel stability requires setting a lower collusive price as this weakens the incentive to cheat. As a result price can move opposite to demand in a collusive equilibrium, but for the same demand and cost structures, price moves with demand in a noncollusive equilibrium.[30]

Haltiwanger and Harrington (1991) pursued this idea further but considered instead a deterministic demand cycle in which demand gradually shifts out then shifts in, with the pattern repeating itself. Such a demand pattern fits seasonal movements in demand that are relatively well anticipated. In contrast to the preceding analysis, both the current gain and future loss from cheating change over time. Take two points on the cycle where the current demand function is the same but differ in that one point is during the boom phase—demand is rising (and thus will be higher in the immediately ensuing periods)—and the other is during the bust phase—demand is falling. For the same price the current gain from cheating is the same at both points because demand is the same. However, the future loss from cheating is higher during the boom because a firm forgoes more profits from competition (compared to collusion), since demand is anticipated to be relatively strong. Thus, contrary to Rotemberg and Saloner (1986), collusion is easier during the boom phase so the firms set higher prices.[31] When the peak of the cycle and the period prior to it are compared, it is clear that the stronger demand at the peak implies a higher current gain from cheating and forgone future profits are lower (i.e., cheating before the peak means forgoing collusion when demand is strongest). Thus collusion is more difficult at the peak, which requires price to be set lower. The implication is that the price path will peak prior to demand, so the price path will lead the demand cycle. Once again, this is a pricing pattern that runs counter to noncollusive pricing where the price path follows the demand cycle.[32]

As described in section 6.1.4, another key collusive marker is that price and quantity can be subject to large and persistent changes *in the absence of large demand and cost changes*. This work begins with the seminal paper of Green and Porter (1984; also see Porter 1983b). The context is the repeated quantity game but with imperfect information. In each period firms choose quantities and then observe price. Price depends on firms' quantities and an unobserved iid demand shock (recall that such shocks were observed in Rotemberg and Saloner 1986). As a firm's quantity is never observed by other firms, a deviation cannot be directly observed. However, price is observed, and in expectation, a higher quantity will result in a lower price. Of course, since price depends on an unobserved demand shock, a low price could be due to a low demand shock rather than some firm cheating by producing above their collusive quota. There is then imperfect monitoring of collusion by the cartel's members.

An equilibrium is characterized in which, during the collusive phase, firms choose some designated collusive quantity. If the realized price is ever too low (a threshold price is specified as part of the collusive strategy), then firms switch to a punishment phase that is static Nash equilibrium quantities for T periods, after which they return to the collusive phase. A collusive equilibrium quantity is one in which a firm maximizes its payoff, taking into account that a higher quantity increases current expected profit but lowers future expected profits by making a punishment more likely (where the probability of a punishment is the probability that the realized price falls below the threshold price). Equilibrium then entails stochastic regime switches where a one-time low demand shock triggers a movement from the collusive phase to the punishment phase—associated with it is a fall in the average price—and after T periods there is a regime switch back to the collusive phase—with a rise in the average price.[33] One then observes abrupt changes in average price that cannot be explained by contemporaneous demand and cost movements.[34]

A summary of the discussion above is as follows:

Collusive Marker Under certain conditions, price and quantity are negatively correlated, price leads a demand cycle, and the stochastic process on price is subject to regime switches under collusion; whereas price and quantity are positively correlated, price follows a demand cycle, and price is not subject to regime switches under competition.

A second collusive marker concerns price stability. Two papers taking very different approaches show that under certain conditions, prices are more stable under collusion. Consider a setting in which firms choose price, and each firm's cost is iid over time and across firms and is private information. In each period colluding firms exchange messages about their costs and then choose price. These messages are not required to be truthful, and side payments are not permitted. In characterizing an optimal collusive mechanism, there is a tension between efficiency and the amount of collusion. Because the firms have homogeneous products, the unconstrained joint profit-maximizing scheme is to have the firm with the lowest cost produce all output in that period at its monopoly price. The problem is inducing firms to truthfully reveal their cost, since a firm with high cost may want to signal it has low cost in order to be able to produce. To induce a high-cost firm to provide an accurate cost report, the collusive price may need to be set relatively low when a firm's cost report is low, for then a high-cost firm would not find it profitable to mimic a low-cost firm. Although a mechanism may exist to induce truthful revelation of firms' costs, it may not be optimal for firms to use it because it requires such low prices.

Athey, Bagwell, and Sanchirico (2004) characterize the best strongly symmetric perfect public equilibria in this setting.[35] When firms are sufficiently patient, the collusive equilibrium is to have price and (equal) market shares fixed over time, and not to respond to firms' costs. Inefficiency prevails as it is too costly to induce revelation. Thus prices are perfectly stable in response to cost fluctuations, and this also means that price is more stable than in the absence of collusion.[36] When firms are moderately patient, there is partially rigid pricing, so the price function is a step function of cost in which case price is often unchanged but then experiences a large change. This also serves to distinguish collusion from competition.[37]

In all the models reviewed thus far, firms were not concerned about detection. Suppose instead that buyers detect collusion from suspicious price changes.[38] In exploring how detection avoidance impacts cartel pricing, Harrington and Chen (2006) do not presume that buyers know how a cartel prices, nor are consciously looking for collusion. Rather, it is assumed that buyers become suspicious when the observed price series is sufficiently anomalous or inexplicable where their beliefs as to what is anomalous depend on the history of prices.

Suppose that cost is a random walk with normally distributed shocks. Hence the noncollusive price is similarly structured. Buyers believe price changes are normally distributed but do not know the moments of the distribution. With bounded memory, they observe price changes and use the sampling moments in their beliefs. This gives buyers a set of beliefs on the current price change. With these beliefs, they can then determine the likelihood of observing the actual price change and in fact do so for a series of price changes. It is assumed that detection is more likely when buyers perceive the most recent price series as being less likely. The cartel is aware of how its price path affects beliefs and thereby the probability of detection. Upon cartel formation, firms inherit the noncollusive price and buyers' beliefs that are predicated on price changes when firms were not colluding. In a sense, detection occurs when buyers pick up the "break" in the pricing function associated with cartel formation. Ideally a cartel would like to raise price fast and have it adjust quickly to cost shocks, but it must temper any such price movements by the prospect of detection.

The optimal cartel price path is found to have a transition phase—in which price rises largely irrespective of cost—and a stationary phase—in which price is responsive to cost. While price is sensitive to cost in the stationary phase, it is much less variable than cost, the noncollusive price, or the simple monopoly price. Intuitively, though the cartel might want to raise price considerably in response to a series of large positive cost shocks, such a price series may be perceived as unlikely by buyers and thus induce an investigation. To avoid triggering detection, the cartel doesn't respond commensurately to large cost shocks. Relative to noncollusive pricing, the impact of cost shocks on price is muted and takes a longer time to pass through. Thus the variance of price is lower with collusion. Examining collusion at auctions of frozen perch, Abrantes-Metz et al. (2006) find that the price variance during collusion is indeed distinctly lower then what is observed after the cartel was discovered (excluding the transition from collusion to noncollusion). Mixed evidence is provided by Bolotova, Connor, and Miller (2005) who find a lower price variance under collusion for lysine but a higher price variance for citric acid.

Collusive Marker Under certain conditions the variance of price is lower under collusion.

A notable caveat to the preceding claim is that the price variance can be higher under the collusive theory of Green and Porter (1984). Although collusion does not result in a higher price variance within either a collusive regime or a punishment regime, the price variance is higher when data span the two regimes.[39] Of course, none of the collusive markers identified are universal, and each must be used with caution.

The last set of collusive price markers concerns the relationship between firms' prices. It is common wisdom that parallel price movements are a collusive marker. Although there is a fair amount of documentation of identical bids at auctions (e.g., see Mund 1960, Joint Executive Committee 1961, and Comanor and Schankerman 1976), in very few cases has collusion been found. More broadly, evidence that parallel pricing is a feature of collusion is ambiguous.

Let us first consider this issue in the context of an auction. McAfee and McMillan (1992) explore a symmetric IPV first-price sealed bid auction with the objective of characterizing the best collusive mechanism. A mechanism takes bidders' reports of their valuations and then assigns bids (and possibly side payments) to the ring members. The mechanism is required to be incentive compatible in the sense that reports are truthful. To ensure the incentive compatibility of the prescribed bidding behavior at the auction, one can suppose the situation is infinitely repeated and the identity of the winning bidder and the amount bid are revealed after each auction. Thus any cartel member that cheated by bidding too high (or participating when they were not suppose to) would be discovered in the event of success (i.e., winning the auction) and be subsequently punished in future auctions. As long as bidders are sufficiently patient, no cheating at the auction will occur.

If side payments are not allowed, the optimal mechanism is one in which all bidders report their valuation to the ''cartel manager'' prior to the auction, and bidders whose valuation exceeds the auction's reserve price are supposed to submit a bid equal to the reserve price. Because the cartel includes all bidders, the auctioneer randomly selects a winner from among those submitting the reserve price. To show that it is incentive compatible for buyers to truthfully report their valuations in the pre-auction cartel meeting, first note that all that matters is that a firm truthfully report that its valuation is either above or below the reserve price. If its valuation is above the reserve price, truthfully saying so gives it a chance to win the item at a price below its valuation and saying otherwise forgoes that profitable opportunity. A bidder whose valuation is below the reserve price will not want to say it is above it, since this means winning the item and paying a price above its valuation. Furthermore, if the mechanism was such that a bidder's report (above the reserve price) influenced its chances of being the winning bidder, bidders would have an incentive to report that their valuation is higher than it actually is. Thus the cartel can do no better than this scheme, even though it is inefficient, since the bidder with the highest valuation does not win for sure. The notable property is that all bidders bid the same price (which is the reserve price). Thus one gets a strong prediction of parallel pricing behavior.[40]

Two points are worth adding. An equivalent mechanism is bid rotation where one selected bidder (whose report exceeds the reserve price) bids the reserve price and all others do not participate (or submit bids below the reserve price). (I will return to bid rotation below where I discuss collusive markers based on market share.) Second, if the cartel can engage in side payments, then the optimal mechanism is efficient because the bidder with the highest valuation wins as long as its value exceeds the reserve price. One such mechanism is for the cartel members to hold their own first-price sealed bid auction prior to the actual auction. If the highest bid exceeds the reserve price, then that bidder bids the reserve price (all others don't bid or bid less) and pays each of the other bidders an equal share of the difference between his bid in the first auction and the reserve price.[41]

An important assumption in ensuring that cartel members will bid or participate as prescribed is that the winning bidder and the winning price be revealed after each auction. To see what would happen if that information is not available, consider the case of no side payments. According to the collusive scheme, all bidders (who declared their valuation exceeds the reserve price) are to bid the reserve price with the auctioneer randomly choosing a winner. Alternatively, a bidder could bid a little bit higher than the reserve price and win the auction for sure. As long as the winning bid is not revealed, there will be no evidence that any bidder cheated. Since no punishment will ensue, there is an incentive to deviate from the collusive bids. Therefore this mechanism does not work if the auctioneer does not reveal the winning bid.[42]

Recent work by Marshall and Marx (2007) explores such an information setting in which no ex post information is provided regarding the identity of the winning bidder and the winning bid. Furthermore Marshall and Marx enrich the first-price sealed bid auction setting with heterogeneous IPV and allow for the cartel to be less than all-inclusive—some bidders are not members of the cartel. With this informational setting, the situation is one of imperfect monitoring. The cartel member who was designated to submit the highest bid cannot distinguish failing to win the item because a noncartel member outbid it or another cartel member cheated and outbid it.

To ensure that cartel members want to bid as prescribed, Marshall and Marx (2007) show that for some valuations, two cartel members' bids will need to be clustered. Using the (truthful) reports of their valuations at the pre-auction meeting, the cartel selects the bidder with the highest report—let us refer to him as the cartel representative (at the auction)—to bid at a certain level with all other cartel members told to bid less. Absent concerns about cheating, the cartel representative would bid optimally in line with the cartel's valuation and the distribution on noncartel members' bids. The problem, however, is that if the bid is too low, another cartel member may cheat by outbidding the cartel representative's bid. To destroy that incentive to cheat, the cartel representative must set a higher bid so that the other cartel members do not want to outbid it and are content to set a lesser bid. But now suppose these other cartel members all set very low bids. The problem that emerges is that the cartel representative will have an incentive to bid lower because the only reason to bid so high was to discourage cheating. To keep that from happening, one of the other cartel members must set a bid a little below the cartel representative's bid. This will keep the cartel representative from cheating without affecting whether the cartel representative wins. Bids clustered in this way are unique to when bidders collude.[43]

Collusive Marker Under certain conditions firms' prices are more strongly positively correlated under collusion.

In a standard static oligopoly model, some recent work has considered whether parallel pricing is more common under collusion. Buccirossi (2006) considers a static setting with stochastic cost and demand shocks and compares Nash equilibrium prices with joint profit-maximizing prices. It is shown that more parallel behavior generally does not occur under collusion. Although noncollusive prices are more correlated when there are independent demand shocks, they are *less* correlated under independent cost shocks. At Nash equilibrium a firm's price is increasing in both firms' costs, which induces some correlation even if shocks are independent. Interestingly the joint profit-maximizing price of a firm depends only on its own cost, so firms' prices are independent.[44]

One final result is worth mentioning. Blair and Romano (1989) offer a simple test for identifying who is and who is not a member of a cartel. Upon cartel formation the members will generally lower their quantities. The aggregate supply of cartel members must decline,[45] though individual firm's supply need not when firms have different costs. But what is true for standard oligopoly models is that nonmembers will always *raise* their quantity as they take advantage of the cartel members' reducing their supply. A firm reducing its quantity then identifies as a cartel member while a firm raising its quantity as not a member of the cartel. This does not provide a marker for collusion, but it does offer a way in which to identify a cartel's members.

6.2.2 Predictions on Market Share

The markers relating to market share show how collusion imposes more intertermporal structure on market share. To establish this point, let us return to the Bertrand price-setting when firms' costs are stochastic and private information. Cartel members can convey messages about their costs prior to setting price and quantity. As mentioned earlier, an optimal equilibrium can have firms keeping prices and market shares fixed, so there are indeed stable market shares. This was mentioned for when costs are iid across firms and over time, but it also holds when firms' costs are persistent over time (Athey and Bagwell 2004). In general, firms settle on a collusive outcome with stable market shares when cost persistence is sufficiently high relative to firms' patience.

This result is due to the following logic: When cost persistence increases, it becomes more valuable to a firm to signal that it has low cost, since it influences not only current beliefs (and potentially the current collusive output quotas) but also future beliefs on cost and thus can enhance a firm's future market share. Given this augmented incentive for a firm to report its cost is low (even when its cost is actually high), inducing truthful revelation either requires firms to be more patient—so they are content to wait for higher market share in the more distant future when they may truly have low cost—or to set lower prices (thus reducing the gain in current profit to a high cost firm from reporting it is low cost). When firms are not very patient, the preference is to forgo efficiency in order to support higher collusive prices. Market shares are then more stable over time under collusion.

Collusive Marker Under certain conditions market share is more stable under collusion.

When instead patience is high relative to persistence, the best collusive equilibrium may have market shares moving over time as firms achieve a more efficient mechanism in which a firm with lower cost has a higher market share (Athey and Bagwell 2001, 2004). This is shown in a simple situation where cost is high or low. The way the mechanism works is to engage in intertemporal market share favors. A firm that announces low cost and receives a high market share in the current period can expect a lower market share in the next period. This induces the firm to truthfully reveal. That is, if it is high cost and announces low cost, the firm sacrifices future market share when indeed it might truly be low cost. (Note that market share is especially valuable to a firm when it has low cost.) Thus market shares are predicted to change over time (with firms' costs), and furthermore a firm's market share is negatively correlated over time. This is a history-dependent modification of a bid rotation scheme. Note that with this cost structure, market share will be iid over time in the absence of collusion.[46]

Similar results of intertemporal market sharing arise in models of repeated auctions, which, contrary to the preceding model, do not allow messages to be sent and assume prices to be private information. The solution is a history-dependent bid rotation scheme; the probability of winning is decreasing in the frequency with which a bidder has won in the past. Thus firms are favored that have tended to lose recent auctions (Blume and Heidhues 2003; Skrzypacz and Hopenhayn 2004).[47]

Collusive Marker Under certain conditions a firm's market share is more negatively correlated over time under collusion relative to competition.

Several recent price-fixing cartels engaged in various forms of intertemporal market sharing, including the citric acid cartel of 1991–95 (Connor 2001), the graphite electrodes cartel of 1992–97 (Levenstein, Suslow, and Oswald 2004), and the vitamins cartel, in particular, vitamins A and E, over 1989–99 (European Commission 2003).

6.2.3 Discussion

Although the collusive pricing literature is rich and offers some behavioral patterns that can help us distinguish collusion from competition, it is deficient in some serious ways. Ideally we would want markers that are fairly universal and require minimal data. None of the markers just mentioned satisfy these criteria. While some markers require only price data—such as the collusive marker of lower price variance—others require ancillary information—such as controlling for demand movements—which makes an intensive investigation necessary. Regardless of the data requirements, these markers are far from universal. Distinguishing features of collusion may only emerge when collusion is sufficiently imperfect so that ICCs bind. Thus strong cartels may not be identified by some of these markers. But the problem is well known to be much more severe than that; there are many collusive equilibria, and a marker may be peculiar to a particular equilibrium selection. Of special concern is that collusion may be present but a marker is not satisfied.

Collusive theory is in addition beset by two methodological weaknesses. With a few rare exceptions, existing models do not distinguish between tacit and explicit collusion. Yet the objective is to have markers of explicit collusion; it is not just to distinguish collusion from competition but also explicit collusion from tacit collusion. Features unique to explicit collusion include communication among firms and side payments. Since communication is a defining feature of explicit collusion, research that encompasses it is particularly valuable and includes McAfee and McMillan (1992), Athey and Bagwell (2001, 2004), Athey, Bagwell, and Sanchirico (2004), and Marshall and Marx (2007). Despite this work a major lacuna exists in both our understanding of when firms explicitly collude and what are its distinguishing features. In that tacit collusion is generally not subject to antitrust penalties, firms choosing to explicitly collude either means (1) they were unable to tacitly collude or (2) the incremental profit from colluding explicitly rather than tacitly exceeds the expected penalties. Yet there is really no research that addresses these two issues. For example, research that characterizes industry traits conducive to collusion does not distinguish between explicit and tacit collusion. But what are the traits that result in explicit collusion rather than tacit collusion? There is then the second issue about how the operating practices of an explicit cartel differs from that of firms who are tacitly colluding. This speaks directly to identifying markers of explicit collusion.

A second methodological problem is that most theories presume cartel members are ignorant of detection.[48] The characterization of firm behavior does not take account of the incentive to avoid creating suspicions among buyers, competitors outside of the cartel, and the antitrust authorities. This results in a failure of theory to address two critical issues. First, it fails to describe the properties of the cartel price path during the transition from the inherited noncollusive price to a stationary collusive outcome. In the absence of detection concerns, existing logic argues that once cartelized, the price path would immediately jump to the new collusive price. Just to the contrary, actual cartel price series show a clear transition with the price path gradually moving up from the noncollusive price level. Some documented examples include citric acid (see figure 6.1), lysine (Connor 2001), graphite electrodes (Harrington 2004a), and vitamin C (Levenstein and Suslow 2001). In essence, most theories characterize the stationary phase, even though the transition phase may offer the greatest hope for detecting cartels since it is during that phase that cartel members must surely raise the price–cost margin. To my knowledge, Harrington (2004b, 2005) and Harrington and Chen (2006) are the only papers to characterize the transition from a noncollusive stationary outcome to a collusive stationary outcome; figure 6.1 provides a typical simulated price path from Harrington and Chen (2006). If we are to detect cartels, a necessary condition is having theories that are able to produce cartel price paths that match the data, and this requires taking account of the transitional phase as well as the stationary phase.

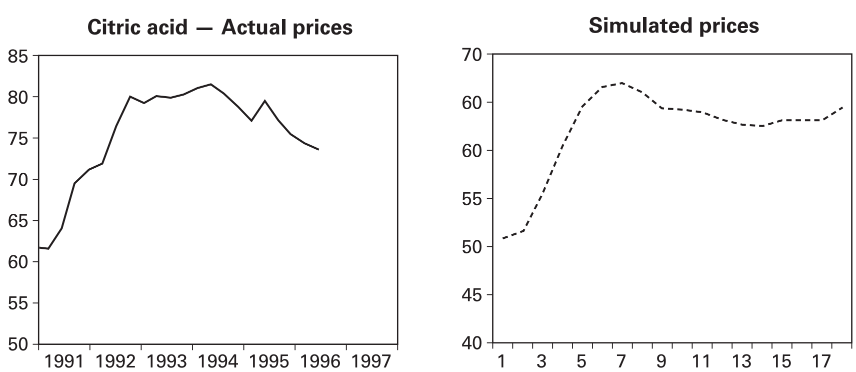

Figure 6.1
Actual (Connor 2001) and simulated (Harrington and Chen 2004) cartel price paths

A second issue is that by ignoring the possibility of detection, models do not address the issue of how a cartel can avoid "failing" a test for collusion by acting strategically. This is both a matter of whether it is feasible for the cartel to beat such a test and, if it is feasible, whether it is costly to do so. It is obviously a crucial issue when designing a test. I discuss it more fully in the next section.

6.3 Beating a Test for Collusion

An important issue about any detection method is: Can a cartel easily beat the test? In Bajari and Ye (2003) firms' bids are independent under the competitive model and lack of independence is taken as evidence consistent with collusion. However, as the authors note, this test can be circumvented by the cartel members appropriately scaling their "competitive bids" (which means scaling up in the case of a procurement auction). Since the competitive bids are independent, an affine transformation of them will be independent and thus be consistent with competition. The same is true for the bid-ranking test of Porter and Zona (1993). Similarly exchangeability can be beat with such a transformation of competitive bids. Although colluding firms' bid functions may then be different, they cannot be distinguished from a noncollusive solution where firms' valuations are drawn from different distributions. The ability of colluding firms in an auction to beat such tests is nicely shown in LaCasse (1995). The model is one in which bidders at an auction decide whether to collude and the antitrust authority decides whether to pursue an investigation based on the observed bids. At a Bayes-Nash equilibrium the posterior probability that a cartel has formed depends only on the winning bid and is independent of all other bids; the reason is that they are strategically chosen to be uninformative.

Although a cartel *could* beat these tests, there is the empirical issue as to whether they *do* beat them. In fact Porter and Zona (1993) and Bajari and Ye (2003) reject independence of firms' bids, so, if firms are not colluding, they are not being very smart about it. Bajari and Summers (2002, p. 145) note that: "...in all case studies of collusion of which we are aware, failures of conditional independence and exhangeability accompanied collusion." However, one can infer that cartels are not being smart—which may indeed be the case—or instead that this is evidence *against* collusion because a smart cartel will not behave in this manner. It is certainly evidence against the collusive theory of LaCasse (1995), since one can instead infer that there is misspecification in cost and demand conditions. A troubling element here is the dependence of inferences on the specification of the collusive model and the selection of an equilibrium. The modeler has a lot of discretion, and whether one assumes a smart or naïve cartel makes a big difference.

Fortunately there are other tests of collusion for which it is not costless for firms to beat. In Porter and Zona (1999), an unconstrained cartel finds it optimal to bid high in nearby collusive markets but to bid low in more distant competitive markets. The resulting bids decrease in distance, which was taken as evidence of collusion. Cartel members could avoid failing this test by making their bids increasing in distance, but that would require lowering their bids in collusive markets—which means earning less profit on contracts won—and/or raising their bids in competitive markets—which means reducing the chance of winning those contracts. In choosing their bids, a smart cartel will trade off cartel profit with the probability of detection. It can then reduce the power of a test but not eliminate it entirely.

It may also be difficult for cartel members to beat some tests based on identifying a structural break (the method described in section 6.1.2). Because collusion must mean a change in the process generating price—for that is the express purpose of forming a cartel—in principle, one should be able to pick up a break by monitoring the average price change. Once again, a cartel can reduce the power of this test by manipulating price changes—for example, making them modest and including price decreases amongst price increases—but it forgoes profit in doing so. In general, the transition from the non-collusive outcome to the collusive stationary path—as opposed to properties of the collusive stationary path—can be particularly fruitful for detection because mimicking competition is especially costly in terms of profit given that the cartel inherits a price well below where it likes it to be.

As the discussion above reveals, some tests of collusion have power even with smart cartels because it means lower profit from circumventing them.[49] A second reason that tests have power comes from the need to maintain cartel stability. Ensuring that a price path respects ICCs can restrict the feasibility of looking "competitive." In Marshall and Marx (2007), the cartel needs to cluster bids to avoid cheating. In Rotemberg and Saloner (1986), the cartel needs to lower prices during times of strong demand. Alternatively, they could have price move with demand, but that would require yet lower prices. The cartel may prefer to have countercyclical pricing and to trade off higher prices with a higher chance of detection. The feasibility in beating a test for collusion is further exacerbated when firms are heterogeneous, since then the cartel must balance diverse preferences. For example, in Harrington (1989), less patient firms must be given higher market shares to stabilize the cartel. Generally, it is the firm that has the greatest incentive to deviate, which limits the set of feasible policies and thus makes it harder to both maintain cartel stability and avoid detection. All this becomes even more acute when there is imperfect monitoring. Periodic reversion to lower prices may be required to maintain collusion, but the resulting structural break could trigger detection. Can a cartel design a policy that deters cheating without inducing rejection of the null hypothesis of no structural change? Or is there a fundamental tension between practices that promote compliance and those that avoid detection?

6.4 An Activist Policy of Screening for Collusion

Screening refers to a cost-effective method for identifying industries whose behavior is sufficiently suggestive of collusion so as to warrant verification, which refers to an intense investigation that directly contrasts collusion and competition as competing explanations of market behavior. Although the antitrust authorities do not currently screen for price-fixing, history is scattered with attempts. Going back to at least the 1950s, the US Department of Justice collected reports of identical bids at government procurement auctions (Joint Executive Committee 1961). Over twenty-five years ago, Joseph Gallo proposed a computer program to identify collusion at sealed-bid auctions (Gallo 1977). More recently, attempts have been made at various antitrust authorities. At the Bureau of Economics of the US Federal Trade Commission, Director Jonathan Baker used price increases after an industry-specific trough in demand to identify the exercise of market power (*FTC History* 2003, pp. 108–110), while Director Luke Froeb made progress in developing a screen in terms of the price variance (Abrantes-Metz et al. 2006). The question is: Can we effectively screen for collusion and, if so, what will it take to make it work?

There are at least three criteria for systematic and ubiquitous screening. First, evidence of collusion (preferably explicit collusion) must be discernible by just looking at prices, market shares, or other easily available data. Second, the test to be conducted should be routinizable so that it can be conducted with minimal human input. These first two criteria indicate that one is imagining an empirical exercise far removed from the typical industry analysis involving data on price, quantity, and cost and demand shifters, and then performing many modifications to a sophisticated econometric model. The third criterion is that the screen should be costly for the cartel to beat.

The objective is to screen industries as a matter of course, even where there is no hint of collusion. To be practical, screening must then rely on easily available data, which in many cases will mean exclusively price data. However, in some instances quantity and some cost or demand shifters may also be accessible at low cost. Consider a product with a primary input that trades on commodity markets. An example is raw sugar used in the production of refined sugar (Genesove and Mullin 1998). If cartel members manufacture in one country and sell in another—such as with the vitamins cartel—then exchange rate fluctuations provide an easily available cost shifter.

Although high-frequency price data are not often easily available, there is a growing number of possibilities. The government has access to bid data from auctions for which it is involved, ranging from defense procurement to Treasury bills. Online price data is another source. There is a growing amount of online retailing, and many scholars have already "scraped" data off of Web pages. Shopbots are present to perform some of this work. Furthermore some Web sites are beginning to collect price data from conventional retailers. This is currently being done with gasoline prices,[50] though the voluntary nature of reports makes the data sketchy. Then some markets—like financial markets, electric power, and some commodity markets—offer high-frequency data that, at a price, are available.

With these data the empirical exercise must be simple enough to be largely automated. One possibility is looking for certain collusive markers such as low price variance, low market share variance, high correlation in bids at an auction, negative correlation in market shares, and negative correlation in price and quantity. For example, Abrantes-Metz et al. (2006) make progress in developing a screen for low-price variance.

A second approach is to identify structural breaks in the stochastic process producing prices or some other measure of firm behavior. As new data arrive, a test for a structural break is conducted. The problem with using, say, a Chow test is that one can expect to eventually reject the hypothesis of parameter stability even if the model is stable. Fortunately, Chu, Stinchcombe, and White (1996) provide appropriate tests for conducting continual monitoring for structural breaks. Examination of spreads for certain Nasdaq securities shows a very quick switch from quoting all eighths to avoiding odd eighths, and this is reflected in a sharp increase in the spread (see Christie and Schultz 1999, fig. 2). A monitoring of structural change would have probably picked it up. Likely structural breaks to look for include an increase in the average price change, a fall in the price variance, an enhanced correlation among firms' prices, and greater market share stability.

Another possibility is to develop software that picks up anomalies. By an anomaly is meant, for example, the avoidance of odd-eighth quotes in Nasdaq markets or the inclusion of low-digit numbers on a million dollar bid, which, in the case of the FCC spectrum auctions, acted as a signal between bidders (Cramton and Schwartz 2000). To see how a bit of thought here might produce some interesting screens, consider the recent use of an empirical regularity to detect tax fraud. Benford's law (Hill 1995) is the property of many data series whereby the first digit, the second digit, and so forth, have a particular distribution that is, surprisingly, not uniform but rather logarithmic. The probability distribution on the first k digits is

$$\log_{10}\left[1 + \left(\sum_{i=1}^{k} d_i \times 10^{k-i}\right)^{-1}\right],$$

where $d_i \in \{0, 1, \ldots, 9\}$ is the ith digit. For example, the frequency with which the first digit is 1 is about 30 percent and is 2 is about 18 percent. This also has the implication that digits are not independent. For example, the unconditional distribution on the second digit differs from the distribution on the second digit conditional on the first digit. This bizarre regularity helped uncover tax fraud because the fraudulent accounting numbers did not satisfy Benford's law (Geyer and Williamson 2004).

Ideally any data screen should also satisfy the property that it is costly for the cartel to beat the test. A screen that became sufficiently successful and can be costlessly beat may ultimately be beat. This is not entirely obvious, however, because new cartels are continually born and some could be naïve if information about detection methods doesn't easily spread across industries. Furthermore a firm's management that learns about how detection is being conducted may learn too late if it is by being caught colluding. The point is that the learning environment—in terms of the extent of learning from others and the opportunities for experiential learning—may be such that the learning process does not converge to where all or even most prospective cartels know how authorities detect. Nevertheless, it is certainly a desirable property for a test to be costly to beat, as then it will have power even against smart cartels.

Screening appears to be effectively used in a wide variety of contexts, including insider trading, credit card fraud, and tax evasion. What allows detection is an ample supply of data—whether it is hourly trading volume and bid and ask prices for a security, daily credit card purchases, or annual tax returns. These data serve two key purposes. First, data are available to be screened. Second, many ex post verifiable cases allow fraud to be empirically identified. Two general methods are deployed in utilizing the data. Supervised methods involve the development of canonical models of fraudulent and nonfraudulent behavior using samples of such behavior. A particular case is then classified into one of those two categories. In contrast, unsupervised methods look for deviations from some benchmark, searching for anomalies or outliers.

How could we implement screening for collusion as part of an activist policy? First, build a library of cartels and use it to empirically identify collusive markers. Although there is a wealth of cases,[51] there has not been much research distilling behavioral patterns among them. We do have some tentative findings that the variance of prices is lower with collusion (Abrantes-Metz et al. 2006; Bolotova et al. 2005) and that cartel formation is preceded with a steep price decline (Grout and Sonderegger 2005), but much more needs to be done. The antitrust authorities could be of great assistance here if they were to establish a policy that, as part of a plea agreement with colluding firms, all relevant data be made public. There is certainly a social justification for such a policy, since making data available to scholars will promote advances in our understanding of cartels, which is the basis for more effective antitrust enforcement. Second, construct high-frequency price data series for more markets. Perhaps the government could induce buyers to provide these data under the condition of privacy, especially as there is a potential benefit to them from doing so. Third, develop new empirical methods for picking up structural change and statistical anomalies. These are likely to be the most robust methods for identifying markets worthy of closer scrutiny.

Notes

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1. For some industry traits associated with collusion, see Symeonedis (2003), Motta (2004), and Grout and Sonderegger (2005).

2. See *Chemical Week*, vol. 164, issue 24, June 12, 2002.

3. Useful references are Lieber (2000), Connor (2001), and Eichenwald (2001).

4. "The industry was investigated for cartel activity after buyers complained to the European Commission about the rapid increase in prices." Graham Hind, "English cutlers 'hit by cartel'," *The Times* (London), August 21, 1994; cited in Levenstein, Suslow, and Oswald (2004).

5. *Ferromin International Trade Corporation et al. v. UCAR et al.*, In the United States District Court for the Eastern District of Pennsylvania, Second amended complaint, filed May 1, 1999, at para. 50.

6. John Clifford and Bill Rowley, "Tackling cross-border conspiracy," *International Corporate Law*, May 1995.

7. A survey of the manner in which some cartels were detected is provided in Hay and Kelley (1974).

8. This information is based on private communication with Peter A. G. van Bergeijk of the Nederlandse Mededingingsautoriteit (December 16, 2004).

9. For a detailed discussion of the role of economic analysis in judicial decisions, see Werden (2004).

10. The term "competition" will mean that firms are not colluding but not necessarily that competition is perfect. Whether competition includes tacit collusion is left unanswered as the distinction between tacit and explicit collusion is a murky one in the economics literature. I will use "competitive" and "noncollusive" interchangeably.

11. For some related work on this method, see Bajari (2001), and for a more general discussion, Bajari and Summers (2002). Hendricks and Porter (1989) is an early general discussion of detecting collusion at auctions.

12. As supporting ancillary evidence, in the late 1980s (prior to this data set), firm 2 received a prison sentence for bid rigging while firms 4 and 5 paid damages for colluding with firm 2.

13. Section 6.2 provides details on what theory suggests to look for.

14. Kühn (2001) provides a nice discussion about communication practices in connection with collusion.

15. For an analysis of how this approach—using post-cartel prices to estimate the impact of collusion on price—leads to underestimates of the effect of collusion, see Harrington (2004a).

16. For a general discussion of these econometric methods, see Hansen (2001).

17. There is another rationale for looking for structural breaks which is that sharp changes in price—inexplicable in light of cost and demand shifts—are consistent with theories of collusive pricing under imperfect monitoring, while not being easily reconcilable within a competitive theory. However, this is better thought of as an example of the method described in section 6.1.4—where I do discuss it—in that the model nests competition (the case of no regime switches) and collusion (the case of regime switches) and the issue is which model better fits the data.

18. However, as shown in section 6.1.4, such data could still be used to substantiate collusion.

19. For other analyses of collusion in the school milk market, see Lanzilotti (1996) and Scott (2000).

20. For a review of nonparametric approaches to analyzing behavior at auctions, see Athey and Haile (2004).

21. Also see Porter (1985).

22. For a related approach, see Bresnahan (1987).

23. It is also true that the noncollusive model with multiple supply performs significantly better than the single-unit noncollusive model and only marginally worse than the single-unit collusive model.

24. For a discussion of these methods, see Bresnahan (1989).

25. Interestingly Asch and Seneca (1976) find that collusive industries are less profitable than noncollusive industries.

26. A second role for theory is to provide models of competition and collusion that can be estimated and contrasted. This fits into the empirical method based on finding the model that best fits the data.

27. A useful reference is Motta (2004).

28. Standard treatments can be found in Tirole (1988) and Vives (1999).

29. This would hold, for example, if demand is linear and "higher demand" means a rise in the intercept.

30. Under certain conditions these results are robust to when demand shocks are serially correlated (Kandori 1991). Recall that a noncollusive equilibrium for a different model can generate a similar prediction. For example, suppose that when demand increases, firm demand becomes more elastic. Then price competition will intensify as demand becomes stronger, so price can fall as demand rises even when firms do not collude. Increased firm demand elasticity due to greater consumer search has been used to explain why retail prices are lower for many items during the Christmas season despite demand having shifted out.

31. However, if there are sufficiently tight capacity constraints, then price can return to being pro-cyclical (Fabra 2004).

32. For further work on demand fluctuations, see Bagwell and Staiger (1997) who find that if the demand growth rate is positively correlated over time, then the price path is sometimes procyclical but never countercyclical.

However, if the growth rate is negatively correlated, then the price path is sometimes countercyclical but never procyclical.

33. This equilibrium can be modified to allow T to be randomly selected at the start of each punishment phase, so the length of time in the punishment regime is random.

34. Abreu, Pearce, and Stachetti (1986) consider maximal punishments in this setting and also get regime switches, though characterized by a different stochastic process. Like the previous model, movement from the collusive to the punishment regime occurs when price is sufficiently low and thus when the contemporaneous demand shock is low. In contrast, the punishment phase does not entail static Nash equilibrium but yet higher quantities (and thus lower profits). Firms get out of this punishment phase only when the realized price is sufficiently *low*. There are then regime switches but the process is always Markovian; the probability distribution on price in a period depends only on the previous period's price and regime (cooperative or punishment).

35. These equilibria have the property that continuation payoffs are the same for all firms, but can vary across histories. Punishment then entails low profits for all firms. This model assumes a continuum of costs and downward-sloping demand, while further work—which I will review shortly—generally assumes two cost types and perfectly inelastic demand (Athey and Bagwell 2001, 2004).

36. When colluding firms instead have private information about the market demand function (but do not exchange messages), Hanazono and Yang (2005) similarly show that collusion can result in rigid prices. When firms are sufficiently patient and signals are sufficiently uninformative, the best strongly symmetric perfect public equilibria has firms' prices being unresponsive to demand signals.

37. As described later, in other circumstances collusive prices and market shares can be sensitive to firms' costs for this class of models.

38. In many price-fixing cases these are industrial buyers, involving vitamins, lysine, and graphite electrodes, for example. Generally, the antitrust authorities do not actively engage in detection but rather respond to complaints (McAnney 1991).

39. I thank Margaret Slade for this point.

40. LaCasse (1995) also considers this setting but where the antitrust authority actively engages in detection and the bidders, who might form a cartel, are cognizant of this fact. The challenge from the authority's standpoint is that a low winning bid might be due to the existence of a cartel or instead that all bidders have low valuations. Equilibrium entails bidders using a mixed strategy to determine whether to form a cartel and the authority randomizing in their decision to perform an investigation with that probability decreasing in the winning bid.

41. Also see Graham and Marshall (1987) and Mailath and Zemsky (1991) for analyses of collusion at second-price auctions.

42. One way around this is with bid rotation for, even if nothing is revealed about the auction outcome, at least the bidder that was chosen to win and the bidder that cheated know that a deviation occurred and thus could respond aggressively.

43. The authors note that at a (noncollusive) equilibrium for a complete information auction setting, the bidder with the highest valuation bids at the second highest valuation and the second highest bid mixes just below his valuation. Although there is clustered bidding as well, it is necessarily among the two highest bids, while this needn't be the case in Marshall and Marx (2007).

44. Smith (2003) derives a similar result in a setting with cost shocks and firms choosing quantities.

45. This is proved in Farrell and Shapiro (1990) for a joint profit-maximizing cartel.

46. This analysis assumes firms' costs are independent. Aoyagi (2002) considers when firms' costs are correlated and also finds collusion entails an intertemporal market-sharing scheme.

47. One problem with a collusive marker of negatively correlated market shares is that such a prediction would seem consistent with a noncollusive model in which firms have capacity constraints which apply over multiple periods. For example, a firm that wins a large contract in the current procurement auction may not have the capacity left to bid for contracts in the next period, or even if it does, there is an opportunity cost to using up capacity. A firm with little spare capacity ought to bid less aggressively knowing that if it wins then it'll have no capacity for the next auction, which might involve a particularly profitable contract being auctioned off.

48. Exceptions include Besanko and Spulber (1989, 1990), LaCasse (1995), McCutcheon (1997), Cyrenne (1999), Harrington (2004b, 2005), and Harrington and Chen (2006).

49. An insightful discussion on this issue is provided in Porter (2005) who poses five problems that a cartel must solve to be effective and how, in solving those problems, they might reveal that a cartel exists.

50. For example, www.gaspricewatch.com.

51. Some are reviewed in Connor (2001) and Levenstein and Suslow (2001).

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