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DETECTING CARTELS: PRICE RIGIDITY AND THE APPLICATION OF THE ICSS ALGORITHM

by

Ping-Ying Cheng

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ABSTRACT

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This paper proposes that the Iterative Cumulative Sums of Squares (ICSS) Algorithm can be applied to help better detect periods of collusive behavior in markets by analyzing changes in the variance of product prices over time. Price rigidity is a common characteristic of oligopolies and has been theoretically proven in many studies. The kinked-demand-curve explains that firms would prefer to stay at the agreed upon monopoly price rather than cutting prices to earn more market share during a single period. An infinitely repeated Bertrand game model developed by Athey, Bagwell, and Sanchirico (2004) claims that if the firms are sufficiently patient, the optimal symmetric collusive scheme can be reached when the equilibrium-path price wars are absent and the price is rigid. Harrington and Chen (2006)'s dynamic programming framework established an optimal cartel price path which has a transition phase and a stationary phase. The stationary phase shows that price in collusive regime is much less volatile than price in competitive regime.

In order to detect the existence of cartel, this paper employs the ICSS algorithm developed by Inclan and Tiao (1994) to detect multiple changes of variance in a given time series. The flat glass antitrust litigation in early 1990s was detected by this technique and had the results that periods of December 1982 to June 1984 and November 1987 to February 1990, with the lower variance relative to the periods before and after were defined as suspected collusion periods. By applying the model for damage analysis, the price of flat glass was confirmed to be overcharged by the producers during the conspiracy periods detected by the ICSS algorithm rather than the class periods certified by the court.

The steel industry in the 1920s and 1930s had market power in agreeing on price-fixing. This industry was analyzed using the ICSS algorithm and found relatively smaller steel price variance for the periods of August 1924 to November 1931 and June 1938 to December 1939. The damage analysis has shown that customers for steel products were overcharged by steel producers during these periods rather than the periods in the literature.

Based on empirical results, the ICSS algorithm provides a fast and simple method of detecting the existence of cartels and collusive behavior. This is the first study to apply the ICSS algorithm in forensic economics to detection of this behavior and appears to be successful in detecting periods of anticompetitive behavior. In the future, it might provide an alternative method to more easily discover and prosecute anticompetitive behavior.

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Chapter 1

Introduction

A *cartel* is group of firms brought together with intent to collude and obtain profit which would otherwise not be available. Bian (1959) defines *collusion* as, “implying . . . that the rival sellers in some manner arrive at an understanding as to what price to charge or what outputs to produce, or both.” The goal of firms forming cartels is to limit competition and thus increase firms’ profits. Firms’ jointly maximized profits level could be reached by restricting output and increasing price. Section 2 of the Sherman Antitrust Act states, “Every person who shall monopolize, or attempt to monopolize, or combine or conspire with any other person or persons, to monopolize any part of the trade or commerce among the several States…shall be deemed guilty of a felony.” Under the Sherman Antitrust Act, cartel behavior in the United States is illegal; therefore, government agencies make the effort to detect, prosecute, and penalize these practices. This paper proposes that the Iterative Cumulative Sums of Squares (ICSS) algorithm can be applied to help better detect periods of collusive behavior in markets by analyzing changes in the variance of product prices over time.

Firms within an industry often have the temptation to meet in an attempt to fix prices and restrict output; these attempts have varying degrees of success. This is a problem which has come to the forefront in recent years, with early economists also discussing firms’ attempts to attain monopoly profits. Adam Smith (1776) once remarked, “People of the same trade seldom meet together, even for merriment and diversion, but the conversation ends in a conspiracy against the public, or in some contrivance to raise prices.” These temptations would leave firms immune from severe competition and result in cooperative relations with their rivals. Because of the various strategic concerns in maintaining a cartel, immediate issues which firms face are coordination, cheating, and market entry. Some cartels work well for firms fixing their prices and last for a long period of time. Some cartels collapse in a very short of time and have little or no effect on purchasers or industry structure. Others have successfully fixed prices for certain periods and then the cartel fell apart due to new innovations, new entries, or other non-price related competition. Following Stigler (1964), it is a well-established proposition that if any firm in a cartel can secretly cut its price below the agreement but remain above marginal cost, it will gain larger profits than by complying with the agreement. Many economists have argued this ability to cut prices below agreed upon levels to increase profit will lead to the collapse of a cartel. Subsequent literature established the theoretical work that cheating could be deterred, and a cartel could form and survive for periods when firms are patient and well-informed.

The majority of theoretical collusion literature discusses the game theoretic concerns of cheating and its prevention. In Stigler's (1964) study, he emphasized that the incentive to cheat is the most important reason for the instability undermining attempts to collude. Unlike a one shot game, if firms have repeated interactions, this continuous interaction theoretically can provide the incentive of future collusive profit and thus deter firms from cheating. Most of the literature has theoretically claimed that firms' repeated interaction over time supports collusion. Benoit and Krishna's (1985) article provides a theoretical basis for the argument that firms' repeated interaction across space or markets may also support collusion. Since the interaction between firms is over time, firms determine continuing or deviating from the collusive behavior by weighting the expected benefit from cheating today with the expected cost of cheating; this expected cost is the reduction of future discounted profit due to cheating. If the cost of cheating is higher than the benefit, firms will stay in the collusive agreement and refrain from undercutting the collusive price.

Cheating is a major problem of cartel not only at the time of formation but also during the collusive period. Stigler (1964) argues that cartels are fundamentally unstable. His argument is based on the concept that firms agree to restrict output, but then engage in secret cheating to individually increase profit that induces price wars. Firms may try to collude again after price wars occur, but the incentive to gain profit by increasing production at the price level above marginal cost would remain so great that the cartel could not last. The action of the cartel's breaking down and re-forming causes fluctuations in market price for that product. Many modern economists have accepted Stigler's thought that cheating is the major threat which causes the instability of cartels, but these economists derive completely different results from collusion. For example, Green and Porter (1984) argue that a price war is not the result of cheating, but actually the solution to deter cheating. Since a price war is costly, firms refrain from cheating in order to prevent its occurrence. Unless a cartel has a formal organization and a perfect monitoring system, firms are unable to determine if changes in market price are due to a change of demand or some member's secretly lowering prices. As a result, firms arguably respond to this change in market prices with price wars, effectively undermining their profit advantage.

The most common way to identify a cartel's attempt to monopolize a market and the timing of the cartel's conspiracy period is through physical evidence, such as documents regarding planned coordinated price announcements, perhaps attained from employee witnesses or "whistleblowers." Suslow (2005) defines distinct cartel episodes as occurring within an industry if the cartel contract was restructured due to the exit of a key member or the entry of a significant new member. Suslow's methods show that the duration of a cartel may be shorter than a cartel contract, and cartels may dissolve and reform later. Eckbo (1976) defines cartel success or "efficiency" in terms of the ability to raise prices 200% above the unit costs of production and distribution. He reviewed 51 significant international cartel organizations. Only 19 of these cartels were "efficient," although these cartels did not last very long. Those lasting for four years or more were those industries with high concentration of production, inelastic demand, high cartel market share, member cost advantage, and with no government intervention.

With the conspiracy period defined, one can determine the economic effect arising from the cartel by comparing the prices and profits within the conspiracy period with those that would have resulted without the conspiracy. However, physical evidence may be unsatisfactory when trying to identify the true timing of a cartel's negative economic impact. As the literature previous discussed shows, attempts to collude may initially fail, or perhaps fail altogether (due to the incentives to cheat, for example). However, even when the cartel's attempt to collude is successful, there is almost always some *delay* between the cartel's initial attempts to coordinate its conduct (i.e., the conspiracy period) and the successful cartel's sustained effect on price (i.e., the damage period).

Because it is difficult to analyze damages outside of the conspiracy period (as officially designated in an allegation against a cartel), analyses that account for the aforementioned "delayed effect" are rarely attempted. This is a shortcoming in the applied practice of damage estimation since empirical and theoretical literature supports the idea of a delayed effect. Some cartel studies report that the coordinated price really starts to take effect a few months after the creation of the cartel; other cartel studies report that the coordinated price begins with the creation of the cartel, but the coordinated price increase does not reach joint profit-maximizing levels.

There are two approaches to discover cartels. One approach is structural and the other is behavioral. The structural approach includes identifying the characteristics which are thought to be conducive to collusion. For example, an industry characterized by fewer firms, more homogenous products, and stable demand has a higher propensity to form a cartel. The behavioral approach, unlike the structural approach, entails either observing the means with which the firms use to coordinate their behavior, or observing the result attributable to the coordination of firms. The means with which the firms coordinate their behavior is often a type of direct communication (i.e., memos). In many cases, cartels have been detected by evidence of such communication. Besides observing the means of coordination, the behavioral approach may also involve observing the market impact of that coordination. Suspicions may arise from the pattern of firms' prices, quantities, or some other aspect of market behavior. A parallel movement in prices among producers or an unexplainable increase in prices may make purchasers become suspicious of cartel behavior. Beside these two unusual prices movements, the more stable price movements over time also signal suspicion of the existence of a cartel. This sign is even more practical in detecting the collusion during an economic recession. Instead of firms lowing prices during recessions, a cartel fixes the prices to minimized lower profit expectations due to the bad economy. The main issue in this paper is whether there is some kind of testing methodology which can successfully identify the timing and duration of collusive behavior.

This paper focuses on observing the impact on the market price attributable to cartel conspiracies among firms. Many studies have theoretically or empirically shown that the price variance changes during the conspiracy period. Therefore, based on data analysis, once the variance "change point" in time series price data is found (without a commensurate variance change in costs), it could mark the beginning or the ending of the conspiracy period.

A paper by Abrantes-Metz, Froeb, Geweke, and Taylor (2006) studies the price movement over time to compare the variance of prices between conspiracy and competitive periods. In the Abrantes-Metz et al. paper, the industry of interest was prosecuted by the Antitrust Division of the U.S. Department of Justice for rigging the bids to supply seafood to military installations. The authors collected data from the time period around the cartel's collapse to estimate price variance across the collapse of the bid-rigging conspiracy. Both prices and costs were compared between the "collusive" and "competitive" regimes. Figure 1 shows their comparison of prices and costs in the "collusive" regime, which is the left of the vertical line, and prices in the "competitive" regime, which is the right of the vertical line; the period between those two vertical lines is the transition from collusion to competition. They found that the mean price decreased by 16%, and the standard deviation increased by 263% after the collapse of collusion. Hence, they concluded that the conspiracy had the impact not only on increasing the price level, but also on decreasing the price variance.

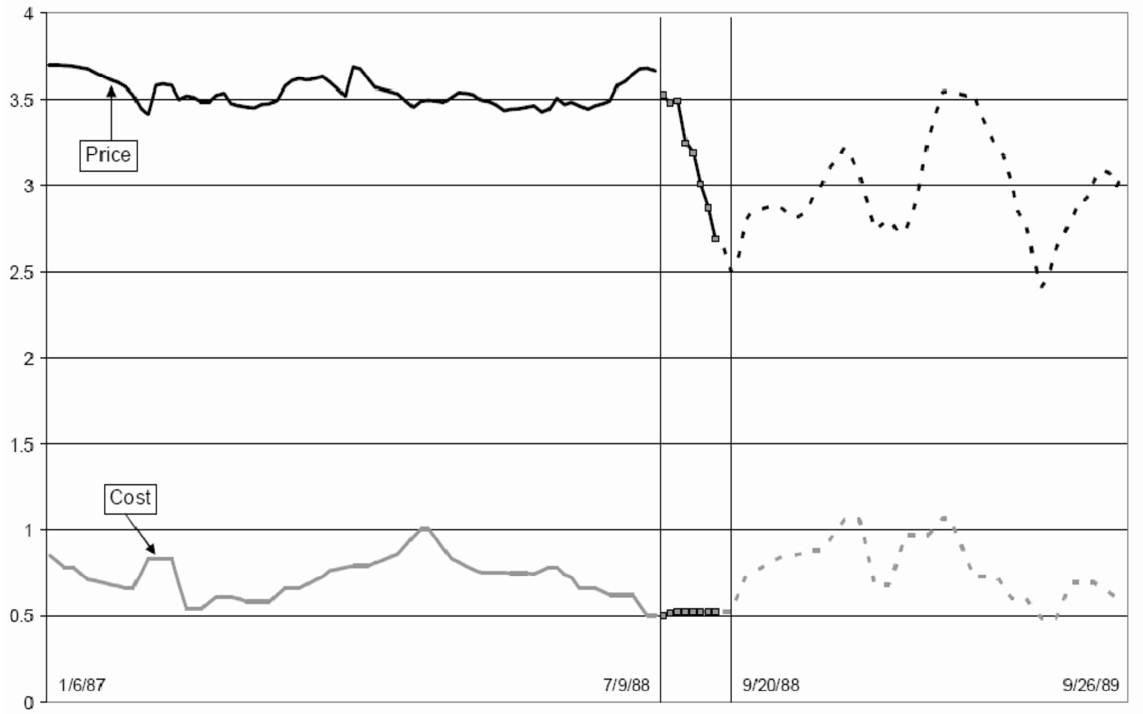

Figure 1. Collusion and the Variance of Frozen Perch Prices and Costs: 1/6/87-9/26/89
Source: Abrantes-Metz, Froeb, Geweke, and Taylor (2006)

This paper attempts to find the variance change point in time series price data to detect a cartel's damage period. Inclan and Tiao (1994) propose a general procedure to detect variance change points based on the Iterative Cumulative Sums of Squares (ICSS) algorithm. In their study, the main issue is detecting multiple variance change points within a given time series. By studying the centered cumulative sum of squares, the authors provide an intuitive basis for the ICSS algorithm. Inclan and Tiao claim the results of ICSS are very comparable to those results from the Bayesian approach and from the likelihood ratio test when the series are of a moderate size. Moreover, unlike the latter two approaches, the ICSS algorithm does not require a heavy computational burden. The ICSS algorithm has been applied in many studies within finance literature. A more in-depth literature review on studies which applied ICSS method will be discussed in the

Chapter 3. This paper is the first paper to apply the ICSS algorithm in forensic economics. Hence, the main issue in this paper is to apply the ICSS algorithm in detecting the changing points of variance of prices in markets where collusive behavior has occurred to help determine the beginning and ending of the conspiracy period.

The remainder of this paper is organized as follows: Chapter 2 provides a literature review of price rigidity in collusion theory including a repeated game model and a dynamic collusion pricing model; Chapter 3 provides an introduction to the ICSS algorithm methodology and its applications; Chapter 4 applies the ICSS algorithm to detect the duration of two cartels: the flat glass and steel in separate industries. Chapter 5 provides a conclusion and discussion.

Chapter 2

Literature Review: Price Rigidity in Collusion Theory

A Kink-Demand-Curve Example

One common characteristic in markets exhibiting collusive behavior is price rigidity. Firms cannot adjust prices continuously. One reason is that it is costly for firms to do that; however, another reason is that any price reaction of firms to others' changes brings in the issue of regaining or consolidating market share. A simple formalization of short-run price rigidities and reaction is from Maskin and Tirole's (1988) study that assumes that firms do not choose their prices simultaneously. Two firms produce a homogenous good. Firm 1 chooses its price at odd periods (2k+1), and Firm 2 chooses at even periods (2k). Due to the assumption that firms can not adjust price quickly, the price chosen by firm *i* would last for two periods:

$$p_{i,t+1} = p_{i,t} \; ; \; p_{i,t+3} = p_{i,t+2} \; ; \ldots$$

To maximize the present value of its profit, the objective function of firm *i* is

$$\sum_{t=0}^{\infty} \delta^t \Pi^i(p_{i,t}, p_{j,t}). \qquad (2.1)$$

where Π^i is the profit fuction of firm i, and $\delta^t$is the discount rate at period t.

A perfect equilibrium would show that a firm's price choice simply depends only on the information related to its payoff. Firm 1's profit at the time 2k+1 is affected by the price from Firm 2, $p_{2,2k+1}$. This is what called payoff-relevant. Based on the assumption in this model, Firm 2 charges the same price in the period 2k+1 as the price in the period 2k. Hence, the price that Firm 1 charges at 2k+1 is the reaction toward Firm 2's price at 2k; that is, $p_{1,2k+1} = R_1(p_{2,2k})$. In this model, a firm's strategy is conditioned on little information (the observed rival's price). This information is so little that a firm's strategy is constant with rationality. Firm 2 acts in the similar way, $p_{2,2k+2} = R_2(p_{1,2k+1})$. Both Firm 1 and Firm 2's reaction function are called Markov reaction functions. When firms use Markov strategies[1] to reach a perfect equilibrium, that equilibrium is a Markov perfect equilibrium.

Firm 1's reaction at time 2k+1 by observing Firm 2's price at 2k is to maximize its objective function with the expectation of the firms' reactions: R_1 (.) and R_2 (.). Firm 1's inter-temporal profit function at time 2k+1 is

$$V^1(p_2) = \max_{p_1}\Big[\pi^1(p_1, p_2) + \delta\pi^1\big(p_1, R_2(p_1)\big) + \delta^2\pi^1\Big(R_1\big(R_2(p_1)\big), R_2(p_1)\Big) + \cdots\Big]. \quad (2.2)$$

Here $p_1$and p_2 in the first term in the bracket represent Firm 1 and Firm 2's prices at time 2k+1, respectively; however, the price Firm 2 charges at this period is the same as at time 2k. In the next period, Firm 1 will keep price at p_1 with Firm 2's reaction $R_2(p_1)$. Firm 1 then will react to $R_2(p_1)$ by charging its price at $R_1\big(R_2(p_1)\big)$ in the following two periods, and so on. As a result, , in the equilibrium, the price Firm 1 charges at 2k+1 based on the reaction to Firm 2's price at 2k is to maximize the whole value in the brackets for all p_2. Firm 2 behaves similarly to maximize its inter-temporal profit.

A kinked-demand-curve example is presented here. The kinked-demand-curve is an "imagined demand curve" in a producer's mind. If he raises his price, he must expect to lose business to his rival, which implies that his demand curve tend to be elastic going up, while if he reduces his price he will not expect to gain customers from his rival due to retaliations; this action implies that his demand curve tends to be inelastic going down.

[1] A player playing a Markov strategy, conditions his action of a period *t* only at his state at this given period.

As a result, a producer's imagined demand curve has a "kink" at the current price (Hall and Hitch 1939; Sweezy 1939). It is assumed, for simplicity, that each firm has a demand curve $D(p) = 1 - p$ and its cost is zero. A discrete price grid is used in this example:

$$p_h = h/6, h = 0,1, \dots 6. \tag{2.3}$$

Since competitive price is the price that firms charge at marginal cost level, the competitive price here is p_0; meanwhile, the monopoly price is the price firms charge when marginal revenue equals demand, $p_3 = 1/2$. Table 1 shows this symmetric reaction function, where $R_1(.) = R_2(.) = R(.)$, with a discount factor sufficiently close to 1. The first column is the current price charged by a firm, and the next column is the reaction from its rival. The value in the right column is the profit when firms charge p. For example, when $p_4 = 2/3$ is charged, the quantity of demand will be $1/3$ and the profit will be $2/9$.

Table 1
A Kinked-Demand-Curve Example

P	R(p)	π(p)
p_6	p_3	0
p_5	p_3	5/36
p_4	p_3	8/36
p_3	p_3	9/36
p_2	p_1	8/36
p_1	{ p_3 with probability α p_1 with probability 1-α	5/36
p_0	p_3	0

Note. α depends on δ.
Source: Tirole (1988), *The Theory of Industrial Organization*.

The price at the steady state, where both firms charge the same price, is the monopoly price, p_3. If a firm increases its price to be above the monopoly price, its rival would not follow it but stay at p_3 due to the higher profit (9/36 > 8/36). On the contrary, if a firm cut down its price to p_2, a price war will occur. The reaction of its rival on the price at p_2 will be p_1. During the price war, firms would prefer returning to the price at the steady state, the monopoly price. Nevertheless, no firm wants to raise its price first because it would lose its market share in the short run.

In the above example, if firms are at the steady state (charging price at p_3), no firm would deviate from that state. Firm 1's inter-temporal profit is the sum of current and future discounted profit:

$$V(p_3) = (1 + \delta + \delta^2 + \delta^3 + \cdots) \times \frac{1}{8} = \frac{\frac{1}{8}}{(1-\delta)} \tag{2.4}$$

Firm 1 can earn a profit of 2/9 today by gaining the whole market rather than a profit of 1/8 by sharing the market with Firm 2 if it cuts its current price to p_2. However, this action of Firm 1 causes its rival to cut down the price, and thus Firm 1 will receive zero profit in the next period. Firm 1 cannot adjust its price until the period after the next period. However, even though Firm1 could adjust its price back to the monopoly price, p_3, Firm 2 will have one period lag to raise its price back to p_3 based on Markov reaction functions. As a result, Firm 1's inter-temporal profit today by charging its price at p_2 became:

$$\frac{2}{9} + \delta \cdot 0 + \delta^2 \cdot 0 + (\delta^3 + \delta^4 + \cdots)\frac{1}{8} < V(p_3), when\ \delta\ close\ to\ 1. \tag{2.5}$$

From this equation, Firm 1 gains $\left(\frac{2}{9} - \frac{1}{8}\right) = \frac{7}{72}$ by cutting its price to p_2 today, but lose its profit at 1/8 in the following two periods. Although there are many equilibriums which exist, the profits in the Markov perfect equilibrium are always bounded away from the competitive profit.

A Repeated Bertrand Game Model

Athey, Bagwell, and Sanchirico (2004) studied an infinitely repeated Bertrand game with the assumptions of publicly observed prices and privately observed and independent and identically distributed cost shock in each period by firms. They found that "a rigid-pricing scheme, where a firm's collusive price is independent of its current cost position, sacrifices efficiency benefits but also diminishes the information cost." Within their model and assumptions, the optimal symmetric collusive scheme can be reached when the equilibrium-path price wars are absent and the price is rigid.

The Repeated Game. Each firm in this model observed the history of its own cost draws (θ), price schedules(p), and the realized prices of its rivals(ρ), but cannot observe rival cost types or rival schedules. The firm *i's* payoffs are defined as

$$u_i(\{\boldsymbol{\theta}^t, \boldsymbol{p}^t\}) = \sum_{t=1}^{\infty} \delta^{t-1} \pi(\rho_i^t, \theta_i^t) m_i(\boldsymbol{\rho}^t) \qquad (2.6)$$

The sequence $\{\boldsymbol{\theta}^t, \boldsymbol{p}^t\}$ represents a vector of types and price schedules at date t, and $\{\boldsymbol{\rho}^t\}$ represents a public history of realized price vectors; $m(.)$ is what is called the market-share-allocation function. When firm *i's* vector of realized price is $\boldsymbol{\rho}$, its market share would be $m_i(\boldsymbol{\rho})$.

The symmetric perfect public equilibrium (SPPE) is the focus in Athey et al.'s model. This equilibrium implies that all firms suffer industry-wide future punishments and rewards together, and their strategies depend only on the history of realized prices which are publicly observed. By applying the tools of dynamic programming from the Abreu, Pearce, and Stacchetti 1990 study, Athey et al. defined

$\bar{v}(\rho_i; \boldsymbol{p}_{\mathbf{i}}) \equiv E_{\theta_{-i}}\left[v\left(\rho_i, \boldsymbol{p}_{-i}(\boldsymbol{\theta}_{-i})\right)\right]$ as the expected continuation payoff, where ρ_i is the price a firm selects, and $\boldsymbol{p}_{-i}$ is the expected price schedules that other firms will adhere to. They simplified each firm's expected payoff from the symmetric price schedule to be $E_{\theta_i}[\bar{\pi}(p(\theta_i), \theta_i; p) + \delta\bar{v}(p(\theta_i); p)]$ and created the following Factored Program.

The Factored Program: Firms choose price schedule *p* and continuation payoff function *v* to maximize

$$E_{\theta_i}[\bar{\pi}(p(\theta_i), \theta_i; p) + \delta\bar{v}(p(\theta_i); p)]$$

$$\text{subject to: } \forall \rho \in \mathbb{R}_+^n, v(\rho) \in V_s \text{ , and}$$

$$\forall \tilde{p}, E_{\theta_i}[\bar{\pi}(p(\theta_i), \theta_i; p)] + \delta\bar{v}(p(\theta_i); p) \geq E_{\theta_i}[(\tilde{p}(\theta_i), \theta_i; p) + \delta\bar{v}(\tilde{p}(\theta_i); p)].$$

$$\text{where } V_s \subset \mathbb{R}. \tag{2.7}$$

The lemma from Athey et al.'s Factor Program is that "Any symmetric public strategy profile $\mathbf{s}^* = (s^*, ..., s^*)$ is an optimal SPPE, if and only if its corresponding factorization (p^*, v^*) which solves the Factored Program."

The constraints of the Factored Program were put into two groups to formulate the Interim Program for a repeated game with private information. The group of off-schedule constraints is to prevent firms having off-schedule deviation, firms choosing a price which is not in the range of *p*.[2] The group of on-schedule constraints is to prevent firms having on-schedule deviation, or firms choosing a price in the range of *p* based on other cost level rather than their own. An example of on-schedule deviation is that a firm with high-level cost charges prices the same as firms with low-level to win market share.

[2] The range of *p* is a price strategy reflecting cost realization.

The Interim Program: Firms choose price schedule p and continuation payoff function v to maximize

$$E_{\theta_i}[\bar{\pi}(p(\theta_i), \theta_i; p) + \delta\bar{v}(p(\theta_i); p)]$$

Subject to:

Off-Schedule Constraints: $\forall \rho' \notin p([\underline{\theta}, \overline{\theta}])$,

(IC-off1)$\forall \boldsymbol{\theta}_{-i}$, $v(\rho', \boldsymbol{p}_{-i}(\boldsymbol{\theta}_{-i})) \in \mathcal{V}_s$

(IC-off2)$\forall \theta_i$, $\bar{\pi}(p(\theta_i), \theta_i; p) + \delta\bar{v}(p(\theta_i); p) \geq \bar{\pi}(\rho', \theta_i; p) + \delta\bar{v}(\rho'; p)$

On-Schedule Constraints: $\forall \hat{\theta}_i$,

(IC-on1)$\forall \boldsymbol{\theta}_{-i}$, $v\left(p(\hat{\theta}_i), \boldsymbol{p}_{-i}(\theta_{-i})\right) \in \mathcal{V}_s$

(IC-on2)$\forall \theta_i$, $\bar{\pi}(p(\theta_i), \theta_i; p) + \delta\bar{v}(p(\theta_i); p) \geq \bar{\pi}\left(p(\hat{\theta}_i), \theta_i; p\right) + \delta\bar{v}\left(p(\hat{\theta}_i); p\right)$.

(2.8)

All letters above in bold represent vectors. Now the off-schedule constraints tell that a firm has a higher expected payoff by charging a price based on cost level (including its own and other possible cost levels) than by charging a price not based on cost levels. Meanwhile, the on-schedule constraints mean that a firm has higher expected payoff by charging a price at its own cost level than by charging a price at the imitating cost level.

Collusion among Patient Firms and Mechanism Design. Before finding out the characterizations of the optimal model in this repeated game model, with the assumption that firms are patient, a mechanism design program was developed by relaxing some constraints from the Interim Program. When firms are sufficiently patient, the off-schedule deviation can be relaxed without loss of generality since firms are not attracted by off-schedule deviation anyway. The first on-schedule (IC-on1) can be relaxed by replacing with $\forall \hat{\theta}_i, \overline{v}(p(\hat{\theta}_i), p) \in \overline{\mathcal{V}}_s$, where $\overline{\mathcal{V}}_s \equiv \sup \mathcal{V}_s$[3]. Then the Interim Program yielded a new program.

The Mechanism Design Program**:** Firms choose price schedule *p* and a punishment function *T* to maximize

$$E_\theta[\Pi(\theta,\theta;p) - T(\theta)]$$

Subject to: For all $\theta, T(\theta) \geq 0$;

$$\text{(IC-onM) } \forall \hat{\theta}, \theta, \Pi(\theta,\theta;p) - T(\theta) \geq \Pi(\hat{\theta},\theta;p) - T(\hat{\theta}), \quad (2.9)$$

where $\Pi(\hat{\theta},\theta;p) \equiv \bar{\pi}(p(\hat{\theta}_i), \theta_i; p)$ representing the current profit of a type θ firm announcing that its type is $\hat{\theta}$. The function, $T(\hat{\theta}) \equiv \delta[\overline{\mathcal{V}}_s - \overline{v}(p(\hat{\theta}_i), p)]$, is a general "transfer" or "punishment" function that a firm expects to have when announcing $\hat{\theta}$. The value of $T(\hat{\theta})$ greater than zero indicates a firm announced its type $\hat{\theta}$ and there is a price war. In contrast, the zero value of $T(\hat{\theta})$ indicates a firm's announcement of its type $\hat{\theta}$ and there is no price war.

Based on their Mechanism Design Program, Athey et al. proposed that:

> "Suppose (p^*, T^*) solves the Mechanism Design Program and $T^* \equiv 0$. Then $\exists \hat{\delta} \in (0,1)$ such that, for all $\delta \geq \hat{\delta}$, there exists an optimal SPPE which is stationary, wherein firms adopt p^*after all equilibrium-path histories, and p^* solves the following program: maximize $E_\theta[\Pi(\theta,\theta;p)]$ subject to $\forall \hat{\theta}, \theta, \Pi(\theta,\theta;p) \geq \Pi(\hat{\theta},\theta;p)$."

They then developed two implications to establish this result: that $(p^*, T^* \equiv 0)$ is optimal in the Mechanism Design Program. Since $T(\theta)$ is a transformation of the expected payoff

[3] According to Athey et al. (2004), this relaxed constraint allows $v \equiv \overline{\mathcal{V}}_s$, even though $\overline{\mathcal{V}}_s \in \mathcal{V}_s$ is not for sure.

function, $(p^*, v^* \equiv \overline{\mathcal{V}}_s)$ is a solution to the Interim Program[4] as long as other constraints are also satisfied. As a result, the first implication is that $(p^*, v^* \equiv \overline{\mathcal{V}}_s)$ is weakly superior to any SPPE factorization; mathematically,

$$E_\theta\left[\Pi(\theta, \theta; p^*) + \delta \overline{\mathcal{V}}_s\right] \geq \overline{\mathcal{V}}_s. \qquad (2.10a)$$

When firms are very patient, in each period, firms repeatedly play $p^*$and $T^* \equiv 0$, which satisfy the on-schedule constraint, as long as no firm deviates in the future. The off-schedule deviation is always deterred by the punishment of all firms playing the Static Nash Equilibrium. Hence, the other implication is

$$E_\theta[\Pi(\theta, \theta; p^*)]/(1-\delta) \leq \overline{\mathcal{V}}_s. \qquad (2.10b)$$

From inequalities 2.10 a and b, an equation is established as $\overline{\mathcal{V}}_s = E_\theta[\Pi(\theta, \theta; p^*)]/(1-\delta)$. This optimal SPPE shows that firms play p^* in every period and this p^*solves the static program: maximize $E_\theta[\Pi(\theta, \theta; p)]$ subject to $\forall \hat{\theta}, \theta, \Pi(\theta, \theta; p) \geq \Pi(\hat{\theta}, \theta; p)$, under the conditions that firms are sufficiently patient and $(p^*, T^* \equiv 0)$ solves the Mechanism Design Program.

To analyze the characteristics of (p, T) which satisfies the constraints in the Mechanism Design Program, the constraints are reduced by the following lemma: "(p, T) satisfies (IC-onM) if and only if (p, T)satisfies: (i) $p(\theta)$ is weakly increasing, and (ii) $\Pi(\theta, \theta; p) - T(\theta) = \Pi(\bar{\theta}, \bar{\theta}; p) - T(\bar{\theta}) - \int_\theta^{\bar{\theta}} \Pi_\theta(\tilde{\theta}, \tilde{\theta}; p) d\tilde{\theta}$, where $\Pi_\theta(\theta, \theta; p) = \frac{\partial}{\partial \theta} \Pi(\hat{\theta}, \theta; p|_{\hat{\theta}=\theta}) < 0$."

[4] $T(\hat{\theta}) \equiv \delta[\overline{\mathcal{V}}_s - \overline{v}(p(\hat{\theta}_i), p)]$ and $T^* \equiv 0$, so $\overline{v}(p(\hat{\theta}_i), p) \equiv \overline{\mathcal{V}}_s$, which implies $v^* \equiv \overline{\mathcal{V}}_s$.

One easy way to understand (ii) is to consider a firm with the cost type $\theta_l$which is below $\overline{\theta}$. If this firm does not pretend to be type $\overline{\theta}$, it will gain the same profit as the firm with type $\overline{\theta}$ plus an extra portion from its lower cost. By the same token, a firm with cost type lower than θ_l will earn a little extra than the firm with type θ_l does. So for any type θ, a firm earns the profit which equals the profit that the firm with the top cost type plus the accumulate efficiency rents (due to lower cost) of higher types. So what (ii) saying is that the profit of a firm with any cost type is the same as the profit earned by the firm with the highest cost type plus its accumulated efficiency rent of higher types. This theory implies as long as the profit-at-the-top is relatively larger than the accumulated efficiency rent, a firm with the highest cost type will have less possibility to behave as a lower cost type.

The magnitude of the efficiency rents can be transformed into the allocation of market share across firms' types. A firm expects its market share $M(\widehat{\theta};p) \equiv \overline{m}\left(p(\hat{\theta};p)\right)$ when it announces its type $\hat{\theta}$, and all firms announce their types truthfully. The magnitude of the efficiency rents now can be written:

$$-\int_{\theta}^{\overline{\theta}} \Pi_{\theta}(\tilde{\theta},\tilde{\theta};p)d\tilde{\theta} = \int_{\theta}^{\overline{\theta}} M\,(\tilde{\theta};p)d\tilde{\theta}. \qquad (2.11)$$

In Athey et al.'s (2004) finding, given an original incentive-compatible scheme and market-share allocation, an alternative incentive-compatible scheme can be constructed that delivers the same market-share allocation without using wars, while also providing the same profit-at-the-top. They, therefore, claim a lemma that *"*Given a scheme (p,T)that satisfies (IC-onM) and $T \geq 0$, and associated market-share allocation

$M(\theta;p)$, there exists an alternative scheme $\left(\tilde{p}, \tilde{T} \equiv 0\right)$ which also satisfies (IC-onM), and such that $M(\theta;p) = M(\theta;\tilde{p})$and $\Pi(\bar{\theta},\bar{\theta};p) - T(\bar{\theta}) = \Pi(\bar{\theta},\bar{\theta};\tilde{p})$."

Following this lemma, the interim profit of firm with type θ in the above lemma can be re-written as below by using equation 2.11:

$$\Pi(\theta,\theta;p) - T(\theta) = \Pi(\bar{\theta},\bar{\theta};p) - T(\bar{\theta}) + \int_{\theta}^{\bar{\theta}} M\left(\tilde{\theta};p\right)d\tilde{\theta}. \quad (2.12)$$

Another of their findings is called the Revenue Equivalence Theorem. In that theorem, firms start with the scheme(p,T), which satisfies on-schedule constraints. If any other scheme $\left(\tilde{p},\tilde{T}\right)$ which also satisfies the on-schedule constraints provides the same profit-at-the-top $\left(\Pi(\bar{\theta},\bar{\theta};p) - T(\bar{\theta})\right)$ and the same market-share allocation $\left(M(\theta;p) = M(\theta;\tilde{p})\right)$, this scheme will yield the same interim profit for all types of firms as that they initially have because the same efficient rent is maintained for all cost types $\left(\int_{\theta}^{\bar{\theta}} M\,(\theta;p)d\theta = \int_{\theta}^{\bar{\theta}} M\,(\theta;\tilde{p})d\theta\right)$.

In short, by taking account for the incentive constraint, firms choose their price scheme to determine the profit-at-the-top and choose whether to implement the corresponding market-share allocation along with corresponding price wars. As long as firms determine the profit-at-the -top and the market-share allocation, their interim profits are fixed with their own cost type.

Optimal Collusion among Patient Firms. Several steps were taken by Athey et al. (2004) in analyzing the optimal collusion among patient firms. A fully sorting[5] symmetric collusive scheme was first considered. Then they studied whether wars are

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[5] The definition of fully sorting is $p(\theta)$ is strictly increasing.

required on an equilibrium-path for an optimal SPPE. Finally, the optimal pricing scheme was established.

The possible profits with strictly increasing pricing function in the first period can be formed based on the SPPE constructed in the previous section. Because the pricing increase with firms' cost level, a firm with the highest cost has no sales and with the profit-at-the-top equal to $-T(\bar{\theta})$. Meanwhile, for any kind of fully sorting scheme, the market share allocation is always $M(\theta; p) = [1 - F(\theta)]^{n-1}$ because a firm only wins market share while all other firms announce their types with higher cost levels. Since the same market share allocations yield the same efficiency rents, fully sorting pricing schemes which satisfy on-schedule constraint are different only when their profit-at-the-top, $-T(\bar{\theta})$, is different. Therefore, the fully sorting pricing schemes which yield the best profit-at-the top are at the place that $T(\bar{\theta})$ equals zero. However, one of the fully sorting pricing schemes, the Nash-pricing Function, p^e, has $(p^e, T \equiv 0)$ satisfying (IC-onM). In the previous section, it was proved that $T \equiv 0$ corresponds to $\bar{v}(p(\theta), p) = \overline{\mathcal{V}}_s$ for all θ. As a result, the best collusive scheme that is fully sorting in the first period yields expected payoffs equal to $\pi^{NE} + \delta\overline{\mathcal{V}}_s$, the profit from the static Nash Equilibrium plus the discounted profit from the best available continuation SPPE.

Now consider the fully sorting pricing scheme in every period, and $\overline{\mathcal{V}}_s^{FS}$ is super than any other set of SPPE; then based on the discussion in the previous paragraph, $\overline{\mathcal{V}}_s^{FS}$ could be written as $\overline{\mathcal{V}}_s^{FS} = \pi^{NE} + \delta\overline{\mathcal{V}}_s^{FS}$. After this equation being rearranged, $\overline{\mathcal{V}}_s^{FS}$ is then expressed as $\overline{\mathcal{V}}_s^{FS} = \pi^{NE}/(1 - \delta)$; this equation means that the optimal SPPE with the condition that pricing is fully sorting in every period is simply firms playing the static Nash equilibrium.

No Wars on Equilibrium Path. This proposition by Athey et al. (2004) based on their lemma from their Mechanic Design Program and their Revenue Equivalence Theorem. First, from that lemma, any original scheme (p, T) including a price war could be replace an alternative no price war scheme which also satisfies the on-schedule constraints, provides the same profit-at-the-top, and maintains the same market-share allocation. Since the profit-at-the-top and the market-share allocation are the same, this alternative no price war scheme also provides the same rent efficiency and thus the same interim profit based on the Revenue Equivalence Theorem. The instruments to control the SPPE are price and war; thus, by trading war with higher prices, the no war scheme which provides the same interim profit as the original scheme exists. Incorporating the stationary proposition from the Mechanism Design Program into this argument, the following proposition is addressed:

"Allow for any distribution function F. If (p^*, T^*) is a solution to the Mechanism Design Program, then there exists as well a solution $\left(\tilde{p}, \tilde{T}\right)$ with $\tilde{p}(\theta) \leq p(\theta)$ and $\tilde{T}(\theta) \equiv 0$. Thus, if firms are sufficiently patient, there then exists an optimal SPPE that is stationary: firms use the pricing scheme $\tilde{p}(\theta)$ following every history along the equilibrium path, and $E_\theta \Pi(\theta, \theta; \tilde{p})/(1-\delta) = \overline{V}_s$."

After establishing the claim that the alternative schemes exist, Athey et al. then characterize the optimal SPPE pricing scheme when firms are patient, which implies a sufficient large δ[6],

(i) If the distribution function $F(\theta)$ is log-concave, or the difference between customer's reservation price, *r*, and the highest cost type, $\overline{\theta}$, is sufficiently large, the optimal SPPE would be that a firms charges the price at *r* in each period regardless of its own cost type, as long as all firms charge the price at *r* in all previous periods.

(ii) When firms are sufficiently patient, they can always have a higher profit in a single period by playing rigid pricing than playing the static Nash equilibrium. $\left(\overline{\mathcal{V}}_{\mathrm{s}}^{\mathrm{FS}} \geq \pi^{\mathrm{NE}}/(1-\delta)\right)$.

To prove the characteristics of the optimal SPPE above, a firm's expected payoff function is written from equation (2.12) with $T(\theta) \equiv 0$ (no price war).

$$E_{\theta}[\Pi(\theta,\theta;p)] = E_{\theta}\left[\pi\left(p(\overline{\theta}),\overline{\theta}\right)\cdot M\left(\overline{\theta};p\right) + \int_{\theta}^{\overline{\theta}} M\left(\tilde{\theta};p\right)d\tilde{\theta}\right]. \qquad (2.13)$$

[6] A sufficient large δ weights the future pay off more. Without this condition, firms would more like to deviate in the current period. This implies the condition that firms are sufficiently patient.

By borrowing the some rules from Bulow and Robert's (1989) study on optimal auction, the efficiency rent in the right bracket can be rewritten in the following way,

$$\int_{\theta}^{\overline{\theta}} M(\tilde{\theta};p)d\tilde{\theta} = \int_{\underline{\theta}}^{\overline{\theta}} f(\theta) \int_{\theta}^{\overline{\theta}} M(\tilde{\theta};p)d\tilde{\theta}\, d\theta = \int_{\underline{\theta}}^{\overline{\theta}} \int_{\underline{\theta}}^{\overline{\theta}} f(\theta)\, M(\tilde{\theta};p)Z(\theta,\tilde{\theta})d\tilde{\theta}d\theta$$

$$= \int_{\underline{\theta}}^{\overline{\theta}} M(\theta;p) \int_{\underline{\theta}}^{\theta} f(\tilde{\theta})\, d\tilde{\theta}d\theta = \int_{\underline{\theta}}^{\overline{\theta}} \left(F(\theta) - F(\underline{\theta})\right) M(\theta;p)d\theta$$

$$= \int_{\underline{\theta}}^{\overline{\theta}} F(\theta)\, M(\theta;p)d\theta = \frac{F}{f}(\theta) \cdot M(\theta;p)d\theta.^{7} \qquad (2.14)$$

Substituting the equation (2.14) into the term represents efficiency rent in the equation (2.13); firms' objective function is rewritten as

$$E_{\theta}[\Pi(\theta,\theta;p)] = E_{\theta}\left[\pi\left(p(\overline{\theta}),\overline{\theta}\right) \cdot M\left(\overline{\theta};p\right) + \frac{F}{f}(\theta) \cdot M(\theta;p)d\theta\right]. \qquad (2.15)$$

The profit-at-the-top, the first term in the right-hand side bracket, is determined by the profit of the firm with the highest cost level. To maximize the profit-at-the-top, all firms need to set the same price to prevent the firm with the highest cost level from under-pricing. As a consequence, firms gain the most profit by fixing their $p(\theta) \equiv r$ in each period.

The $F(\theta)/f(\theta)$ in the second term measures the contribution of an increase in type θ's profit to the firm's expected profit. The log-concave F is to make sure that $F(\theta)/f(\theta)$ is non-decreasing. Consequently, market share is allocated to the firms with higher types and away from those with lower types; these are also more efficient firms. This allocation of market share improves firms' cartel profits. As a result, firms' rigid-

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[7] $Z(\theta,\tilde{\theta})$ is defined to be zero for $\tilde{\theta} > \theta$ and one for $\tilde{\theta} \leq \theta$, which can be understood intuitively that firm's real cost type will not greater than the lowest cost realized in the market, otherwise the efficient rent will not exist.

pricing scheme $p(\theta) \equiv r$ not only maximized a firm's profit-at-the-top but also the expected efficiency rent term, $E_\theta\left[\frac{F}{f}(\theta) \cdot M(\tilde{\theta}; p)\right]$.

Before constructing a mathematic proof that a rigid-pricing scheme maximized the expected efficiency term, First Order Stochastic Dominance (FOSD) is introduced here first (Hadar & Russell, 1969). A random variable A has first-order stochastic dominance over the random variable B if for any outcome x, A gives at least as high a probability of receiving at least x as does B. In notation form,

$$Pr[A > x] \geq Pr[B > x] \text{ for all } x.$$

If the cumulative distribution function of A is F_A and of B is F_B , then A first-order stochastically dominating B means

$$F_A(x) \leq F_B(x) \text{ for all } x.$$

One of the results derived from FOSD is that if A first-order stochastically dominates B, then

$$E[h(A)] \geq E[h(B)] \text{ for all increasing function } h. \qquad (2.16)$$

Now considering that a firm has an expectation of its market share to be $1/n$, $E_\theta[M(\theta; p)] = 1/n$, before knowing its cost type, the probability distribution can be defined as:

$$\Phi(\theta; p) = n \int_{\underline{\theta}}^{\theta} M(\tilde{\theta}; p) f(\tilde{\theta}) d\,\tilde{\theta}. \qquad (2.17)$$

A rigid-pricing scheme p^R, implies $M(\theta, p^R) \equiv 1/n$. Since a price scheme is non-decreasing with cost type, market share allocation, $M(\theta, p)$, is non-increasing. This theory implies that given any kind of cost type, a rigid-pricing scheme provides the smallest market share allocation. Thus,

$$\Phi(\theta; p^R) = n \int_{\underline{\theta}}^{\theta} M(\tilde{\theta}; p^R) f(\tilde{\theta}) d\,\tilde{\theta} \leq \Phi(\theta; p) = n \int_{\underline{\theta}}^{\theta} M(\tilde{\theta}; p) f(\tilde{\theta}) d\,\tilde{\theta} \quad (2.18)$$

This means that $\Phi(.\,; p^R)$ dominates $\Phi(.\,; p)$ by FOSD for all p. In words, a rigid-pricing scheme puts the most weight on high-cost types. If $F(\theta)/f(\theta)$ is non-decreasing, with the derived result from FOSD (2.16), it follows that

$$E_\theta\left[\frac{F}{f}(\theta) \cdot M(\theta; p^R)\right] = \frac{1}{n}\int_{\underline{\theta}}^{\overline{\theta}} \frac{F}{f}(\theta) d\Phi(\theta, p^R) \geq \frac{1}{n}\int_{\underline{\theta}}^{\overline{\theta}} \frac{F}{f}(\theta) d\Phi(\theta, p)$$

$$= E_\theta\left[\frac{F}{f}(\theta) \cdot M(\theta; p)\right] \quad (2.19)$$

for all p non-decreasing. Finally, only a rigid-pricing scheme can be optimal because of the equation, $0 = \frac{F}{f}(\underline{\theta}) < \frac{F}{f}(\theta)$ for $\theta > \underline{\theta}$, with the assumption that f is greater than zero. If a pricing scheme is not rigid, more weight would be placed on $\frac{F}{f}(\underline{\theta})$.

When firms adopt a pricing scheme, $p(\theta) \equiv r$, the profit-at-top is maximized; meanwhile, this pricing scheme itself is also a optimal rigid-pricing scheme, guaranteeing the send term in firms' objective function. In short, when the cost distribution is log-concave, the optimal SPPE can be reached if firms are sufficiently patient and play rigid pricing at *r* in each period. This implies that the variability of firms' prices over time is smaller under a collusive regime than competitive regime.

A Dynamic Collusion Pricing Model

In many antitrust cases, it is the buyers, not the antitrust authorities, playing the important role in detecting a cartel's price-fixing behavior, for example, lysine and vitamin cases. Hence, in addition to focusing on the stability of the collusion, firms also devote efforts in avoiding detection from buyers. When setting prices, the cartel will consider what price pattern will, or will not, cause the buyer to suspect the existence of the cartel. An abnormal or unexplainable price pattern makes buyers become suspicious and take steps to engage in detection. Harrington and Chen (2006) pursue this idea and develop a novel theory of belief formation. In Harrington and Chen's theory, buyers have their own beliefs about price changes based on the historical prices, and when the likelihood of the recent prices based on this belief is very small, buyers will more likely become suspicious that a cartel may exist. Based on this theory, a dynamic programming problem is set up to present the process of the buyers forming their belief of price changes which determine the endogenous terminal date of a cartel. This terminal date determines the profit after the collusion is detected; the penalties are based on the price and cost during the collusion period.

There are several properties that have been found in Harrington and Chen's dynamic program system. Two phases construct the cartel price path: a transition phase and a stationary phase. In the stationary phase, price is much less volatile than price in a competitive regime or a monopoly regime. In the transition phase, under some specific parameter set in this model, the price path is rising, overshooting, and converging into stationary phases. This dynamic model shows that it takes more time for cost shocks passing through to price under a collusion regime. Although Harrington and Chen's dynamic model is obviously exploratory, the price paths from this model are more like the collusion pricing in the real business world than those that have been developed by the theory of collusive pricing. The following is the brief summary of their program system.

Market Condition. The Oligopoly Market is assumed to be symmetric and faces linear fixed market demand function overtime.

$$D(p) = a - bp, \qquad a, b > 0 \tag{2.20}$$

With the assumption of constant marginal cost which is allowed to vary stochastically, the industry profit becomes:

$$\pi(p, c^t) \equiv (p - c^t)(a - bp) \qquad \text{, where } c^t \text{ is the unit cost at time t.} \tag{2.21}$$

More assumptions were established for that stochastic marginal cost. First, c^t is a random walk with the boundary of $[\underline{c}, \overline{c}]$ and $0 \leq \underline{c} < \overline{c} < a$. The cost shock at time t, which is notated as ε^t, is assumed normally distributed and *i.i.d.* overtime. So costs are a stochastic process we can represent as:

$$c^t = v(c^{t-1} + \varepsilon^t) \equiv max\left\{\underline{c}, min\{c^{t-1} + \varepsilon^t, \overline{c}\}\right\} \tag{2.22}$$

Let $\hat{p}(c^t)$represent the price the firms charge when the collusion does not exist. Then the profit of the industry is expressed as:

$$\hat{\pi}(c^t) \equiv (\hat{p}(c^t) - c^t)\left(a - b\hat{p}(c^t)\right) \tag{2.23}$$

The present value of the industry's payoff at time t, $W(c^t)$, is the sum of discounted future expected profit.

$$W(c^t) = \hat{\pi}(c^t) + \delta \int W\left(v(c^t + \varepsilon)\right) f\left(\varepsilon; \mu_\varepsilon, \sigma_\varepsilon^2\right) d\varepsilon. \tag{2.24}$$

where δ is the discount factor and $\delta \in (0, 1)$; $f(\varepsilon; \mu_\varepsilon, \sigma_\varepsilon^2)$ is the density function for the normal distribution of ε.

Cartel Detection. Firms realize they have some probability of being detected when forming a cartel, and being detected involves being charged penalties. Instead of being detected by antitrust authorities, in reality, many cartel cases are detected by purchasers in the industries. For example, as McAnney (1991) discusses in his study:

> As a general rule, the [Antitrust] Division follows leads generated by disgruntled employees, unhappy customers, or witnesses from ongoing investigations. As such, it is very much a reactive agency with respect to the search for criminal antitrust violations. … Customers, especially federal, state, and local procurement agencies, play a role in identifying suspicious pricing, bid, or shipment patterns. (pp. 529, 530)

What often catches purchaser attention and alerts others to the existence of collusion behavior is anomalous pricing. Hence, in Harrington and Chen's (2006) study, they constructed a model that makes purchasers think there is possibility that firms are colluding. Unlike other papers using a Bayes-Nash equilibrium to form the collusion and non-collusive pricing function, their model does not assume that purchasers know the collusive pricing function or purposely look for it. The assumption in this model is that when some abnormal thing happens in the pricing pattern, buyers will be suspicious of the possibility of the formation of a cartel.

The underlying concept behind this model is that buyers have beliefs about the price process. Hence, when the buyers feel the observed price series significantly differs from their beliefs, they become suspicious about the possibility of cartel forming. Hence, the task in Harrington and Chen's study is to model what it means for buyers to observe an anomalous event. In the previous section, the stochastic process of a firm's marginal cost is a random walk with a normally distributed cost shock. As a consequence, the buyers' belief of the price series is also a random walk. So price at time t can be written as:

$$p^t = p^{t-1} + \eta^t \tag{2.25}$$

Here buyers know that η^t is normally distributed because they presume that the price function determined by the cost and the change in costs is normally distributed. However, buyers have no idea what the coefficients are of the costs which construct the price function and also do not know the moments of cost distribution. As a result, purchasers do not know the moments of the distribution of price changes, such as mean and variance. Hence, the way in which purchasers derive their belief of those moments of the distribution of price changes depends on their observed prices. The moments constructed by the buyers are the price changes from the k periods which buyers could memorize up to the current period t. The path of the price change could be show as:

$$\{\Delta p^{t-k}, \dots \Delta p^{t-1}\}, \qquad \text{where } \Delta p^{\tau} \equiv p^{\tau} - p^{\tau-1}$$

As a consequence, the *i*th moment of the distribution in t is based on purchasers' memory; it is expressed as,

$$m_i^{t-1} \equiv \frac{\sum_{\tau=t-k}^{t-1} (\Delta p^{\tau})^i}{k} \tag{2.26}$$

Purchasers assume that the price change over period is normal distributed based on the sampling moments, $N(m_1^{t-1}, m_2^{t-1} - (m_1^{t-1})^2)$. When buyers test a sequence of z < k most recent observed prices up to the price at period t, the likelihood of the z most recent price changes is specified to be

$$l^t \equiv \Pi_{\tau=t+1-z}^{t} f(\Delta p^{\tau}; m_1^{\tau-1}, m_2^{\tau-1} - (m_1^{\tau-1})^2) \tag{2.27}$$

The highest likelihood that the price change could be assigned over a period of time is the maximum likelihood. Since the time that buyers observe the price change is known, from z to t, the maximum likelihood is denoted as

$$ml^t \equiv \Pi_{\tau=t+1-z}^{t} \max_{y^\tau} f(y^\tau; m_1^{\tau-1}, m_2^{\tau-1} - (m_1^{\tau-1})^2)$$

$$= \Pi_{\tau=t+1-z}^{t} f(m_1^{\tau-1}; m_1^{\tau-1}, m_2^{\tau-1} - (m_1^{\tau-1})^2) \qquad (2.28)$$

The realized likelihood relative to maximum likelihood, $L^t \equiv l^t/m^{lt}$, determines purchasers' suspicions. It is assumed that the probability of detection decreases as the relative likelihood increases. The function can be formed as

$$\psi(L^t) \equiv \alpha_0 + \alpha_1(1 - L^t)^{\alpha_2}, \qquad \alpha_0 \geq 0, \alpha_1, \alpha_2 > 0 \qquad (2.29)$$

The constant, α_0, is the effect of detection not related to price, such as an incidental discovery or an internal whistleblower.

The first step to numerically implementing the model with anomalous event is to manipulate the moments:

$$m_i^t = \left(\frac{1}{k}\right) \sum_{\tau=t-k+1}^{t} (\Delta p^\tau)^i = \left(\frac{1}{k}\right) \sum_{\tau=t-k}^{t-1} (\Delta p^\tau)^i + \left(\frac{1}{k}\right) \left[(\Delta p^t)^i - (\Delta p^{t-k})^i\right]$$

$$= m_i^{t-1} + \left(\frac{1}{k}\right) \left[(\Delta p^t)^i - (\Delta p^{t-k})^i\right] \qquad (2.30)$$

This manipulation shows that to update moment *i* due to the observed price change from period *t-1* to *t*, a weight of *1/k* is transferred from the *t-k*th observation to *t*th observation. Now instead of being transferred from only one observation, a weight of *1/k* is transferred from all past observations and assigned to a new observation. The *i*th moment of the equation could be re-written as:

$$m_i^t = \left(\frac{1}{k}\right)\sum_{\tau=t-k+1}^{t}(\Delta p^\tau)^i + \left(\frac{1}{k}\right)\left\{(\Delta p^t)^i - \frac{1}{k}\left[(\Delta p^{t-1})^i + (\Delta p^{t-2})^i + \cdots + (\Delta p^{t-k})^i\right]\right\}$$

$$= m_i^{t-1} - \left(\frac{1}{k}\right)m_i^{t-1} + \left(\frac{1}{k}\right)(\Delta p^t)^i$$

$$= \left(\frac{k-1}{k}\right)m_i^{t-1} + \left(\frac{1}{k}\right)(\Delta p^t)^i \quad (2.31)$$

This equation can be generalized as the following:

$$m_i^t = (\lambda_i)m_i^{t-1} + (1-\lambda_i)(\Delta p^t)^i \quad (2.32)$$

By using an analogous procedure, the approximation of the likelihood is then

$$l^t = \left[l^{t-1}/(l^{t-1})^{\frac{1}{z}}\right]f(\Delta p^t; m_1^{t-1}, m_2^{t-1} - (m_1^{t-1})^2)$$

$$= (l^{t-1})^{(z-1)/z}f(\Delta p^t; m_1^{t-1}, m_2^{t-1} - (m_1^{t-1})^2) \quad (2.33)$$

Similar steps were used for the maximum likelihood, and we can thus derive the relative likelihood:

$$L^t = (L^{t-1})^\xi\left[\frac{f(\Delta p^t; m_1^{t-1}, m_2^{t-1} - (m_1^{t-1})^2)}{\max_y f(y; m_1^{t-1}, m_2^{t-1} - (m_1^{t-1})^2)}\right], \qquad \xi \in (0,1) \quad (2.34)$$

The value of ξ reflects the magnitude of the price change observations used by purchasers in testing. However, instead of knowing k state variables, now purchasers' focus will be on the three state variables, (m_1^t, m_2^t, L^t).

Some further assumptions are made to simplify the model; Φ, which represents the set of price changes, is assumed to be finite for numerical purposes. As a result, the price changes in purchasers' beliefs are a discrete normal distribution. A probability density function of a normal distribution, $f(.,\mu,\sigma^2)$, is replaced with $h(.,\mu,\sigma^2)$ where:

$$h(\eta';\mu,\sigma^2) \equiv \begin{cases} \dfrac{f(\eta',\mu,\sigma^2)}{\sum_{\eta\in\Phi} f(\eta,\mu,\sigma^2)} & if\ \ \eta' \in \Phi \\ 0 & otherwise \end{cases} \tag{2.35}$$

Harrington and Chen (2006) then assume that the cartel's damages will evolve in the following manner:

$$X^t = \beta X^{t-1} + \gamma x(p^t, c^t)$$

where $\beta \in [0,1], \gamma \geq 0, p^t$ is the cartel price at time t . (2.36)

The symbol X^t is the cartel's damages at the time when the cartel is detected. Since it is difficult to document the damage occurred in the period prior to the detection, a deterioration rate, $1-\beta$, is assigned in (2.36). In the other words, instead of catching the full damage from previous period, X^t includes only part of the damage from the previous period. The level of damages at the current period t is expressed as $x(p^t, c^t)$ with a multiplier, γ, which is the firm's expectation of the payment if the cartel is caught. To be consistent with U.S. antitrust practices, a specific formula is constructed:

$$x(p^t, c^t) = \left(p^t - \hat{p}(c^t)\right)(a - bp^t) \tag{2.37}$$

The competitive benchmark, or "but for" price in the equation (2.37) is $\hat{p}(c^t)$, so the price overcharged by the cartel is $p^t - \hat{p}(c^t)$.

The problem that a cartel faces is choosing the price in the current period, t, with the state variables $(p^{t-1}, X^{t-1}, c^t, m_1^{t-1}, L^{t-1})$. The symbols p^{t-1} and X^{t-1} represent the price and accumulated damage prior to the current period respectively; c^t is the cost in the current period. The first moment of the price change in the purchasers' belief is donated as m_1^{t-1}, and the relative likelihood that purchasers attach to recent prices is donated as L^{t-1}. If the price change in the current period is given as η^t, the equations of motion can be expressed as:

$$\mathrm{p}^t = \mathrm{p}^{t-1} + \eta^t$$

$$c^{t+1} = v(c^t + \varepsilon^{t+1})$$

$$X^t = \beta X^{t-1} + \gamma x(\mathrm{p}^{t-1} + \eta^t, c^t)$$

$$m_1^t = \lambda(\mathrm{m}_1^{t-1}) + (1-\lambda)\eta^t$$

$$L^t = (L^{t-1})^{\xi}\varphi(\eta^t, \mathrm{m}_1^{t-1}),$$

$$\text{where } \varphi(\eta^t, \mathrm{m}_1^{t-1}) \equiv \left[\frac{h(\eta^t;\ \mathrm{m}_1^{t-1}, \mathrm{w}_1^2\sigma_\varepsilon^2)}{h(m_1^{t-1};\ \mathrm{m}_1^{t-1}, \mathrm{w}_1^2\sigma_\varepsilon^2)}\right] \quad (2.38)$$

The price the cartel chooses will not be lower than the lowest costs among cartel members, $\underline{c}$. Meanwhile, the highest price that the cartel can charge, $\overline{p}$, is higher than the joint profit-maximizing price. To make sure price changes remain within this boundary, the set of price changes is slightly modified as,

$$\Phi(p^{t-1}) \equiv \{\eta \in \Phi: \mathrm{p}^{t-1} + \eta \in [\underline{c}, \overline{p}]\} \quad (2.39)$$

By adopting the equations in (2.38), the cartels' objective function is defined recursively:

$$V(p^{t-1}, X^{t-1}, c^t, m_1^{t-1}, L^{t-1}) = \max_{\eta^t \in \Phi(p^{t-1})} \pi(p^{t-1} + \eta^t, c^t) + \delta\psi\left((L^{t-1})^{\xi}\varphi(\eta^t, m_1^{t-1})\right)$$

$$\times\left[\int W\big(v(c^t + \varepsilon)\big) f(\varepsilon; \mu_\varepsilon, \sigma_\varepsilon^2)\, d\varepsilon - \beta X^{t-1} - \gamma x(p^{t-1} + \eta^t, c^t) - F\right]$$

$$+\delta\left[1 - \psi\left((L^{t-1})^{\xi}\varphi(\eta^t, m_1^{t-1})\right)\right] \times \int V(p^{t-1} + \eta^t, \beta X^{t-1}$$

$$+\gamma x(p^{t-1} + \eta^t, c^t), v(c^t + \varepsilon), \lambda(m_1^{t-1}) + (1-\lambda)\eta^t, (L^{t-1})^{\xi}\varphi(\eta^t, m_1^{t-1})\,)$$

$$\times f(\varepsilon; \mu_\varepsilon, \sigma_\varepsilon^2) d\varepsilon. \quad (2.40)$$

This first term in the function above represents what the cartel earns as current profit by increasing price by η^t. The expected future profit that a cartel can earn depends on the probability of a cartel's being detected, $\psi\left((L^{t-1})^{\xi}\varphi(\eta^t, m_1^{t-1})\right)$. If the cartel is detected, firms receive non-collusive profits after detection and need to pay the penalties of overcharges and fines. If the cartel is not detected, the cartel's expected future profit is that which is attached to colluding, given the new values to the state variables.

By using certain specific parameters, Harrington and Chen (2006) then produced a collection of price paths to identify how a cartel price path compares to that for a non-collusive industry. Several results came from the price patterns they produced. Figure 2 shows their simulated cartel price path:

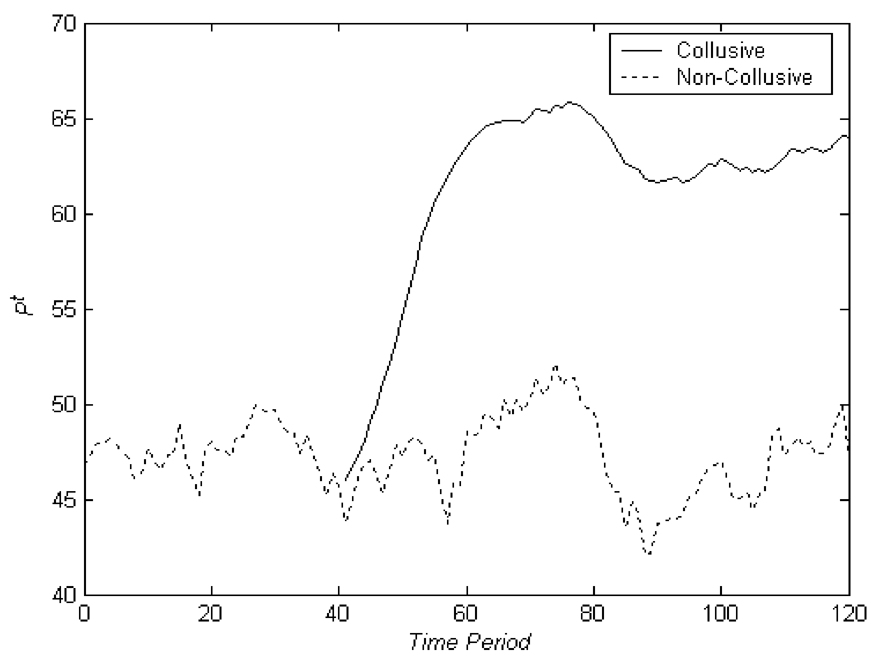


Figure 2. Simulated Cartel Price Path
Source: Harrington and Chen (2006)

According to their simulated price path, they first found that there are a transition phase and a stationary phase on the cartel price path. The price moves largely independent of cost in the transition phase and is responsive to cost in the stationary phase. The price rises steadily and may decrease modestly in the transition state. The next finding is that two conditions cause the period to become shorter, and the price path rises faster in the transition phase. One condition occurs when the variance of cost shock is greater and the other one is at the time the purchasers' beliefs are more sensitive to recent price changes. Their final finding regarding the simulated price path, which is also the main concern in this study, is that the variability of the cartel price is much less than the non-collusive price.

Based on the theories discussed in this chapter and many empirical studies[8], the lower variance on price series is a remarkable marker for firms' collusive behavior. Because of this result of firms' collusive behavior on price patterns, a methodology which can detect the change of variance will be able to detect the true timing of successful collusive periods.

[8] An example has been discussed in Introduction.

Chapter 3

The Iterated Cumulative Sums of Squares Algorithm

Inclan and Tiao (1994) studied the detection of multiple changes of variance in a sequence of time series. They consider data series that exhibit a stationary behavior for some time; then suddenly the variability of the error term changes; it stays constant again for some time at this new value, until another change occurs. Their approach proposes using cumulative sums of squares to search for change points systematically at different pieces of the series. This approach is based on a centered version of the cumulative sum of squares in Brown, Durbin, and Evens' (1975) study.

Centered Cumulative Sums of Squares

In order to detect the point of variance change of a series, the variance of a given sequence of observations should be studied retrospectively. Let $C_k = \sum_{t=1}^{k} A_t^2$ represents the cumulative sum of squares of a series of uncorrelated random variables $\{A_t\}$ with mean zero and variances σ_t^2, t = 1, 2… and then the centered (and normalized) cumulative sum of squares can be written as

$$D_k = {}^{C_k}/_{C_t} - {}^{k}/_{T}, k = 1, \dots, T, \text{with } D_0 = D_T = 0 \qquad (3.1)$$

If the series is with homogenous variance, the plot of D_k against k will oscillate around 0. If there is a sudden change in variance at some observation, the plot of D_k will have a high probability of showing a pattern going out of some specified boundaries. These boundaries are decided from the asymptotic distribution of D_k which assumes constant variance. Because of this behavior of D_k , a variance change point can be searched via $\max_k|D_k|$; k^* is assumed to be the value of k so that $\max_k|D_k|$ is attained at k. Then we should see if the maximum absolute value goes over a predetermined boundary. If it does, we may conclude two things: the change point is near k^*, and k^* can be taken as an estimate of the change point. According to the theory of variance homogeneity, the asymptotical behavior of $\sqrt{T/2}\, D_k$ is similar to that of a Brownian bridge, where the asymptotic critical value of $D^*_{.05}$ equals 1.358 ($D^*_{.10}$ equals 1.224) (see Table 2). Hence, that the upper and lower boundaries in the D_k plot are at ±1.358 (±1.224). When D_k falls out of these boundaries, the possible change of variance exists.

Figure 3(a) represents a white noise series with homogenous variance, and Figure 3(b) is a series with two changes of variance. The first break is at t=235, and the other break is at t=279. The variances are $\sigma_t^2 = \tau_0^2 = 0.000093, t = 1, \ldots, 234; \sigma_t^2 = \tau_0^2 = 0.001288, t = 235, \ldots 278$; and $\sigma_t^2 = \tau_3^2 = 0.00384, t = 278, \ldots 368$. The C_k functions of these two series are shown in Figure 3(c) and 3(d). Figure 3(c) shows the C_k functions of the series with constant variance, where C_k presents roughly a straight line with slope $\sigma^2 = 0.00005$. The plot in Figure 3(d) appears as some broken lines consisting of several straight pieces. These broken lines occur when there are changes in the variance of the series.

Although the example shown in Figure 3(d) has the slope of C_k dramatic changes when there is a change in variance, in some series, the slope of C_k changes slightly. Since sometimes the change of slopes in C_k is not dramatic and the C_k function is always positive, the plot of D_k presents a better picture. Even with a slight change in the plot of C_k, the slope of D_k shows a drastic change with a change of sign. When the variance changes to a smaller value, the slope of D_k creates a peak; in contrast, when the variance changes to a greater value, the slope creates a trough. Unlike C_k which appears as a straight line with a positive slope, the plot of D_k is a horizontal visual reference. Figures

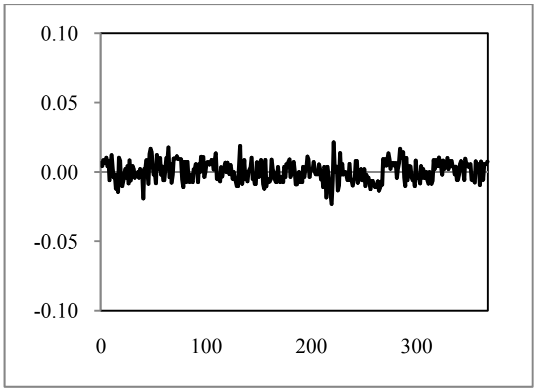
3(e) and 3(f) are the plots of D_k of the series with constant variance and the series with two variance changes, respectively. However, as we can see in the figure 3(f), there are many points which fall out of the boundaries; in order to detect the real change points of volatility, Inclan and Tiao (1994) generate the ICSS algorithm which will be discussed in the next section.

Table 2

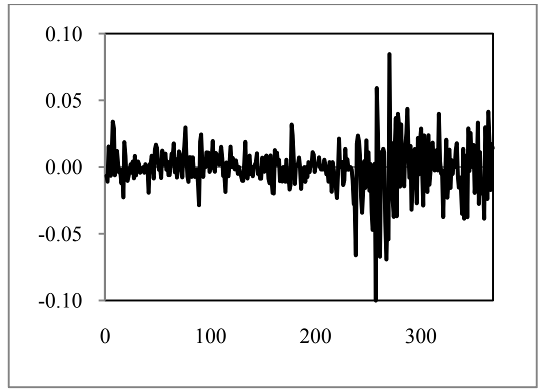
Empirical and Asymptotic Quantiles of $max_k \sqrt{T/2}\,|D_k|$

T	100		200		300		400		500		∞
p	q_D	SE	q_D	SE	q_D	SE	q_D	SE	q_D	SE	D^*_{1-p}
.05	.44	.003	.47	.003	.47	.003	.48	.003	.049	.003	.520
.10	.50	.003	.52	.003	.53	.003	.53	.003	.054	.002	.571
.25	.60	.004	.63	.003	.63	.003	.64	.003	.065	.003	.677
.50	.75	.004	.78	.003	.78	.003	.79	.003	.080	.003	.828
.75	.94	.004	.97	.004	.97	.004	.97	.004	1.00	.004	1.019
.90	1.14	.006	1.16	.006	1.18	.007	1.18	.006	1.20	.006	1.224
.95	1.27	.009	1.30	.004	1.31	.008	1.31	.010	1.33	.009	1.358
.99	1.52	.004	1.55	.012	1.57	.028	1.57	.020	1.60	.018	1.628

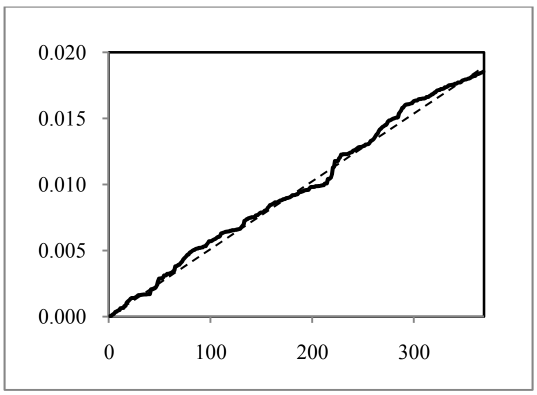
Note. Estimated from 10,000 replicates of series of T independent N(0,1) observations D^*_{1-p} is defined by $P\{\sup_t |W^0_t| < D^*_{1-p}\} = p$.
Source: Inclan and Tiao (1994)



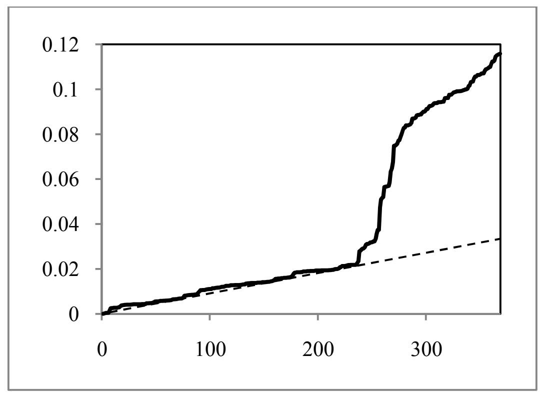
(a)
N(0.0,00005) white noise
Homogeneous Variance



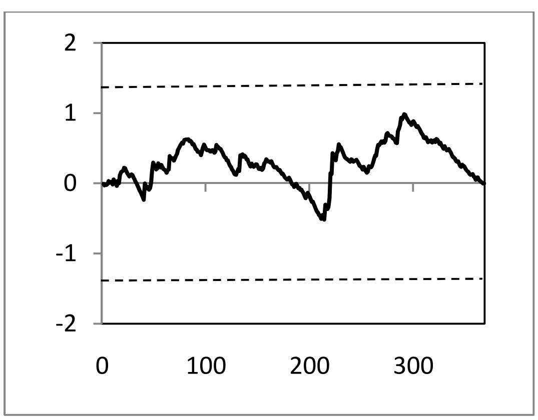
(b)
Two variance changes: (235, 279)
Variances are: 0.00009, 0.00129, and0.00038



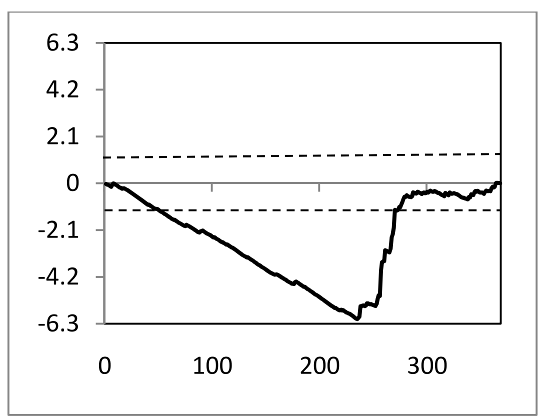
(c)
Cumulative Sum of Squares



(d)
Cumulative Sum of Squares



(e)
Centered Cumulative Sum of Squares (D^k plot)



(f)
Centered Cumulative Sum of Squares (D^k plot)

Figure 3. Cumulative Sum of Square and Centered Cumulative Sum of Squares Plots
Source: The IBM stock closing prices as reported by Box and Jenkins (1976)

The ICSS Algorithm

The D_k function does not always provide a satisfactory procedure. It may provide a satisfactory procedure only when the possible existence of a single point of change is taken into consideration. The question regarding the usefulness of the D_k function arises when multiple points of variance change on an observed series are points of interest. This problem can be solved by following an iterative scheme. The scheme depends on the successive application of the D_k function to pieces of the series. When a possible change point is found, the function divides it consecutively.

It is assumed that $A[t_1 : t_2]$ represents the series $A_{t1}, A_{t1+1}\dots, A_{t2}$, $t_1 < t_2$ and $D_k(A[t_1 : t_2])$ represents the range over which the cumulative sums are obtained. The steps below are the procedure of iterated cumulative sums of squares algorithm,

Step 1: Set $t_1 =1$;

Step 2: Find $k^*(A[t_1:T])$, which is the point where $\max_k|D_k(A[t_1:T])|$ is obtained, by calculating $D_k(A[t_1:T])$, where T is the total time zone.

Let $M(t_1:T) = \max_{t_1 \le k \le T} \sqrt{(T - t_1 + 1)/2}|D_k(A[t_1:T])|$. Compare M and D^*, which is 1.358 (or 1.224), when p=.95 (or p=.10). If $M > D^*$, we consider there to be the change point at k^*, and proceed to next step. If $M < D^*$, k^* is not considered to be the change point in the series and the algorithm stops.

Step 3: Let $t_2 = k^*$. Then calculate $D_k(A[t_1:t_2])$, and compare $M(t_1:t_2)$ and D^*. If $M > D^*$, then there is a new change point, and we need to repeat Step 3 until $M < D^*$. Then the first change point is $k_{first} = t_2$. Similarly, let $t_1 = k^* + 1$ and calculate $D_k(A[t_1:T])$. When $M < D^*$, let $k_{last} = t_1 - 1$.

Step 4: When $\mathrm{k_{first}} < \mathrm{k_{last}}$, we need to repeat Step 2 and Step 3 on the series between $\mathrm{k_{first}}$ and $\mathrm{k_{last}}$.

Step 5: Finally, we should arrange the possible change points in an increasing order if we find out two or more change points are possible. Suppose *cp* is the vector of all the possible change point found so far. Then we define the two extreme values $cp = 0$ and $p_{N_{T+1}} = 1$, where $\mathrm{N_T}$ is the total change points found in the previous steps. To check each possible change point, we calculate $D_k\left(A\left[cp_{j-1} + 1 : cp_{j+1}\right]\right), j = 1, \ldots, N_T$. We should keep the point only if $M\left(cp_{j-1} + 1 : cp_{j+1}\right) > D^*$. This step needs to be repeated until both of the following requirements are met: the number of change points does not change any more, and the points found in each new pass are "close" to those in the previous pass.

The Literature with Applications of the ICSS Algorithm

The ICSS Algorithm has been commonly used in the finance research field. Many economists, researchers, and policy makers are interested in volatility changes in a variety of stock markets, exchange markets, and future markets. Among those researching these market structures, the ICSS algorithm is used very often in detecting changes of volatility.

Aggarwal, Inclan, and Leal (1999) examined whether global or local events are more important in causing large shifts in the volatility of emerging stock markets. At the same time, they also examined the events which cause large shifts in the volatility; these events tend to be social, political, or economic events. Unlike many other studies in which regime shifts are first indentified, their study first detected shifts in volatility from the data, and then examined local and global events that occurred around those time periods. The method that they used to detect points of sudden changes in variance is the ICSS algorithm. After the changes points were detected, they introduced a dummy variable into the variance equation of the GARCH model to account for the sudden changes in variance. They concluded their finding that those major changes in volatility seem to be related to important country-specific political, social, and economic events. The only global events which cause significant change in the volatility of several stock markets is the crash in October 1987.

Bracker and Smith (1999) found that copper futures returns are characterized by negative skewness and excess kurtosis which contribute to their volatility. They first detected alternating sub-periods of volatility by using the ICSS algorithm to identify break-points in the series, and then they compared the ability of random walk, GARCH, EGARCH, AGARCH, and the GJR model to capture the volatility within each ICSS identified sub-period.

Malik (1999) detected time periods of sudden changes in volatility by using the ICSS algorithm for the Japanese yen, British pound, Canadian dollar, French franc, and German mark from January 1990 to September 2000. He then examined economic events surrounding those shifts and incorporated these sudden changes in variance to the standard GARCH model. By accounting for volatility shifts in the model, the persistence in volatility was reduced.

Knowing that financial market participants are interested in what events can change the volatility pattern of financial assets and how unanticipated shocks determine the persistence of volatility over time, Malik and Hassan (2004) studied these issues by detecting time periods of sudden changes in volatility by using the ICSS algorithm. They examined financial, industrial, consumer, health, and technology sectors in Dow Jones indexes with the data series cross from January 1992 to August 2003. They found that accounting for volatility shifts in the standard GARCH model considerably reduces the estimated volatility persistence. These results have important implications regarding asset pricing, risk management, and portfolio selection.

Solakoglu and Demir (2009) studied the sensitivity of firm value to fluctuations in exchange rates using a market model for Turkey's financial sector. They utilized the ICSS algorithm to identify the breakpoints in their samples. Based on the breaks, they selected a stable period to analyze what roles the firm-specific factors play on significant exposure to exchange-rate movements. Then they used a logistic regression and considered only significant exposures. Their results indicate that exchange rates movement more likely has less effect on larger firms. Family ownership, on the other hand, causes an increase in the probability of observing significant exposure.

Wong and Moore (2009) also used the ICSS algorithm to investigate sudden changes in volatility in the stock markets of new European Union (EU) members. The data in their study is a weekly series and the sample period is from 1994 to 2006. They first identified shifts in volatility with the ICSS algorithm. After the breakpoints of variance changes were identified, Wong and Moore modified the standard GARCH model by including the dummy variables for these breakpoints. By utilizing the ICSS algorithm, they detected a time period of sudden change in variance of returns and the length of this variance shift. Their study shows that sudden changes in volatility seem to arise from the evolution of emerging stock markets, exchange rate policy changes, and financial crises.

Chapter 4

Two Empirical Studies

The majority of applications of the ICSS algorithm have been in finance. One reason is that it is easier for researchers to access financial data and reach the number of data points required for this technique. As mentioned in the previous chapter, the ICSS algorithm detects breakpoints better when the sample size is greater than two hundred observations. The other reason is that for financial researchers or investors to obtain a more profitable asset portfolio, changes in volatility persistence are one of their main concerns.

Using the theory that data series should exhibit price rigidity in the collusion period, (i.e., smaller variance within the cartel period), this is the first study to adopt the ICSS algorithm in forensic economics. Two empirical cases, the flat glass and steel industries, are studied in this chapter. Monthly data were used in these cases. In most antitrust investigations, the daily transaction data are available between sellers and buyers, and thus data sets of sufficient size are not unexpected.

Flat Glass Antitrust Litigation in the late 1980s and early 1990s

In 1993, two ex-executives of Libbey-Owens-Ford Company ("LOF," a subsidiary of the British glass producer Pilkington LLC), which is one of five major flat glass manufacturers, alleged that during the early 1990s, LOF had conspired with its competitors to fix the price of the glass product it sold.(In re Flat glass Antitrust Litigation, 2002) Because of their allegation, in 1997, the plaintiff filed several private antitrust lawsuits to allege LOF and its competitors violated the Sherman Act and the Clayton Act. (In re Flat glass Antitrust Litigation, 2002). These lawsuits were consolidated and were certified by the court with a conspiracy period between August 1991 and December 1995. The plaintiffs contended that the five major producers of flat glass conspired to fix prices and allocate markets in both flat glass and automotive replacement markets during the class period. The five major manufacturers were LOF; AFG Industries, Inc. ("AFG"); Ford Motor Co. ("Ford"); Guardian Industries Corp. ("Guardian"); and PPG Industries, Inc ("PPG"). The plaintiffs alleged that the defendants formed and maintained their conspiracy through a series of letters, conversations, and meetings, including at industry trade shows. The plaintiffs' allegations regarding price-fixing in the market for flat glass are relatively straightforward. Therefore, this study will focus on the allegation of the defendants' conspiracy in flat glass (In re Flat glass Antitrust Litigation, 2004).

The Background of the Flat Glass Industry. Flat glass is glass produced through what is called a float process in various options of size, thickness, and tint.[1] The U.S. flat glass industry earns multi-billions of dollars in revenue annually. However, this "big money" industry was almost exclusively shared among five producers- PPG, LOF, AFG, Guardian, and Ford. These five companies manufacture well over 90% of the flat glass sold in the United States. Their market shares for 1995, based on shipments, are presented in Table 3.

After the float process, flat glass could be sold as is, and this kind of flat glass is used primarily in construction. Flat glass also can be "fabricated" into a variety of products by subjecting it to a variety of processes. For example, the automobile industry

[1] Float Process is to poured molten glass over a bath of a high-density liquid, such as molten tin. As the glass floats on the top of the bath, it is polished under controlled temperatures. Finally, the glass is fed into an "annealing oven" where it gradually cools and hardens.

uses a substantial amount of fabricated flat glass. Flat glass may be molded and combined with other parts to produce windshields as well as side and rear windows.

Table 3
Market Shares of Major Flat Glass Producers in 1995

Company	Market Share
PPG	28%
LOF(Pilkington)	19%
AFG(Asahi)	19%
Guardian	15%
Ford	15%
Total	**97%**

Source: In re Flat Glass Antitrust Litigation (MDL No. 1200), No. 03-2920, (3d Cir.2004).

In this antitrust case, the plaintiffs offered substantial evidence tending to show that the defendant companies mentioned previously had a motive to enter into a price-fixing conspiracy because of the characteristics of this industry. First of all, the flat glass market was concentrated mainly in the defendants as described above. Since this market was controlled by this small amount of manufacturers and the fixed cost of entry to this industry was very high, no “fringe market” was available for smaller firms. This limitation results in the entry barriers to the flat glass industry being very high. Secondly, flat glass is generally a standardized product or what called a "commodity" product even though it may vary in tint or thickness. This "commodity" characteristic results in the price being the main reason that affects the purchasing decision. Flat glass is sold primarily on the basis of price, and although it may vary in tint or thickness, it is generally a standardized product. The plaintiffs also showed that the demand for flat glass was in decline in the beginning of the 1990s, and the defendants had excess capacity. According to the economic theory, a decrease in demand and an excess in supply would cause the price to decrease. According to many economics text books, these characteristics of the flat glass industry make this industry susceptible to efforts to maintain collusion pricing.

Beside the characteristics of the flat glass industry, the evidence showing that the price increase was not correlated with any changes in costs or demand is an "anti-competitive" behavior. For example, in July of 1992, a PPG executive noted that "no one believes that demand will be robust enough to support a price increase without significant discipline on the part of all float producers." After a price increase of flat glass in September 1992 was implemented by the producers, a note from the same executive addressed that this increase was not supported by basic supply and demand. (In re Flat glass Antitrust Litigation, 2004).

Documents of Manufacturers' Conspiracy. "Traditional" conspiracy evidence comes from documents of the firms' agreements. A series of evidence shows that these five manufacturers agreed to raise the price of flat glass during three specific time frames: June-July of 1991, September-October of 1992, and May-June of 1993.

In LOF's responding document to the Antitrust Division, even though it does not directly state that it agreed with PPG to raise prices, one could infer such an agreement from LOF's reference to an "across-the-board" price increase. According to *Black's Law Dictionary*, "across-the-board" means "applying to all classes, categories, or groups." LOF's statement could be interpreted into three reasonable ways: First, LOF agreed with one or more competitor to increase the price of all types of flat glass; Second, LOF agreed with all its competitors to increase prices on one or more category of flat glass; and Third, LOF agreed with all its competitors to increase the price of all types of flat glass.

On July 15, 1991, one of the defendants, AFG, first raised its prices, but none of its competitors followed suit. However, not too long after AFG's action, LOF executives expressed that an 8% increase in flat glass prices would "hold" at a board meeting. After meeting with two board members, PPG raised its flat glass prices by basically the same amount that LOF executives thought would "hold." During this period, the price being increased by the same amount among flat glass manufacturers was initially successful, but later became unsuccessful due to some of manufacturers' failing to "hold the line."

According to an internal email, a Ford Regional Sales Manager had known the precise date and amount that LOF was going to announce a price increase almost three months ahead of time. Although a PPG executive did not believe that the market would support a price increase, PPG and its competitors raised their prices by the same amount, all within eight days of each other. After the price increases were announced, executives from the various flat glass manufacturers participated in a trade show. At that show, an executive from Guardian gave an executive from Pilkington a guarantee that Guardian would be "fully supportive of the price increase proposition."

In December of 1992, AFG and LOF discussed a price increase plan in May or June 1993. Meanwhile, LOF also referred to such an increase for its budget for the fiscal year 1994. A few months later, AFG faxed to PPG and Guardian a copy of a 5.5% increase of the flat price which it planned to announce on May 17, 1993. After receiving this fax, PPG announced an identical increase on May 12, and the rest of the flat glass producers quickly followed suit. In an LOF report, it stated that LOF was "monitoring the market to make sure that all stick to the rules." This time all flat glasses manufacturers held this price increase firmly. In other words, no manufactures deviated at this time, and this price increase was considered successful.

Data. Due to the legal issue, the internal transaction data of flat glass in this antitrust case could not be revealed. In order to get an approximation of the flat glass transaction price, the Producer Price Index (PPI) was used in this study. The Producer Price Index Program measures the average change overtime in the selling prices received by domestic producers for their output. Therefore, PPI for flat glass was considered a good approximation for the flat glass transaction data. The monthly flat glass PPI from January 1980 to December 1996 was obtained from Bureau of Labor Statistics. The reason this time frame was chosen is that it ended after the claimed class period and before the litigation started, and also provided sufficient observations.

One thing to address here is that the residual which is the regression result of the price of products on demand and supply factors may be considered a comparable data series for applying the ICSS algorithm. However, the residual is actually not as good as the price to be studied here based on theoretically and empirically reasons. Based on the theories discussed in Chapter 2, it is price rigidity rather than residual rigidity within the collusion period. Empirically, the daily and weekly transaction data are available in litigation cases and thus provide sufficient amount of data for the ICSS algorithm to use. However, data represented demand and supply factors are usually obtained from public sources and thus cannot provide sufficient amount of data. Therefore, in this study, the modified price series is used for the examination of the ICSS algorithm.

The Results of the ICSS Algorithm. According to those theories discussed in Chapter 2, the variance of price is lower within the collusion period than within the competitive period. Based on this characteristic of pricing patterns in the collusion period, the ICSS algorithm is applied here to detect the change of the price variance.[2] The change of price variance provides the possibility of collusion existing. Figure 4 shows the PPI series for flat glass. One condition of the series that ICSS can be utilized is that the series needs to have a zero mean. Hence, the PPI for flat glass was modified by the equation 4.1 to get a modified series which has a zero mean and still has the approximate volatility for the PPI of flat glass. The following equation

$$\hat{p} = \frac{p}{\bar{p}} - 1 = \frac{p - \bar{p}}{\bar{p}} \qquad (4.1)$$

Where $\hat{p}$ represent the modified price series, p is the PPI for flat glass, $\bar{p}$ is the average of the PPI for flat glass over time. This modified series reflects the percentage deviation of the PPI above or below the average PPI for flat glass. The modified series for flat glass PPI shows in Figure 5. The time periods of a shift in volatility of the modified series which are identified by the ICSS algorithm are shown in Table 4.

[2] The ICSS Algorithms were running by *WinRats*, version 7.30. published by Estima.

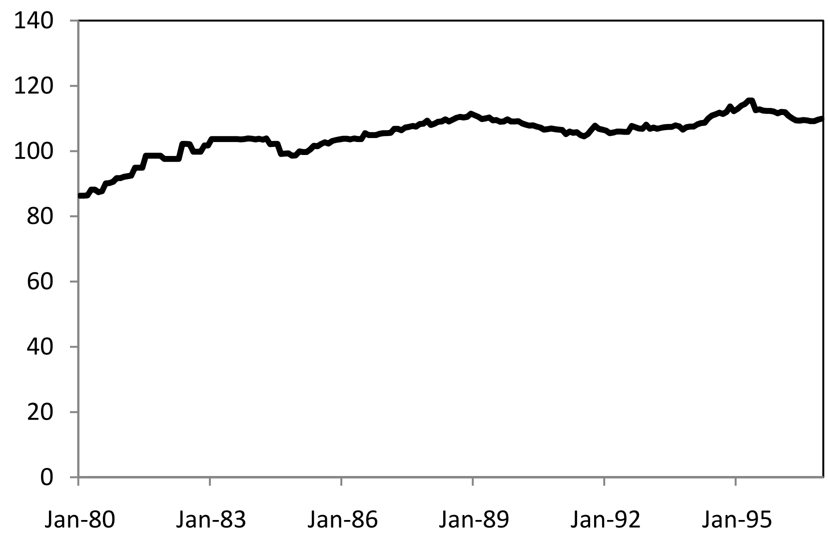


Figure 4. Producer Price Index for Flat Glass (1980-1996)

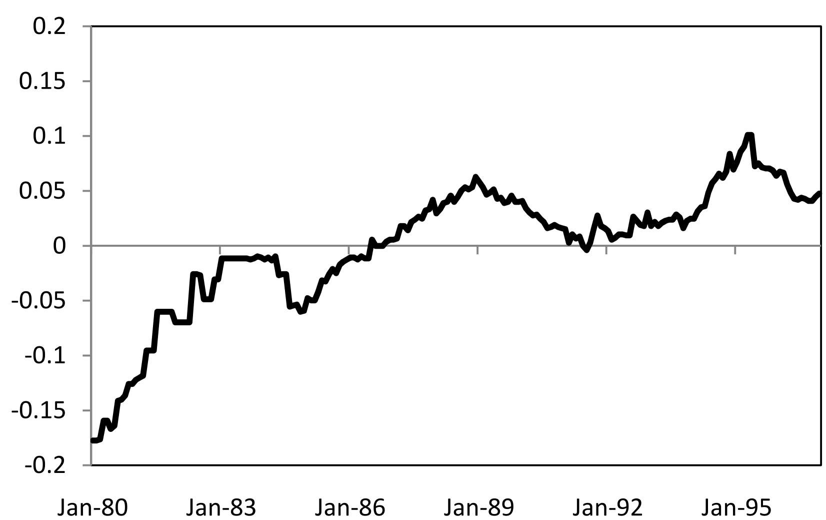


Figure 5. Modified Series of PPI for Flat Glass PPI (1980-1996)

Table 4
Sudden Changes in Volatility of PPI for Flat Glass

Producer Price Index	No. of change points	Time Period	Variance	Standard Deviation
Flat Glass	7	January, 1980-March, 1982	18.10317	4.25478
		April, 1982-November, 1982	2.52852	1.59013
		December, 1982-June, 1984	0.38900	0.62370
		July, 1984-May, 1985	1.20167	1.09621
		June, 1985-October, 1987	3.06679	1.75123
		November, 1987-February, 1990	0.62068	0.78783
		March, 1990-February, 1994	0.78134	0.88393
		March, 1994-December, 1996	3.00377	1.74291

Note. All variance were multiplied by 10^4, and all standard deviation were multiplied by 10^2.

The time periods of December1982 to June 1984 and November 1987 to February 1990 have a lower variance than the periods before and after. The variance of the period of December1982 to June 1984 was about 0.39, which is about six times lower than the previous period and about three times lower than the following period. The variance of the period before November 1987 to February 1990 is more than five times larger than the variance of November 1987 to February 1990. Even though the variance of the period after November 1987 to February 1990 does not increase dramatically, it still shows the possible cheating or falling apart of the defendants' collusive behavior. Therefore, these two time periods, December 1982 to June 1984 and November 1987 to February 1990, with the relatively lower variances are the suspected time periods that the defendants' successful collusive behavior possibly existed, more precisely, the time periods that the price was affected by the existing collusion.

Damage Analysis. To estimate the damage in class action price-fixing litigation, forensic economists first determine the percentage of overcharge, which is the extent to which prices during the conspiracy were higher than they would have been absent the conspiracy. Hence, overcharges are frequently measured by comparing actual prices during the conspiracy to competitive-benchmark prices that reflect the prices existing in a more competitive environment. The competitive benchmark prices are the prices charged by the defendants within the periods of an unsuccessful conspiracy. Beside the effect from defendant's collusive behavior, other forces may cause prices to differ between the conspiracy period and the pre- and post-conspiracy periods. To distinguish the effects of these forces from the effect of the conspiracy, the damage analysis relies on the statistical technique of regression analysis.

The class of models referred to as linear regression models is used to estimate the relationship between the price of product and the explanatory variables (demand and supply and the conspiracy variables). To study the movement of the price of flat glass in response to demand and supply factors, the demand and supply equations are combined into a single equation (by equating the quantity demanded to the quantity supplied), which is a reduced form equation. The price of flat glass is thus dependent on both demand and supply factors. Since the price-fixing conspiracy is an exogenous event – that is not induced by the natural forces of demand and supply – that might influence price, the regression equation also contains a dummy variable for the period of the suspected conspiracy. Estimating the reduced form equation through regression analysis yields parameter estimates for all of the demand and supply variables, as well as the conspiracy variable. The regression model for this flat glass study is a reduced form equation as:

$$LFLAT = F\ (FRIT,\ NATGAS,\ WAGE,\ CONSTRUCTION,\ CONSPIRE) \qquad (4.2)$$

where, *LFLAT* = Logged value of monthly Producer Price Index for flat glass.

FRIT = Frit composite index.

NATGAS = The monthly price series of natural gas.

WAGE = The quarterly wages for all employees in the industry of flat glass (in millions).

CONSTRUCTION = The value of construction put in place (in millions).

CONSPIRE = The Dummy variable indicating the conspiracy periods.

The main purpose of this model is to explain the behavior of flat glass prices in response to demand, supply, and other factors. This model uses the natural log of PPI for flat glass as dependent variable.

The demand for flat glass is closely linked to the general level of economic activity, especially construction activity. Hence, monthly seasonally adjusted series of the value of construction put in place[3] is used to measure demand for flat glass from construction activity. Real gross national product (GNP) was considered as a variable to capture the effect from economic activity on demand other than construction. However, the collinearity diagnostic shows that the variable *GNP* has very high multicollinearity problem with the variable *FRIT*, and thus *GNP* was excluded in this model.

The supply variables in this model are basically the costs which determine the production of flat glass. The cost of production of flat glass is a function of raw material cost, wages, and energy costs. If there is any change in the cost of these inputs, the supply

[3] This series is in 1996 dollars and obtained from U.S. Census Bureau.

curve will shift and lead to a change in the market prices. Frit and cullet are the two main raw materials used in manufacturing flat glass. Frit is a combination of several inputs, mostly silica sand, soda ash, and limestone and dolomite. Cullet is crushed glass and is obtained from the production process itself. Since cullet is internally generated and the cost of cullet is essentially the cost of producing flat glass, the cost of cullet is ignored in this analysis. Frit constitutes about 80% of the input mix for the production of flat glass, and cullet the remaining 20%.

To measure the cost of frit, an index was used in the model. This index is a weighted average of PPIs for glass sand (99.4% of which is silica dioxide), natural sodium carbonate and sulfate (soda ash), and lime including quick, hydrated, and dead burned dolomite (limestone and dolomite). The weights assigned to each of the individual series are 62%, 20%, and 18%, respectively. The PPI of glass sand was first introduced in June 1982. Hence, the missing value of PPI for glass sand was imputed by a regression model, which is presented in Appendix. The major energy source in producing flat glass is natural gas; thus the monthly price series of natural gas[4] was used as another supply variable. The impact of labor costs on the prices of flat glass products is represented by quarterly wages for all employees in flat glass industry.[5]

The impact of the conspiracy on the price of flat glass is estimated by using a conspiracy dummy variable. This variable has a value of one during the conspiracy periods and zero in the rest of the periods. The parameter estimate of the conspiracy dummy indicates that the amount of the actual prices was higher or lower (depending on

[4] The price series was obtained from the Department of Energy, Monthly Energy Review, Table 9-11.

[5] The quarterly wages were obtained from Quarterly Census of Employment and Wages, Bureau of Labor Statistics.

the sign of the parameter estimate) because of the conspiracy. The model with the conspiracy periods defined by the ICSS algorithm will first be presented in this damage analysis, and then the model with the class conspiracy period certified by the court.

Table 5
Flat Glass Model

Variable Name	Coefficient [t]	
	Conspiracy Periods	
	Defined by the ICSS algorithm	Based on Court's certified class Period[a]
CONSPIRE	0.05103 [12.98]***	-0.01164 [-1.74]*
FRIT	0.00392 [17.28]***	0.00340 [9.50]***
NATGAS	-0.00350 [-0.86]	0.00299 [0.53]
WAGE	0.00006865 [0.45]	0.00037089 [1.84]*
CONSTRUCTION	0.20431 [4.93]***	0.21881 [3.75]***
INTERCEPT	4.10190 [183.35]***	4.11341 [133.11]***
R^2	0.8652	0.7544
$Adj\text{-}R^2$	0.8618	0.7482
F	254.23	121.62

Note. Dependent variable = *Lflat*
June1980-December 1996.
Coefficients are followed by t-statistics in brackets
* = significant at 90%; **=significant at 95%; ***=significant at 99%.
[a] Author’s model with certified conspiracy period of August 1991 - December 1995.

The result of the regression for flat glass study is presented in Table 5. The second column contains the results of using the "suspected" conspiracy period from the ICSS algorithm. The coefficient of the variable named *CONSPIRE* reflects the different amount that defendants charge between the conspiracy period and the non-conspiracy period. Since the dependent variable is the log value of PPI for flat glass, the positive coefficient of value 0.05103 means that producers overcharge on flat glass price by about 5.1%. The coefficient of *FRIT*, which has the expected positive and significant sign, reflects that one unit increase in the Frit composite index will increase flat glass price by about 0.4%, given the value of other variables constant. The negative coefficient of *NATGAS* means one unit change of natural gas price will decrease flat glass price by about 0.35%, given the value of other variables constant; however, this coefficient is not significant, implying that this coefficient is not different from zero. The variable *WAGE* has the coefficient with the expected positive sign even though not at a significant level. The positive coefficient of the variable *CONSTRUCTION* shows that given other variables constant, a million dollar increase in construction put in place will increase the flat glass price by about 20.4%. The large value for R^2, *Adjusted* R^2, and *F-statistics* show that this regression model with the conspiracy period defined by the ICSS algorithm fits the data very well.

The positive coefficient of the variable *CONSPIRE* has claimed that the ICSS algorithm did successfully detect the conspiracy periods. In order to prove that the conspiracy period detected by the ICSS algorithm provides a better result than the conspiracy period from the physical evidence, the result of the same econometric model with the class certified conspiracy period of August 1991 to December 1995 is shown in the third column in Table 5. Unlike the model with the conspiracy period from the ICSS detection, the coefficient in this model has a negative sign and is statistically significant.

The value of this coefficient tells that defendants undercharge the flat glass price by about 1.2%, which means that defendants did not cause damage on the purchasers during the certified class period.

The conspiracy periods detected by the ICSS algorithm do not overlap with certified class periods in court; however some public documents have pointed out that the collusive behavior among defendants in this antitrust case could start as early as 1986.(In re Nelson v. Pilkington, 1998). For example, the ex-chief executive officer of LOF, who alleged the conspiracy among the defendants in the early 1990s, had been at that CEO position from 1986 to 1993 and was charged with conspiracy, mail and wire fraud, and money laundering. Therefore, the results from the ICSS algorithm can explain that the truly "successful" collusive period started in 1987 and broke down in 1990. Although no physical evidence shows collusive behavior during period of late 1982 to the middle of 1984, which may due to no purchasers or authorities' awareness, the producers did overcharge their customers in pricing of flat glass.

To calculate the total damage on purchasers due to the defendants' collusive behavior, the sales from defendants to purchasers during conspiracy periods need to be collected. Due to the legal issue, the actual sales between defendants and purchasers in this case are internal information and could not be revealed. However, manufacturers' shipments, inventories, and orders in the industry of stone, clay, and glass product are available from U.S. Census Bureau. Based on the definition of *census*, manufacturers' shipments measure the dollar value of products sold by manufacturing establishments and are based on net selling values after discounts and allowances are excluded. Hence, manufacturers' shipments could estimate the sales in the industry of stone, clay, and glass products. This industry included three categories of products: glass containers, kitchen articles and pottery, and other stone, clay, and glass products. The total value of dollars for shipments for this industry during December 1982 to June 1984 was $76.7 billion. If 10% of the total shipments belongs to flat glass, a 5.1 % overcharge from producers of flat glass causes the damage to purchasers up to $391 million (10%×$76.7 billion×5.1%). Similarly, the total value of dollars for shipments between November 1987 and February 1990 was $146.3 billion. With the assumption of 10 % of shipments belonging to flat glass products, the producers had overcharged sales by $746.4 million (10%×$146.3 billion×5.1%), which is total amount of the purchasers' damage during that period. As a result, the total damage to purchasers of flat glass products during these two collusive periods was about $1.14 billion.

The Steel Industry in the 1920s and 1930s

The producers in the steel industry have significant ability in agreeing on price-fixing because the firms in the industry have monopoly power. The demand the steel industry faces is inelastic, and thus firms can earn more profit by increasing the price in the market. Also, due to large capital investments to enter the market, there are substantial barriers to the entry of new firms.

Table 6
Major Mergers in 1898 - 1901

Year	Company		Number of Companies
Basic Steel Producers:			
1898	Federal Steel	15% of ingot capacity	[a]
1899	National Steel	12% of ingot capacity	8
1900	Carnegie Steel	18% of ingot capacity	[a]
Steel Finishers:			
1898	American Tin Plate	About 75% of tin plate output	36
1898	American Steel and Wire	About 80% of wire and wire products	19
1899	National Tube	75% of wrought tubing	13
1899	American Steel Hoop	Barrel hoops and cotton ties	9
1900	American Sheet Steel	About 70% of sheet steel capacity	17
1900	American Bridge	About half of structural steel business	26
1900	Shelby Steel Tube	About 90% of seamless tube output	13

[a] Federal Steel combined two major steel producers and a number of ore and transportation firms. Carnegie Steel was a reorganization of an earlier group of affiliated firms.
Source: Weiss (1961), *Economics and American Industry*.

Concentration and Entry. The steel industry in America was not very concentrated until the end of the 1890s. A series of mergers in the steel industry occurred at the end of the 1890s. Some important mergers which occurred between 1898 and 1901 are listed in Table 6. In 1901, a group of businessmen led by J.P. Morgan established a corporation named United States Steel. This corporation was comprised of those combinations in Table 6 and controlled the majority of Minnesota iron ore reserves.

United States Steel was the largest corporation in the American steel industry up to that time and also the first billion-dollar corporation in the United States. At that time, 44% of the reported steel ingot capacity and 66% of output in the United States were controlled by United States Steel. When it was initially organized, the ingot capacity of United States Steel was more concentrated near the Great Lakes because it had no important basic plants east of the Pittsburgh area, south of the Ohio, or west of the Mississippi. As a result, United States Steel was even more powerful regionally than in the country as a whole. By acquiring the Tennessee Coal, Iron and Rail road Company in 1907, United States Steel dominated the steel industry in the South. In the West, United States Steel did not produce steel until 1930. It started building its first fully integrated eastern plant in 1951.

This market power of United States Steel caused the federal government to bring an antitrust suit against it in 1911. The federal government attacked United States Steel and its components as combinations in restraint of trade. The Supreme Court made a judgment in this case in 1920. The Court denied the federal government's accusation in favor of United States Steel since there was no significant evidence that competitors were abused or that the public were exploited. Hence, its control of half of the steel industry was not illegal according to the Sherman Act.

The steel industry was no longer dominated by United States Steel in the early twentieth century. Although it was still the largest producer, there were other seven big firms in steel industry. Figure 6 shows the relative shares of eight big steel firms and other small steel firms. These eight big firms accounted for about almost 80% of the shares of total steel ingot capacity from the 1920s to the 1950s.

Since the beginning of the 20th century, firms in the America steel industry increased their market share mainly by mergers. No firms had the ability to use other methods to increase their share by more than 4% of industry capacity. Among the top three big steel companies, Bethleham was the only company with the ability to increase its share by as much as 2% by growing internally. In the steel companies' point of view, it is usually more profitable to grow its corporation by acquiring and expanding firms than by building new plants. First, it usually would cost a steel company much less to acquire or to expand firms than to build a new plant. Furthermore, by acquiring plants, a steel company also acquired existing customers belonging to those plants. Finally, the acquired plants would disappear from the list of rivals of the acquiring company. However, this trend of mergers in the steel industry was not good for the public. The small amount of firms caused less possibility of competition. Meanwhile, less investment in new steel capacity means less growing in the entire economy.

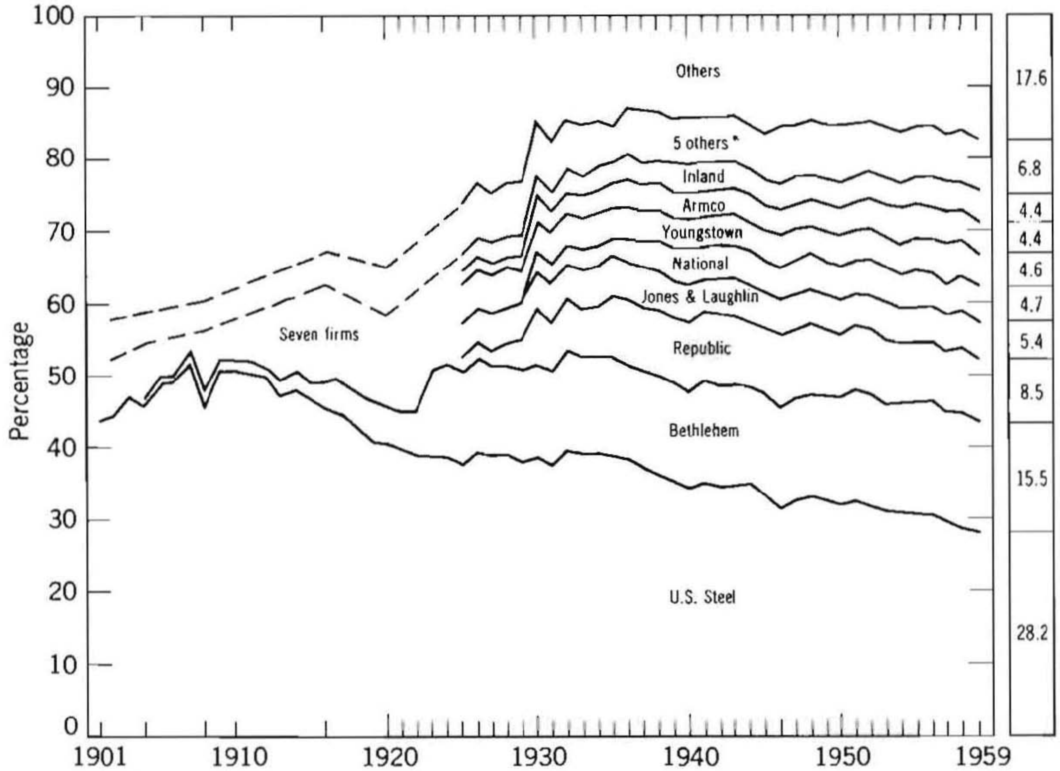


Figure 6. Shares of Total Steel Ingot Capacity
Source: Weiss (1961), *Economics and American Industry*.

Inelastic Demand Curves. These big firms tended to behave very much as one dominant seller in the steel industry. One main reason for these firms doing so is that the demand curves they faced were inelastic. Several reasons cause the demand curve of the steel industry to be more inelastic. The first reason is that most steel is used as an ingredient of some other product for customers. A change in steel prices will not affect the prices of most of these finished goods very much. For example, if it costs $150 worth of steel to make an automobile, a 20% raise in the steel price would increase the price of an automobile by $30. These increased amounts of the automobile would not significantly reduce the number of automobiles being sold out. The other reason that the demand of steel is inelastic is that there are not many good substitutes for steel. The prices of copper in 1930s were between 5.79¢ and 13.39¢ per pound, aluminum prices were between 19.9¢ and 23.8¢, and hot-rolled steel bars were between 1.58¢ and 2.40¢. Figure 7 shows the prices of these three kinds of metal from the year 1897 to 1960. The price of hot-rolled steel is far lower than the other two kinds of metal. An estimate by the economists retained by United States Steel in 1938 shows that the elasticity of demand for steel is 0.3 to 0.4.

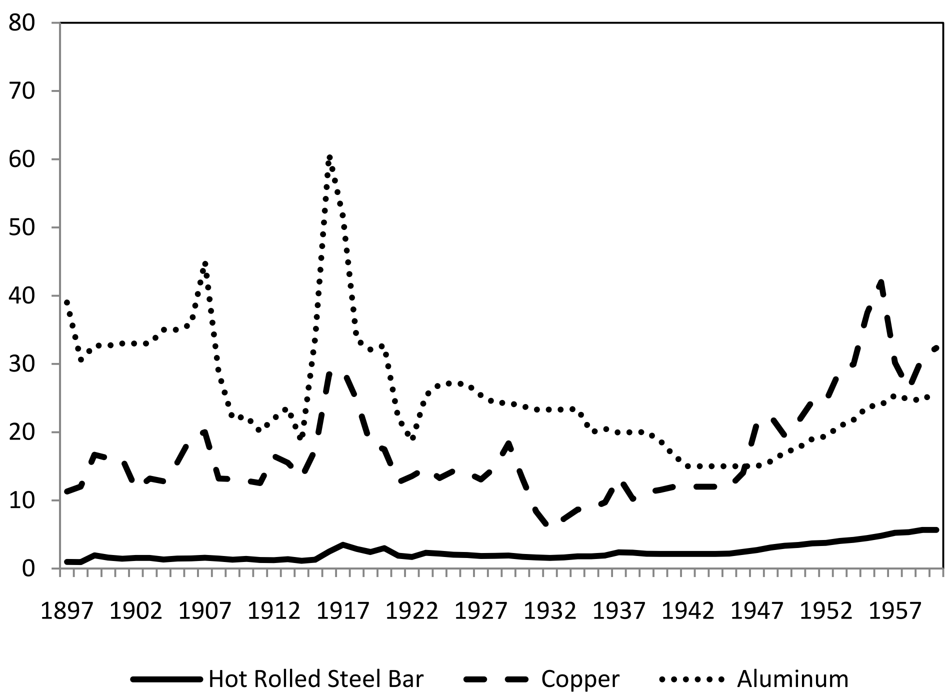


Figure 7. Annual Average Primary Price of Steel, Copper and Aluminum (Cents per pound)
Source: Metal Prices in the United States through 1998. U.S. Geological Survey.

The Steel Industry in Deep Depressions. Some individual steel companies sometimes attempted to secretly cut down the price in order to get more customers in economic downturns when these companies were operating far below their capacity. Once price cutting became widespread, the steel industry leader would adjust the official price to reflect this price-cutting behavior. These secret price cuttings induced several price competitions during the depressions of 1921-22, 1931-33, and 1938 (Weiss, 1967).

The competition in 1921-22 was due to the unequal amounts of overcapacity among steel firms. There was a shortage in the supply of steel during the post-World War I period which gave many independent firms the opportunity to charge higher prices. However, charging higher prices causes antagonism from their customers toward these independent firms. On the contrary, unlike independent firms, United States Steel maintained stable prices. When the shortage of steel did not exist anymore and the recession occurred, these smaller firms were having troubles. During the recession, United States Steel was able to keep operating at reasonable a level capacity. However, the independent firms were only running at 20% to 35% of capacity. The low operating rate of capacity caused these firms to suffer severe losses. In order to earn back costumers, independent firms went into a price competition in the steel industry. What stopped this competition was that United States Steel announced that it would match any price cut by any major independent firm. Also the organization of mergers embracing the leading price cutter had begun.

A main source of price cutting in the early 1930s was National Steel. National Steel is a combination of many firms and thus had efficient new plants, its own ore, and an aggressive management. As a result, unlike other independent firms, National Steel was in a better position to take such actions as price cutting.

During the Great Depression, most steel prices declined. However, the price decrease of different steel products varied. On the average, from 1929 to 1933, finished steel prices fell about 20%. However, prices of sheet and strips dropped much more than this percentage while price of heavy steel product dropped much less. While cold rolled strip prices fell by 39%, rail prices went down only 9%.[6] What made this a huge difference in price reductions was that the demand for most heavy steel products was much more than the demand for sheet and strip. The main usage of sheet and strip is consumer goods such as appliances and automobiles. In contrast, the primary usage of heavy steel products was in capital goods and construction, the demand for which declined most during the depression.

The first explanation for this lower price of sheet and strip is that some firms such as National Steel could have a great reduction in cost and be able to offer lower prices because they had installed the continuous strip firms. Another explanation is that this section of the steel industry is relatively less concentrated than other heavy steel product sections. Finally, the main customers of sheet and strip, especially automobile companies, are big buyers. These buyers have more power to negotiate lower prices.

Unlike the previous competition impeded by the United States Steel, this competition was hindered by the government. Congress passed the National Industrial Recovery Act in 1933. This Act permitted industries to work out "codes" to control competition and provide government enforcement in stopping competition. Among all industries, the steel industry was one of the first to join this Act. The way the steel industry worked out its codes to avoid secret price competition was its codes required producers to file their minimum prices with the American Iron and Steel Institute and to give ten days notice prior to price changes. The code had been forcing the producers to operate their oligopoly price policy since almost any price cuts would be met by other producers.

[6] TNEC Hearings, op. cit., 10719-10721.

Price competition came back in the depression of 1937-1939 when United States Steel made a formal price reduction due to its announced prices not being competitive at that time. A study made in connection with wartime price controls in 1943 showed more price competition in the steel industry within this period.

According to Weiss' study, the steel industry participants behaved as monopolists due to the small number of firms and an inelastic demand curve in the 1920s and 1930s except 1921-22, 1931-33, and 1938.

Data. The wholesale prices of semi-manufactured steel billets, prices of composite iron and steel, and prices of composite finished steel are obtained from the *Survey of Current Business* which is available in Federal Reserve Archival System for Economic Research (FRASER). Due to data availability, the collected prices were from January 1923 to December 1939. All metal prices were converted into cents per pound and are monthly data and transformed into the modified series by the formula (4.1) discussed in the previous flat glass case.

Figure 8 and Figure 9 show three different steel price series in cents per pound and in modified numbers. The movements of these three price series were very similar, and they closely parallel each other. However, in Baker's (1989) opinion, the price of semi-manufactured steel is preferred to the price series of composite finished steel. The reason is that semi-manufactured products are close to supply substitutes. Products close to supply substitutes are able to be thought of as homogeneous goods. Therefore, the price of semi-manufactured steel is used in this study to be examined by the ICSS algorithm and in damage analysis.

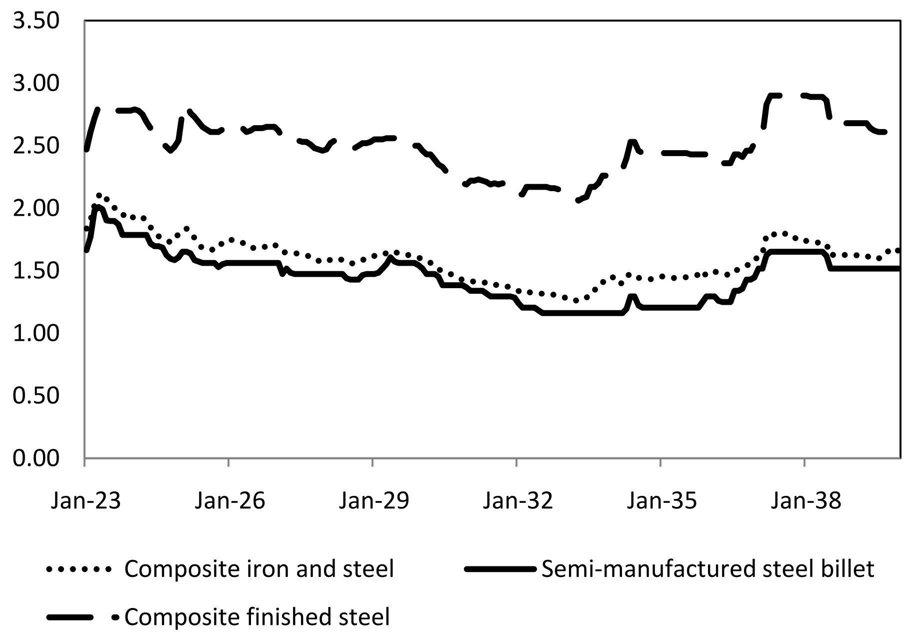


Figure 8. U.S. Steel Prices 1923-1939 (Cents per pound)
Source: Survey of Current Business

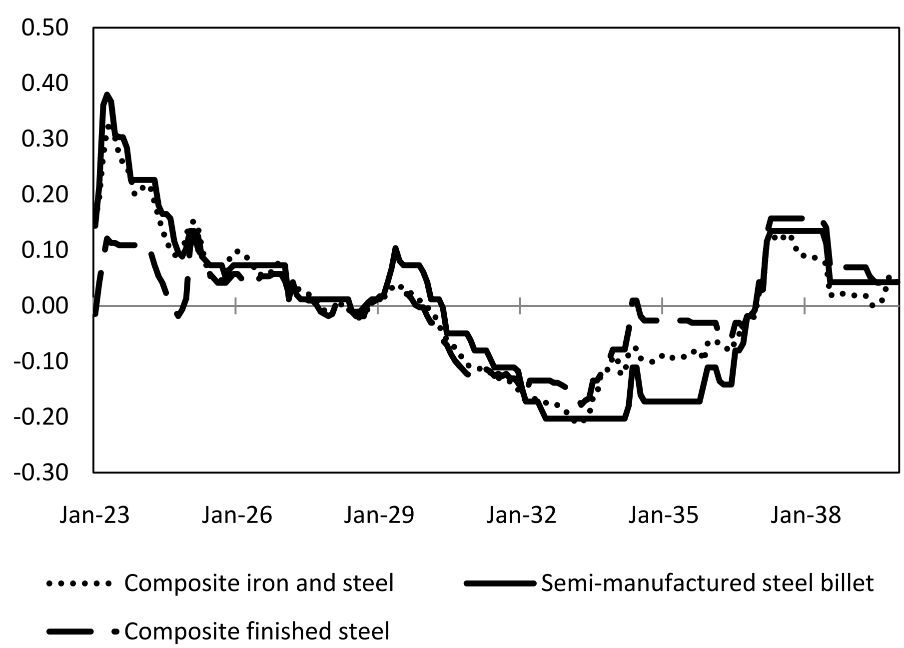


Figure 9. Modified U.S. Steel Prices 1923-1939 (Mean=0)

Table 7
Sudden Changes in Volatility of Steel Billets Prices

Modified prices series	No. of change points	Time period	Variance	Standard deviation
Semi-manufactured Steel Billets	3	January, 1923 – July, 1924	0.00492	0.07016
		August, 1924 – November, 1931	0.00429	0.06549
		December, 1931 – May, 1938	0.01598	0.12641
		June, 1938 - December, 1939	0.00025	0.01583

The Results of the ICSS Algorithm. At least until the 1960's, the American Steel Industry had been an oligopolistic industry and individual firms behaved monopolistically by displaying a fixed price policy. To detect when the fixed price policy was successfully implemented, the ICSS algorithm was used and the results are in Table 7. This table provides the information on the price competition and the collusion in American Steel Industry. Here again those periods with relatively small variances were suspected periods under price-fixing policy.

The variance in the period of August 1924 to November 1931 is almost 6 times smaller than the variance in the period after. Although the variance in the period before the period of August 1924 to November 1931 is only slightly larger, a more successful collusive period is considered in the period of August 1924 to November 1931.[7] The variance of the period June 1938 to December 1939 is more than fifty times smaller than the variance in the previous period. Therefore, a fixed pricing or collusion regime seemed

[7] The overcharge would be larger if the period before August is also considered to be collusive period.

successfully established after June 1938. Weiss' study states that there was price cutting during 1931 to 1933, and 1938. However, according to the result from the ICSS algorithm, the secret price-cutting among producers might happen over the total period from 1931 to 1938. Although history did not record any competition during this period prior to August 1924, there could be some price competition which was not detected at that time due to its size. For example, some firms used secret price-cutting, but when being monitored by other firms, they returned to collusive behavior. In short, the suspected collusive periods were the periods of August 1924 to November 1931, and June 1938 to December 1939.

Damage Analysis. As discussed in the flat glass study in the previous section, to estimate the damage in the steel industry in 1920s to 1930s, the percentage overcharge by steel producers needs to be determined first. Therefore, in order to measure overcharge on purchasers of steel products, the actual prices during the conspiracy periods and during competitive periods again need to be compared. Forces other than producers' collusive behaviors may cause prices to differ between the conspiracy period and the pre- and post-conspiracy periods (non-conspiracy periods); hence, these forces and the force from conspiracy are included in the model in analyzing producers' damage on their customers.

The model for this steel study is adapted from the model and variables in Baker's (1989) study and modified to be a reduced form as:

$$LP = F\ (IRP, WAGE, ALUM, CAR, RAIL, Y, CONSPIRE) \qquad (4.2)$$

where, *LP* = Logged value of wholesale price of semi-manufactured steel billets.

IRP = Prices of composite pig iron prices.

WAGE = Monthly factory wages (per week) in iron and steel and their products (excluding machinery).

ALUM = Monthly prices of aluminum prices.

CAR = Numbers of U.S. passenger cars.

RAIL = Numbers of rail freight cars shipped.

Y = Industrial Production Index.

CONSPIRE = Dummy variable indicating the conspiracy periods.

The main purpose of this model is to explain the behavior of steel prices in response to demand, supply, and other factors. This model uses the natural log of the wholesale price of semi-manufactured steel billets as dependent variable. The primary factors that affect the demand of the steel are the output of the automobile, rail, and construction sectors of the economy. The monthly U.S. production of passenger cars and the quantity of rail freight cars shipped which represent the output of the automobile and rail sectors were obtained from the *Survey of Current Business*. The industrial production seasonal adjusted combined index, which is converted to the index based on 1919=100, is used as a proxy variable for the construction sector of the economy. Finally, Baker claims that the price of aluminum is likely both a demand substitute and a demand complement for steel. Thus, the price of aluminum is included in this model as a demand-shift variable and was obtained from the trade publication *Metal Statistics*.

Two supply-shift variables are employed in this damage-analysis model. They are the price of composite pig iron and monthly average factory weekly wages in iron and steel and their products (excluding machinery).[8] They were also both obtained from the *Survey of Current Business*. A conspiracy variable is used to measure the impact of the conspiracy on the prices of semi-manufactured steel. This variable within the suspected collusion period detected by the ICSS algorithm is assigned the value of one and zero otherwise. Hence, this conspiracy dummy variable is assigned one for the period of August 1924 to November 1931and the period of June 1938 to December 1939.

To confirm that detection by the ICSS algorithm provides better conspiracy periods, the conspiracy periods based on physical evidence were compared in this study. According to Weiss' study, that steel producers had secretly cut prices in 1931 to 1933 and 1938, these periods could be seen as competitive periods, or non-collusive periods. As a result, conspiracy periods in physical evidence could be defined by periods other than those competitive periods. Since no specific months are listed in his study but only years are available, there would be 67,392 possible combinations of conspiracy periods[9]. These possible conspiracy periods are also used in this model to examine whether the steel producers overcharge the price for steel within the conspiracy periods implied from

[8] Since the data of wage for iron and steel and their products (not including machinery) were only available before February 1938, U.S. Steel corp. wage rate were used for data before February 1938.

[9] Based on Weiss' study, the first competitive periods could start from January 1931 to December 1931 and end from January 1933 to December 1933, and the second competitive periods could start from January to December 1938 and similarly end from January to December 1938. As a result, there are 67,392 possible combinations.

Weiss' study. In other words, it outlines whether the collusive behaviors were successful during these periods based on his study.

The second column in Table 8 is the result of the model with the conspiracy periods of the detection from the ICSS algorithm. The variable of interest in this model, *CONSPIRE*, has a positive and significant coefficient with the value of about 0.59. What this positive coefficient means is that steel producers overcharge up to 5.9% from their purchasers. The coefficient of the variable, *IRP*, tells that a $1 increase on the price of pig iron will increase the steel price by about 3%, given other variables are constant. The variable, *WAGE*, has the coefficient with the value of about 0.0042, which means that given that other variables are constant, a $1 increase in the average weekly wage in the steel industry will increase the steel price by about 0.4%. The interpretation of the coefficient for *ALUM* is that a 1¢ increase in the price of aluminum will result in the price of steel increasing by about 1%. All the coefficients of these three variables representing the forces from the supply for the steel are positive and significant as what should be expected.

Table 8

Steel Model

Variable Name	Coefficient [t]	
	Conspiracy periods	
	Defined by the ICSS algorithm	Based on the documents[a]
CONSPIRE	0.05852 [4.33]***	0.02339 [1.56]
IRP	0.03027 [15.62]***	0.02519 [14.36]***
WAGE	0.00416 [1.77]*	0.01083 [6.15]***
ALUM	0.00972 [3.45]***	0.01797 [8.38]***
CAR	-0.00002369 [-0.48]	-0.00006753 [-1.32]
RAIL	0.00844 [4.89]***	0.00897 [5.01]***
Y	0.00000793 [0.02]	0.00032218 [0.92]
INTERCEPT	2.50389 [27.20]***	2.26322 [30.75]***
R^2	0.8652	0.8542
$Adj - R^2$	0.8604	0.8490
F	179.77	164.00

Note. Dependent variable = *LRP*

Janurary1923-December 1941

Coefficients are followed by t-statistics in brackets

* = significant at 90%; **=significant at 95%; ***=significant at 99%.

[a] the periods exclude December 1931 to December 1933, and October 1938.

The variables in this model representing the forces from the demand for the steel are as follows: *CAR*, *RAIL*, and *Y*. The negative coefficient of *CAR* states that if the automobile sector increases its production by one thousands passenger cars, the price of steel will decrease by 0.002%; however, this value is not statistically significant, which means that the change of the production of passenger cars had no significant effect on the price of steel. The interpretation for the coefficient of the variable, *RAIL*, is if the manufacturers increase one thousand railway freight cars in the total of their shipment, the price of steel will rise by 0.8%. This coefficient has an expected positive sign and is statistically significant. The variable, *Y*, which captures the rest of the economic activity which may affect the demand for the steel, has an expected positive coefficient although not at a significant level. The measurement of "goodness of fit", R^2, $Adj\text{-}R^2$, and *F-test*, indicates that this model has captured most of the variability in the dependent variable, the price of steel.

To confirm that the conspiracy period detected by the ICSS algorithm provides a better model for damage analysis, the model with the conspiracy periods defined by the literature was used as a comparison. As was discussed in the previous section, there are many possible outcomes of the model due to the lack of the specific month in those conspiracy years recorded in the literature. Therefore, the values in the third column in Table 8 are the results from the most competitive model from all the outcomes. In other words, in the defined conspiracy period from January 1923 to November 1931, January 1936 to September 1938, and November 1938 to December 1939, the model provides better result than the model with other possible conspiracy periods based on the literature. Here a better result is defined by a higher and statistically significant coefficient of conspiracy dummy variables, more accurate signs of the rest of the variables, better measurements of "goodness for fit." The model with the literature defined conspiracy period has a positive coefficient of the variable, *CONSPIRE*, as expected. However, the value of this coefficient is smaller than the one defined by the ICSS algorithm, and also is not statistically significant; this value is not statistically different form zero. In other words, according to the model statistically speaking, the producers did not overcharge for steel during those conspiracy periods. The sign of the rest of the variables in this model are as expected except the variable, *CAR*. This is the same as the model with the ICSS algorithm defined conspiracy periods. However, its R^2, $Adj\text{-}R^2$, and *F-test* are smaller than the model with the conspiracy periods defined by the ICSS algorithm.

The first antitrust lawsuit in the steel industry was brought by the federal government in 1911, and the Supreme Court made a decision in favor of the producers. (US v. United States Steel, 1920) The court concluded that even if the producer had the intent to behave as a monopolist, it did not abuse its rivals or exploit the public. Since then, although it was illegal for producers of steel to enter "formal" price-fixing or marketing agreements, merger and informal price leadership were within the law until 1945. The antitrust lawsuits in the steel industry were not successful because the Court did not find that the producers' collusive behaviors substantially lessened competition; in other words, no damage to the public existed. (US v. Republic Steel Corp.,1935). The result of the conspiracy periods based on the literature tells the same story as from the Court. However, using the ICSS algorithm, this study has successfully shown that the damage did exit in the steel industry in the 1920s and 1930s. The conspiracy periods were not those shown in the physical evidence but those periods with the relative lower variance.

With the estimate of the amount overcharged by the steel producers on the price of steel, the damage on the purchasers now could be calculated if the quantity of the steel billets sold was available. Although the quantity of the steel billets sold during the conspiracy periods was not available, the production of steel ingots could be used to estimate it and is available in the *Survey of Current Business*. If on the average, 90% of the production of steel ingots were sold, the total sales of during the conspiracy period were the product of the wholesale price for the steel billets, the quantity of the steel ingot produced, and the percentage assumed to be sold. The estimated sales of steel ingots during the first successful conspiracy period of August 1924 to November 1931 were about $9.6 billion. Therefore, the 5.9% overcharge would cause the damage to purchasers of steel products up to about $567.3 million. Producers' sales during the other successful conspiracy period of June 1938 to December 1939 were estimated to be about $1.98 billion. Given the overcharge rate from the producers, the purchasers overpaid on steel product up to $116.5 million. Hence, the total damage on customers who purchased steel within these two conspiracy periods is about $683.8 million.

In both empirical studies for the flat glass and steel industries, the conspiracy periods detected by the ICSS algorithm has successfully found damage by the producers. By using the damage analysis model in this study, the conspiracy periods defined by courts or literature in these two cases did not show any statistically significant overcharge from the producers. However, as was mentioned in previous sections, cheating may have occurred during collusive periods, and some informal evidence of the existing or breakdown of cartel agreements might not be released. As a result, the ICSS algorithm does provide forensic economists an alternative method in detecting successful cartels.

Chapter 5

Conclusion

Most cartels have negative effects on purchasers and participating firms' potential competitiors. The Sherman Antitrust Act states that cartel behavior in the United States is illegal and government agencies should make efforts to detect, prosecute, and penalize these practices. This paper proposes that the Iterative Cumulative Sums of Squares (ICSS) Algorithm can be applied to help better detect periods of collusive behavior in markets by analyzing changes in the variance of product prices over time.

Price rigidity is a common characteristic of oligopolies and has been theoretically proven in many studies. One well-known explanation of this behavior is the kinked-demand-curve. The relationship between collusive behavior and kinked demand curves is based on the assumption that firms do not choose their prices simultaneously and that any price-cutting behavior by a firm will cause the retaliation of a further price-cutting from rivals. As a result, price wars would occur, and firms would earn lesser profits. Therefore, firms would prefer to stay at the agreed upon monopoly price, rather than cutting prices to earn more market share during one period.

A more recent study by Athey et al. (2004) discussing price rigidity during collusive periods was developed using an infinitely repeated Bertrand game. This model suggests the theory that a firm's collusive price is independent of its current cost position in a rigid-pricing scheme. Moreover, this rigid-pricing scheme sacrifices efficiency benefits but also diminishes the information costs. By assuming the prices are publicly observed and the costs are privately observed and independent and identically distributed, this model proves that if the firms are sufficiently patient the optimal symmetric collusive scheme can be reached when equilibrium-path price wars are absent and the price is rigid. This theorem implies that the variability of firms' prices over time is smaller under a collusive regime than a competitive regime.

The other recent study by Harrington and Chen (2006) develops price rigidity in the collusive period using a dynamic programming framework. This study argues that any suspicious price change will secure buyers' attention, and they will begin to investigate the existence of the cartel; in order to avoid detection, the cartel sets prices to be more stable over time. In this study, buyers' suspicion of the existence of a cartel does not come from their knowledge of what a cartel price should be but from the observation that the price series is sufficiently anomalous or inexplicable when compared to the history of prices. In other words, buyers have their ideas about whether price changes are reasonable based on the history of price changes. Knowing that price patterns affect buyers' beliefs and thus can affect the probability of detection, firms inherit the non-collusive price and buyers' expectance of price changes based on non-collusive periods when they form a cartel. This dynamic programming system has established an optimal cartel price path which has a transition phase and a stationary phase. In the transition phase, under some specific parameter set in this model, the price path is rising, overshooting, and converging into stationary phases. On the other hand, price in a collusive regime is much less volatile than price in a competitive regime.

Since price rigidity in collusive periods has been proven in many theoretical studies, the ICSS algorithm, which detects multiple changes of variance in a given time series, is applied in this study. This technique was developed by Inclan and Tiao in 1994 and is commonly used in studies of finance. Inclan and Tiao considered series that present a stationary behavior for some time, then suddenly the variability of the error term changes; it stays constant again for some time at this new value, until another change occurs. They first used cumulative sums of squares to search for change points systematically at different piece of series and then used an algorithm to find multiple change points in an iterative way.

To apply the ICSS algorithm in detecting the existence of cartel, two empirical cases were studied in Chapter 4. The first case is the flat glass antitrust litigation in the early 1990's. The flat glass industry was concentrated among five major manufacturers (PPG, LOF, AFG, Guardian, and Ford). The entry barriers to the flat glass industry were very high due to high market concentration and high fixed costs of entry to this market. Flat glass in general is recognized as a commodity product, and thus price is the decisive factor affecting purchasing decisions. Because of these characteristics, price-fixing by manufacturers in this industry was more apt to be successful. Agreements between these five manufacturers have revealed the collusive behavior in the flat glass industry in the early 1990s.

By using the ICSS algorithm to test the Producer Price Index of flat glass, two suspected collusive periods, December 1982 to June 1984 and November 1987 to February 1990, reveal lower variance relative to other periods. In order to confirm producers' collusive behavior, the damage analysis is applied to see whether purchasers of flat glass products were overcharged during those suspected collusive period. After accounting for other forces from the demand and supply factors of PPI for flat glass, the positive coefficient of the conspiracy dummy variable relates that producers of flat glass overcharged flat glass products by over 5%. This percentage of overcharge by producers caused the total damage up to about $1.14 billion. On the contrary, by using the class certified conspiracy period, the coefficient of the conspiracy dummy variable shows that producers undercharged rather than overcharged their customers. In other words, even though physical evidence shows that producers in the flat glass industry colluded during the class certified period, there is no evidence showing that they overcharge on prices of flat glass in the damage analysis model of this study. In short, during the conspiracy periods detected by the ICSS algorithm, the manufacturers' did successfully collude in overcharging the price of flat glass.

The other empirical study discussed is the steel industry in 1920s to 1930s. Producers in steel industry had significant ability to collude and agree on set prices because of the characteristics of the market they operated during that time. At the turning of the 20th century, the steel industry was concentrated among eight large firms due to industry consolidation. These eight major steel firms accounted for almost 80% market share of total steel ingot capacity from the 1920s to the 1950s. Moreover, since most steel is used as an ingredient of other products, and there are not many good substitutes of steel, the demand curves that the steel producers faced were relatively inelastic. The concentration and the inelastic demand of the steel industry allow firms in this industry to have significant market power if they were to act in concert to increase prices.

The suspected collusive periods detected by the ICSS algorithm in the steel industry were the periods of August 1924 to November 1931 and June 1938 to December 1939. Similarly, whether steel producers did overcharge steel prices during these collusion periods, or whether steel producers' collusive behaviors were successful, damage analysis was employed to confirm it. The coefficient of the conspiracy variable is about 0.059 and is significant at 99% level, which states that the producers of steel did overcharge steel by about 5.9% during the successful conspiracy periods. The conspiracy periods based on the literature, in contrast, demonstrate that there is no significant overcharge from the producers in the damage analysis model of this study. The total damage on the purchasers during these conspiracy periods is up to $683.8 million.

Based on empirical results, the ICSS algorithm provides a fast and simple method of detecting the existence of cartels and collusive behavior. This is the first study to apply the ICSS algorithm in forensic economics to detection of this behavior and appears to be successful in detecting periods of anticompetitive behavior. This study is just like most medical experiments in labs; many limitations occur during the entire experiment process. For example, most of the time instead of testing humans, new medication only could test on rats. Whether what works on rats will work on humans will not be discovered until the reaction from humans is proven, and that reaction may differ due to different individual physique. Similar, the ICSS algorithm has successfully detected the collusive periods in two empirical studies. In the future, this methodology will be expected to be examined in the antitrust litigation cases with more specific data.

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Appendix

To project the missing value of variable of glass sand prior to June 1982 in the model for flat glass study, an explanatoy model is constructed. Glass sand (Silica sand) is the most common ingredient in glass. It makes up about 60 to 70 % of the glass batch. Hence the production of a glass product is the major factor for demand of glass sand. The varaible used here to present this demand factor is total inventory in millions of dollars in the industry of stone, clay, and glass. The data of this total inventory were obtained from U.S. Census.

The main factor for the cost of producing glass sand is fuel. All glass sand in North America is dried at the silica processing plant before being shipped to the glass manufacturing plant. Drying is the most expensive unit operation in processing glass sand, and most sulica sand is dried using a fluidized bed dryer. The energy source for fluid bed dryers is fuel. The variable used to represent the cost of fuel is the PPI for light fuel oils. The other energy cost for glass sand is electricity. For example, the machine in magnetic separation of processing glass sand is operated by electricity. The PPI for industrial electric power is used as the variable of electricity. Both PPI for light fuel oils and industrial electric power were obtained from Bureau of Labor Statistics. In short, the model in predicting the PPI for glass sand is:

$$\widehat{LSAND} = \underset{[127.93]^{***}}{3.56706} + \underset{[2.86]^{***}}{0.00001676}\, Inventory + \underset{[2.26]^{**}}{0.00027911}\, Fuel + \underset{[23.18]^{***}}{0.00885}\, Electricity$$

$R^2 = 0.9482$ Adj $R^2 = 0.9473$ F-test = 1042.85

where $\widehat{LSAND}$ = the predict log value of PPI for glass sand.