Strategic Leniency and Cartel Enforcement

Nathan H. Miller*

Abstract

The cornerstone of cartel enforcement in the United States and elsewhere is a commitment to the lenient prosecution of early confessors. A burgeoning game-theoretical literature is ambiguous regarding the impacts of leniency. I develop a theoretical model of cartel behavior that provides empirical predictions and moment conditions, and apply the model to the complete set of indictments and information reports issued over a twenty year span. Statistical tests are consistent with the notion that leniency enhances deterrence and detection capabilities. The results have implications for market efficiency and enforcement efforts against cartels and other forms of organized crime. (JEL K4, L4)

In 1993, the Department of Justice (DOJ) introduced a new leniency program, with the intent of destabilizing existing cartels and deterring new cartels. The program commits the DOJ to the lenient prosecution of early confessors. In particular, it guarantees complete amnesty from federal prosecution to the first confessor from each cartel, provided that an investigation into the confessor's cartel is not already underway. It also offers discretionary penalty reductions to conspirators that confess when an investigation is already ongoing. The new leniency program has become the cornerstone of cartel enforcement efforts in the United States (e.g., Scott D. Hammond 2004) and recently has inspired antitrust authorities in Australia, Canada, the European Union, Japan, South Korea, and elsewhere to introduce similar programs (Organization for Economic Cooperation and Development 2002, 2003).

*Economics Department, University of California, Berkeley, 501 Evans Hall #3880, Berkeley CA 94720-3880 (e-mail: nmiller@econ.berkeley.edu). I am grateful to my advisor, Richard Gilbert, for his advice and patience. I thank Severin Borenstein, Joseph Farrell, Russell Pittman, Carl Shapiro, John Sutton, Sofia Villas-Boas, Gregory Werden, Catherine Wolfram, two anonymous referees, and seminar participants at the Department of Justice, the Federal Trade Commission, the Unversity of Iowa, the University of North Carolina, and the University of California, Berkeley for valuable comments. The Institute of Business and Economic Research provided financial support.

This paper tests the efficacy of the new leniency program. The results have implications for market efficiency and enforcement efforts against cartels and other forms of organized crime.

A burgeoning game-theoretical literature is ambiguous regarding the impacts of leniency. A common finding is that leniency may destabilize cartels because conspirators can simultaneously cheat on the cartel and apply for leniency (e.g., Giancarlo Spagnolo 2004, Joe Chen and Joseph E. Harrington 2007, Harrington 2008). Leniency also may destabilize cartels when conspirators can exploit the policy to raise rivals' costs in subsequent periods (Christopher J. Ellis and Wesley W. Wilson 2001). Alternatively, leniency may stabilize some types of collusive arrangements (e.g., Spagnolo 2000, Ellis and Wilson 2001, Chen and Harrington 2007), and may encourage new cartels to form when detection probabilities change stochastically if firms anticipate smaller penalties (Massimo Motta and Michele Polo 2003, Harrington 2008). The effects of leniency also may depend on market concentration (Ellis and Wilson 2003), whether fines are proportional to accumulated cartel profits (Evguenia Motchenkova 2004), and the degree of firm heterogeneity (Motchenkova and Rob van der Laan 2005). In virtually all the models, the effects of leniency hinge on specific parameters, the values of which are unknowable theoretically and difficult to estimate empirically.[1]

This paper provides the first independent empirical evaluation of leniency in cartel enforcement, as it is applied in the United States. Much of our extant knowledge regarding the efficacy of the new leniency program comes from DOJ Antitrust Division officials, who consistently laud the program:

> The Amnesty Program is the Division's most effective generator of large cases, and it is the Department's most successful leniency program (Gary R. Spratling 1999).
>
> To put it plainly, cartel members are starting to sweat, and the amnesty program

[1]Patrick Rey (2003) and Spagnolo (2007) provide excellent summaries of this theoretical literature. On a related subject, Spagnolo (2004) and Cecile Aubert, Rey and William E. Kovacic (2006) note that rewarding confessors may enhance enforcement capabilities.

> feeds off that panic (Hammond 2000).
>
> It is, unquestionably, the single greatest investigative tool available to anti-cartel enforcers (Hammond 2001).
>
> Because cartel activities are hatched and carried out in secret, obtaining the cooperation of insiders is the best... way to crack a cartel (R. Hewitt Pate 2004).[2]

It may be prudent to view this rhetoric with skepticism. The game-theoretical literature suggests that antitrust authorities have incentives to over-represent their enforcement capabilities because leniency is more powerful when firms anticipate only short-lived cartel profits (e.g., Jeroen Hinloopen 2003, Motchenkova 2004, Chen and Harrington 2007). The DOJ attempts to manage firm perceptions for exactly this reason:

> antitrust authorities must cultivate an environment in which business executives perceive a significant risk of detection by antitrust authorities if they enter into, or continue to engage in, cartel activity (Hammond 2004).

Moreover, the DOJ maintains strict confidentiality regarding the identity of amnesty applicants (e.g., Spratling 1999). Although it is possible to make inferences in some cases, more commonly the identity (or even existence) of a leniency applicant is unknowable from publicly available data. The combination of potentially perverse incentives and lack of institutional transparency helps motivate this analysis.

I develop a theoretical model of cartel behavior that helps overcome the difficulty, common to all empirical research on collusion, that active cartels are never observed in the data. Specifically, I analyze a first-order Markov process in which industries transition stochastically between collusion and competition. I show how changes in the rate at which cartels

[2] Spratling was Deputy Assistant Attorney General in 1999. Hammond is Deputy Assistant Attorney General and served as Director of Criminal Enforcement in 2000 and 2001. Pate is Assistant Attorney General.

form and the rate at which they are discovered affect the time-series of cartel discoveries. The model generates intuitive empirical predictions that can be used to assess the efficacy of antitrust innovations (such as the leniency program). In particular, an immediate increase in cartel discoveries following an innovation is consistent with enhanced detection capabilities, and a subsequent readjustment below pre-innovation levels is consistent with enhanced deterrence capabilities.

I take the theoretical model to the complete set of indictments and information reports issued by the DOJ between January 1, 1985 and March 15, 2005.[3] I use these documents to construct a time-series of cartel discoveries. The introduction of the new leniency program on August 10, 1993 provides an exogenous shock that identifies the effect of leniency on cartel formation and detection rates. Before that date, the DOJ offered leniency only on a discretionary basis and only before an investigation had started. Whereas the DOJ received only seventeen leniency applications between 1978 and 1993, it has averaged roughly one application per month since (e.g., Anne K. Bingaman 1994, Spratling 1999, Hammond 2003).

I use reduced-form Poisson regression to test whether cartel discoveries increase immediately following leniency introduction (consistent with enhanced detection) and whether discoveries subsequently fall below initial levels (consistent with enhanced deterrence). I am able to control for economic conditions, the budget of the Antitrust Division, and other factors that may influence cartel discoveries. By way of preview, the time-series of cartel discoveries is consistent with the notion that the introduction of the new leniency program enhanced the detection and deterrence capabilities of the DOJ. The number of discoveries increases immediately following the leniency introduction and then falls below pre-leniency levels. The changes are statistically significant, large in magnitude, and robust to various specification and sample choices. The results lend credence to the DOJ rhetoric and indicate that the new leniency program may have the intended effects.

[3]Information reports do not require a grand jury and are typically filed in conjunction with a plea agreement from one or more defendants.

The analysis is subject to at least two important caveats, and the results may best be interpreted with caution. The first caveat is that the theoretical model requires one to draw inferences about the pool of undiscovered cartels with information gleaned from discovered cartels. Valid inference is possible so long as discovered cartels are representative in some fashion. In the theoretical model, I assume that the antitrust authority discovers all cartels with equal probability. The second caveat is that the regression sample is essentially a single time-series with one exogenous policy change. Cross-sectional variation could provide more robust identification, and the recent introduction of leniency programs by other antitrust authorities may provide this variation for future studies. Early evidence suggests that the experience of the United States may generalize. For example, the European Commission revised its leniency program in 2002 to include automatic amnesty for the first confessor. The Commission received leniency applications in more than twenty cases during the first year of the revised program, relative to only sixteen cases during the previous six years combined (Bertus Van Barlingen 2003, Van Barlingen and Marc Barennes 2005).

Independently, Harrington and Myong-Hun Chang (2007) develop an alternative framework with which to test the efficacy of cartel enforcement innovations. Their framework differs from the one developed here because it generates empirical predictions for the time-series of observed cartel durations rather than for the time-series of cartel discoveries.[4] Unfortunately, empirical applications of their framework may be frustrated by measurement problems associated with reported durations. For example, conventional wisdom holds that the start and end dates of collusive activity reported by the DOJ may be negotiated as part of a plea agreement. The theoretical model developed here may have advantages to the extent that cartel discoveries are more cleanly observed.

The empirical results most closely relate to those of Steffan Brenner (2005), who shows that the initial introduction of leniency within the European Union in 1996 had little discern-

[4]Harrington and Chang (2007) show that effective antitrust innovations raise the average duration of detected cartels in the short run by discouraging the operations of less stable (and shorter-lived) cartels.

able effect on the duration of detected cartels. As discussed above, the European Commission did not guarantee amnesty to first confessors until 2002. Thus, putting aside the measurement problems associated with cartel durations, Brenner's results are consistent with those presented here because they suggest that guaranteed amnesty to first confessors may be an important component of successful leniency programs. Other related empirical work includes that of Vivek Ghosal and Joseph Gallo (2001) and Ghosal (2004), which documents the relationships between antitrust caseloads and various political and economic factors.

The results may have important market efficiency implications. Cartels are generally thought to expropriate consumer surplus and create deadweight welfare loss. Although criminal law treats collusion as *per se* illegal, the data analyzed here indicate that the DOJ detected cartels in more than 200 distinct industries over the sample period. The price effects of collusion are large. John M. Connor and Yuliya Bolotova (2006) and Connor (2006) calculate a median overcharge of 28 percent, based on meta-analysis of more than 600 cartels. The estimate is similar to those reported in a spate of case studies (e.g., Jeffrey H. Howard and David Kaserman 1989, Luke M. Froeb, Robert A. Koyak and Gregory J. Werden 1993, John E. Kwoka 1997, Robert H. Porter and J. Douglas Zona 1999, Connor 2001, Lawrence J. White 2001).[5]

The paper proceeds as follows. Section I introduces the model of industry behavior and derives empirical predictions. Section II discusses the data construction and motivates the regression sample. Section III outlines the empirical strategies. Section IV presents the main results and robustness checks, Section V explores some additional checks, and Section VI concludes.

[5] Michael D. Whinston (2006) provides an overview of this literature.

I The Theoretical Model

A Industry behavior

Assume that an antitrust authority enforces competition, albeit imperfectly, in $n = 1, 2, \ldots N$ industries over $t = 1, 2, \ldots$ periods. Industries collude or compete in each period, and may change states between periods. Industries that compete during period t collude during the next period with probability a_t. The antitrust authority discovers industries that collude (cartels) during period t with probability b_t and these industries compete in the subsequent period. Cartels that avoid discovery abandon collusion for other reasons with probability c_t. The transition parameters a_t, b_t and c_t can be interpreted as the formation rate, the detection rate, and the dissolution rate, respectively, and are determined outside of the model. Each must lie along the open interval between zero and one. For notational convenience, I define the parameter vector $\boldsymbol{\theta} = (a_t, b_t, c_t, N)$.

The distribution of industries across the collusive and competitive states follows a first-order Markov process in expectations and, provided that the transition parameters are constant, the distribution converges to a steady state regardless of initial conditions. To start, denote the number of industries that start colluding after period t as U_t, the number of cartels that the antitrust authority detects after period t as V_t, and the number of cartels that abandon collusion after period t as W_t. These "flow" quantities each sum a series of identical industry-specific Bernoulli events and have binomial distributions characterized by the relevant transition parameter(s) and the pre-existing distribution of industries across the collusive and competitive states (e.g., Casella and Berger 2002):

$$
\begin{aligned}
&U_t \sim \text{binomial}(Y_t, a_t), && \text{E}[U_t] = a_t Y_t, \\
(1) \qquad &V_t \sim \text{binomial}(X_t, b_t), && \text{E}[V_t] = b_t X_t, \\
&W_t \sim \text{binomial}(X_t - V_t, c_t), && \text{E}[W_t] = c_t(1 - b_t) X_t,
\end{aligned}
$$

where X_t and Y_t denote the number of industries that collude and compete during period t, respectively. Thus, for example, the expected number of discoveries after period t is simply the detection rate times the number cartels active during period t.

Equation 1 yields a distribution of industries across the collusive and competitive states that follows a first-order Markov process in expectations:

$$\text{(2)} \qquad \mathrm{E}\begin{bmatrix} X_{t+1} \\ Y_{t+1} \end{bmatrix} = \begin{bmatrix} 1-b_t-c_t(1-b_t) & a_t \\ b_t+c_t(1-b_t) & 1-a_t \end{bmatrix} \mathrm{E}\begin{bmatrix} X_t \\ Y_t \end{bmatrix}.$$

The process, like all Markov processes governed by transition probabilities strictly bounded between zero and one, converges to a unique steady state provided that the probabilities are fixed across periods. The steady state vector, $[X^* \; Y^*]'$, has the expression:

$$\text{(3)} \qquad \begin{bmatrix} X^* \\ Y^* \end{bmatrix} = \tfrac{1}{a+b+c(1-b)} \begin{bmatrix} a \\ b+c(1-b) \end{bmatrix} N.$$

Convergence to the steady state vector occurs regardless of the initial conditions. Consider the arbitrary vector $[X_t \; Y_t]'$. The numbers of firms that collude and compete, respectively, in expectation during period $t+\tau$ ($\tau > 0$) have the closed form expressions:

$$\text{(4)} \qquad \begin{aligned} \mathrm{E}[X_{t+\tau}] &= \frac{a}{a+b+c(1-b)}\left(1+\frac{b+c(1-b)}{a}(1-a-b-c(1-b))^{\tau}\right)X_t \\ &+ \frac{a}{a+b+c(1-b)}\left(1-(1-a-b-c(1-b))^{\tau}\right)Y_t\,, \\ \mathrm{E}[Y_{t+\tau}] &= \frac{a}{a+b+c(1-b)}\left(\frac{b+c(1-b)}{a}-\frac{b+c(1-b)}{a}(1-a-b-c(1-b))^{\tau}\right)X_t \\ &+ \frac{a}{a+b+c(1-b)}\left(\frac{b+c(1-b)}{a}+(1-a-b-c(1-b))^{\tau}\right)Y_t. \end{aligned}$$

These convergence paths are obtainable via difference equations. It may be apparent, however, that as τ trends to infinity, the expected state vector $\mathrm{E}[X_{t+\tau} \; Y_{t+\tau}]'$ converges to the steady state vector $[X^* \; Y^*]'$.

B The Number of Cartel Discoveries

An antitrust innovation, such as the leniency policy, affects the number of cartels that the antitrust authority discovers over time. I model an antitrust innovation as an exogenous change in the formation and/or detection rates during the arbitrary period $t = s$. I hold the dissolution rate and the number of industries constant.[6] Equations 1 and 3 give the expected steady state number of cartel discoveries prior to the innovation:

$$\mathrm{E}[V_t|\; t < s; \boldsymbol{\theta}] = \frac{b_1 a_1}{a_1 + b_1 + c(1-b_1)} N, \tag{5}$$

where a_1 and b_1 represent the formation and detection rates prior to the innovation. After the innovation, the expected number of cartel discoveries converges to:

$$\lim_{t\to\infty} \mathrm{E}[V_t|\; \boldsymbol{\theta}] = \frac{b_2 a_2}{a_2 + b_2 + c(1-b_2)} N, \tag{6}$$

where a_2 and b_2 represent the new formation and detection rates. Equations 1 and 5 give the path of convergence:

$$\begin{aligned} \mathrm{E}[V_t|\; t \geq s; \boldsymbol{\theta}] \quad &= \quad \frac{b_2 a_2}{a_2 + b_2 + c(1-b_2)} \left(1 + \frac{b_2 + c(1-b_2)}{a_2} (1 - a_2 - b_2 - c(1-b_2))^{t-s}\right) X_1^* \\ &+ \quad \frac{b_2 a_2}{a_2 + b_2 + c(1-b_2)} \left(1 - (1 - a_2 - b_2 - c(1-b_2))^{t-s}\right) Y_1^* \; . \end{aligned} \tag{7}$$

To help build intuition, Figure 1 plots the expected convergence paths after four differ-

[6] Leniency has ambiguous implications for the dissolution rate. Suppose that some firms abandon collusion due to the introduction of a leniency program. The extent to which these firms apply for leniency determines whether the dissolution rate increases or decreases. Provided that leniency is partial (as it is the U.S., due to potential civil damages) the effect on dissolution depends on the probability of *ex post* detection and the relevant expected fines. An earlier version of this paper, posted on the journal's webpage, uses structural estimation techniques to deal flexibly with the issue. It shows that the main results hold under a number of different assumptions regarding the effect of leniency on the dissipation rate.

ent innovations. Panels A and B isolate changes in the detection and formation rates, respectively. In particular, Panel A features an increase in the detection rate ($b1 = 0.2,\ b2 = 0.3$) and holds the other parameters constant ($N = 100,\ a1 = a2 = 0.2,\ c = 0.0$). The number of expected cartel discoveries is higher immediately following the innovation because the antitrust authority discovers a greater proportion of active cartels, but this effect dampens as the enhanced detection shrinks the pool of active cartels. By contrast, Panel B features a decrease in the formation rate ($a1 = 0.2,\ a2 = 0.1$) and holds the other parameters constant ($N = 100,\ b1 = b2 = 0.2,\ c = 0.0$). There is no immediate change but discoveries again fall gradually as enhanced deterrence shrinks the pool of active cartels.

[Figure 1 about here.]

Panels C and D combine simultaneous changes in the detection and formation rates. Panel C features an increase in the detection rate ($b1 = 0.2,\ b2 = 0.3$) and a decrease in the formation rate ($a1 = 0.2,\ a2 = 0.1$), and holds the other parameters constant ($N = 100,\ c = 0.0$). The changes may be characteristic of "successful" innovations in that they are consistent with enhanced detection and deterrence capabilities. The number of expected cartel discoveries is higher immediately following the innovation due to the detection rate increase. The detection and formation rate changes both shrink the pool of active cartels over time, so discoveries then fall accordingly. Discoveries fall below initial levels because the formation rate decrease is sufficiently large. Panel D features a decrease in the detection rate ($b1 = 0.2,\ b2 = 0.15$) and an increase in the formation rate ($a1 = 0.2,\ a2 = 0.4$), and holds the other parameters constant ($N = 100,\ c = 0.0$). The changes may be characteristic of "failed" innovations. Discoveries drop initially and then rise above initial levels.

These expected convergence paths provide the intuition that underlies the main results:

Result 1: *An immediate rise in the expected number of cartel discoveries after an innovation is sufficient to establish an increase in the detection rate.*

Result 2: *If expected discoveries rise immediately after an innovation then a subsequent readjustment below initial levels is sufficient to establish a decrease in the formation rate.*

I provide proofs in an appendix. The theoretical results have the empirical analogues that an immediate increase in cartel discoveries following the introduction of the leniency program is consistent with enhanced detection capabilities, and that a subsequent readjustment below pre-leniency levels is consistent with enhanced deterrence capabilities.

II Data and Sample Information

The data consist of all indictments and information reports filed for violations of Section 1 of the Sherman Act between January 1, 1985 and March 15, 2005.[7] Information reports do not require a grand jury and are typically filed in conjunction with plea agreements from one or more defendants. The data include 809 information reports and 222 indictments. Each document – regardless of whether it is an indictment or an information report – includes the name of the alleged conspirator, the affected geographic and product markets, and approximate start and end dates of the conspiracy, as well as various other information.

The documents do not typically provide a one-to-one map to the cartels: many cartels appear to result in two or more documents, and many documents list multiple firms and/or individuals that participated in a single cartel. I group the conspirators into cartels to facilitate evaluation on the cartel level. The procedure introduces some subjectivity because the DOJ does not explicitly identify co-conspirators across documents. The groupings nonetheless may be reasonably accurate due to the wealth of geographic, product, and temporal data. In *ex post* comparisons, the groupings match well various cartel descriptions provided by the DOJ. I identify a total of 342 distinct cartels.

The theoretical model develops predictions and moment conditions for the number of

[7] Documents filed after December 1, 1994 are available for download from the DOJ Antitrust Division website, <www.usdoj.gov/atr/cases.htm>.

cartel discoveries. I create a series of six-month periods to track discoveries. The periods alternately begin on August 10 and February 10, so that they fit the introduction of the new leniency program on August 10, 1993. There are forty periods in the data and I calculate the number of discoveries in each.[8] Figure 2 plots the total number of discoveries per period. The vertical bar marks the introduction of leniency. The pattern of first-order magnitude is a downward trend over the sample; the comparative statics developed in the theoretical model are second-order at best. Although an optimist might argue that discoveries are high relative to trend around the introduction of leniency, it is not clear that the theoretical model enables an appropriate analysis of the time-series.

[Figure 2 about here.]

In order to mitigate the nuisance trend, I include only the first cartel discovery per industry in the main regression sample (207 of 339 cartels qualify).[9] The excluded intra-industry discoveries are more prevalent early in the sample, when more cartels are local in geographic scope. Indeed, the bulk of intra-industry cartels operate contemporaneously in different geographic areas: more than 85 percent of intra-industry discoveries occur within five years of the original discovery and these cartels are 68 percent more likely to be local in scope.[10] The sample selection rule also has secondary conceptual advantages. Since the DOJ often parlays the discovery of a cartel into information on similar cartels (e.g., Ghosal 2006),

[8] I drop three cartels that have filing dates before February 10, 1985 or after February 9, 2005. The main results are robust to the use of three-month and twelve-month periods.

[9] The industry classifications are relatively straight-forward. The DOJ is usually quite specific when designating the affected industry (i.e., the product market). Examples include "military household goods storage," "pipe supply bids," and "traffic signals and lighting construction." Further, the DOJ tends to use identical language across all documents that pertain to the same industry.

[10] As a representative example, consider the case of collusion among chain link fence manufacturers. The DOJ prosecuted three cartels in this industry during the 1980s. The cartels appear mutually exclusive in the data, in the sense that no firm was indicted for participation in more than one cartel. The first cartel operated in some southern states between December 1984 and July 1986. The second cartel operated in the Midwest also between December 1984 and July 1986, and the third cartel operated in some western states between April 1984 and June/July 1986. The DOJ issued indictments for the three cartels on August 14, 1987, October 16, 1989, and March 27, 1991, respectively. Only the southern cartel is included in the regression sample.

the exclusion of intra-industry discoveries removes potentially misleading discoveries and bolsters observational independence. Further, the rule reduces measurement error caused by the grouping procedure because it avoids double-counting when a single cartel is incorrectly classified as two (or more) cartels.[11]

Figure 3 plots the main regression sample. The vertical bar again marks the introduction of leniency. The comparative statics of the theoretical model are more apparent, and the raw data provide some preliminary insight. There are an average of 6.47 discoveries in the 17 six-month periods preceding leniency. The number of discoveries is higher in the two periods immediately following leniency introduction (these periods have 10 and 9 discoveries, respectively). The remaining 21 periods average only 3.71 discoveries, nearly 40 percent fewer than the pre-leniency periods. This difference is easily statistically significant – a difference-in-means test returns a p-value of 0.0008. Thus, evaluated within the framework of the theoretical model, the increase in discoveries around leniency introduction is consistent with enhanced detection capabilities, and the subsequent decrease in discoveries below pre-leniency levels is consistent with enhanced deterrence capabilities.[12]

[Figure 3 about here.]

III Empirical Framework

I use reduced-form Poisson regression to test whether the data are consistent with changes in the formation and detection rates after the introduction of the leniency program. The regression model expresses the probability that V_t, the number of cartel discoveries, has the

[11]For robustness, I experiment with different sample selection rules. The results are similar when I exclude cartels with a previously indicted conspirator and/or cartels whose discovery is known to have been influenced by previous investigations in different industries (e.g., the DOJ discovered the sodium gluconate cartel through its investigation of the citric acid cartel). Notably, the results do not depend materially on the inclusion/exclusion of the Akzo Nobel and Archer Daniels Midland cartels discovered during of the 1990s.

[12]Discoveries jump the period before introduction of the leniency program. I explore the possibility that cartels anticipated leniency introduction in Section IV. The results are robust to various treatments of the final pre-leniency period.

realization v_t as:

$$\text{(8)} \qquad \text{Prob}(V_t = v_t \mid \boldsymbol{x}_t) = \frac{\exp(-\lambda_t)\lambda_t^{v_t}}{v_t!}, \qquad v_t = 0, 1, 2, \ldots,$$

where the conditional mean λ_t is:

$$\text{(9)} \qquad \lambda_t = \exp(\boldsymbol{x}_t'\boldsymbol{\beta}),$$

the vector $\boldsymbol{x}_t$ contains regressors, and $\boldsymbol{\beta}$ is a vector of parameters. The regressors include LENIENCY, which equals 1 if the period postdates the introduction of leniency and 0 otherwise, as well as polynomials in TIME1 and TIME2. The variable TIME1 equals 1 during the first period, 2 during the second period, and so on. The variable TIME2 equals 1 in the second period following leniency introduction, 2 in the next period, and so on.[13]

I perform two statistical tests. In the first, I examine whether the number of cartel discoveries increases immediately after the introduction of leniency. Result 1 of the theoretical model suggests that such an increase is consistent with enhanced detection capabilities. Because the regression model generates an immediate increase in discoveries if and only if the LENIENCY coefficient is positive, I test the hypothesis:

$$H_0 : \beta_{LEN} \leq 0 \text{ versus } H_1 : \beta_{LEN} > 0,$$

where β_{LEN} denotes the LENIENCY coefficient. In the second statistical test, I examine whether the number of cartel discoveries subsequently decreases below initial levels. Result 2

[13]Two econometric issues are worthy of mention. The Poisson regression model provides consistent estimates even when the dependent variable is not generated specifically from a Poisson process (e.g., Colin A. Cameron and Pravin K. Trivedi 1998). The model is thus suitable for analyzing discoveries, which are distributed binomial by Equation 1. Also, statistical inference is valid under the assumption of equidispersion, i.e., the equality of the conditional mean and the conditional variance. For robustness, I estimate the more flexible negative binomial regression model. The coefficients are virtually identical to those obtained from Poisson regression. The dispersion parameter is nearly zero and a likelihood ratio test fails to reject the null of equidispersion (p-value$= 0.50$).

of the theoretical model suggests that such a decrease is consistent with enhanced deterrence. In the regression model, changes in the number of discoveries correspond to changes in the conditional mean. Thus, I test the hypothesis:

$$H_0 : \lambda_{t|t>>s} \geq \lambda_s \text{ versus } H_1 : \lambda_{t|t>>s} < \lambda_s,$$

where λ is the conditional mean and s is the period of leniency introduction.

For robustness, I estimate the Poisson regression model controlling for potentially confounding influences. Ghosal and Gallo (2001) suggest that the DOJ caseload may be countercyclical and positively associated with the Antitrust Division budget allocation, and I create variables that proxy these factors. The first variable, ΔGDP, is the semi-annual growth rate of the real gross domestic product. The second variable, FUNDS, is the average Antitrust Division budget allocation. I also create the variable FINES, which captures total corporate fines issued by the Antitrust Division during the previous fiscal year. The means of the three variables are 0.015, 0.088, and 0.128, respectively, though I demean the variables before estimation to ease interpretation.[14]

IV Regression Results

I first consider the effects of leniency on detection capabilities. Table 1 presents the main Poisson regression results. In each regression, the units of observation are six-month periods and the dependent variable is the number of cartel discoveries. Column 1 includes LENIENCY and a fifth-order polynomial in TIME2. The estimated LENIENCY coefficient

[14] The data are available from the Antitrust Division website (<www.usdoj.gov/atr/public/10804a.htm> and <http://www.usdoj.gov/atr/public/workstats.htm>) on a fiscal year basis. I define FUNDS as the weighted-average of the budget allocations for periods that include two fiscal years. Of course, this variable is potentially endogenous or codetermined with leniency. I lag FINES in order to mitigate potential endogeneity issues. Both FUNDS and FINES are measured in billions of real 2000 dollars. The main results hold when the control variables enter in logarithmic form.

of 0.474 corresponds to an immediate 60.66 percent increase in discoveries and is statistically significant at the one percent level, consistent with enhanced detection. Columns 2, 3, and 4 feature different polynomials in TIME1 and TIME2. Specifically, Column 2 includes a first-order polynomial in TIME1, Column 3 includes a fourth-order polynomial in TIME2, and Column 4 includes a sixth-order polynomial in TIME2. The estimated LENIENCY coefficients correspond to immediate 71.88, 60.90, and 59.12 percent increases in discoveries, respectively, and the coefficients remain statistically significant in each case.

[Table 1 about here.]

Table 2 shows that the result is robust to the inclusion of control variables and the use of different period lengths. Columns 1, 2, and 3 alternately include Δ GDP, FUNDS, and FINES, and Column 4 includes all four control variables. The estimated LENIENCY coefficients remain positive and statistically significant, and correspond to immediate 54.86, 83.79, 61.48, and 61.33 percent increases in discoveries, respectively, when evaluated at the mean of the control variables. Interestingly, the results provide little support for the empirical findings of Ghosal and Gallo (2001) that antitrust activity is countercyclical and correlated with the Antitrust Division budget. Columns 4 and 5 use three-month periods and twelve-month periods, respectively. The estimated LENIENCY coefficients remain positive and significant, and correspond to immediate 89.52 and 46.98 percent increases in discoveries.[15]

[Table 2 about here.]

Turning to the effect of leniency on deterrence capabilities, Figure 4 plots the estimated conditional means (i.e., predicted values) for the regressions shown in Table 1, along with

[15] Ghosal and Gallo (2001) and Ghosal (2004) show that the party of the President may correlate with DOJ antitrust case activity. The data studied here indicate that Republican administrations discovered an average of 10.58 cartels per year (including only the first cartel per industry) versus an average of 10.00 per year for Democrat administrations. The small number of regime changes (two) hampers meaningful identification of any party effects within the Poisson regression framework.

95 percent confidence intervals for the estimates. Panel A includes LENIENCY and fifth-order polynomial in TIME2. The predicted value for periods before the leniency program is 6.47. Following the post-leniency spike in discoveries, the predicted values quickly fall below this level, consistent with greater deterrence capabilities. The differences are statistically significant and large in magnitude: the mean predicted value for periods at least three years after leniency introduction is 3.78, which corresponds to a 41.61 percent reduction relative to pre-leniency levels. Panels B, C, and D feature different polynomials in TIME1 and TIME2. Panel B includes a first-order polynomial in TIME1, Panel C includes a fourth-order polynomial in TIME2, and Panel D includes a sixth-order polynomial in TIME2. In each case, the predicted values after leniency quickly fall below the pre-leniency level. The mean predicted values for periods at least three years after leniency are 37.53, 41.60, and 41.67 percent lower than pre-leniency levels, respectively, and the differences remain statistically significant.[16]

[Figure 4 about here.]

Figure 5 shows that the result is robust to the inclusion of control variables and the use of different period lengths. Panels A, B, and C alternately include Δ GDP, FUNDS, and FINES, and Panel D includes all four control variables. In each case, the predicted values after leniency fall below the pre-leniency level. The mean predicted values for periods at least three years after leniency are 42.54, 5.10, 44.87, and 38.95 percent lower than pre-leniency levels, respectively, when evaluated at the mean of the control variables. The differences are statistically significant in each case.[17] Panels E and F use three-month and twelve-month periods, respectively. Again, the predicted values after leniency fall below

[16]Significance at the five percent level is maintained for all periods, with the exceptions of the final period in Panel C and the final three periods in Panel D.

[17]The plotted predicted values and confidence intervals are adjusted to exclude the influence of the control variables. Significance at the five percent level is maintained for all periods in Panels A and C, for one period in Panel B and for six periods in Panel D. In general, the results are somewhat weaker when a control for the Antitrust Division budget is included. The budget trends upwards during the sample but has little year-to-year variation: the regression of FUNDS on a linear time trend yields an R^2 of 0.9352.

the pre-leniency levels. The mean predicted values for periods at least three years after leniency are 41.03 and 41.21 percent lower than pre-leniency levels, and the differences are statistically significant. Overall, the results provide statistical support for enhanced detection and deterrence capabilities due to the introduction of the new leniency program.

[Figure 5 about here.]

V Additional Robustness Tests

A Did cartels anticipate the new leniency program?

The empirical strategy rests on the assumption that cartels did not anticipate the introduction of the new leniency program. The assumption may be justifiable because Bingaman – the Assistant Attorney General who announced the program – was appointed fewer than two months prior to introduction. Nonetheless, an interesting feature of the data is that discoveries actually spike prior to the introduction of the new leniency program and, at first glance, one may be tempted to explain the spike as an anticipation effect. More detailed inquiry is not supportive. Of the twelve cartels discovered in the period immediately preceding leniency, nine were discovered more than three months prior to introduction (before the appointment of Bingaman). Still, for robustness, I regress discoveries on LENIENCY and a fifth-order polynomial in TIME2, excluding the period before leniency. The resulting Poisson regression coefficient of 0.499 is statistically significant at the one percent level. I also redefine LENIENCY and TIME2 as if the leniency program was introduced one period sooner (i.e., on February 10, 1993). The resulting coefficient of 0.491 is again statistically significant at the one percent level. The main findings appear to be robust to different treatments of this particular pre-leniency period.[18]

[18] Alternatively, one might expect firms to delay their leniency applications until the introduction of the new leniency program. The empirical evidence cuts against this story. To the extent that firms delayed

B The new leniency program versus placebo interventions

The empirical strategy imposes an exogenous breakpoint at the date of leniency introduction. If alternative breakpoints – i.e., placebo interventions – better fit the data then one might conclude that the relationship between leniency introduction and the time-series of discoveries is unlikely to be causal and that the results are due to misspecification. By contrast, if the fit is superior when the breakpoint is imposed at leniency introduction then the data provide support for the specification. To investigate, I estimate the main Poisson regression model (Table 1, Column 1) for every possible breakpoint in the data and compare the maximized log-likelihoods across the regressions.

Figure 6 plots the results. Each point on the graphs represents the maximized log-likelihood of one regression specification. The point located at zero on the horizontal axis represents the maximized log-likelihood produced when the breakpoint is imposed at leniency introduction. The points to the left (right) of zero represent the log-likelihoods produced when the breakpoint is imposed before (after) leniency introduction. Panel A uses six-month periods. As shown, the maximized log-likelihood produced by leniency (-87.03) is greater than those produced by the placebo interventions that precede leniency introduction. It is also greater than those produced by all but one of the placebo interventions that postdate leniency introduction. The single offending placebo intervention corresponds not to a spike in discoveries, but rather to the sharp drop that occurs in the third period after leniency introduction. Panels B and C show that the results are similar when three-month or twelve-month periods are used. In the twelve-month case, the regression fit is globally maximal when the breakpoint is imposed at leniency introduction. Overall, the procedure provides some support for the empirical specification.

leniency applications the number of discoveries should be low immediately prior to the introduction of the new leniency program and again in the second period after leniency introduction (as opposed to the more gradual fall implied by the theoretical model). Neither holds in the data. The number of discoveries is high before leniency introduction and in the second period after leniency introduction.

[Figure 6 about here.]

C Does the probability of detection depend on time in state?

The theoretical model is memoryless, in the sense that the length of time an industry operates in the collusive or competitive states does not affect the transition probabilities. One might expect the memoryless property to fail in the data, for example because the DOJ levies more substantive fines against longer-lived cartels. To examine the memoryless property empirically, I consider the empirical cumulative distribution function of observed cartel durations,

$$\widehat{F}(D) = (\text{number of cartels with duration} < D)/(\text{total number of cartels}).$$

Under the memoryless property, $\log(1 - \widehat{F}(D))$ should be approximately linear in D (e.g., Peter G. Bryant and E. Woodrow Eckard 1991). Measuring cartel duration as the difference in years between the the estimated start and dates, the relationship is indeed approximately linear: the OLS regression of $\log(1 - \widehat{F}(D))$ on cartel duration yields an adjusted R^2 of 0.9944. Bryant and Eckard (1991) report a similar result for cartel discoveries over the period 1961-1988.

More direct statistical tests are available. The memoryless property implies a constant hazard rate of discovery. One can therefore use the observed cartel durations to estimate the parameters of an appropriately flexible distribution and then examine whether the data reject a constant hazard rate. To implement this procedure, I estimate a Weibull model via maximum likelihood and test the null hypothesis that the shape parameter is one (the Weibull distribution collapses to the constant hazard exponential distribution when the shape parameter is one). Estimation on the regression sample yields a shape parameter of 0.9826, and a likelihood ratio test fails to reject the null hypothesis. Again, Bryant and

Eckard (1991) report a similar result for earlier cartels. Together, the robustness check are consistent with the memoryless property of the theoretical model.

VI Conclusion

Antitrust authorities in the United States guarantee early cartel confessors full amnesty from criminal prosecution. The game-theoretical literature is ambiguous regarding the impacts of this strategic leniency. I provide some empirical evidence. In particular, I show that the number of cartel discoveries increases around the date of leniency introduction and then falls below pre-leniency levels, and argue that the pattern is consistent with enhanced cartel detection and deterrence capabilities. The results may best interpreted with caution due to the lack of cross-section variation in the data and other reasons, but the recent introduction of leniency in the European Union and elsewhere should permit future research endeavors to exploit cross-sectional variation.

The results have the usual market efficiency implications. Interestingly, however, they may also be relevant to law enforcement efforts against organized crime. Spagnolo (2000, 2004) argues that the incentives that govern cartel behavior are quite similar to those that govern gang activities, long-term corruption, and drug trafficking. In each, the lack of enforceable contracts may create free riding, hold-up, and moral hazard problems, and conspirators may employ long-term relationships to support cooperation. Relationships may also generate evidence that one or more conspirators can sell to enforcement authorities in exchange for lenient treatment. In principle, therefore, the theoretical literature on strategic leniency and the empirical results presented here may extend to organized crime.

Of course, the application of strategic leniency to the problem of organized crime is not novel. Nearly 23 percent of drug traffickers sentenced by U.S. courts in fiscal year 2005 received sentences shorter than the mandatory minimum in exchange for testimony and/or other incriminating evidence against co-conspirators in line with the U.S. Sentencing Guidelines (U.S. Sentencing Commission 2005). However, these grants of leniency are generally negotiated *ex post* and at the discretion of the prosecuting authority. The results presented here suggest that the provision of automatic leniency under a set of transparent and well-advertised conditions may strengthen the ability of criminal enforcement agencies to deter and detect organized criminal behavior.

References

[1] **Aubert, Cecile, Patrick Rey, and William E. Kovacic.** 2006. The Impact of Leniency and Whistle-Blowing Programs on Cartels. *International Journal of Industrial Organization*, 24 (6): 1241-1266.

[2] **Bingaman, Anne K.** 1994. "Report from the Antitrust Division, Spring 1994." Speech presented at the Antitrust Spring Meeting of the American Bar Association, Washington, DC.

[3] **Brenner, Steffan.** 2005. "An Empirical Study of the European Corporate Leniency Program." Unpublished.

[4] **Bryant, Peter G. and E. Woodrow Eckard.** 1991. "Price Fixing: The Probability of Getting Caught." *Review of Economonics and Statistics*, 73 (3): 531-536.

[5] **Cameron, A. Colin and Pravin K. Trivedi.** 1998. *Regression Analysis of Count Data.* Econometric Society Monograph No. 30, Cambridge: Cambridge University Press.

[6] **Casella, George and Roger L. Berger.** 2002. *Statistical Inference*, 2nd ed. Pacific Grove, CA: Duxbury.

[7] **Chen, Joe and Joseph E. Harrington, Jr.** 2007. "The Impact of the Corporate Leniency Program on Cartel Formation and the Cartel Price Path." In *The Political Economy of Antitrust*, eds. Vivek Ghosal and Johan Stennek. Oxford: Elsevier.

[8] **Connor, John M.** 2001. "Our Customers Are Our Enemies": The Lysine Cartel of 1992-1995. *Review of Industrial Organization*, 18 (1): 5-21.

[9] **Connor, John M.** 2006. "Price-Fixing Overcharges: Legal and Economic Evidence." In *Research in Law and Economics*, Ed. John B. Kirkwood. Oxford: Elsevier.

[10] **Connor, John M., and Yuliya Bolotova.** 2006. "Cartel Overcharges: Survey and Meta-Analysis." *International Journal of Industrial Organization*, 24 (6): 1109-1137.

[11] **Ellis, Christopher J. and Wesley W. Wilson.** 2003. "Cartels, Price-Fixing, and Corporate Leniency Policy: What Doesn't Kill Us Makes Us Stronger." http://darkwing.uoregon.edu/∼wwilson.

[12] **Froeb, Luke M., Robert A. Koyak, and Gregory J. Werden.** 1993. "What Is the Effect of Bid-Rigging on Prices?" *Economic Letters*, 42 (4): 419-423.

[13] **Ghosal, Vivek and Joseph Gallo.** 2001. "The Cyclical Behavior of the Department of Justice's Antitrust Enforcement Activity." *International Journal of Industrial Organization*, 19 (1), 27-54.

[14] **Ghosal, Vivek.** 2004. “Regime Shifts in Antitrust.” http://www.econ.gatech.edu/faculty/vivek-ghosal.

[15] **Ghosal, Vivek.** 2006. “Discovering Cartels: Uncovering Dynamic Interrelationships between Criminal and Civil Antitrust Investigations.” http://www.econ.gatech.edu/faculty/vivek-ghosal.

[16] **Hammond, Scott D.** 2000. “Fighting Cartels – Why and How? Lessons Common to Detecting and Deterring Cartel Activity.” Speech presented at the Third Nordic Competition Policy Conference, Stockholm, Sweden.

[17] **Hammond, Scott D.** 2001. “When Calculating the Costs and Benefits of Applying for Corporate Amnesty, How Do You Put a Price Tag on an Individual’s Freedom?” Speech presented at the Fifteenth Annual National Institute on White Collar Crime, San Francisco, CA.

[18] **Hammond, Scott D.** 2003. “A Summary Overview of the Antitrust Division’s Criminal Enforcement Program.” Speech presented at the annual meeting of the New York State Bar Association, New York, NY.

[19] **Hammond, Scott D.** 2004. “Cornerstones of an Effective Leniency Policy.” Speech presented at the ICN Workshop on Leniency Programs, Sydney, Australia.

[20] **Harrington, Joseph E., Jr.** 2008. “Optimal Corporate Leniency Programs.” *Journal of Industrial Economics*, 56 (1): 215-246.

[21] **Harrington, Joseph E., and Myong-Hun Chang.** 2007. “Modelling the Birth and Death of Cartels with an Application to Evaluating Antitrust Policy.” http://www.econ.jhu.edu/people/harrington.

[22] **Hinloopen, Jeroen.** 2003. “An Economic Analysis of Leniency Programs in Antitrust Law.” *De Economist* 151 (4): 415-432.

[23] **Howard, Jeffery H. and David Kaserman.** 1989. “Proof of Damages in Construction Bid Rigging Cases.” *The Antitrust Bulletin*, 34: 359-393.

[24] **Kwoka, John E., Jr.** 1997. “The Price Effects of Bidding Conspiracies: Evidence from Real Estate Auctions.” *The Antitrust Bulletin*, 42: 503-516.

[25] **Motchenkova, Evguenia.** 2004. “The Effects of Leniency Programs on the Behavior of Firms Participating in Cartel Agreements.” Unpublished.

[26] **Motchenkova, Evguenia and Rob van der Lann.** 2005. “Strictness of Leniency Programs and Cartels of Asymmetric Firms.” CentER Discussion Paper 74, Tillburg University.

[27] **Motta, Massimo and Michele Polo.** 2003. “Leniency Programs and Cartel Prosecution.” *International Journal of Industrial Organization*, 21 (3): 347-379.

[28] **Newey, Whitney K. and Kenneth D. West.** 1987. "A Simple Positive Semi-Definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix." *Econometrica*, 55 (3), 703-708.

[29] **Organization for Economic Cooperation and Development** 2002. *Fighting Hard Core Cartels: Harm, Effective Sanctions and Leniency Programmes.*

[30] **Organization for Economic Cooperation and Development** 2003. *Hard Core Cartels. Recent Progress and Challenges Ahead.*

[31] **Pate, R. Hewitt.** 2004. "International Anti-Cartel Enforcement." Speech presented at the 2004 ICN Cartels Workshop, Sydney, Australia.

[32] **Porter, Robert H., and J. Douglas Zona.** 1999. "Ohio School Milk Markets: An Analysis of Bidding." *RAND Journal of Economics.* 30 (2): 263-288.

[33] **Rey, Patrick.** 2003. "Towards a Theory of Competition Policy." In *Advances in Economics and Econometrics: Theory and Applications*, eds. M. Dewatripont, L.P. Hansen, and S.J. Turnovsky. Cambridge: Cambridge University Press.

[34] **Spagnolo, Giancarlo.** 2000. "Optimal Leniency Programs." F.E.E.M. Nota di Lavoro No. 42.00.

[35] **Spagnolo, Giancarlo.** 2004. "Divide et Impera: Optimal Deterrence Mechanisms against Cartels (and Organized Crime)." Center for Economic Policy Research Discussion Paper No. 4840.

[36] **Spagnolo, Giancarlo.** 2007. "Leniency and Whistleblowers in Antitrust." In *Handbook of Antitrust Economics*, Ed. P. Buccirossi. Cambridge: M.I.T. Press.

[37] **Spratling, Gary R.** 1999 "Making Companies an Offer They Shouldn't Refuse." Speech presented at the Bar Association of the District of Columbia's 35^{th} Annual Symposium on Associations and Antitrust, Washington, DC.

[38] **U.S. Sentencing Committee.** 2005. *Sourcebook of Federal Sentencing Statistics.*

[39] **Van Barlingen, Bertus.** 2003. "The European Commission's Leniency Notice after One Year of Operation." *Competition Policy Newsletter*, 2: 16-21.

[40] **Van Barlingen, Bertus and Marc Barennes.** 2005. "The European Commission's 2002 Leniency Notice in Practice." *Competition Policy Newsletter*, 3: 6-16.

[41] **Whinston, Michael D.** 2006. *Lectures on Antitrust Economics.* Cambridge: The MIT Press.

[42] **White, Lawrence J.** 2001. "Lysine and Price Fixing: How Long? How Severe?" *Review of Industrial Organization*, 18 (1): 23-31.

APPENDICES

A Proofs

Proof of Result 1. Suppose that an antitrust innovation occurs during the period $t = s$ and the economy is in its steady state prior to the innovation. By Equation 2, the expected number of active cartels in both period $s-1$ and period s is $\frac{a1}{a1+b1+c(1-b1)}$. Thus, the expected number of discoveries in these periods, $\mathrm{E}[V_{s-1}]$ and $\mathrm{E}[V_s]$ are:

$$\frac{b1 * a1}{a1 + b1 + c(1 - b1)} \quad \text{and} \quad \frac{b2 * a1}{a1 + b1 + c(1 - b1)},$$

respectively. If $\mathrm{E}[V_s] > \mathrm{E}[V_{s-1}]$ then $b2 > b1$.

Proof of Result 2. An immediate increase in expected discoveries necessarily implies a higher detection rate, i.e. $b1 < b2$, by Result 1. After the immediate increase, expected discoveries converge monotonically towards a new steady state along the convergence path defined in Equation 5. The new steady state level of expected discoveries is increasing in the detection rate:

$$\frac{\partial}{\partial b}\left[\frac{ab}{a + b + c(1 - b)}\right] = \frac{a^2 + ac}{(a + b + c(1 - b))^2} > 0,$$

so an increase in the detection rate does not generate a readjustment below initial levels. The new steady state level of discoveries is also increasing in the formation rate:

$$\frac{\partial}{\partial a}\left[\frac{ab}{a + b + c(1 - b)}\right] = \frac{b^2 + cb - cb^2}{(a + b + c(1 - b))^2} > 0,$$

so that a decrease in the formation rate can generate a readjustment below initial levels. It follows that if $b1 < b2$ and $\frac{a_1 b_1}{a_1+b_1+c(1-b_1)} > \frac{a_2 b_2}{a_2+b_2+c(1-b_2)}$ then $a1 > a2$.

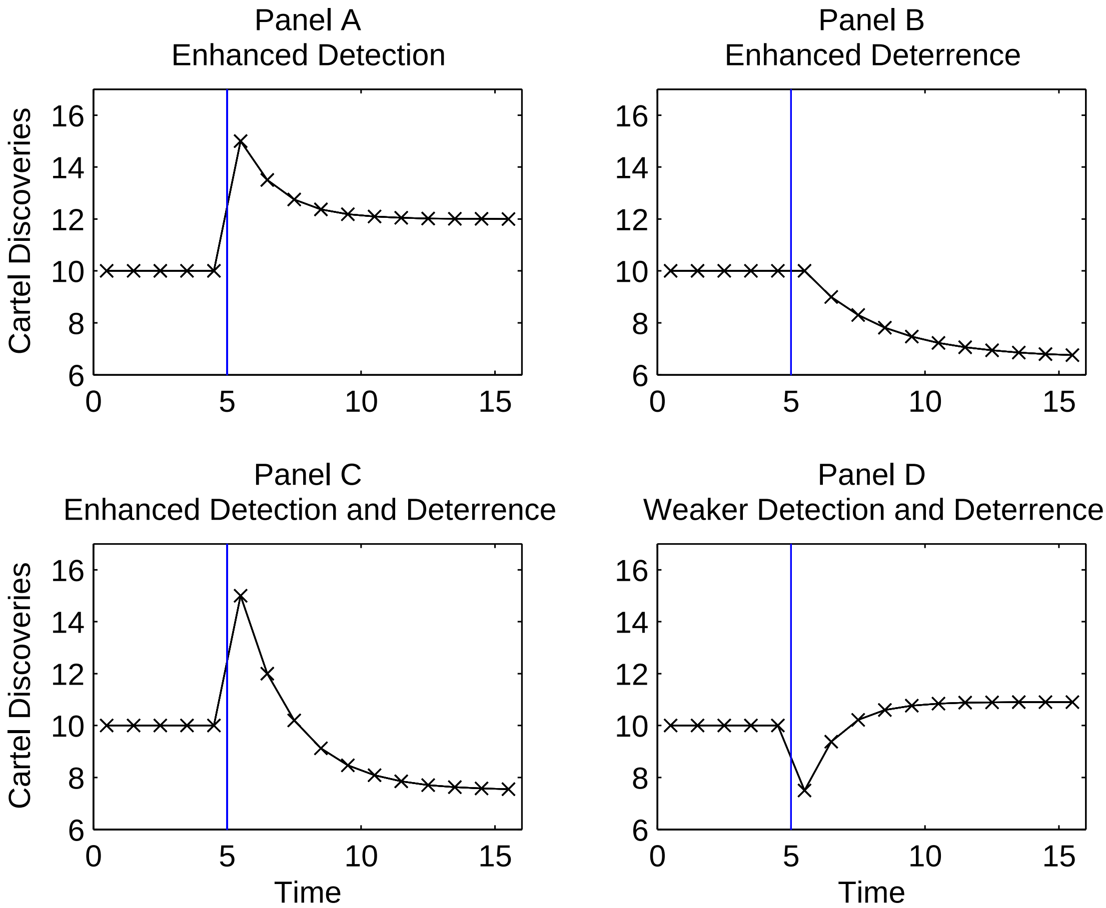

Figure 1: The expected number of cartel discoveries by period. The vertical bar represents an innovation in cartel enforcement. Panel A features an increase in the detection rate (N=100, a1=a2=0.2, b1=0.2, b2=0.3, c=0). Panel B features an decrease in the formation rate (N=100, a1=0.2, a2=0.1, b1=b2=0.2, c=0). Panel C features an increase in the detection rate and a decrease in the formation rate (N=100, a1=0.2, a2=0.1, b1=0.2, b2=0.3, c=0). Panel D features a decrease in the detection rate and an increase in the formation rate (N=100, a1=0.2, a2=0.4, b1=0.2, b2=0.15, c=0).

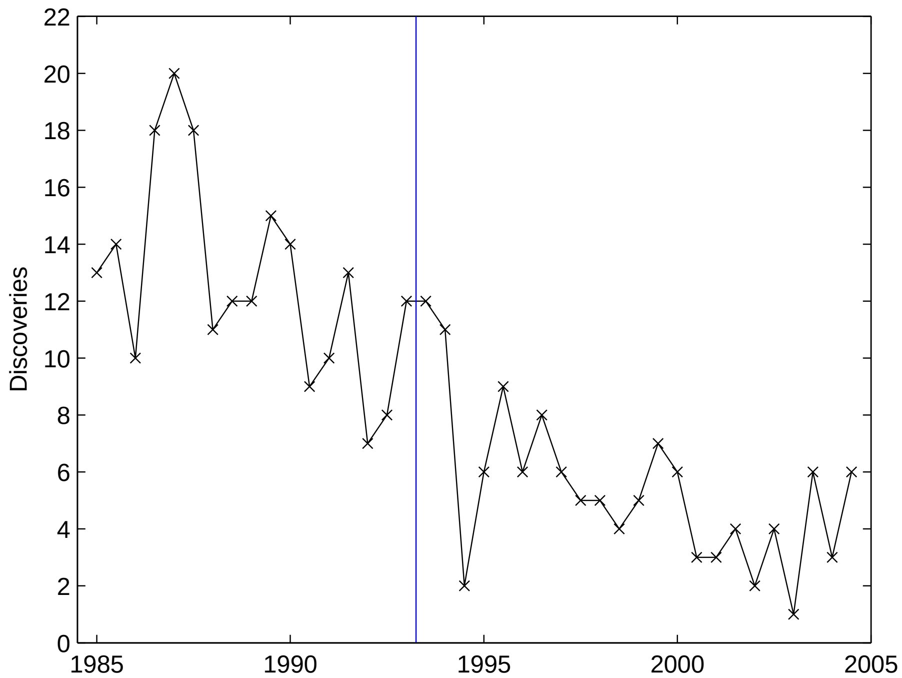

Figure 2: The total number of cartel discoveries per six-month period. The sample runs from February 10, 1985 to February 9, 2005. The vertical bar marks the introduction of the new leniency program on August 10, 1993.

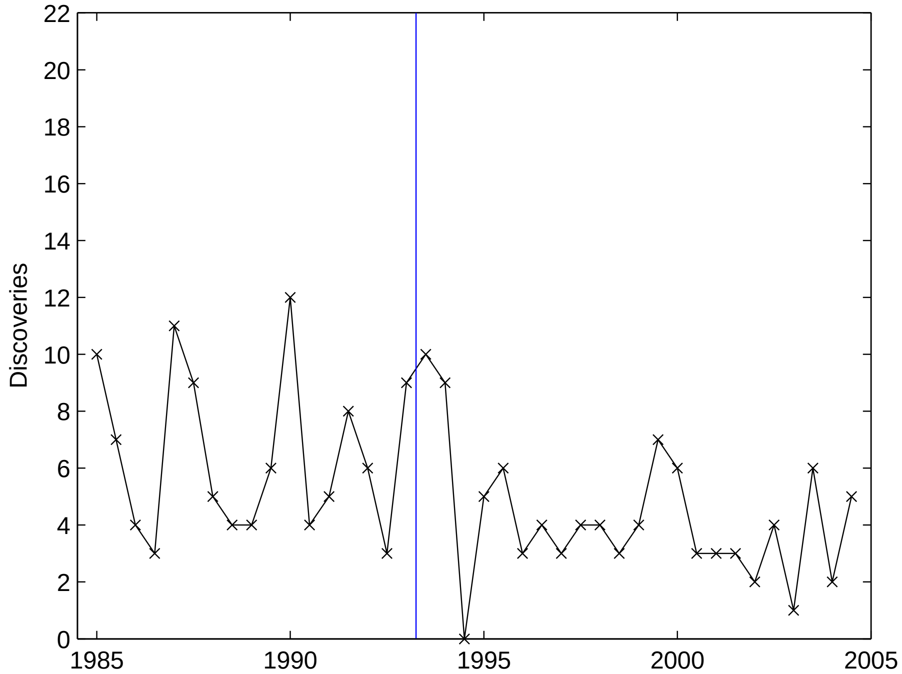

Figure 3: The number of cartel discoveries per six-month period (including only the first cartel per industry). The sample runs from February 10, 1985 to February 9, 2005. The vertical bar marks the introduction of the new leniency program on August 10, 1993.

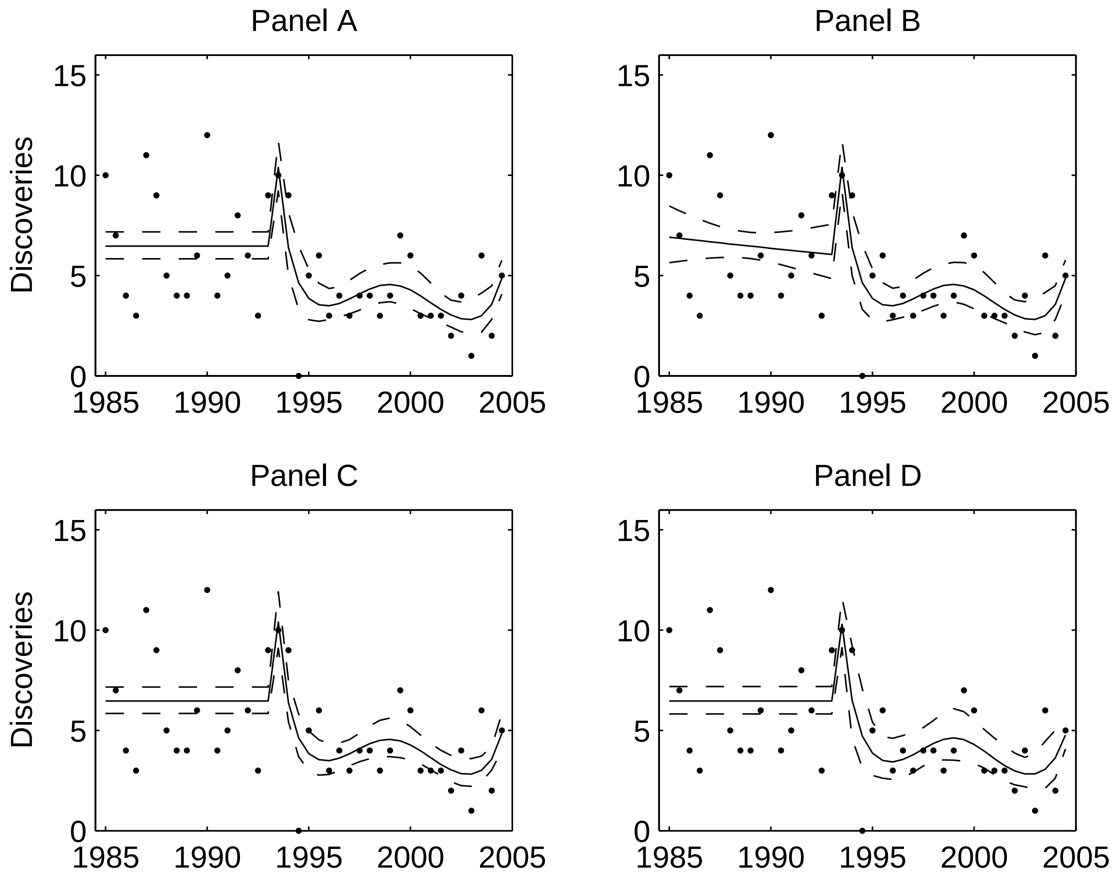

Figure 4: The estimated number of cartel discoveries per six-month period. The estimation procedure is Poisson regression. The solid lines are estimated conditional means and the dashed lines bound 95 percent confidence intervals for these means. The dots are the underlying data. The Panel A regression specification includes LENIENCY and a fifth-order polynomial in TIME2. Panel B includes LENIENCY, a first-order polynomial in TIME1, and a fifth-order polynomial in TIME2. Panel C includes LENIENCY and a fourth-order polynomial in TIME2. Panel D includes LENIENCY and a sixth-order polynomial in TIME2.

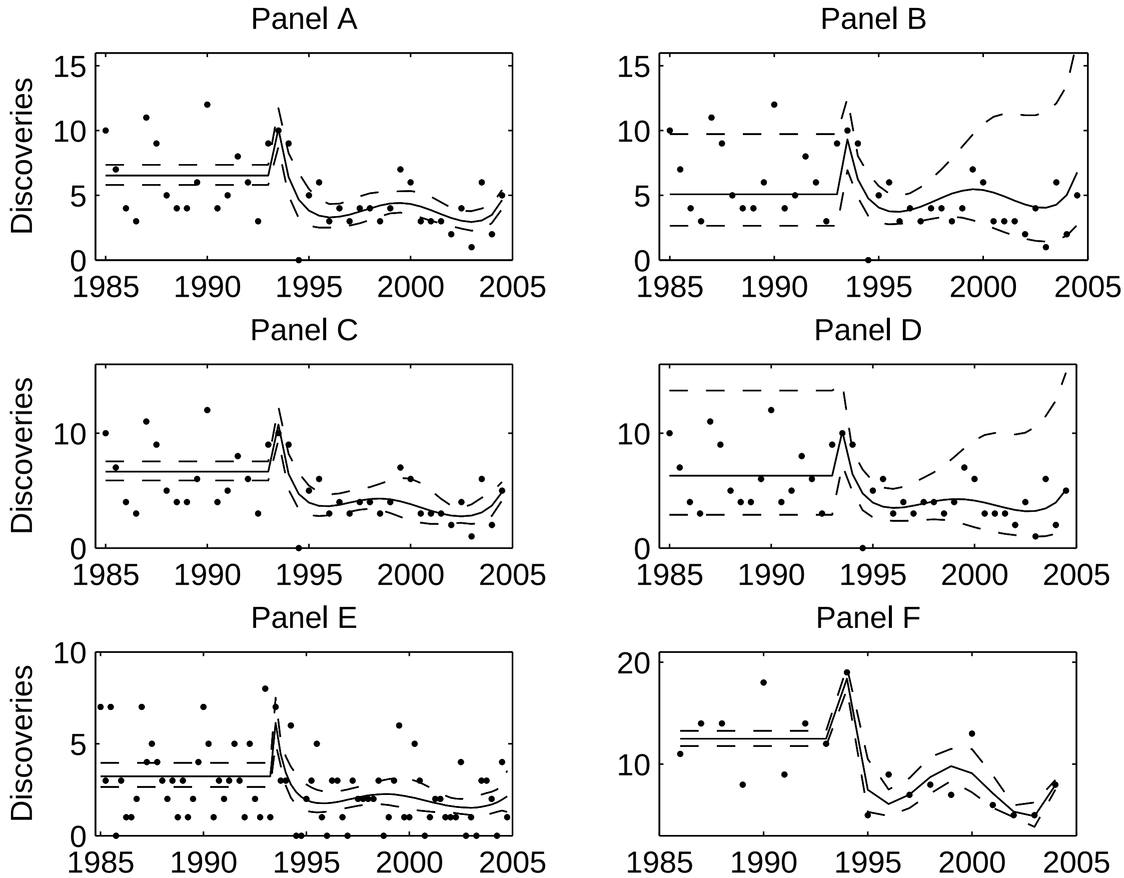

Figure 5: The estimated number of cartel discoveries. The estimation procedure is Poisson regression. The solid lines are estimated conditional means and the dashed lines bound 95 percent confidence intervals for these means. The dots are the underlying data. The units of observations in Panels A, B, C, and D are six-month periods. The units of observation in Panels E and F are three- and twelve-month periods, respectively. All regressions include LENIENCY and a fifth-order polynomial in TIME2. Also, Panel A includes Δ GDP, Panel B includes FUNDS, Panel C includes FINES, and Panel D includes all three control variables.

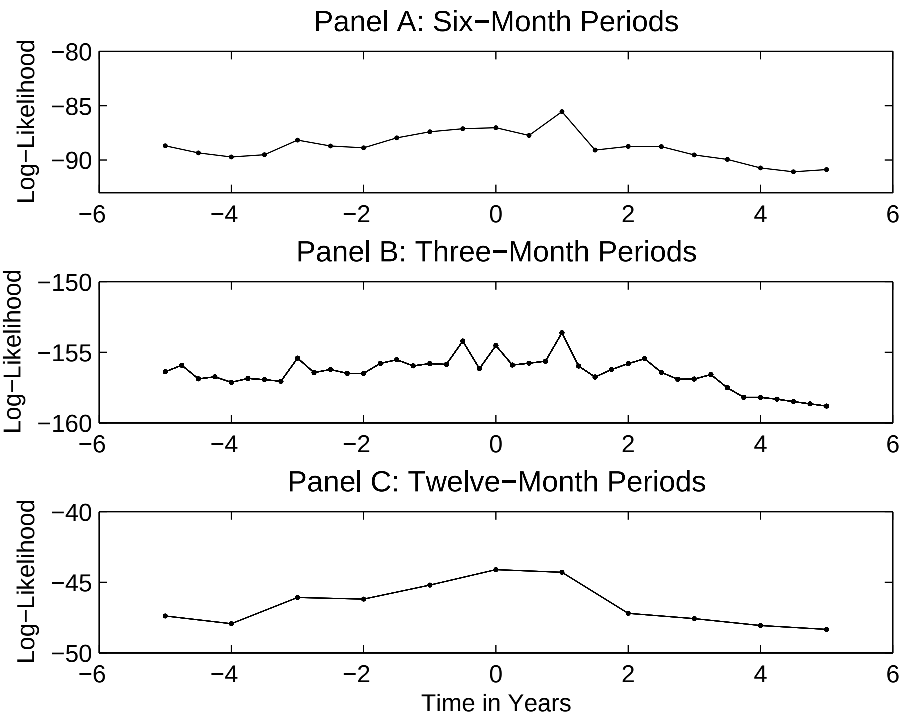

Figure 6: The new leniency program versus placebo interventions. Each point represents the maximized log-likelihood of a Poisson regression. The points located at zero on the horizontal axes are produced by breakpoints that correspond to leniency introduction. The points to the left (right) of zero are produced by placebo interventions that predate (postdate) leniency introduction. Panel A features six-month periods, Panel B features three-month periods, and Panel C features twelve-month periods.

Table 1: Poisson Regression Results

Variables	(1)	(2)	(3)	(4)
Leniency program dummy				
LENIENCY	0.474***	0.550***	0.476***	0.464***
	(0.080)	(0.133)	(0.087)	(0.079)
Polynomials in time				
TIME1	None	1^{st} Order	None	None
TIME2	5^{th} Order	5^{th} Order	4^{th} Order	6^{th} Order
Pseudo-R^2	0.102	0.102	0.102	0.102
Number of Obs.	40	40	40	40

Table 1 shows the main Poisson regression results. The dependent variable is the number of cartel discoveries per period (including only the first cartel per industry). The units of observation are six-month periods. The sample includes the first cartel discovery in each industry. The variable LENIENCY equals 1 if the period postdates August 10, 1993 and 0 otherwise. The variable TIME1 equals 1 in the first period, 2 in the second period, and so on. The variable TIME2 equals 1 in the second period following leniency introduction, 2 in the next period, and so on. Regressions also include an intercept term. Standard errors are robust to heteroscedasticity and fourth-order autocorrelation and are shown in parentheses (e.g., Newey and West 1987). Significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively.

Table 2: Poisson Regression Results, Robustness Checks

	Control Variables				3 Month Periods	12 Month Periods
Variables	(1)	(2)	(3)	(4)	(5)	(6)
Leniency program dummy						
LENIENCY	0.437***	0.609***	0.479***	0.478*	0.639***	0.385***
	(0.099)	(0.203)	(0.080)	(0.250)	(0.146)	(0.039)
Control variables						
ΔGDP	11.808			11.432		
	(8.154)			(9.042)		
FUNDS		-9.409		-2.419		
		(12.694)		(15.211)		
FINES			0.263	0.248		
			(0.301)	(0.282)		
Pseudo-R^2	0.108	0.103	0.102	0.109	0.059	0.193
Number of Obs.	40	40	40	40	80	19

Table 2 shows the Poisson regression results. The dependent variable is the number of cartel discoveries per period (including only the first cartel per industry). The units of observation in Columns 1, 2, 3, and 4 are six-month periods. The units of observation in Columns 5 and 6 are three-month and twelve-month periods, respectively. The variable LENIENCY equals 1 if the period postdates August 10, 1993 and 0 otherwise. All regressions include an intercept and a fifth-order polynomial in TIME2, which equals 1 in the second period following leniency introduction, 2 in the next period, and so on. The variable ΔGDP is the semi-annual growth rate of the real gross domestic product, the variable FUNDS is the average Antitrust Division budget allocation, and the variable FINES is total corporate fines issued by the Antitrust Division during the previous fiscal year. Standard errors are robust to heteroscedasticity and fourth-order autocorrelation and are shown in parentheses (e.g., Newey and West 1987). Significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively.