Strategic Leniency and Cartel Enforcement*

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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. Reduced-form statistical tests are consistent with the notion that leniency enhances deterrence and detection capabilities. Direct estimation of the model, via the method of moments, yields a 59 percent lower cartel formation rate and a 62 percent higher cartel detection rate due to leniency. The results have implications for market efficiency and criminal enforcement.

Keywords: cartel enforcement, leniency program, amnesty, organized crime
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> "The data obstacle to addressing these questions is that we only observe *discovered* cartels, so we do not know the frequency of cartels in the economy. Until we find a way in which to surmount that obstacle, the ultimate impact of leniency programs on cartel formation and the duration of cartels will remain an open question."
>
> ∼ Joseph E. Harrington (forthcoming)

1 Introduction

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, provided that an investigation is not already underway. It also offers discretionary penalty reductions to conspirators (both firms and employees) 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., Hammond 2004) and has recently inspired antitrust authorities in Australia, Canada, the European Union, Japan, South Korea, and elsewhere to introduce similar programs (OECD 2002, 2003). 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 collusive arrangement and apply for leniency (e.g., Spagnolo 2004, Chen and Harrington 2007, Harrington forthcoming). Leniency also may destabilize cartels when conspirators can exploit the policy to raise rivals' costs in subsequent periods (Ellis and 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 even encourage new cartels to form when detection probabilities change stochastically because firms anticipate smaller penalties in the event of detection (Motta and Polo 2003, Harrington forthcoming). The effects of leniency also may depend on market concentration (Ellis and Wilson 2003), whether fines are proportional to accumulated cartel profits (Motchenkova 2004), and the degree of firm heterogeneity (Motchenkova and 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 applied in the United States.[2] 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 (Spratling 1999).
>
> To put it plainly, cartel members are starting to sweat, and the amnesty program 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 (Pate 2004).[3]

It may be prudent to view this rhetoric with some degree of 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., 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).[4] 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

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

[2]Brenner (2005) evaluates the efficacy of the 1996 European Commission leniency notice. I discuss his methodology and results below.

[3]Gary R. Spratling was Deputy Assistant Attorney General in 1999. Scott D. Hammond is Deputy Assistant Attorney General and served as Director of Criminal Enforcement in 2000 and 2001. R. Hewitt Pate is Assistant Attorney General.

[4]Thus, for example, when the DOJ prosecutes a firm for price-fixing violations it does not list co-conspirators by name in the publicly available legal documents.

available data. The combination of potentially perverse incentives and lack of institutional transparency motivates 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 form and the rate at which they are discovered affect the expected 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. The model also supplies moment conditions that can identify the formation and detection rates in more structural estimation.

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.[5] 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., Bingaman 1994, Spratling 1999, Hammond 2003).

I pursue two complementary empirical strategies. First, 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. Second, I exploit functional forms supplied by the theoretical model to identify the formation and detection rates, and I estimate these parameters directly via the method of moments. The econometric procedure selects formation and detection rates that minimize the "distance" between the time-series of cartel discoveries predicted by the theoretical model and the time-series of discoveries observed in the data. The procedure helps quantify the specific impact of leniency on detection and deterrence capabilities.

By way of preview, the time-series of cartel discoveries is consistent with the notion

[5] An information reports does not require a grand jury and is typically filed in conjunction with a plea agreement from one or more defendants.

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. Reduced-form statistical tests indicate that the changes are statistically significant under a number of alternative sample and specification choices. More structural estimation, based on the minimum distance procedure, yields a 59 percent decrease in the cartel formation rate and a 62 percent increase in the cartel detection rate in response to leniency introduction. The results lend credence to the DOJ rhetoric and indicate that leniency programs may have the intended effects.

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. I assume that the antitrust authority discovers all cartels with equal probability. The assumption is not testable, though I show in an appendix that the theoretical predictions regarding cartel discoveries are robust to alternative assumptions. 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 (Van Barlingen 2003).

The paper makes three separate contributions to the literature. First, I develop a theoretical model that guides the empirical evaluation of the new leniency program. The model is fairly intuitive and general, and may help facilitate the evaluation of other criminal enforcement efforts, both in antitrust and (potentially) in other settings characterized by unobservable criminal action and observable detection. Second, I construct and analyze data on cartels discovered between 1985 and 2005. The descriptive statistics may be of some interest to antitrust economists. To my knowledge, no other work has analyzed cartel-level data from the United States since Bryant and Eckard (1991). Finally, I interpret the data within the framework of the theoretical model and show that the time-series of cartel discoveries is consistent with the notion that the new leniency program increased the detection and deterrence capabilities of the DOJ.

Independently, Harrington and Chang (2007) develop an alternative framework with which to test the efficacy of cartel enforcement innovations. Their framework differs from the one developed here namely in that it generates empirical predictions for the time-series of observed cartel durations, rather than for the time-series of discoveries.[6] Unfortunately, empirical applications of the Harrington and Chang (2007) 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, and that the DOJ may devote little effort to accurately identifying determine the true end date of collusion so long as prosecution can proceed within the statute of limitations. The theoretical model developed here may have advantages to the extent that cartel discoveries are more cleanly measured.

The empirical results most closely relate to those of Brenner (2005), who shows that the initial introduction of leniency within the European Union in 1996 had little discernable effect on the duration of detected cartels. As discussed above, the European Commission did not guarantee amnesty to first confessors until 2002. Thus, assuming away 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 Ghosal and 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 this collusion appear large. Connor (2004) and Connor and Bolotova (2005) 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., Howard and Kaserman 1989, Froeb, Koyak and Werden 1993, Kwoka 1997, Porter and Zona 1999, Connor 2001, White 2001).[7]

The results also may be relevant to law enforcement efforts against organized crime generally. Spagnolo (2000, 2004) shows 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 haz-

[6]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.

[7]Whinston (2006) provides an overview of this literature.

ard 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 other forms of 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.

The paper proceeds as follows. Section 2 introduces the model of industry behavior and derives empirical predictions and moment conditions. Section 3 discusses the data construction, provides summary statistics, and motivates the regression sample. Section 4 outlines the empirical strategies. Section 5 presents the main results and robustness checks. Section 6 provides an early empirical analysis of the European Commission's 2002 Leniency Notice. Section 7 concludes.

2 The Theoretical Model

2.1 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 reasons discussed below, let the parameter vector $\theta = (a_t, b_t)$ and the parameter vector $\eta = (c_t, N)$.[8]

The setup imbeds two simplifying assumptions that help generate clean predictions. First, the system 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. This property is testable and I show in Section 5 that the data provide some support. Second, the industries are identical and independent, in the sense that industries share transition probabilities and the transitions of one industry have no effect on other industries. In an appendix, I examine a deterministic game-theoretical model, akin to that of Spagnolo (2004), and show that the main predictions of the theoretical model are robust to industry-level heterogeneity.

2.2 A steady state in expectations

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. Further, closed-form expressions for both the steady state and the path of convergence are available.

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):

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

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:

[8] In Appendix B, I show that these assumptions correspond to a reduced-form version of the economic model employed by Harrington (forthcoming).

$$\mathrm{E}\left[\begin{array}{c} X_{t+1} \\ Y_{t+1} \end{array}\right] = \left[\begin{array}{cc} 1-b_t-c_t(1-b_t) & a_t \\ b_t+c_t(1-b_t) & 1-a_t \end{array}\right] \mathrm{E}\left[\begin{array}{c} X_t \\ Y_t \end{array}\right]. \tag{2}$$

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:

$$\left[\begin{array}{c} X^* \\ Y^* \end{array}\right] = \tfrac{1}{a+b+c(1-b)} \left[\begin{array}{c} a \\ b+c(1-b) \end{array}\right] N. \tag{3}$$

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:

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

These convergence paths are obtainable via difference equations, and I sketch the algebraic steps in Appendix A. 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 $[X^* \; Y^*]'$.

2.3 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, though I relax these constraints in the empirical application.[9]

[9] Appendix B shows that leniency has ambiguous implications for the dissolution rate. The intuition is simple. Consider an effective leniency program that destabilizes cartels. It might (or might not) be optimal for firms that abandon collusion to apply simultaneously for leniency, depending on the extent of leniency and the probability of detection. The extent to which the firms choose to apply for leniency determines whether the dissolution rate increases or decreases. For now, I hold the dissolution rate constant to improve

Equations 1 and 3 give the expected steady state number of cartel discoveries prior to the innovation:

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

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:

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

where a_2 and b_2 represent the new formation and detection rates. Equations 1 and 4 give the path of convergence:

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

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

the tractability of the theoretical model. The empirical application deals flexibly with the issue.

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 Appendix A. 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. Additionally, the expected path of discoveries – as expressed in Equations 5 and 7 – provides a moment that can be exploited for direct estimation of the parameters.

3 Data and Sample Information

3.1 Data construction

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.[10] Information reports do not require a grand jury and are typically filed in conjunction with plea agreements from one or more defendants. The DOJ saves resources by issuing information reports rather than indictments, which may help explain why the data include 809 information reports versus 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.

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

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 is necessarily *ad hoc* because the DOJ does not explicitly identify co-conspirators across documents. Nonetheless, the groupings may be reasonably accurate due to the wealth of geographic, product, and temporal data.[11] In *ex post* comparisons, the groupings match well various cartel descriptions provided by the DOJ. I identify a total of 343 distinct cartels.

3.2 Sample statistics

Table 1 contains summary statistics for the duration, geographic scope, industry classification, and size of the cartels. The average cartel lasts for 4.61 years, when duration is measured as the difference between the start and end dates estimated by the DOJ. Because this duration measure may contain substantial noise, I calculate an upper bound as the time in years between the start and indictment dates. This upper bound has a sample mean of 6.98 years. Interestingly, the means of both measures are quite similar to those calculated by Bryant and Eckard (1991) for cartels prosecuted between 1961 and 1988.[12]

[Table 1 about here.]

To describe the geographic scope of the cartels, I create three dummy variables that equal one if the affected market is local, regional, or at least national, respectively. I define local markets as those that are strictly contained within a single state, regional markets as those that include all of a state and/or parts of multiple states, and national markets as those that span a more substantial proportion of the country. As shown, 43 percent of the cartels operated in local markets, 34 percent operated in regional markets and 23 percent operated in national markets. The documents do not specify whether the affected geographic market is international in scope but do provide the headquarters of prosecuted firms. Nine percent of the sample cartels include an international firm.

[11] As discussed below, the regression sample minimizes grouping errors.

[12] Some of the estimated start and end dates are not specific but rather designate only a month or, worse, only a year. I choose the earliest date within the specified range as the start date and the latest date as the end date. For example, if the listed start and end date is "May 2000," I use May 1, 2000 as the start date and May 31, 2000 as the end date. Estimated start and end dates for a given cartel sometimes differ across documents. Again, I use the earliest start date and the latest end date. I proxy the end date with the filing date when the end date is missing.

Next, I map the DOJ product market descriptions into the North American Industry Classification System (NAICS). As shown the sample cartels are evenly spread among the construction, manufacturing, wholesale trade, retail trade, and "other" industries. Finally, the DOJ prosecuted a mean of 3.24 firms per cartel. Of course, the DOJ may not prosecute all conspirators, due to leniency or other reasons. To pursue this idea further, Table 2 provides the empirical distribution of firms prosecuted. The DOJ pursued legal action against only one firm in fully thirty percent of the cases despite the fact that, by definition, cartels require the participation of multiple firms.[13]

[Table 2 about here.]

Table 3 provides split-sample means, based on whether the document's filing date predated or postdated the introduction of the new leniency program on August 10, 1993. Two changes appear to be first-order. First, the number of cartel discoveries drops from 218 before leniency (on average, 25.65 per year) to 125 after leniency introduction (on average, 10.64 per year). Second, cartels detected in the later period tend to be broader in geographic scope – the fraction of cartels that were local decreased from 50 percent to 31 percent, the fraction that were national increased from 12 percent to 41 percent, and the fraction with an international firm increased from 1 percent to 23 percent. Difference-in-means t-statistics indicate statistical significance in each case. These changes could be due to the leniency program, expanding market boundaries, and/or other factors that affect cartels or cartel enforcement.

[Table 3 about here.]

3.3 The regression sample

The theoretical model develops predictions and moment conditions for the number of cartel discoveries and the duration of these cartels. I create a series of six-month periods to track these factors. 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 and the average duration of discovered cartels in each.[14] I include only the first cartel discovery per industry in the calculations (207

[13] The empirical distributions before and after leniency introduction are similar: The DOJ pursued legal action against only one firm in 31 percent of the cases prior to the leniency program and in 30 percent of the cases after the introduction of leniency.

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

cartels qualify). Subsequent intra-industry discoveries would, if included, threaten observational independence because the DOJ often parlays discoveries into information regarding related cartels. The sample selection rule also minimizes any mistakes associated with the *ad hoc* grouping procedure because it avoids double-counting when a single-industry cartel is erroneously classified as two (or more) distinct cartels.[15]

Panel A of Figure 2 plots the number of discoveries per six-month period over the sample. The vertical bar represents the introduction of the new leniency program. Discoveries average 6.3 per period prior to leniency without an apparent trend. Discoveries are higher in the periods surrounding leniency introduction. The final pre-leniency period features nine discoveries, and the first two leniency periods feature ten and nine discoveries, respectively. Discoveries average 3.7 over the remaining periods. Within the framework of the theoretical model, the surge in discoveries around leniency introduction is suggestive of enhanced detection capabilities, and the subsequent drop in discoveries is suggestive of enhanced deterrence capabilities.[16]

[Figure 2 about here.]

The remaining panels of Figure 2 explore the sample selection rule in greater detail. Panel B plots total discoveries per six-month period, inclusive of all cartels. Total discoveries trend downward over the sample period, to the extent that the comparative statics of the theoretical model are of second-order magnitude at best. The downward trend may be related to the broadening of geographic scope observed over the sample period: a cartel that operates across several geographic markets leaves less room for other cartels in the same industry to operate. Consistent with this logic, the cartels excluded by the sample selection rule are 67.65 percent more likely to operate in a local geographic market than included cartels. Further, Panels C and D show that local cartels and excluded cartels, respectively, trend downwards together over the sample period. In robustness checks, I show that the

[15] The sample selection rule simply sharpens the research question: I focus on whether leniency affects the ability of the DOJ to detect independent cartels rather than whether leniency facilitates intra-industry discoveries. For robustness, I experiment with more strict 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 on the inclusion/exclusion of the Akzo Nobel and Archer Daniels Midland cartels discovered over the course of the 1990s.

[16] Discoveries jump the period before introduction of the leniency program, which suggests that cartels may have anticipated the introduction of the program. I explore this possibility in Section 5. The results are robust to various treatments of the final pre-leniency period.

empirical methodology can accommodate total discoveries, and that the main results hold under this accommodation.

4 Empirical Framework

4.1 Poisson Regression

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 realization v_t as:

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

where the conditional mean λ_t is:

$$\lambda_t = \exp(x_t'\beta), \tag{9}$$

the vector x_t contains regressors, and β 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.[17]

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:

$$H_0 : \beta_{LEN} \leq 0 \text{ versus } H_1 : \beta_{LEN} > 0, \tag{10}$$

where β_{LEN} denotes the LENIENCY coefficient. In the second statistical test, I examine

[17]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., Cameron and 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 more flexible negative binomial regression models and show that the data fail to reject the equidispersion assumption.

whether the number of cartel discoveries subsequently decreases below initial levels. Result 2 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:

$$H_0 : \lambda_{t|t>>s} \geq \lambda_s \text{ versus } H_1 : \lambda_{t|t>>s} < \lambda_s, \tag{11}$$

where λ is the condition 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.[18]

4.2 Direct Estimation

I employ the method of moments to select the formation and detection rates that minimize the distance between the time-series of cartel discoveries predicted by the theoretical model and the time-series of discoveries observed in the data. The estimator is:

$$\widehat{\theta}_{MM} = \arg\min_{\theta \in \Theta} \frac{1}{T} \sum_{t=1}^{T} (V_t - \mathrm{E}[V_t|\ t; \theta; \eta])^2, \tag{12}$$

where V_t is the number of discoveries during period t, $\mathrm{E}[V_t|t; \theta; \eta]$ is the expected number of discoveries, as defined by Equations 5 and 7, the parameter vector θ includes the formation and detection rates, and the parameter vector η contains the dissolution rates and the number of industries. The functional form of $\mathrm{E}[V_t|\ t; \theta; \eta]$ identifies either θ or η as a function of the

[18]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. 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.

other. I estimate θ (the parameter vector of interest) and normalize η.[19] The method of moments estimator is exactly identified and solves the first-order condition:

$$0 = \sum_{t=1}^{T} \frac{\partial \mathrm{E}[V_t|\ t; \theta; \eta]}{\partial \theta} (V_t - \mathrm{E}[V_t|\ t; \theta; \eta]). \tag{13}$$

Evaluated at the true population parameters, θ_0 and η_0, the first-order condition holds in expectation. The derivatives, $\partial \mathrm{E}[V_t|t; \theta; \eta]/\partial \theta$, can be interpreted as efficient instrumental variables. The asymptotic properties of the method of moments are well developed (e.g., Ruud 2000 and Greene 2003), and the estimator has the asymptotic distribution:

$$\sqrt{T}(\widehat{\theta}_{MM} - \theta_0) \rightarrow^d N \left(0,\ \left[\sum_{t=1}^{T} D_t D_t' \right]^{-1} \left[\sum_{t=1}^{T} D_t \Omega_t D_t' \right] \left[\sum_{t=1}^{T} D_t D_t' \right]^{-1} \right), \tag{14}$$

where D_t is the 4×1 vector of derivatives, $\frac{\partial \mathrm{E}[V_t|\ t;\ \theta_0;\ \eta_0]}{\partial \theta}$, for period t, and Ω_t is the variance of V_t. The theory suggests that the errors should be correlated across time, and I use the Newey and West (1987) variance estimator to account for autocorrelation.[20]

5 Results

5.1 Poisson Regressions

I use reduced-form Poisson regressions to test whether the leniency program enhanced detection and deterrence capabilities. A rise in cartel discoveries immediately after leniency

[19] Some discussion of identification may be useful. For a given η, the estimation procedure selects the pre-leniency formation and detection rates such that the expected number of discoveries in each pre-leniency period approximates the mean observed discoveries of the pre-leniency periods, i.e. it selects a_1 and b_1 so that $\mathrm{E}[V_t|\ t < s; \theta; \eta] \approx \frac{1}{s-1} \sum_{t<s} V_t$. The primary source of identification for the new detection rate b_2 is the difference between the mean observed discoveries of the pre-leniency periods and the number of discoveries in the first period after leniency introduction. Changes in the number of discoveries after leniency introduction identify the new formation rate a_2, and also provide a secondary source of identification for b_2. I show in robustness checks that the results are consistent across a broad range of normalization choices for η.

[20] For example, if more cartels are discovered in one period then fewer remain to be discovered in the next. The Newey-West variance estimator is robust to p^{th}-order autocorrelation and has the expression:

$$\frac{1}{T} \sum_{t=1}^{T} \widehat{D}_t \widehat{\Omega} \widehat{D}_t' = \frac{1}{T} \sum_{t=1}^{T} \widehat{D_t \epsilon_t} \widehat{\epsilon_t D_t}' + \sum_{j=1}^{p} \left(1 - \frac{j}{1+p} \right) \left(\frac{1}{T-j} \sum_{t=j+1}^{T} \left(\widehat{D}_t \widehat{\epsilon}_t \widehat{\epsilon}_{t-j} \widehat{D}_{t-j}' + \widehat{D}_{t-j} \widehat{\epsilon}_{t-j} \widehat{\epsilon}_t \widehat{D}_t' \right) \right),$$

where $\widehat{\epsilon}_t$ is the scalar error associated with period t, i.e., $\widehat{\epsilon}_t = V_t - E[V_t|\ t; \widehat{\theta}; \eta]$. I set $p = 4$ in the baseline regressions, but the results are robust to alternative choices.

introduction is consistent with establish enhanced detection capabilities. A subsequent readjustment below initial levels is consistent with enhanced deterrence capabilities.

Starting with detection, Table 4 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 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.[21]

[Table 4 about here.]

Table 5 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.[22]

[Table 5 about here.]

Turning to deterrence, Figure 3 plots the estimated conditional means (i.e., predicted values) for the regressions shown in Table 4, along with 95 percent confidence intervals for

[21] Valid statistical inference in the Poisson regression model depends on equidispersion, i.e., the equality of the conditional mean and variance. For robustness, I estimate the more flexible negative binomial regression model. The coefficients are virtually identical to those obtained from the Poisson regression. The dispersion parameter is nearly zero and a likelihood ratio test fails to reject the null of equidispersion (p-value= 0.50).

[22] 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.

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 Pane 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.[23]

[Figure 3 about here.]

Figure 4 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.[24] Panels E and F use three-month and twelve-month periods, respectively. Again, the predicted values after leniency fall below 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 4 about here.]

[23]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.

[24]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.

5.2 Direct Estimation

Table 6 presents the results of direct estimation, via the method of moments, for a specific set of normalization choices. I let the total number of industries (N) be 1,000 and let the dissolution rates before and after leniency introduction ($c1$ and $c2$) be 0.40. As shown, the estimated cartel formation rate falls from 0.0156 before leniency to 0.0064 after leniency introduction. The difference of -0.0092 is statistically significant and represents a 59.20 percent reduction. The estimated detection rate rises from 0.2297 to 0.3714. The difference of 0.1416 is statistically significant and represents a 61.65 percent increase. Each of the parameters is precisely estimated. Figure 5 plots the regression fit against the data. The estimation procedure fully captures the increase in discoveries around leniency introduction as well as the subsequent downward adjustment. The result is consistent with substantial effects of leniency on the ability of the DOJ to deter and detect cartels.[25]

[Table 6 about here.]

[Figure 5 about here.]

Table 7 shows that the results are consistent across different normalization choices. Column 1 features a lower constant dissolution rate ($c1 = c2 = 0.30$), Column 2 features a higher constant dissolution rate ($c1 = c2 = 0.50$), Column 3 features a dissolution rate increase following leniency introduction ($c1 = 0.40$, $c2 = 0.50$), Column 4 features a dissolution rate decrease ($c1 = 0.50$, $c2 = 0.40$), Column 5 features fewer industries ($N = 500$), and Column 6 features more industries ($N = 3,000$). In each case, the minimum distance procedure suggests that the formation rate fell and the detection rate rose following leniency introduction, and that the changes are statistically significant. In percentage terms, the magnitude of the effects are quite similar across columns – the estimated reduction in the formation rate ranges from 55.80 to 64.34 percent, and the estimated increase in the detection rate is close to 61.60 percent in each column.[26]

[25]The standard errors account for fourth-order autocorrelation ($p = 4$) ala Newey and West (1987). The data suggest that autocorrelation may indeed be present: an OLS regression of the Table 6 residuals ϵ_t on the lagged residuals $\epsilon_{t-1}, \ldots, \epsilon_{t-4}$ returns coefficients of -0.49, -0.56, -0.47, and -0.18, consistent with negative autocorrelation. Further, the test statistic $TR^2 = 12.73$ exceeds the $\chi^2_{4,0.95}$ critical value of 9.49, so the data reject the null of zero autocorrelation (Breusch 1978, Godfrey 1978). The main results are robust to alternative choices of p, including $p = 0$.

[26]The parameter estimates differ across columns in absolute terms. At least two effects merit discussion. First, the overall magnitude of the estimated formation and detection rates change with the normalized dissolution rate (e.g., Column 1 vs. Column 2). Because the dissolution rate is fundamentally unidentifiable, the estimation procedure cannot identify the rate magnitudes (by contrast, the rate changes are robustly

[Table 7 about here.]

Table 8 shows that the results are similar across a number of robustness regressions. First, to account for potentially confounding influences, I use Poisson regression to remove the variance in cartel discoveries due to economic growth, the Antitrust Division budget allocation, and the magnitude of corporate fines, and then use these adjusted discoveries as the dependent variable in the minimum distance procedure.[27] Column 1 presents the results. The formation rate falls from 0.0138 before leniency to 0.0056 after leniency introduction. The difference is statistically significant and represents a 59.06 percent reduction. The detection rate rises from 0.2741 to 0.4411. The difference is statistically significant and represents a 60.90 percent increase. Together, the findings suggest that the main results may reflect real change rather than spurious correlations.

[Table 8 about here.]

Next, I consider alternative period lengths. Columns 2 and 3 present estimation results based on three-month and twelve-month periods, respectively. Again, the formation rates fall after the introduction of leniency. The changes are statistically significant and represent 71.60 and 55.70 percent reductions. Similarly, the detection rates increase after leniency introduction. The changes are statistically significant and represent 1.0482 and 0.5477 percent increases. Thus, alternative period lengths do not appear to substantially affect the direction of the main results, but the estimated rate changes are somewhat larger in magnitude with shorter periods.

In Column 4, I relax the assumption that the number of industries is constant over the sample period. The formation and detection rate parameters remain identifiable provided that some growth pattern is specified. I estimate the model under the assumption that the number of industries is subject to constant proportional growth. That is, I let the number of industries be:

$$N = n * \exp(\rho * \text{TIME1}), \tag{15}$$

identified). Second, the estimated formation rates are higher when the smaller number of industries is smaller (Column 5 vs. Column 6). This is exactly what one would expect from the estimation procedure because the formation rate and the number of industries act as substitutes in the maintenance of a cartel pool of a given size.

[27] I use Poisson regression to model the number of discoveries as a function of LENIENCY, a fifth-order polynomial in TIME2, an intercept, and the control variables (Δ GDP, FUNDS, and FINES), as in Table 5, Column 4. I then calculate the predicted values, evaluated at the means of the control variables, and the residuals. The sum of these two measures is the adjusted number of discoveries and serves as the dependent variable in the direct estimation of the formation and detection rates.

where n is the base number of industries and ρ is the constant growth rate. The growth rate is identifiable and its estimation provides a specification test: the flexible model is equivalent to the baseline model only when $\rho = 0$.[28] As shown, estimation based on the familiar normalization choices $n = 1,000$ and $c1 = c2 = 0.40$ yields a growth parameter that is small ($\widehat{\rho} = -0.0074$) but precisely estimated (standard error = 0.0013). The findings regarding the formation and detection rates are similar to those of the baseline regressions, although the formation rate decrease is somewhat smaller (53.83 percent) and the detection rate increase is somewhat larger (72.41 percent).

Finally, the assumption of constant proportional industry growth makes estimation based on total discoveries (inclusive of all cartels) feasible. Column 5 presents the results of this estimation. The growth rate is negative ($\widehat{\rho} = -0.0283$) and statistically significant (standard error = 0.0014), and accounts for the downward trend in total discoveries over the sample period. Again, the findings regarding the formation and detection rates are similar to those of the baseline regressions, although the formation rate decrease and the detection rate increase are somewhat smaller in magnitude (41.23 and 28.09 percent, respectively). The findings provide some comfort in that the main results are robust to different sample selection treatments. In particular, one need not restrict attention to the first cartel in each industry to generate the main results.

5.3 Remaining Issues

5.3.1 Did cartels anticipate the leniency program?

An interesting feature of the data is that discoveries actually spike prior to the introduction of the leniency program. At first glance, one is tempted to explain the spike as an anticipation effect. The data are not supportive. Of the twelve cartels discovered in the period immediately preceding leniency, nine were discovered more than three months prior to introduction. The Assistant Attorney General who introduced the program – Anne Bingaman – was appointed fewer than two months prior to introduction. Nonetheless, I regress discoveries on LENIENCY and a fourth-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 0.487 is again statistically significant at the one percent level. Thus, the main findings appear to

[28]The growth parameter is identified primarily by trends in discoveries over the pre-leniency periods.

be robust to different treatments of this particular pre-leniency period.[29]

5.3.2 Is the spike in cartel discoveries just noise?

The results weigh heavily the increase in cartel discoveries surrounding the introduction of leniency. However, the data are noisy and discoveries also seem higher than trend in some periods that predate the leniency program (Figure 2, Panel D). A skeptic might argue that the concurrence of leniency introduction and a spike in discoveries could reasonably exist in the data due to pure chance. In order to assess the likelihood of this possibility, I redefine LENIENCY and TIME2 as if the leniency program was introduced during earlier periods. In particular, I focus on the spike that occurs in period eleven (February 10 to August 9, 1990). I regress the number of discoveries on LENIENCY and a fifth-order polynomial in TIME2, as in Column 1 of Table 4. The LENIENCY coefficient is relatively small (0.300) and is not statistically significant (t-stat= 1.07), which suggests that the spike in discoveries surrounding the true date of leniency introduction is somewhat distinctive and may not be the result of pure chance.

More generally, the estimation procedure depends on the exogenous imposition of August 10, 1993 as a structural breakpoint. It is natural to question the robustness of the breakpoint, especially given the spike in discoveries preceding leniency introduction. In particular, one might suspect that the empirical model may be misspecified to the extent that alternative breakpoints better fit the data. To address this concern, I redefine LENIENCY and TIME2 as if the leniency program was introduced in other periods, and then regress the number of discoveries on LENIENCY and a fifth-order polynomial in TIME2 for each possible breakpoint. The fit of the regression – as measured by the pseudo-R^2 – is maximal when the breakpoint is imposed on August 10, 1993, which suggests that the data can deliver the correct breakpoint.

[29] Alternatively, one might expect firms to delay their leniency applications until the introduction of the new leniency program, in which case the empirical model would overestimate the impact of the new leniency program on the detection rate. The empirical evidence cuts against this story. To the extent that firms delayed leniency applications, two patterns should be present in the data. First, the number of discoveries should be low immediately prior to the introduction of the new leniency program. Second, the number of discoveries should drop quickly between the first and second periods 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 remains high through the second period after leniency introduction.

5.3.3 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. The property helps generate clean predictions and is particularly important for the duration moments. Yet it may fail in the data, especially to the extent that the DOJ levies more substantive fines on longer-lived cartels. To examine the memoryless property empirically, I test the null hypothesis that the probability of detection is constant in the duration of collusion, i.e., that cartels face a constant hazard rate. The memoryless property implies that cartel duration has the exponential distribution. I estimate a Weibull model via maximum likelihood and test whether the shape parameter equals one – under that constraint, the Weibull distribution collapses to an exponential and features a constant hazard rate. Estimation on the regression sample yields a shape parameter of 0.9826, and a likelihood ratio test fails to reject the null hypothesis that the underlying population parameter equals one.[30]

5.3.4 Do civil damages matter?

On June 22, 2004, President Bush signed the Antitrust Criminal Penalty Enhancement and Reform Act (ACPERA), which de-trebled civil damages for amnesty recipients.[31] One might expect the number of cartel discoveries to increase following that date. To investigate, I extend the sample through July 2007. Figure 6 plots the results, using ten six-month periods between June 22, 2002 and June 22, 2007. As shown, there is no discernable increase in discoveries immediately following the introduction of ACPERA. The results suggest that the ACPERA may have little substantial impact on detection capabilities.

[Figure 6 about here.]

6 Preliminary Evidence from the European Union

The European Commission's 2002 Leniency Notice may facilitate further empirical evaluations of strategic leniency. The 2002 Leniency Notice is analogous to the new leniency

[30] I measure cartel duration as the difference in years between the start and end dates, as estimated by the DOJ. The results are similar for cartels discovered before and after leniency, respectively. As an alternative approach, I consider the empirical cumulative distribution function of observed cartel durations, $\widehat{F}(D) =$ (number of cartels with duration $< D$)/(total number of cartels). Under the memoryless property, $\log(1 - \widehat{F}(D))$ should be approximately linear in D (e.g., Bryant and Eckard 1991). 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 similar results for cartel discoveries over the period 1961-1988.

[31] Hammond (2005) provides a detailed description of the ACPERA.

program in the United States because both guarantee immunity to confessors that report before an investigation opens and offer potential fine reductions to confessors that report after an investigation opens. Furthermore, both replaced regimes in which immunity grants were discretionary and relatively ineffective in inducing cooperation from members of previously undetected cartels.[32] In principle, therefore, one could use the methods outlined in Sections 2 and 4 to sign and measure the effect of the 2002 Leniency Notice on the ability of the Commission to detect and deter cartels.

The Commission publishes non-confidential versions of its antitrust decisions on its website.[33] The documents are richer than the indictments and information reports made available by the DOJ. Each uniquely identifies a single cartel and its conspirators, so that *ad hoc* grouping across documents is unnecessary. The documents provide the date(s) of any leniency application(s) as well as the dates of "dawn raids" and information requests. They specify explicitly whether the investigation was initiated in response to a leniency application. The documents also provide case results, including which firms qualified for full/partial leniency, the aggravating and attenuating circumstances, and the fines levied against each conspirator. As in the DOJ indictments and information reports, the documents list the affected geographic and product markets and approximate start and end dates.

Figure 7 plots the number of discoveries per twelve-month period. The Commission introduced the 2002 Leniency Notice on February 14, and I set the periods to start on that date. I define discovery as occurring on the date of the first leniency application, dawn raid, or information request. The first-order trend is a fall in the number of discoveries, to the extent that there are no discoveries in the data after 2004. This downward trend is due primarily to publication lag. Among observed cartels, the average time between initial discovery and decision publication is roughly four years. Although the Commission has received leniency applications from more than 80 alleged cartels since the introduction of the 2002 Leniency Notice (Van Barlingen and Barennes 2005), non-confidential versions of antitrust decisions are available for only eight cartels. Although the data are currently unsuitable for analysis, they remain promising for future research regarding strategic leniency and other factors.

[Figure 7 about here.]

[32] Only three conspirators qualified for immunity under the 1996 Leniency Notice (Arbault and Peiro 2002).
[33] The documents are available at <http://ec.europa.eu/comm/competition/cartels/cases/cases.html>.

7 Conclusion

Antitrust authorities in the U.S. and elsewhere guarantee early cartel confessors full amnesty from state prosecution. The game-theoretical literature is ambiguous regarding the impacts of this leniency. In this paper, I provide empirical evidence regarding the efficacy of leniency based on the experience in the United States. 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 by the DOJ over a twenty-year span. Reduced form statistical tests are consistent with the notion that leniency enhances deterrence and detection capabilities. Direct estimation of the model, via the method of moments, yields a 59 percent lower cartel formation rate and a 62 percent higher cartel detection rate due to leniency.

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APPENDICES

A Derivations and Proofs

Derivation of Equation 4. Consider the arbitrary vector $\mathrm{E}[X_t\ Y_t]'$, where X_t and Y_t represent the number of firms that collude and compete during period t, respectively. By Equation 2, the vector $\mathrm{E}[X_{t+\tau}\ Y_{t+\tau}]'$ can be expressed as:

$$\mathrm{E}\begin{bmatrix} X_{t+\tau} \\ Y_{t+\tau} \end{bmatrix} = \begin{bmatrix} 1-b-c(1-b) & a \\ b+c(1-b) & 1-a \end{bmatrix}^{\tau} \begin{bmatrix} X_t \\ Y_t \end{bmatrix},$$

where a, b, and c represent the formation, discovery, and dissolution rates, respectively. Factoring the transition matrix into matrices of eigenvalues and eigenvectors yields:

$$\mathrm{E}\begin{bmatrix} X_{t+\tau} \\ Y_{t+\tau} \end{bmatrix} = \begin{bmatrix} 1 & 1 \\ \frac{b+c(1-b)}{a} & 1-a \end{bmatrix} \begin{bmatrix} 1 & 0 \\ 0 & (1-a-b-c(b-1))^{\tau} \end{bmatrix} \begin{bmatrix} 1 & 1 \\ \frac{b+c(1-b)}{a} & 1-a \end{bmatrix}^{-1} \begin{bmatrix} X_t \\ Y_t \end{bmatrix}.$$

Finally, inverting and combining matrices yields the matrix form of Equation 4:

$$\mathrm{E}\begin{bmatrix} X_{t+\tau} \\ Y_{t+\tau} \end{bmatrix} = \frac{a}{a+b+c(1-b)} \begin{bmatrix} A & B \\ C & D \end{bmatrix} \begin{bmatrix} X_t \\ Y_t \end{bmatrix},$$

where the matrix elements A, B, C, and D are defined such that:

$$\begin{array}{rcl} A & = & 1+\frac{b+c(1-b)}{a}(1-a-b-c(1-b))^{\tau} \\ B & = & 1-(1-a-b-c(1-b))^{\tau} \\ C & = & \frac{b+c(1-b)}{a}+\frac{b+c(1-b)}{a}(1-a-b-c(1-b))^{\tau} \\ D & = & \frac{b+c(1-b)}{a}-(1-a-b-c(1-b))^{\tau}. \end{array}$$

Proof of Result 1. Only a change in the detection rate can immediately affect the expected number of cartel discoveries: whereas the detection rate directly affects discoveries, the formation rate affects discoveries only indirectly through the number of active cartels. To see this formally, 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. Suppose that an innovation changes the detection and/or formation rates. If discoveries increase immediately and then fall below pre-innovation levels then the innovation features a lower formation rate. To see this formally, 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 4. 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 decreasing 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 $a1 > a2$. □

B Theoretical Micro-Foundations

In this appendix, I provide micro-foundations that support the industry-level theoretical model presented in Section 2. This additional theoretical work closely follows Harrington (forthcoming), and, in the interest of brevity, I refer readers to that paper for formal proofs.

To start, let the economy include $i = 1, 2, \ldots, I$ industries, each of which consists of $N \geq 2$ identical firms. Firms interact over $t = 1, 2, \ldots$ discrete periods and share a discount factor $\delta \in [0, 1]$. A stage-game Nash equilibrium exists with payoffs of π_N per firm. Firms may collude and earn payoffs of π_C. If a firm cheats on a collusive arrangement then competition reverts to the stage-game Nash equilibrium during a single-period punishment phase, after which firms may renegotiate. Firms that cheat on an collusive arrangement earn the one-time payoff π_D and firms that are cheated earn the one-time payoff π_B. Let $\pi_B < \pi_N < \pi_C < \pi_D$.

Denote the probability that the antitrust authority discovers an active cartel in industry i and period t as $\alpha_{it} \in [0, 1]$. The antitrust authority also discovers inactive cartels that operated during period $t-1$ with the same probability. Let the probability α_{it} be stochastic and independent across industries and periods, and have the twice differentiable cumulative distribution function G. In the event of discovery, each firm pays the fixed amount F and the authority enforces the stage-game Nash equilibrium during the subsequent period. The authority fines firms that voluntarily report collusion a reduced amount θF, with $\theta \in [0, 1]$. In the event that m firms in the same cartel voluntarily report, the antitrust randomly awards the reduced amount to one firm, so the expected fine is $\frac{m-1+\theta}{m} F$.

In each period, firms observe α_{it} and then decide to compete, collude, and/or voluntarily report collusion. Next, the antitrust authority discovers active and newly defunct cartels, as determined by the α_{it} draws. I focus on a subgame perfect Nash equilibrium characterized by the following cut-off strategy:

1. A firm competes if $\alpha_{it} \in (\alpha^0, 1]$.
2. A firm competes and voluntarily reports past collusion if $\alpha_{it} \in (\alpha^0, 1]$, $\alpha_{it} \in (\theta, 1]$, and the firm colluded in the previous period.
3. A firm colludes if $\alpha_{it} \in [0, \alpha^0]$.

The optimality of this strategy is easily established. First, it is always optimal to compete when other firms compete, regardless of the cut-off value α^0. Second, if $\alpha_{it} \leq \theta$ then the expected fines associated with reporting to the antitrust authority (θF) exceed those associated with not reporting ($\alpha_{it} F$), so firms prefer to abandon collusion without reporting. If instead $\alpha_{it} > \theta$ then the other firms can be expected to report, so the expected fines associated with not reporting (F) exceed those associated with reporting ($\frac{m-1+\theta}{m} F$). Finally, is it optimal to collude if the following incentive compatibility constraint holds:

$$\begin{aligned}\Phi(\alpha, \alpha^0, \theta) \equiv & \underbrace{\left[\pi_C + \delta(1-\alpha)\mathrm{E}[V_C|\, \alpha^0, \theta] + \alpha(\frac{\delta}{1-\delta}\pi_N - F)\right]}_{\text{payoff of collusion}} \\ - & \underbrace{\left[\pi_D + \delta\mathrm{E}[V_N|\, \alpha^0, \theta] - \min\{\alpha, \theta\}F\right]}_{\text{payoff of cheating}} \geq 0, \qquad \text{(B-1)}\end{aligned}$$

where $\mathrm{E}[V_C|\ \alpha^0, \theta]$ is the expected future payoff of sustained collusion and $\mathrm{E}[V_N|\ \alpha^0, \theta]$ is the expected payoff associated with the punishment phase. Under reasonable assumptions, the function $\Phi(\alpha, \alpha^0, \theta)$ is decreasing in the detection probability α. Thus, provided that collusion is sustainable for some α draw (i.e., $\Phi(0, \alpha^0, \theta) \geq 0$) and unsustainable for another (i.e., $\Phi(1, \alpha^0, \theta) < 0$), there exists a unique α^0 such that it is optimal to collude if and only if $\alpha_{it} \leq \alpha^0$.

Figure 8 provides some graphical intuition. In Region A, the probability of detection is sufficiently small to support collusion (i.e., $\Phi(\alpha, \alpha^0, \theta) \geq 0$). In Region B, the probability of detection is too large to support collusion but not large enough to generate voluntary reports to the antitrust authority. In Region C, the probability of detection is sufficiently large to generate voluntary reports. The stochastic nature of this probability over time creates industry-level movement between the collusive and competitive states. An optimal cut-off value of collusion (denote it $\overline{\alpha}_0$) solves the maximization problem:

$$\overline{\alpha}_0 = \max\{\widetilde{\alpha} : \Phi(\widetilde{\alpha}, \widetilde{\alpha}, \theta) \geq 0\}. \tag{B-2}$$

Thus, the degree of leniency (i.e., the value of θ) directly affects firm decisions to collude/compete and, in the case of competition, affects whether firms voluntarily report past collusive activity to the antitrust authority.

[Figure 8 about here.]

The cut-off strategy generates a first-order Markov process akin to that developed in Section 2. As before, let X_t and Y_t denote the number of industries that compete and collude during period t. The quantities X_t and Y_t have the characteristic that:

$$\mathrm{E}\begin{bmatrix} X_{t+1} \\ Y_{t+1} \end{bmatrix} = \begin{bmatrix} 1-\widetilde{b}-\widetilde{c} & \widetilde{a} \\ \widetilde{b}+\widetilde{c} & 1-\widetilde{a} \end{bmatrix} \mathrm{E}\begin{bmatrix} X_t \\ Y_t \end{bmatrix}, \tag{B-3}$$

where the transition parameters $\widetilde{a}$, $\widetilde{b}$, and $\widetilde{c}$, are defined as follows:

$$\begin{aligned} \widetilde{a} &= G(\alpha^0) \\ \widetilde{b} &= \mathrm{E}[\alpha|\ \alpha < \alpha^0]G(\alpha^0) + 1\{\alpha^0 < \theta\}\left(G(\theta) - G(\alpha^0)\right) + \left(1 - G\left(\max\{\theta, \alpha^0\}\right)\right) \\ \widetilde{c} &= 1\{\alpha^0 < \theta\}\left(1 - \mathrm{E}[\alpha|\ \alpha^0 < \alpha < \theta]\right)\left(G(\theta) - G(\alpha^0)\right). \end{aligned} \tag{B-4}$$

Thus, the detection rates estimated in Section 5 ($b1$ and $b2$) represent the summed report and detection rates of the Harrington (forthcoming) model. It may also be notable that game-theoretical models of strategic leniency are capable of rich empirical predictions.

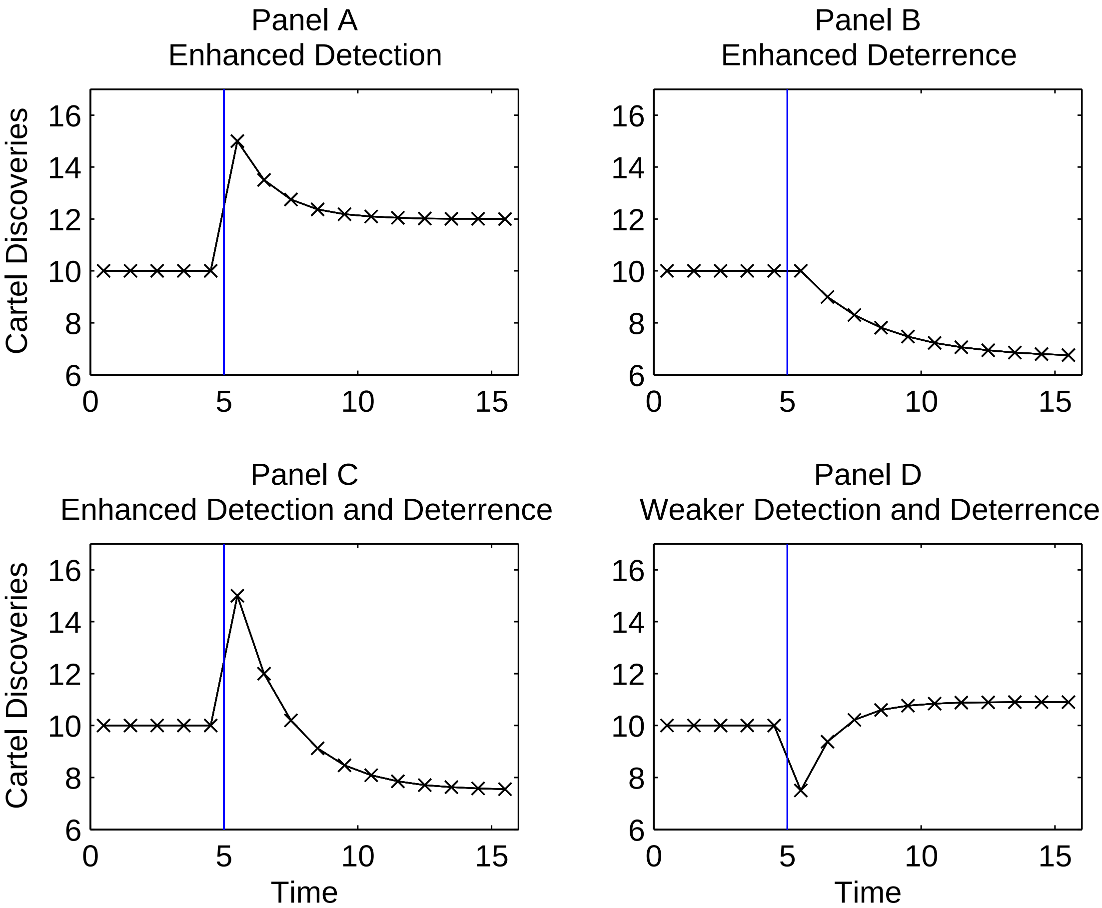

Figure 1: The expected number of cartel discoveries by period. The vertical bar represents an innovation in cartel enforcement. Panel A features an increase in the detection rate (N=100, a1=a2=0.2, b1=0.2, b2=0.3, c=0). Panel B features an decrease in the formation rate (N=100, a1=0.2, a2=0.1, b1=b2=0.2,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

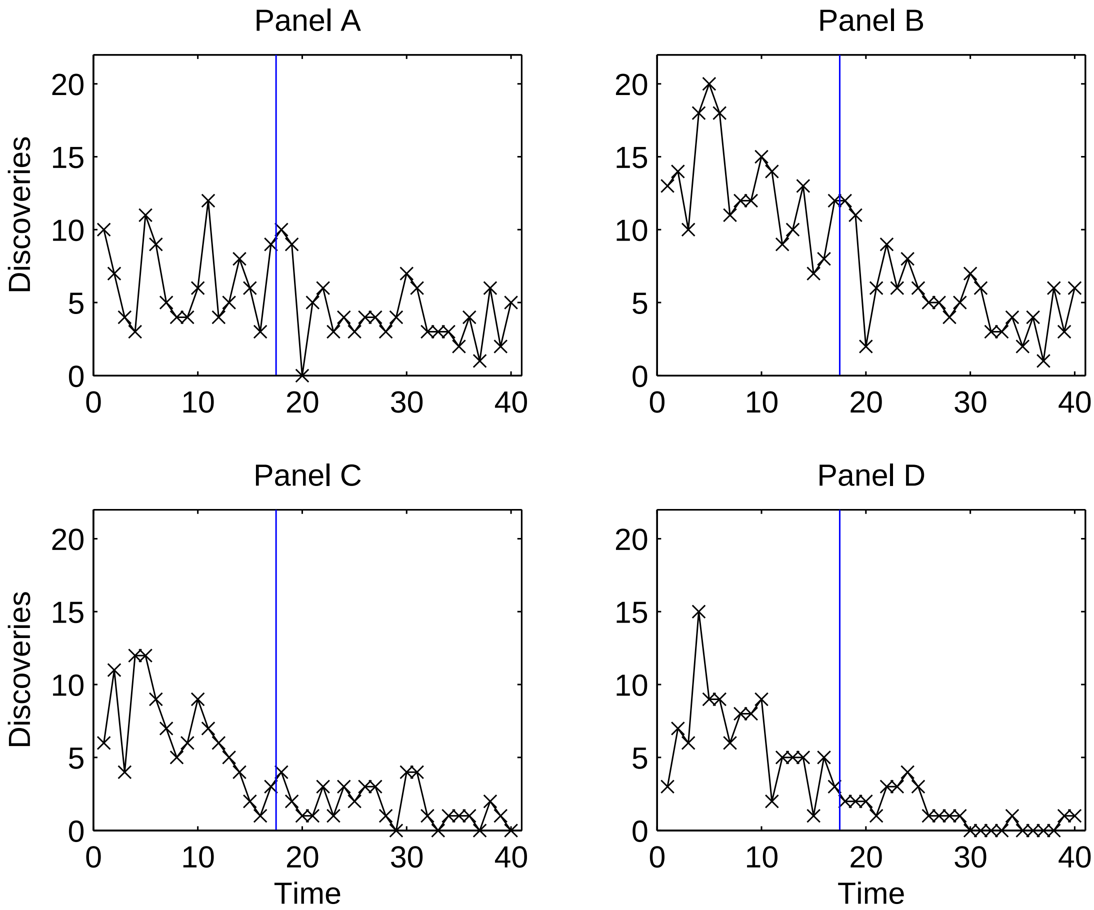

Figure 2: The number of cartel discoveries per six-month period. The sample runs from February 10, 1985 to February 9, 2005. The vertical bar represents the introduction of the new leniency program on August 10, 1993. Panel A includes only the first cartel discovery per industry and represents the main regression sample. Panel B includes all cartels. Panel C plots cartels that are local in geographic scope and Panel D plots cartels whose discovery is predated by the discovery of another cartel in the same industry.

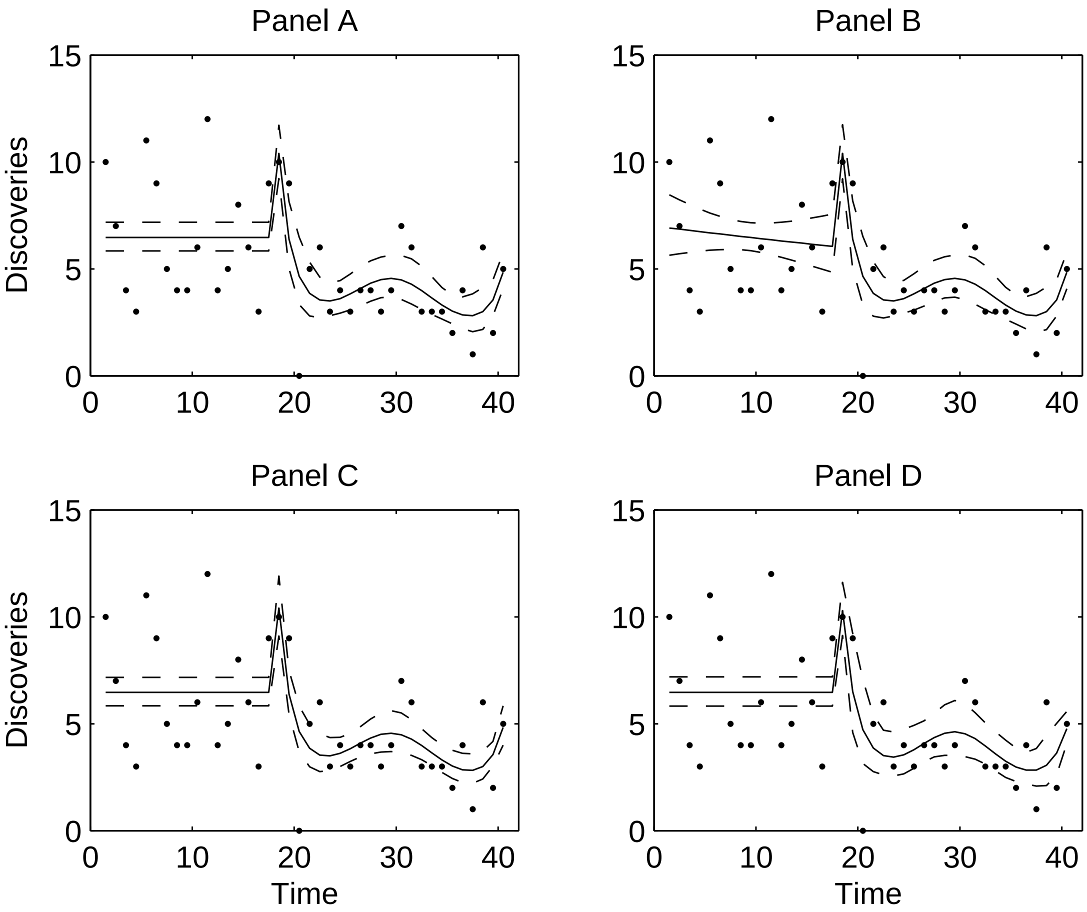

Figure 3: The estimated number of cartel discoveries per six-month period. The estimation procedure is Poisson regression. The solid black lines are estimated conditional means and the dashed lines bound 95 percent confidence intervals for these means. The Panel A regression specification includes LENIENCY 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.

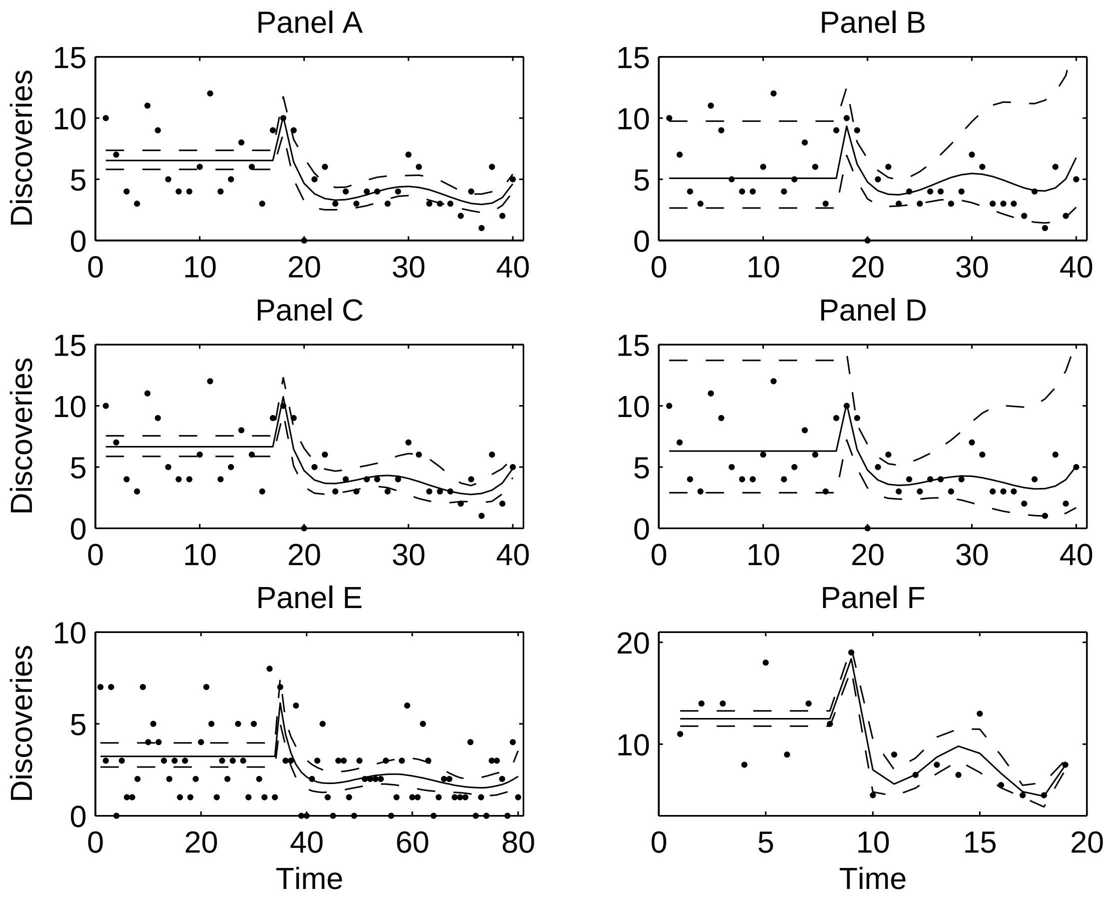

Figure 4: The estimated number of cartel discoveries. The estimation procedure is Poisson regression. The solid black lines are estimated conditional means and the dashed lines bound 95 percent confidence intervals for these means. The units of observations in Panels A, B, C, and D are six-month periods. 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.

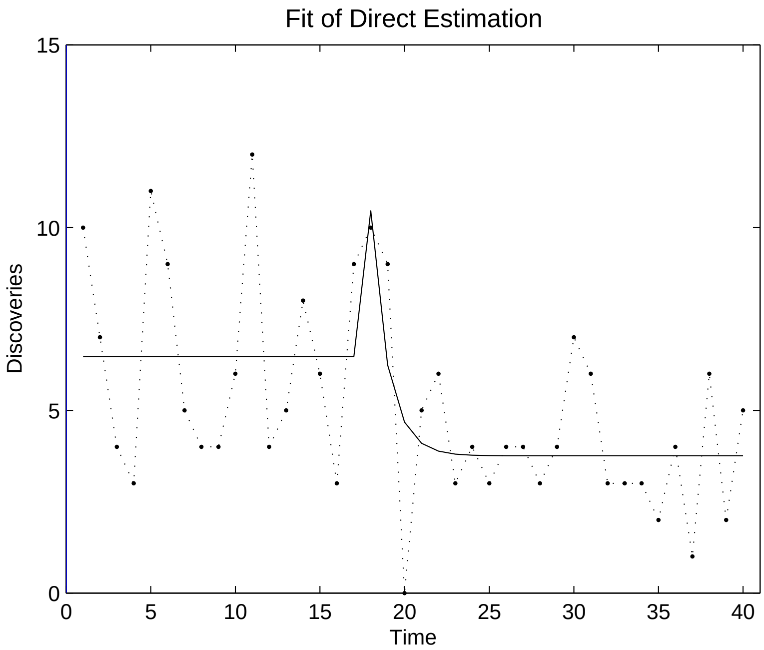

Figure 5: The estimated number of cartel discoveries per six-month period. The estimation procedure is the method of moments. Estimation normalizes the number of industries (N) to 1,000 and the dissolution rate before and after leniency introduction ($c1$ and $c2$) to 0.40.

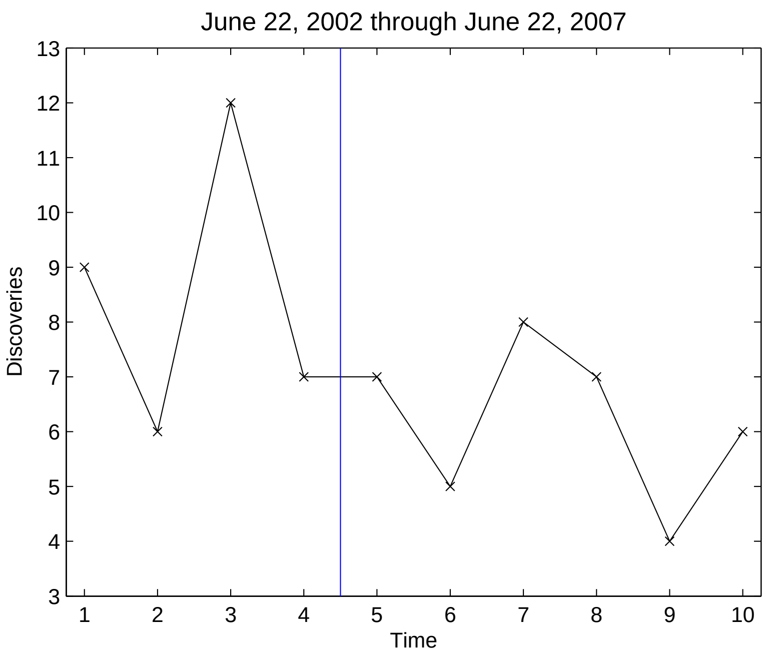

Figure 6: The number of cartel discoveries per six-month period. The sample runs from June 22, 2002 to June 22, 2007. The vertical bar represents the introduction of the Antitrust Criminal Penalty Enhancement and Reform Act on June 22, 2004. Only the first cartel discovery per industry is included.

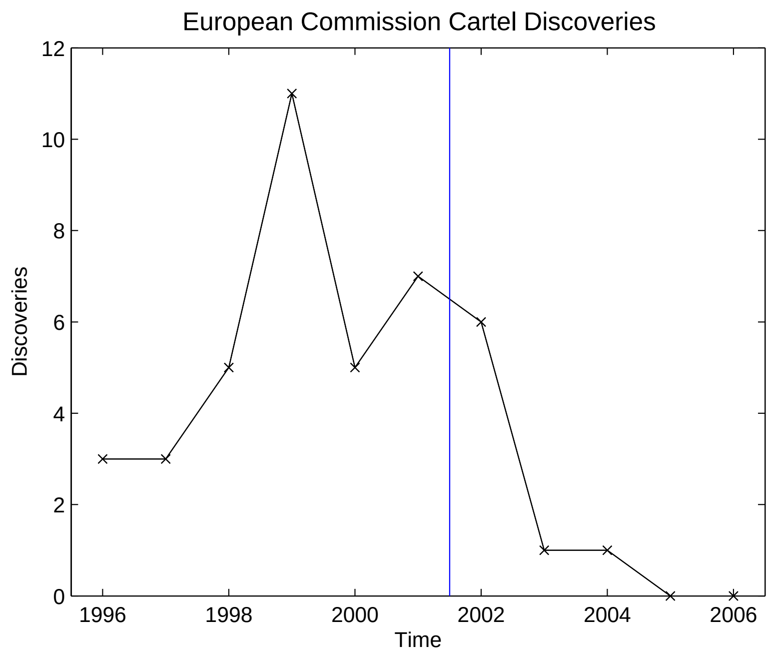

Figure 7: The number of European Commission cartel discoveries per twelve-month period. The sample runs from February 14, 1992 to February 13, 2006. The vertical bar represents the introduction of the 2002 Leniency Notice.

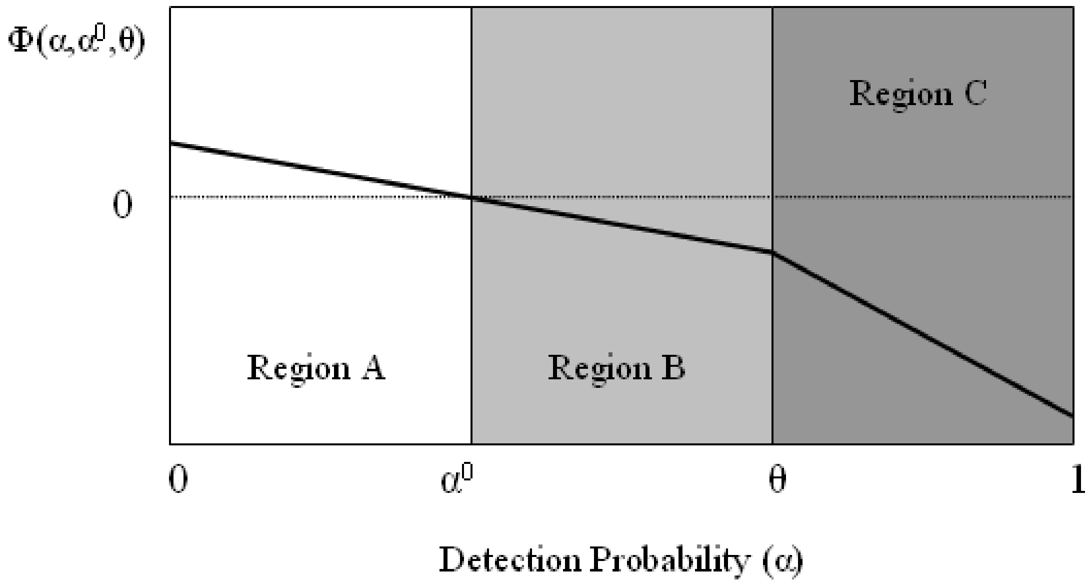

Figure 8: A graphical representation of the subgame perfect Nash equilibrium cut-off strategy. Firms collude when the detection probability is low (Region A), compete when the detection probability is moderate (Region B), and voluntarily report existing or past collusion to the antitrust authority when the detection probability is high (Region C).

Table 1: Summary Statistics

Variable	Mean	Std Dev
Cartel Duration		
Years between start and end dates	4.61	4.78
Years between start and indictment	6.98	4.65
Geographic Scope		
Local market (1=yes)	0.43	0.50
Regional market (1=yes)	0.34	0.47
National market (1=yes)	0.23	0.42
International firm (1=yes)	0.09	0.29
Industry Classification Code		
Construction (1=yes)	0.26	0.44
Manufacturing (1=yes)	0.16	0.37
Wholesale trade (1=yes)	0.22	0.42
Retail trade (1=yes)	0.15	0.36
Other (1=yes)	0.21	0.41
Cartel Size		
# of firms prosecuted	3.24	3.68

Summary statistics for 343 cartels. The data are gleaned from the complete set of indictments and information reports issued by the Department of Justice between January 1, 1985 and March 15, 2005.

Table 2: The Size of Cartels

# of Firms	Frequency	Percent	Cumulative Percent
1	103	30.03	30.03
2	78	22.74	52.77
3	62	18.08	70.85
4	34	9.91	80.76
5 or more	66	19.24	100.00

The empirical distribution for the number of firms prosecuted per cartel. The data are gleaned from the complete set of indictments and information reports issued by the Department of Justice between January 1, 1985 and March 15, 2005.

Table 3: Sample Means Before and After the New Leniency Policy

Variables	Before Leniency (1)	After Leniency (2)	Difference in Means t-Statistic (3)
Cartel Duration			
Years between start and end dates	4.55	4.72	0.33
Years between start and indictment	7.00	4.95	0.09
Geographic Scope			
Local market (1=yes)	0.50	0.31	-3.51***
Regional market (1=yes)	0.37	0.28	-1.72**
National market (1=yes)	0.12	0.41	6.37***
International firm (1=yes)	0.01	0.23	7.15***
Industry Classification Code			
Construction (1=yes)	0.34	0.12	-4.58***
Manufacturing (1=yes)	0.13	0.21	1.82*
Wholesale trade (1=yes)	0.17	0.32	3.37***
Retail trade (1=yes)	0.14	0.16	0.44
Other (1=yes)	0.22	0.19	-0.62
Cartel Size			
NFIRMS	3.36	3.02	-0.82
Number of Obs.	218	125	

Split-sample means for 343 cartels discovered before and after the introduction of the new leniency program on August 10, 1993. The data are gleaned from the complete set of indictments and information reports issued by the Department of Justice between January 1, 1985 and March 15, 2005. Statistical significance at the 10 percent, 5 percent and 1 percent levels is indicated by *, **, and ***, respectively.

Table 4: 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 4 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. Significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively.

Table 5: Poisson Regression Results, Robustness Checks

Variables	(1)	(2)	(3)	(4)	3 Month Periods (5)	12 Month Periods (6)
	Control Variables					
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 5 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, and 3 are six-month periods. The units of observation in Columns 4 and 5 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. Significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively.

Table 6: Direct Estimation

	Parameter Estimates	Standard Errors	95% Confidence Intervals
Formation Rates			
$a1$	0.0156	0.0014	[0.0128, 0.0184]
$a2$	0.0064	0.0005	[0.0054, 0.0074]
Detection Rates			
$b1$	0.2297	0.0269	[0.1759, 0.2835]
$b2$	0.3714	0.0441	[0.2832, 0.4596]
Rate Changes after Leniency Introduction			
$a2 - a1$	-0.0092***	0.0009	[-0.0110, -0.0074]
$b2 - b1$	0.1416***	0.0173	[0.1070, 0.1762]
$\frac{a2-a1}{a1}$	-0.5920		
$\frac{b2-b1}{b1}$	0.6165		

Results of direct estimation, via the method of moments. 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 estimated parameters include the formation rate before and after leniency introduction ($a1$ and $a2$) and the detection rate before and after leniency introduction ($b1$ and $b2$). The estimation normalizes the number of industries (N) to 1,000 and the dissolution rate before and after leniency introduction ($c1$ and $c2$) to 0.40. Standard errors and confidence intervals are robust to fourth-order autocorrelation and are shown in parentheses. For the rate changes, statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively.

Table 7: Direct Estimation, Different Normalization Choices

	(1)	(2)	(3)	(4)	(5)	(6)
Formation Rates						
$a1$	0.0116	0.0261	0.0223	0.0179	0.0330	0.0050
$a2$	0.0051	0.0098	0.0099	0.0064	0.0131	0.0021
Detection Rates						
$b1$	0.2845	0.1487	0.1481	0.2288	0.2224	0.2350
$b2$	0.4597	0.2404	0.2395	0.3698	0.3594	0.3799
Rate Changes after Leniency Introduction						
$a2 - a1$	-0.0065***	-0.0163***	-0.0125***	-0.0115***	-0.0198***	-0.0029***
	(0.0004)	(0.0037)	(0.0026)	(0.0013)	(0.0023)	(0.0003)
$b2 - b1$	0.1752***	0.0917***	0.0914***	0.1410***	0.1371***	0.1449***
	(0.0149)	(0.0216)	(0.0216)	(0.0173)	(0.0177)	(0.0172)
$\frac{a2-a1}{a1}$	-0.5595	-0.6235	-0.5580	-0.6434	-0.6016	-0.5859
$\frac{b2-b1}{b1}$	0.6160	0.6169	0.6167	0.6163	0.6164	0.6167

Results of direct estimation, via the method of moments. 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 estimated parameters include the formation rate before and after leniency introduction ($a1$ and $a2$) and the detection rate before and after leniency introduction ($b1$ and $b2$). Columns 1 through 4 feature 1,000 industries. Column 5 features 500 industries, and Column 6 features 3,000 industries. Column 1 features a lower constant dissolution rate ($c1 = c2 = 0.30$), Column 2 features a higher constant dissolution rate ($c1 = c2 = 0.50$), Column 3 features a dissolution rate increase following leniency introduction ($c1 = 0.40$, $c2 = 0.50$), and Column 4 features a dissolution rate decrease ($c1 = 0.50$, $c2 = 0.40$). Columns 5 and 6 feature the baseline dissolution rate ($c1 = c2 = 0.40$). Standard errors are robust to fourth-order autocorrelation and are shown in parentheses. For the rate changes, statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively.

Table 8: Direct Estimation, Robustness Checks

	Control Variables (1)	3 Month Periods (2)	12 Month Periods (3)	Industry Growth (4)	All Cartels (5)
Formation Rates					
$a1$	0.0138	0.0226	0.0155	0.0161	0.0294
$a2$	0.0056	0.0064	0.0069	0.0074	0.0173
Detection Rates					
$b1$	0.2741	0.0662	0.6461	0.2410	0.3493
$b2$	0.4411	0.1356	1.0000	0.4156	0.4475
Industry Growth Rate					
ρ				-0.0074***	-0.0283***
				(0.0013)	(0.0014)
Rate Changes after Leniency Introduction					
$a2 - a1$	-0.0081***	-0.0162***	-0.0086***	-0.0087***	-0.0121***
	(0.0006)	(0.0026)	(0.0004)	(0.0010)	(0.0017)
$b2 - b1$	0.1669***	0.0694***	0.3539***	0.1745***	0.0981***
	(0.0160)	(0.0114)	(0.0195)	(0.0239)	(0.0176)
$\frac{a2-a1}{a1}$	-0.5906	-0.7160	-0.5570	-0.5383	-0.4123
$\frac{b2-b1}{b1}$	0.6090	1.0482	0.5477	0.7241	0.2809

Results of direct estimation, via the method of moments. The dependent variable in Columns 2, 3, and 4 is the number of cartel discoveries per period (including only the first cartel per industry). The dependent variable in Column 5 includes all cartel discoveries. The units of observation in Columns 1, 4, and 5 are six-month periods. The units of observation in Columns 2 and 3 are three-month and twelve-month periods, respectively. The estimated parameters include the formation rate before and after leniency introduction ($a1$ and $a2$), the detection rate before and after leniency introduction ($b1$ and $b2$), and, in Columns 4 and 5, the industry growth rate (ρ). The estimation normalizes the number of industries (N) to 1,000 and the dissolution rate before and after leniency introduction ($c1$ and $c2$) to 0.40. Standard errors are robust to heteroscedasticity and fourth-order autocorrelation. For the industry growth rate and the rate changes, statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively.