Does enforcement deter cartels? A tale of two tails[*]

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Abstract

This paper investigates the deterrent impact of competition enforcement on cartels. It is shown theoretically that if enforcement is effective in deterring and constraining cartels then there will be fewer cartels with low overcharges and fewer with high overcharges. This prediction provides an indirect method for testing whether the enforcement of competition law is proving effective. Using historical data on legal cartels to generate the counterfactual, we find significantly less mass in the tails of the overcharge distribution, compared to the distribution for illegal cartels. This result is robust to controlling for confounding factors, and although further work is desirable, we interpret this as the first tentative confirmation of effective deterrence.

Keywords: anti-cartel enforcement, deterrence, cartel overcharge.

JEL Classification codes: C46, K14, K21, L41

"*No modern development in antitrust law is more striking than the global acceptance of a norm that condemns cartels as the market's most dangerous competitive vice [but] is modern cartel enforcement attaining its deterrence goals?*" William Kovacic (OECD Conference, October 2013), former Chair of the U.S. Federal Trade Commission

When an active cartel is convicted and shut down, competition policy is working. It is only because there is a competition law prohibiting collusion and a government agency (or private plaintiffs) enforcing the law that the cartel is no longer operating. Evidence that anti-cartel enforcement is *disabling* cartels is then easy to find. What is more difficult is determining whether anti-cartel enforcement is *deterring* cartels from forming and *constraining* the prices set by those cartels that are not deterred. It could well be the case that, in spite of the best efforts of competition authorities, just as many cartels form and collusive prices are just as high as if collusion was legal. While such a bleak reality seems unlikely, there is very little evidence addressing these fundamental questions concerning the efficacy of competition policy: Are cartels being deterred? Are cartel overcharges lower? The absence of evidence is not due for a lack of want to address these important questions but rather because they are intrinsically challenging. While we observe the overcharges of some cartels (those that formed and were detected), we do not know the overcharges they would have set in the absence of competition law and enforcement. While we observe some of the cartels that form, we do not know the cartels that would have formed in the absence of competition law and enforcement.[1]

The objective of this paper is to develop and implement a strategy for assessing

[1] To be clear, the "absence of competition law and enforcement" means that a cartel can operate without concern of being shut down and forced to pay penalties. It does not mean they are able to enforce a collusive agreement through the use of contracts enforced by the courts.

whether competition law and enforcement is effective in deterring some cartels from forming and constraining the overcharges set by those cartels that do form. Using the standard theory of collusion, we first derive a testable implication if firms are taking into account anti-cartel enforcement when they decide on whether to form a cartel and what prices to charge. We show that colluding firms will be less likely to have *high* overcharges if they recognise the prospect of being detected and penalised. This property comes from competition policy *constraining* the collusive price because it makes collusion less stable, either because firms have a stronger incentive to cheat (due to a lower value attached to colluding) or detection is more likely when price is higher. We next show that colluding firms are also less likely to have *low* overcharges if they recognise the prospect of being detected and penalised when deciding whether to form a cartel. This property comes from competition policy *deterring* those cartels from forming that anticipate having low overcharges. In interpreting these results, it is useful to keep in mind that the issue is not whether there is a chance of a cartel being convicted (clearly there is because cartels are routinely convicted) but rather whether firms act *as if* there is a *substantive* chance of conviction when deciding whether to form a cartel and what price to set. That is an empirical question.

The testable hypothesis from the theory of collusion is then: If competition law and enforcement substantively enters the calculus of cartel formation and collusive price-setting, then the overcharge distribution for illegal cartels will have less mass in the lower tail (because low overcharge cartels do not form) and less mass in the upper tail (because price is constrained), compared to when they are not taking account of competition law and enforcement. To test this hypothesis, we construct a counterfactual overcharge distribution drawn from historical data on cartels which were observed under legal regimes (either regimes in which cartels were not illegal or where exemptions were granted.) This is then compared to the equivalent historical distribution for illegal cartels. If illegal cartels are not taking into account the prospect of competition law and enforcement then we should not find any difference between the overcharge distributions for illegal and legal cartels. If, however, they are taking account of anti-cartel enforcement in their decision-making, then the overcharge distribution for illegal cartels should have less mass in both tails than the overcharge distribution for legal cartels. Our empirical analysis provides supporting evidence for this hypothesis: When competition law and enforcement is present, cartels are less likely to set high overcharges and also less likely to set low overcharges.

Execution of this empirical strategy is, however, vulnerable to two possible sources of sample selection bias. Ideally, one would want a random assignment of cartels in terms of legal status. Of course, there is not random assignment. Whether a cartel is legal depends on the time and place (is there a competition law?) and the industry (is that industry exempt from competition law?). For example, a majority of illegal cartels in our data set existed after 1945, while a majority of legal cartels occurred prior to 1945. If the overcharge distribution for all cartels - whether legal or illegal - has less mass in the tails post-1945 compared to pre-1945 then that would bias our empirical analysis to finding an effect of competition policy when there is none. We employ two alternative approaches for correcting for such potential selection bias. The first is to control for all observable potentially confounding factors in a multiple quantile regression model. The second is to apply a propensity score matching quantile procedure to ensure that in estimating the treatment effects, legal and illegal cartels have similar characteristics. Results are robust to this correction, whichever way it is conducted. Nevertheless, there are inevitable data constraints on what can be observed on such a large historical database. Therefore, we interpret our positive results as preliminary, and conditional on the quality of the available data.

While legal cartels have no reason to hide themselves, illegal cartels do and this creates a second possible source of sample selection bias. In using the distribution on overcharges for discovered illegal cartels, it is presumed to be a random sample of the distribution on overcharges for all illegal cartels. However, as characterised in Harrington and Wei (2016), the set of *discovered* illegal cartels will typically be a biased sample of the set of all illegal cartels. Furthermore, if the likelihood of being discovered is correlated with the extent of the overcharge, then the distribution on overcharges for *discovered* illegal cartels can differ from that for legal cartels even if the distribution for illegal cartels (discovered and undiscovered) is the same as that for legal cartels. While we are unable to offer a correction, or test for this type of bias, we critically examine how it might affect our analysis and conclude that it is unlikely to produce our empirical findings.

While there is a copious literature on the deterrent effect of law,[2] strangely little has focused on measuring the impact of enforcement on deterrence and the number of cartels or price. The body of literature most relevant to ours stems from the seminal work by Block et al. (1981). Some studies have provided important insights for evaluating the impact of cartel enforcement: Harrington and Chang (2009), Brenner (2009), Block and Feinstein (1986), Feinberg (1980), and Zhou (2011). More recently, Miller (2009) shows qualitatively that the introduction of the 1993 U.S. leniency programme increased the strength of deterrence. Amongst policy makers, there have been occasional qualitative survey studies involving interviews of competition practitioners, lawyers and companies, which have attempted to quantify what they refer to as deterrence multipliers - see Office of Fair Trading (2007), and Office of Fair Trading (2011). But overall, there is only a sparse literature attempting to answer the origi-

[2] Previous works on the optimal type and amount of criminal sanctions, include Elzinga and Breit (1973), Landes (1983), Kobayashi (2001), Ginsburg and Wright (2010), Werden et al. (2012), Katsoulacos and Ulph (2013), and Katsoulacos et al. (2015). Recently some research has attempted a more direct examination of deterrence in a controlled laboratory environment, for example Bigoni et al. (2012).

nal question posed in Block et al. (1981): whether and how anti-cartel enforcement is influencing firm behaviour. The purpose of the current paper is to provide a first step in that direction.

The remainder of the paper is structured as follows. Section 1 presents the theory, Section 2 describes the data and presents key descriptive statistics. Section 3 discusses the choice of empirical estimators, and presents results and sensitivity tests. Section 4 assesses the possibility of selection bias. Section 5 concludes.

1 Theory

The purpose of this section is to show that the standard model of collusion has implications for how the distribution of overcharges depends on the legal status of cartels. To keep the analysis manageable, the canonical setting of symmetric firms and perfect monitoring is assumed. As the main result is driven by forces that will be operative in richer models, we later argue that the hypothesis delivered by the theory is a robust one.

Consider an oligopoly with $n \geq 2$ firms that offer symmetrically differentiated products and have identical cost functions. Let $\pi\left(p_i, \underline{p}_{-i}\right)$ be a firm's profit when its price is $p_i \in \mathbb{R}_+$ and the vector of prices for the other $n-1$ firms is $\underline{p}_{-i} \in \mathbb{R}_+^{n-1}$. Assume $\pi\left(p_i, \underline{p}_{-i}\right)$ is continuously differentiable in all firms' prices, quasi-concave in a firm's own price, and increasing in other firms' prices.

There is assumed to exist a symmetric static Nash equilibrium,

$$p^n = \arg\max_{p_i} \pi\left(p_i, \left(p^n, ..., p^n\right)\right).$$

$\pi(p)$ is a firm's profit when all firms charge a common price p and is assumed to be continuously differentiable and strictly quasi-concave. Hence, the joint profit-maximising price exists,

$$p^m \equiv \arg\max_p \pi(p).$$

The associated profits are denoted:

$$\pi^n \equiv \pi(p^n, (p^n, ..., p^n)), \ \pi^m \equiv \pi(p^m).$$

It is assumed $\pi^n < \pi^m$ and $p^m > p^n$.

Firms interact for an infinite number of periods with a common discount factor $\delta \in (0,1)$. When firms illegally collude and charge a price p, there is a probability $\sigma(p)$ that the cartel is discovered, penalised, and permanently shut down.[3] $\sigma(p)$: $\mathbb{R}_+ \to [0,1]$ is a continuously differentiable non-decreasing function.[4] As it is firms communicating to coordinate their prices that determines illegality, and not whether they succeeded in doing so, we assume a cartel has a change of being caught and convicted even when it sets the competitive: $\sigma(p^n) > 0$. The penalty $F(p) : \mathbb{R}_+ \to \mathbb{R}_+$ is a continuously differentiable non-decreasing function with $F(p^n) > 0$ so that the act of colluding always brings with it some penalty, which is consistent with antitrust practice.[5]

A cartel is assumed to select the best (symmetric) collusive price using the grim

[3] It is straightforward to extend the analysis to when the cartel can re-form with some probability, and we conjecture that all of our conclusions would remain the same.

[4] The dependence of the probability of paying penalties on price is considered in Block et al. (1981) in a static setting and Harrington (2004, 2005) in a dynamic setting. For a discussion of various sources of detection, see Hay and Kelley (1974).

[5] In many jurisdictions, such as the EU, the penalty is largely determined by firm sales and cartel duration. In the U.S., customer damages depend on the overcharges and quantities sold over the life of the cartel. Allowing for the penalty to depend on duration or past prices would greatly complicate the analysis. Such a possibility is considered in Harrington (2004, 2005). Based on the forces driving our theoretical predictions, we conjecture that they are robust to richer formulations of penalties.

punishment.[6] Let $V^c(p)$ denote the collusive value associated with collusive price p and $V^n \equiv \pi^n/(1-\delta)$ denote the non-collusive value. $V^c(p)$ is recursively defined by:

$$V^c(p) = \pi(p) + \delta(1-\sigma(p))V^c(p) + \delta\sigma(p)V^n - \sigma(p)F(p),$$

which we can solve to yield

$$V^c(p) = \frac{\pi(p) - \sigma(p)F(p) + \delta\sigma(p)V^n}{1-\delta(1-\sigma(p))}. \tag{1}$$

The incentive compatibility constraint (ICC) is

$$\pi(p) + \delta(1-\sigma(p))V^c(p) + \delta\sigma(p)V^n - \sigma(p)F(p) \geq \pi^d(p) + \delta V^n - \sigma(p)F(p) \tag{2}$$

where

$$\pi^d(p) \equiv \arg\max_{p_i} \pi(p_i, (p, ..., p))$$

is a firm's maximal deviation profit. Note that the expected penalty $\sigma(p)F(p)$ appears on both sides of the ICC so that a firm is liable for the penalty whether or not it sets the collusive price. This assumption reflects the common legal practice that collusion is a per se offense. It is the act of communicating to coordinate behavior that is illegal (or taken as evidence of illegality), and not the actual prices that are charged. Re-arranging (2), we have

$$\delta(1-\sigma(p))\left[V^c(p) - V^n\right] \geq \pi^d(p) - \pi(p). \tag{3}$$

The optimal collusive price is that which maximises $V^c(p)$ in (1) subject to the

[6] We discuss later why we believe the main result is robust to the punishment.

ICC in (3).[7]

Define p_I^* as the optimal collusive price when the cartel is illegal, which means $\sigma(p^n) > 0$. Setting $\sigma(p) = 0\ \forall p$ in (1) and (3) yields the optimal collusive price when the cartel is legal, which is denoted p_L^*. We interpret p_L^* and p_I^* as upper bounds on the collusive price when the cartel is legal and illegal, respectively. As shown later, p_L^* always exists but p_I^* may not exist because there is no collusive price satisfying (3). Proofs are in Appendix A.

Proposition 1 *i)* $p_I^* \leq p_L^*$; *ii) if* $\sigma'(p^m) > 0$ *then* $p_I^* < p_L^*$; *and iii) if* $p_L^* < p^m$ *then* $p_I^* < p_L^*$.

Let us assess the impact of a cartel's legal status on price as described by Prop. 1.[8] Conditional on a cartel operating, legal cartels will price at least as high as illegal cartels. If the probability of detection and conviction is higher when the collusive price is higher (more specifically, $\sigma'(p^m) > 0$) then an illegal cartel will price strictly lower. Even when the probability of detection is independent of price, if a legal cartel is constrained in the price that it sets (that is, $p_L^* < p^m$) then again making collusion illegal will cause price to be strictly lower. The intuition is straightforward. First, the prospect of incurring penalties reduces the value to colluding which makes cartel members more inclined to cheat. In order to ensure that collusion is stable (that is, equilibrium conditions are satisfied), the collusive price may need to be set lower compared to when the cartel is legal. Second, the desire to reduce the likelihood of detection will induce an illegal cartel to lower its price relative to when collusion is

[7] In the last 15-20 years, leniency programs have been adopted by many jurisdictions. A previous version of the paper allowed for leniency programs and our main results are robust. We chose not to encompass it here because it is an unnecessary complication and most of the cartels in our data existed prior to the advent of leniency programs.

[8] Some recent papers also consider the impact of competition law enforcement on overcharges when penalties depend on price and show that the result is robust to alternative modelling assumptions. See Katsoulacos et al. (2015), Katsoulacos and Ulph (2013) and Houba et al. (2010).

legal. To summarise, if both legal and illegal cartels are stable for a given set of market conditions then the constraint of competition law lowers the collusive price. It also means a lower overcharge, which is defined as $(p^c - p^n)/p^n$ where p^c is the collusive price.[9]

While the upper bound on the collusive price is lower when collusion is illegal, we'll now show that the lower bound to the collusive price is *higher* when collusion is illegal. For this purpose, define $\underline{p}_L^*$ and $\underline{p}_I^*$ as the greatest lower bound to the optimal collusive price when collusion is legal and illegal, respectively,

$$\underline{p}_L^* \equiv \inf\left\{p_L^*\left(\delta\right) : \delta \in (0,1)\right\}, \underline{p}_I^* \equiv \inf\left\{p_I^*\left(\delta\right) : \delta \in (0,1)\right\}.$$

Proposition 2 $\underline{p}_I^* > \underline{p}_L^* = p^n$.

When collusion brings with it some expected penalty, collusion is profitable only if the rise in price from colluding is large enough to compensate for that penalty. Cartels that are unable to sustain sufficiently high overcharges will then be unstable and thus not form. Hence, the overcharge must be bounded above zero when the cartel is illegal. A corollary to this result is: If $\sigma(p^n) > 0$ then there is a lower bound on the discount factor $\widetilde{\delta} > 0$ such that p_I^* exists if and only if $\delta \geq \widetilde{\delta}$.[10] In comparison, the lower bound on the discount factor for legal collusion to be stable is zero.

[9] In some jurisdictions in recent years, the penalty is proportional to revenue. As shown in Bageri et al. (2013), a revenue-based penalty can cause the optimal collusive price to exceed the monopoly price when the probability of paying penalties is fixed and ICCs are not binding. In that situation, it is possible that illegality could cause higher overcharges. Our results hold as long as the probability of paying penalties is sufficiently sensitive to price so that the expected penalty $\sigma\left(p\right) F(p)$ is increasing in price.

[10] The proof is by contradiction. Let us suppose that an optimal collusive price for an unlawful cartel, $p_I^*(\delta)$, exists for all $\delta > 0$. For a lawful cartel, $\lim_{\delta \to 0} p_L^*(\delta) = p^n$. Given that $p_L^*(\delta) < p^m$ implies $p_I^*(\delta) < p_L^*(\delta)$ by Prop. 1, it follows that $\lim_{\delta \to 0} p_I^*(\delta) = p^n$. However, that result contradicts a lower bound on $p_I^*(\delta)$ above p^n.

1.1 Hypothesis and numerical analysis

Let us summarise the preceding results. Holding fixed the set of market conditions, if collusion is stable both when it is legal and illegal then the optimal collusive price is (weakly) higher when the cartel is legal. Hence, the upper bound on the collusive price is lower when collusion is illegal. This result suggests that legal cartels are more likely than illegal cartels to have high overcharges. However, it is also the case that the lower bound on the collusive price is higher when collusion is illegal. This result suggests that legal cartels are more likely than illegal cartels to have low overcharges. The creation and enforcement of a competition law prohibiting collusion is then predicted to compress the distribution of overcharges for it reduces the frequency of both low markups and high markups.

Before moving on, let us discuss the robustness of these results. The higher lower bound for unlawful collusive prices comes from the lower value attached to an illegal cartel because of penalties. Firms will collude only if they can set an overcharge large enough to offset expected penalties. That result is quite general and does not rely on symmetry, perfect monitoring, or the type of punishment (in particular, it would hold as well for a punishment more severe than reversion to a static Nash equilibrium). The lower upper bound for unlawful collusive prices is implied by a higher price making detection more likely (so an illegal cartel prefers a lower price) and a lower collusive value because of expected penalties (so the ICC is tighter and thus an illegal cartel cannot sustain as high a price). Again, these forces are not tied to either symmetry or perfect monitoring, and the form of the punishment does not matter as long as the punishment is not more severe when firms illegally collude.[11]

[11] If the punishment was more severe then it could possibly loosen the ICC and allow the illegal cartel to set a higher price. However, there is no reason to think that firms would punish a deviation more severely when the cartel is illegal than when it is legal. Even if it that were true, the punishment would have to be sufficiently more severe to offset the lower collusive value, if it is to result in a

One model extension that could work against Prop. 1 is allowing the probability of detection to be sensitive to price changes. As shown in Harrington (2004), a member of an illegal cartel is less inclined to deviate when the lower prices induced by that deviation makes detection (and paying penalties) more likely. While that effect works in the direction of loosening the ICC and raising the collusive price, it would have to be sufficiently strong relative to the other effects (i.e., a lower price level is preferred because it reduces the probability of detection and a lower collusive value makes cheating relatively more profitable and thus requires price to be lower) in order for the optimal collusive price to be higher for illegal cartels. For this reason, we believe Prop. 1 delivers a robust result.

The predicted differences between overcharges for legal and illegal cartels are predicated upon competition law influencing the behaviour of firms when deciding whether to form a cartel and, in the event a cartel is formed, the prices that they set. It is clear that if a competition authority is catching and convicting cartels then, in fact, $\sigma(p) > 0$. Furthermore, cartelists recognise that they might be caught when they conduct their meetings in secret, instruct each other not to retain a written record, and, more generally, actively try to avoid detection. Nevertheless, there is still the question of whether firms act *as if* $\sigma(p) > 0$ in their decisions to form a cartel and the price to charge. Having formed an illegal cartel, are firms induced to moderate the price increase to maintain cartel stability (because the prospect of paying penalties lowers the collusive value which then tightens the equilibrium condition) or to make detection less likely (when $\sigma'(p) > 0$)? When deciding to form a cartel, do firms perceive $\sigma(p) > 0$ and, as a consequence, are deterred from forming a cartel when the anticipated overcharge is insufficient to result in the expected rise in profits exceeding the expected penalties? While the detection and conviction of

looser ICC for illegal cartels.

cartels is evidence that competition policy is disabling some cartels, it is not evidence that it is deterring some cartels from forming or constraining the overcharges set by cartels.

The theoretical results derived provide an avenue to testing the claim that competition policy is deterring some cartels from forming and constraining the prices charged of those cartels that do form. The testable hypothesis from the theory which we will take to the data is the following:

Hypothesis: If firms take account of the possibility of enforcement when deciding whether to form a cartel and what price to charge (when a cartel is formed) then the distribution of overcharges for illegal cartels will have less mass in the lower tail and less mass in the upper tail than the distribution of overcharges for legal cartels.

As a corollary, effective enforcement need not imply that the average overcharge is lower. In fact the impact on average overcharge is ambiguous. First, the cartels that form under either the legal or illegal regimes have lower overcharges when collusion is illegal, and second, the low-overcharge cartels no longer form under the illegal regime. There is then no theoretical basis for more effective competition policy to result in a lower average cartel overcharge. Rather, it should manifest itself through less mass in the tails of the distribution of overcharges.

For the purpose of illustration, a numerical example is provided to show how effective competition enforcement is reflected in the distributions of overcharges (as described in Hypothesis). Like the data set that will be examined, consider a population of markets that vary in terms of market conditions (specifically, demand and cost functions) and the ease with which firms can collude (as captured by the discount factor). Specifying a standard representative consumer model of differentiated products with quadratic utility, $d \in [0,1]$ measures the extent of similarity in firms' products where $d = 0$ is independent products and $d = 1$ is homogeneous goods.[12] Firms have a common constant marginal cost c and a common discount factor $\delta \in (0,1)$. Assume two firms and normalize the other demand parameters so that a market is defined by (c, d, δ).[13]

To limit the number of parameters, the penalty and probability of detection are assumed not to vary with the collusive price. However, so that the penalty is related to market conditions, F equals half of monopoly profit. For a market (c, d, δ), we calculate the symmetric Nash equilibrium price, the collusive price when collusion is legal ($\sigma = 0$), and the collusive price when collusion is illegal ($\sigma = 0.05$). From these prices, the legal overcharge, $\frac{p_L^* - p^n}{p^n}$, and illegal overcharge, $\frac{p_I^* - p^n}{p^n}$, are calculated.

A population of markets is represented by a set of random draws on (c, d, δ) according to independent truncated normal distributions. Figure 1 reports the kernel estimates. Reflecting the properties in Hypothesis, the overcharge distribution for legal cartels has more mass in the lower and upper tails. Let us now turn to examining the empirical overcharge distributions in order to assess whether they have this property.

2 The database and descriptive statistics

To test this hypothesis we conduct an empirical comparison between legal and illegal cartels, employing an existing database already in the public domain. This has been constructed over a number years by John Connor and various associates, and, to our knowledge, is the most extensive aggregation of past empirical studies of cartel

[12] Details regarding the theoretical model and the numerical analysis are in Appendix B.

[13] The case of heterogeneity with respect to the number of firms can be captured by d in that it controls the intensity of competition.

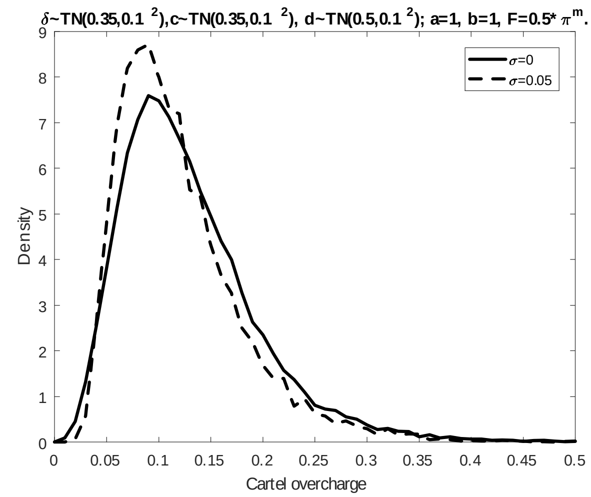

Figure 1: The simulated density of overcharges, with and without enforement

overcharge. Here, we use the most recent published form (Connor, 2014, Appendices 1 and 2). It covers approximately 500 cartels and includes 1500 observations on episodic overcharge (many cartels had more than one episode). In effect, this is a meta-analysis of hundreds of previous studies drawn from across the world and over time. This is appropriate for our purpose since it includes a sizeable number of legal cartels. These were cartels which operated in countries and time periods when cartels were not illegal, or were granted exemptions from cartel laws (notably export cartels). Each cartel is classified by whether it was illegal, legal or 'extra-legal' and it is explained in Connor (2014, p.33) that:

> "Three-fourths of the cartels (75%) were found to be in violation of antitrust laws [...] Eighteen percent of the remaining cartelized markets are known or believed to be "legal," because they operated prior to the enactment of antitrust laws in the jurisdictions in which they functioned or because they were organized and registered under antitrust exemptions, such as export cartels or ocean shipping conferences. About 7% of the

> cartels may be described as “extra-legal” because there was nothing in the case material indicating that an antitrust authority punished them."

From his published tables, we have constructed our legal sample to include all those that Connor categorises as ‘legal’, and a small number (ten) of his ‘extra-legal’ category.[14] In all, this gives us a sample of 107 legal cartels and 395 illegal cartels, and these cartels account for 390 and 1107 episodes respectively.

For each cartel/episode, we employ the mean episodic overcharge. Overcharge is defined (Connor 2014, p.6-10) as $[(p^c - p^n)/p^n] \times 100$ where p^c is the observed cartel price and p^n is the "but for" price, i.e. the price which would have obtained had the cartel not existed. The methods used to recover the but for price vary across the primary sources, but include prices observed before and after cartels’ existence, price observed during price wars etc.[15] The database also reports various other characteristics of the cartels, including their geographical and chrononological locations, and these are used in Section 3 below.

Table 1 provides the first informal test of our hypothesis, by comparing the two samples. The median is slightly larger for legal cartels, and a Mann Whitney test confirms that this is significant; but what is relevant for our purposes are the two tails of the legal distribution. At the lower end, overcharges of 5% or less occur twice as frequently in the legal sample than in the illegal sample; at the upper end, overcharges of at least 50% are nearly twice as frequent in the legal sample compared to the illegal.

[14] From our readings of his extra-legal cases, most were probably illegal or sometimes not even strictly cartels at all; but in these ten cases we believe that the cartels were genuinely legal. Our judgements are based largely on the case details provided in Connor (2014), and in some cases supplemented by literature searches on the specific cartels.

[15] More detailed information on the counterfactual price used in the individual studies is given in Connor (2014).

Table 1: Legal versus Illegal Cartels: Descriptive Statistics

	Legal overcharge	Illegal overcharge
Cartels	107	395
Cartel episodes	390	1107
Median episodic overcharge	27.0	22.0
Overcharge 5% or less	21.7%	10.7%
Overcharge 5-50%	50.6%	74.2%
Overcharge more than 50%	27.7%	15.1%

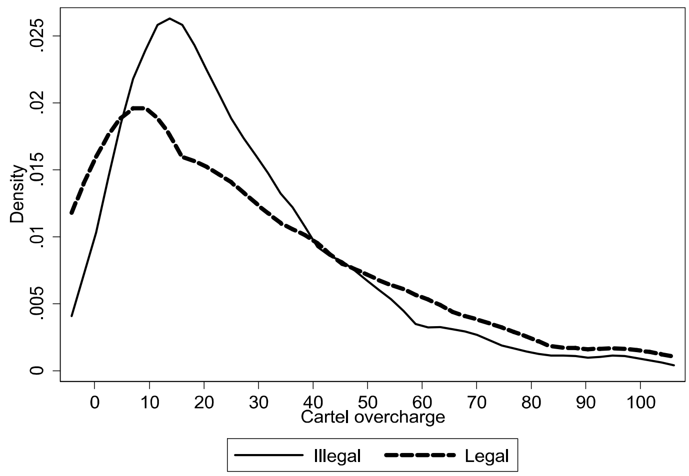

Figure 2: Density plot of overcharge under illegal and legal regimes

Figure 2, which shows the kernel density plots, provides visual confirmation (the two curves intersect at 6% and 40% overcharges). A conventional Kolmogorov–Smirnov test strongly rejects the hypothesis of no difference (p=0.000) between the two samples.

3 The distributional effect of cartel legality

This finding establishes a statistically significant difference between the distributions of legal and illegal cartels in Connor's database - one previously unnoticed by Connor or other researchers (e.g. Bolotova 2009, Table 4) who have not looked beyond a comparison of sample means. In itself, this is an interesting historical fact, but as a direct test of our above hypothesis it is insufficient for two reasons. First, assignment into the treatment (i.e. whether a regime legalises cartels) is unlikely to be random (i.e. other things are unlikely to be equal across the two sub-samples), and this raises a potential bias in any unconditional comparison such as in Figure 2. Second, it should be recalled that this dataset includes, of course, only detected cartels. For illegal cartels in particular, there is a further potential bias if detection varies systematically with overcharge. In this section, we address the first of these potential biases; the second is discussed in the next section.

3.1 Quantile Regression

An analytically convenient methodology for comparing the two distributions is quantile regression analysis (as discussed in Koenker and Bassett, 1978). More specifically, we are interested in the quantile treatment effect (QTE), where for a given centile, the QTE corresponds to the horizontal distance between two cumulative distribution functions.

Let $T = 1$ if the cartel is in a legal regime, and $T = 0$ if it is in the illegal regime. Correspondingly, overcharge is denoted as $Y(1)$, and $Y(0)$, and the τ-th quantile of overcharge is $q_{1,\tau}$ and $q_{0,\tau}$. Following Firpo (2007)[16] the quantile treatment effect (QTE) is given by:

$$\widehat{QTE} = \widehat{q}_{1,\tau} - \widehat{q}_{0,\tau} \tag{4}$$

where $\widehat{q}_{j,\tau} \equiv \inf_q \Pr(Y(j) < q) \geq \tau,\ j \in \{0,1\}$. A simple quantile regression using only information of legality is effectively the regression equivalent of Figure 2.

[16] Our choice of Firpo's method is based on our assumption of exogenous treatment (see below).

The problem with Equation (4) is that for any given individual, we observe $q_{1,\tau}$ or $q_{0,\tau}$, but never both. As assignment into the treatment (i.e. whether a regime legalises cartels) is unlikely to be random (i.e. other things are unlikely to be equal across the two sub-samples), we face a potential bias in the unconditional treatment effect estimate.

Further examination of the 107 legal cartels reveals that 88 occurred in jurisdictions/time periods without applicable cartel law, while 13 were export cartels and 6 were other exemptions or government-tolerated. In most jurisdictions, the prohibition of cartels only dates from the second half of the twentieth century, or later, so it is likely that more of the legal cartels occurred relatively longer ago. This is confirmed by Connor's own statistics: 70% of legal episodes occurred pre-1945, as opposed to 15% of illegal. To provide a visual check on whether time affects our headline story, Figure 3 shows the empirical density curves for legal/illegal cartel episodes for the pre-1945 and the post-1974 part of our sample (we chose these cutoff points to have an equal number of years in both sub-samples). Figure 3 suggests that our story in the two tails is robust even when we compare only cartels from the same time periods.

Nevertheless, there may be other reasons why the unconditional independence assumption may not hold, and we address these next.

3.2 Correcting for selection bias

Rosenbaum and Rubin (1983) explain that, for Equation (4) to provide unbiased estimates, two assumptions must be satisfied. The first is the unconfoundedness assumption (as referred to above as independence): the overcharges under legal and illegal regimes (i.e. the quantiles of the two distributions) should be independent of assignment into the legal group once we control for a vector X of observable

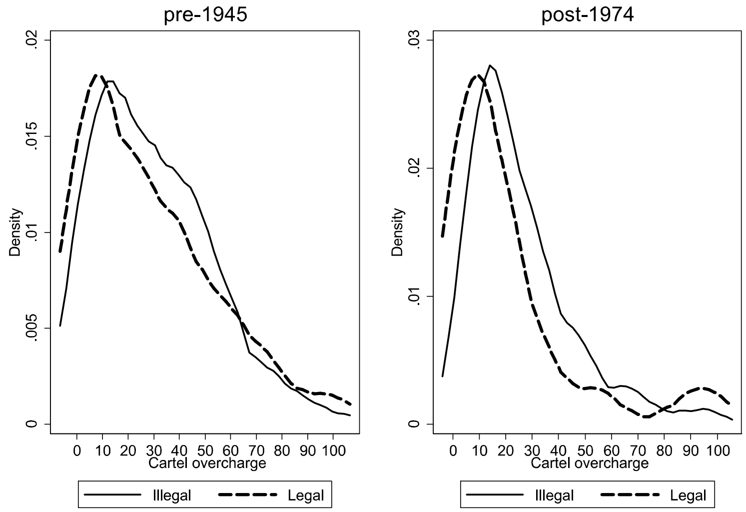

Figure 3: Density plots of overcharge (legal/illegal) for pre-1945 and post-1974 years

differences between the two regimes: $(q_{1,\tau,i}, q_{0,\tau,i}) \perp\!\!\!\perp T_i \mid X_i$. Conditional on X the illegal overcharge distribution is the same as the overcharge distribution of legal cartels had they not been legal (and vice versa). The second is the overlap assumption: each observation i has some non-zero probability of being in the legal and in the illegal groups at each combination of covariate values: $0 < \Pr(T_i = 1 \mid X) < 1$ (i.e. the covariate distributions are similar for the legal and illegal sub-samples).

We offer two alternative approaches for correcting for selection bias. The first is a straightforward multiple quantile regression controlling for X to derive the quantile estimators $\widehat{q}_{1,\tau,i}(X)$, and $\widehat{q}_{0,\tau,i}(X)$. From Connor's data, we identify X, which might explain, or control for whether a cartel is legal or illegal:

- Whether it occurred before 1945.
- Its geographical coverage (US, EU, Asia, International), to allow for heterogeneity across jurisdictions.

- Its industry (manufacturing, raw materials, transportation, services).
- Its type of agreement (bid rigging or other).

One potential problem with this approach is that - as we will show below - the overlap assumption appears to be violated in our data.

For this reason, in the second approach, we re-define our sample by matching and re-weighting the observations. Here, we employ a two-step method: the first step estimates the propensity of "receiving the treatment" (being in a legal regime), and the second uses weights derived from the propensity of treatment and matches the observations for the two samples. We discard all unmatched episodes. This constructed counterfactual overcharge distribution is then used to estimate the QTE.

There are a number of ways that matching can be effected. Figure 4 compares the empirical distribution of propensity scores (estimated in a logit model[17]) for the unmatched and the matched samples, in order to visually identify the matching method that generates a counterfactual (illegal regime) that is closest to the treatment (legal regime). Each panel shows that the density curves (frequency) of the propensity scores. The top left panel begins with the propensity scores without matching. It suggests that the overlap assumption (similar covariate distribution for the two groups) is likely to be violated. The top right panel shows 1-on-1 matching without replacement in the matched sample. Here propensity scores for 364 legal cartel episodes are sorted in descending order and are matched with 364 illegal cartel episodes with the higest propensity scores. The rest of the sample is discarded. This achieves little improvement - there are many more legal cases with high propensity scores and more illegal cases with low propensity scores, suggesting that there is a limited number of illegal cartel episodes that match in their characteristics to legal cartel episodes.

[17] The coefficients of the propensity score generating equation are given in Table 5 in Appendix C.

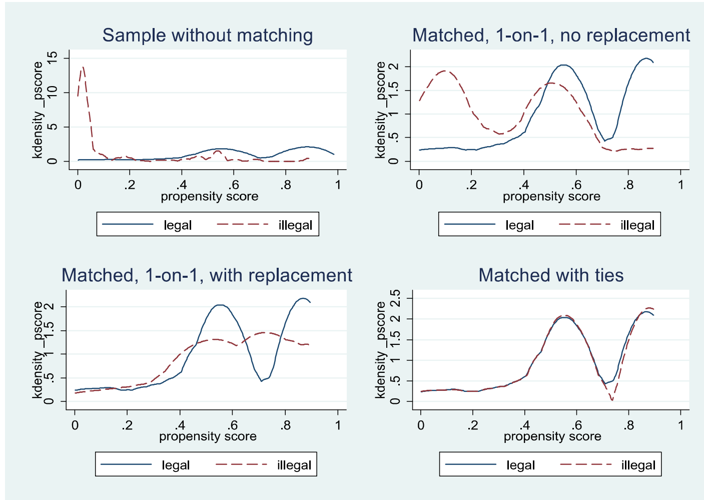

Figure 4: Legal/illegal propensity scores by matching type

The situation improves with 1-on-1 matching with replacement (bottom left panel). In this case those illegal cartel episodes that are most similar to legal cartel episodes are matched with many legal cartel episodes. This method does not limit the number of times an illegal observation can be paired with an legal one. As a result, 364 legal cartel episodes are matched with the most similar 26 illegal episodes. However, 1-on-1 matching still ignores the fact that there is potentially a large number of ties (e.g. where one illegal observation can be matched with more than one legal observation), because we are matching based on categorical variables. For this reason we also looked at matching with ties. Using ties with replacement means that each legal cartel can be matched with multiple illegal cartels and vice versa (in our sample we match 364 legal cartel episodes with 565 illegal episodes of varying weight).[18] The bottom right panel of Figure 4 shows that the weighted matched (with ties) sample offers a good match between legal and illegal cases, and this is therefore our preferred choice.

[18] The smallest weight is 0.07 (272 illegal episodes are matched with this weight) and the highest is 20.2 (5 illegal episodes).

As an alternative robustness check, we follow Firpo (2007), who uses propensity scores to weight, rather than match, the observations, i.e. inverse probability weights (IPW). IPW estimators allow us to retain a larger sample size, which has efficiency advantages, but is not the best choice when the estimated treatment probabilities get too close to 0 or 1, and here we have a large number of propensity scores close to zero, so we need to trim observations to eliminate those with extreme weights. Although this is not as efficient as removing observations that cannot be matched based on their propensity scores, it allows us to verify that our results are not sensitive to the choice of the matching method.

3.2.1 Assessing the key assumptions

As discussed above, one of the main assumptions required for unbiased QTE estimates is that assignment into the treatment group (legal regime) is exogenous to the outcome variable (overcharge), and that the covariate vector X fully determines selection into the treatment. Our data on the characteristics of cartels is limited, nevertheless, we believe that the variables included in X are important determinants of whether cartels are legal or illegal. Moreover, whether a country legalises cartels does not depend on the magnitude of cartel overcharges. Put differently, if a cartel is illegal, then it will not become legal just because it has a lower overcharge and vice versa.

To show that the generated counterfactual offers a good match not only for the distribution of propensity scores but also for the distribution of the individual covariates, Table 2 reports the means and standard deviations of the legal and illegal sub-samples for the unmatched and the matched cases. Matching makes the legal and illegal samples very similar in their distributions, suggesting a close similarity of the covariate distributions for the treated and untreated samples. Simple tests, using normalised differences, confirm that there are no significant differences between legal

Table 2: Mean (standard deviation) of the covariates for the unmatched and matched samples

	Unmatched		Matched	
	Illegal	Legal	Illegal	Legal
Pre 1945 cartels	0.146	0.862	0.850	0.852
	(0.354)	(0.346)	(0.358)	(0.355)
US cartels	0.232	0.364	0.418	0.361
	(0.422)	(0.482)	(0.494)	(0.481)
European cartels	0.310	0.318	0.331	0.333
	(0.463)	(0.466)	(0.471)	(0.472)
Asian cartels	0.0876	0.0590	0.0328	0.0328
	(0.283)	(0.236)	(0.178)	(0.178)
Bid rigging	0.238	0.0282	0.0246	0.0301
	(0.426)	(0.166)	(0.155)	(0.171)
Manufacturing	0.663	0.797	0.825	0.820
	(0.473)	(0.402)	(0.380)	(0.385)
Transportation	0.0307	0.0513	0.0213	0.0191
	(0.173)	(0.221)	(0.145)	(0.137)
Raw materials	0.141	0.133	0.145	0.142
	(0.348)	(0.340)	(0.352)	(0.350)
Services	0.0949	0.0179	0.00820	0.0191
	(0.293)	(0.133)	(0.0902)	(0.137)
N	1497		1117	

and illegal cartels for all the covariates.

Table 2 also sheds some light on the weights generated by the propensity score matching - and how we consequently re-weight the legal and illegal samples. It is clear that much larger weight is assigned to pre-1945 illegal cartels, and illegal bid rigging cartels; relatively more weight is also given to US and less to Asian cartels.

3.3 Results

Table 3 reports the estimated QTEs for the estimators described above.[19] In effect, these show the differences between the two samples at each of the quantiles. The first column reports the results without controlling for any covariates. For example, the 25th centile for the legal sample is 4.2% lower than for the illegal, which means that the smallest 25% of legal cartels set lower overcharges than the smallest 25%

[19] For the regressions on cartel episodes (columns 1-4), standard errors are clustered by cartels.

of illegal cartels. As can be seen, the legal sample has significantly lower quantiles than the illegal distribution up to and including the 30th centile. In the upper tail, the reverse is true; for example, the 75% centile is 16% larger for the legal sample; this means that the highest overcharge legal cartels set larger overcharges than the highest illegal cartels. As can be seen this is significantly so from the 50th centile upwards. These results are effectively the regression equivalent of Figure 2. However, if assignment into the treatment is not random, then these estimates are likely to be biased.

Column (2) reports the results for multiple quantile regression model where we control for the vector of observables X by adding them to the quantile regressions.[20] The results are qualitatively unchanged in that the lower tail of the legal distribution is defined by significantly smaller overcharges than the illegal distribution (up to and including the 35th centile), and the upper tail is defined by significantly larger overcharges for the legal than the illegal distribution (from the 80th centile upwards). Alternatively, Column (3) shows the QTEs when the two distributions are matched and weighted, as described above, by following propensity scores and including ties (standard errors were calculated using a weighted var-cov matrix). Again, the key finding is confirmed: the lower legal tail occurs at smaller overcharges (up to the 20th centile) and the upper legal tail occurs at higher overcharges (from the 80th centile upwards). To show that our results are not sensitive to the choice of matching and weighting method, Column (4) reports QTE estimates when we used inverse probability weights.[21] The fifth column of Table 3 reports results from a robustness check to be described below.[22]

[20] Table 7 in Appendix C contains the full results, including the coefficients for the covariates.

[21] Because we have some very small propensity scores - i.e. high inverse probabilities, we trimmed some of these observations. We chose our cut-off point at the 6th and 94th percentiles, in order to match the sample size with Column (3) and provide comparable results.

[22] Table 6 also shows regression results for the four matching methods exposed in Figure 4.

Table 3: Estimates of quantile treatment effects (treatment - legal, control - illegal)

Centiles	Simple quantiles Unit of observation: cartel episodes	Multivariate quantiles Unit of observation: cartel episodes	PS weighted/matched Unit of observation: cartel episodes	IPW weighted/matched Unit of observation: cartel episodes	PS weighted/matched Unit of observation: cartels
5th	-1.600*	-2.200**	-3	0	-4.500***
	(0.818)	(1.001)	(.)	(2.846)	(58.53)
10th	-5***	-4.600***	-5.600***	-5.100*	-6.300***
	(0.767)	(1.273)	(0.672)	(2.625)	(1.284)
15th	-7.200***	-5.700***	-4.900***	-6.900**	-5.270**
	(1.087)	(1.364)	(1.708)	(2.685)	(2.592)
20th	-6.300***	-5.500***	-5.400*	-6.400**	-1.750
	(1.009)	(1.359)	(3.196)	(2.667)	(2.668)
25th	-4.200***	-4.800***	-2.900	-5.600**	-1.500
	(1.034)	(1.268)	(4.715)	(2.635)	(2.722)
30th	-2.800**	-5.600***	-5.500	-6.300**	-1.230
	(1.247)	(1.620)	(6.440)	(2.561)	(2.876)
35th	-1.500	-5.500***	-7.900	-5.500**	-1.640
	(1.287)	(1.978)	(6.808)	(2.719)	(3.288)
40th	-0.300	-4.300*	-8	-6.300**	2.040
	(1.478)	(2.198)	(5.715)	(3.002)	(3.234)
45th	0.900	-1.800	-6	-5.900*	2.600
	(1.662)	(2.243)	(5.257)	(3.217)	(3.590)
50th	5***	-1.000	-4.200	-4.600	2.500
	(1.654)	(2.501)	(5.332)	(3.311)	(3.974)
55th	5.200***	-1	-6	-1.100	1.620
	(1.985)	(2.745)	(4.803)	(3.793)	(4.284)
60th	6.500***	-0.600	-4	-3	-1.920
	(2.202)	(3.000)	(5.267)	(3.965)	(4.274)
65th	9.500***	0.300	1	-4.000	8.080
	(2.468)	(3.254)	(6.237)	(4.095)	(5.334)
70th	16***	3.800	6	-2.400	16.80**
	(2.634)	(3.921)	(6.868)	(4.586)	(6.698)
75th	16***	7.500	4.500	4	18.59**
	(3.384)	(5.001)	(6.931)	(6.532)	(7.998)
80th	24.40***	15.90**	17.90**	5	35.32***
	(4.476)	(7.612)	(8.542)	(6.952)	(9.864)
85th	44.00***	34.10***	41.00**	16.00*	52.50***
	(6.830)	(10.02)	(17.31)	(9.484)	(15.84)
90th	82.80***	77.60***	97.80***	34.80**	76.25**
	(13.99)	(17.19)	(31.16)	(16.72)	(35.72)
95th	154***	171.6***	173.4***	138.5***	149.5*
	(24.70)	(25.20)	(58.53)	(45.13)	(84.39)
N	1497	1497	1008	1007	270

Standard errors in parentheses
* $p<0.10$ ** $p<0.05$ *** $p<0.01$

In summary, these estimates confirm that low-overcharge cartels are significantly more frequent in legal regimes, and high-overcharge cartels are also significantly more frequent under the legal regime. Both findings are robust to the estimation method.

3.3.1 Independence of episodes within cartels

The above results are all based on the cartel episode as the unit of observation, and this provides the large sample useful for the above distributional tests. However, as a sensitivity test, we have re-estimated all equations using the individual cartel as the unit of observation. Here we measure overcharge as the mean of the episode charges for that cartel. Column (5) in Table 3 shows these results.[23] This reduces the sample size to a quarter of its original size, but the substantive results remain statistically robust: the illegal sample has significantly less mass in its tails, where here the lower tail is the bottom 15% and the upper tail is the top 30% of the distribution.

3.3.2 Quality of data

In a further sensitivity test, we acknowledge previous critiques of Connor's database. Although his database is beyond comparison in both its breadth and scale, some authors have previously questioned the quality of some of the overcharge estimates.[24] We have therefore screened the database, now only including estimates whose primary sources were published in peer-reviewed academic journals and books.[25] Again, results are qualitatively unchanged, as shown in Table 4 in Appendix C.

[23] The cartel level effect in the tails is even more pronounced if we exclude bid rigging cartels from our sample (bid rigging cartels typically do not appear in the legal sample).

[24] OXERA (2009), and Boyer and Kotchoni (2011).

[25] More details on these journals and estimates are given in Connor (2014).

3.4 Omitted variables

The central finding of the paper is that the enforcement of competition law is constraining cartel conduct. The evidence in support of that finding is that the distribution of overcharges for illegal cartels has less mass in the lower and upper tails compared to the overcharge distribution for legal cartels, which, by the canonical theory of collusion, implies that competition law is deterring low-overcharge cartels from forming and constraining the overcharges of those cartels that do form.

That argument presumes the set of illegal cartels is comparable to the set of legal cartels. While the analysis using propensity scores established comparability for the variables in our data set, it is possible there are omitted variables that systematically vary between legal and illegal cartels in such a way as to offer an alternative explanation of the lower and upper tail results that does not involve constraining cartel conduct.

The most likely candidate is the number of firms, as it is a key driver of overcharges and cartel formation. Suppose the overcharge is monotonic in the number of firms. If the distribution of the number of firms for illegal cartels has less mass in the lower and upper tails compared to legal cartels, it follows that the overcharge distribution for illegal cartels has less mass in the lower and upper tails. What is difficult is coming up with an explanation for why illegal cartels would have fewer cartels with a small number of firms and fewer cartels with a large number of firms, compared to legal cartels.

One possibility is that markets with few firms are less likely to have an illegal cartel because they can tacitly collude, while firms in such markets would still choose to have a legal cartel. That would predict fewer illegal cartels with a small number of firms relative to legal cartels. If the overcharge is decreasing in the number of firms then it would explain the upper tail result for the overcharge distributions. However, that theory does not explain the lower tail result. One could augment it with a second theory: Suppose cartels are highly unstable in markets with many firms so duration is short and firms are almost indifferent about cartelizing. As a result, firms do not form illegal cartels but still form legal cartels. That would explain the lower tail result.[26]

While it is then possible to patch together an alternative theory to explain the lower tail result with a second alternative theory to explain the upper tail result, an advantage of our theory is that it explains both the lower and upper tail results, which is appealing from the perspective of parsimony.[27]

4 Selection bias due to differential detection?

The above estimators are designed to correct for one potential source of bias - resulting from non-random assignment of detected cartels. We now consider an alternative source - the possibility that detected (i.e. observed) illegal cartels are a non-random sample from the population of all illegal cartels.

For this discussion, suppose initially that the enforcement of competition law did not, in fact, impact the decision to form a cartel, nor the decision as to what price to charge; that is, firms act as if the probability of being caught and convicted is

[26] Another possibility is that illegality makes coordination more difficult, and that force is particularly acute when there are many firms. That would predict fewer illegal cartels with many firms, relative to legal cartels. However, note that enforcement is then impacting cartel formation and thus is consistent with our finding that enforcement is constraining cartels; it is just that the mechanism is different from our theory. Hence, that type of alternative explanation does not alter the paper's main conclusion.

[27] From "Occam's razor" in Wikipedia: "*For each accepted explanation of a phenomenon, there may be an extremely large, perhaps even incomprehensible, number of possible and more complex alternatives, because one can always burden failing explanations with ad hoc hypotheses to prevent them from being falsified; therefore, simpler theories are preferable to more complex ones because they are more testable.*"

approximately zero. In that case, the overcharge distribution for illegal cartels would be the same as for legal cartels (conditional on covariates). If that were true, could selection bias associated with the detection of illegal cartels produce our empirical finding? That would occur only if the illegal cartels with low or high overcharges are less likely to be discovered than illegal cartels with more moderate overcharges. We consider some possible sources of correlation between overcharges and the likelihood of detection and assess whether they could offer an alternative explanation of our results.

The possibility of a correlation between the likelihood of discovery and the overcharge has already been recognised in our theoretical model, for it was assumed the probability of detection and conviction is non-decreasing in price, $\sigma'(p) \geq 0$. If $\sigma'(p) >> 0$ then illegal cartels with a low price (and, therefore, low overcharge) are less likely to be in our sample, which could have produced the lower tail property. That is, legal cartels are more likely to have low overcharges than illegal cartels in our data set because illegal cartels with low overcharges are less likely to be discovered (and thus to appear in the data set). However, this source of bias would not produce the upper tail result. If the probability of detection is increasing in price then illegal cartels with high overcharges would be *more* likely to be discovered in which case high overcharges would be more likely for cartels that are illegal, which runs contrary to the evidence.

Another source of bias is the presence of some third factor that causes overcharges and discovery to be correlated. Suppose cartels vary in the probability of internal collapse, and let λ denote the per-period probability of that event. It is shown in Harrington and Wei (2016) that variation in λ across (illegal) cartels creates selection bias in the sample of discovered cartels because more stable cartels are more likely to be detected. The intuition is simple: The longer a cartel is alive, the more chances there are for it to be uncovered by customers or the competition authority. Extending the theory in Section 1 to allow for an exogenous probability of collapse λ, we have shown that the optimal collusive price is non-increasing in λ. Not surprising, a lower value for λ means a more stable cartel which raises the collusive value which then loosens the equilibrium condition and thus allows a higher collusive price to be supported. In sum, variation across illegal cartels in the likelihood of internal collapse results in a positive correlation between the size of the overcharge and the likelihood of detection (and thus appearing in the data set). The more stable cartels have higher overcharges and are more likely to eventually be discovered because of their longer duration. While there is then bias in the overcharge distribution for illegal cartels, for the same reasons as given above, this bias is inconsistent with the upper tail result.[28]

As another possibility, suppose markets are heterogenous in buyer size; for example, compare retail markets with many, small buyers and markets for intermediate goods with a few, large buyers. Cartels operating in markets with large buyers could have a higher rate of detection (due to buyer sophistication) and lower overcharges (due to buyer bargaining power). Hence, cartels in markets with small buyers would be undersampled and, as they tend to have higher overcharges, this would produce the upper tail result. However, there would not be the lower tail result because the cartels in markets with large buyers would be oversampled and they have low overcharges.

[28] Harrington and Wei (2016) show that this result is true even if internal collapse makes detection more likely. Let the probability of discovery be ρ when the cartel is active and β when the cartel collapsed. First note that if $\beta = 1$ (so collapse implies discovery for sure), then the population of discovered cartels is the same as the population of all cartels because, eventually, every cartel either is discovered or collapses (and is then discovered); hence, there is no selection bias. When $\beta < 1$, the population of discovered cartels is a biased sample of the population of cartels. However, as long as the inter-cartel variation in the rate of internal collapse λ is sufficiently larger than the variation in the likelihoods of discovery ρ and β (which seems plausible as λ is driven by industry-specific factors, while ρ and β are influenced by a common enforcement policy) then Harrington and Wei (2016) show there is an over-sampling of the most stable cartels. As the most stable cartels have the highest overcharges, selection bias results in an oversampling of high-overcharge illegal cartels which works against the upper tail result.

Again, there is an alternative explanation for one but not both results.[29]

Finally, a possible source of selection bias comes from a competition authority's decision as to which (suspected) cartels to prosecute. Prosecution bias is a concern for our empirical analysis only if the likelihood of taking on a case depends on the overcharge. While one might imagine that cases for which the overcharge is thought to be low may be less likely to be prosecuted, that is unlikely for two reasons. First, competition authorities are probably more interested in avoiding cases for which the probability of a conviction is low, and that probability is determined by the extent of non-economic evidence concerning communications among firms rather than economic evidence pertaining to overcharges. Second, it is very difficult to assess ex ante the size of the overcharge. Estimating overcharges requires estimating the but for price which is a rather involved exercise. In sum, we do not think it is likely that competition authorities tend to avoid prosecuting cartels with low overcharges. And, even if that was the case, this source of bias would at most be consistent with the lower tail result, and would run against finding evidence for the upper tail result.

In summary, while the data set of discovered illegal cartels is most likely a biased sample, we were unable to devise a mechanism that would cause (observed) illegal cartels to be less likely to have both low overcharges and high overcharges compared to legal cartels. Based on the analysis of this section and the preceding section, we believe the most plausible explanation for our empirical finding is that illegal cartels are acting as if there is some prospect of being caught and penalised, and thus are being deterred or constrained by the existence and enforcement of a competition law prohibiting collusion.

[29] One could also imagine that the overcharge is higher for cartels in markets with large buyers because bargaining power depresses the but for price. In that case, the detection bias produces the lower tail result but not the upper tail result.

5 Conclusion

One of the central issues regarding competition policy is whether the enforcement of anti-cartel laws has been effective in deterring and constraining cartels. Are the efforts of competition authorities causing some cartels not to form? For those cartels that do form, is enforcement causing them to limit their price increases? These questions are as challenging as they are important because we do not observe deterred cartels and it is very difficult to assess what prices a cartel would have charged had there not been enforcement. In light of the almost total absence of empirical analysis addressing these questions, this paper contributes by providing an innovative approach rooted in the canonical theory of collusion and then implementing it using historical data on legal and illegal cartels. The approach delivers the first broad evidence that competition policy is providing effective in deterring some cartels from forming and constraining the overcharges of the cartels that do form.

Using the theory of collusion, we have shown that if competition policy is effective then low-overcharge cartels will be deterred from forming because the expected penalty makes them unstable and unprofitable. In addition, high-overcharge cartels are also less likely to be observed because effective anti-cartel enforcement will tend to destabilize collusion and that will force colluding firms to limit their price increases. Thus the theory predicts that a well-functioning competition policy will manifest itself with fewer low-overcharge cartels and fewer high-overcharge cartels.

The empirical contribution derives from a novel comparison of the distributions of overcharges for cartels subject to competition law and enforcement and those that were not. Consistent with the predicted impact of effective competition policy coming from the theory, the overcharge distribution for illegal cartels is found to have less mass in both the lower and upper tails compared to the distribution for legal cartels. This finding is robust when we control for the time periods, jurisdictions and industries in which the cartels occurred.

These results may have important implications for assessing the welfare effects of competition law and enforcement. The benefits from enforcement are typically seen as the elimination of the overcharge for those years that the cartel would have operated had the competition authority not discovered and convicted it.[30] Our analysis suggests that these benefits have been underestimated. First, the presence of a competition authority may have caused the cartel to set a lower overcharge, in which case consumers would have faced an even higher price had there not been enforcement. Second, some cartels are deterred from forming and that is another unmeasured welfare gain. While the latter has previously been recognised, our study is one of the few to provide evidence that it is occurring.[31]

Nevertheless, our empirical contribution should not be overstated at this stage. What we have shown is a robustly significant difference between historical legal and illegal cartels in the tails of their distributions. What is contestable is that this difference is necessarily attributable to effective deterrence, rather than some other unobserved (by us) factors which differed between these two samples, beyond the issue of legality. It is not obvious what these variables might be, or why they should impact on the tails of the distribution, but we cannot exclude the possibility. For this reason, although we view our evidence as important because this is a subject where little has been previously quantified, it is preliminary, rather than conclusive. Future empirical work is clearly called for, perhaps using alternative approaches to constructing the counterfactual.

[30] See for example OFT (2010, p.17).

[31] Davies and Ormosi (2014) present a framework for using the information on the tails in order to calibrate the relative magnitude of deterred and undetected cartel harm.

6 Appendix

A Proofs

Proof of Proposition 1

Let us first show that, with or without competition law, the optimal collusive price is bounded above by p^m. Taking the first derivative of the collusive value with respect to price and simplifying, we derive:

$$\begin{aligned} & \frac{\partial V^c(p)}{\partial p} \\ = \; & \frac{[1-\delta(1-\sigma(p))]\,\pi'(p) - (1-\delta)\,F(p)\sigma'(p) - [\pi(p) - \pi^n]\,\delta\sigma'(p) - [1-\delta(1-\sigma(p))]\,\sigma(p)\,F'(p)}{[1-\delta(1-\sigma(p))]^2} \end{aligned} \tag{5}$$

By the strict quasi-concavity of $\pi(p)$, $\sigma'(p) \geq 0$, and $F'(p) \geq 0$,

$$\frac{\partial V^c(p)}{\partial p} < 0 \;\forall p > p^m. \tag{6}$$

Next consider the ICC in (3). Given that $\pi(p)$ is non-increasing in p $\forall p \geq p^m$ and $\pi^d(p)$ is increasing in p $\forall p$ then the RHS of (3) is increasing in p $\forall p \geq p^m$. Given $V^c(p)$ is decreasing in p $\forall p > p^m$ and $\sigma(p)$ is non-decreasing in p then the LHS of (3) is decreasing in p $\forall p > p^m$. Hence, if the ICC holds for some $p^o > p^m$ then it holds $\forall p \in [p^m, p^o]$. This property allows us to conclude that the optimal collusive price is bounded above by p^m. For suppose not so that the optimal collusive price is $p^* > p^m$. Given that $V^c(p)$ is decreasing in price at $p = p^*$ by (6) and the ICC holds $\forall p \in [p^m, p^*]$ then the cartel strictly prefers a lower price to p^* which is a contradiction. From hereon, we can focus our attention on collusive prices no higher than p^m.

Let us prove (iii). If $p_L^* < p^m$ then the ICC is violated for a legal cartel at collusive prices above p_L^* :

$$\delta\left(\frac{\pi(p)}{1-\delta} - V^n\right) \gtreqqless \pi^d(p) - \pi(p) \text{ as } p \lesseqqgtr p_L^*, \text{ for } p \in [p_L^*, p^m]. \tag{7}$$

Because the LHS of (3) is strictly less than the LHS of (7) when $\sigma(p) > 0$, (7) implies that the ICC for an illegal cartel is violated at collusive prices at or above p_L^*:

$$\delta(1-\sigma(p))\left(\frac{\pi(p) - \sigma(p)F(p) + \delta\sigma(p)V^n}{1-\delta(1-\sigma(p))} - V^n\right) < \pi^d(p) - \pi(p) \ \forall p \in [p_L^*, p^m]. \tag{8}$$

It follows that $p_I^* < p_L^*$.

Next let us prove (ii). Examining (5), if $\sigma'(p^m) > 0$ then it follows from the strict quasi-concavity and continuous differentiability of $\pi(p)$ and the continuous differentiability of $\sigma(p)$ and $F(p)$ that $\exists\varepsilon > 0$ such that

$$\frac{\partial V^c(p)}{\partial p} < 0 \ \forall p \in [p^m - \varepsilon, p^m].$$

Return to the ICC in (3). Given $\pi(p)$ is non-increasing in p $\forall p \geq p^m$ and $\pi^d(p)$ is increasing in p then, by the continuous differentiability of $\pi(p)$, $\exists\varepsilon > 0$ such that the RHS of (3) is increasing in p $\forall p \in [p^m - \varepsilon, p^m]$. Given $V^c(p)$ is decreasing in p at $p = p^m$ and $\sigma(p)$ and $F(p)$ are non-decreasing in p then, by the continuous differentiability of $V^c(p)$, $\exists\varepsilon > 0$ such that the LHS of (3) is decreasing in p $\forall p \in [p^m - \varepsilon, p^m]$. Hence, if (3) holds for $p = p^m$ then it holds $\forall p \in [p^m - \varepsilon, p^m]$. It follows that: If $\sigma'(p^m) > 0$ then $p_I^* < p^m$. For suppose not and the optimal collusive price is instead p^m. By setting a slightly lower price, the collusive value is higher and the ICC is still satisfied which is a contradiction.

Given $\sigma'(p^m) > 0$ implies $p_I^* < p^m$, (ii) can be proved. If, at the optimal collusive price, the ICC does not bind for a legal cartel then $p_L^* = p^m$ and, given we've shown $p_I^* < p^m$, we have $p_I^* < p_L^*$. If instead the ICC does bind for a legal cartel then $p_L^* < p^m$ in which case $p_I^* < p_L^*$ follows from (iii).

Finally, property (i) is immediate. If $p_L^* < p^m$ then $p_I^* < p_L^*$ follows from (iii). If $p_L^* = p^m$ then $p_I^* \leq p_L^*$ follows from $p_I^* \leq p^m$.

Proof of Proposition 2

Let us first show that $\underline{p}_L^* = p^n$ (which is well-known but a proof is provided for completeness). When $\sigma(p) = 0\ \forall p$, the ICC in (3) for a legal cartel can be simplified and re-arranged to:

$$\left(\frac{\delta}{1-\delta}\right)\left(\frac{\pi(p) - \pi^n}{\pi^d(p) - \pi(p)}\right) \geq 1. \tag{9}$$

Consider the LHS of (9) as the collusive price converges to the competitive price, and apply l'Hôpital's rule,

$$\lim_{p \to p^n}\left(\frac{\delta}{1-\delta}\right)\left(\frac{\pi(p) - \pi^n}{\pi^d(p) - \pi(p)}\right) = \lim_{p \to p^n}\left(\frac{\delta}{1-\delta}\right)\left(\frac{d\pi(p)/dp}{(d\pi^d(p)/dp) - (d\pi(p)/dp)}\right). \tag{10}$$

Define the best response function,

$$\psi_i(\underline{p}_{-i}) \equiv \arg\max_{p_i} \pi_i\left(p_i, \underline{p}_{-i}\right),$$

and perform the following steps on (10):

$$
\begin{aligned}
& \lim_{p \to p^n} \left(\frac{\delta}{1-\delta} \right) \left(\frac{d\pi\left(p\right)/dp}{\left(d\pi^d\left(p\right)/dp\right) - \left(d\pi\left(p\right)/dp\right)} \right) \\
= & \lim_{p \to p^n} \left(\frac{\delta}{1-\delta} \right) \times \\
& \left(\frac{\sum_{j=1}^{n} \left(\frac{\partial \pi_i (p,(p,\ldots,p))}{\partial p_j} \right)}{\left(\frac{\partial \pi_i (\psi_i(p,\ldots,p),(p,\ldots,p))}{\partial p_i} \right) \sum_{j \neq i} \left(\frac{\partial \psi_i (p,\ldots,p)}{\partial p_j} \right) + \sum_{j \neq i}^{n} \left(\frac{\partial \pi_i (\psi_i(p,\ldots,p),(p,\ldots,p))}{\partial p_j} \right) - \sum_{j=1}^{n} \left(\frac{\partial \pi_i (p,(p,\ldots,p))}{\partial p_j} \right)} \right)
\end{aligned}
$$

$$
\begin{aligned}
= & \lim_{p \to p^n} \left(\frac{\delta}{1-\delta} \right) \left(\frac{\sum_{j=1}^{n} \left(\frac{\partial \pi_i (p,(p,\ldots,p))}{\partial p_j} \right)}{\sum_{j \neq i} \left(\frac{\partial \pi_i (\psi_i(p,\ldots,p),(p,\ldots,p))}{\partial p_j} \right) - \sum_{j=1}^{n} \left(\frac{\partial \pi_i (p,(p,\ldots,p))}{\partial p_j} \right)} \right) \\
= & \left(\frac{\delta}{1-\delta} \right) \left(\frac{\sum_{j=1}^{n} \left(\frac{\partial \pi_i (p^n,(p^n,\ldots,p^n))}{\partial p_j} \right)}{\sum_{j \neq i} \left(\frac{\partial \pi_i (\psi_i(p^n,\ldots,p^n),(p^n,\ldots,p^n))}{\partial p_j} \right) - \sum_{j=1}^{n} \left(\frac{\partial \pi_i (p^n,(p^n,\ldots,p^n))}{\partial p_j} \right)} \right) \\
= & \left(\frac{\delta}{1-\delta} \right) \left(\frac{\sum_{j \neq i} \left(\frac{\partial \pi_i (p^n,(p^n,\ldots,p^n))}{\partial p_j} \right)}{\sum_{j \neq i} \left(\frac{\partial \pi_i (p^n,(p^n,\ldots,p^n))}{\partial p_j} \right) - \sum_{j \neq i} \left(\frac{\partial \pi_i (p^n,(p^n,\ldots,p^n))}{\partial p_j} \right)} \right) = +\infty.
\end{aligned}
$$

Thus, if $\delta > 0$ then (9) holds for some $p > p^n$ which means a legal cartel can always sustain a collusive price. However, as we'll show next, the collusive price must be close to the competitive price when δ is close to zero. The ICC is re-arranged to

$$
\delta \left[\pi\left(p\right) - \pi^n \right] \geq \left(1-\delta\right) \left[\pi^d\left(p\right) - \pi\left(p\right) \right]. \tag{11}
$$

As $\delta \to 0$, the LHS goes to zero. Hence, (11) can only hold if the RHS converges to zero which implies $p \to p^n$. In sum, when collusion is legal and $\delta > 0$, there exists an optimal collusive price exceeding the competitive price p^n though the optimal collusive price can be arbitrarily close to p^n. For a legal cartel, the infimum for the collusive price is p^n.

Turning to the case of illegal collusion, a necessary condition for (3) to hold is $V^c(p) > V^n$. Note that

$$\begin{aligned}\lim_{p\to p^n} V^c(p) &= \lim_{p\to p^n} \frac{\pi\left(p\right)-\sigma(p)F(p)+\delta\sigma(p)V^n}{1-\delta(1-\sigma(p))} = \frac{\pi^n-\sigma(p^n)F(p^n)+\delta\sigma(p^n)V^n}{1-\delta(1-\sigma(p^n))} \\ &= \frac{(1-\delta)V^n-\sigma(p^n)F(p^n)+\delta\sigma(p^n)V^n}{1-\delta(1-\sigma(p^n))} = V^n - \frac{\sigma(p^n)F(p^n)}{1-\delta(1-\sigma(p^n))} < V^n,\end{aligned}$$

because $\sigma(p^n)F(p^n) > 0$. Given that the ICC for an illegal cartel is violated when the collusive price is sufficiently close to p^n, it follows that there is a lower bound on the collusive price that exceeds p^n. For an illegal cartel, the infimum for the collusive price exceeds p^n.

B Numerical analysis

Consider a duopoly that offers symmetrically differentiated products. A representative consumer chooses quantities to maximize net surplus:

$$\max_{(q_1,q_2)} aq_1 + aq_2 - \left(\frac{1}{2}\right)\left(bq_1^2 + bq_2^2 + 2dq_1q_2\right) - p_1q_1 - p_2q_2,$$

where $a, b > 0, d \in (0, b)$. The first-order conditions yield the inverse demand functions:

$$\begin{aligned}\frac{\partial U}{\partial q_1} &= a - bq_1 - dq_2 - p_1 = 0 \Leftrightarrow P_1\left(q_1,q_2\right) = a - bq_1 - dq_2 \\ \frac{\partial U}{\partial q_2} &= a - bq_2 - dq_1 - p_2 = 0 \Leftrightarrow P_2\left(q_1,q_2\right) = a - bq_2 - dq_1\end{aligned}$$

which can be inverted to derive the demand functions for firms 1 and 2, respectively,

$$\left(\frac{1}{b^2-d^2}\right)[a(b-d)-bp_1+dp_2]$$

$$\left(\frac{1}{b^2-d^2}\right)[a(b-d)-bp_2+dp_1].$$

However, these demand functions are relevant only as long as both are positive. Taking account of corner solutions, firm 1's demand function is

$$D_1(p_1,p_2)=\begin{cases}\max\left\{\left(\frac{1}{b^2-d^2}\right)[a(b-d)-bp_1+dp_2],0\right\} & \text{if } \frac{1}{d}(bp_2-a(b-d))\leq p_1\\ \left(\frac{1}{b}\right)(a-p_1) & \text{if } p_1<\frac{1}{d}(bp_2-a(b-d))\end{cases}$$

and firm 2's demand function is analogously defined.

Each firm has a common marginal cost $c\in[0,a)$. The Nash equilibrium price is $p^n\equiv\frac{a(b-d)+bc}{2b-d}$ and the joint profit-maximizing price is $p^m\equiv\frac{(b-d)(a+c)}{2(b-d)}$. Conditional on the probability of detection σ, the optimal collusive price $p^*(\sigma)$ is defined by:

- ICC is not binding: If $\delta(1-\sigma)[V^c(p^m)-V^n]\geq\pi^d(p^m)-\pi(p^m)$ then $p^*(\sigma)=p^m$.
- ICC is binding: If $\delta(1-\sigma)[V^c(p^m)-V^n]<\pi^d(p^m)-\pi(p^m)$ and $\exists p\in(p^n,p^m)$ such that $\delta(1-\sigma)[V^c(p)-V^n]\geq\pi^d(p)-\pi(p)$ then

$$p^*(\sigma)=\max\left\{p\in(p^n,p^m):\delta(1-\sigma)[V^c(p)-V^n]=\pi^d(p)-\pi(p)\right\}.$$

If $\sigma>0$ then $p^*(\sigma)$ may not exist because collusion is not sustainable.

Set $(a,b)=(1,1)$ and $F=\pi^m/2=\frac{(a-c)^2}{8(b+d)}$. Let $TN(\mu,s)$ denote a truncated normal distribution with mean μ and standard deviation s. Randomly select (c,d,δ) according to the following distributions: $c\sim TN(0.35,0.1)$ with support $[0,1]$, $d\sim$

$TN(0.5, 0.1)$ with support $[0.1, 0.9]$, and $\delta \sim TN(0.35, 0.1)$ with support $[0.01, 0.99]$.[32] Given a draw on (c, d, δ), calculate p^n, $p^*(0)$, $p^*(0.05)$ and the legal and illegal overcharges. Kernel estimation is performed on a data set of overcharges from 100,000 random draws on (c, d, δ).

C Tables

[32]Given that the probability of detection is independent of the collusive price, the upper tail result (Prop. 1) occurs only when the ICC is binding; that is, the expected penalty reduces the collusive value which tightens the ICC which then requires the collusive price to be lowered. So that the upper tail result is visually observable, the discount factor is kept low in order for the ICC to generally bind. More plausible values for the discount factor could be specified if the probability of detection is assumed to be increasing in the collusive price. In that case, the upper tail result occurs even when the ICC is not binding.

Table 4: Estimates of quantile treatment effects (treatment - legal, control - illegal) for peer-reviewed publications only

Quantiles	Simple quantile	Multivariate quantile	PS weighted	IPW weighted
5th	0	-2.300***	0	0
	(0.471)	(0.588)	(0.579)	(2.665)
10th	-5***	-5.650***	-4.600***	-5**
	(1.099)	(1.070)	(0.947)	(2.501)
15th	-6.500***	-7.250***	-7***	-7.900***
	(1.039)	(1.494)	(0.785)	(2.481)
20th	-5.700***	-7.800***	-6.100***	-8.900***
	(1.402)	(1.697)	(1.038)	(2.586)
25th	-3.900**	-6.900***	-3.200**	-8.700***
	(1.885)	(1.900)	(1.579)	(2.618)
30th	-2.600	-7.450***	-4.600**	-8.800***
	(1.892)	(2.210)	(1.952)	(2.829)
35th	-1.900	-5.300**	-6.700***	-6.200**
	(1.994)	(2.644)	(2.153)	(2.902)
40th	0.600	-5.400*	-5.700**	-8.500***
	(2.378)	(3.093)	(2.342)	(3.138)
45th	0.200	-3.500	-2.500	-7**
	(2.246)	(3.311)	(2.271)	(3.526)
50th	4	-2.600	-4.100*	-6.600*
	(2.614)	(3.380)	(2.260)	(3.637)
55th	5*	-1.600	-2.500	-4.600
	(2.835)	(3.337)	(2.718)	(3.944)
60th	4.600	-3	-3.500	-4.600
	(2.891)	(3.848)	(2.723)	(4.114)
65th	7.500**	-2.500	-3	-7
	(3.378)	(4.133)	(3.354)	(4.394)
70th	12.80***	0	0	-4.800
	(4.281)	(5.648)	(4.381)	(4.949)
75th	13.10***	4.800	0	-3
	(4.880)	(6.062)	(4.736)	(6.871)
80th	23***	11.35	4.200	4.300
	(7.104)	(9.788)	(6.351)	(7.893)
85th	38***	26*	22.10**	15.00
	(11.29)	(14.48)	(10.76)	(13.51)
90th	78***	53.45**	62***	28.40
	(21.42)	(26.79)	(20.54)	(23.73)
95th	159.4***	114*	102.5***	123*
	(33.09)	(68.84)	(31.33)	(66.24)
N	730	730	586	644
		standard errors in parentheses		
* p<0.10	** p<0.05	*** p<0.01		

Table 5: Logit regression results used for propensity scores

Pre-1945 cartel (1 - Yes, 0 - No)	3.861***
	(0.215)
US cartel (1 - Yes, 0 - No)	0.132
	(0.387)
European cartel (1 - Yes, 0 - No)	-0.481
	(0.383)
Asian cartel (1 - Yes, 0 - No)	1.093**
	(0.492)
Global cartel (1 - Yes, 0 - No)	-0.0676
	(0.410)
Bid Rigging cartel (1 - Yes, 0 - No)	-0.933**
	(0.378)
Manufacturing cartel (1 - Yes, 0 - No)	-1.284***
	(0.401)
Raw materials cartel (1 - Yes, 0 - No)	-2.382***
	(0.452)
Services cartel (1 - Yes, 0 - No)	-1.683***
	(0.573)
Observations	1419
Standard errors in parentheses	

Table 6: Quantile regression results for the four matched samples shown in Figure 4

Quantiles	(1)	(2)	(3)	(5)
5th	-2.200	0	-4.600	-3
	(1.482)	(.)	(.)	(54.40)
10th	-4.600***	-4***	-4.600***	-5.600***
	(0.964)	(1.040)	(0.536)	(0.672)
15th	-5.700***	-4.700***	-4	-4.900***
	(0.990)	(0.976)	(13.94)	(1.708)
20th	-5.500***	-4.400***	-6.500	-5.400*
	(1.424)	(1.376)	(12.71)	(3.196)
25th	-4.800***	-2.900	-9.800	-2.900
	(1.263)	(1.856)	(25.57)	(4.715)
30th	-5.600***	-1.600	-21.50	-5.500
	(1.735)	(1.929)	(19.41)	(6.440)
35th	-5.500**	-0.200	-18.20	-7.900
	(2.294)	(2.161)	(12.63)	(6.808)
40th	-4.300	0.100	-15	-8
	(2.793)	(2.504)	(15.97)	(5.715)
45th	-1.800	2	-10	-6
	(2.628)	(2.482)	(13.88)	(5.257)
50th	-1.000	5*	-5.600	-4.200
	(2.790)	(2.601)	(13.79)	(5.332)
55th	-1	5	-20	-6
	(2.839)	(3.103)	(14.01)	(4.803)
60th	-0.600	6.200*	-16	-4
	(3.286)	(3.311)	(17.92)	(5.267)
65th	0.300	7.800**	-10*	1
	(3.525)	(3.730)	(5.629)	(6.237)
70th	3.800	15.30***	0	6
	(4.511)	(4.709)	(6.429)	(6.868)
75th	7.500	17***	0.500	4.500
	(4.923)	(4.991)	(7.588)	(6.931)
80th	15.90*	24.80***	13.90	17.90**
	(8.518)	(7.999)	(8.820)	(8.542)
85th	34.10***	46.50***	41**	41.00**
	(12.87)	(17.20)	(18.15)	(17.31)
90th	77.60***	106***	107.5***	97.80***
	(28.49)	(29.00)	(25.92)	(31.16)
95th	171.6***	174***	201.5***	173.4***
	(27.60)	(53.13)	(54.40)	(58.53)
N	1497	736	390	1008

t statistics in parentheses
* $p<0.10$ ** $p<0.05$ *** $p<0.01$

Table 7: Results of the multivariate quantile regressions

	q5	q10	q15	q20	q25	q30	q35	q40	q45	q50	q55	q60	q65	q70	q75	q80	q85	q90	q95
Legal	-2.200** (1.001)	-4.600*** (1.273)	-5.700*** (1.364)	-5.500*** (1.359)	-4.800*** (1.268)	-5.600*** (1.620)	-5.500*** (1.978)	-4.300* (2.198)	-1.800 (2.243)	-1.000 (2.501)	-1 (2.745)	-0.600 (3.000)	0.300 (3.254)	3.800 (3.921)	7.000 (5.001)	15.90** (7.612)	34.10*** (10.02)	77.60*** (17.19)	171.6*** (25.20)
Pre1945	0 (0.997)	0.900 (1.267)	1.700 (1.358)	2.300* (1.353)	3.000** (1.263)	5.600*** (1.613)	6.800*** (1.970)	8.600*** (2.188)	8.800*** (2.233)	10.70*** (2.490)	11.30*** (2.733)	13.30*** (2.987)	16*** (3.240)	16.50*** (3.904)	16.90*** (4.979)	14.50* (7.579)	17.50* (9.973)	16.60 (17.11)	4.800 (25.09)
US	-0.700 (1.619)	-0.000000238 (2.059)	1 (2.207)	2.200 (2.199)	1.600 (2.052)	2.700 (2.621)	0.900 (3.201)	1.300 (3.555)	2 (3.628)	0.800 (4.047)	1.800 (4.441)	3.500 (4.854)	3.500 (5.265)	5.500 (6.344)	10.40 (8.092)	10.90 (12.32)	11 (16.21)	13.20 (27.80)	20 (40.78)
EU	0.300 (1.586)	0.900 (2.017)	1.700 (2.162)	3.700* (2.154)	2.900 (2.010)	3.300 (2.568)	0.900 (3.136)	0.800 (3.483)	1.700 (3.554)	-0.200 (3.964)	2.100 (4.350)	4.200 (4.755)	6.200 (5.157)	7.200 (6.215)	8.600 (7.926)	12.90 (12.06)	15 (15.87)	20.20 (27.24)	42.40 (39.94)
Asia	-1.900 (1.882)	0.600 (2.393)	4.250* (2.565)	5.200** (2.556)	5.000** (2.385)	5.400* (3.047)	3.400 (3.721)	3.100 (4.133)	3.900 (4.217)	2.500 (4.704)	1.900 (5.162)	3.800 (5.642)	7.200 (6.119)	8.500 (7.374)	16* (9.405)	20.40 (14.32)	30.50 (18.84)	35.80 (32.32)	79.10* (47.40)
Global	1.100 (1.649)	5.300** (2.097)	6.900*** (2.248)	8.700*** (2.239)	8.600*** (2.090)	9.200*** (2.669)	6.600** (3.260)	7.500** (3.621)	8.800** (3.695)	7.500* (4.121)	8.600* (4.523)	9.800** (4.944)	11.50** (5.362)	11.20* (6.461)	13.70* (8.241)	15.90 (12.54)	19.40 (16.50)	30.60 (28.32)	34.50 (41.53)
Bid rigging	0 (0.989)	0 (1.258)	0.950 (1.348)	1.500 (1.343)	0.700 (1.254)	0.500 (1.601)	1.100 (1.955)	1.400 (2.172)	0.900 (2.217)	-0.200 (2.472)	-0.700 (2.713)	-1.800 (2.965)	-0.500 (3.216)	-0.100 (3.876)	-3.700 (4.943)	-5 (7.524)	-0.800 (9.900)	-1.400 (16.99)	-9.600 (24.91)
Manufacturing	-3.400** (1.656)	-4.200** (2.105)	-3.100 (2.257)	-1.500 (2.248)	-2.500 (2.098)	-1.900 (2.680)	0.500 (3.273)	1.700 (3.636)	2.800 (3.710)	0.100 (4.138)	0 (4.541)	0.300 (4.963)	-1.600 (5.383)	-3.300 (6.487)	-2.600 (8.274)	0 (12.59)	6.700 (16.57)	11.20 (28.43)	6.700 (41.69)
Raw materials	-4.600*** (1.773)	-5.100** (2.254)	-3.100 (2.416)	-2.100 (2.407)	-2.600 (2.247)	-1.700 (2.870)	1.100 (3.505)	1.800 (3.893)	2.200 (3.973)	0.100 (4.431)	-0.100 (4.862)	-1.600 (5.315)	-3.300 (5.764)	-5.800 (6.946)	-5.200 (8.859)	-3.500 (13.48)	2.600 (17.74)	14 (30.44)	14.70 (44.64)
Transportation	-1.300 (2.363)	-4 (3.005)	-2.200 (3.221)	-2.600 (3.209)	-3.300 (2.995)	-2.000 (3.825)	1.500 (4.671)	0.500 (5.189)	0 (5.295)	-4.500 (5.906)	-6.600 (6.481)	-7.000 (7.084)	-1 (7.683)	-4.300 (9.259)	-10.80 (11.81)	-8.400 (17.97)	-7.500 (23.65)	-4.800 (40.58)	-27.40 (59.51)
Services	-2.900 (1.967)	-5.800** (2.501)	-3.400 (2.681)	-0.400 (2.671)	0.600 (2.493)	3.000 (3.184)	3.600 (3.889)	3.600 (4.319)	4.700 (4.408)	2.800 (4.916)	8 (5.395)	18.10*** (5.897)	22.30*** (6.396)	28.10*** (7.707)	32.10*** (9.830)	67*** (14.96)	99.20*** (19.69)	117.2*** (33.78)	177.9*** (49.54)
Constant	5.300** (2.158)	7.900*** (2.744)	7.100** (2.941)	6.300** (2.930)	8.900*** (2.735)	8.700** (3.493)	10.50** (4.266)	10.80** (4.739)	11.40** (4.836)	17.40*** (5.393)	18.90*** (5.919)	19.90*** (6.469)	22.10*** (7.016)	25.80*** (8.455)	27.30** (10.78)	28.10* (16.41)	25.80 (21.60)	24.20 (37.06)	42.90 (54.34)
Observations	1497	1497	1497	1497	1497	1497	1497	1497	1497	1497	1497	1497	1497	1497	1497	1497	1497	1497	1497

Standard errors in parentheses
* p<0.10 ** p<0.05 *** p<0.01

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