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Does enforcement deter cartels? A tale of two tails

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Highlights

- This paper presents a theoretical model of cartel enforcement and deterrence
- It shows that effective policy tends to deter cartels with low or high overcharges
- This provides an indirect route to test whether enforcement of cartel law is effective
- We use historical data on legal cartels to generate the counterfactual
- There is significantly less mass in the tails of the illegal overcharge distribution
- This result is robust to controlling for confounding factors
- We interpret this as the first tentative confirmation of effective deterrence

ACCEPTED MANUSCRIPT

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

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Abstract

This paper investigates the deterrent impact of anti-cartel enforcement. 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 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 illegal cartels. This result is robust to controlling for confounding factors, and we interpret this as the first tentative confirmation of effective deterrence.

Keywords: anti-cartel enforcement, deterrence, cartel overcharge

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"*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 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

[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.

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 (2017), 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.

As reviewed in [15], there is an extensive theoretical literature examining the effect of competition policy on collusive prices and cartel formation. As the contribution of this paper is in developing and executing a method for testing the deterrent effect of competition policy on cartels, the literature review will focus on the empirical research that contributes to that objective.

Given the obvious challenge that deterred cartels are, by their nature, unobserved, the empirical literature has been relatively sparse.[2] However, this lack of information has spawned a variety of methodologies for using data on variables we do observe for making deductions about those we do not. The most direct approach is to use the observed number of cases. [25] interprets the immediate increase in cartel discoveries after the introduction of the US leniency programme, followed by a subsequent readjustment below pre-leniency levels, as consistent with enhanced deterrence capabilities. [6] uses a cartel birth-death model to make inferences on EU cartel detection rates. [1] applies a logic similar to Miller, to the long-term trends in cartel discoveries observed in an international panel of CAs. They find evidence of an inverse U-shape relationship, which they attribute to the gradual increase over time in deterrence as CAs become more successful in their enforcement.

A number of less direct, but inventive, approaches have also been employed. [27], drawing on ecological methods, shows how recidivism can be used to identify the latent cartel rate from which changes over time can reveal something about changing deterrence. [16] show theoretically how a change in the duration of detected cartels can be used as a measure of policy effectiveness. Both [10] and [11] examine post-detection changes in merger rates in previously cartelised markets to impute whether explicit collusion may have been replaced by tacit collusion.[3]

Our own empirical approach here will be to compare the frequencies and characteristics of cartels observed under legal and illegal jurisdictions. Perhaps surprisingly, relatively little work has been undertaken to

[2] CMA (2017) provides a useful overview of the literature from a policy maker's perspective.
[3] [11] shares with the current paper its use of Connor's extensive historical database.

date making such comparisons. A recent notable exception is [20] which offers a detailed picture of what happens absent competition policy by employing data from a period of legal cartels, Finnish manufacturing industries 1951-1990. Although they have no explicit counterfactual, they are able to draw some inter-temporal conclusions: if not illegal, cartels are typically long-lived and their frequency increases inexorably over time: by the end of their period, they observe that almost all industries were cartelised.

Finally, [9] employs the estimates from the current paper to calibrate a framework which is designed to quantify the relative magnitudes of deterred cartel harm relative to detected and undetected harms. Even employing the most conservative of their estimates, they show that deterred harm is seven times greater than detected (i.e. observed), harms.[4]

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,

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

$\pi(p)$ is a firm's profit when all firms charge a common price p and is assumed to be continuously differentiable

[4] 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 (the ratio of deterred to detected harms); for example, [26]. These multipliers are typically in the region of five upwards.

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.[5] $\sigma(p) : \mathbb{R}_+ \to [0, 1]$ is a continuously differentiable non-decreasing function.[6] 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 chance of being caught and convicted even when it sets the competitive price: $\sigma(p^n) > 0$. 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.

A cartel is assumed to select the best (symmetric) collusive price using the grim punishment.[7] 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

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

Define

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

[5] 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.

[6] The dependence of the probability of paying penalties on price is considered in [3] in a static setting and Harrington (2004, 2005) in a dynamic setting. For a discussion of various sources of detection, see [18].

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

as a firm's maximal deviation profit. The incentive compatibility constraint (ICC) is

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

where $\theta \in \{0,1\}$ is a parameter that captures the possibility of a leniency program. If there is no leniency program then $\theta = 1$ and a firm that deviates is liable for penalties.[8] If there is a leniency program (with full leniency) then $\theta = 0$ in which case it is optimal for the deviating firm to apply for leniency and avoid the penalty. Re-arranging (2), we have

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

The optimal collusive price is that which maximises $V^c(p)$ in (1) subject to the ICC in (3).

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.

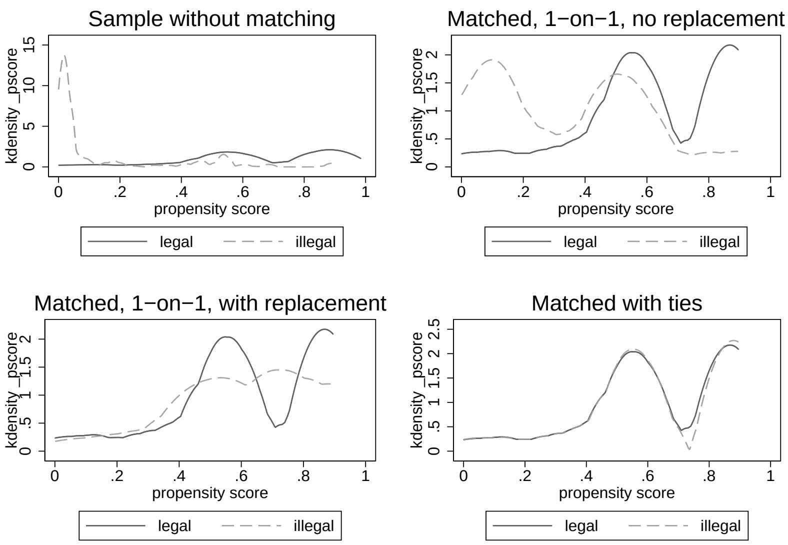
Proposition 1. *i) $p_I \leq p_L$; ii) if $\sigma'(p^m) > 0$ then $p_I < p_L$; and iii) if $p_L < p^m$ then $p_I < p_L$.*

Let us assess the impact of a cartel's legal status on price as described by Prop. 1.[9] 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 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.

[8] 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.

[9] 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 [22], [23] and [19].

Figure C.4: Legal/illegal propensity scores by matching type



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).[34] The bottom right panel of Figure C.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.

Appendix D. Tables

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

Table D.4: Estimates of quantile treatment effects under different matching methods (treatment - legal, control - illegal) for peer-reviewed publications only

Quantiles	Simple quantile	Multivariate quantile	PS weighted	CEM weighted	IPW weighted
5th	0	-2.300***	0	0	0
	(0.471)	(0.588)	(0.579)	(.)	(2.665)
10th	-5***	-5.650***	-4.600***	0	-5**
	(1.099)	(1.070)	(0.947)	(0.686)	(2.501)
15th	-6.500***	-7.250***	-7***	-4***	-7.900***
	(1.039)	(1.494)	(0.785)	(1.276)	(2.481)
20th	-5.700***	-7.800***	-6.100***	-4.800***	-8.900***
	(1.402)	(1.697)	(1.038)	(1.186)	(2.586)
25th	-3.900**	-6.900***	-3.200**	-2.700*	-8.700***
	(1.885)	(1.900)	(1.579)	(1.441)	(2.618)
30th	-2.600	-7.450***	-4.600**	-1.900	-8.800***
	(1.892)	(2.210)	(1.952)	(1.640)	(2.829)
35th	-1.900	-5.300**	-6.700***	-2	-6.200**
	(1.994)	(2.644)	(2.153)	(1.817)	(2.902)
40th	0.600	-5.400*	-5.700**	-0.200	-8.500***
	(2.378)	(3.093)	(2.342)	(2.051)	(3.138)
45th	0.200	-3.500	-2.500	-1.500	-7**
	(2.246)	(3.311)	(2.271)	(1.790)	(3.526)
50th	4	-2.600	-4.100*	2.600	-6.600*
	(2.614)	(3.380)	(2.260)	(1.984)	(3.637)
55th	5*	-1.600	-2.500	4.500**	-4.600
	(2.835)	(3.337)	(2.718)	(2.153)	(3.944)
60th	4.600	-3	-3.500	5.800**	-4.600
	(2.891)	(3.848)	(2.723)	(2.447)	(4.114)
65th	7.500**	-2.500	-3	7.500***	-7
	(3.378)	(4.133)	(3.354)	(2.895)	(4.394)
70th	12.80***	0	0	9.500**	-4.800
	(4.281)	(5.648)	(4.381)	(3.866)	(4.949)
75th	13.10***	4.800	0	10***	-3
	(4.880)	(6.062)	(4.736)	(3.796)	(6.871)
80th	23***	11.35	4.200	18***	4.300
	(7.104)	(9.788)	(6.351)	(5.318)	(7.893)
85th	38***	26*	22.10**	36***	15.00
	(11.29)	(14.48)	(10.76)	(8.329)	(13.51)
90th	78***	53.45**	62***	80***	28.40
	(21.42)	(26.79)	(20.54)	(17.30)	(23.73)
95th	159.4***	114*	102.5***	162.4***	123*
	(33.09)	(68.84)	(31.33)	(27.57)	(66.24)
N	730	730	586	730	730

standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table D.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
* p<0.10, ** p<0.05, *** p<0.01

Benchmarks for each category
Geographical: rest of the world
Cartel type: non bid rigging
Industry: other industries (transp, constr.)

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