Measuring the Effectiveness of Anti-Cartel Interventions in the Shadow of Recidivism[1]

Yannis Katsoulacos[2], Evgenia Motchenkova[3], David Ulph[4]

October 2022

Abstract

It is important to measure the effectiveness of Competition Authority (CA) anti-cartel enforcement, recognising that the total effect may be larger than the direct effect routinely measured by CAs because of the indirect/behavioural effects of interventions - primarily on deterrence. However existing measurement methodologies assume that prosecuting and penalising cartels brings price-fixing in an industry to an end forever. It is increasingly recognised that following successful prosecutions, collusion may re-emerge and that the extent of such recidivism depends on the structure of post-prosecution interventions. Failure to allow for possible re-emergence could produce biased measures of CA effectiveness. We develop a framework for measuring the effectiveness of anti-cartel interventions that admits that recidivism could arise depending on the nature of post-prosecution interventions. Our general model nests the no recidivism assumption as a special case and, hence, improves upon the existing methodologies. The new framework enables us to measure the extent of bias arising from the failure to allow for recidivism, and we show that it can be significant. We make a number of other significant extensions to existing frameworks. In particular, we allow for indirect price effects as well as indirect deterrence effects and analyse the marginal effects of CA interventions.

JEL Classification: L4 Antitrust Policy, K21 Antitrust Law, D43 Oligopoly and Other Forms of Market Imperfection, C73 Stochastic and Dynamic Games; Repeated Games

Keywords: Antitrust Enforcement, Antitrust Law, Cartel, Oligopoly, Repeated Games.

[1] For helpful comments on this version and previous drafts we thank Joe Harrington, Gregory Werden, Steve Davies, Peter Ormosi, Thomas Ross, Fabienne Ilzkovitz, Iwan Bos, Peter Dijkstra, Anna Rita Bennato, Anette Boom and participants at the Tinbergen Institute O&M (2015), EARIE (2016), CRESSE (2019), IIOC (2017), BECCLE (2017) conferences as well as participants at the conference "*Looking Beyond the Direct Effects of the Work of Competition Authorities: Deterrence and Macroeconomic Impact*", 17-18 September 2015, Brussels and at seminars in the Competition Commissions of Serbia (May 2016) and Greece (December 2016).

[2]Department of Economic Science, Athens University of Economics and Business, Patission 76, Athens 104 34, Greece. Email: katsoul@aueb.gr or ysk@hol.gr

[3]Department of Economics, VU University Amsterdam, TILEC and Tinbergen Institute, De Boelelaan 1105, 1081 HV Amsterdam, The Netherlands. Email: emotchenkova@feweb.vu.nl

[4]School of Economics and Finance, University of St Andrews, St Andrews, Fife, KY16 9AR, Scotland, UK. Email: du1@st-andrews.ac.uk

1. Introduction

Empirical evidence shows that collusive conduct has been and continues to be extremely extensive and can have a sizable negative impact on consumer welfare.[5] Consequently for many years enforcement against cartels has been a central part of the enforcement activities of Competition Authorities (hereafter CAs) throughout the world. It is important for CAs and others to measure the effectiveness of these activities in order to both assess the return on the resources used by CAs and also assist in resource prioritisation with in a CA.[6]

CAs are confident that by using some well developed methodologies they can calculate reasonably well the *direct* impact of their interventions – essentially the harm caused by the cartel against which they have intervened.[7] However, while it is widely recognised that CA interventions have *indirect/behavioural* effects – e.g. on pricing and particularly on deterrence - which could make the total effects of their interventions many times larger than the direct effects, the methodologies for measuring these indirect effects are less well established.[8] In particular, a problem with the existing methodologies (e.g. Davies et al., 2018) is that they effectively assume that there is no recidivism – so a cartel enforcement action by a CA brings a permanent end to price-fixing behaviour by the firms involved in the cartel.

We extend the existing literature in a number of ways. We develop a general framework for measuring the effectiveness of anti-cartel interventions that allows for cartel re-emergence. Our general model nests the no recidivism assumption as a special case and, hence, improves upon the existing methodologies. As also recognised by Harrington (2017), the model produces a very rich framework for measuring CA performance that allows for indirect price effects as well as indirect deterrence effects; it also allows us to measure separately the marginal effects of CA interventions. We show that the extent of bias arising from the failure to allow for recidivism can be significant. There are three sets of considerations which point to the conclusion that, when measuring the effectiveness of CA interventions, it is essential to take the possibility of recidivism seriously.

First, there is the growing empirical evidence about the extent of recidivism. This literature has been somewhat confused due to the lack of a unanimously established definition of the term and hence of what should be estimated. A very clear review of the state of affairs and discussion of alternative notions of recidivism is Levenstein et al. (2015). They note that under the strictest definition adopted by Werden et al. (2011) – that recidivism exists if the firms involved in a cartel that has been fined initiate a new cartel - then analysis of datasets of EU and US cartels leads to

[5] See for example, Connor and Lande (2012, 2013). There is evidence that cartels undermine not just allocative but also productive and dynamic efficiency (Gunster et al., 2011).

[6] Indeed performance criteria based on the welfare impact of enforcement activities are common at least in mature jurisdictions, such as for US authorities, DGCOMP, CMA, ACM etc – see, for example, Avdasheva et al. (2017). A comprehensive survey of methodologies currently used for assessing the effectiveness of CA's antitrust enforcement activities competition policy, including policy towards cartels, is contained in Davies and Ormosi (2010 and 2012), while evaluations of policy in US are contained in Baker (2003) and Werden (2008). Studies of the effects of particular antitrust policies including leniency policy are set out in Harrington and Chang (2009, 2015) and Miller (2009).

[7] See the conference organized by DG Comp and National Competition Authorities, e.g. "*Looking Beyond the Direct Effects of the Work of Competition Authorities: Deterrence and Macroeconomic Impact*", 17-18 September 2015, Brussels and "*Impact Assessment of Interventions of CAs*", 16 November 2016, Amsterdam.

[8] See Dierx et al. (2018) for a survey. For experimental work trying to obtain a direct measurement of deterrence in a controlled laboratory environment see Bigoni et al. (2012, 2015).

the conclusion that recidivism *does* exist but does not exceed 1% of the discovered cartels.[9] However if, following a successful cartel prosecution, there was a process of merger and entry activity[10], a cartel of a similar size could re-emerge in the same industry containing some but not all of the original cartelists. Aguzzoni et al. (2013), Levenstein et al. (2015, 2016) provide evidence that this looser notion of recidivism exists on a more significant scale.[11] Levenstein et al. (2016) puts this at around 2% for EU and US.

Secondly in many instances cartelists may respond to prosecution in ways that maintain collusive activity in an industry at a high level but is *not captured by empirical work* that draws on evidence from prosecuted cartels. Thus, as stressed by Levenstein et al. (2015), Harrington (2004, 2012) and Chowdhury et al. (2016)[12] "one obvious possibility is that having explicitly colluded in the past, firms will tacitly collude in the future. Having established norms, customer relationships, mechanisms for making prices transparent, etc., cartel members may find it much easier to engage in tacit collusion without explicit communication (having potentially) the same negative impact on consumers but escape legal scrutiny".[13]

Thirdly the issue is not whether recidivism exists but how the level of recidivism relates to post-cartel interventions by CAs. Empirical evidence in US and EU may simply reflect the fact that because CAs in these countries *are* diligent and their post-cartel measures *are* effective, recidivism in the strict sense of Werden et al. (2011) is low. In cases where this is not so recidivism would be much higher. As Levenstein et al. (2015) say "the lesson (from the empirical findings in US and EU) is that consistent enforcement is effective". Recidivism may arise when there are lapses in enforcement.[14] Consequently, the fact that empirical evidence shows that in the EU and US there is no recidivism in the strict sense of Werden et al. (2011) does NOT imply that it is unnecessary to have a methodology for measuring the effectiveness of enforcement that takes into account the possibility of recidivism. Allowing for the potential of recidivism in our methodology for measuring the effectiveness of enforcement allows us to capture both the benefits that

[9] The EU dataset (Marvao, 2016) concerns 117 cartels in the period 1998 – 2014. The US DoJ dataset of Levenstein and Suslow (2016) spans the period 1961 – 2013. Marvao (2016) looks at different definitions of recidivism and concludes that 10 of the firms included in the sample can be classified as repeat offenders. Four of them started to participate in a new cartel after being previously fined. Six other firms only ended their participation in a cartel after being find for participation in another cartel. In the theoretical model of this paper we focus on the strictest definition of recidivism, where the firms involved in a cartel that has been fined initiate a new cartel in the same market.

[10] For evidence on this see Davies et al. (2015).

[11]Also, Connor (2016) and Davies and Ormosi (2010) cite evidence that cartels re-emerge in industries in which a cartel had previously been prosecuted by a CA. Further, Marvao and Spagnolo (2018) based on empirical analysis of EU cartel cases point out that "recidivism is a serious problem and may well require a different (fining) approach". More recent empirical work by Mariuzzo et al. (2020), which covers a sample of 339 listed cartel member firms, prosecuted by the European Commission between 1992 and 2015, finds the rate of recidivism close to 13%. They document that for example companies such as Atochem and Akzo appear in the original dataset 9 and 7 times, respectively, and have been involved in several cartels over the sample period.

[12] They investigate experimentally post-cartel tacit collusion, occurring after the detection of explicit cartels and find that this occurs robustly with or without the presence of fines and leniency programs.

[13] As well as being undetectable by empirical work. See e.g. Levenstein et al. (2015), page 6. The replacement of explicit collusion with tacit after cartel shutdown has also been recently documented in Starc and Wollmann (2022) for generic drug cartels.

[14] The fact that in EU there is a recognition of the *potential* seriousness of recidivism and associated *effort to minimize it*, is reflected in EC taking this into consideration in sanctioning in more than 40% of the cartel decisions. See Barennes and Wolf (2011).

are accruing to those economies (like EU and US) that have diligent agencies, which reduce the presence of recidivism close to zero, as well as the potential costs to other countries that do not have such effective agencies.[15]

This means that any framework of measuring the effectiveness of CAs has to recognise explicitly the *potential* for recidivism and how this is influenced by post-prosecution interventions. For otherwise there is the risk of there bring an upward bias in the existing measures of CA effectiveness. The question is how large that bias might be.

In this paper we provide a conceptual framework for measuring the effectiveness of CA cartel interventions when there is a possibility that, following a successful prosecution by a CA, a cartel might re-emerge in either the short-run or in the long-run. We examine the total and marginal impact on welfare of a range of ante- and post-cartel[16] interventions by CAs, and show how these can be decomposed into a direct effect and two indirect/behavioural effects – on deterrence and on price. By nesting the assumption of no recidivism as a special case we assess the extent of the potential bias in measures that assume recidivism away. We show that this bias can be substantial.

In our model we have three intervention parameters:

- the probability that in any given period a cartel will be successfully prosecuted.
- the probability that, in the period immediately following a successful prosecution the industry reverts to competitive behaviour;
- the probability that, if an industry in which a cartel was previously prosecuted is acting competitively at the start of any period, it continues to act competitively at the start of the next period.[17]

The first parameter reflects measures and resources that a CA directs into detection, investigation and prosecution - activities on which much of the literature has focussed.[18] The second and third parameters reflect measures and resources that CAs directs into preventing re-emergence of collusive behaviour following prosecutions, and comprise:

- *short-term interventions* which are implemented for a limited period of time immediately following the successful prosecution of a cartel and which aim to prevent the re-emergence of price-fixing behaviour,[19] and
- *longer-term interventions* potentially involving sustained monitoring of activities of the firms in industries in which a cartel has previously been prosecuted.[20]

Making such a distinction enables us to treat the short-term re-emergence of cartels as different

[15]See, for example, work by Wilson (2015) presented at the OECD - Global Forum on Competition - "Serial Offenders" on 30 October 2015, which points out a substantial number of cartels uncovered in the South African construction industry, which involved the same firms contravening the Competition Act on multiple occasions.

[16] "Post-cartel interventions" are those that aim to minimize recidivism. Little attention has been paid to these until Levenstein et al. (2015), who also seem to be the ones that introduced the term. We prefer the term post-prosecution interventions which we will use in what follows.

[17]These last two parameters reflect in part the behaviour of firms facing certain post-prosecution activities by CAs, rather than being direct measures of such intervention activity. For tractability reasons we treat them as exogenous.

[18]Following the standard approach we assume that this is strictly less than 1 to capture the fact that CAs don't have the resources to investigate every industry all the time.

[19]Examples of such short term interventions are: closer control and monitoring of firms in the markets, where cartels are just discovered; the imposition of remedies for a limited period of time in order to restore competitive environment; and, in some jurisdictions, the jailing or debarring of officials that were responsible for price-fixing.

[20] See also the extensive discussion of measures in Levenstein et al. (2015).

from that in the long-run. For, while it is plausible to assume that, for the relatively small number of industries in which cartels have recently been prosecuted, CAs can monitor activities for a limited period of time with an intensity that ensures that in the short run price-fixing activity is brought to an end with a high probability, it is implausible to assume that CAs could indefinitely sustain this intense level of monitoring or take adequate measures in every industry in which they have ever prosecuted a cartel. Consequently, in the long term the probability of collusive activity re-emerging is likely to be much higher than in the short-term – as borne out by the evidence of Ormosi (2014) cited above.

A final feature of our model is that we explicitly take into account the nature of the penalty regime – i.e. the penalty base[21] and the penalty rate – which enables us to also address the issue of how the effectiveness of the three interventions parameters above depends on the penalty regime.

Our major findings are as follows. First, the direct effect that CAs measure is an imperfect measure of the *true* direct effect because their measure is static/a-temporal and fails to capture the long-term benefits of having a programme of interventions which faces cartels with the prospect that, if they do choose to re-form, they will be detected and successfully prosecuted and have their collusive activity disrupted for a period of time. As such the measure used by CAs can either overstate the true measure by implicitly assuming that a cartel prosecution brings cartel activity to an end forever, or understate the true measure be failing to value what future disruption they do achieve. For a plausible range of values CAs may be measuring only 20% - 40% of the true direct effect of having a sustained programme of interventions.

Second, under the standard no recidivism assumption in the existing literature – i.e. that successful prosecution of a cartel brings collusive activity to an end forever - the ratio of the total effect of CA interventions to the direct effect that CAs measure varies between 12.4 - 14.2.[22]

Third, if, as is the case for most existing penalty regimes, penalties are based on revenue then both the total and marginal indirect price effects of interventions may be negative. The marginal effect of an increase in the penalty rate is around ten times smaller than the marginal effect of an increase in the probability of successful prosecution. Potentially the most powerful marginal effect is that of longer-term post-cartel interventions aiming at *preventing re-emergence of cartels*.

The next section sets out a formal model. In section 3 we map our CA enforcement parameters into three outcome measures of the impact of CA activity on cartel behaviour; the degree of disruption of collusive activity, the level of deterrence and the cartel price. In section 4 we map these outcomes onto welfare. We determine the harm that society suffers despite the presence of measures of a CA, and from this determine various measures performance of CA performance which we decompose into direct and indirect effects. Section 5 develops a numerical example and provides illustrative calculations of the direct and indirect effects. Section 6 concludes.

[21]Katsoulacos et al. (2015) show that the cartel price can be above or below the price that would arise if there were no CA (i.e. the monopoly price) depending on which penalty based is used – which matters for the sign of both the total and marginal indirect price effect.

[22]However this ratio is extremely sensitive to the underlying assumption. Even assuming that CAs can completely prevent the re-emergence of collusion in the short term, *and* that it re-emerges in the long-term only according to the strictest criteria and in the toughest regimes - and so with probability of just 2% - this ratio drops by 12.7%. If post-cartel enforcement measures are not as effective as they probably have been in EU and US and if the long-run probability of recidivism is, say, 10% then the ratio drops by 41%.

2. The Model

In this section we set out our model of cartel behaviour and how it is affected by the enforcement activities of a CA.

There is a continuum of industries, of a single type[23] characterised by the production of a homogeneous product with identical constant unit cost c and demand function $Q(p)$. Industries differ in the exogenous number of firms, n, that operate in each industry. Within each industry n symmetric firms compete in prices.[24] We let $R(p) = pQ(p)$ and $\pi(p) = (p-c)Q(p) = R(p) - cQ(p)$ denote, respectively, industry revenue and profits when the price is p. For what follows it will be useful to let $p^M(c) \equiv \arg\max_{p \geq c} \pi(p)$ and $\pi^M(c) \equiv \underset{p \geq c}{MAX}\ R(p) - cQ(p) \equiv \pi\left(p^M(c)\right)$ denote, respectively, the monopoly price and monopoly profits that would prevail if the market were served by a monopolist with constant unit costs c. By the Envelope Theorem monopoly profits are a strictly decreasing function of c. We assume that the demand function is such that the monopoly price is a strictly increasing function of c.

We let $p^C > c$ denote the price that will prevail if the industry is cartelized. We model the cartel as an infinitely-repeated collusive game supported by a simple grim trigger strategy profile in the presence of antitrust enforcement.[25] In every period, the n symmetric firms decide whether to form a cartel and, if so, what price to set.[26] If firms collude there is constant probability $\beta,\ 0 < \beta \leq 1$, that in each period the CA may detect and successfully prosecute the cartel, in which case the CA imposes a penalty at the constant rate $\rho > 0$ on cartel revenue $R\left(p^C\right)$ - the penalty regime widely used by many CAs.[27]

We assume that, in the period following a successful prosecution by a CA there is a probability $\sigma, 0 \leq \sigma \leq 1$ that the industry reverts to competitive behaviour. This generalises the assumptions

[23] As discussed later the analysis can be generalised to the case where there is a distribution of types, but to fix ideas, we set out the analysis for the case of a single type.

[24] There is Bertrand competition, so when an industry acts competitively price is driven down to costs and profits are zero. Also if a cartel is to be able to raise price above costs all n firms have to be in it.

[25] This approach is widely accepted and has been employed in e.g. Motta and Polo (2003), Harrington (2005), Houba et al. (2012, 2018), or Katsoulacos et al. (2015).

[26] As pointed out by a referee, in this paper the length of a period is implicitly defined as being the length of time over which a cartel member who deviates from cartel agreement can enjoy cartel profits before cartel members respond and implement the grim trigger strategy. There are three other activities taking place over time: (i) cartels that are in existence are being detected prosecuted and shut down; (ii) cartels that have been shut down by a competition authority are re-forming ; (iii) firms that have been competing may decide to get together and form a cartel. We recognise that the length of time over which these activities take place may in practice be different from that taken to respond to price deviations. But this issue arises in all models of cartel behaviour in the face of a competition authority, and the magnitudes of the parameters β, σ and λ will, in part, reflect this difference in time-scale so there is no inconsistency in our definition of a period.

[27] The penalty base in our framework does not depend on cartel duration. In a stationary infinitely-repeated game framework it is not feasible to incorporate cartel duration explicitly, though, to the extent that, in a stationary setting, duration depends on the probability of conviction, we could capture this by allowing the penalty base to depend also on β. Much of our analysis will generalize to other penalty regimes, but since our focus is on how recidivism affects the measurement of CA effectiveness we confine attention to the penalty regime used in practice.

in the literature which typically assumes that, following prosecution by a CA, either the cartel restarts with probability 1 (i.e. σ = 0) as for example in Motta and Polo (2003) or Houba et al. (2018) or that the cartel comes to an end (i.e. σ = 1) as for example in Davies et al. (2018) or Harrington (2004). Both these extremes are nested as special cases of our model. In addition, following prosecution there is a constant per-period probability $\lambda, 0 \le \lambda \le 1$ that, if the industry is competitive at the start of a period, it remains competitive at the start of next period. We can think of σ (resp. λ) as measuring the short–term (resp. long-term) effect of the efforts by a CA to prevent the re-emergence of collusion following a cartel prosecution.[28]

Given these assumptions it is straightforward to show that the expected present value of profits to a single firm from participating in a collusive agreement with price p^C, when facing intervention parameters β, σ, λ and a penalty imposed at rate $\rho > 0$ on a base $R\left(p^C\right) > 0$ is:[29]

$$V\left(p^C\right) = (1-d)\frac{\left[\pi\left(p^C\right) - \beta\rho R\left(p^C\right)\right]}{n(1-\delta)} \tag{1}$$

where $\delta, 0 < \delta < 1$ is the discount factor, and

$$d = \frac{\delta\beta\sigma}{(1-\delta\lambda) + \delta\beta\sigma} \Rightarrow 0 \le d \le 1, \tag{2}$$

measures what we call the *degree of disruption* of collusive activity brought about by CA post-prosecution interventions. Note first that if cartels immediately reform after being detected and penalised by a CA, then $\sigma = 0$, which implies $d = 0$ and the corresponding expression in (1) is then precisely the expression given in Katsoulacos et al. (2015) for the expected present value of profits of a member of an infinitely-lived cartel, that is nevertheless subject to random prosecution and penalties. So d is the fractional reduction in the expected present value of the profits of such an infinitely-lived cartel that is brought about by the disruptive post-prosecution interventions by the CA which may force the industry to behave competitively for at least some periods in the future.

If a firm defects from the collusive agreement in a particular period it sets a price $p^D(p) < p^C$ that undercuts the cartel price and, for a single period, gets the entire industry profits at that lower price. Additionally, the defector incurs no penalty that would arise should the cartel be investigated and prosecuted in that period.[30] The defector will wish to obtain the greatest profits it can, so, if

[28] Strictly speaking σ and λ are not pure intervention parameters. They reflect both intervention activities of CA's and behavioural responses to those interventions. However, the standard repeated games framework does not allow endogenizing these responses. A similar approach (with exogenously given probabilities of moving between collusive and competitive states) has been adopted in Harrington and Ye (2017).

[29] This expression is obtained by solving the system of two recursive equations which define the expected present value of industry profits if the industry is in a cartelised/collusive (respectively competitive) phase at the start of any period, $\tilde{V}^{CART}$ $\left(\text{resp. } \tilde{V}^{COMP}\right)$:

$$\tilde{V}^{CART} = (1-\beta)\left[\pi\left(p^C\right) + \delta\tilde{V}^{CART}\right] + \beta\left\{\left[\pi\left(p^C\right) - \rho B\left(p^C\right)\right] + \delta\left[\sigma\tilde{V}^{COMP} + (1-\sigma)\tilde{V}^{CART}\right]\right\} \text{and}$$

$$\tilde{V}^{COMP} = \delta\left[\lambda\tilde{V}^{COMP} + (1-\lambda)\tilde{V}^{CART}\right]$$

[30] This assumption is also adopted in Motta and Polo (2003). Alternative assumptions are examined in Spagnolo (2004), Buccirossi and Spagnolo (2007), Chen and Rey (2013), Jansen and Sorgard (2016). However, adopting these

the cartel sets a price above the monopoly price $p^M(c)$ the defector will set the monopoly price, while, if the cartel sets a price at or below the monopoly price, the defector slightly undercuts that price and so effectively takes the cartel profits. Consequently, the one-period defection profits are:[31]

$$\pi^D\left(p^C\right)=\begin{cases}\pi^M(c), & p^C>p^M(c)\\ \pi\left(p^C\right), & c\le p^C\le p^M(c)\end{cases}. \tag{3}$$

Following the standard grim-trigger strategies, we assume that the other members of the cartel punish the defector by reverting to Nash behaviour for ever more. Then for a cartel to be stable it is necessary that

$$(1-d)\frac{\left[\pi\left(p^C\right)-\beta\rho R\left(p^C\right)\right]}{\Delta}\ge\pi^D\left(p^C\right), \tag{4}$$

where, as in Katsoulacos et al. (2015), $\Delta=n(1-\delta)$ is what we call the *intrinsic difficulty* of holding the cartel together. Given that n varies across industries, so too does Δ. For reasons that will become clear we consider only values of $\Delta\in[0,1]$, and, purely for notational simplicity, assume that Δ is uniformly distributed on this interval.

We assume that the cartel sets a price that maximises the expected present value of profits, $V(p)$, subject to the stability condition (4).[32] So we formally define the cartel price as

$$p^C=\arg\max_p(1-d)\frac{\left[\pi(p)-\beta\rho R(p)\right]}{\Delta}\ \text{ subject to }(1-d)\frac{\left[\pi(p)-\beta\rho R(p)\right]}{\Delta}\ge\pi^D(p). \tag{5}$$

From the cartel stability condition, (4), stable cartels exist as long as

$$\Delta\le(1-d)\frac{\left[\pi\left(p^C\right)-\beta\rho R\left(p^C\right)\right]}{\pi^D\left(p^C\right)}\ . \tag{6}$$

Notice that if there were no CA and so $\beta=0\Rightarrow d=0$ then obviously (i) $p^C=p^M(c)$ and (ii) $\pi^D\left(p^C\right)=\pi\left(p^C\right)=\pi^M(c)$, and so (6) becomes $\Delta\le 1$ - which is the justification of restricting

---

different assumption would not affect the main results developed in our paper. In particular, the opposite assumption, where price deviating firms are liable, only relaxes the ICC in (4) and does not have any impact on the value function in (1). This implies that level of cartel disruption and collusive prices will not be affected and only level of cartel deterrence can change. However, it will not cause any changes in the measure of cartel harm and CA performance measures developed in section 4. Moreover, given the presence of leniency programs the defecting firm will optimally choose to deviate and apply for leniency immediately, which ensures 100% immunity from fines both in the US and the EU, and is equivalent to the assumption of not penalizing price-deviating firms.

[31] This formula for defection profits was first given in Katsoulacos et al. (2015) who examined the effects of different penalty regimes on cartel behaviour, including the possibility that, when penalties are imposed on revenue the cartel price would be above the monopoly price.

[32] For tractability reasons we focus on homogeneous products. Introducing differentiated products makes it difficult to obtain closed form analytical solutions for the main outcomes specified in expressions (2), (5) and (7). However this should not affect the qualitative directions of price and deterrence effects, as shown also in Bos et al. (2018), where a similar model is formulated in a symmetrically differentiated oligopoly setting, though, as we already stressed under a specific assumption that detection and prosecution implies permanent shut down of a cartel.

attention to this range of values for Δ. However, if there is an active CA that is carrying out investigations and imposing positive penalties then $\beta\rho > 0$, which, from (2), implies $d > 0$. Additionally since, from (3), $\pi^D\left(p^C\right) \geq \pi\left(p^C\right)$, it follows that the RHS of (6) is strictly less than 1. So we define

$$D = 1-(1-d)\frac{\left[\pi\left(p^C\right)-\beta\rho R\left(p^C\right)\right]}{\pi^D\left(p^C\right)}\ , \tag{7}$$

as the *degree of deterrence* achieved by an active CA, since it is the fraction of stable cartels that would have been in existence in the absence of a CA that now no longer exist in the presence of an active CA.

Finally, notice that our model has four CA enforcement parameters – β, σ, λ and ρ.[33] The first three can be thought of as *intervention parameters* since their magnitude reflects the level of resources that CAs deploy to the various underlying activities.

3. Effects of CA Enforcement Activities

In this section we analyse how the four enforcement parameters $\left(\beta, \sigma,\ \lambda \text{ and } \rho\right)$ affect the behaviour of cartels facing an active CA – i.e. one for which $\beta\rho > 0$. In particular we are interested in how these parameters affect: (i) the *degree of disruption* of cartel activities, *d*; (ii) the cartel price p^C; (iii) the *degree of deterrence*, *D*. In section 4 we will map these outcomes into various welfare measures.

3.1. Cartel Disruption

Analysis of the *degree of disruption* of collusive activity, *d*, in expression (2) immediately implies:

Proposition 1

(i) *The penalty rate, ρ, has no effect on d;*

(ii) $\sigma = 0 \Rightarrow d \equiv 0$ *whatever the values of* β and λ

(iii) *If* $\sigma > 0$ *then d is strictly increasing in* β, σ and λ, *taking a maximum value* $\bar{d} = \delta > 0$ *when* $\beta = \sigma = \lambda = 1$.[34]

This proposition implies that the degree of disruption of collusive activity, *d*, is strictly increasing in all intervention parameters β, σ and λ. While the penalty rate ρ has no effect on degree of disruption. The intuition is as follows. Higher efforts put by a CA into detection, investigation and

[33] As such our model is considerably richer than Davies et al. (2018) which has just what they call a detection probability – essentially β.

[34] Notice that it then follows from (1) that $V\left(p^C\right) = \dfrac{\pi\left(p^C\right)-\rho B\left(p^C\right)}{n}$ since, under these conditions, a cartel will only last for a single period, during which it will definitely be penalised.

post-prosecution activities will reduce the expected present value of the cartel profits. So the fractional reduction in the expected present value of the cartel profits, *d*, will be higher.

3.2. Cartel Pricing

In Katsoulacos et al. (2015) we show that under a revenue-based penalty regime as considered here the stability condition does not affect the cartel pricing decision. We also show that the unconstrained maximisation in (5) is equivalent to maximising $(1-\beta\rho)\left(p-\frac{c}{1-\beta\rho}\right)Q(p)$. From this we immediately obtain:

Proposition 2

(i) *The cartel price is* $p^C = p^M\left(\frac{c}{1-\beta\rho}\right)$.

(ii) *The cartel price is above that which would prevail in the absence of a competition authority,* $p^M\left(c\right)$

(iii) *The cartel price is a strictly increasing function of* $\beta\rho$[35] *but is independent of* σ *and* λ.

This proposition re-establishes the distortive price effects of simple revenue-based penalties first analysed in Bageri et al. (2013) and Katsoulacos and Ulph (2013). The intuition is as follows. If there were no CA the cartel would set the monopoly price, $p^M\left(c\right)$, which is characterised by marginal revenue equal to marginal cost. When there is a CA and a threat of the expected financial penalty, marginal cost will change, implying cartel price different from the simple monopoly price. So under any penalty regime cartels will set the price-overcharge taking into account how it affects both operating profits and the financial penalty they will incur if prosecuted. Currently employed simple revenue-based penalty regime leads to an increase in marginal cost relative to marginal revenue and so a reduction in output below the monopoly output and a price above the monopoly price. Furthermore, since under a revenue-based penalty regime marginal costs increase in both β and ρ, the cartel price will also increase in these two enforcement parameters.

3.3. Cartel Deterrence

Given result of Proposition 2, it follows from (7) that:

$$D = 1-(1-d)\frac{(1-\beta\rho)\pi^M\left(\frac{c}{1-\beta\rho}\right)}{\pi^M(c)}. \tag{8}$$

Before proceeding, notice that if we define the function

---

[35] This result is specific to revenue-based penalty regimes. More generally if a penalty regime results in a cartel price lower than the monopoly price then toughening the regime will lower the price.

$$f(\beta\rho) \equiv (1-\beta\rho)\pi^M\left(\frac{c}{1-\beta\rho}\right) \qquad (9)$$

then we have the following result:

Lemma: $f'(\beta\rho) < 0$.

Proof: From (9) we have that

$$f'(\beta\rho) \equiv -\pi^M\left(\frac{c}{1-\beta\rho}\right) + \frac{c}{1-\beta\rho}\frac{d\pi^M}{dc}\left(\frac{c}{1-\beta\rho}\right). \qquad (10)$$

As noted above, from the Envelope Theorem monopoly profits are a strictly decreasing function of unit costs so the second term is negative. QED

Using the above lemma we can analyse how changes in enforcement parameters influence cartel deterrence, *D*. The next proposition summarises the results of this analysis.

Proposition 3: *If* $\sigma > 0$ then

(i) $\dfrac{\partial D}{\partial x} = \dfrac{\partial d}{\partial x}.\dfrac{f(\beta\rho)}{\pi^M(c)} > 0; \quad x = \sigma, \lambda;$

(ii) $\dfrac{\partial D}{\partial \beta} = \dfrac{\partial d}{\partial \beta}.\dfrac{f(\beta\rho)}{\pi^M(c)} - (1-d)\rho\dfrac{f'(\beta\rho)}{\pi^M(c)} > 0;$

(iii) $\dfrac{\partial D}{\partial \rho} = -(1-d)\beta\dfrac{f'(\beta\rho)}{\pi^M(c)} > 0$

Proof: Follows immediately from (8), Proposition 1 and the above Lemma.

So increases in all enforcement parameters increase deterrence, but do so through different channels: increasing post-prosecution activities, σ and λ, work solely through increasing the degree of disruption; increasing the probability of successful prosecution, β, works through both its impact on disruption and through its impact on the toughness of penalties; while increasing the penalty rate, ρ, works only through toughening the penalty and so decreasing cartel profits.

As shown in Katsoulacos et.al. (2017), we can obtain a useful approximation for *D* by taking a first-order Taylor approximation of $f(\beta\rho)$ around the value $\beta\rho = 0$. This gives

$$\frac{f(\beta\rho)}{\pi^M(c)} \approx 1-\beta\rho\frac{p^M(c)}{p^M(c)-c} = 1-\beta\rho\frac{1+\theta^M}{\theta^M} = 1-\beta\rho\eta\left(p^M(c)\right), \qquad (11)$$

where, $\theta^M = \dfrac{p^M(c)-c}{c}$ is the monopoly overcharge in this type of industry and $\eta(p) = -\dfrac{pQ'(p)}{Q(p)} > 0$ is the elasticity of demand. These equivalent formulations follow from the standard first-order conditions for profit-maximising monopoly profits, and guarantee that, evaluated at the monopoly price, the elasticity of demand is greater than 1. As noted by Katsoulacos et. al.(2018) they also show that a feature of revenue-based penalties is that the degree of deterrence is *lower* the *higher* the monopoly overcharge.

Substitute (11) into (8) and we get:

$$D \approx 1-(1-d)\left[1-\beta\rho\eta\left(p^M(c)\right)\right] \tag{12}$$

which is a simple formula showing how the degree of deterrence is determined by both the four CA enforcement parameters and a summary statistic of the industry type – the elasticity of demand at the monopoly price.

The following table summarises all our comparative static predictions about the effects of CA enforcement activities on the three outcomes measures: disruption, deterrence and collusive price.

Table 1: Summary Comparative Static Predictions

	d	D	p^C
β	+	+	+
σ	+	+	0
λ	+	+	0
ρ	0	+	+

4. Measuring the Effectiveness of CA Enforcement Activities

In this section we show how the three outcome measures d, D, p^C introduced above determine the harm created by collusion and various measures of the effectiveness of CA enforcement actions.

Before proceeding we note that, since stable cartels would never form in industries with $\Delta > 1$ even if there were no CA enforcement, in order to measure CA performance it makes sense to confine attention to industries where cartels would have formed in the absence of an active CA. So in all the follows we confine attention to what we call the benchmark set of industries – i.e. those with $\Delta \in [0,1]$.

We assume that the relevant welfare objective for a CA is consumer surplus[36] and let $CS(p)=\int_p^\infty Q(x)dx$ denote the flow of consumer surplus in a period when the price is *p*.

4.1 Cartels, Welfare and Harm

[36] Everything that follows will go through in a completely analogous fashion if the CA uses a total welfare standard, and just replace the function $CS(p)$ with $TW(p)=CS(p)+\pi(p)$.

In this sub-section we measure the harm that is suffered from the collusive activity that arises despite the efforts of a CA that generates outcomes $\left(d, D, p^C\right)$ by comparing the flow of consumer surplus that arises in these circumstances with that which would have arisen under perfect competition.

By an argument analogous to that used to establish (1), the constant per-period flow of consumer surplus generated in any industry in which cartels emerge is

$$CS = (1-d)CS\left(p^C\right) + dCS\left(c\right). \tag{13}$$

Taking account of the fact that stable cartels exist in only a fraction $1-D$ of the benchmark industries, while the remaining fraction will be competitive and generate a flow of consumer surplus $CS(c)$, the total/average consumer surplus across all the benchmark industries is:

$$\begin{aligned}\overline{CS}\left(d, D, p^C\right) &= (1-D)CS + DCS(c) \\ &= (1-D)\left[(1-d)CS\left(p^C\right) + dCS(c)\right] + DCS(c)\end{aligned}, \tag{14}$$

where the final equality follows by substituting in (13). If every benchmark industry were perfectly competitive all the time, then the flow of consumer surplus would be $CS(c)$. So the harm actually suffered, despite the active intervention of a CA that generates outcomes $\left(d, D, p^C\right)$ is:

$$H\left(d, D, p^C\right) = CS(c) - \overline{CS}\left(d, D, p^C\right). \tag{15}$$

Substitute (14) and we get:

$$H\left(d, D, p^C\right) = (1-D)(1-d)\left[CS(c) - CS\left(p^C\right)\right]. \tag{16}$$

So the harm $H\left(d, D, p^C\right)$ suffered is just the loss of consumer surplus due to collusion $\left[CS(c) - CS\left(p^C\right)\right]$ multiplied by the fraction of industries $(1-D)$ in which cartels are not deterred from forming, multiplied again by $(1-d)$ which is the fraction of time for which, in industries where cartels are not deterred, collusive activity is not being disrupted by the post-prosecution interventions of the CA. Clearly the harm is smaller: the larger is the degree of disruption, *d*; the larger is the degree of deterrence, *D*; the smaller is the cartel price, p^C.

4.2 *Direct and Indirect Effects of Anti-Cartel Enforcement*

To measure the effectiveness of a CA we compare the harm suffered from collusive activity – despite the enforcement actions of a CA – with that which would have arisen had there been no CA. This gives us what we call the *total effect* (on welfare) of the CA's enforcement actions. We then show how to decompose the *total effect* into a *direct effect* plus two *indirect effects* – on price and deterrence.

4.2.1 *The Total Welfare Effect of a Competition Authority*

To measure the welfare effects of having an active CA in place we compare the total harm that arises when there is an active competition authority in place - as given by (16) - with that which would have arisen had there been no CA – which, following Davies et al. (2018), we will call *Potential Harm*.

Now if there were no CA – and so $\beta = 0$ - then it follows from Section 3 that we would have $d = D = 0;\ p^C = p^M$, and so, from (16), the *Potential Harm* that could have been suffered by the economy from collusive activity would be

$$H^0 = \left[CS(c) - CS\left(p^M\right)\right]. \tag{17}$$

Consequently the *Total Effect* (*TE*) of having an active competition authority is:

$$TE = H^0 - H\left(d, D, p^C\right) = \left[CS(c) - CS\left(p^M\right)\right] - (1-d)(1-D)\left[CS(c) - CS\left(p^C\right)\right]. \tag{18}$$

From the properties of the Harm function discussed above it follows that the *Total Effect* is larger: the larger is the degree of disruption, *d*; the larger is the degree of deterrence, *D*; the smaller is the cartel price, p^C.

4.2.2 *Decomposing the Total Effect into Direct and Indirect Effects*

To decompose this *Total Effect* into a *Direct Effect* and two *Indirect/behavioural Effects* (on price and deterrence) we can re-write (18) as

$$TE = \left\{d(1-D)\left[CS(c) - CS\left(p^C\right)\right]\right\} + \left\{D\left[CS(c) - CS\left(p^C\right)\right]\right\} + \left\{CS\left(p^C\right) - CS\left(p^M\right)\right\}. \tag{19}$$

The first term on the RHS of (19) is the *Direct Effect* (*DE*) of having an active CA in place. For those industries in which cartels are NOT deterred it shows the gain in consumer surplus from blocking cartel activity for a certain fraction of time through disruptive interventions by the CA. Notice that the *Direct Effect* is larger:

- the larger is *d* - so the <u>more</u> effective is the CA at disrupting cartel activity;
- the smaller is *D* - so the <u>less</u> effective is the CA in deterring cartels;[37]
- the higher is p^C - so the <u>less</u> effective is the CA in driving down the price set by cartels.

So, as also noted by Davies et al. (2018), Sorgard (2015)[38] and others,[39] a large *Direct Effect* may not always be a source of congratulation for a CA.

---

[37] This observation suggests there are potential internal incentive problems for a CA trying to pursue a policy of directing resources to maximise the total effect of its actions. For if staff performance is assessed on effectiveness of clearing up cases, then there could be advantages in having a weak deterrent effect since there would be a larger pool of cases to be worked with some "low hanging fruit" to be picked.

[38] However neither Davies and Ormosi (2014) nor Sorgard (2015) take any account of the indirect price effect, so their comments are based purely on the observation that a large direct effect could be consistent with a weak deterrent effect.

[39] See also Ilzkovitz and Dierx (2016) who analyse the interactions between measures of direct and deterrent effects using EC DG Comp data.

The second term on the RHS of (19) is the (*Indirect*) *Deterrence Effect* (IE_D) of having a CA, for it measures the gain in consumer surplus that society obtains because the anticipated enforcement activities of the CA deter cartels from forming in a fraction *D* of the benchmark industries[40]. Notice that the expression for the *Deterrence Effect* does not contain *d*, for the very good reason that, if a CA deters cartels from forming in certain industries, society obtains all of the benefit from its doing so irrespective of what proportion of harm the CA would have disrupted had these cartels actually formed. However, as noted in Proposition 3, the better is the CA at disrupting cartel activity, the higher is the degree of cartel deterrence, *D,* and so the larger is the *Deterrence Effect*. Also, as with the *Direct Effect*, the *Deterrence Effect* is larger the higher is the cartel price.

The third term on the RHS of (19) is the (*Indirect*) *Price Effect* (IE_p), for it measures the impact on consumer surplus that arises because, anticipating the intervention of the CA, cartels now set the price p^C rather than the price p^M that they would have set had there been no CA. Notice that the expression for this effect contains neither *d* nor *D*, because the cartel price affects not just the magnitude of the harm suffered by the undeterred and undisrupted cartel activity but also the magnitudes of the Harm that would have been suffered had collusive pricing not been deterred and/or disrupted. The *Price Effect* is positive if $p^C < p^M$ but smaller in absolute magnitude the higher is p^C, but if, as is the case in our model with a revenue-based penalty, $p^C > p^M$ then the *Price Effect* is negative and larger in absolute magnitude the higher is p^C.

So we have the following simple arithmetical decomposition of the *Total Effect*:

$$TE = DE + IE_D + IE_p \,. \tag{20}$$

Figure 1 below illustrates Potential Harm, H^0, harm actually suffered, H and the decomposition of the *Total Effect* $\left(TE = H^0 - H\right)$ into three effects as given in (20). It is drawn for the case considered here where there are revenue-based penalties and consequently $p^C > p^M$ and so the price effect is negative.

We noted above that the magnitude of the *Direct Effect* is an increasing function of the level of disruption, *d*, but a decreasing function of the level of deterrence, *D*. This is just a straightforward implication of the formula for the *Direct Effect* given by the first term on the RHS of (19). But we also know from Proposition 3 that there is a behavioural effect at work through which the level of deterrence is itself an increasing function of the level of cartel disruption. If we substitute (12) into the first term on the RHS of (19) we get

$$DE = d(1-d)\left[1-\beta\rho\eta\left(p^M(c)\right)\right]\left[CS(c)-CS\left(p^C\right)\right]. \tag{21}$$

[40] Davies et al. (2018) call this Deterred Harm.

The first part of expression (21), $d(1-d)$, implies inverted parabolic structure of *DE* as a function of *d* with maximum at *d=1/2*. This gives rise to the following proposition:

Proposition 4: *For a given level of penalty toughness of the penalty regime, βρ, and corresponding cartel price, p^C, the magnitude of the Direct Effect is an inverse-U shaped function of the level of disruption, d, and takes its maximum value when $d=\frac{1}{2}$.*

Notice that, even though there are complex interactions between these three effects, nevertheless as (20) shows, the total effect is obtained by a straightforward summation of the Direct Effect and the two Indirect Effects. Figure 1 below illustrates the total effect as well as its three components. The total effect given by $TE = H^0 - H$ is the sum of the areas A and B less G in the Figure 1. More specifically, $TE = DE + IE_D + IE_p = (A+E)+(B+F)-(E+F+G) = A+B-G.$

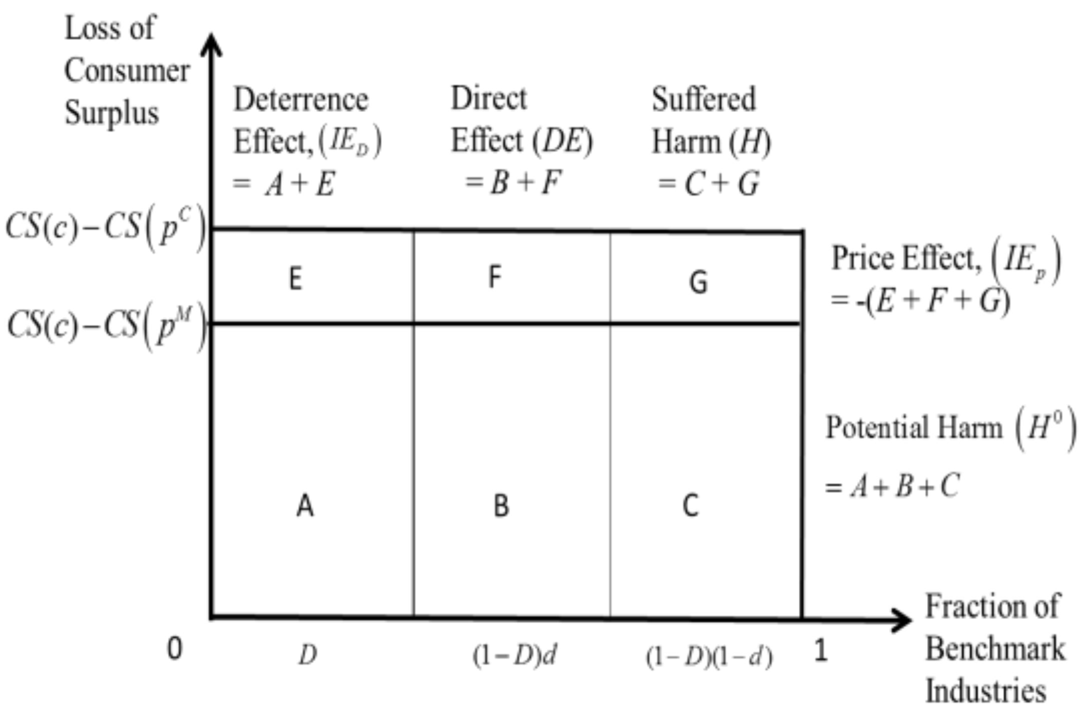

Figure 1: Total Effect, $TE = H^0 - H$

4.3 CA Performance Measures

The absolute magnitude of the *Total Effect* is not the most informative measure of CA performance, because it is just an absolute number in some unit of currency, and it is hard to know whether this is a good or bad outcome without having something to compare it to. Consequently in the literature two performance measures have been proposed:

The first is the *Total Effect* relative to *Potential Harm,* $\frac{TE}{H^0}$, which shows how much of the *potential harm* that would have been suffered in the absence of a CA is being removed through the enforcement actions of the CA. From (17) and (18) we have:

$$\frac{TE}{H^0} = 1 - \frac{H\left(d, D, p^C\right)}{H^0} = 1-(1-d)(1-D)\frac{\left[CS(c)-CS\left(p^C\right)\right]}{\left[CS(c)-CS\left(p^M\right)\right]}. \qquad (22)$$

Since, by definition, H^0 is independent of any CA intervention parameters this measure directly inherits all the properties of *TE* and so is an increasing function of *d* and *D* but a decreasing function of p^C. If there were no price effect and so $p^C = p^M$ then we would have:

$$\frac{TE}{H^0} = D + d(1-D)\,. \qquad (23)$$

The second performance measure is the ratio of the *Total Effect* to the *Direct Effect* that CAs measure. Having a measure for this is useful because it gives CAs a way of measuring their performance by bypassing the problems of trying to measure the indirect/behavioural effects of their actions – primarily deterrence – and simply scaling up something which they can and do measure.

In order to define this performance measure we first have to characterise how CAs measure the direct effect and compare this to the true measure of the *Direct Effect* as defined above in (19). We take it that what CAs measure is derived by taking the number of cartels that they both prosecute and bring to an end in a given period – which they can directly observe – and then multiply this by a measure of the loss of consumer surplus that was being generated by those cartels. Call this the *Measured Direct Effect,* and denote it by *MDE.*

Now within our model the number of cartels that a CA prosecutes and shuts down in a given period is $\beta\sigma(1-D)$, for $1-D$ is the number of cartels that exist, β, is the fraction of those that are successfully prosecuted in a given period and, of those, σ is the fraction for which collusive activity is shut down in that period.[41] So the *Measured Direct Effect* is:

$$MDE = \beta\sigma(1-D)\left[CS(c)-CS\left(p^C\right)\right]. \qquad (24)$$

This differs from the true direct effect, *DE,* as defined above. Indeed from (2), (19) and (24) we have

$$\frac{MDE}{DE} = \frac{\beta\sigma}{d} = \frac{1}{\delta} + (\beta\sigma - \lambda)\,. \qquad (25)$$

So if the long-term interventions of a CA to prevent re-emergence of collusive behaviour are weak relative to short term interventions – i.e. if $\lambda < \beta\sigma$ - then $\frac{MDE}{DE} > \frac{1}{\delta} > 1$ and so the direct effect as calculated by CAs will overstate the true measure of the *Direct Effect* since it implicitly assumes

[41] We stress that a CA can be assumed to directly observe $\beta\sigma(1-D)$ without necessarily knowing the magnitude of individual terms in this expression

that CA interventions stop cartels forever. However, if a CA's long-term interventions to prevent re-emergence of collusive behaviour are sufficiently strong relative to its short term interventions – specifically if $\lambda > \beta\sigma + \frac{1-\delta}{\delta}$ - then the direct effect as measured by CAs will understate the true measure, because, being an essentially a-temporal measure it ignores the benefits of all the future interventions which the CA will be undertaking. So we have established:

Proposition 5: *The direct effect that CAs measure, MDE, is not the true Direct Effect, DE, because it ignores the long-term implications of its intervention activities.* ***.*** *It will either under- or over-estimate the true Direct Effect depending on the strength of its long-term interventions as measured by λ.*

Coming back to the second performance measure, it follows from (24) that the ratio of the *Total Effect* of a CA's interventions to the *Measured Direct Effect* is:

$$\frac{TE}{MDE} = \frac{1}{\beta\sigma}\left\{\left[\frac{CS(c)-CS\left(p^M\right)}{CS(c)-CS\left(p^C\right)}\right]\left(\frac{1}{1-D}\right)-(1-d)\right\}. \qquad (26)$$

4.4 Marginal Effects of Changes in Enforcement Parameters

The performance measures developed above are based on a comparison of the harm that society suffers from collusion despite the presence of an active CA with that it would have suffered had there been no CA. While useful, the counterfactual of there being no CA at all is very stark and, certainly from the point of view of internal resource deployment decisions, CAs will be interested in the effects of making just small, marginal, adjustments to the resources they put into anti-cartel enforcement activities.[42]

There are two ways of obtaining such marginal effects. One would be to use numerical simulations of the kind we report in the next section and simply change the underlying enforcement parameters by a small amount away from some given values. Alternatively one could use calculus to derive analytical expressions for the marginal reduction in harm bought about by increases in our four enforcement parameters.

Differentiating (16) we see that the marginal reduction in harm from a small increase in enforcement parameter $k = \beta, \sigma, \lambda, \rho$ is:

$$-\frac{\partial H}{\partial k} = \left\{-\frac{\partial H}{\partial d}\left(\frac{\partial d}{\partial k}\right)\right\} + \left\{-\frac{\partial H}{\partial D}\left(\frac{\partial D}{\partial k}\right)\right\} + \left\{\frac{\partial H}{\partial p^C}\left(-\frac{\partial p^C}{\partial k}\right)\right\}, \qquad (27)$$

[42] Of course to best understand how to deploy resources one also needs to take account of the marginal costs of changing various enforcement parameters. This is not something on which we have sufficient information, so we confine attention to the marginal effects on welfare, which can still be highly informative when, for example one has two forms of enforcement that have very similar marginal costs.

where we have written the expression in this particular way because, as discussed above, harm is reduced by increasing d and D but by cutting p^C.

The first term on the RHS is what we call the *marginal direct effect* of a change in *k* because it represents the effects of changing the degree of disruption holding the degree of deterrence and the cartel price constant. The second and third terms are, respectively the *marginal deterrence effect* and the *marginal price effect*. So just as in (20) the overall marginal effect of a parameter change can be additively decomposed into a marginal direct effect and two marginal indirect effects – on deterrence and on price.

The magnitudes of the effects in (27) depend on the units in which harm and the parameters are measured, which makes comparison of the strength of different enforcement parameters difficult. To overcome that we can use the standard device of measuring everything in a unit-free elasticity form:

$$\left(-\frac{\partial H}{\partial k}.\frac{k}{H}\right)=\left\{-\left(\frac{\partial H}{\partial d}.\frac{d}{H}\right)\left(\frac{\partial d}{\partial k}.\frac{k}{d}\right)\right\}+\left\{\left(-\frac{\partial H}{\partial D}.\frac{D}{H}\right)\left(\frac{\partial D}{\partial k}.\frac{k}{D}\right)\right\}+\left\{\left(\frac{\partial H}{\partial p^C}.\frac{p^C}{H}\right)\left(-\frac{\partial p^C}{\partial k}.\frac{k}{p^C}\right)\right\}, \tag{28}$$

where, from (16), we have:

$$\left(-\frac{\partial H}{\partial d}.\frac{d}{H}\right)=\frac{d}{1-d};\quad \left(-\frac{\partial H}{\partial D}.\frac{D}{H}\right)=\frac{D}{1-D};\quad \left(\frac{\partial H}{\partial p^C}.\frac{p^C}{H}\right)=\frac{p^C Q\left(p^C\right)}{\left[CS(c)-CS\left(p^C\right)\right]}. \tag{29}$$

From Propositions 1-3 it is possible to work out the elasticities relating to the effects of all the various enforcement actions on our three outcome measures and then use (28) and (29) to calculate the relative effectiveness of different actions. As summarised in Table 1 above it is clear that the various actions work through different channels, so there are few simple conclusions at this level of generality. The next section reports some numerical calculations.

5. Numerical Example and Illustrative Calculations

To demonstrate the power of the framework presented above, in this section we set out a numerical example and use this to calculate the outcomes of the CA enforcement actions as set out in Section 3 and the consequent measures of CA performance as derived in Section 4.

Our primary focus is on showing how sensitive CA performance measures are to assumptions made about the ability of CA interventions to prevent recidivism, so we will not undertake an exhaustive investigation of different parameter values. However, in the Appendix we set out the formulae for all the expressions that are used in the calculations that follow, so an interested reader can perform calculations for alternative parameter values and/or conduct different thought experiments.

For our numerical example we normalise prices by setting with c = 1 and assume a simple linear demand function of the form $Q(p)=1+\varepsilon-p$ where $\varepsilon=\dfrac{1}{\eta(1)}$ is the inverse of the price elasticity of demand evaluated as the competitive/but-for price $p = 1$. We thus have a simple 1-dimensional characterisation of the industry type as discussed in Section 2. Although, as in the rest of the paper, we carry out all the calculations for a single industry type – i.e. single value of ε - it would be straightforward to generalise to some distribution of types.

5.1 Calibration of parameters

Our numerical example has two model parameters ε and δ plus the four enforcement parameters: $\beta, \sigma, \lambda, \rho$. To ensure that $p^C < 1 + \varepsilon$, we need to assume that $\varepsilon > \frac{\beta\rho}{1 - \beta\rho}$. We consider the calibration of each parameter in turn.

ε: In their work Connor and Lande (2012) suggest that the elasticity of demand lies in the range 0.95 to 1.65 with an average value of 1.3. However, Levenstein et al. (2015) argue that cartels are more prevalent in industries with more inelastic demand. So we perform calculations for the case when the elasticity of demand at the competitive price ε = 1. Given the demand function assumed above, for this value of ε the monopoly price would be 1.5.

δ: In our model the discount rate, δ, is the rate at which cartels discount future profits and CAs discount future consumer surplus. There is little agreement on what value this should take, with a wide variety of values being used in different studies.[43] We use δ = 0.9 in our calculations.

β: In their analysis Davies et al. (2018), cite empirical evidence that the probability of detection[44] ranges from 0.1 to 0.33, and assume a uniform distribution between these bounds. Following the work of Bryant and Eckart (1991), a widely used value is $\beta = 0.15$. In our calculations we will report results for the three values $\beta = 0.1, 0.2, 0.3$, and so encompass the range of values in the literature.

σ: As noted above, existing literature relies on two extreme assumptions either $\sigma = 1$ or $\sigma = 0$. As argued in the introduction, we want to nest the assumption that prosecution brings collusion to an end forever as a special case, so we certainly want to allow σ to take the value $\sigma = 1$. However, our framework allows us to test the sensitivity of the conclusions to this implicit assumption, so we also present values for various performance measures for the case where σ is starkly lower and so present calculation for the case $\sigma = 0.8$.

λ: As with σ we want to nest the assumption that prosecution brings collusion to an end forever as a special case, so one value that we want to allow λ to take is $\lambda = 1$. As mentioned in the introduction some authors believe that in jurisdictions such as US and EU the long-run probability of collusion re-emerging is of the order of 2%, though it could be closer to 10% elsewhere so we will also use a values of λ = 0.98 and 0.9. As shown above, the ratio of the direct effect as measured

[43]As is well known the value of this parameter will in practice be affected by considerations such as the frequency of interaction between cartel members and the evolution of demand, that will vary widely across industries, and from which we abstract here. We also performed a sensitivity analysis with respect to discount factor and other parameters of the model. The detailed results on sensitivity analysis are available from authors upon request.

[44] In our model β is the probability of successful prosecution, which is the probability of detection multiplied by the probability of successful prosecution if detected. However, for cartels, we can take it that the latter probability is high so we can use evidence on detection probabilities to obtain values of β.

by CAs to the true direct effect is sensitive to the relative value of λ so we also consider a fourth much lower value of $\lambda = 0.1$.

ρ: Finally we have assumed throughout that penalties are based on revenue and that neither the penalty rate nor the probability of detection depend on the cartel price. In line with rates that apply in countries that use revenue as the penalty base we assume a 10% penalty – i.e. $\rho = 0.1$.

5.2 The Effect of CA Interventions on Outcomes d, D, p^C

In this subsection and the next two we set $\varepsilon = 1, \delta = 0.9, \rho = 0.1$ and present tables showing how various measures of interest vary across the different combinations of values for the intervention parameters β, σ, λ set out in the previous sub-section. Tables, 1a, 1b, and 1c set out the results relevant to this sub-section.

Table 1a: Degree of Disruption, *d*

λ	σ	1			0.8		
	β	0.1	0.2	0.3	0.1	0.2	0.3
1.0		0.474	0.643	0.730	0.419	0.590	0.684
0.98		0.433	0.604	0.696	0.379	0.550	0.647
0.9		0.321	0.486	0.587	0.275	0.431	0.532
0.1		0.090	0.165	0.229	0.073	0.137	0.192

Table 1b: Degree of Deterrence, *D*

λ	σ	1			0.8		
	β	0.1	0.2	0.3	0.1	0.2	0.3
1.0		0.489	0.664	0.754	0.436	0.615	0.712
0.98		0.450	0.628	0.723	0.398	0.577	0.679
0.9		0.342	0.517	0.624	0.297	0.465	0.574
0.1		0.117	0.215	0.298	0.101	0.188	0.265

Table 1c: Cartel Price, p^C

λ	σ	1			0.8		
	β	0.1	0.2	0.3	0.1	0.2	0.3
1.0		1.505	1.510	1.515	1.505	1.510	1.515
0.98		1.505	1.510	1.515	1.505	1.510	1.515
0.9		1.505	1.510	1.515	1.505	1.510	1.515
0.1		1.505	1.510	1.515	1.505	1.510	1.515

These results confirm all the qualitative predictions of the theory in Section 3 as summarised in Table 1. In particular the cartel price is above the monopoly price (which ,as noted above, is 1.5) and is an increasing function of β.

The important point about the quantitative magnitude of these effects is just how sensitive the degree of disruption, *d* and the degree of deterrence, *D* are to the possibility of the re-emergence of collusion in the long-term. So, even if we accept that CA interventions shut down cartels in the short term – i.e. $\sigma = 1$ – and if we take an averagely good CA with a $\beta = 0.2$, then if there is just a 2% chance that cartels might re-emerge in the long term – i.e. $\lambda = 0.98$ – the degree of disruption drops by 6% and the degree of deterrence by 5%. If collusion re-remerges with a probability of 10% - i.e. $\lambda = 0.9$ - then these drop by 24% and 22% respectively.

5.3 The Effect of CA Interventions on Performance Measures

Tables 2a and 2b below set out the results for the two performance measures considered in Section 4.3.

Table 2a: Share of Harm Removed, TE/H^0

λ	σ	1			0.8		
	β	0.1	0.2	0.3	0.1	0.2	0.3
1.0		0.730	0.879	0.932	0.670	0.840	0.907
0.98		0.686	0.851	0.914	0.623	0.807	0.884
0.9		0.550	0.749	0.842	0.487	0.692	0.797
0.1		0.191	0.336	0.448	0.162	0.290	0.394

Table 2b: Ratio of Total Effect to Measured Direct Effect, TE/MDE

λ	σ	1			0.8		
	β	0.1	0.2	0.3	0.1	0.2	0.3
1.0		14.197	12.918	12.398	14.753	13.455	12.879
0.98		12.381	11.282	10.805	12.851	11.759	11.245
0.9		8.308	7.658	7.325	8.589	7.983	7.651
0.1		2.155	2.116	2.090	2.232	2.207	2.192

A number of interesting conclusions emerge from these Tables.

(a) If we look at the share of harm removed, Table 2a, then we see that this varies quite a lot with the effectiveness of the CA in detecting and successfully prosecuting cartels. This finding is in line with that reported in Davies et al. (2018) - Result 1 and Table 2. Indeed for the case where $\sigma = 0.8$ and $\lambda = 0.9$ the figures are very close to theirs which varies from just over a third to just over 80% with an average of around 63%. However the figures are considerably higher, and more tightly spread (from 73% to 88% to 93%) if CA interventions effectively close down cartels for ever – i.e. $\sigma = \lambda = 1$.

(b) If we look at the ratio of the total effect of CA interventions to the measured direct effect, Table 2b, then if CA interventions prevent cartel re-emergence in both the short-run and long-run - i.e. if $\sigma = \lambda = 1$ – then the overall effect varies from around 12.4 times larger than the measured direct effect to 14.2 times larger depending on how good the CA is in successfully detecting and prosecuting cartels as reflected in the parameter β. However this measure of performance is also very sensitive to the long-term probability of cartel re-emergence, λ. So, for a CA with an averagely good rate of detecting and prosecuting cartels ($\beta = 0.2$) the ratio drops from 12.9 to 11.3 (a 12.7% fall) if there is just a 2% chance of cartels re-emerging in the long-run ($\lambda = 0.98$), and by 41% if there is a 10% chance (λ=0.9).

What might seem puzzling in Table 2b is that the ratio is a decreasing function of the both the probability of successful prosecution, β, and the effectiveness of interventions in stopping cartel re-emergence in the short-term, σ. But this is explained by the way in which the ratio of the measured direct effect to the true direct varies with these variables, as shown in Table 2c below.

Table 2c: Ratio of Measured to True Direct Effect, MDE / DE

λ	σ	1			0.8		
	β	0.1	0.2	0.3	0.1	0.2	0.3
1.0		0.211	0.311	0.411	0.191	0.271	0.351
0.98		0.231	0.331	0.431	0.211	0.291	0.371
0.9		0.311	0.411	0.511	0.291	0.371	0.451
0.1		1.111	1.211	1.311	1.091	1.171	1.251

Table 2c illustrates the findings of equation (25) as discussed in section 4.3 above that:

- the ratio of the measured direct effect (*MDE*) to the true direct effect (*DE*) is an increasing function of both β and σ but a decreasing function of λ;
- if λ is sufficiently low then the measured direct effect can overstate the true direct effect;
- but if λ is sufficiently high then the measured direct effect will overstate the true direct effect of interventions because, being an a-temporal measure, it ignores all the long-term benefits of having a programme of interventions, which faces cartels with the prospect that, if they do re-form, they will be caught, prosecuted and face the prospect of having their activities disrupted for a period of time.

What is striking about Table 2c is the extent of this mis-measurement. What CAs measure may be only around 20% - 40% of the true direct effects of their programme of interventions.

5.4 Marginal Effects of a Competition Authority's Interventions

In this sub-section we set out the results of our calculations of the % reduction in harm brought about by a 1% increase in each of the intervention parameters.

Table 3a: Probability of Successful Prosecution, $\left(-\frac{\partial H}{\partial \beta}.\frac{\beta}{H}\right)$

λ	σ	1			0.8		
	β	0.1	0.2	0.3	0.1	0.2	0.3
1.0		0.972	1.336	1.538	0.861	1.231	1.446
0.98		0.890	1.258	1.470	0.782	1.150	1.372
0.9		0.667	1.023	1.253	0.574	0.913	1.143
0.1		0.204	0.381	0.536	0.171	0.324	0.462

Table 3b: Short-Term Post-Prosecution Intervention, $\left(-\frac{\partial H}{\partial \sigma}.\frac{\sigma}{H}\right)$

λ	σ	1			0.8		
	β	0.1	0.2	0.3	0.1	0.2	0.3
1.0		0.947	1.286	1.459	0.837	1.180	1.367
0.98		0.865	1.208	1.392	0.758	1.099	1.293
0.9		0.643	0.973	1.174	0.550	0.862	1.064
0.1		0.180	0.330	0.458	0.147	0.273	0.384

Table 3c: Long-Term Post-Prosecution Intervention, $\left(-\frac{\partial H}{\partial \lambda}.\frac{\lambda}{H}\right)$

λ	σ	1			0.8		
	β	0.1	0.2	0.3	0.1	0.2	0.3
1.0		8.526	11.571	13.135	7.535	10.623	12.304
0.98		6.468	9.030	10.403	5.665	8.216	9.668
0.9		2.741	4.148	5.005	2.343	3.676	4.536
0.1		0.018	0.033	0.045	0.015	0.027	0.038

Table 3d: Penalty Rate, $\left(-\frac{\partial H}{\partial \rho}.\frac{\rho}{H}\right)$

λ	σ	1			0.8		
	β	0.1	0.2	0.3	0.1	0.2	0.3
1.0		0.0242	0.0504	0.0787	0.0242	0.0504	0.0787
0.98		0.0242	0.0504	0.0787	0.0242	0.0504	0.0787
0.9		0.0242	0.0504	0.0787	0.0242	0.0504	0.0787
0.1		0.0242	0.0504	0.0787	0.0242	0.0504	0.0787

A number of conclusions emerge from these tables.

(i) The probabilities of successful prosecution and detection, β, and of preventing the re-emergence of collusion in the short term, σ, have very similar marginal effects on harm reduction – with elasticities that are around 1.

(ii) However the most effective intervention at the margin is that of preventing the long-term re-emergence of cartels, with an extremely high elasticity – particularly when $\lambda = 1$. So letting cartels re-emerge with even quite a small probability can have a very big impact on harm. This confirms the discussions in the previous two subsections about the powerful effects of λ on measures of CA performance.

(iii) Marginal changes in the penalty rate have a very small effect on reducing harm. In part this is because of our assumption of a simple revenue-based penalty regime with constant penalty rate, under which an increase in the penalty rate makes the cartel price even higher, and so partially offsetting the beneficial deterrence effects of tougher penalties.

5.5 *The Role of Penalties in Driving CA Performance*

As noted by Harrington (2017), the framework developed in this paper is extremely rich and enables one to explore a whole range of issues through conducting various thought experiments. To illustrate this we briefly set out the findings from one such thought experiment.

An important issue facing all CAs is how much of what they achieve is being driven by penalties and how much by resource intensive investigations. There are many ways one might get at this issue, but one thought experiment one might conduct by way of a partial answer is to ask what would happen to various measures of cartel performance if, while there continued to be investigations, prosecutions and post-prosecution interventions, cartels did not have to pay a penalty. To address this, we continue to set $\varepsilon = 1$ and $\delta = 0.9$, but now set $\rho = 0$.

Tables 4a – 4b below contain analogous calculations to those undertaken to produce Tables 2a – 2b on the assumption that $\rho = 0.1$.

Table 4a: Share of Harm Removed, TE/H^0

λ	σ	1			0.8		
	β	0.1	0.2	0.3	0.1	0.2	0.3
1.0		0.723	0.872	0.927	0.662	0.832	0.900
0.98		0.678	0.843	0.908	0.614	0.797	0.875
0.9		0.540	0.736	0.829	0.474	0.676	0.781
0.1		0.172	0.303	0.405	0.141	0.255	0.347

Table 4b: Ratio of Total Effect to Measured Direct Effect, TE / MDE

λ	σ	1			0.8		
	β	0.1	0.2	0.3	0.1	0.2	0.3
1.0		13.737	12.214	11.432	14.233	12.689	11.848
0.98		11.954	10.647	9.947	12.364	11.062	10.322
0.9		7.951	7.169	6.693	8.172	7.431	6.954
0.1		1.889	1.815	1.752	1.906	1.843	1.788

At first sight what is striking about these results is how close the figures in Tables 4a and 4b are to those in Tables 2a and 2b. This is consistent with the figures in Table 3d about the very low elasticity for the penalty rate.

What this brings out is that the most significant financial cost to cartels of CA interventions is not so much the financial penalty they face but the loss of cartel profits from the disruption of cartel activity by a CA.

6. Conclusions

We have presented a model of cartel formation capturing the process of cartel re-emergence that allows an explicit characterization of the effects on welfare of a wide range of policy instruments.

There are two major contributions. The first has been to show that the presence of recidivism can significantly affect measures of CA performance and consequently any measures of performance that fail to adequately take account of the possibility of recidivism should be treated with considerable caution. In particular the measures of the direct effect of their interventions produced by CAs will not necessarily capture the true direct effect.

The second, as recognised by Harrington (2017), has been to produce a very rich framework for measuring CA performance that extends the existing literature in a number of ways: we allow for indirect price effects as well as indirect deterrence effects; we can measure separately the marginal effects of interventions. Given this richness we have carried out a range of calculations of the various effects, for a limited range of parameters. However we have provided Appendices containing all the relevant formulae so anyone interested in undertaking alternative calculations can easily do so.

There are a number of directions in which our work could be further developed. One is to allow more explicitly for heterogeneity of industry types. This could be done relatively easily within our existing framework by introducing a distribution of demand elasticities (calculated at the competitive price) – and hence a distribution over our model parameter, ε. Second our model is based on homogeneous products with Bertrand competition. There are many interesting issues to pursue for models with differentiated products[45] and alternative forms of competition. In particular this could affect the magnitude of the financial costs to cartels of having their activities disrupted. Finally our model is based on a simple revenue-based penalty regime, characterised by a fixed penalty rate applied to cartel revenue. We have argued elsewhere – Katsoulacos et al. (2015, 2017) - that this has poor welfare properties and have advocated alternative penalty regimes, such as a sophisticated revenue-based penalty regime whereby the penalty rate applied to a penalty base that remains cartel revenue. It would be interesting to understand how the measures of CA performance would be affected by the adoption of such alternative penalty regimes.

[45] See Kovacic et. al. (2018), for a discussion which emphasises the importance of multiple/repeat offending in this context.

References

Aguzzoni, L., G. Langus and M. Motta (2013), "The Effect of EU Antitrust Investigations and Fines on a Firm's Valuation", *The Journal of Industrial Economics*, Volume LXI, 290-338.

Avdasheva S., S Golovaneva and Y Katsoulacos (2017), "Optimal institutional structure of Competition Authorities under reputation maximization: a model and empirical evidence from the case of Russia" Discussion Paper available at http://www.cresse.info/default.aspx?articleID=3388

Bageri, V., Y. Katsoulacos and G. Spagnolo (2013), "The Distortive Effects of Antitrust Fines Based on Revenue", *The Economic Journal*, 123 (572), 545-557.

Baker, J.B., (2003), "The case for antitrust enforcement", *Journal of Economic Perspectives*, 17 (4), 27-50.

Barennes, M. and G. Wolf (2011), "Cartel Recidivism in the Mirror of EU Case Law", *Journal of European Competition Law & Practice*, 2(5), 423

Bigoni, M., S.-O. Fridolfsson, C. Coq and G. Spagnolo, (2012), "Fines, leniency and rewards in antitrust", *RAND Journal of Economics*,43 (2), 368.390.

Bigoni, M.,S.-O. Fridolfsson, C. Coq and G. Spagnolo, (2015), "Trust, Leniency, and Deterrence", *Journal of Law, Economics and Organization*, 31, 663 – 689.

Bos, I., S. Davies, J. Harrington and P.L. Ormosi, (2018), "Does enforcement deter cartels? A tale of two tails", *International Journal of Industrial Organization*, 59, 372-405.

Bryant, P.G., and E.W. Eckard, (1991), "Price Fixing: The Probability of Getting Caught," *The Review of Economics and Statistics*, 73, 531-536.

Buccirossi, P. and G. Spagnolo (2007), "Optimal Fines in the Era of Whistle blowers - Should Price Fixers Still Go to Prison?" in *The Political Economy of Antitrust*, by V. Goshal and J. Stennek (Eds.), Elsevier: Amsterdam.

Chen, Z. and P. Rey (2013), "On the design of leniency programs", *Journal of Law and Economics*, 56, 917-957.

Chowdhury S.M and C.J Crede (2016) "Post-cartel tacit collusion: Determinants, consequences and prevention", School of Economics, Centre for Behavioural and Experimental Social Sciences, UEA, Norwich, 3 December 2016.

Connor, J. M. and R. H. Lande, (2012), 'Cartels as rational business strategy: new data demonstrates that crime pays', 34 *Cardozo Law Review* 427.

Connor, J. M. and R. H. Lande, (2013), "Cartel Fine Severity and the European Commission: 2007-2011, *European Competition Law Review* 34, 58-77.

Connor (2016), "Oceanic Disparities in Cartel-Recidivism: Attitudes and Penalties" *ABA Review*, Spring, pp 8-14.

Davies, S. W. and P. L. Ormosi, (2010) "Assessing Competition Policy: Methodologies, Gaps and Agenda for Future Research”, CCP Working Paper, 10 – 19.

Davies, S. W. and P. L. Ormosi, (2012) “A comparative assessment of methodologies used to evaluate competition policy”, *Journal of Competition Law and Economics* 8 (4), 769.-803.

Davies, S.W. and P.L. Ormosi (2014) “The Economic Impact of Cartels and Anti-Cartel Enforcement”, CCP Working Paper, 13-7.

Davies, S., F. Mariuzzo, P. Ormosi, (2018), “Quantifying the deterrent effect of anti-cartel enforcement”, *Economic Inquiry*, 56 (4), 1933–1949.

Davies, S., P. Ormosi and M. Graffenberger (2015), Mergers after Cartels: How Markets React to Cartel Breakdown, *The Journal of Law and Economics*, 58(3), 561-583.

Deloitte, (2007) The deterrent effect of competition enforcement by the OFT (Office of Fair Trading) 962.

Dierx, A., F. Ilzkovitz, Y. Katsoulacos and D. Ulph (2018), “The Deterrent Effects of Competition Policy” Chapter 11 in *Ex-post economic evaluation of competition policy: The EU experience* (Dierx and Ilzkovitz eds), Kluwer (forthcoming).

Gunster A., M. Carree and M.van Dijk (2011), “Do cartels undermine economic efficiency?”, The American Economic Association. Retrieved from: https://www. aeaweb. org/aea/2012 conference/program/retrieve. php

Harrington, J. (2004) “Post cartel pricing during litigation”, Journal of Industrial Economics, 52, 517 – 533.

Harrington, J. (2005) "Cartel Pricing Dynamics in the Presence of an Antitrust Authority," *The Rand Journal of Economics* 35, 651-673.

Harrington, J. (2005) "Optimal Cartel Pricing in the Presence of an Antitrust Authority," *International Economic Review* 46, 145-170.

Harrington, J. (2012) “A theory of tacit collusion” John Hopkins University Department of Economics Discussion Paper Archive Number 588.

Harrington, J. (2014), “Penalties and the deterrence of unlawful collusion”, *Economics Letters*, 124, 33-36.

Harrington, J. (2017), *The Theory of Collusion and Competition Policy*, MIT Press.

Harrington J. and M. Chang (2009) “Modelling the Birth and Death of Cartels with an Application to Evaluating Antitrust Policy," *Journal of the European Economic Association*, 7(6), 1400–1435

Harrington, J. and M. Chang (2015), “When Can We Expect a Corporate Leniency Program to Result in Fewer Cartels?”, *Journal of Law and Economics*, 58, pp.417-449.

Harrington, J. and L. Ye (2017), “Coordination on List Prices and Collusion in Negotiated Prices”, paper presented at BECCLE 2017 conference, Bergen.

Houba, H., E. Motchenkova, and Q. Wen (2010) "Antitrust enforcement with price-dependent fines and detection probabilities," *Economics Bulletin*, 30(3), 2017-2027.

Houba, H., E. Motchenkova, and Q. Wen (2012) "Competitive Prices as Optimal Cartel Prices", *Economics Letters,* 114(1), 39-42.

Houba, H., E. Motchenkova, and Q. Wen (2018), "Legal Principles in Antitrust Enforcement", *The Scandinavian Journal of Economics,* 120(3), 859-893.

Ilzkovitz F. and A. Dierx (2016), "The Broad Impact of Competition Policy: How to measure the Deterrent Effects?", paper presented at CRESSE 2016 conference, Rhodes, 1 July 2016.

Jensen, S., O. Kvaloy, T. Olsen and L. Sorgard (2013), "Crime and Punishment: When tougher antitrust enforcement leads to higher overcharge", NHH Discussion Paper 4-2013.

Jensen, S. and Sørgard, L. (2016), Fine Schedule with Heterogeneous Cartels: Are the Wrong Cartels Deterred?, *Journal of Competition Law and Economics 12*, 263–277.

Katsoulacos, Y. and D. Ulph (2013) "Antitrust Penalties and the Implications of Empirical Evidence on Cartel Overcharges", *The Economic Journal*, 123 (572), 558-581.

Katsoulacos, Y., E. Motchenkova and D. Ulph, (2015). "Penalizing Cartels: The Case for Basing Penalties on Price Overcharge", *International Journal of Industrial Organization*, 42, pages 70-80.

Katsoulacos, Y., E. Motchenkova and D. Ulph, (2016). "Measuring the Effectiveness of Anti-Cartel Interventions: A Conceptual Framework ", Tinbergen Institute Discussion Papers, 16-002/VII.

Katsoulacos, Y., E. Motchenkova and D. Ulph, (2017). "Penalizing on the basis of the severity of the offence: a sophisticated revenue-based policy for sanctioning cartels", Tinbergen Institute Discussion Paper Series; vol. 17, no. 120/VII

Kovacic, W., R. Marshall and M. Meurer, (2018), "Serial Collusion by Multi-Product Firms", *CPI*, August 2018

Levenstein, M.C. and V.Y. Suslow (2011), "Breaking Up Is Hard to Do: Determinants of Cartel Duration", *Journal of Law and Economics* 54, 455- 92.

Levenstein, M.C. and V.Y. Suslow (2012), "Cartels and Collusion - Empirical Evidence". Ross School of Business Paper No. 1182. Available at SSRN: http://ssrn.com/abstract=2182565

Levenstein, M.C. and V.Y. Suslow (2015), "Price Fixing Hits Home: An Empirical Study of US Price Fixing Conspiracies", Working Paper.

Levenstein, M., C. Marvao and V. Suslow (2015) "Serial Collusion in Context: Repeat Offences by Firm or by Industry?". OECD DAF/COMP/GF (2015)12.

Levenstein, M., C. Marvao and V. Suslow (2016), "Preventing Cartel Recidivism", *Antitrust,* 30(3), 157-171.

Levenstein, M.C. and V.Y. Suslow (2014) "Price fixing hits home: an empirical study of price fixing conspiracies in the US", mimeo, University of Michigan, Jan. 2014.

London Economics, (2011), "The impact of competition interventions on compliance and deterrence." Office of Fair Trading, OFT1391.

Mariuzzo, F., P. Ormozi, and Z. Majied (2019), "Public and Private Sanctions: The Case of Cartels", SSRN Electronic Journal, January 2019, http://dx.doi.org/10.2139/ssrn.3315305

Marvao C. (2015), "The EU Leniency Program and Recidivism" *Review of Industrial Organisation*.

Marvao C. and G. Spagnolo (2018), "Should Price Fixers (finally) go to Prison? – Leniency Inflation, Damages Directive and Criminalization in the EU", mimeo, August 1, 2018

Miller, N. H. (2009)."Strategic Leniency and Cartel Enforcement." *American Economic Review,* 99**,** 750-768.

Motta, M. and M. Polo (2003), "Leniency Programs and Cartel Prosecution", *International Journal of Industrial Organization* 21, 347-379.

Ormosi, P. L., (2014), "A tip of the iceberg? the probability of catching cartels". *Journal of Applied Econometrics* 29 (4), 549-566.

Sorgard, L. (2015), "Merger Control (and more): Direct and Indirect Effect" *mimeo,* presentation to Conference "*Looking Beyond the Direct Effects of the work of Competition Authorities: Deterrence and Macroeconomic Impact*, Brussels 17-18th September 2015.
Available at: http://ec.europa.eu/competition/information/macroeconomy/index.html

Starc, A. and T. G. Wollmann, "Does Entry Remedy Collusion? Evidence from the Generic Prescription Drug Cartel" (April 4, 2022). Becker Friedman Institute for Economics Working Paper No. 2022-49, SSRN: https://ssrn.com/abstract=4076263 or http://dx.doi.org/10.2139/ssrn.4076263

Werden, G.J., (2008). "Assessing the effect of antitrust enforcement in the United States" *De Economist* 156 (4), 433.451.

Werden, G.J., S.D. Hammond and B.A. Barnett (2011), "Recidivism Eliminated: Cartel Enforcement in the United States Since 1999",CPI Antitrust Chronicle, October 2011 (1), Available at SSRN: http://papers.ssrn.com/ abstract =1927864

Wilson, R. (2015) Endemic collusion in the South African construction industry: reasons & implications. OECD - Global Forum on Competition - "Serial Offenders", 30 October, DAF/COMP/GF(2015)10: http://www.oecd.org/competition/globalforum/competition-industries-endemic-collusion.htm

Appendix

In this Appendix we set out all the formulae that arise from the simple numerical example set out in Section 5 and that are used to calculate first the output measures and then all the performance measures. Recall that we have normalised the units in which price and output are measured so that $c=1$ and $Q(p)=1+\varepsilon-p$ and so $\varepsilon=\frac{1}{\eta(1)}$ - our first model parameter - is the inverse of the price-elasticity of demand evaluated at the competitive/but-for price. It follows from this that for any price p, $1\le p\le 1+\varepsilon$ consumer surplus is

$$CS(p)=\frac{1}{2}\left(1+\varepsilon-p\right)^2 \ . \tag{A1}$$

Monopoly Outcome

From standard theory the monopoly price and the elasticity of demand at the monopoly price are:

$$p^M=1+\frac{\varepsilon}{2};\quad \eta\left(p^M\right)=1+\frac{2}{\varepsilon} \ . \tag{A2}$$

Cartel Outcomes

Introducing our second model parameter $\delta, 0\le\delta\le 1$ and our four enforcement parameters $(\beta,\sigma,\lambda,\rho)\in[0,1]^4$ then from (2), Proposition 2(i) and (12) we have:

$$d=\frac{\delta\beta\sigma}{(1-\delta\lambda)+\delta\beta\sigma};\quad p^C=\frac{1+\frac{1}{1-\beta\rho}+\varepsilon}{2};\quad D=1-(1-d)\left[1-\beta\rho\left(1+\frac{2}{\varepsilon}\right)\right]. \tag{A3}$$

Note: To ensure $p^C<1+\varepsilon$, need to assume $\varepsilon>\frac{\beta\rho}{1-\beta\rho}$.

Performance Measures

From (A1), (A2) and (A3) we have:

$$CS(c)-CS\left(p^M\right)=\frac{3\varepsilon^2}{8};\quad CS(c)-CS\left(p^C\right)=\frac{\varepsilon^2}{8}\left[4-\left(1-\frac{\beta\rho}{\varepsilon(1-\beta\rho)}\right)^2\right]>\frac{3\varepsilon^2}{8}. \tag{A4}$$

From (18), (22) and (26) we have:

$$\begin{aligned}
\frac{TE}{H^0}&=1-(1-d)(1-D)\frac{\left[CS(c)-CS\left(p^C\right)\right]}{\left[CS(c)-CS\left(p^M\right)\right]};\\
\frac{TE}{MDE}&=\frac{1}{\beta\sigma}\left\{\left[\frac{CS(c)-CS\left(p^M\right)}{CS(c)-CS\left(p^C\right)}\right]\left(\frac{1}{1-D}\right)-(1-d)\right\}
\end{aligned} \tag{A5}$$

where, from (25),

$$\frac{MDE}{DE} = \frac{\beta\sigma}{d} = \frac{1}{\delta} + (\beta\sigma - \lambda) \,. \tag{A6}$$

Marginal Effects

From (28) we have:

$$\begin{aligned}&\left(-\frac{\partial H}{\partial k}.\frac{k}{H}\right) = \\ &\quad \left\{-\left(\frac{\partial H}{\partial d}.\frac{d}{H}\right)\left(\frac{\partial d}{\partial k}.\frac{k}{d}\right)\right\} + \left\{\left(-\frac{\partial H}{\partial D}.\frac{D}{H}\right)\left(\frac{\partial D}{\partial k}.\frac{k}{D}\right)\right\} + \left\{\left(\frac{\partial H}{\partial p^C}.\frac{p^C}{H}\right)\left(-\frac{\partial p^C}{\partial k}.\frac{k}{p^C}\right)\right\}\end{aligned} \tag{A7}$$

where, from (29),

$$\left(-\frac{\partial H}{\partial d}.\frac{d}{H}\right) = \frac{d}{1-d}; \quad \left(-\frac{\partial H}{\partial D}.\frac{D}{H}\right) = \frac{D}{1-D}; \quad \left(\frac{\partial H}{\partial p^C}.\frac{p^C}{H}\right) = \frac{\frac{1}{4}\left[(1+\varepsilon)^2 - \left(\frac{1}{1-\beta\rho}\right)^2\right]}{\left[CS(c) - CS\left(p^C\right)\right]}, \tag{A8}$$

while, from (A3), we have:

$$\frac{\partial d}{\partial \beta}.\frac{\beta}{d} = \frac{\partial d}{\partial \sigma}.\frac{\sigma}{d} = \frac{(1-\delta\lambda)}{(1-\delta\lambda)+\delta\beta\sigma}; \quad \frac{\partial d}{\partial \lambda}.\frac{\lambda}{d} = \frac{\delta\lambda}{(1-\delta\lambda)+\delta\beta\sigma}; \quad \frac{\partial d}{\partial \rho}.\frac{\rho}{d} = 0 \tag{A9}$$

$$\frac{\partial p^C}{\partial \sigma}.\frac{\sigma}{p^c} = \frac{\partial p^C}{\partial \lambda}.\frac{\lambda}{p^c} = 0; \quad \frac{\partial p^C}{\partial \beta}.\frac{\beta}{p^c} = \frac{\partial p^C}{\partial \rho}.\frac{\rho}{p^c} = \frac{\beta\rho \big/ (1-\beta\rho)}{1+\left(1-\beta\rho\right)(1+\varepsilon)} \,. \tag{A10}$$

$$\frac{\partial D}{\partial x}.\frac{x}{D} = \left(\frac{\partial d}{\partial x}.\frac{x}{d}\right)\frac{d\left[1-\beta\rho\left(1+\frac{2}{\varepsilon}\right)\right]}{\beta\rho\left(1+\frac{2}{\varepsilon}\right) + d\left[1-\beta\rho\left(1+\frac{2}{\varepsilon}\right)\right]}, \quad x = \sigma, \lambda;$$

$$\frac{\partial D}{\partial \beta}.\frac{\beta}{D} = \left(\frac{\partial d}{\partial \beta}.\frac{\beta}{d}\right)\frac{d\left[1-\beta\rho\left(1+\frac{2}{\varepsilon}\right)\right]}{\beta\rho\left(1+\frac{2}{\varepsilon}\right) + d\left[1-\beta\rho\left(1+\frac{2}{\varepsilon}\right)\right]} + \frac{(1-d)\beta\rho\left(1+\frac{2}{\varepsilon}\right)}{d+(1-d)\beta\rho\left(1+\frac{2}{\varepsilon}\right)}; \tag{A11}$$

$$\frac{\partial D}{\partial \rho}.\frac{\rho}{D} = \frac{(1-d)\beta\rho\left(1+\frac{2}{\varepsilon}\right)}{d+(1-d)\beta\rho\left(1+\frac{2}{\varepsilon}\right)}$$

Notice that the formulae in (A9) – (A11) mirror Propositions 1 – 3.