The economic impact of cartels and anti-cartel enforcement

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Looking beyond the direct effects of the work of competition authorities
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This presentation is based on:

Motivation

- How much consumer harm do cartels cause?
- Nearly all evaluation based (inevitably) on cases detected and intervened by CAs. These may be only the tip of iceberg. What about:
  - deterred cases (surely the main purpose of any law)
  - undetected cases ("failures" of the CA)
- Can we get from the observed part to the total population of anticompetitive harm?
We address two main questions:

- what do we know about the total population of harm (shades of Harberger, 1954)?
- which part of the population harm is ‘selected’?

Population harm is skewed: many cases with small harm, few large harm cases, which are not all equally likely to be selected.

We provide a parametric form for estimating total anticompetitive harm from the harm that we observe, in a way that accounts for possible selection bias.

Previous empirical results are plugged into this framework and the magnitudes of total, deterred and undetected harms are estimated using a Monte Carlo process.
Framework
A simple framework of case selection

- Suppose the total amount of cartel-induced harm is given by $H$.
- Denote the magnitude of all deterred harm by $W$ and its ratio to all harm by $\omega := \frac{W}{H}$.
- Denote the magnitude of all detected harm by $S$, and its ratio to all undeterred harm by $\sigma := \frac{S}{H-W}$.
- The ratio of detected (observed, sampled) harm to total population harm is given by $(1 - \omega)\sigma$.dataTable
The simple multiplier

If the harm detected and remedied by the CA ($H^S$) is a *random sample* of the population, then the magnitude of detected (sampled) harm is: $H^S = (1 - \omega)\sigma H$, and:

- total population harm is $H^S / ((1 - \omega)\sigma)$,
- of which $H^S \omega / ((1 - \omega)\sigma)$ is deterred, and
- $H^S (1 - \sigma) / \sigma$ is undetected.
But... selection bias

- Are the cases detected and intervened by the CA representative of the cases it deters, or the cases that it fails to detect?
- That question drives the rest of this paper.
- Note, in passing, that it has much wider-reaching relevance to all IO research which uses data on detected cases to draw inferences about the population of all cases.
  - For example, the ‘typical’ cartel has 7 members, lasts 7 years, and overcharges by 15-20%. Or does it?
Sample selection
Set up as a sample selection problem

- Think of the cases undeterred, detected & intervened by the CA as the observed (selected) sample, drawn from a larger potential population, which also includes unobserved, deterred, or undetected cases.
- If inferences are to be made from the sample about the population, we need to know something about:
  - the harm population distribution
  - how the probability of selection, \( \lambda := (1 - \omega) \sigma \) varies with case harm, \( h \)
- To keep things simple, we distinguish a simplified trichotomy: low-middle-high harm cases (L, M, H)
- We assume for simplicity that selection can vary across the three segments but not within each segment.
Population distribution positively skewed: potentially, high harm cases may be very harmful
Sample selection

Assume that each segment is sampled, but with different sample proportions $\lambda_i \ (i = L, M, H)$, thus $\lambda = \sum_i \lambda_i P_i$.

Proposition

With random sampling across segments, the simple multiplier ($H^S / \lambda$) is an unbiased estimator of aggregate population harm $H$. With differential sampling, it is typically biased; the direction and magnitude of bias depends on (i) the sampling differential and (ii) the relative sizes of mass in the tails.

\[ H = \frac{H^S}{\lambda + (\lambda_M - \lambda_L)(P_L - H_L) - (\lambda_M - \lambda_H)(H_H - P_H)} \]
Cartel overcharge data

- Which part of the harm distribution are we most likely to observe? i.e. what are the likely relative magnitudes of the sampling proportions $\lambda_L$, $\lambda_M$ and $\lambda_H$.
- Use cartel overcharge as a proxy for 'cartel harm'
- Extensive cartel overcharge dataset in Connor (2014).
Composition of 'legal' cartels

- 'Illegal' cartels: found to be in violation of antitrust laws.
- 'Legal' cartels: operated prior to the enactment of antitrust laws in the jurisdictions in which they functioned or because they were organised and registered under antitrust exemptions, such as export cartels or ocean shipping conferences.
- 'Extra-legal' cartels: there was nothing in the case material indicating that an antitrust authority punished them.
- Our legal sample: all those that Connor categorises as 'legal', supplemented by a small number (six) of his 'extra-legal' category.
- Sample of 103 unambiguously legal cartels, whilst 399 were unambiguously illegal (349 and 1154 episodes respectively).
Figure: Density plot of overcharge under illegal (deterrence) and legal (no deterrence) regimes
Testing the difference between the legal and illegal samples

- We rely on quantile regressions (QR). Benefits of QR over LS:
  - LS focuses on the average relationship between regressors and the dependent variable. In this case we are more interested in the relationship at different levels of cartel overcharge.
  - LS gives large weight to large deviations in the observed sample (the largest overcharge observation in our sample is 1800). Quantile regression provides least absolute deviations estimators, which are more robust to outliers.

- The $\alpha$-th quantile of $F(h)$ for $0 \leq \alpha \leq 1$ is given by $F(h_\alpha) = \alpha$. If the inverse function $F^{-1}$ exists then the quantile is given by $h_\alpha = F^{-1}(\alpha)$. The quantile $h_\alpha$ is the overcharge that splits the sample into proportions of $\alpha$ below and $1 - \alpha$ above $h_\alpha$. 

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Impact of cartels
### QR results

<table>
<thead>
<tr>
<th>Illegal $h$</th>
<th>$\Delta$ in legal $h$</th>
<th>Std. Err.</th>
</tr>
</thead>
<tbody>
<tr>
<td>$h_5$***</td>
<td>2.8</td>
<td>-2.80</td>
</tr>
<tr>
<td>$h_{10}$***</td>
<td>5.3</td>
<td>-5.30</td>
</tr>
<tr>
<td>$h_{15}$***</td>
<td>8.5</td>
<td>-7.50</td>
</tr>
<tr>
<td>$h_{20}$***</td>
<td>10</td>
<td>-5.40</td>
</tr>
<tr>
<td>$h_{25}$**</td>
<td>11.8</td>
<td>-3.80</td>
</tr>
<tr>
<td>$h_{30}$</td>
<td>13.3</td>
<td>-0.30</td>
</tr>
<tr>
<td>$h_{35}$</td>
<td>15.3</td>
<td>0.20</td>
</tr>
<tr>
<td>$h_{40}$</td>
<td>17.3</td>
<td>1.70</td>
</tr>
<tr>
<td>$h_{45}$</td>
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</tr>
<tr>
<td>$h_{50}$*</td>
<td>22.3</td>
<td>4.70</td>
</tr>
<tr>
<td>$h_{55}$***</td>
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<td>$h_{60}$</td>
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<tr>
<td>$h_{65}$**</td>
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<td>$h_{70}$**</td>
<td>35</td>
<td>9.00</td>
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<td>$h_{75}$***</td>
<td>40</td>
<td>10.00</td>
</tr>
<tr>
<td>$h_{80}$*</td>
<td>48.2</td>
<td>8.70</td>
</tr>
<tr>
<td>$h_{85}$*</td>
<td>55.4</td>
<td>15.80</td>
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<tr>
<td>$h_{90}$**</td>
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<td>29.00</td>
</tr>
<tr>
<td>$h_{95}$</td>
<td>126</td>
<td>42.00</td>
</tr>
</tbody>
</table>

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Impact of cartels

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How does sampling probability change with harm?

- If cartels are illegal, harm is more likely to be sampled in the middle segment: $\lambda_L < \lambda_M > \lambda_H$.
  - either because low and high harm cases are less likely to be detected,
  - and/or because these cases are more likely deterred

- To distinguish between these two possibilities we look at detection rate first.
How does detection rate change with harm?

- **Leniency detection**: Harrington et al. (2012), Fonseca et al. (2012), etc: the probability of leniency applications increases with harm.

- **Ex-officio detection**: no evidence, but there is a growing understanding that it is price fluctuations, rather than levels, that lead to investigations (Harrington, 2004, 2005).

**Assumption**

*The probability of cartel detection is non-decreasing with case harm: \( \sigma_L \leq \sigma_M \leq \sigma_H \).*
How does deterrence change with harm?

Combining the above:

- If detection increases with harm it must follow that the probability of **cartel deterrence** is highest for higher harms $\omega_{L,M} < \omega_H$, although we cannot tell whether $\omega_L <, >, \text{ or } = \omega_M$.

- If detection is invariant with harm it must follow that $\omega_L > \omega_M < \omega_H$, although we cannot tell whether $\omega_L <, >, \text{ or } = \omega_H$. 

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Monte Carlo experiments
Estimating total potential, deterred, and undetected harm

- **Total potential harm**: \( H = \frac{H^S}{\lambda + (\lambda_M - \lambda_L)(P_L - H_L) - (\lambda_M - \lambda_H)(H_H - P_H)} \)

- **Deterred harm**: we re-deﬁne the population so as to include only all undeterred cases; i.e. \( H \) above is interpreted as population of undeterred harm, and the sample proportions are the proportions of undeterred harm which is detected, \( \lambda = \sigma \). Given estimates of total and undeterred harms, deterred harm is derived as the residual.

- **Undetected harm**: Undetected harm is the residual undeterred harm which is not detected.
Three building blocks of the simulations

For the simulations we need:

- The asymmetry in the harm distribution \((P_{L,H} \text{ and } H_{L,H})\),
- The aggregate deterrence and detection rates \((\omega \text{ and } \sigma)\), and
- How these rates vary with cartel harm \((\omega_L, \sigma_L, \omega_H, \sigma_H \text{ and thus } \lambda_L, \lambda_H)\).
Connor’s (2014) overcharge data to define the three segments $L$, $M$, and $H$.

- $H_L = 0.01$, $P_L = 0.15$, $H_H = 0.78$ and $P_H = 0.35$. 

Davies and Ormosi Impact of cartels
The aggregate detection rate

- For the simulation we model both $\sigma$ and $\omega$ as random variables.
- In the case of $\sigma$, there is a fairly large existing literature attempting to estimate the cartel detection rate.
- Connor and Lande report the results of 25 previous econometric studies, which yield estimates within the range 0.1 to 0.33.
- We therefore specify $\sigma$ here as a random variable with a uniform distribution bounded by this range: $\sigma \sim U(0.1, 0.33)$. 

For $\omega$, the deterrence rate, there is much less to go on from the previous literature.

Therefore, we shall not rule out any possible value between 0 and 1 but assume relatively smaller probabilities of extreme values.

Thus, we assume a symmetric distribution within these bounds, as described by a beta distribution $\omega \sim \text{Beta}(\alpha, \beta)$, where $\alpha = \beta = 2$. This implies mode and mean of $\omega = 0.5$, but with non-trivial probabilities of all other values between 0 and 1.
The disaggregated sampling rates

Detection rate increases with harm:

a) **Rate of detection**: we take three numbers from the distribution $U(0.1, 0.33)$, rank them in ascending order, and assign them to $\sigma_L$, $\sigma_M$, and $\sigma_H$ in this order, which ensures that $\sigma_L \leq \sigma_M \leq \sigma_H$.

b) **Rate of deterrence**: First we draw three numbers from the distribution $Beta(2, 2)$ and then rank them in ascending order. We assign the greatest to $\omega_H$, and decide with a fair draw whether $\omega_L$ or $\omega_H$ is smaller. This ensures that $\omega_H > \max(\omega_L, \omega_M)$ in every draw, whilst allowing for all possible values of deterrence.
The disaggregated sampling rates

Detection is invariant with harm:

a) **Rate of detection**: each draw of aggregate $\sigma$ from $\sigma \sim U(0.1, 0.33)$ implies the same value for each segment, $\sigma = \sigma_L = \sigma_M = \sigma_H$.

b) **Rate of deterrence**: we generate three numbers from a beta distribution, $Beta(2, 2)$, and rank them in ascending order. We then set $\omega_M$ as the lowest value, and decide randomly with a fair draw whether $\omega_L$ or $\omega_H$ is larger. This ensures that $\omega_M < \min(\omega_L, \omega_H)$ for every draw.
Monte Carlo simulation results

Results are multipliers of detected harm

<table>
<thead>
<tr>
<th>variable</th>
<th>mean</th>
<th>median</th>
<th>p5</th>
<th>p95</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>INCREASING DETECTION RATE</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>total harm</td>
<td>13.655</td>
<td>11.387</td>
<td>5.855</td>
<td>28.878</td>
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<tr>
<td>deterred harm</td>
<td>9.506</td>
<td>7.276</td>
<td>2.247</td>
<td>24.143</td>
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<tr>
<td>undetected harm</td>
<td>3.149</td>
<td>2.921</td>
<td>2.227</td>
<td>4.875</td>
</tr>
<tr>
<td>ω</td>
<td>0.504</td>
<td>0.499</td>
<td>0.276</td>
<td>0.748</td>
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<tr>
<td>ω&lt;sub&gt;L&lt;/sub&gt;</td>
<td>0.403</td>
<td>0.396</td>
<td>0.112</td>
<td>0.723</td>
</tr>
<tr>
<td>ω&lt;sub&gt;M&lt;/sub&gt;</td>
<td>0.403</td>
<td>0.395</td>
<td>0.112</td>
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<tr>
<td>ω&lt;sub&gt;H&lt;/sub&gt;</td>
<td>0.692</td>
<td>0.708</td>
<td>0.407</td>
<td>0.924</td>
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<td>0.157</td>
<td>0.292</td>
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<tr>
<td>σ&lt;sub&gt;L&lt;/sub&gt;</td>
<td>0.158</td>
<td>0.147</td>
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<tr>
<td>σ&lt;sub&gt;M&lt;/sub&gt;</td>
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<td>0.216</td>
<td>0.131</td>
<td>0.299</td>
</tr>
<tr>
<td>σ&lt;sub&gt;H&lt;/sub&gt;</td>
<td>0.273</td>
<td>0.282</td>
<td>0.185</td>
<td>0.326</td>
</tr>
</tbody>
</table>
Monte Carlo simulation results

Result

According to the point (mean) estimate, total potential anticompetitive harm from cartels is 13.7 larger than the harm detected and observed by the CA. Within this, deterred harm is 9.5 times higher and undetected harm over 3 times greater than the CA’s detected harm.

- Detected harm is only the tip of an iceberg of potential cartel harm
- Most harm is unobserved, either because they are not detected or mainly because they are deterred.
Monte Carlo simulation results

Result

*In terms of the 90 percent bounds, the total harm lies in a range of between 5.9 and 28.9 times greater than the observed harm, deterred harm between 2.2 and 24.1 times greater, and undetected harm between 2.2 and 4.9 greater - in each case, depending on the strength of deterrence and detection.*

- Detected harm is only a small fraction (at most one sixth) of total potential harm – the tip of the iceberg;
- Deterrence is at least twice as effective as detection as a means for removing harm;
- Undetected harm is at least twice as large as detected harm.
### Assessing the 'success' of competition policy

<table>
<thead>
<tr>
<th></th>
<th>mean</th>
<th>p5</th>
<th>p95</th>
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<tbody>
<tr>
<td>detected</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td>7.30%</td>
<td>17.10%</td>
<td>3.50%</td>
</tr>
<tr>
<td>deterred</td>
<td>9.51</td>
<td>2.25</td>
<td>24.1</td>
</tr>
<tr>
<td></td>
<td>69.40%</td>
<td>38.40%</td>
<td>83.40%</td>
</tr>
<tr>
<td>Success (detected + deterred)</td>
<td>76.70%</td>
<td>55.50%</td>
<td>86.90%</td>
</tr>
</tbody>
</table>

- Lower bound: ‘poorly’ performing CA ($\omega = 0.28$ and $\sigma = 0.16$);
- Upper bound: ‘good’ CA ($\omega = 0.75$ and $\sigma = 0.29$).
Concluding remarks
Conclusion

- For policy-makers, deterrence is arguably the most important arm of cartel policy, and harm due to undetected cartels is likely to be considerable.

- Measuring the success of a CA simply by calculating the amount of harm it removes by virtue of cartel busts can be misleading.

- A ‘poor’ CA may actually detect more harm than a ‘good’ CA, simply because its inability to deter leaves far more cartels out there to be detected.

- Undetected harm is 2-4 times the detected harm: The treble damages rules are good approximation.