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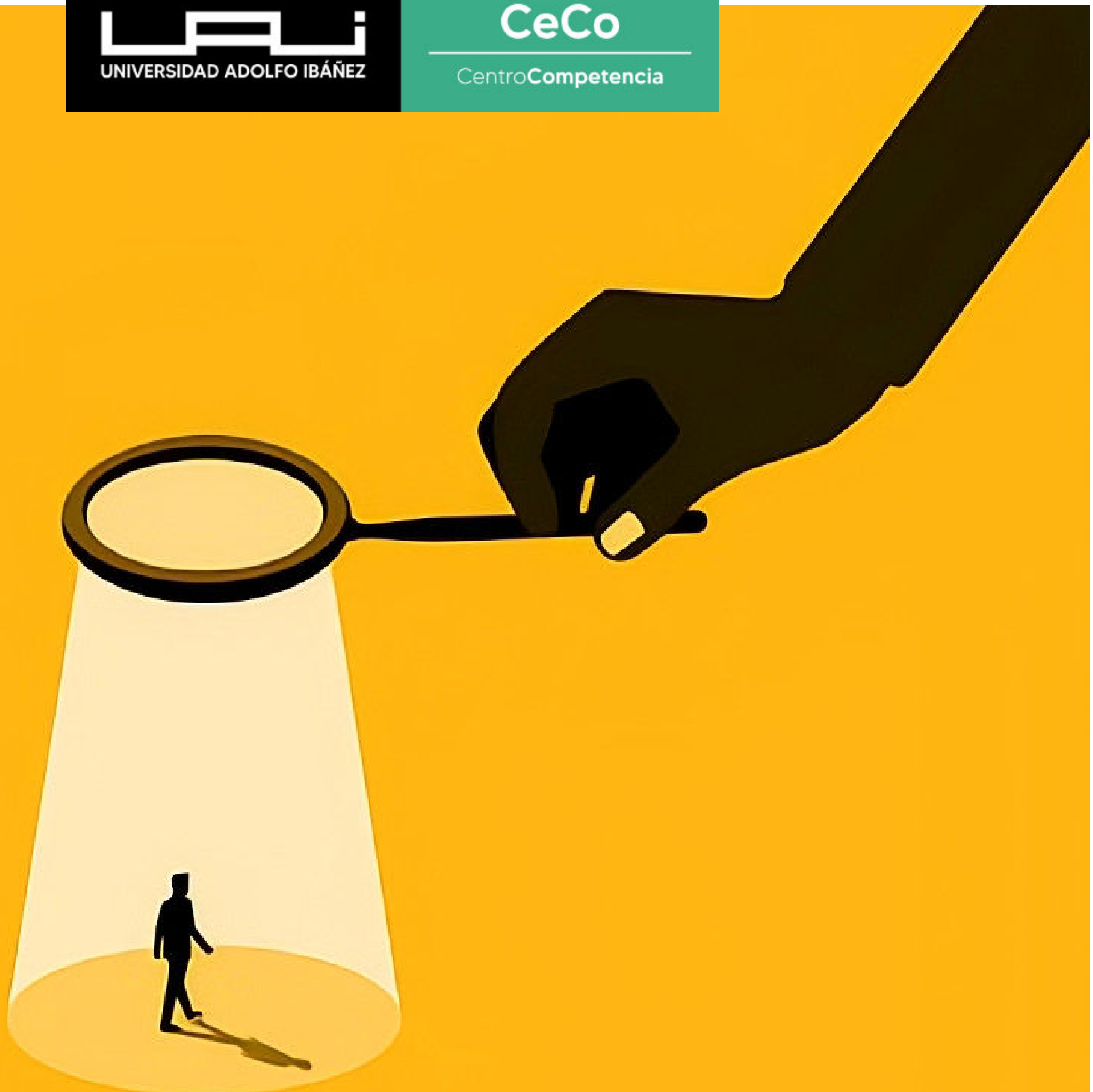

PROBABILITY OF CARTEL DETECTION: AN APPLICATION TO THE PERUVIAN CASE

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PROBABILITY OF CARTEL DETECTION: AN APPLICATION TO THE PERUVIAN CASE[1,2]

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Abstract: This paper provides the first empirical estimate of cartel detection probability in Peru, addressing a key gap in antitrust enforcement. Using a birth-and-death Markov model calibrated via maximum likelihood on INDECOPI's cartel decisions since 1992, we estimate an annual detection probability ranging from 18% - 31%, with a midpoint estimate of 25%. This figure lies at the upper bound of international benchmarks and offers a robust empirical basis to inform fine-setting practices and enhance deterrence in competition policy.

1 This article is an adapted version of the authors' original manuscript, completed in June 2025 (hereinafter, the date of completion). It includes clarifications and editorial refinements, without altering the study's original objectives, methodology, data or results. The views expressed herein are solely those of the authors and do not necessarily reflect the views of their past, current, or future employers. The authors do not take any position on the authority's conclusions about the existence of an illegal conduct.

2 First submission (English or Spanish draft): February 19, 2026. Final submission: May 06, 2026.

I. INTRODUCTION

Fines in cartel cases serve multiple objectives. Among these, deterrence is consistently emphasized as a relevant policy aim by major competition authorities[3]. To assess if a fine optimally deters cartels, the economic theory formalized by Becker (1968), and later refined by Landes (1983) and Polinsky and Shavell (2000), offers a normative benchmark according to which fines should at least equal the expected extra profit from the conduct, which can be computed as the illegal profits divided by the probability of detection.

The optimal deterrence "formula", which introduces the complexity of incorporating a probability of detection, is followed by the antitrust Commission for the Peruvian competition authority (INDECOPI)[4]. In this Commission's practice, the way in which such probabilities have been informed has evolved over time and followed different criteria, without any apparent empirical basis —beyond references to studies from other jurisdictions in some of the Commission's decisions[5].

While the optimal deterrence approach acknowledges the importance of likelihood of detection, the absence of an empirical benchmark for the Peruvian case to guide a probability reflecting the features of Peruvian cartels risks making enforcement inconsistent: if sanctions are computed following the optimal deterrence framework, then an overestimated detection probability weakens the deterrent effect of fines. Conversely, an underestimated one may lead to disproportionate penalties.

This project aims to fill that empirical gap by being, to our knowledge, the first to empirically estimate the probability of cartel detection for Peru. We adopt the birth-and-death Markov process introduced by Bryant and Eckard (1991), which has been applied in the literature to infer detection rates from observed cartels' duration. By calibrating this model using historical data on cartels sanctioned by INDECOPI's antitrust Commission (hereinafter, the Commission), we estimate a country-specific annual detection probability, providing an empirical reference point for policy and enforcement design.

The remainder of the paper is structured as follows. Section 2 outlines the Commission's methodology for the graduation of fines and some cartel enforcement milestones. Section 3 reviews the key contributions in the literature on cartel detection probabilities. Section 4 outlines the birth-and-death model and the estimation procedure. Section 5 describes the dataset used to estimate the probability of detection. Section 6 presents our findings and sets the framework for the interpretation of results, and section 7 concludes.

II. INSTITUTIONAL FRAMEWORK

This section provides an overview of key changes in cartel enforcement in Peru, focusing on the evolution of policies that may have influenced cartel formation and self-reporting (section 2.1); and a brief description of the evolution of the Commission's fine-setting practices for horizontal agreements, as inferred mainly from its decisions (section 2.2).

3 See, for instance, European Commission (2011), acknowledging the punishing and deterrence goals of fines.
4 This commission is the main authority at the first instance, responsible for determining whether investigated conducts brought by the Competition Directorate (former Technical Secretariat) constitute anticompetitive practices, and for imposing corresponding sanctions.
5 See, for instance, the decisions 022-2014 (file 010-2012), 078-2016 (file 008-2010), 099-2017 (file 005-2014), among others listed in the Appendix.

2.1 Key changes in Peruvian cartel enforcement

Peru's first comprehensive competition law, Legislative Decree (LD) 701, was enacted in November 1991 and marked the beginning of a structured antitrust enforcement in the country. The law underwent several amendments over time. A particularly significant reform came in April 1996, more than four years after the LD 701, with the introduction of a provision allowing alleged offenders the possibility to be exempted from sanctions in exchange for information on the conduct under investigation[6]. Although not explicitly framed as such, this reform effectively established Peru's first leniency program.

However, no leniency applications were submitted while LD 701 was in effect[7]. One possible reason could have been that, while this law allowed for immunity from administrative sanctions, Article 232 of the Peruvian Penal Code still permitted criminal prosecution for cartel conduct, thus deterring potential applicants.

This issue was addressed in 2008 with the enactment of a new competition law, LD 1034, which repealed Article 232. Thus, anticompetitive conducts were no longer criminalized[8]. Following its entry into force[9], the Commission began receiving leniency applications, with the first request being in 2012[10]. As Calderon (2023) presents, until 2022 a total of 27 applications were filed, although the yearly number stagnated since 2019.

While several factors could have contributed to such stagnation, this stability coincided with the enactment of Law 31040 in 2020, which reinstated criminal prosecution. As noted by Calderon (2023) and Bonifaz (2023), the change may have jeopardized leniency applications, as the law failed to provide immunity from criminal prosecution for those participating in the program. However, in 2023, Law 31775 was enacted, exempting criminal liability from those undertakings who obtained full exemption by INDECOPI.

In sum, cartel enforcement in Peru has evolved through alternating phases of administrative and criminal prosecution, with potential effects on tools such as the leniency program. The evidence suggests that, among other factors, the removal of criminal sanctions may have enabled the program's operation, with criminal liability seeming to have weakened the firms' incentives to apply to leniency.

2.2 INDECOPI's fine-setting practices over time for horizontal agreements

Another aspect of cartel enforcement in Peru that has undergone significant changes is the methodology for fine calculation. In the early years of INDECOPI, which was founded in November 1992, most of the Commission's decisions offered limited information on how fines were determined (if imposed at all), lacking explanations of the framework applied.

A shift emerged around the mid-2000s when the Commission's decisions started adopting the principles of optimal deterrence theory. This shift was later reinforced by legislative amendments with the entry into force of LD 1034 in 2008, which adapted the criteria for setting sanctions to explicitly include the detection probability as a determining factor.

In the first applications of the optimal deterrence approach, the probability was proposed on a case-by-case basis, without an evident standardized methodology, resulting in considerable variations, going from 30%

6 The amendment was introduced by LD 807.
7 Organization for Economic Co-operation and Development (OECD), OECD-IDB Peer Reviews of Competition Law and Policy: Peru (2018), https://doi.org/10.1787/b624f9da-en.
8 For further references, see Calderón (2023).
9 Additional amendments were introduced through LD 1205, which established graduated ranges of exoneration depending on the order of leniency applications, with Type A Leniency granting immunity.
10 OECD, OECD-IDB Peer Reviews of Competition Law and Policy: Peru (2018).

up to 100%. In response, INDECOPI published guidelines in 2013, proposing a more structured approach and recommending probabilities between 41% and 60% for collusive practices[11]. In parallel, the Commission began citing estimates produced in other jurisdictions (see section 3) where the difference between the adopted range and the results from the literature was evident.

As time elapsed, the Commission's rulings showed an alignment with INDECOPI's 2013 range, diverting only in the pharmaceutical products cartel (detection probability of 15%)[12]. However, it was not until the Chimbote LPG cartel decision in December 2017 when the Commission explicitly formalized a new criterion[13]. According to this, the probability shall range from 15% - 60%, depending on the characteristics of each case, such as the existence of leniency applications, the type of coordination, or the access to evidence (see Table 1). As will be seen in section 3, the lower end of the new range was more closely aligned with empirical evidence from other jurisdictions.

Table 1. Criteria for assigning detection probability, 2017 - 2020

	Detection probability range		
Characteristics	**60%**	**30%**	**15%**
Type of investigation	Whistleblower or Type A leniency	Authority initiative	Authority initiative
Access to database	Yes (exact/complete)	Yes (approximate)	No
Strategy to conceal or destroy evidence	No	Yes (fragmented, dispersed evidence)	Yes (explicitly)
Coordination mechanism	-	-	Third party intervention

Source: Decision 099-2017.

The last change appeared in 2021 with the passing of the Supreme Decree 032-2021-PCM that approved a new methodology for fines under the jurisdiction of INDECOPI. This law slightly modified the criteria for defining the detection probability and established a new and narrower range between 26% and 54% (see Table 2), while stating that the authority's decision might fluctuate in 4.63% around the values established in the Supreme Decree.

11 INDECOPI, Propuesta Metodológica para la Determinación de Multas en el Indecopi (April 2013), https://repositorio.indecopi.gob.pe/backend/api/core/bitstreams/1f379c47-cd85-49c4-b3f9-5b2255a274b3/content.
12 File 008-2010, see Appendix. Decision published in October 2016.
13 File 005-2014, see Appendix. Decision published in December 2017.

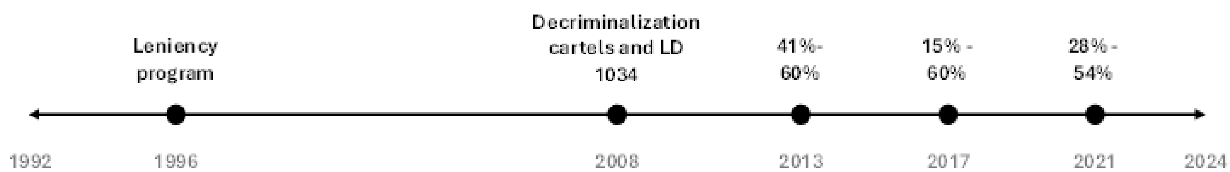
Table 2. Criteria for the adoption of detection probability since 2021

	Detection probability range		
Characteristics	**53.81%**	**41.38%**	**26.49%**
Start of investigation	Self-report and scheduled supervision activities	Complaints and third parties' reports	Unscheduled supervision activities
Access to database	Yes (exact/complete)	Yes (fragmented, dispersed evidence)	No
Strategy to conceal or destroy evidence	-	-	Yes

Source: Adapted based on the information provided in the Supreme Decree 032-2021-PCM.

In summary, Peru's policy tools regarding to horizontal agreements have undergone extensive changes since the creation of INDECOPI, involving the leniency program, cartel criminalization, and the adoption of optimal deterrence theory for fine setting. The timeline in Figure 1 provides a summary of the main milestones described in this section.

Figure 1. Main milestones in Peru related to cartel enforcement



Regarding fine calculation, despite the numerous shifts, a limitation that has persisted is the lack of a consistent and empirical approach to assigning detection probabilities. Although recent guidelines devoted efforts to provide a range, they fail to account for empirically supported probabilities that reflect historical cartel features in Peru and, to our understanding, neither the guidelines nor the Commission's decisions explain how the ranges or the permitted fluctuations were determined.

III. LITERATURE REVIEW

The estimation of cartel detection probabilities has received increasing attention in competition policy. The seminal work of Bryant and Eckard (1991) introduced a structural model in which cartel birth and death processes follow exponential distributions, allowing a constant detection probability to be inferred from observed cartels' duration using a birth-death Markov framework. Applying this approach for the United States (U.S.), the authors found that the annual probability of detecting a price-fixing agreement was between 12.8% and 17.4%.

This methodology has been adopted in subsequent research. For instance, Combe et al. (2008) applied it to the European Union (EU) context, finding an annual constant detection rate between 12.9% – 13.2%.

The authors highlighted concerns about under-detection, since the estimates are conditional on cartels being detected and should be interpreted as upper bounds. Similarly, in Spain, Garcia-Verdugo et al. (2020) estimated a constant annual detection rate of 10.7%.

Harrington and Wei (2017) preserved the assumption of a constant detection rate but adapted it to a discrete-time framework and extended the approach by disentangling the probability of cartel collapse from the probability of detection. They emphasized that previous studies conflated these two processes. As a result, they argued that annual detection estimates should be interpreted as upper bounds. Based on U.S. data, they estimated this upper bound at 17.4%.

The literature has also explored alternative methodologies to account for potential variation in detection rates, relaxing the assumption of a constant estimate. For instance, Ormosi (2014) applied a capture-recapture model, treating detection as a process with possible repeated 'captures' and offering a flexible, time-varying alternative to structural models. The author concluded that the probability of detection of cartels in the EU stays between 10% and 20%. Moreover, Park et al. (2018) followed a Bayesian framework to estimate posterior detection probabilities conditional on observed enforcement outcomes, so the estimate is interpreted as a probability of sanction. Using U.S. data, the paper suggests estimates above 11.4%, converging to a value around 23.0%.

These empirical efforts converge on a key insight: the estimates of the detection probability of cartels are relatively low and likely heterogeneous across jurisdictions, ranging from 10% to 23% despite the methodological differences (see Table 3). While recent literature has highlighted the limitations of the approach developed by Bryant and Eckard (1991), it remains a foundational benchmark for estimating detection rates and continues to inform the evaluation of some recent methodologies. For this reason, our study considers Bryant and Eckard (1991) as an adequate approach to estimate the probability of cartel detection in Peru.

Table 3. Summary of cartel detection probability estimates from revised studies

Paper	Country or region	Method	Estimate
Bryant and Eckard (1991)	U.S.	Birth-death	12.8%-17.4%
Combe et al. (2008)	EU	Birth-death	12.9%-13.2%
Ormosi (2014)	EU	Capture-recapture	10.0%-20.0%
Harrington and Wei (2017)	U.S.	Birth-death-recovery	17.4%
Park et al. (2018)	U.S.	Bayesian model	11.4%-23.0%
García-Verdugo et al. (2020)	Spain	Birth-death	10.7%

Source: Studies cited in section 3.

IV. METHODOLOGY

Bryant and Eckard (1991) use a birth-and-death process, which assumes that cartels form and dissolve over time according to a continuous-time Markov process, where interarrival times and durations follow exponential distributions. Such modelling framework implies that the parameters of interest depend only on the current state and not on past history; in other words, the probabilities of passing from one state to another are independent of how long the process has been in place (the so-called memoryless property). As a result, the process settles at a steady state, allowing for identification of constant transition probabilities. Section 4.1 summarizes the model framework and the estimation approach, while section 4.2 highlights some guidelines for the interpretation of results and the identification of the model.

4.1 Analytical framework

Formally, assume that no cartel exists at time *T0*, but they begin to form at any time *t* > *T0*. We only observe cartels within the time window [*T1, T2*], meaning that the analysis excludes cartels that "died" before *T1* or those that still are "alive" after *T2*.

Let N(T) denote the number of active cartels at time *T ϵ [T1, T2]*. The changes in N(T) are modeled by a birth-and-death process, in which new cartels are formed at a birth rate θ, and existing cartels are terminated at a death rate λ, which is our parameter of interest. In this framework, cartel "death" is defined as the end of the cartel's conduct, though this event is only observed ex post, upon discovery and investigation. As will be discussed later, this will have implications for the interpretation of the estimates as upper bounds.

The model assumes that the duration of a cartel, *Li*, and its interarrival time *Ai* —that is, the time between the formation of successive cartels— are independently and exponentially distributed, with means *θ-1* and *λ-1*. The parameters *θ* and *λ* are estimated using maximum likelihood, based on the durations of n cartels observed to end within the time window [*T1, T2*]. The likelihood function is:

$$L(\theta,\lambda) = \theta^n \lambda^n \, exp[-\theta(T_2 - T_1)] \, exp\left[-\lambda \sum_{i=1}^{n} L_i\right] exp\left[\frac{\theta}{\lambda}\left(e^{\lambda T_1}\right)\left(1 - e^{-\lambda(T_2 - T_1)}\right)\right]$$

The final exponential term accounts for the partial observability of the process: only cartels that died within the observation period [*T1, T2*] are included in the analysis, while those that collapsed before *T1* or after *T2* remain unobserved. If the observation window is not sufficiently far from *T0*, both parameters are estimated by numerically maximizing the full likelihood function. However, when this assumption is relaxed, the process reaches a steady state, the correction term becomes negligible, and the maximum likelihood estimators simplify to:

$$\hat{\lambda} = \frac{n}{\sum_{i=1}^{n} L_i} \qquad \hat{\theta} = \frac{n}{T_2 - T_1}$$

The results imply that the death rate accounts for the inverse of the average cartel duration, while the birth rate equals the inverse of the mean interarrival time. Intuitively, if most observed cartels are short-lived, this suggests a high probability of detection, and vice versa. Similarly, frequent cartel formations would imply a high birth rate, as reflected by a higher number of active cartels in the steady state.

4.2 Interpretation and identification

The estimator λ represents the average rate of cartel detection, conditional on prosecution. Since duration can only be computed for detected cartels, undetected or ongoing cartels are naturally excluded from the sample as they remain unobservable, and consequently, this estimate constitutes an upper bound on the true detection probability. In other words, if the full universe of cartels were observed —including those that collapsed without an investigation from the authority and those still active—, the estimated detection probability would be lower. Similarly, θ captures only the arrival rate of caught cartels, rather than all cartel formations.

The identification of the model relies on three key assumptions:

- **Stationarity:** Fixed parameters, λ and θ, over time.
- **Full observability:** Complete duration data information for all detected cartels.
- **Constant hazard rate:** Implied by exponential duration distributions.

The stationarity assumption is satisfied when the cartel formation process has been running sufficiently long before observations begin; that is, when T_1 (start of observations) is large relative to T_0 (start of the process). We consider reasonable that this condition likely holds here, as cartel conspiracies in Peru presumably were in place well before INDECOPI's establishment, as by definition illicit activities justify the introduction of enforcement institutions. The full observability assumption requires that cartel durations can be measured for all cases in the sample. This assumption is addressed through our data construction methodology detailed in section 5.

The assumption that the hazard rate is constant deserves closer scrutiny as it has the most substantive behavioral implications for cartel detection dynamics. The hazard rate represents the probability of an event failing at a specific time t, given that it has survived up to that time. A constant hazard rate therefore matches the memoryless property of the exponential distribution, and it implies that the likelihood of cartel detection remains constant throughout its lifetime. Therefore, under this assumption, a cartel is equally likely to be detected whether it has just formed or has been operating for years.

More formally, and following Bryant and Eckard (1991), suppose that at any time *t*, there exists a function $E(t)$ capturing the information available to enforcement authorities at time *t*, given that a conspiracy has not been detected before *t*. If $E(t) \propto t^{\alpha-1}$ for some parameter α, then the hazard rate is not constant, and the relevant variables follow a Weibull distribution rather than an exponential one. The shape parameter α determines the nature of the hazard:

- When $\alpha > 1$, the hazard rate increases over time (detection probability increasing with age).
- When $\alpha < 1$, the hazard rate decreases over time.
- When $\alpha = 1$, the Weibull distribution reduces to the exponential case, consistent with our baseline assumptions in section 4.1.

To check whether the distributional assumption fits the observed data, in section 6 we test the exponential specification to an alternative one based on the Weibull distribution, using graphical diagnostics and likelihood ratio tests.

V. DATA

Our initial sample comprises 63 horizontal agreements sanctioned by the Commission between 1992 and 2024. Their identification comes from INDECOPI's answers to information requests and their institutional statistical summaries, from which later the copies of the decisions were mapped through INDECOPI's website or additional information requests[14].

Table 4 classifies these 63 cases into two groups. The first one, named the prosecuted cases, gathers 52 proceedings where the Commission concluded that the investigated parties engaged in concerted practices. To our knowledge, this would represent nearly the universe of prosecuted cases since 1992. Any missing cases might have been decided before 2006, the last year for which INDECOPI's summary statistics are available [15-16]. The second group consists of 11 settlement cases, which accounts for all cases settled by the Commission from 2005 onward[17], while the sample from 1992 - 2004 is based only on decisions that could be found on INDECOPI's website[18].

In both groups, the decisions are categorized by the type of conduct involved in the infringement. Hard-core cartels refer to classic antitrust violations, such as price-fixing and market allocation. In contrast, recommendations involve cases where individuals or associations publicly encouraged coordination in commercial conditions among competitors. The latter are excluded from our analysis, as we focus primarily on cartels.

Table 4. Distribution of cases by granularity of infringement duration and case type

	Imprecise	Year level	Month level	Day level	Total
Group 1: Prosecuted cases					
Hard-core cartels	4	3	11	27	45
Recommendations	3	-	1	3	7
Sub-total (A)	**7**	**3**	**12**	**30**	**52**
Group 2: Settlement cases					
Hard-core cartels	-	2	2	3	7
Recommendations	4	-	-	-	4
Sub-total (B)	**4**	**2**	**2**	**3**	**11**
Total (A + B)	**11**	**5**	**14**	**33**	**63**

Source: Authors' analysis of the Commission's decisions.

The cornerstone of our analysis is the duration of each case, as inferred from the Commission's decisions, which provide a reference for the starting and ending dates of the infringement based on economic and

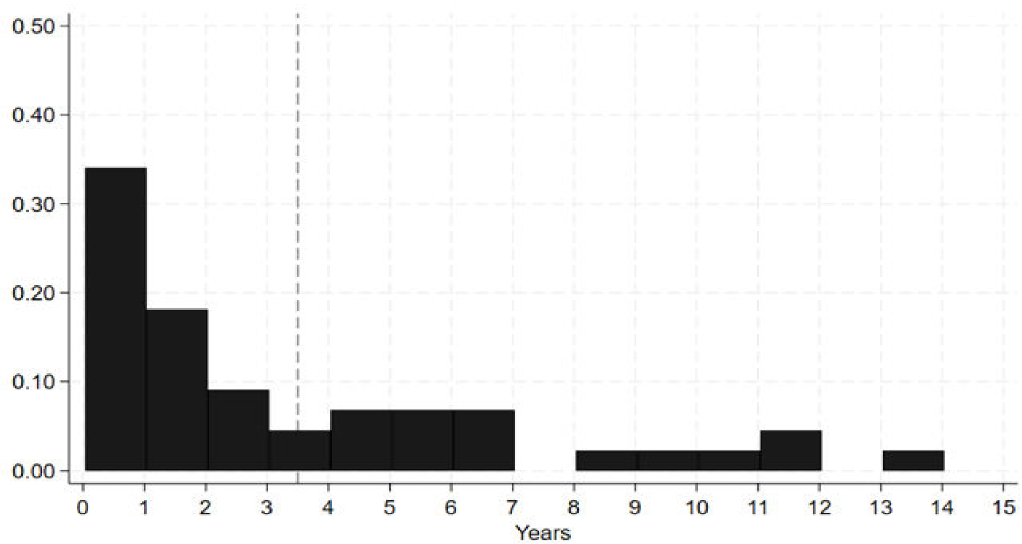
14 For this work, we reviewed only the information contained in the Commission' decisions. The reports from the Competition Directorate or Tribunal's decisions were not examined —except in the turkey case (see below).
15 The statistical summaries track the official number of cases decided by the Commission each year. INDECOPI's website provides only complete digital records from 2006 onward, so no reference exists to ensure that all cases for earlier years are being accounted for. For the period 1992–2005, the universe of cases has been estimated using INDECOPI's responses to information requests and decisions available on its website.
16 After the date of completion, two additional decisions were identified: 050-1996 concerning a price-fixing agreement in passenger transport in Puno (file 094-1994), and 052-2004, addressing similar conduct in passenger transport in Iquitos (file 034-2003). Neither case is included in the dataset.
17 Validated through information requests and Reyna (2024).
18 After the date of completion, an additional decision was found (006-1993) concerning a price fixing agreement in liquid fuels. This case is not included in the dataset.

hard evidence gathered by the Commission[19]. In 11 cases, we deemed that the content of the decision was insufficient to determine the duration of the conduct, therefore these cases are excluded from our analysis.

After dropping cases involving recommendations and with imprecise data about the duration of cartels, additional data cleaning was performed that led to the exclusion of four additional cases[20]. Therefore, the final sample for the analysis consists of 44 cartels sanctioned by the Commission. For these cases, duration was calculated daily as the difference between the reported end and start dates in the decisions. When the infringement period was reported only at the monthly or annual level, the duration was computed from the beginning of the start month/year to the end of the month/year.

Figure 2 shows the relative frequency of cartel durations for the 44 cases in the sample. Around half of the cases had a duration of no longer than two years, and the average duration of a cartel detected by INDECOPI is 3.5 years (gray dashed line in Figure 2).

Figure 2. Relative frequency of cartel durations (in years)



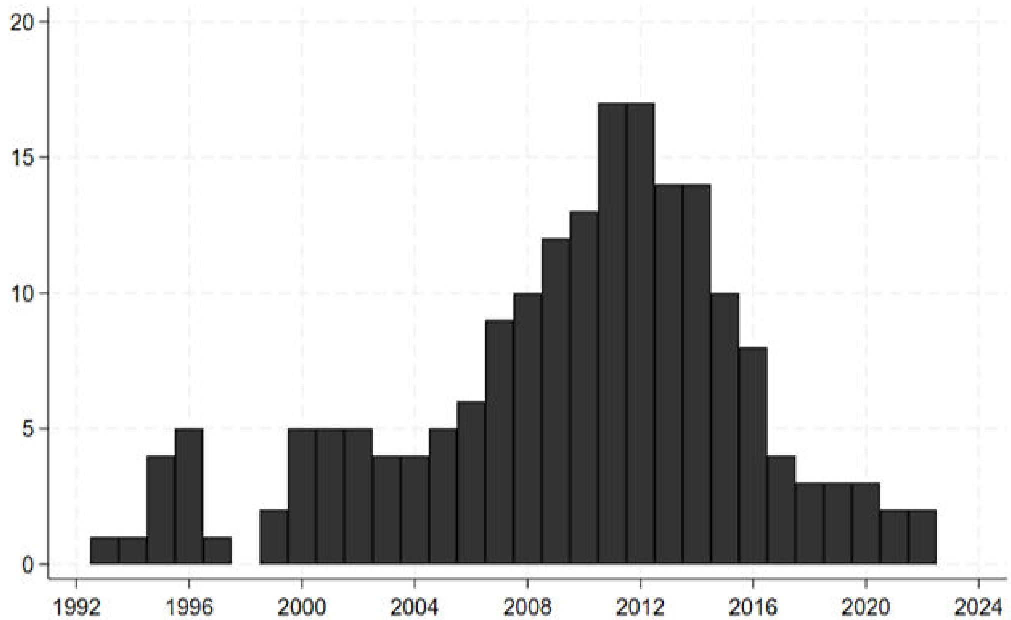
Source: Authors' analysis of the Commission's decisions.

Figure 3 shows the number of active cartels per year. The data reveal a buildup of cartel activity beginning after 2004, peaking around 2011–2012, when 17 of the 44 cartels were active. This was followed by a sharp decline until 2017, after which the number of active cartels stabilized at around 2 to 4 per year. From 2023 onward, none of the cartels in our sample were still active.

19 In some cases, the start and end dates were also approximated by considering the Commission's discussion in the background and facts of the case.

20 First, the whole turkey case (file 007-2020) was excluded because the Competition Tribunal classified it as a vertical conduct. Second, one of the two marine pilotage cases (files 003-2001 and 008-2001) was dropped, as the Commission found they involved the same conduct, parties, and period. The last two cases were excluded due to their interarrival times —either to avoid missing values that impede estimation, or because they began in recent years, which could distort the analysis, especially if its start date is far apart from the rest of the sample.

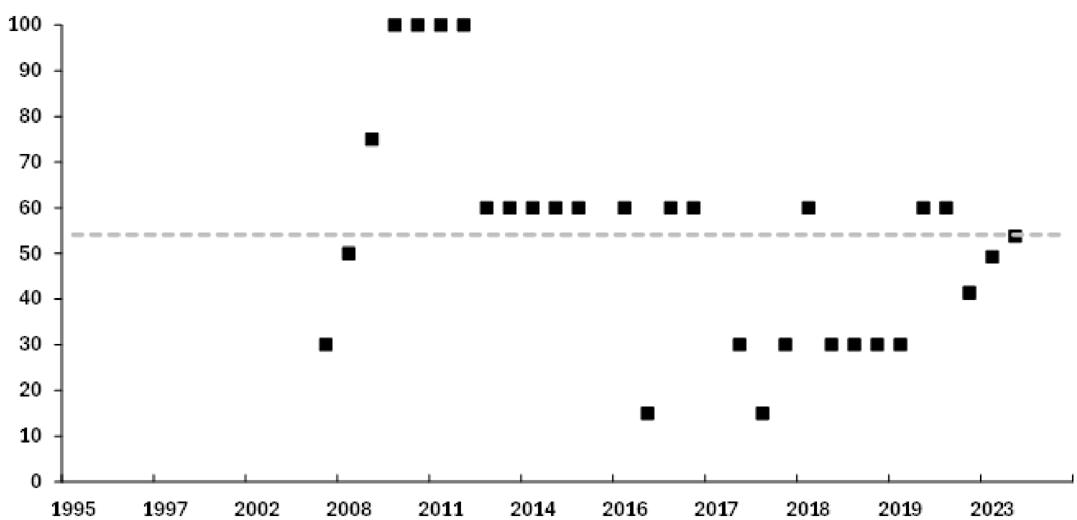
Figure 3. Number of active cartels per year



Source: Authors' analysis of the Commission's decisions.

Finally, Figure 4 shows the evolution of detection probabilities across the cases in the sample, ordered chronologically based on their corresponding decision's publication date. The figure plots 29 cases out of our 44 observations sample, the missing cases were either decided before the adoption of the methodology, or instances where the relevant information is unavailable. Overall, the practice of assigning a detection probability has shown considerable volatility. On average, among the cases with available data, the detection probability has settled around 54%.

Figure 4. Detection probability (in percentage) by cartel



Source: Authors' analysis of the Commission's decisions.

VI. RESULTS

This section first examines the validity of assuming an exponential distribution for our dataset (section 6.1). We then present our results, with a focus on the estimated detection probability (section 6.2).

6.1 Testing the exponential assumption

As described in section 4, a key assumption of the birth-and-death framework is that cartel durations and interarrival times follow an exponential distribution. This property implies that the likelihood of being found is constant throughout a cartel's lifetime, thus it is equally likely to be detected whether at its beginning, or the longer it has been going on.

To assess this assumption, we conduct two complementary tests. First, we visually inspect the distribution of cartel durations and emergence times. Second, using a likelihood-ratio test, we test whether the data better fits an exponential or a Weibull distribution.

Graphical Inspection: Taking duration as a reference, we plot the empirical survival function, defined as 1 – ECDF(t), which represents the share of cartels still active beyond duration t and where:

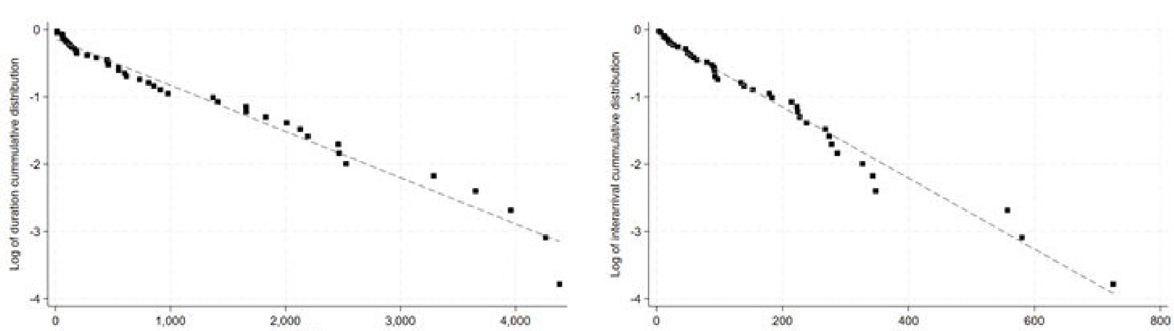
$$ECDF(t) = \frac{Number\ of\ observations\ <\ t}{Total\ number\ of\ observations}$$

If the exponential distribution assumption with parameter β holds, this function satisfies:

$$log\ (1 - ECDF(t)) = -\beta t$$

Thus, a linear trend in the log-survival plot —and similarly in the log-interarrival plot—offers preliminary support for the exponentiality assumption. The panels of Figure 5 report the visual inspection for both cartel duration and interarrival times, respectively. The plots show a linear relationship, suggesting that the memoryless property holds empirically. This result is confirmed when running a regression between the cumulative density function for each variable and time (gray lines in Figure 5). The slopes of the corresponding regressions are highly statistically significant at the 99% confidence level and the R2 are not below 0.97. Thus, these results quantitatively corroborate the conclusions drawn from the figure.

Figure 5. Exponential fit for cartels' duration and interarrival



Source: Authors' analysis of the Commission's decisions.

Likelihood-Ratio Test: We formally test the exponential distribution assumption for cartel duration and interarrival times by comparing a restricted Weibull model with shape parameter p = 1 (i.e., exponential) against an unrestricted Weibull model.

The estimates for cartel duration are shown in Table 5. The shape parameter is estimated at 0.81. Using these results, we proceed to evaluate the null hypothesis of p = 1 using a likelihood-ratio test. The test yields a result that fails to reject the null hypothesis at the 5% significance level[21] —as can also be inferred from the confidence intervals ranging from 0.64 to 1.03—, so no significant improvement in the fit of the distribution results from allowing a flexible shape parameter, supporting the use of the exponential distribution.

Table 5. Estimation of the shape parameter for cartel duration, unrestricted Weibull

	Estimate	Std. error	z	P > z	95% Confidence Interval	
Constant	0.003	0.002	-7.55	0.000	0.001	0.014
ln *p*	-0.206	0.121	-1.70	0.089	-0.043	0.032
p	0.814	0.099			0.642	1.032
1 / p	1.228	0.149			0.969	1.558

Source: Authors' estimation.

Table 6 shows that the shape parameter for the unrestricted Weibull distribution of cartel interarrival is 0.92. Testing the null hypothesis of p = 1 using a likelihood-ratio test yields results that fail to reject the null hypothesis at any conventional significance level[22]. As before, this ratifies the use of the exponential distribution for cartel interarrival.

Table 6. Estimation of the shape parameter for cartel interarrival, unrestricted Weibull

	Estimate	Std. error	z	P > z	95% Confidence Interval	
Constant	0.008	0.002	-7.62	0.000	0.002	0.028
ln *p*	-0.073	0.117	-0.63	0.530	-0.302	0.156
p	0.929	0.108			0.739	1.168
1 / p	1.076	0.126			0.856	1.353

Source: Authors' estimation.

In summary, both the graphical inspection and the likelihood-ratio test support that the distribution of the data can be fitted through an exponential distribution. Consequently, we proceed with the maximum likelihood estimation following Bryant and Eckard (1991) methodology.

21 LR test statistic: $\chi^2(1)=3.16$, and p-value 0.076.
22 LR test statistic: $\chi^2(1)=0.41$, and p-value 0.523.

6.2 Estimation of detection and formation rates

Once validated the use of an exponential distribution, we estimate the model parameters by maximizing the full likelihood function derived in section 4, and accounting for the finite observation window between 1992 and 2024. As shown in Table 7, the estimated daily probability of cartel detection is λ = 0.0008, corresponding to an annual detection probability of approximately 25%[23], which fluctuates between 18% and 31%, considering the confidence interval of the parameter.

Table 7. Estimation of the daily detection and formation rates

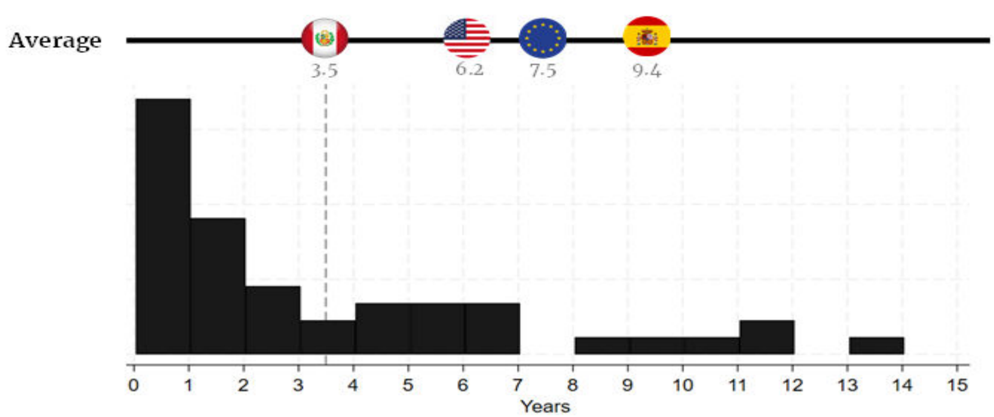
	Estimate	95% Confidence interval
θ	0.0055*** (0.0008)	[0.0039 – 0.0072]
λ	0.0008*** (0.0001)	[0.0006 – 0.0010]

Note: Estimates from maximum likelihood. Standard errors in parenthesis. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Source: Authors' estimation.

These figures are broadly consistent with those found in the literature (10% - 23%), placing Peru at the upper end of the distribution. This conclusion holds even when the comparison is limited to studies that apply Bryant and Eckard (1991) methodology, which report estimates between 10% and 18%. Nonetheless, the whole interpretation of these results should be approached with caution.

Firstly, while cross-country comparisons help validate our estimates, they should not be used to infer the relative strength of enforcement efforts across jurisdictions as detection probabilities are inversely related to the cartels' durations, so a higher detection probability reflects shorter cartel lifespans. Indeed, by taking the inverse of our yearly estimate, the implied cartel duration is around 3.5 years. This is particularly relevant when comparing our results to studies summarized in Table 3, where sanctioned cartels typically had longer duration as shown in Figure 6. In any case, this suggests only that cartels uncovered in Peru are primarily short-lived. Moreover, differences in estimated probabilities may also reflect structural or behavioral characteristics of cartels that vary across countries.

Figure 6. Cartel duration and comparison between jurisdictions



Source: Authors' analysis, Bryant and Eckard (1991), Combe et al. (2008), García-Verdugo et al. (2020).

23 Compound estimation for a year of 365. All annual estimates are computed following this procedure.

Secondly, when compared to the historical average probability of 54% inferred from previous cases, the results would seem to suggest a severe mismatch between INDECOPI's practice and empirical evidence. However, such a comparison masks the underlying assumption behind that each cartel is equally likely to be found. While this has been the standard in literature (where estimation was an ex-ante exercise so to contribute to literature and drive policy recommendations), an evaluation of existing policy requires more caution. INDECOPI's approach of applying different cartel detection probabilities based on some observed features making them easier or harder to detect seems plausible.

Therefore, to explore an empirical counterpart to INDECOPI's practice, we re-estimate probabilities for cartel subsamples, where each case is allocated according to the detection probability originally attributed by the Commission (namely, "easy" and "medium-hard")[24].

Table 8. Estimation of detection probability parameters by cartel type

	Estimate	95% Confidence interval
Panel A: Easy to detect cartels (18 observations)		
θ	0.0043***	[0.0023 – 0.0063]
	(0.0010)	
λ	0.0008***	[0.0004 – 0.0012]
	(0.0002)	
Panel B: Medium-hard to detect cartels (11 observations)		
θ	0.0076***	[0.0031 – 0.0121]
	(0.0023)	
λ	0.0004***	[0.0000 – 0.0008]
	(0.0002)	

Note: Estimates from maximum likelihood. Standard errors in parenthesis. *** p < 0.01, ** p < 0.05, * p < 0.10. Source: Authors' estimation.

Table 8 reports the results of this exercise. For cartels classified as easier to detect, the estimate implies a yearly probability of approximately 26%, while for medium-high difficulty cartels, the estimate is lower and translates into a yearly probability of roughly 14% - both significant at any conventional significance level (p-value 0.000). These figures fall outside of the range of probabilities currently used by INDECOPI (26.49%-53.81%).

At face value, and within the Bryant and Eckard 1991 framework, this result would imply that, ceteris paribus, the current fine calculation approach used by INDECOPI is not achieving the Becker-Landes "optimal deterrence" effect. However, and once again, it is worth emphasizing that this model takes as the sole main inputs the duration of conspirations and the time between the formation of subsequent cartels —an approximation that disregards other aspects that might be at play yet providing information on the underlying phenomenon.

While the assumption that among these subgroups each cartel could be equally likely to be found (therefore ignoring cartel specific granularities), as it is an approximation implicitly chosen by the Commission, what cannot be considered a granularity is the Peruvian institutional context: participation in a conspiration has

24 Respectively 60% and 30% - 15% under 2013 guidelines, 53.81% and 41.38% - 26.49% under DS 032-2021-PCM. Our analysis groups "hard" and "medium" in a single category since "hard" counts only 2 observations.

been criminally prosecuted over several periods —and this is a factor that is more than likely to play a role on all the elements of the analysis.

Therefore, in order to acknowledge this dimension, we ran an additional exploratory check to estimate detection probabilities separately for the earlier antitrust regime (LD 701), and the subsequent antitrust law (LD 1034), which repealed criminal prosecution. Results, reported in Table 9, indicate a markedly higher implied annual detection probability under LD 701 (61.3%) compared to LD 1034 (17.3%). However, estimates for the former are accompanied by wide confidence intervals.

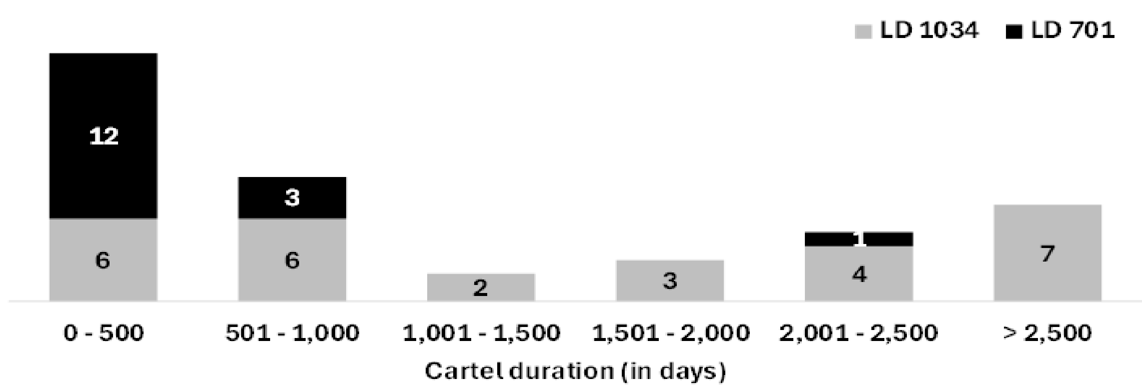
Table 9. Estimation of detection probability parameters by legal regime

	Estimate	95% Confidence interval
Panel A: LD 0134 (28 observations)		
θ	0.0063***	[0.0040 – 0.0087]
	(0.0012)	
λ	0.0005***	[0.0003 – 0.0007]
	(0.0001)	
Panel B: LD 701 (16 observations)		
θ	0.0045***	[0.0023 – 0.0068]
	(0.0011)	
λ	0.0026***	[0.0013 – 0.0039]
	(0.0006)	

Note: Estimates from maximum likelihood. Standard errors in parenthesis. *** p < 0.01, ** p < 0.05, * p < 0.10. Source: Authors' estimation.

These results therefore indicate that, assuming that within each legal regime cartels were equally likely to be found, the average probability of a cartel being detected is higher under a regime that criminally prosecuted conspirators, than under one that does not. While it is intuitively reasonable to believe that criminalization entails stronger deterrent effects (see, for instance, Gordon and Squires, 2008), the results in this framework must be explained in light of its limitation. As shown in Figure 7, cartels sanctioned under DL 701 were significantly shorter-lived than those under DL 1034. Accordingly, the model interprets this as evidence of a higher probability of detection.

Figure 7. Distribution of cartel durations by legal regime



Source: Authors' analysis of the Commission's decisions.

While this mechanical link limits the interpretability of these estimates, for instance, as a metric to differentiate probabilities across cases or as evidence of genuinely stronger deterrence or enforcement under different antitrust regimes, it does invite for deeper reflection on the possible explanations for the stark divergence in the duration of conspiration, and perhaps only after that, about the inferred probabilities.

For instance, with respect to the distinction by regime, one could argue that LD 1034 and the introduction of leniency mechanisms enabled the authority to uncover longer-standing, more stable cartels as explained by Miller (2009). Yet, from a game-theoretic standpoint, by lowering the expected cost of detection, these same programs may have contributed to the persistence of collusion ex ante (Motta and Polo, 2003). In other words, while our regime-specific estimates do not allow for conclusive claims about enforcement intensity, they point to meaningful differences in cartel dynamics across legal frameworks. Explaining these differences remains an important avenue for future research.

VII. CONCLUSION

This study contributes to the empirical literature on probability of cartel detection by providing an estimate for Peru following the approach developed by Bryant and Eckard (1991), yielding an estimate of a time invariant detection probability. Despite this simplifying assumption, this choice was motivated by the fact that different methodologies in other jurisdictions all provide consistent results —and in some cases confirm— with the baseline framework from Bryant and Eckard (1991), which remains the standard in this literature.

Calibrating the model on the Commission's cartel decisions from 1992 to 2024, we find an annual detection probability ranging from 18% to 31%, with an overall point estimate of 25%. This lies at the higher end of the ones seen in literature[25], and by being so, it highlights the methodology's dependency on the length of the found cartels.

Given that INDECOPI applies optimal fine theory —under which detection probability is a key parameter for setting sanctions—, we contribute to the broader policy debate by providing empirical counterparts to the probabilities used by the Commission. Our results thus offer an evidence-based benchmark grounded on country-specific cartels, reinforcing the importance of anchoring enforcement tools in observed cartel behavior.

That said, beyond the inherent limitations of any empirical analysis[26], certain conditions are relevant when interpreting the results and comparing them with INDECOPI's current framework. As in all studies relying on this framework, our estimates are an upper bound for the true probability of cartel detection, as they are based on the detected subpopulation of all existing cartels. Moreover, since duration is drawn from the Commission's decisions and reflect only periods for which evidence of collusion was found by the authority, the actual durations are likely underestimated, suggesting that the estimate is upward biased[27].

Subject to these caveats, a simple comparison between our point estimates and the historical average, and between our subgroup estimates and the official ranges, would, at face value, point at underdeterrent fines. Hence, our results invite reflection on whether the bounds currently adopted by the Commission realistically

25 See, for instance, Bryant and Eckard (1991), Combe et al. (2008), García-Verdugo et al. (2020).
26 For instance, the original sample size and the need to drop non-hard-core cartels from the assessment.
27 The recorded duration excludes, for example, initial phases of coordination between conspirators, and periods for which the authority lacked sufficient evidence to substantiate the finding of collusion.

foster deterrence within Becker Landes framework. In that sense, our estimates offer a foundation for future research on broader deterrence assessments and their alignment with optimal fine theory (Allain et al., 2015; Combe and Monnier, 2011).

Peru's alternation between periods of criminal prosecution and its efforts to operationalize optimal sanctioning make it a unique setting to study cartel deterrence. While our estimates would suggest higher detection under criminal enforcement, such outcome is likely to only reflect the mechanical link between duration and probability. Nonetheless, it emerges clearly that cartels were shorter-lived under the criminal regime; and the question of how institutional changes affect conspiracy formation and dissolution is left to further research. Overall, while the birth-and-death approach has limited explanatory power regarding cartel features or enforcement efforts, it provides a benchmark for understanding the underlying detection probability in Peru.

INDECOPI's efforts for a fair cartel prosecution, through the estimation of illicit profits, as well as weighting for detection probabilities, are clear and unique in their kind making Peru's cartel a case to be followed and observed. As the country's policy continues to evolve, ensuring that detection probabilities are periodically reassessed and measured across different methodologies, will be essential for aligning enforcement with the desired deterrent goals.

#	Case file	Conduct type	Start date	End date	Product
1	n. a.	Hard-core cartel	01/04/1993	23/12/1993	Passenger transport
2	116-1994	Hard-core cartel	(*)	(*)	Passenger transport
3	146-1994	Hard-core cartel	(*)	(*)	Musical works
4	157-1994	Hard-core cartel	(*)	(*)	Organ meats
5	035-1995	Recommendations	25/07/1995	26/07/1995	Bread
6	038-1995	Hard-core cartel	16/03/1995	31/07/1995	Wheat flour
7	077-1995	Hard-core cartel	13/06/1996	30/09/1996	Bread
8	016-1996	Hard-core cartel	01/10/1995	17/09/1996	Pharmaceutical chemists
9	024-1996	Hard-core cartel	19/09/1995	31/03/1996	Steel cylinders
10	029-1996	Hard-core cartel	01/05/1995	31/07/1996	Poultry meat
11	030-1996	Hard-core cartel	30/05/1996	26/11/1997	Bread
12	031-1996	Hard-core cartel	13/08/1993	31/10/1994	Sodium silicate
13	001-2000	Hard-core cartel	(*)	(*)	Distribution networks
14	004-2000	Hard-core cartel	01/01/2000	30/04/2000	Travel agencies
15	005-2000	Hard-core cartel	10/12/1999	02/06/2000	Tuk-tuks
16	003-2001	Hard-core cartel	08/01/2001	06/03/2001	Marine pilotage
17	008-2001	Hard-core cartel	08/01/2001	06/03/2001	Marine pilotage
18	003-2002	Recommendations	16/03/2001	04/01/2002	Notaries
19	004-2002	Hard-core cartel	01/12/2001	28/02/2002	Car insurance
20	004-2004	Hard-core cartel	01/10/2000	31/01/2003	Car insurance
21	008-2004	Hard-core cartel	01/04/2000	14/04/2000	Travel agencies
22	002-2008	Hard-core cartel	01/01/1999	30/06/2004	Medical gases
23	014-2008	Hard-core cartel	30/09/2007	21/05/2009	Freight transport
24	015-2008	Recommendations	18/08/2008	19/08/2008	Passenger transport
25	001-2009	Recommendations	(*)	(*)	Evaporated milk
26	002-2009	Recommendations	19/09/2008	26/05/2009	Dockworkers
27	007-2009	Hard-core cartel	15/08/2008	15/10/2008	Passenger transport
28	008-2009	Hard-core cartel	08/11/2004	21/05/2009	Freight transport
29	014-2009	Hard-core cartel	01/01/2007	15/03/2007	Passenger transport
30	003-2010	Hard-core cartel	04/09/2011	03/11/2011	Passenger transport
31	008-2010	Hard-core cartel	01/01/2008	31/03/2009	Medicines
32	004-2011	Recommendations	01/05/2010	31/12/2011	Construction services
33	005-2011	Hard-core cartel	01/06/2006	30/11/2007	Notaries
34	006-2012	Hard-core cartel	01/01/2010	31/12/2011	Tourist services
35	008-2012	Hard-core cartel	12/08/2010	25/10/2012	Hemodialysis

36	010-2012	Hard-core cartel	05/01/2007	04/10/2010	Passenger transport
37	011-2012	Recommendations	(*)	(*)	Bread
38	012-2012	Hard-core cartel	01/03/2012	30/11/2012	Passenger transport
39	003-2013	Recommendations	20/08/2008	20/08/2008	Passenger transport
40	007-2013	Recommendations	(*)	(*)	Textbooks
41	009-2013	Hard-core cartel	30/03/2011	30/11/2013	Bread
42	002-2014	Recommendations	25/11/2011	25/11/2011	Passenger transport
43	004-2014	Hard-core cartel	13/12/2009	26/06/2014	LPG
44	005-2014	Hard-core cartel	23/06/2012	27/02/2014	LPG
45	011-2015	Hard-core cartel	06/10/2005	01/08/2011	LPG cylinders
46	013-2015	Recommendations	16/10/2010	12/01/2011	Mango
47	014-2015	Hard-core cartel	01/01/2009	31/12/2013	Shipping lines
48	015-2015	Hard-core cartel	20/12/2010	31/12/2010	Passenger transport
49	017-2015	Hard-core cartel	01/01/2005	31/12/2014	Toilet paper
50	004-2016	Hard-core cartel	02/10/2014	31/03/2015	Passenger transport
51	005-2016	Hard-core cartel	05/07/2011	15/05/2015	NGV
52	006-2016	Hard-core cartel	04/05/2012	31/10/2014	Liquid fuels
53	003-2017	Hard-core cartel	01/01/2001	31/12/2012	Roro cargo
54	009-2018	Hard-core cartel	01/01/2008	31/12/2016	Plastic bottles
55	012-2018	Hard-core cartel	01/01/2011	21/12/2016	Printing services
56	002-2019	Hard-core cartel	15/10/2019	06/07/2016	Textbooks printing
57	001-2020	Hard-core cartel	14/11/2012	19/10/2016	Infrastructure projects
58	004-2020	Hard-core cartel	01/01/2014	30/11/2020	License printing
59	007-2020	Hard-core cartel	16/11/2009	31/12/2016	Whole turkey
60	007-2021	Hard-core cartel	01/01/2011	30/09/2017	Construction employees
61	008-2022	Hard-core cartel	01/04/2021	13/10/2021	Bottled water
62	009-2022	Hard-core cartel	01/10/2010	31/05/2022	Real estate
63	003-2023	Hard-core cartel	01/08/2011	31/05/2022	Real estate

Note: Start and end dates were estimated by the authors using information from the Commission's discussion in the background and facts of the case, or in the estimation of fines. (*) indicates cases where start and/or end dates could not be determined simultaneously with a sufficient degree of accuracy/reasonableness from the decisions. The list does not necessarily represent the whole universe of cartels sanctioned by the Commission. Source: INDECOPI.

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