Synthesis of Thesis Contributions: *The Importance of Stochastic Approaches and Innovative Models in the Economics of Deterrence: The Case of Illegal Activities*

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Abstract

This paper presents a synthetic summary of the doctoral thesis entitled *"The Importance of Stochastic Approaches and Innovative Models in the Economics of Deterrence: The Case of Illegal Activities"* defended on July 30, 2024.[1] The thesis aims to propose optimal policies to combat crime by combining economic analysis, stochastic models, and numerical simulations. It is divided into two parts: the first focuses on the *economic approach to deterrence*; the second proposes a *stochastic approach to anti-recidivism*. The main contributions of the thesis are presented in this paper.

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Keywords : Deterrence, Arrest, Punishment, Recidivism, Reputation

Introduction

The economics of deterrence is based on the hypothesis of *rational behavior*: individuals compare the expected benefit of an illegal activity to the expected cost of the sanction. This idea, popularized by Becker (1968), is part of a utilitarian tradition where punishment is designed as a means to influence will and prevent the commission of an illegal act.

The thesis recalls that the probability of arrest and conviction, as well as the severity of the sanction, constitute the main tools of deterrence (Polinsky & Shavell, 2000, 2002, 2007). The objective is to find a level of sanction that deters without creating disproportionate social costs (Miceli, 2016). Furthermore, the thesis highlights the necessity of integrating other motivations for crime, particularly the aspect of reputation, to better understand criminal behaviors (Fluet & Mungan, 2022; Iacobucci, 2014; Mungan, 2016).

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[1]The full thesis studies crime from the perspective of economics and applied mathematics. It proposes innovative extensions to classical deterrence models and develops a stochastic framework to analyze recidivism.

1 Economic Approach to Deterrence

1.1 Standard Modeling Framework

Inspired by optimal law enforcement models from Garoupa (2001) and Polinsky and Shavell (2007), the thesis assumes that a potential offender receives a monetary benefit b when committing a crime. They are arrested with probability p and, conditional on arrest, punished with probability q. If the monetary sanction is s, the expected utility is

$$\mathbb{E}[U] = (1-p)(b) + p\big[(1-q)b + q(b-s)\big] = b - pqs. \tag{1}$$

Equation (1) reproduces the canonical form of the Becker model when the sanction depends only on the probability of punishment (Garoupa, 2001). The Authority chooses (p, q, s) to maximize social welfare, taking into account the cost of law enforcement $C(p, q)$, which is generally increasing and convex. An upper limit is set for the sanction $\bar{S}$ to reflect legal constraints.

The maximization problem is written as

$$\begin{gathered} \max_{p,q,s} W(p,q,s) = \int_{pqs}^{\bar{b}} (b-h) f(b) db - C(p,q) \\ \text{s.t. } 0 \leq s \leq \bar{S} \end{gathered} \tag{2}$$

where h denotes the social harm. The first-order conditions associated with this problem are:

$$\begin{aligned} &C_p = qs(h-pqs)f(pqs) \\ &C_q = ps(h-pqs)f(pqs) \\ &(h-pqs)f(pqs)(pq) = 0 \Rightarrow s = \frac{h}{pq} \end{aligned} \tag{3}$$

In these expressions, $C_p = \frac{\partial C}{\partial p}$ and $C_q = \frac{\partial C}{\partial q}$ represent the marginal costs of arrest and conviction.

At the optimum, the marginal cost of increasing the probability of arrest (C_p) or conviction (C_q) must equal the marginal social benefit of deterrence, i.e., the social gain from deterring crimes.

The condition $s = \frac{h}{pq}$ reveals a relationship of equilibrium between the severity of the sanction (s) and the certainty of arrest and punishment (p and q).

If p and q are high (high probability of arrest and conviction), the expected cost of the sanction (pqs) is already significant. If p and q are low, the low probability of punishment must be compensated by a very high sanction (s) to achieve the same level of expected cost and internalize the social harm h.

1.2 Extension with Non-Monetary Benefit

To account for the non-monetary dimension of crime, the thesis introduces a reputation component r (Fluet & Mungan, 2022): an offender gains reputation when they commit an act without being apprehended. The offender's reputation among peers is preserved if they are not detected despite the crime they have committed. Table 1 summarizes the three possible states of nature and their respective gains: no arrest (E_1), arrest that neutralizes reputation (E_2), and punishment (E_3).

By weighting these gains, the expected utility becomes

$$\mathbb{E}[U] = (1-p)(b+r) + p\big[(1-q)(b) + q(b-s)\big] = b - pqs + r - pr. \tag{4}$$

Table 1: States of Nature and Expected Utilities

State E_i	Gain $u_i(b,r,s)$	Probability δ_i
E_1 : no arrest	$u_1 = b + r$	$1 - p$
E_2 : arrest and neutralization	$u_2 = (b + r) - r = b$	$p(1 - q)$
E_3 : sanction	$u_3 = b - s$	pq

Equation 4 explains the double effect of law enforcement: probability p influences reputation, and probability q affects monetary gain. When $p = 1$, the utility reduces to the canonical model $b - qs$ (Becker, 1968). The thesis infers that for crimes primarily motivated by reputation, it is more effective to increase the probability of arrest rather than the severity of the sanction.

In our deterrence model, which incorporates a non-monetary gain r (reputation) and distinguishes between arrest (p) and punishment (q), social welfare is written as:

$$W(p,q,s) = \int_0^{\tilde{r}} \int_{qs}^{\bar{b}} (r + b - h)dG(r)dF(b) - C(p,q) \tag{5}$$

where $\tilde{r} = p.r$ denotes the expected reputation.

We consider reputation r to be exogenous and not directly controllable by the Authority. The Authority can only neutralize it by increasing the probability of arrest, which leads to the simplified form of welfare:

$$W(p,q,s) = \int_{p(r+qs)}^{\bar{b}} (r + b - h)\, dF(b) - C(p,q), \quad s \leq S \tag{6}$$

1.3 Optimization and Discussion

By calculating the first-order conditions, we obtain

$$\begin{aligned}
&C_p = (r + qs)\left(r + p(r + qs) - h\right) f\left(p(r + qs)\right) \\
&C_q = ps\left(r + p(r + qs) - h\right) f\left(p(r + qs)\right) \\
&pq\left(r + p(r + qs) - h\right) f\left(p(r + qs)\right) = 0 \Rightarrow s = \frac{h - r(1 + p)}{pq}
\end{aligned} \tag{7}$$

Table 2: Summary of Optimal Sanction s^* by Scenario

Case	**Hypotheses**	s^*
Complementarity	$p > 0, q > 0, r \geq 0$	$s^* = \dfrac{h - r(1 + p)}{pq}$
Certain Arrest	$p = 1, r = 0$	$s^* = \dfrac{h}{q}$
Substitutability	$p = q, r = 0$	$s^* = \dfrac{h}{p^2}$

When arrest and punishment are perfectly substitutable and have the same marginal cost, the optimal sanction increases with $\frac{1}{p^2}$. If the probability of detection p is low, the sanction must be very high to compensate and achieve optimal deterrence. This result is consistent with Becker's logic: low certainty requires maximum fines. These results show that arrest is the main tool for neutralizing reputation, while the sanction primarily acts on monetary gains. The optimal policy combines control and punishment in a way that minimizes social costs.

2 Propositions of Innovative Models

2.1 Revisiting Marginal Deterrence

To better reflect the heterogeneity of crimes, the thesis extends the deterrence model to multiple types of offenses and accounts for the severity of harm. A key innovation is to adjust sanctions proportionally (Miceli, 2016) to the severity of the harm and inversely to the probability of arrest.

The thesis proposes a marginal deterrence policy (Shavell, 1992), where the sanction increases dynamically with the harm.

The proposed model extends marginal deterrence by assuming that the probability of detection (p_i) decreases as the severity of the offense (h_i) increases. The hypothesis is that more serious crimes, such as bank robberies, are better planned and therefore more difficult to detect than minor offenses, such as pickpocketing. The probability of identifying the perpetrators of serious crimes, such as bank robberies or sophisticated computer hacking, is lower than for minor offenses like pickpocketing. These major crimes are often better prepared, which makes detection more difficult and the social harm more significant.

The model is based on the following relationships:

- Social harms (h_i) increase: $h_i = \lambda h_{i-1}$, with $\lambda > 1$.
- The probability of detection (p_i) decreases: $p_i = \frac{p_{i-1}}{\alpha}$, with $\alpha > 1$.

The external costs or harms suffered by society are determined by $h_1 < h_2 < \cdots < h_n$. For each type of offense, the Law Enforcement Authority combines the frequency of control and the appropriate sanction for each situation:

$$\{(s_1, p_1); (s_2, p_2); \ldots; (s_n, p_n)\}$$

The offender undertakes illegal activity i if the following conditions are met (Shavell, 1992):

$$\begin{gathered} b_i \geq p_i s_i \\ \text{and } b_i - p_i s_i \geq b_{i-1} - p_{i-1} s_{i-1} \geq 0 \\ b_n - p_n s_n \geq \cdots \geq b_1 - p_1 s_1 \geq 0 \end{gathered} \tag{8}$$

By combining the constraints related to the severity of the harm and those related to the decreasing probability of detecting more complex offenses, social welfare is written as:

$$\begin{gathered} W = \sum_{i=1}^{n} \left(\int_{p_i s_i}^{\bar{b}} (b_i - h_i)\, dF(b_i) - C(p_i) \right) \\ \text{s.t. } h_i = \lambda h_{i-1} \\ p_i = \frac{p_{i-1}}{\alpha} \end{gathered} \tag{9}$$

The following main results are derived:

- An increase in the severity of harm (λ) has a negative effect on social welfare ($\frac{\partial W}{\partial \lambda} < 0$).
- An improvement in detection accuracy (α) has a positive effect on social welfare ($\frac{\partial W}{\partial \alpha} > 0$), and vice versa.
- The **optimal monetary sanction** for an offense i is $s_i^* = \frac{h_i}{p_i}$.
- The optimal sanction for the most serious offense is $s_n^* = (\lambda\alpha)^{n-1} \frac{h_1}{p_1}$, which implies an exponential increase in sanctions to compensate for the difficulty of detection.

This approach proposes a **dynamic penal policy** where sanctions must be adjusted not only to the increasing severity of offenses but also to the challenges of their detection. The sanction for a serious crime must be significantly higher to maintain deterrence in the face of a low probability of capture.

2.2 Deterrence and Reparation Mechanism

The justice system should aim for effective deterrence by adjusting the sanction (s) to compensate for the harm (h) and taking into account the probability of detection (p). The sanction is thus higher when the probability of detection is low, thereby ensuring adequate compensation for the harm. Based on this observation, we intuitively establish the following condition linking the sanction s, the probability of detection p, and the harm h:

$$s(1-p) + hp = 0. \tag{10}$$

This relationship assumes that a sanction that is too high combined with a low probability of arrest leads to *over-deterrence*, while a sanction that is too low leads to *under-deterrence*. The optimal equilibrium lies between these extremes and maximizes social welfare.

To justify this intuition, the thesis develops a social welfare model that separates the contribution of illegal gains b from legal revenues y. If f and z denote the densities of b and y (with F and Z their cumulative distribution functions), the aggregated social welfare is written as:

$$W(b,y) = \int_{ps}^{\bar{b}} \int_{(1-p)h}^{\bar{y}} (y-b) \, \mathrm{d}F(b) \, \mathrm{d}Z(y) \; - \; C(p), \tag{11}$$

The authority designs two mechanisms:

- The *deterrence mechanism* $M(b)$ minimizes the illicit gain by choosing the pair (p,S) to solve $\underset{(p,s)}{min} W_b$, with $W_b = \int_{ps}^{\bar{b}} b \, \mathrm{d}F(b) - C(p)$.
- The *reparation mechanism* $M(y)$ maximizes legal revenues by choosing (p,h) to solve $\underset{(p,h)}{max} W_y$, with $W_y = \int_{(1-p)\,h}^{\bar{y}} y \, \mathrm{d}Z(y) - C(p)$.

The equality of the optimal values $M(b) = M(y)$ imposes a condition of *certain equivalence* between deterrence and reparation. By maximizing social welfare $W(b,y)$, we obtain the equivalence conditions between the two mechanisms:

$$\begin{cases} p^2 S f(pS) = h(1-p)^2 z(h(1-p)) \\ -pS^2 f(pS) = h^2(1-p) z(h(1-p)) \end{cases}$$

The resolution of this system of equations leads to the following optimal condition for the equilibrium between deterrence and reparation:

$$S(1-p) + hp = 0$$

This equation shows that a higher sanction (S) is necessary when the probability of detection (p) is low, in order to compensate for the harm (h) and achieve optimal deterrence. It establishes a direct link between the reparation policy and the deterrence policy.

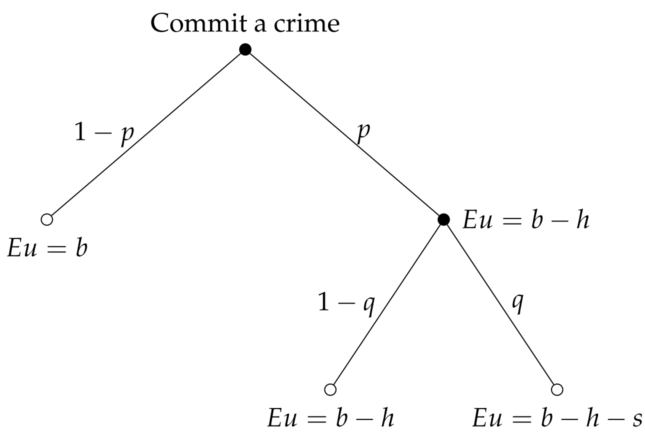
2.3 Distinction Between Arrest and Punishment

A major contribution of the thesis is the dissociation of the events of *arrest* and *punishment*. Unlike some previous works that equate the probability of arrest and the probability of punishment Garoupa (2001) and Polinsky and Shavell (2007), we postulate that conviction is conditional on arrest and propose to study these probabilities separately. In the reparation and deterrence model, reparation for harm is impossible without prior detection, and the sanction cannot be applied without an arrest.

In this context, we propose an approach that combines the civil procedure of reparation (tort liability) and the criminal procedure of law enforcement. To reconcile the reparation of harm and the deterrence of illegal acts, we are based on the following hypotheses:

- Reparation of harm is impossible without prior detection of the perpetrator;
- The sanction cannot be applied without detection of the perpetrator;
- Conviction is an event dependent on detection;
- Reparation for damage can be total when detection is certain ($p = 1$).

Figure 1: Diagram of Events Related to the Commission of an Illegal Act



Source: Author

Figure (1) illustrates these states and transitions, highlighting that harm cannot be repaired or a sanction applied without prior detection, and that optimization involves a trade-off between costs and probabilities.

States of Nature and Expected Utility. The possible scenarios for an offender can be summarized into three states of nature: (i) no arrest, with a gain of b; (ii) arrest followed by reparation of the harm, with a gain of $b-h$; and (iii) arrest followed by reparation of the harm and application of the sanction $b-h-s$. These states occur with probabilities $(1-p)$, $p(1-q)$, and $p\,q$ respectively. We can deduce the expected utility:

$$Eu_{p,q} = (1-p)\,b + p\big[(1-q)(b-h) + q(b-h-s)\big], \tag{12}$$

the expansion of which leads to a concise expression:

$$Eu_{p,q} = b - p\,h - p\,q\,s. \tag{13}$$

This equation highlights the combined effect of the probability of arrest p, the probability of punishment q, and the sanction s on the offender's expected gain.

Social Welfare The public authority aims to maximize social welfare by considering both victim reparation and deterrence. In a first step, the optimization program is written as:

$$\max_{p,q,s} W = \int_{p\,q\,s}^{\bar{b}} \int_{p\,h}^{\bar{h}} (b-y)\,\mathrm{d}F(b)\,\mathrm{d}Z(y) - C(p,q) \quad \text{s.t. } s \leq \bar{S}, \tag{14}$$

where F and Z are the distributions of illegal gains and harms. To simplify, we assume that harm h is exogenous and that the Authority can only act on detection or arrest to prevent or repair the harm.

The program then simplifies to:

$$\max_{p,q,s} W = \int_{p(h+qs)}^{\bar{b}} (b-h)\,\mathrm{d}F(b) - C(p,q). \tag{15}$$

Optimal Solutions By maximizing W with respect to p, q, and s, the first-order conditions are written as:

$$\begin{aligned} C_p &= (h+q\,S)\big(h - p(h+q\,S)\big)\,f\big(p(h+q\,S)\big) \\ C_q &= p\,S\,\big(h - p(h+q\,S)\big)\,f\big(p(h+q\,S)\big) \\ p\,q\,&\big(h - p(h+q\,S)\big)\,f\big(p(h+q\,S)\big) = 0 \end{aligned} \tag{16}$$

The analysis of these equations leads to the following propositions:

- *Substitutability*: if marginal costs are equal and if $p=q$, the optimal sanction is $s^* = \frac{h}{p^2}$ (which generalizes the rule $\frac{h}{p}$). The probability of arrest can then substitute for the severity, but a low level of detection requires a very high sanction.
- *Complementarity*: if arrest necessarily precedes punishment and if $p=1$, the optimal sanction is $s^* = \frac{h}{(1-q)}$. A near-certain detection allows for a reduction in the severity of the sanction, whereas a low probability of conviction requires a high sanction.

These results underscore the need for fine-tuning between the probability of control and the level of sanction to reconcile reparation and deterrence.

Table 3: Optimal Sanction s^* Under Different Scenarios

Case	Assumptions	Optimal Sanction s^*
General Case	$p > 0, q > 0$	$s^* = \frac{h(1-p)}{pq}$
Certain Arrest	$p = 1$	$s^* = \frac{h}{q}$
Perfect Substitutability	$p = q$	$s^* = \frac{h(1-p)}{p^2}$

3 Stochastic Approach to Anti-Recidivism

The second part of the thesis addresses recidivism using stochastic tools. The central idea is that repeated criminal behaviors are influenced by adaptive expectations: the offender and the authority adjust their expectations based on past sanctions. Two models are presented: an adaptive expectations model and a Markovian model.

3.1 Adaptive Expectations Model

Inspired by Nerlove (1958), the adaptive expectations model assumes that the offender forms expectations about the illegal gain $\tilde{b}_t$ and the sanction $\tilde{s}_t$ by updating past information according to smoothing rules:

$$\tilde{b}_t = (1-\beta)\,\tilde{b}_{t-1} + \beta\, b_{t-1}, \qquad \tilde{s}_t = (1-\alpha)\,\tilde{s}_{t-1} + \alpha\, s_{t-1}, \quad 0 < \alpha, \beta < 1. \tag{17}$$

By iteration, these relationships can be rewritten as geometric series: $\tilde{b}_t = \beta \sum_{i=0}^{\infty}(1-\beta)^i b_{t-i-1}$ and $\tilde{s}_t = \alpha \sum_{j=0}^{\infty}(1-\alpha)^j s_{t-j-1}$, which shows that expectations are weighted averages of past outcomes.

The authority combines this dynamic with Becker's deterrence strategy, for which the offender compares their expected gain to the expected sanction according to $\tilde{b}_t = p\,\tilde{s}_t$. Assuming perfect expectations ($\tilde{b}_t = b_t$, $\tilde{s}_t = s_t$), the thesis result shows that the socially acceptable benefit $\hat{b}$ and the sanction $\hat{s}$ satisfy

$$\hat{b} = p\left(\frac{\alpha(1-\beta)}{\beta(1-\alpha)}\right)\hat{s}. \tag{18}$$

This result stems from equating expectations and the expectation formulas; it illustrates how the interaction between the speed of expectation adjustment (α, β) and the detection policy (p) determines the ratio between the acceptable gain and the sanction.

The first-order condition associated with the maximization of intertemporal welfare leads to a relationship between the severity of the sanction and the harm. By deriving W with respect to s_t and separating the periods into two groups — k periods of reparation and $n-k$ periods of punishment — we obtain:

$$(n-k)\,\bar{p}\,\hat{s} = k\,\hat{h}, \quad \text{soit} \quad \hat{s}^* = \left(\frac{k}{n-k}\right)\frac{\hat{h}}{\bar{p}}. \tag{19}$$

Thus, the optimal sanction increases with the number of recidivism offenses (k) and decreases with the average detection probability $\bar{p}$. If $n = 2k$ and $\bar{p} = 1$, we get $\hat{s} = \hat{h}$, which means full reparation of the harm. More generally, the deterrence dynamic implies that the sanction follows the relationship $\hat{s} = \lambda_k\,\hat{b}/p$, where λ_k is a factor increasing with the number of repetitions. This mechanism of increasing sanctions highlights the importance of adapting penalties to the frequency of the offense: when the expected sanction reaches the level of the harm, the incentive to re-offend disappears and recidivism is neutralized.

3.2 Markovian Model

The dynamics of recidivism are modeled using a four-state Markov chain Beltrami (2013):

E1: Honest (respect for the law: absorbing state)[2]

E2: Crime (violation of the law)

E3: Arrest (detection)

E4: Punishment (sanction)

The transition probabilities between these states are grouped in the transition matrix M:

$$M = \begin{pmatrix} 1 & (1-\beta)(1-r) & (1-\alpha)(1-r) & (1-r) \\ 0 & (1-\beta)r & (1-\alpha)r & r \\ 0 & \beta & 0 & 0 \\ 0 & 0 & \alpha & 0 \end{pmatrix} \tag{20}$$

Where:

- β is the probability of being detected.
- α is the probability of being punished after detection.
- r is the probability of recidivism after an offense.

Key Results from Scenario Analysis

The analysis of different scenarios allowed for the following conclusions regarding the impact of penal policies:

- **Absence of Arrest and Sanction ($\beta = 0, \alpha = 0$)**: The recidivism rate tends toward its maximum ($r = 1$), confirming that without state intervention, recidivism is not deterred. The probability that an individual becomes honest after n transitions is $p_1^{(n)} = 1 - r^n$, while the probability of recidivating is $p_2^{(n)} = r^n$.
- **Certain Arrest, Absence of Sanction ($\beta = 1, \alpha = 0$)**: Simple arrest without sanction is not an effective deterrent. The recidivism rate remains high, as the absence of tangible consequences for criminal acts does not change offenders' behavior.
- **Certain Arrest and Sanction ($\beta = 1, \alpha = 1$)**: A zero-tolerance policy, with systematic arrest and sanction, is the only scenario where the recidivism rate decreases in the long term. The probability of recidivating after n sanctions is $p_4^{(n)} = r^n$, a value that decreases as the number of sanctions increases.

These results explicitly show that improving the probability of detection α and the probability of conviction β reduces the risk of recidivism and accelerates the return to an honest state. Thus, the Markovian model corroborates the idea that strengthening control and punishment accelerates the neutralization of criminal behaviors.

[2] An absorbing state is a state that, once entered, cannot be left.

4 Policy Implications and Recommendations

Based on the models presented, the thesis formulates several recommendations:

- **Joint Optimization of Sanction and Detection.** The optimal level of sanction must depend on the harm and the probability of detection. An excessively high sanction combined with a low probability of detection leads to unnecessary social costs (over-deterrence), while a sanction that is too low generates under-deterrence.
- **Differentiation Based on Crime Motivation.** When the non-monetary gain (reputation) is significant, it is more effective to increase the probability of arrest rather than the severity of the sanction, because arrest directly reduces reputation. Conversely, for purely monetary gains, the focus should be on the probability of punishment.
- **Progressive Sanction Policy.** Simulations suggest calibrating the sanction based on the increasing severity of offenses to maintain deterrence effectiveness. A static approach can quickly become unsuitable.
- **Importance of Detection and Reparation.** Reparation for harm is impossible without detection, and the sanction cannot be applied without arrest. Penal policy should therefore integrate a component of reparation before punishment and ensure effective detection processes.
- **Combating Recidivism.** Stochastic models show that adaptive anticipation of the sanction and a gradual increase in penalties reduce the recidivism rate. Markovian processes illustrate that by strengthening detection (α) and sanction (β), the probability of returning to an honest state is increased.

Conclusion

This thesis makes important theoretical and methodological contributions to the economic analysis of criminal law. On the one hand, it extends classical deterrence models by distinguishing between the probability of arrest and conviction and by integrating a non-monetary motivation for crime. The optimal conditions for sanction and detection, as well as the analysis of social costs, inform the design of more balanced penal policies. On the other hand, the use of stochastic approaches—adaptive expectations models and Markov processes—provides tools for understanding the dynamics of recidivism and developing prevention strategies. Finally, the thesis highlights the need for a penal policy that combines reparation, deterrence, and rehabilitation, as well as the importance of a dynamic adaptation of sanctions to address evolving criminal behaviors.

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