Crime Deterrence and Damage Repair Mechanisms

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JOB MARKET PAPER

August 2025

Abstract

This paper focuses on extending optimal law enforcement models to analyze the mechanisms of deterrence and damage compensation within a penal system under social cost criteria. We particularly examine the crucial distinction between arrest and punishment, as well as the policy and economic implications of optimal deterrence strategies. Our results show that the balance between deterrence and compensation depends strongly on the probability of detection and the severity of sanctions, thereby providing concrete insights to improve public policies in the field of law and economics.

JEL Codes: K14, K42

Keywords: Deterrence, Arrest, Punishment, Reputation

Introduction

The economic theory of deterrence, initiated by Becker (1968), argues that individuals engage in illegal activity when the expected benefits exceed the anticipated costs associated with criminal sanctions. From this perspective, effective law enforcement requires an optimal combination between the probability of detecting offenders and the severity of imposed sanctions (Garoupa, 2001; Polinsky & Shavell, 2007).

Traditional models, however, do not sufficiently account for the need to distinguish between apprehension (arrest) and conviction (punishment), which are two separate but interdependent events. Similarly, the existing literature generally pays limited attention to the mechanism of damage compensation, often neglected in favor of a purely deterrence-oriented approach (Polinsky & Shavell, 2000, 2007).

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This paper provides a significant extension of standard models by explicitly integrating two complementary mechanisms: deterring criminal behavior through adequate sanctions, and compensating victims for the harm suffered. Our theoretical framework demonstrates that these two objectives, often considered separately in the literature, must be simultaneously optimized to ensure a socially efficient equilibrium (Garoupa, 1997; Polinsky & Shavell, 2000).

First, we revisit the classical marginal deterrence model, emphasizing the importance of adjusting sanctions to the severity of harm and the probability of detection, in line with recent contributions (Friehe & Miceli, 2014; Shavell, 1992). We then propose an innovative model that clearly distinguishes between arrest and punishment, demonstrating the essential complementarity between these two stages of law enforcement. Finally, we extend our framework by exploring the conditions required for optimal damage compensation, which depends on the prior apprehension of offenders.

1. Revisiting Marginal Deterrence

The theory of marginal deterrence, as explored in various academic studies, offers diverse perspectives on the implementation and effectiveness of sanctions to address illegal or harmful behavior.

In this section, we aim to extend and deepen our understanding of marginal deterrence models presented in prior research. The objective is to build upon the foundations established by key studies in the field, exploring in greater depth the nuances and practical implications of these models. By analyzing these works, we seek to offer enriched insights that go beyond the initial conclusions, highlighting the need to increase the severity of sanctions in line with the magnitude of the harm, inspired by the concept of marginal deterrence. This approach aims to broaden our current knowledge and contribute significantly to the ongoing discussion on the effectiveness of sanctions in combating illegal behavior.

1.1. Measuring Severity

The idea of increasing the level of sanction according to the severity of the offense is not new. Friehe and Miceli (2014) highlight the need for more severe sanctions to deter offenders from committing more harmful acts. The importance of measuring the extent of harm is emphasized in many studies, including Shavell (1992), who argue that sanctions should be proportional to the severity of the damage caused. This quantification makes it possible to establish a scale of sanctions corresponding to different levels of harm, facilitating the fair and proportionate application of justice. In this respect, Friehe and Miceli (2014) emphasize that even a small increase in sanction for minor acts can have a significant impact on deterring more serious crimes, particularly in situations where offenders evaluate risks sequentially.

Another perspective stresses that the *social perception* of harm plays a crucial role in the design of deterrence policies. Zimring and Hawkins (1968) addressed this view, arguing that socialization and cultural norms influence the perception of harm and, consequently, penal responses. Sanctions must therefore align not only with the *objective* severity of harm but also with the *social perception* of that harm. They questioned the absolute effectiveness of criminal law as a deterrent, noting that for many individuals, social factors such as socialization play a more significant role in law compliance. Their analysis suggests that understanding criminal behavior requires a multidimensional approach that includes social and cultural factors.

From another angle, Mookherjee and Png (1994) discuss the importance of balancing sanctions with the harm caused by various levels of criminal activity. They point out that the optimality of law enforcement policies depends heavily on the costs associated with monitoring and punishment. This analysis demonstrates the importance of a differentiated approach to legislation, where the costs and benefits of various enforcement strategies must be carefully weighed.

Similarly, Shavell (1992) explore how expected sanctions influence the choice between harmful acts of different severities. They note that individuals who are not fully deterred may choose less harmful acts when expected sanctions increase with the severity of harm. This idea suggests that marginal deterrence plays a crucial role in discouraging criminal behavior, and that sanction policies should be designed to reflect this reality. Motchenkova et al. (2012) propose a strategy for setting fines and enforcement probabilities to deter illegal activities. They show that the expected penalty should be precisely adjusted to match the offender's benefit, implying a calculated approach to achieve maximum deterrence. By contrast, Ekelund et al. (2006) provide a historical analysis of the principle of marginal deterrence, particularly in the context of multiple murders. They observe that multiple homicides do not appear to be deterred by executions, indicating a marginal cost of additional murders close to zero. This finding raises important questions about the effectiveness of extreme sanctions in deterring the most severe crimes.

On one hand, it is widely recognized that accurately modeling the magnitude of harm is challenging due to the diversity of factors involved and the inherent subjectivity of their assessment. On the other hand, for analytical simplicity and to enable comparison, we can assume a hierarchy of harms such as $h_1 < h_2 < \cdots < h_n$ to understand their relative magnitude. This subsection develops these ideas in detail.

The magnitude of harm in crimes and offenses varies considerably, ranging from the direct nature of harm (physical, financial, emotional) to broader indirect impacts on society and the environment. This diversity makes modeling a complex task. As highlighted by Shavell (1987b), each type of harm has its own characteristics and implications, complicating the establishment of a uniform severity scale. To facilitate modeling, we propose a simplified hierarchical approach.

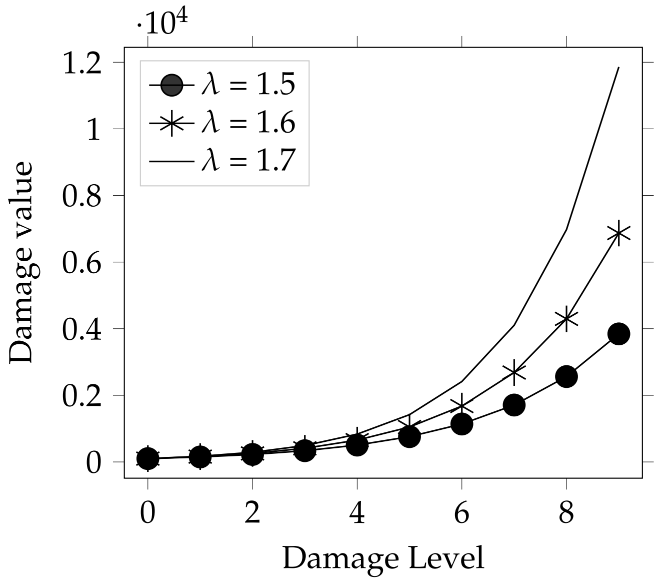
Although reductive, this hierarchy allows us to organize harms to assess their relative severity. Such a scale provides a framework for comparing and evaluating sanctions and deterrence policies. To formalize this hierarchy, we introduce a weighting parameter that evaluates the inequality between different harm levels, considering factors such as harm intensity, victim impact, and broader social consequences:

$$\begin{gathered} h_i = \lambda h_{i-1} \\ \text{for } i = 1, 2, \ldots, n, \text{ with } \lambda > 1 \\ h_1 < h_2 < \cdots < h_n \end{gathered} \tag{1}$$

Here, h_1 represents the least severe harm and h_n the most severe. λ measures the increase in severity of h_i relative to h_{i-1}, such that $h_i > h_{i-1}$ implies $\lambda > 1$.

Equation (1) describes a non-linear progression in harm severity, where each level h_i is a multiple of the preceding one, with λ representing the growth factor between consecutive levels. This progression is typical in situations where each successive step represents a significant aggravation compared to the previous one.

Figure 1: Severity of Harm Measured by λ



Source: Author

The curves in Figure 1 illustrate the increase in harm severity across different levels, measured by the factor λ. Three different values of λ (1.5, 1.6, 1.7) are used to show how harm severity evolves.

For $\lambda = 1.5$, the increase in harm severity is relatively moderate. For $\lambda = 1.6$, growth is faster, with more substantial increases at each step. For $\lambda = 1.7$, the increase is steep, leading to rapid growth in harm severity. This visually demonstrates that the higher the value of λ, the faster and more significant the increase in harm severity at each successive level.

Table 1: Illustration of Damage Increment

	Harm Value		
Harm Level i	$\lambda = 1.5$	$\lambda = 1.6$	$\lambda = 1.7$
0	100.0	100.0	100.0
1	150.0	160.0	170.0
2	225.0	256.0	289.0
3	337.5	409.6	491.3
4	506.25	655.36	835.21
5	759.38	1 048.58	1 419.86
6	1 139.06	1 677.72	2 413.76
7	1 708.59	2 684.35	4 103.39
8	2 562.89	4 294.97	6 975.76
9	3 844.34	6 871.95	11 858.79

Source: Author

We observe an exponential increase in harm value (h) with the harm level (i). Higher values of λ correspond to faster increases in harm, consistent with its interpretation as a multiplier of severity.

This hierarchy is essential to understand and model marginal deterrence, especially in systems where sanction severity is proportional to the harm caused by wrongful acts. It highlights the importance of adjusting sanctions not only to immediate harm but also to the broader scale of increasing harm in more serious offenses.

1.2. Avoidance of Detection

The relationship between detection avoidance and the probability of apprehension is complex and involves multiple factors. Sanchirico (2006) extends the existing theoretical framework by integrating detection avoidance and reveals that sanctions are relatively ineffective in discouraging such behavior, while the structural design of the evidence-gathering process, including investigation, proves to be more dissuasive.

Malik (1990) further explores this idea, noting that offenders engage in activities that reduce the probability of detection and punishment. He highlights the potential inefficiency of imposing excessively high fines due to the associated avoidance costs and underlines the importance of monitoring individuals in contexts where full deterrence is not optimal.

Friehe (2008) adds another dimension by showing that offenders differ in their probability of detection, and that optimal sanctions should increase with the offender's ability to avoid detection. This section broadens the perspective by endogenizing differences in detection probabilities, allowing individuals to choose their level of "education" or skills, which may reverse the optimal sanction level if the full benefits of education are not accounted for. His study also illustrates that incentives for seemingly unrelated decisions can be influenced by the sanction structure.

Professional criminals, likely to generate activities with severe harm, stand out due to their accumulation of specific skills and knowledge that make them difficult to detect. Their capacity is reinforced by experience in exploiting opportunities and avoiding detection (Cohen & Felson, 1979; Felson & Clarke, 1998). Their sophisticated use of neutralization techniques allows them to morally justify their actions and avoid detection, while social learning theory suggests that these criminal behaviors are learned and refined over time (Akers, 2017; Sykes & Matza, 1957). Moreover, in an information economy characterized by asymmetry, these criminals manipulate information effectively to remain hidden (Akerlof, 1970).

Information asymmetry is thus a powerful tool in the hands of professional criminals. By manipulating and controlling information, they manage to operate in the shadows, often escaping surveillance systems. The adoption of advanced technologies has also transformed criminal activity, with professional offenders employing sophisticated methods that make their detection even more complex (Brenner, 2010). In addition, these criminals often adopt strategies of decentralization and diversification of their activities, dispersing their actions to reduce the risk of detection and capture (Braithwaite, 1989).

Furthermore, observational learning and imitation play a crucial role, as professional criminals continuously improve their techniques by learning from the successes and failures of others (Bandura, 1977). This continuous improvement process, combined with the increasing complexity of their operations, makes such criminals particularly elusive for law enforcement.

Given the effort criminals put into avoiding detection, the probability of detection decreases with each successive offense level:

$$\begin{gathered} p_i = \frac{p_{i-1}}{\alpha} \\ p_1 > p_2 > \cdots > p_n \end{gathered} \tag{2}$$

where p_1 is the probability of detecting the least severe offense and p_n for the most severe offense, with $\alpha > 1$. The factor α measures the decreasing precision of detection as the difficulty of identifying the offender increases, so that $p_i < p_{i-1}$.

Equation (2) establishes a decreasing sequence for detection probabilities (p_i), from minor offenses to more serious ones. It also implies a geometric decrease in detection probability for increasingly severe crimes. Since $\alpha > 1$, dividing by α at each level reduces the probability of detection. A higher α means a faster decline in detection probability as the severity and complexity of offenses increase.

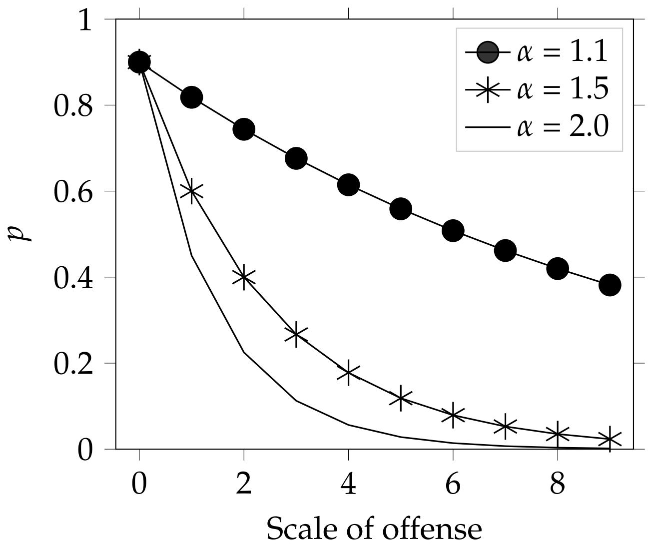
Table 2: Illustration of Declining Detection Probability

	Detection Probability		
Harm Level i	$\alpha = 1.1$	$\alpha = 1.5$	$\alpha = 2.0$
0	0.9	0.9	0.9
1	0.818	0.6	0.45
2	0.744	0.4	0.225
3	0.676	0.267	0.113
4	0.615	0.178	0.056
5	0.559	0.119	0.028
6	0.508	0.079	0.014
7	0.462	0.053	0.007
8	0.420	0.035	0.004
9	0.382	0.023	0.001

Source: Author

Table 2 illustrates how detection probability decreases with the increasing complexity of crimes, especially for higher values of α. This sequence suggests that more serious crimes are increasingly difficult to detect, due to more sophisticated planning, secrecy, or the use of advanced methods to avoid detection.

Figure 2: Detection Probability as a Function of α



Source: Author

The curves in Figure 2 show the drop in detection probability as crime complexity increases, for different values of α (1.1, 1.5, 2.0). The higher the α, the faster the probability of detection falls, indicating that highly complex crimes are very unlikely to be detected.

This visualization highlights the growing challenge that complex crimes pose for law enforcement: the more complex the crime, the harder it is to detect, especially with a high α.

For criminal justice systems, this implies the need to allocate greater resources, technology, and investigative methods to address more severe crimes. The declining detection probability for serious offenses requires deterrence strategies with increasingly severe sanctions to compensate for the lower probability of apprehension and maintain effective deterrence.

1.3. Proposal of the New Marginal Deterrence Model

The extended marginal deterrence model presented in this subsection is based on the main assumption that the monitoring technology, represented by p_i (detection probability), varies with the severity of offenses causing greater harm, whose perpetrators are harder to identify.

For illustration, consider that bank hacks or armed robberies are well-prepared or premeditated acts. Thus, identifying bank robbers may be significantly more difficult than identifying pickpockets. Consequently, the probability of arrest for minor theft is higher than for a major, well-planned crime.

Let $b_1 < b_2 < \cdots < b_n$ with $b_i \in [0, \bar{b}]$ denote the gains from illegal acts, following independent probability distributions $F(b_i)$ and $f(b_i)$. External costs or social damages are denoted by $h_1 < h_2 < \cdots < h_n$. For each type of offense, the law enforcement authority chooses a pair of sanction and detection probability:

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

The offender engages in illegal activity i if (Shavell, 1992):

$$\begin{gathered} b_i \geq p_i s_i \\ b_i - p_i s_i \geq b_{i-1} - p_{i-1} s_{i-1} \geq 0 \\ b_n - p_n s_n \geq \cdots \geq b_1 - p_1 s_1 \geq 0 \end{gathered} \tag{3}$$

Combining the constraints of increasing harm severity and decreasing detection probability, social welfare is expressed as:

$$\begin{gathered} W = \sum_{i=1}^{n} \int_{p_i s_i}^{\bar{b}} (b_i - h_i) dF(b_i) - C(p_i) \\ \text{s.t. } h_i = \lambda h_{i-1}, \quad p_i = \frac{p_{i-1}}{\alpha} \end{gathered} \tag{4}$$

Proposition 1

- *An increase in harm severity negatively affects social welfare ($\frac{\partial W}{\partial \lambda} < 0$).*

- *Improved detection precision positively affects social welfare ($\frac{\partial W}{\partial \alpha} > 0$), while a decrease negatively impacts it ($\frac{\partial W}{\partial \alpha} < 0$).*

Proof 1 By differentiating W with respect to λ and α, we obtain the results, showing that higher λ (more severe harm) reduces social welfare, whereas improved detection α can increase welfare by reducing impunity.

Proposition 2

- *The optimal monetary sanction for act i is $s_i^* = \frac{h_i}{p_i} = (\lambda\alpha)\frac{h_{i-1}}{p_{i-1}}$.*
- *The optimal sanction for the most severe offense is $s_n^* = (\lambda\alpha)^{n-1}\frac{h_1}{p_1}$.*
- *The optimal detection probability satisfies $s_i(h_i - p_i^* s_i) f(p_i^* s_i) - C'(p_i^*) = 0$ with $h_i = \lambda h_{i-1}$ and $p_i^* = \frac{p_{i-1}^*}{\alpha}$.*

Proof 2 See detailed proof below.

The partial derivatives of W with respect to s_i, for $i = 1, 2, \ldots, n$, are:

$$\begin{cases} \frac{\partial W}{\partial s_1} = 0 \Leftrightarrow p_1\left(h_1 - p_1 s_1^*\right) f\left(p_1 s_1^*\right) = 0 \\ \frac{\partial W}{\partial s_2} = 0 \Leftrightarrow p_2\left(h_2 - p_2 s_2^*\right) f\left(p_2 s_2^*\right) = 0 \quad \text{where } h_2 = \lambda h_1,\ p_2 = \frac{p_1}{\alpha} \\ . \\ . \\ \frac{\partial W}{\partial s_n} = 0 \Leftrightarrow p_n\left(h_n - p_n s_n^*\right) f\left(p_n s_n^*\right) = 0 \quad \text{where } h_n = \lambda h_{n-1},\ p_n = \frac{p_{n-1}}{\alpha} \end{cases}$$

From this, we deduce that $s_i^* = \frac{h_i}{p_i} \quad \forall i = 1, \ldots, n$, or equivalently $s_i^* = (\lambda\alpha)\frac{h_{i-1}}{p_{i-1}}$. By recursion, we obtain $s_n^* = (\lambda\alpha)^{n-1}\frac{h_1}{p_1}$.

Similarly, the partial derivatives of W with respect to p_i, for $i = 1, 2, \ldots, n$, are:

$$\begin{cases} \frac{\partial W}{\partial p_1} = 0 \Leftrightarrow s_1\left(h_1 - p_1^* s_1\right) f\left(p_1^* s_1\right) - C(p_1^*) = 0 \\ \frac{\partial W}{\partial p_2} = 0 \Leftrightarrow s_2\left(h_2 - p_2^* s_2\right) f\left(p_2^* s_2\right) - C(p_2^*) = 0 \quad \text{where } h_2 = \lambda h_1,\ p_2^* = \frac{p_1^*}{\alpha} \\ . \\ . \\ \frac{\partial W}{\partial p_n} = 0 \Leftrightarrow s_n\left(h_n - p_n^* s_n\right) f\left(p_n^* s_n\right) - C(p_n^*) = 0 \quad \text{where } h_n = \lambda h_{n-1},\ p_n^* = \frac{p_{n-1}^*}{\alpha} \end{cases}$$

It follows that

$$s_i\left(h_i - p_i^* s_i\right) f\left(p_i^* s_i\right) - C'\left(p_i^*\right) = 0, \quad \text{where } h_i = \lambda h_{i-1},\ p_i^* = \frac{p_{i-1}^*}{\alpha}.$$

This proposition shows that, to maintain effective deterrence across different offense levels, the sanction policy must not only account for the increasing severity of harm, but also adjust penalties to compensate for the declining probability of apprehension for harder-to-detect offenses. A serious offense must carry a significantly higher penalty than a minor one to ensure adequate deterrence.

Table 3: Sanction as a Function of Harm Severity and Detection Probability

Optimal Sanction $\lambda = 3$ and $\alpha = 2$								
h_1	h_2	h_3	p_1	p_2	p_3	$\frac{h_1}{p_1}$	$\frac{h_2}{p_2}$	$\frac{h_3}{p_3}$
100	300	900	1	0.5	0.25	100	600	3 600
300	900	2700	0.95	0.475	0.238	316	1 895	11 368
...	...	...	...	...	...	...	...	...
1 150	3 450	10 350	0.1	0.05	0.025	11 500	69 000	414 000

Source: Author

In Table 3, the values of h_1, h_2, and h_3 illustrate a geometric increase in harm at each successive level with $\lambda = 3$. For example, $h_1 = 100$ is tripled to obtain $h_2 = 300$, and then tripled again to $h_3 = 900$. This progression reflects a significant escalation in harm severity.

The probabilities p_1, p_2, and p_3 show a geometric decrease in line with offense complexity and severity, with $\alpha = 2$. An initial probability of 1 for the least severe offense is halved at each successive level, reflecting the increasing difficulty of detecting more severe crimes.

The columns $\frac{h_1}{p_1}$, $\frac{h_2}{p_2}$, and $\frac{h_3}{p_3}$ represent the calculated sanctions for each harm level. These values grow significantly with each level, indicating that sanctions must become progressively harsher to maintain adequate deterrence. This increase reflects both the rising severity of harm and the need to offset the declining detection probability.

The table clearly shows that required sanctions increase exponentially with offense severity. This pattern highlights the interaction between harm severity, detection probability, and the necessary adjustment of sanctions. It underlines the importance of a flexible and adaptive penal strategy, where sanctions are calibrated to the rising harm levels and the challenges of detecting more complex crimes.

This approach calls for a dynamic and adaptive criminal policy that can adequately respond to the increasing complexity of crimes and the challenges of their detection and prosecution. It provides a framework for balancing sanctions and deterrence in a context where both social harm and enforcement challenges intensify with crime severity.

Up to this point, we have not yet separated arrest and punishment as two distinct but interdependent actions by the law enforcement authority. The next section explores in detail the concept in which a significant distinction exists between the probability of arrest and the probability of punishment.

2. Distinction Between Apprehension and Punishment

In the economic literature on law enforcement, the difference between apprehension and conviction often appears blurred. In reality, committing an offense and being apprehended does not necessarily imply a sanction. For simplicity, earlier studies generally assume that arrest automatically leads to conviction. According to Chopard and Obidzinski (2021), the probability of detection and conviction is ambiguous when potential offenders have perfect knowledge of the fine amount. They assume that punishments are often explained in penal codes, but information about detection probabilities cannot be provided. Potential offenders may only have a vague idea of their own probability of being caught and eventually convicted.

Furthermore, Obidzinski and Oytana (2018) argue that the standard of proof refers to the level of certainty required for a court to convict a suspect. They explain that both the standard of proof and the presumption of innocence are related to the strength of evidence required for conviction: stronger evidence is necessary when a high standard of proof or presumption of innocence is applied.

In practical law enforcement, the process of arrest and conviction is governed by well-defined procedural rules. Arrest is the stage at which a law enforcement officer physically apprehends the accused.

After this stage, the accused is not immediately sanctioned. The next step is the judicial investigation, during which all relevant information is collected, along with material, moral, and legal evidence that can justify the accusation (or result in release otherwise). The enforcement of punishment consists of implementing the court's conviction decision. Thus, the process from arrest to sanction concludes with the court's judgment, either conviction or acquittal.

This section focuses primarily on the idea of clearly separating the two essential stages of law enforcement, as occurs in reality. An attempt is made to formalize and explain the behavior of offenders and the realities of arrest and punishment. Mathematical language is used to define the assumptions and delimit the validity of the theory. Starting from a normative or explanatory perspective, we aim to understand how rational and optimal offenders should behave.

In most studies on crime and sanctions (Becker, 1968; Polinsky & Shavell, 2007), it is suggested that sanctions and detection probability are substitutable. This assumption can be challenged for the following reason: it is inconceivable to punish an individual who has not been apprehended. In other words, the law enforcement authority cannot impose punishment without an arrest. Hence, conviction is a conditional event that depends on detection. Garoupa (2001) shows that the probability and the magnitude of the fine are in fact complementary rather than substitutable.

This section aims to question the lack of distinction between arrest and punishment. We relax the assumption that the probability of arrest is the same as the probability of conviction. We attempt to show that conviction is dependent on detection, supporting the idea of complementarity between apprehension and punishment. This offers an alternative to the traditional view of substitutability between punishment and detection.

The model proposed in this section considers the need to study the non-monetary gain that constitutes one of the motivations for committing an illegal act. Beyond monetary gain, the model incorporates non-monetary determinants that drive criminal behavior. In particular, an individual's *reputation* is at stake among peers if apprehended for a crime.

We rely on two main assumptions: i) sanctions cannot be applied without prior detection, ii) conviction is a conditional event dependent on detection.

For clarity, this section is organized as follows: Subsection 2.1 explains the dual role of reputation, both as a sanction if the offender is apprehended and as a non-monetary gain otherwise; Subsection 2.2 develops the states of nature or possible events associated with committing a crime, including the corresponding utilities and probabilities; Subsection 2.3 presents the proposed model, which integrates the elements introduced in Subsection 2.2; Subsection 2.4 provides the main theoretical results; finally, Subsection 2.5 offers a synthesis of the main contribution and the policy implications of this research.

2.1. Dual Interpretation of Reputation

In this subsection, we consider that reputation can be viewed not only as a penalty if the offender is apprehended, but also as a non-monetary advantage if the offender is not arrested after committing an illegal act.

In the economic literature on law enforcement, forms of sanctions other than legal penalties include extralegal sanctions (Bar-Gill & Harel, 2001), reputational sanctions (Fluet & Mungan, 2022; Iacobucci, 2014), stigmatization (Buchen et al., 2019; Fluet & Mungan, 2022; Harel & Klement, 2007; Mungan, 2015; Rasmusen, 1996), informational sanctions (Iacobucci, 2014; Zasu, 2007), and social norm sanctions (Deffains & Fluet, 2019; Fluet & Mungan, 2022; Zasu, 2007). These sanctions are familiar because they complement the primary legal sanction associated with the offense (Mungan, 2016).

Building on the concept of reputation, we focus particularly on the link between reputational sanction and arrest. Deffains and Fluet (2019) show that legal violations trigger reputational sanctions to the extent that they signal non-compliance with underlying norms, raising the question of offense design. They propose that legal norms should either align with underlying norms, using fines that compensate for deterrence by providing information, or be more demanding and enforced through purely symbolic sanctions. In our analysis, reputational sanction is considered as an additional deterrence mechanism complementing the legal sanction.

Arrest serves to intimidate the offender who engages in criminal activity. It has a psychological effect and reduces the moral or psychological motivation of potential criminals, in the sense that an individual's social relationship or self-esteem in society is diminished. In a society where crime does not occur, everyone maintains a sense of social belonging, and good reputation is the reward for abstaining from criminal activity.

An offender is defined as having a "bad reputation" if they are apprehended following the commission of the act. The reasoning is that the individual loses social legitimacy due to the negative information about their status resulting from the arrest. Consequently, bad reputation is considered the reputational sanction arising from arrest. As Iacobucci (2014) explains, reputational sanctions are not independent of legal sanctions but partially depend on them. Adjusting legal sanctions to account for the reputational effects of misconduct modifies the overall reputational consequences.

2.1.1. Reputational Sanction

In the economic literature on law enforcement, forms of sanctions other than legal penalties include extralegal sanctions (Bar-Gill & Harel, 2001), reputational sanctions (Fluet & Mungan, 2022; Iacobucci, 2014), stigmatization (Buchen et al., 2019; Fluet & Mungan, 2022; Harel & Klement, 2007; Mungan, 2015; Rasmusen, 1996), informational sanctions (Iacobucci, 2014; Zasu, 2007), and social norm sanctions (Deffains & Fluet, 2019; Fluet & Mungan, 2022; Zasu, 2007). These sanctions are well-known because they complement the primary legal sanction associated with the offense (Mungan, 2016).

Building on the concept of reputation, we focus specifically on the link between reputational sanction and arrest. Deffains and Fluet (2019) show that legal violations trigger reputational sanctions insofar as they signal non-adherence to underlying norms, which raises the question of offense design. They propose that legal norms should either align with the underlying norms, with fines that compensate for deterrence by providing information, or be more demanding and enforced through purely symbolic sanctions. In our analysis, reputational sanction is considered as an additional deterrent to crime, complementing the legal sanction.

Arrest serves to intimidate the offender engaging in criminal activity. It has a psychological effect and diminishes the moral or psychological motivation of potential criminals, in the sense that the individual's social relations and esteem within society are degraded. In a society without crime, everyone maintains a sense of social belonging, and an individual's good reputation is the reward for refraining from criminal activity.

An offender is defined as having a "bad reputation" if apprehended following the commission of the act. The rationale is that the individual loses social legitimacy due to negative information about their status resulting from the arrest. Consequently, bad reputation is considered the reputational sanction arising from arrest. As Iacobucci (2014) explains, reputational sanctions are not independent from legal sanctions but partially depend on them. Modifying legal sanctions to account for the reputational effects of misconduct changes the resulting reputational impact.

2.1.2. Reputational Gain

Due to the difficulty of estimating non-monetary gains, to our knowledge, few studies have focused on analyzing non-monetary benefits as a motivation for illegal acts. We attempt to explain that criminal behavior can be motivated by factors other than monetary rewards. This motivation can take several forms: *moral factors*, *psychological satisfaction*, *emotional motives* (e.g., crimes of passion), and *social influence*.

We therefore define non-monetary gain as the advantage associated with preserving the individual's reputation among peers when they are not apprehended despite committing a crime. Other members of society have no information about the offender's illegal behavior unless the offender is caught by law enforcement after committing a harmful act. An offender maintains a "*good reputation*" if they are not detected.

There is a crucial difference between "*being arrested*" and "*being punished*." Indeed, "*being apprehended*" does not necessarily mean that the arrested individual will be punished. From another perspective, arrest itself constitutes a reputational sanction. To clarify, one must distinguish between the formal sanction (fines or imprisonment) imposed by the legal authority and the reputational sanction linked to the social status of the apprehended offender. For example, a criminal's bad reputation in the eyes of neighbors constitutes a reputational sanction if they are arrested for committing an illegal act.

Clearly, not being apprehended provides a double benefit to the offender. In addition to the monetary gain derived from the illegal act, the criminal also maintains their social status, as they are still perceived as an honest individual because they were never apprehended. In most cases, offenders who are arrested face social reintegration challenges due to public opinion, which tends to conclude hastily that criminals are a danger to society. Such circumstances amount to a reputational penalty for the offender.

The generalization of this viewpoint leads to the social exclusion of individuals who have engaged in compromising acts. Conversely, not being apprehended after committing a crime allows the offender to preserve their good reputation or social value, which is inherently non-monetary.

Through this analysis, we seek to establish a relationship between non-monetary motivation, gains, harm, and the probabilities of detection and punishment.

2.2. Studied Environment

We consider a risk-neutral individual whose motivation to engage in criminal activity is driven not only by the monetary gain, denoted by b, but also by a non-monetary gain aggregated as r. These factors may include psychological satisfaction, social esteem, reputation, or other intangible benefits that the offender obtains after committing the crime. They contribute to the utility derived from the criminal act, increasing the offender's utility level upon committing a crime.

Evidently, the law enforcement authority does not know the value of r. We assume that r follows a cumulative distribution function G and a density function g. This implies that the non-monetary motivation is a random variable, with cases where:

i) the crime is purely monetarily motivated,

ii) the crime is purely non-monetarily motivated, and

iii) the motivation is a combination of both factors.

The analysis in this section considers the coexistence of both monetary and non-monetary motivations for crime.

Furthermore, we assume that the non-monetary gain takes the form of reputation r, which is labeled "***good***" or simply "***good reputation***" if the criminal is not apprehended. Intuitively, good reputation does not negatively affect the individual's utility. In other words, an individual maintains a good social reputation even if a crime is committed, as long as the offender is not arrested. This reputation immediately turns into "***bad reputation***" if the individual is apprehended while committing the crime. Thus, bad reputation negatively affects the individual's utility.

Defining the states of nature and the utility function allows us to outline the steps in the realization of a criminal act. We consider three states of nature E_1, E_2, and E_3:

- E_1: The individual commits a crime but is not apprehended.
- E_2: The individual commits a crime and is apprehended (arrested), but not necessarily punished.
- E_3: The individual is arrested and ultimately punished.

State E_1 corresponds to committing a crime without arrest. It is associated with a utility function $u_1(b, r)$ such that $u_1(b, r) = b + r$, where b is the monetary gain and r is the reputational gain. Both variables positively influence u_1.

State E_2 represents the situation where the individual is apprehended. Arrest does not imply immediate punishment. In practice, an arrested individual undergoes administrative or judicial procedures, subject to the presumption of innocence, until a final court decision is made (Obidzinski & Oytana, 2018). Intuitively, arrest destroys the non-monetary reputation r. This state is associated with a utility function $u_2(b, r)$ such that $u_2(b, r) = (b + r) - r = b$. Here, monetary gain remains, but the reputational gain is neutralized.

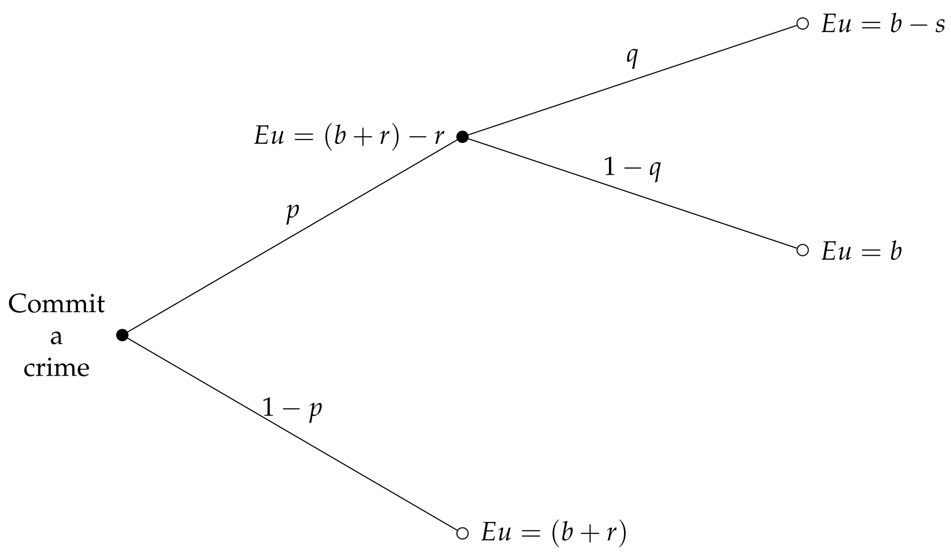
State E_3 corresponds to final punishment. After arrest and due process, the individual receives a sanction s (assumed $s \geq b$). The associated utility function is $u_3(b, s) = b - s$, reflecting the negative effect of punishment on monetary gain.

Punishment is therefore a complementary instrument, fully dependent on arrest. It deters both monetary and non-monetary motivations. It is impossible to punish an offender without prior apprehension. Hence, state E_3 is conditional on the existence of E_2 and E_1.

Each state of nature is associated with a probability, as each event may or may not occur. An individual who commits a crime may or may not be apprehended, and an arrested individual may or may not be punished. This departs from the traditional assumption in law and economics that punishment automatically follows detection.

To visualize all possibilities, Figure 3 illustrates the sequence of events, associated probabilities, and corresponding gains.

Figure 3: Event Tree and Reputation Outcomes



Source: Author

The three states and their respective probabilities and utilities are summarized in Table 4.

We can summarize as follows:

- $(1 - p)(b + r)$: No arrest; the offender keeps both monetary gain b and reputational gain r.

Table 4: Payoffs in the Three States of Nature

E_i	**Utility Function** u_i	**Probability** δ_i
E_1	$u_1(b,r) = b + r$	$(1-p)$
E_2	$u_2(b,r) = (b+r) - r$	$p(1-q)$
E_3	$u_3(b,s) = b - s$	pq

Source: Author

- $p(1-q)[(b+r)-r]$: Arrest without punishment; the offender keeps monetary gain b, but reputation is lost.
- $pq(b-s)$: Arrest and punishment; monetary gain is reduced by sanction s.

From Table 4, we can write the expected utility in the sense of von Neumann et al. (1944)[1]:

$$Eu_i = (1-p)u_1 + p\big[(1-q)u_2 + qu_3\big] \tag{5}$$

Substituting the values of u_i gives:

$$Eu_{p,q} = (1-p)(b+r) + p\big[(1-q)((b+r)-r) + q(b-s)\big] \tag{6}$$

After simplification, we obtain:

$$Eu_{p,q} = b - pq\,s + r - pr \tag{7}$$

Here, $b - pq\,s$ is the expected monetary payoff, while $r - pr$ is the expected non-monetary (reputational) payoff.

Proposition 3 *If there is no arrest and thus no punishment (as the two events are dependent), the offender anticipates a double gain: the monetary gain b plus the reputational gain r.*

Proof 3 If $p = 0$, then necessarily $q = 0$ (since no arrest implies no punishment). Hence, $Eu_{0,0} = b - 0 \cdot 0 \cdot s + r - 0 \cdot r = b + r$.

Proposition 4 *If arrest is certain, the expected reputational gain is zero, and for any value of q, we obtain the canonical deterrence model $b - qs$ of Becker (1968).*

Proof 4 If $p = 1$, then for any q, $Eu_{1,q} = b - 1 \cdot q \cdot s + r - 1 \cdot r = b - qs$.

Proposition 5 *Even if punishment is uncertain ($q = 0$), an optimal probability of arrest ($p > 0$) can be sufficient to nullify the reputational gain ($r = 0$ as the effect of reputational loss after arrest).*

[1]The expected utility model of von Neumann et al. (1944) is $Eu_i = \sum_{i=1}^{n} \delta_i u_i$, with $\sum_{i=1}^{n} \delta_i = 1$. Here $n = 3$ is the number of states of nature, and δ_i the probability associated with state X_i. We have $\delta_1 = (1-p)$, $\delta_2 = p(1-q)$, and $\delta_3 = pq$.

Proof 5 Differentiating expected utility with respect to p:

$$\frac{\partial Eu}{\partial p} = \frac{\partial[b - p(r + qs)]}{\partial p} = -(r + qs)$$

Setting $q = 0$ yields $\frac{\partial Eu}{\partial p} = -r$. Thus, as p increases, reputational gain is neutralized ($r = 0$).

Remarks

In the cost–benefit analysis of crime, several scenarios are possible:

- If $Eu_{p,q} > 0$, the individual will commit the crime because the expected utility of engaging in the criminal activity is positive. If the expected benefit of the criminal activity exceeds the deterrence constraints, crime will persist, i.e., $b - p(r + qs) > 0$. It is advantageous to engage in crime since the gain exceeds the cost.
- If $Eu_{p,q} < 0$, the individual will not commit the crime because the expected utility of committing the crime is negative. In other words, if the expected gain from criminal activity is lower than the deterrence constraints, crime will be deterred, i.e., $b - p(r + qs) < 0$. It is not profitable to become a criminal because the gain is less than the combined cost of detection and punishment.
- If $Eu_{p,q} = 0$, there are two possibilities: if the individual is risk-averse, they will not commit the crime; otherwise, they will proceed with the criminal activity.

We consider the third case, $Eu_{p,q} = 0$, and assume that the individual under study is risk-neutral with respect to the risk of arrest, bad reputation, and sanction. From $Eu_{p,q} = 0$, we obtain the key relationship:
$b = p(r + qs)$

We conclude that an optimal probability of arrest can neutralize the reputational gain (i.e., an optimal arrest probability eliminates r, implying $r = 0$). In this case, the relationship between monetary gain and punishment becomes:
$b = qs$

This is the canonical deterrence equation of Becker (1968), which states that the expected gain must be equivalent to the fine imposed on the offender, where the relevant probability is that of conviction.

2.3. Incorporating Reputation

After meeting the condition that arrest neutralizes the reputational gain, we now focus on how to deter crime by acting on the probability of arrest, the probability of punishment, and the severity of the sanction itself. The level of deterrence can be evaluated by comparing the benefit and cost of the illegal activity and by accounting for the costs of arrest and conviction until the offender's expected gain equals the sanction imposed. There is also an approach to evaluating deterrence strategies based on minimizing the cost of crime detection, which corresponds to maximizing social welfare by establishing an effective level of deterrence or an optimal level of sanction.

The model presented in this section is inspired by Garoupa (1997, 2001), with an extension that explicitly separates apprehension from conviction while including non-monetary gains in social welfare. Considering both monetary and reputational benefits, and the costs generated by crime, social welfare can be expressed as:

$$W = \int_0^{\tilde{r}} \int_{qs}^{\bar{b}} (r + b - h)\, dG(r)\, dF(b) - C(p, q) \tag{8}$$

where $\tilde{r} = p \cdot r$ is the expected reputation, $\bar{b}$ is the maximum monetary benefit, S is the maximum sanction, $C(p, q)$ is the cost of arrest and conviction, and h is the harm suffered by honest individuals as a result of criminal activity. Note that this model does not account for non-monetary social damages, which remain an important field of analysis.

The public authority aims to maximize W:

$$\max_{(p,q,s)} W = \int_0^{\tilde{r}} \int_{qs}^{\bar{b}} (r + b - h)\, dG(r)\, dF(b) - C(p, q) \tag{9}$$

subject to:

$$\tilde{r} = p \cdot \bar{r}, \quad s \leq S$$

To simplify the welfare maximization problem, we assume that reputation r is an exogenous variable that the authority cannot directly influence. Reputation can only be neutralized indirectly through arrest probability. In other words, the authority cannot act directly on r, but can affect it through p. This leads to a simplified welfare expression:

$$\max_{(p,q,s)} W = \int_{p(r+qs)}^{\bar{b}} (r + b - h)\, dF(b) - C(p, q) \tag{10}$$

subject to:

$$s \leq S$$

The first-order conditions $\frac{\partial W}{\partial p} = 0$, $\frac{\partial W}{\partial q} = 0$, and $\frac{\partial W}{\partial s} = 0$ lead to the following relationships:

$$C_p = (r + qS)\big(r + h - p(r + qS)\big) f\big(p(r + qS)\big) \tag{11}$$

where $C_p = \frac{\partial C(p,q)}{\partial p}$ is the marginal cost of arrest.

$$C_q = pS\big(r + h - p(r + qS)\big) f\big(p(r + qS)\big) \tag{12}$$

where $C_q = \frac{\partial C(p,q)}{\partial q}$ is the marginal cost of conviction.

$$pq\big(r + h - p(r + qS)\big)f\big(p(r + qS)\big) = 0 \tag{13}$$

2.4. Results and Discussion

Let $\psi = \big(r + h - p(r + qS)\big)f\big(p(r + qS)\big)$. Then,

$$C_p = \big(r + qS\big)\psi \tag{14}$$

An additional unit increase in the probability of arrest leads to a higher marginal cost of arrest (i.e., $\frac{\partial C(p,q)}{\partial p} > 0$, or equivalently $C_p > 0$). For this inequality to hold, we must have $\psi > 0$, because $\big(r + qS\big)f\big(p(r + qS)\big) > 0$ is always positive.

In practice, this implies that $(r - pr)$ must be positive and $h - pqS$ must also be positive. The sum of two positive elements is positive, so the following conditions must hold to ensure $C_p > 0$:

$$r > pr, \quad h > pqS$$

We observe that an increase in the probability of arrest p reduces the level of reputation. This decline is expressed by $(r - pr)$: as p approaches 1, r approaches 0, i.e., the disappearance of reputation. This highlights the deterrent effect of the arrest probability on criminal behavior when crime is motivated by non-monetary gains. In other words, reputation decreases with p.

Conversely, a reduction in reputation should reduce the offender's willingness to commit further crimes for a given probability of arrest. Therefore, the marginal cost of arrest, even if punishment is improbable ($q = 0$), negatively impacts the non-monetary marginal benefit. If the motivation for the illegal act is purely non-monetary, it is sufficient to act on p to eliminate reputational gain. In this case, there is no need to allocate additional resources to increase q, since doing so would increase enforcement costs. In other words, it is not necessary for q to equal 1; it is sufficient that $q < 1$ to save resources in punishment enforcement.

Arrest thus becomes an instrument that modifies criminal behavior by exerting a deterrent effect on reputation. For $q = 0$, the marginal cost of arrest simplifies to:

$$C_p(0) = r\big(r - pr + h\big)f(pr)$$

which is lower than:

$$C_p(q) = \big(r + qS\big)\big(r - pr + h - pqS\big)f\big(p(r + qS)\big)$$

for any fixed q.

By a similar reasoning, we also have:

$$C_q = pS\psi \tag{15}$$

An additional unit increase in the probability of punishment q raises the marginal cost of punishment ($\frac{\partial C(p,q)}{\partial q} > 0$, hence $C_q > 0$). For this to hold, $\psi = \big(r + h - p(r + qS)\big) > 0$, because $pSf\big(p(r + qS)\big) > 0$ is always positive.

According to our initial hypothesis, arrest must occur (or be certain) before any punishment can be applied. Therefore, $p = 0$ is inconceivable if punishment is to occur. When $p = 1$, we analyze $h - qS$, since the effect of reputation has been neutralized.

An increase in the probability of punishment q reduces the monetary gain until the total harm is offset by the monetary sanction S, i.e., as $q \to 1$, $S \to h$. This demonstrates a deterrent effect of punishment probability on criminal behavior when the motivation is both monetary and non-monetary. In other words, the monetary benefit decreases with q.

From equations (13), (14), and (15), we obtain the following system of equations:

$$\begin{cases} C_p = \big(r + qS\big)\psi \\ C_q = pS\psi \\ pq\big(r + h - p(r + qS)\big)f\big(p(r + qS)\big) = 0 \end{cases} \tag{16}$$

We previously showed that reputation disappears once arrest occurs. After this intervention, crime deterrence relies on q and s to address social harm.

Equation $C_p = \big(r + qS\big)\psi$ can be rewritten as:

$$\psi = \frac{C_p}{r + qS}$$

Using this in $C_q = pS\psi$ yields a relationship between the marginal costs:

$$pS\left(\frac{C_p}{r + qS}\right) = C_q \tag{17}$$

This result can be interpreted in two ways: first, as potential substitutability between arrest and punishment costs; second, as evidence of their complementarity.

Garoupa (2001) discusses the substitutability between the severity and probability of enforcement, given the high costs of law enforcement. Our approach differs: we focus on the substitutability or complementarity between the *costs* of arrest and punishment. If enforcement costs are substitutable, we assume that marginal costs are also substitutable.

Proposition 6 ***Substitutability of arrest and punishment - optimal monetary sanction*** *If the motive for the crime is purely monetary ($r = 0$), under an interior optimum with $p, q \in (0, 1)$ and substitutability ($C_p = C_q$), the optimal monetary sanction as a function of the* *conviction probability q is*

$$S^*(q) \;=\; \frac{h}{q^2}$$

Equivalently, $p^* = \sqrt{\frac{h}{S^*(q)}} = q$ and the s–FOC binds as $p^* q\, S^*(q) = h$.

Proof 6 *From the first-order conditions with respect to p and q in equations (11)–(15), we have*

$$C_p \;=\; (r + qS)\,\psi \quad \text{and} \quad C_q \;=\; pS\,\psi,$$

where

$$\psi \;\equiv\; \big(r + h - p(r + qS)\big)\, f\big(p(r + qS)\big).$$

Under substitutability, we impose equality of marginal costs $C_p = C_q$, hence

$$r + qS \;=\; pS. \tag{18}$$

The first-order condition with respect to s delivers

$$\frac{\partial W}{\partial s} \;=\; p\,q\,\psi \;=\; 0.$$

At an interior optimum ($p > 0$, $q > 0$), this implies $\psi = 0$, i.e.

$$r + h \;=\; p\,(r + qS). \tag{19}$$

Combining equation (18) and equation (19) yields

$$r + h \;=\; p\,(pS) \;=\; p^2\, S \quad \Longrightarrow \quad p^* \;=\; \sqrt{\frac{r + h}{S}}.$$

Using equation (18) again, the associated q^* is

$$q^* \;=\; \frac{p^* S - r}{S} \;=\; \sqrt{\frac{r + h}{S}} \;-\; \frac{r}{S}.$$

Finally, from equation (18) we also have $S\big(p^* - q^*\big) = r$, so

$$S \;=\; \frac{r}{p^* - q^*} \qquad \text{and} \qquad \text{equivalently} \quad S \;=\; \frac{\big(r + qS\big)^2}{r + h} \;\; \text{(via equation (19))}.$$

Purely monetary benchmark. *When $r = 0$, the result reduce to*

$$p^* \;=\; \sqrt{\frac{h}{S}} \quad \text{and} \quad q^* \;=\; p^*,$$

and combining equation (18) with $\frac{\partial W}{\partial s} = 0$ *gives the familiar closed form*

$$S^*(q) \;=\; \frac{h}{q^2}.$$

Proposition 7 ***Complementarity of arrest and punishment - optimal monetary sanction*** *If punishment is complementary to apprehension (it can be imposed only conditional on detection), then at the interior optimum* $p^* = 1$ *and the optimal monetary sanction is*

$$S^*(q) \;=\; \frac{h}{1-q} \qquad 0 < q < 1.$$

Proof 7 *Under complementarity, punishment can be applied only after detection; we consider certain apprehension* $p = 1$*. Plugging* $p = 1$ *into equations (11)–(12) yields*

$$C_1(q) \;=\; (r + qS)\,(h - qS)\,f(r + qS), \qquad C_q(1) \;=\; S\,(h - qS)\,f(r + qS).$$

At an interior optimum with $h - qS \neq 0$*, the condition* $C_1(q) = C_q(1)$ *implies*

$$r + qS \;=\; S \quad\Longleftrightarrow\quad S^* \;=\; \frac{r}{1-q},$$

and all bullets in the lemma follow: $p \neq q$ *in general,* $p = 1$ *with* $0 < q < 1$*, and equality of marginal costs arises only under certain apprehension (*$p = 1$*).*

If the resources allocated to law enforcement are substantial, it is reasonable not to pursue the maximum sanction to avoid resource waste. In some cases, arrest alone may suffice to deter a potential offender. Thus, $q < 1$ is preferable to conserve resources.

If $q = 0$, the optimal sanction reduces to reputational loss, $S^* = r$. If $q \to 1$, the optimal monetary sanction becomes very high, and the maximum sanction can be optimal (Garoupa, 2001). This is consistent with the classic interpretation of maximum fines in Becker (1968) and Polinsky and Shavell (2000), where the sanction is the harm divided by the probability of enforcement.

2.5. Summary and Key Insights

This section demonstrates that punishment cannot be applied without prior detection. To deepen the study of deterrence models in public law enforcement, we have developed an extension of the classic frameworks. The scientific contributions of this research are as follows:

- the relaxation of the standard assumption that the probability of arrest and the probability of punishment are identical,
- the inclusion of non-monetary gains, which constitute one of the key motivating factors for criminal behavior.

Beyond monetary gain, the proposed model incorporates the non-monetary motivation that drives offenders to commit crimes. An offender's reputation vanishes if they are apprehended for a crime.

Unlike the substitutability between severity and certainty often assumed in the literature, we suggest that apprehension and punishment are dependent events. An increase in the probability of arrest (respectively, the probability of punishment) reduces the level of reputation (respectively, the expected monetary gain). This implies a deterrent effect of arrest probability (punishment probability) on crime when the motivation is a non-monetary benefit (monetary gain).

We have shown that if the probability of arrest is optimal, reputation disappears ($r = 0$). If apprehension and punishment costs are substitutable and $p = q$, the optimal sanction is:

$s^* = \frac{h}{p}$

This result is consistent with the theoretical findings of previous work, such as the suggestion of Polinsky and Shavell (2000). If the variables are complementary (or interdependent), we have shown that the maximum sanction is the optimal sanction. Such a policy allows for greater resource savings in the allocation of law enforcement efforts.

In this section, we explored the fundamental distinction between arrest and punishment, emphasizing that punishment—an essential element of the penal system—cannot be effectively implemented without prior arrest. This preliminary arrest phase serves as an indispensable prerequisite for any subsequent punitive action.

In the following section, we focus on the mechanism of deterrence and damage compensation, examining the equivalence between maximizing revenue from legal activity and minimizing both harm and the potential gains from illegal activity.

3. Deterrence and Compensation Mechanisms

In the field of law and economics, it is common to begin the discussion with the approach of Becker (1968), as presented in his seminal 1968 work. We recall that the optimal approach to crime deterrence combines two key elements: the probability of detection and the severity of sanctions (Becker, 1968; Friehe & Miceli, 2017). Consequently, law enforcement plays a crucial role in deterring criminal activity and providing justice[2] to victims.

[2]Recently, Miceli (2021) compared and contrasted two economic theories of criminal justice: the model of Becker (1968) and the model of Adelstein (2017). Becker's model aims to prescribe optimal enforcement policy to maximize social welfare, while Adelstein's model seeks to describe the actual operation of the system in imposing sanctions. This section explores the implications of these perspectives for social welfare and the criminal justice system, and their relation to the debate between deterrence and restorative justice.

In the context of illegal activity that causes harm to victims, it is natural to first repair the harm, then apply punishment.

However, it is impossible to compensate for harm if the perpetrator of the wrongful act is not detected. Judicial sanctioning (criminal procedure) thus follows civil compensation (tort procedure). This section aims to combine civil liability[3] and criminal liability[4].

It can be more efficient to repair harm before applying the sanction. When victims are compensated promptly, the negative externalities of the illegal activity are reduced. This approach aligns with economic efficiency by minimizing the overall social cost of the wrongful act. Moreover, compensating victims can incentivize them to report crimes and cooperate with law enforcement authorities. If victims know they will be adequately compensated, they are more likely to come forward and assist in apprehending and convicting offenders. Such cooperation can strengthen the effectiveness of judicial procedures (Feess & Walzl, 2004; Innes, 2017).

Respecting a legal order that begins with compensation is consistent with procedural regularity and fairness. It ensures that accused individuals have the opportunity to defend themselves and that their guilt or innocence is determined in a fair trial (Meron, 2021). This idea recognizes that harm repair and punishment are sequential decisions. First, the focus is on compensating victims for the harm caused, which can be evaluated and reimbursed using clear criteria. Then, the criminal justice process can proceed, with its foundations strengthened by prior compensation.

Detection of offenders not only facilitates harm compensation but also serves to deter individuals from engaging in illegal activities. Knowing that illegal acts are likely to be detected and sanctioned can discourage potential offenders.

The principle that harm cannot be repaired without prior detection is grounded in the practical requirements of the legal process, the principles of liability, and the need for an effective and fair judicial system. Detection is a fundamental step toward achieving justice and fair victim compensation.

Secondly, we assume that conviction is a detection-dependent event. This assumption underlines the crucial role of detection in the judicial process, especially in criminal cases where conviction leads to sanctions or penalties.

punishment cannot be applied without prior detection. This suggests a direct and dependent relationship between detection and sanction: detection is the necessary first step before the application of punishment. This illustrates the essential role of detection in law enforcement for successful sanction implementation.

[3]The literature on the economic analysis of tort law is extensive; see for example Stigler (1970), Green (1976), Landes and Posner (1987), Cooter (1989), Lando (1997), Craswell (1999), Dari-Mattiacci (2003).

[4]See for example Becker (1968), Garoupa (1997), Polinsky and Shavell (2000, 2007), Harel and Hylton (2012), Miceli (2021).

The alternative approach developed in this section seeks to strike a balance between deterrence and compensation, acknowledging the conflicting objectives of punishment and harm repair. Optimal deterrence may be achieved through legal reforms such as capping the highest possible damages (Craswell, 1999).

In this section, we design three distinct models: We first develop a simple perfect-information model (3.1), where the illegal gains and legal income are perfectly known. We then analyze an imperfect-information model (3.2), implementing the mechanisms proposed in the optimal law enforcement model. Finally, we extend the model (3.3) by distinguishing between the arrest event (which enables harm repair) and the conviction event (which allows punishment to be applied).

3.1. Simplified Model Proposal

In our analysis, we assume that the honest agent does not take any precaution as a form of private deterrence. This assumption implies that the harm suffered by the honest agent is not mitigated unless the criminal act is detected.

Two mechanisms are proposed:

- $m(s)$: the **deterrence mechanism**, which aims to maximize the income from legal activity while imposing sanctions (fines) on illegal activity,
- $m(h)$: the **harm compensation mechanism**, which aims to minimize the damage and illegal gains caused by criminal activity.

Intuitively, these two mechanisms are equivalent and lead to the same result.

We define the following variables:

- p: Probability of detection and conviction
- y: Income of the honest agent undertaking legal activity
- b: Income of the agent undertaking illegal activity
- S: Sanction (fine)
- h: Harm suffered by the honest agent

In a context where crime exists, the utility of the honest agent can be expressed as:

$$\begin{gathered} Eu_y = (1-p)(y-h) + py \\ \text{or equivalently } Eu_y = y - (1-p)h \end{gathered} \tag{20}$$

The expected utility of the dishonest agent is classically defined as:

$$Eu_b = (1-p)b + p(b-S)$$
$$\text{or equivalently } Eu_b = b - pS \tag{21}$$

By assumption, we impose:

$$y - b = h$$

This assumption captures the idea that an honest individual is disadvantaged by choosing legal activity since illegal income may appear more attractive. Here, h measures the gap between the income from legal and illegal activities.

The interpretation of this relationship is that part of the honest individual's wealth is effectively transferred to the offender, and h reflects the impact of b on y. This can also be viewed as a measure of the income inequality between legal and illegal activities: as long as illegal activity is attractive, there will be some harm h.

Conversely, if incomes are equal ($y = b$), there is no harm ($h = 0$) because the individual is indifferent between the two activities. Here, h measures the gap between the returns of illegal and legal activity. If one activity is more attractive, the rational individual will choose the one that maximizes income.

In other words, the harm suffered by the honest agent is directly linked to the financial incentive to engage in illegal activity. If income from illegal activity (b) is substantially higher than legal income (y), the harm to the honest agent (h) is greater, as the potential return to crime is more tempting. Conversely, if illegal returns are relatively low, the harm to the honest agent is smaller because there is less incentive to engage in illegal behavior.

The decision to commit an illegal act is consistent with the idea of Becker (1968): the offender behaves rationally, choosing the illegal activity as long as its expected benefit exceeds that of remaining honest. An individual considers an action that provides a gain b but imposes a harm h.

In this analysis, we continue to assume that the honest agent does not take private precautions as a deterrence mechanism.

3.1.1. Deterrence Mechanism

The first mechanism is deterrence through the enforcement of a sanction, denoted by $m(S)$. Implementing deterrence consists of comparing the income from legal activity with the expected income from illegal activity under the influence of the sanction S. Based on this idea, we can write:

$$m(S) = \max\left(y\,;\, b - pS\right) \tag{22}$$

In this model, $b - pS$ represents the expected utility or gain obtained by an individual engaging in illegal activity, considering different values of the sanction (S). The objective is to compare this expected utility with the wealth of the honest individual (y) and determine whether it is more advantageous to engage in legal or illegal activities.

The max function in equation (22) indicates that the individual chooses the option that maximizes expected utility. If the expected utility of illegal activity $(b - pS)$ exceeds their legal wealth (y), they may choose to engage in illegal activity, considering the risk of detection and the associated sanction. Conversely, if legal wealth is higher than the expected gains from illegal activity, the individual will choose the legal option.

Illustration

Consider the case of tax evasion to illustrate this mechanism. We take a taxpayer with a legal income (or wealth) of 30,000 monetary units (M.U.) per year. This represents the income from an honest job or legal activity. The tax authority has a solid enforcement system, and the probability of being audited and detected for tax fraud is relatively low, estimated at $p = 0.25$ (25%). The authority also imposes severe penalties on tax evaders: if caught, the offender must pay a fine of 20,000 M.U. and may face prosecution.

Tax evasion provides an immediate financial benefit. For each monetary unit evaded, the individual gains 1.50 M.U. However, this gain is illegal, and if the individual is caught, they must pay the fine S and risk judicial proceedings.

Table 5: Expected Utility – Tax Evasion Scenarios

Amount Evaded	Illegal Gain	Sanction	Expected Utility
15,000	15,000 $\times$ 1.5	0.25 $\times$ 20,000	17,500
20,000	20,000 $\times$ 1.5	0.25 $\times$ 20,000	25,000
25,000	25,000 $\times$ 1.5	0.25 $\times$ 20,000	32,500

Source: Author

We now implement the deterrence mechanism. When the individual considers committing tax evasion, they calculate expected utility for different levels of evasion:

- If they evade 15,000 M.U.:

$$\max(30,000\,;\,15,000 \times 1.5 - 0.25 \times 20,000) = \max(30,000\,;\,17,500) = 30,000$$

- If they evade 20,000 M.U.:

$$\max(30,000\,;\,20,000 \times 1.5 - 0.25 \times 20,000) = \max(30,000\,;\,25,000) = 30,000$$

- If they evade 25,000 M.U.:

$$\max(30,000\,;\,25,000 \times 1.5 - 0.25 \times 20,000) = \max(30,000\,;\,32,500) = 32,500$$

Comparing these expected utilities with the individual's legal wealth ($y = 30{,}000$ M.U.) leads to a rational decision:

- If $b - pS > y$, the individual may choose to engage in tax evasion because the potential financial gain exceeds the legal alternative.
- If $b - pS \leq y$, the individual will likely opt for honest tax compliance, since legal income is sufficient and avoids the risk of detection and sanction.

In our case, it is rational for the individual to avoid tax evasion as long as the expected utility from evasion does not exceed 30,000 M.U.

3.1.2. Compensation Mechanism

The second mechanism, denoted $m(h)$, focuses on minimizing the harm and the income from illegal activity. This mechanism represents the compensation of harm using the revenue generated from the illegal activity. It consists in finding the minimum between the revenue from illegal activity and the income from legal activity reduced by the harm suffered by the honest agent. Here, y represents the legal income under the impact of harm h caused by the illegal act:

$$m(h) = \min\big(y - (1-p)h\,;\, b\big) \tag{23}$$

In equation (23), $y - (1-p)h$ represents the expected utility of an individual who remains honest (the victim). The goal is to minimize harm while considering both legal and illegal income sources. The min function indicates that the individual chooses the option that minimizes harm and reduces the illegal activity's net gain.

Example

Consider the case of environmental pollution and clean energy. Suppose an individual earns 50,000 M.U. per year from a legal (clean energy) activity. If an illegal polluter is not apprehended, the honest agent bears the harm. The probability of not being caught for environmental crimes, such as illegal waste dumping, is high, estimated at 0.8 (80%). Each unit of illegal pollution causes a harm of 5,000 M.U. to victims, while each unit of illegal pollution generates an immediate gain of 10,000 M.U.

Table 6: Expected Utility – Illegal Pollution Scenarios

Pollution Units	Harm Caused	Illegal Gain	Expected Utility
1	5,000	10,000	46,000
2	10,000	20,000	42,000
3	15,000	30,000	38,000

Source: Author

We now implement the mechanism. When the individual considers engaging in illegal pollution (b), they compute the expected utility for different levels of pollution and corresponding harm:

- For low pollution (one unit) causing $h = 5{,}000$ M.U.:

$$m(h) = \min\left(50{,}000 - 0.8 \times 5{,}000\,;\, 10{,}000\right) = \min(46{,}000, 10{,}000) = 10{,}000$$

- For moderate pollution (two units) causing $h = 10{,}000$ M.U.:

$$m(h) = \min\left(50{,}000 - 0.8 \times 10{,}000\,;\, 20{,}000\right) = \min(42{,}000, 20{,}000) = 20{,}000$$

- For high pollution (three units) causing $h = 15{,}000$ M.U.:

$$m(h) = \min\left(50{,}000 - 0.8 \times 15{,}000\,;\, 30{,}000\right) = \min(38{,}000, 30{,}000) = 30{,}000$$

If $y - (1-p)h \leq b$, the individual may choose to engage in illegal pollution considering the potential financial gain and the high probability of avoiding detection. If $y - (1-p)h > b$, the individual will likely continue honest employment in clean energy, as the legal income is sufficient and avoids harming the environment and neighboring communities.

Intuitively, for effective deterrence, both mechanisms are equivalent and lead to the same outcome. There is a clear equivalence between the deterrence mechanism and the harm compensation mechanism. In other words, the Authority must ensure that both mechanisms coincide, $m(s) = m(h)$, i.e.,

$$\max\left(y\,;\, b - pS\right) = \min\left(y - (1-p)h\,;\, b\right) \tag{24}$$

3.1.3. Results and Propositions

The equality in equation (24) suggests a deep link between deterrence and harm compensation in the context of law enforcement. On one hand, deterrence seeks to discourage individuals from engaging in illegal behavior by making it less attractive than legal alternatives. One way to achieve this is by imposing sanctions (S) that have a deterrent effect and reduce the expected benefits of illegal actions.

On the other hand, harm compensation aims to indemnify victims for the damages caused by illegal behavior, effectively reducing the negative externalities of the offense. Compensation ensures that victims are reimbursed and that harm is minimized. Both mechanisms share a common goal: reducing the incidence of illegal behavior and its negative consequences. Deterrence seeks to prevent illegal acts from occurring, while harm compensation mitigates the impact of offenses that still occur. When deterrence is effective, the need for harm compensation decreases because fewer offenses take place.

Conversely, when harm compensation is complete, it addresses the consequences of offenses committed and contributes to overall deterrence. This illustrates the balance that law enforcement authorities must strike. To achieve effective deterrence, they must ensure that the potential costs (sanctions) of illegal behavior outweigh the potential benefits (illegal income). Simultaneously, authorities must ensure that harm compensation mechanisms are in place to address the consequences of offenses that occur despite deterrence, including compensating victims and minimizing the harm they suffer.

The equality

$$\max(y\,;\, b - pS) = \min(y - (1-p)h\,;\, b)$$

summarizes the idea that deterrence (max) and harm compensation (min) should lead to the same outcome. In other words, the severity of sanctions (S) must correspond to the harm suffered by victims (h) and the potential benefits of illegal activity (b). If this equation holds, it indicates that the penal system is properly calibrated: the deterrence mechanism effectively reduces illegal behavior, and the harm compensation mechanism ensures that when offenses occur, victims are adequately indemnified.

Proposition 8 *If information on the illegal gain (b) is perfect, then deterrence is effective and harm is avoided when both mechanisms are implemented.*

Proof 8 The individual is deterred when the expected income from legal activity ($y > b - pS$) is more attractive than illegal gains, hence $\max(y\,;\, b - pS) = y$.

Moreover, even in the absence of apprehension, the expected income accounting for potential harm $(y - (1-p)h)$ exceeds the illegal income (b), i.e., $\min(y - (1-p)h\,;\, b) = b$. Since $m(s) = m(h)$, we deduce that $y = b$, hence $y - b = 0$. By our assumption $y - b = h$, we obtain $h = 0$.

Proposition 9 *If the expected income from illegal activity exceeds legal income $(b - pS > y)$ and the potential illegal income in the absence of detection is higher than legal income minus potential harm $(b > y - (1-p)h)$, then the honest agent will suffer harm if the crime is not deterred. As compensation, the sanction must offset the harm.*

Proof 9 If $y < b - pS$ and $y - (1-p)h < b$, then

$$\max(y\,;\, b - pS) = b - pS \quad \text{and} \quad \min(y - (1-p)h\,;\, b) = y - (1-p)h$$

Since $m(s) = m(h)$, we have

$$b - pS = y - (1-p)h$$

and using $y - b = h$, we deduce

$$pS = (1-p)h - h \quad \Rightarrow \quad S = -h$$

The negative sign reflects the net harm borne by the honest agent.

Proposition 10 *If both legal and illegal activities are simultaneously attractive, the optimal solution to repair the harm suffered by the honest agent is*

$$S^* = -\frac{h(2-p)}{p}$$

Proof 10 If $y = b - pS$ and $y - (1-p)h = b$, then

$$\max(y\,; b - pS) = \frac{1}{2}\big(y + b - pS + |y - b + pS|\big)$$
$$\min(y - (1-p)h\,; b) = \frac{1}{2}\big(y - (1-p)h + b - |y - (1-p)h - b|\big)$$

Setting max = min yields

$$|y - b + pS| + |y - b - (1-p)h| = pS - (1-p)h$$

Substituting $y - b = h$:

$$|h + pS| + |h - (1-p)h| = pS - (1-p)h$$

Since $|h + pS|$ and $|ph|$ are positive, we obtain

$$h + pS + ph = ph - h(1-p) \quad \Rightarrow \quad S^* = -\frac{h(2-p)}{p}$$

We observe that if $p = 1$, we recover the result from proposition 9: $S = -h$. In other words, if illegal activity is certain to be detected, the penalty should match the harm caused.

Proposition 9 also implies that the optimal penalty S^* is inversely proportional to both the harm (h) and the detection probability (p). When p approaches 1 (almost certain detection), the penalty (S) is directly linked to the harm (h).

In other words, if illegal activity is almost guaranteed to be detected, the sanction should fully offset the harm caused. The magnitude of harm also influences the optimal sanction: a larger harm requires a higher sanction to compensate victims and deter crime. This equation reflects a balance between deterrence (imposing sanctions to discourage illegal activity) and harm compensation (restoring victims). To achieve optimal deterrence, the sanction must be set at

$$h\frac{2-p}{p}$$

where $\frac{2-p}{p}$ acts as a multiplier[5]. This multiplier is crucial to address the challenge of uncertain detection[6].

Specific Interpretation for $p = 1$ (Certain Detection)

When $p = 1$, i.e., detection is certain, the result simplifies to $S = -h$. This situation can be interpreted as follows:

- If illegal activities are guaranteed to be detected and sanctioned, the penalty (S) should fully compensate the harm (h) caused.
- In essence, the penal system ensures that sanctions directly offset harm, achieving a form of restorative justice. This aligns with the principle that when detection is certain, the sanction should precisely match the harm to provide full victim compensation.

3.2. Extended Model Proposal

We now assume that the law enforcement authority does not have complete information about the values of b and y. We assume $b \in [0, \bar{b}]$ and $y \in [0, \bar{y}]$, with f and z representing the probability density functions of b and y, and F and Z their respective cumulative distribution functions.

Social welfare is defined as:

$$W(b,y) = \int_{pS}^{\bar{b}} \int_{(1-p)h}^{\bar{y}} (b-y)\, dF(b)\, dZ(y) - C(p) \tag{25}$$

The objective is to design mechanisms by which offenders are deterred from committing illegal acts and the harm to honest individuals is compensated. We introduce two mechanisms, $M(b)$ and $M(y)$, expressed respectively as:

$$M(b) = \min_{(p,S)} W_b \quad \text{and} \quad M(y) = \max_{(p,h)} W_y$$

More specifically,

$$M(b) = \min_{(p,S)} W_b \tag{26}$$

where

[5]Craswell (1999) discusses constant multipliers, which can be set below or above the traditional level, and compensatory damages without any multiplier. See also Baumann and Friehe (2015).

[6]For a related approach based on punitive damages in tort law, see Cooter (1989).

$$W_b = \int_{pS}^{\bar{b}} b\, dF(b) - C(p)$$

then

$$M(b) = \min_{(p,S)} \int_{pS}^{\bar{b}} b\, dF(b) - C(p) \tag{27}$$

Mechanism $M(b)$ primarily focuses on deterring illegal activities by minimizing the expected gain from such activities. It highlights the trade-off between the probability of detection (p) and the severity of the sanction (S) in discouraging illegal actions.

The second mechanism is defined as:

$$M(y) = \max_{(p,h)} W_y \tag{28}$$

where

$$W_y = \int_{(1-p)h}^{\bar{y}} y\, dZ(y) - C(p)$$

thus

$$M(y) = \max_{(p,h)} \int_{(1-p)h}^{\bar{y}} y\, dZ(y) - C(p) \tag{29}$$

Mechanism $M(y)$ emphasizes the importance of maximizing income from legal activities while accounting for potential harm. It highlights the trade-off between legal and illegal activity, ensuring that legal activities generate the highest possible returns.

Proposition 11 *Minimizing the monetary benefit of illegal activities through the implementation of the deterrence mechanism $(M(b))$, which is equivalent to maximizing the income from legal activities through the compensation mechanism $(M(y))$, implies that the optimal sanction satisfies:*

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

Proof 11 See derivation below.

We start from the equality $M(b) = M(y)$. This equality implies that the optimal values of (p, S) in $M(b)$ are equivalent to the optimal values of (p, h) in $M(y)$. Both objectives aim to optimize total expected benefits (illegal or legal) while considering the cost of detection.

By computing the first-order conditions—taking the derivative of

$$\int_{pS}^{\bar{b}} b\, dF(b) - C(p)$$

with respect to (p, S) and the derivative of

$$\int_{(1-p)h}^{\bar{y}} y\, dZ(y) - C(p)$$

with respect to (p, h)—and enforcing the equivalence between the two mechanisms, we obtain:

$$\begin{cases} \frac{\partial W_b}{\partial S} = \frac{\partial W_y}{\partial h} \\ \frac{\partial W_b}{\partial p} = \frac{\partial W_y}{\partial p} \end{cases} \tag{30}$$

This leads to the following system of equations:

$$\begin{cases} p^2 S f(pS) = h(1-p)^2 z\big(h(1-p)\big) \\ -S^2 p f(pS) = h^2(1-p) z\big(h(1-p)\big) \end{cases} \tag{31}$$

The system shows that the adjustments (p, S) are directly linked to the harm (h) suffered. The efficiency of the legal framework lies in achieving a balance between deterrence and harm compensation. When these two mechanisms are harmonized, the penal system optimally discourages illegal activity while ensuring that harm is adequately addressed.

From the first equation of the system, we can write:

$$pSf(pS) = \frac{1}{p} h(1-p)^2 z\big(h(1-p)\big)$$

Substituting this into the second equation yields:

$$-\frac{S}{p} h(1-p)^2 z\big(h(1-p)\big) = h^2(1-p) z\big(h(1-p)\big) \tag{32}$$

After simplification, we obtain:

$$S(1-p) + hp = 0 \tag{33}$$

We observe that over-deterrence and under-deterrence are both suboptimal outcomes, and the optimal equilibrium lies in balanced deterrence that maximizes social welfare.

In equation (33), the sanction (S) is inversely related to the probability of detection (p) and directly related to the harm (h).

- When S is excessively high relative to p and h, over-deterrence occurs. Potential offenders are discouraged to the point of avoiding not only illegal but also some legal activities.

- When S is too lenient given p and h, under-deterrence occurs. Potential offenders are not sufficiently dissuaded, leading to an increase in illegal activity.

Both over-deterrence and under-deterrence carry negative consequences:

- Over-deterrence reduces economic efficiency, as individuals may abstain from productive legal activities due to excessive fear of sanctions.
- Under-deterrence increases illegal activity, harming society and undermining the rule of law.

The optimal balance is achieved when deterrence maximizes social welfare. In this equilibrium, the sanction (S) is set at a level that properly discourages illegal activity without excessively discouraging legal activity.

3.2.1. Deterrence Mechanism

We observe an inverse relationship between the fine (S) and the probability of arrest and conviction (p). The higher the probability of being caught, the lower the required fine S is likely to be.

This reflects the deterrence mechanism, where a credible threat of sanction (S) discourages criminals from engaging in illegal activity (represented by the gain b). As the probability of arrest increases, the deterrent effect becomes stronger because the expected cost of sanctions rises, thereby reducing illegal activity.

3.2.2. Compensation Mechanism

When the probability of arrest is certain $(p = 1)$, the resulting harm (h) would be zero $(h = 0)$. This means that with certain detection, the victim would be fully compensated.

Conversely, when the probability of arrest is zero $(p = 0)$, the penalty is also zero $(S = 0)$. This is logical because in the absence of arrest, no penalty can be imposed: one cannot punish an individual who has not been captured.

These results highlight the critical role of incentives in regulating illegal activities. A credible threat of harsher sanctions (S) combined with a higher probability of arrest (p) can effectively deter individuals from engaging in illegal activities. Moreover, full compensation of damages (h) in the case of certain detection reinforces the deterrent effect by ensuring that the victim does not suffer any loss.

This demonstrates that both mechanisms proposed in this section—deterrence and compensation— can significantly influence the behavior of individuals involved in illegal activities.

3.2.3. Policy Implications

The result $S(1 - p) + hp = 0$ highlights the importance of achieving optimal deterrence. Policymakers must strive to find a balance among the sanction (S), the probability of detection (p), and the harm inflicted (h). This balance ensures that the penal system effectively deters illegal activities without excessively discouraging legal activities.

This result differs from those previously found in the literature. For instance, Garoupa (1997) and Polinsky and Shavell (2007) obtained the result $s^* = \frac{h}{p}$, whereas our result corresponds to $S = h\frac{(1-p)}{p}$. Thus, policymakers must be cautious about excessive deterrence, where sanctions are disproportionately high relative to the probabilities of harm and detection. Over-deterrence can have unintended consequences, such as individuals avoiding legal activities out of fear of sanctions, leading to economic inefficiencies.

Policymakers must also take measures to avoid under-deterrence, which arises when sanctions are too lenient given the probabilities of harm and detection. Under-deterrence can lead to an increase in illegal activities and greater harm to society. It may be necessary to strengthen enforcement mechanisms and adjust sanctions accordingly.

Furthermore, policymakers should consider the allocation of resources in law enforcement and criminal justice. The result suggests that allocating resources based on expected harm, the probability of detection, and the severity of sanctions can lead to more efficient outcomes. Since the optimal balance of deterrence factors may vary across types of offenses and contexts, policies should be tailored to specific situations. For example, the approach to deterrence for financial crimes may differ significantly from that for violent offenses.

3.3. Model Comparison

In this subsection, we analyze three deterrence models by comparing the optimal sanctions as a function of the detection probability for a fixed level of harm. The first model, $s = \frac{h}{p}$, is widely documented in the literature (Garoupa, 2001). The other two models, $s = h\frac{(2-p)}{p}$ and $s = h\frac{(1-p)}{p}$, are our extensions, representing scenarios of perfect and imperfect information, respectively. Our study provides insights into deterrence mechanisms under different detection and information conditions.

Through comparative analysis, we can observe the following points.

Table 7: Comparison of Deterrence Models

$h = 100, p$	$s = \frac{h}{p}$	$s = h\frac{(2-p)}{p}$	$s = h\frac{(1-p)}{p}$
0.01	10,000	19,900	9,900
...	...	...	...
0.99	101.01	102.02	1.01

Source: Author

For a low detection probability $(p = 0.01)$:

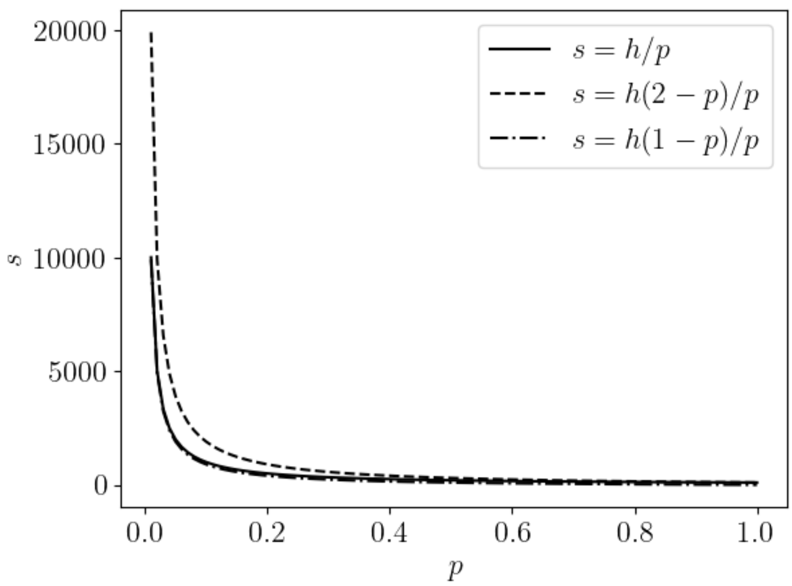
- The standard model $s = \frac{h}{p}$ (Garoupa, 2001) recommends a relatively high sanction of 10,000. This model suggests severe penalties to compensate for low detection probability, thereby reinforcing deterrence.

- Our extension under perfect information, $s = h\frac{(2-p)}{p}$, goes even further with a sanction of 19,900, reflecting a highly aggressive deterrence approach, especially when detection probability is extremely low.
- Our imperfect-information extension, $s = h\frac{(1-p)}{p}$, instead proposes a sanction of 9,900. While still high, it is less severe than the other two models, suggesting a milder deterrence approach.

For a very high detection probability $(p = 0.99)$:

- The standard model $s = \frac{h}{p}$ recommends a light sanction of 101.01, indicating that when detection probability is high, only a modest sanction is needed to maintain deterrence.
- The perfect-information model $s = h\frac{(2-p)}{p}$ prescribes a slightly higher sanction of 102.02, implying a small need for additional deterrence even at high detection levels.
- The imperfect-information model $s = h\frac{(1-p)}{p}$ results in a minimal sanction of 1.01, illustrating that with near-certain detection, the need for severe sanctions drops significantly.

Figure 4: Model Comparison



Source: Author

The standard model $s = \frac{h}{p}$ proposes that the optimal sanction is inversely proportional to the detection probability. This model supports the idea of higher sanctions to compensate for low detection, reinforcing deterrence when the chance of being caught is small.

Our perfect-information extension, $s = h\frac{(2-p)}{p}$, incorporates not only the detection probability but also the magnitude of harm when determining sanctions. This result reflects a more adaptive approach in scenarios where information is perfectly available and reliable.

The second extended model, $s = h\frac{(1-p)}{p}$, represents imperfect-information scenarios. It implies a less aggressive increase in sanctions as detection probability decreases, acknowledging the inherent uncertainty about the illegal gains a criminal may achieve.

Within our proposed framework of deterrence and harm compensation mechanisms, we have not yet distinguished between apprehension and punishment. The next analysis offers a deeper perspective by recognizing that it is inconceivable to repair harm if the offender is not apprehended, and equally impossible to apply punishment without prior apprehension.

3.4. Deterrence and Compensation

In cases of illegal activity causing harm to victims, compensation for damages should precede the application of the sanction. We recall that compensation aims to indemnify victims for the losses and suffering they have endured, while the sanction aims to punish the perpetrator of the illegal act and deter future offenses. Compensation is impossible if the perpetrator of the act is not identified.

3.4.1. New Model Assumptions

This section proposes an approach that combines the civil liability procedure (tort law) with the criminal law enforcement procedure. To reconcile damage compensation with deterrence of illegal acts, we rely on the following assumptions:

- Compensation for damages is impossible without prior detection of the perpetrator.
- Sanctions cannot be applied without identifying the perpetrator.
- Conviction is an event that depends on detection.
- We relax the traditional assumption that the probability of detection equals the probability of conviction.
- Full compensation of damages is possible if detection is certain.

3.4.2. Contextualization

In civil cases, detection is required to identify the party responsible for the harm and hold them accountable through monetary or other reparations (Posner, 1973). In criminal cases, detection is necessary to identify the perpetrator of the offense and hold them accountable through punishment or rehabilitation (Becker, 1968). Combining civil and criminal procedures in the penal system could potentially improve damage detection by streamlining the judicial process and increasing the consistency and efficiency of legal outcomes (Shavell, 1987a).

Using a single integrated procedure for both civil and criminal cases may facilitate the identification of the individuals responsible for harm and, consequently, the repair of damages caused. For an individual to be held liable for their actions, they must first be identified as the perpetrator of the offense. This is why detection is an essential component of the criminal justice process: without detection, it is impossible to impose sanctions or hold individuals accountable for their actions.

Conviction, which is the legal determination of guilt, is also a detection-dependent event. For an individual to be convicted of a crime, they must first be identified as the perpetrator. This emphasizes the critical role of detection in the penal system, as it is a necessary step in the process of ensuring accountability (Polinsky & Shavell, 2000).

Furthermore, it is important to note that the probability of detection and the probability of conviction are not identical. Detection refers to the identification of the perpetrator, while conviction refers to the formal legal determination of guilt. An individual may be identified as the perpetrator but not convicted due to insufficient evidence.

The compensation of damages caused by a crime can be complete if detection is certain. Indeed, if the perpetrator is identified and held accountable, they can be compelled to compensate the victim, which contributes to fully repairing the harm caused (Kaplow & Shavell, 1994).

Integrating civil and criminal procedures in the penal system can improve the likelihood of detection and conviction, and consequently, the likelihood of compensating victims. By using a single unified framework for civil and criminal cases, it becomes easier to identify those responsible for harm and ensure that damages are adequately repaired.

3.4.3. Deepening the New Model of Deterrence and Compensation

The extended model presented in this subsection builds on the optimal law enforcement framework (Polinsky & Shavell, 2007), but introduces a distinction between the probability of apprehension and the probability of punishment, while explicitly incorporating the possibility of compensating victims for the harm caused.

We denote:

- b: monetary benefit from the illegal act
- h: harm caused by the illegal act
- s: monetary sanction
- p: probability of apprehension
- q: probability of conviction

We consider three states of nature, E_1, E_2, and E_3, each associated with detection probabilities and corresponding payoffs in the studied environment:

- E_1: The crime is committed but the perpetrator is not apprehended. The victim suffers the harm, which remains uncompensated. This is advantageous to the offender, who retains the illegal benefit. Probability: $(1-p)$, Utility: b.
- E_2: The crime is committed, and the perpetrator is apprehended. This allows the Authority to compensate the victim for the harm h, but does not necessarily lead to punishment. Probability: $p(1-q)$, Utility: $(b-h)$.
- E_3: The crime is committed, the perpetrator is apprehended, and subsequently punished. Here, the harm is compensated, and the offender pays a monetary sanction s. Probability: pq, Utility: $(b-h-s)$.

Table 8: Compensation and Punishment Across States of Nature

E_i	**Utility Function**	**Probability**
E_1	b	$(1-p)$
E_2	$(b-h)$	$p(1-q)$
E_3	$(b-h-s)$	pq

Source: Author

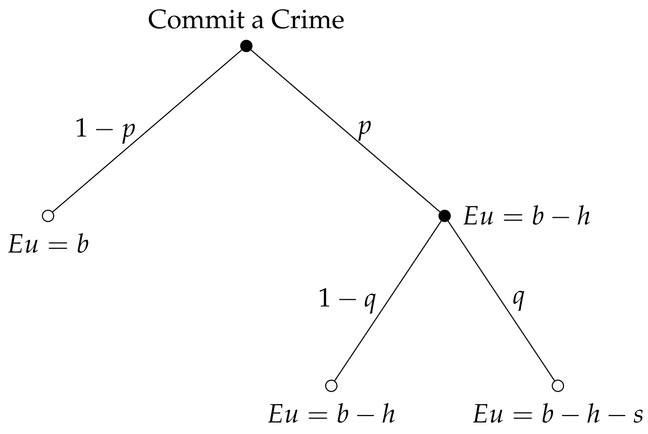
These states of nature depend on the probabilities of detection (p) and punishment (q). Higher probabilities increase the likelihood that the offender will be apprehended and punished, ensuring that the harm is repaired. Conversely, lower probabilities increase the chance that the crime remains unpunished and the harm uncompensated.

Figure illustrates the sequential events, incorporating transition probabilities and payoffs, providing a concise visual representation of the interactions between apprehension and punishment probabilities and their impacts on the expected utility of illegal activity.

The offender's expected utility can be written as:

$$Eu_{p,q} = (1-p)b + p[(1-q)(b-h) + q(b-h-s)] \tag{34}$$

Figure 5: Event Tree of Illegal Act, Compensation, and Punishment



Source: Author

After simplification:

$$Eu = b - p\big(h + qs\big) \tag{35}$$

Proposition 12 *If detection is uncertain, conviction is also uncertain (dependent events), and the offender's expected utility is simply the monetary benefit b.*

Proof 12 If $p = 0$, then $q = 0$ (dependency of events), thus $Eu = b - 0 \cdot (h + 0 \cdot s) = b$.

Proposition 13 *If apprehension is certain ($p = 1$), the harm is repaired ($b = h$) even if punishment is unlikely.*

Proof 13 For $p = 1$, $Eu = b - h - qs$. If the individual is risk-neutral and $Eu = 0$, then $b = h - qs$. Even if $q = 0$ or $s = 0$, we obtain $b = h$. Hence, apprehension alone ensures harm repair.

These propositions highlight the critical role of detection:

- Without detection, punishment is irrelevant, and the offender enjoys the full benefit b.
- With certain detection, harm can be fully repaired, even without punishment.

The public authority seeks to maximize social welfare:

$$\max_{(p,q,s)} W = \int_{p(h+qs)}^{\bar{b}} (b - h)\, dF(b) - C(p, q) \tag{36}$$

The first-order conditions yield:

$$C_p = \big(h + qS\big)\big(h - p(h + qS)\big)f\big(p(h + qS)\big) \tag{37}$$

$$C_q = pS\big(h - p(h + qS)\big)f\big(p(h + qS)\big) \tag{38}$$

and the complementary optimality condition:

$$pq\big(h - p(h + qS)\big) f\big(p(h + qS)\big) = 0 \tag{39}$$

Efficient resource management in the judicial system requires a thorough understanding of the marginal costs associated with apprehension and conviction. The allocation of resources across different agencies and departments (police, courts, prisons) should reflect this understanding to maximize overall efficiency.

The marginal costs of apprehension and conviction, along with their impact on the perceived utility of offenders, can directly influence criminal behavior. If offenders perceive that the risk of apprehension and conviction is low, the prevalence of crime may increase, necessitating a reassessment of law enforcement strategies.

Equation 37 shows that the marginal cost of apprehension depends not only on the direct cost associated with arresting an offender $(h + qS)$, but also on how this cost affects the probability of apprehension (p) and, by extension, the probability of conviction (q) and the sanction (S). The term $f(p(h + qS))$ can be interpreted as a corrective factor that adjusts the cost according to the probability distribution of criminal benefits.

C_p indicates that the marginal cost of apprehension depends not only on the harm h but also on the product of the probability of conviction q and the sanction S. This reflects a strong interdependence between apprehension and punishment: increasing either q or S raises the marginal cost of apprehension, implying that greater emphasis on punishment requires higher investments in apprehension.

Similarly, Equation 38 represents the marginal cost of conviction, which depends on the probability of apprehension (p) and the sanction (S). This relationship indicates that the cost of conviction is not only a function of q, but is also influenced by the efficiency of the apprehension process. Again, the f term plays a role in adjusting the cost based on the distribution of criminal benefits.

C_q reflects a similar relationship but focuses on the marginal cost of punishment. The effect of certain apprehension $(p = 1)$ is particularly notable, underscoring that the effectiveness of punishment is strongly linked to the probability of apprehension. The presence of h in both equations highlights that harm plays a central role in determining marginal costs. In a scenario where apprehension is certain $(p = 1)$, the marginal cost of apprehension (C_p) becomes more directly linked to the justice system's ability to repair the harm h. This suggests that the efficiency of apprehension in terms of harm repair is a key factor in cost calculation. Similarly, for C_q, when $p = 1$, the marginal cost of punishment is influenced by how apprehension contributes to harm repair, emphasizing that the deterrent effectiveness of punishment is crucial to justify its cost.

As for Equation 39, this condition suggests that, at the optimum, one of the factors in the product must be zero to minimize total cost. This implies that in certain circumstances, either the probability of apprehension (p) or the probability of conviction (q) must be extremely low, or that the term in parentheses (related to costs and benefits) must be zero. This condition reflects a balance between law enforcement costs and the expected benefits of crime deterrence.

Proposition 14 ***If apprehension and punishment are substitutable, the following conditions must hold:***

- *Equality between p and q ($p = q$), and equality of marginal costs of apprehension and punishment ($C_p = C_q$) regardless of their respective probabilities.*
- *The optimal probability of apprehension is $p^* = \sqrt{\frac{h}{S}}$.*
- *The equation $p \cdot S\,(h - p\,(h + q \cdot S))\, f\,(p\,(h + q \cdot S)) = 0$ is satisfied, and as a result, the optimal monetary sanction is $S^* = \frac{h}{q^2}$.*

Proof 14 See demonstration below.

From Equation 39, we have:

$$pq\,(h - p(h + qS))\, f\,(p(h + qS)) = 0 \quad \Rightarrow \quad q = \frac{(1-p)h}{pS}.$$

Considering Equations (37) and (38):

$$C_p = (h + qS)\big(h - p(h + qS)\big) f\big(p(h + qS)\big),$$

$$C_q = pS\big(h - p(h + qS)\big) f\big(p(h + qS)\big).$$

After simplification:

$$pS\left(\frac{C_p}{qS}\right) = C_q$$

Using $q = \frac{(1-p)h}{pS}$ and under the substitutability condition $C_p = C_q$, it follows that:

$$S^* = \frac{h}{p^2}.$$

This shows that the optimal monetary sanction is more aggressive than in previous derivations, highlighting a stricter approach toward monetary penalties.

Proposition 15 ***If apprehension and punishment are complementary, the following conditions must hold:***

- *$p \neq q$,*
- *Punishment can only be applied after apprehension, ideally with certain apprehension $p = 1$ and $0 < q < 1$,*

- *Marginal costs equalize only under certain apprehension,* $C_1(q) = C_q(1)$*,*
- *For* $p = 1$*, the equations*

$$C_1(q) = (qS + h)(h - (qS + h))f(qS + h),$$

$$C_q(1) = S(h - (qS + h))f(qS + h)$$

are satisfied, and the optimal monetary sanction is $S^* = \frac{h}{(1-q)}$*.*

Proof 15 Based on Equations (37) and (38), and setting $p = 1$ to satisfy complementarity (punishment applies only after apprehension), we obtain:

$$C_1(q) = (qS + h)(h - (qS + h))f(qS + h),$$

$$C_q(1) = S(h - (qS + h))f(qS + h).$$

Marginal costs equalize only under certain apprehension: $C_1(q) = C_q(1)$. Simplifying yields the optimal sanction: $S^* = \frac{h}{1-q}$.

When substantial resources are allocated to law enforcement for arrests, avoiding the absolute maximum penalty can prevent resource wastage. This analysis suggests that even probable, non-certain apprehension ($0 < q < 1$, $p = 1$) can be sufficiently deterrent, making $q = 1$ unnecessary for efficient resource usage. If $q = 0$, the total repaired damage equals the sanction $S^* = h$. As $q \to 1$, the optimal monetary sanction rises, indicating that a maximum penalty can be optimal for a given sanction probability (Garoupa, 2001). Hence, for a specific q, the maximum sanction lies among the optimal solutions.

Conclusion

This paper proposes a series of innovative theoretical models that extend the classical deterrence approaches in the economic analysis of law. Our contributions lie on several levels.

First, we revisited the **theory of marginal deterrence** by introducing an *explicit hierarchy of harm* and an *endogenous decline in detection probability* as the severity of offenses increases. This approach demonstrates that the optimal sanction grows exponentially with the level of harm to compensate for the greater difficulty of detection. This result formalizes the intuition that severe crimes, which are more sophisticated and rarer, require substantially higher sanctions to ensure effective deterrence.

Second, we proposed a **model that clearly distinguishes between apprehension and punishment**, breaking with the simplifying assumption that conflates the two. Apprehension is presented as a necessary prerequisite to sanctioning and primarily affects the offender's *reputation*, thereby reducing the non-monetary gain linked to impunity. Punishment, in contrast, impacts the monetary gain and complements the deterrent effect of apprehension. This distinction allows us to demonstrate the complementarity between these two stages and to identify the conditions under which their substitutability can be considered to optimize law enforcement resources.

Third, we developed a **mechanism of deterrence and harm compensation** that combines perspectives from civil and criminal liability. We show that there exists a structural equivalence between the maximization of legal income and the minimization of illegal harm, and that the optimal sanction must satisfy functional relationships of the form: $s(1-p) - hp = 0$, or equivalently: $s^* = \frac{h}{p}, \quad s^* = h\frac{(2-p)}{p}, \quad s^* = h\frac{(1-p)}{p}$, depending on the degree of information and the configuration of arrest and punishment probabilities. These results illustrate the fundamental trade-off between severity, detection probability, and social cost.

Finally, the set of models demonstrates that **the optimal enforcement policy is multidimensional**: it must simultaneously adjust the probability of monitoring, the severity of sanctions, and the capacity to repair harm. The proposed extensions provide analytical foundations for designing more effective public policies that combine deterrence and restorative justice, while accounting for budgetary and institutional constraints.

These results open the door to empirical work and practical applications to calibrate criminal and civil policies in a way that maximizes social welfare while ensuring efficient management of public resources.

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