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Should the Standard of Proof be Lowered to Reduce Crime?

Tone Ognedal

Department of Economics, University of Oslo, PB 1095, Blindern, 0317 Oslo, Norway

Abstract

Lowering the standard of proof to increase the conviction rate may increase crime. Even though a lower standard of proof gives a higher expected penalty for all crimes, it reduces the expected penalty for serious crimes relative to the expected penalty for less serious crimes. Consequently, a lower standard of proof is less effective in deterring serious crime. As the proportion of agents with a low opportunity cost if crime increases, the standard of proof should be increased.

JEL classification: K4; K2

Keywords: Standard of proof; Crime; Economic crime; Negligence standards

1. Introduction

A high standard of proof in criminal cases leads to a low probability of conviction. This problem is most severe for crimes that leave circumstantial evidence. Clearly, a low probability of conviction could be compensated for by a high penalty. In practice, however, penalties are constrained by the legal principle that “the penalty should fit the crime”, or by a limited liability for corporate defendants. As a result many countries have resorted to disguised reductions in the standard of proof to obtain a sufficiently high probability of conviction. Some countries like the US and most of the EU, allow for the use of civil sanctions in addition to criminal prosecution for important types of crime. While guilt must

E-mail address: tone.ognedal@econ.uio.no.

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be proven "beyond reasonable doubt" in a criminal case, "preponderance of evidence" is sufficient in a civil case. Hence, if civil sanctions can be used when the evidence is too weak for criminal conviction, the standard of proof is effectively lower.

The reasoning behind such legislation might be that a lower standard of proof increases the probability of conviction and thus raises the expected penalty for crime. In turn, the higher expected penalty should lead to less crime. The basic implication of this paper is that such reasoning is too simplistic. A reduced standard of proof clearly raises the expected penalty for minor violations relative to both obeying the law and committing more serious violations. Thus, agents who can choose the magnitude of the violation, face higher marginal cost of minor crimes, but lower marginal cost of major crimes. Law obedience may thus diverge. A lower standard of proof provides agents contemplating minor violations with stronger incentives to obey the law, while agents contemplating serious crimes face weaker incentives to moderate their crime. As violations become more severe, the overall cost of crime may therefore surge even when the number of violations go down.

One important implication of my approach, demonstrated below, is that a lower standard of proof is a wrong response to a more crime prone society. The right response in a society faced with a higher fraction of crime prone agents is to increase rather than to reduce the standard of proof in order to raise the cost of severe crimes relative to minor ones.

Limiting serious crimes among those who cannot be deterred completely from crime is sometimes referred to as "marginal deterrence". Effective marginal deterrence requires that the difference in expected penalties between moderate and serious crimes must be sufficiently large. Enforcement policies that preserve marginal deterrence are explored in several studies, such as Mookherjee and Png (1994), Shavell (1992) and Wilde (1992). The paper by Shavell demonstrates that if the probability of being apprehended and penalized is independent of how serious the crime is, the penalty should be lower than maximal for the less serious crimes to preserve marginal deterrence.

When evidence is uncertain, as in the cases that I consider below, the probability of being convicted and penalized varies with the seriousness of the crime even if the probability of apprehension is the same for all crimes. The reason is that the more serious the crime, the higher is the probability that it will leave incriminating evidence that meets the standard of proof. Hence, even if the penalty is set equal for all crimes, the expected penalty is higher the more serious the crime is. Lowering the standard of proof reduces the difference in the probability of conviction between small and large crimes, implying that the difference in expected penalties declines. The marginal deterrence can therefore be preserved by choosing an optimal standard of proof even if the penalty is the same for all crimes. The purpose of my paper is to find the standard of proof and the penalty function that minimizes the social cost of crime, when penalties are constrained such that complete deterrence is ruled out.

When court decisions are based on uncertain evidence, innocent defendants may be convicted (Type I errors) and guilty defendants may be acquitted (Type II errors). A lower standard of evidence reduces the number of wrong acquittals, but raises the number of wrong convictions. Proponents of a lower standard of proof seem to believe that deterrence is only related to a reduction in wrong acquittals, implying that crime can be reduced if one is willing to tolerate a greater number of wrongful convictions. This reasoning is wrong. As

I demonstrate below there is no simple trade-off between wrongful convictions and crime.[1] The main point is that a lower standard of proof can very well imply both more crime and more wrongful convictions. The reason is that a lower standard of proof deters small crimes, but encourages severe crimes.

This result, which constitutes the basic claim of my paper, is related to the observation by Kaplov and Shavell (1994) that both wrongful acquittals as well as wrongful convictions reduce the marginal expected penalty. Hence, both Type I and Type II errors reduce crime deterrence. In their paper, Kaplov and Shavell explore how greater accuracy increases deterrence and can be used as a means to reduce crime.[2] Accuracy is costly, and the main point of Kaplov and Shavell is to derive its optimal degree for a given standard of proof.

The focus of my paper, however, is on the optimal standard of proof when the degree of accuracy is given. The two approaches are complementary.

Improving the accuracy of courts' information is not feasible for all types of crime. For instance, for white collar crime such as stock market manipulation the defendants' actions are often known with a high degree of accuracy since the markets are monitored. The problem is to decide whether these actions prove that price manipulation has taken place.[3] For other crimes improving the accuracy may be too costly.

The effect of the standard of proof on the incentive to commit crime is also discussed in Schrag and Scotchmer (1994). In their model the agents face exogenously given opportunities for crime of a given magnitude, such that marginal deterrence is not an issue. When the magnitude of the crime is given to each agent, changes in the number of crimes can be used to measure the effect of policy changes. However, if the agents can choose the magnitude of the crime, the number of crimes can be a misleading measure. The effect of an incremental increase in the magnitude of an already serious violation may do much more harm than the effect from an agent committing a minor violation instead of obeying the law. While the latter scenario increases the number of crimes, the first does not. Hence, a policy that aims at minimizing the number of crimes may not be optimal, since it may imply that the standard of evidence is set too low to discourage violators from choosing serious crimes instead of more moderate ones.

The framework that I develop below, applies to most types of harmful behavior. In this paper I only discuss "intentional crimes" where the violator gains from the losses he inflicts upon others. The framework also applies to "neglect crimes", such as failure to comply with safety standards. For neglect crimes the violator does not gain from the harmful outcome per se, but saves costs from the low effort to reduce the probability of harm. Although the harmful outcome is not intended, the neglect of the regulations is. The authorities observe the actual harm, but not the agent's effort to reduce the harm. Consequently, the problem of efficient deterrence applies. The results that I derive for intentional crimes can therefore also be applied to neglect crime and the discussion of negligence standards.

[1] The optimal tradeoff between Type I errors and Type II errors for a given crime rate is discussed in several studies, such as Miceli (1990) and Davis (1994).

[2] Rubinfeld and Sappington (1987) discuss how evidence can be improved by the judicial process.

[3] The book "Manipulation on trial" (Williamson, 1995), discuss one manipulation case in detail: the trial against the Hunt brothers, who were charged with manipulation of the silver market in the period 1979–1980.

Below, Section 2 presents the model of the paper and I derive the crime-minimizing standard of proof when penalties are constrained. Section 2 also shows how this optimal standard varies with the penalty level, the agent's opportunity cost of crime, and the moral cost of crime. When the costs of crime differ between agents, the standard of proof should ideally differ between them. Equality before the law, however, dictates that there must be a common standard for everybody. Section 3 derives the optimal common standard of proof when the cost of crime between agents differs. In this section I also examine how the optimal standard should change as the composition of those committing crimes changes. Section 4 concludes.

2. The model

An agent commits a crime of magnitude c. For example, c may measure underreporting of incomes, or overreporting of costs, as in cases of tax fraud. The authorities cannot observe c with certainty, however. Instead, they observe some uncertain evidence of the magnitude of crime, X. Hence, X is a stochastic variable, and x is the actual value observed. $F(x, c)$ is the agent's perceived cumulative probability distribution for X, with a given crime level of c. The corresponding density function is $f(x, c)$.

A crucial assumption throughout the paper is that more severe crimes tend to leave more incriminating evidence. Formally, $F_c(x, c) \leq 0$ and $F_{cc}(x, c) \leq 0$ for all c, with strict inequality for some c. This assumption seems natural if the agent cannot manipulate or destroy evidence to make it less incriminating. In many cases, however, the agent can hide part of his crime by manipulating or destroying the evidence. For example, an agent who evades taxes by deducting private expenses from his firm's taxable income may disguise the expenses as equipment for the firm. Such manipulation is normally costly, however. To disguise private expenses as firm expenses, for example, one usually have to choose goods and services that would not be the best choice for private use. In Section A.3 I show that as long as the cost of manipulation is an increasing, convex function of the hidden part of the crime, the assumption that more serious crime leaves more incriminating evidence holds. Although agents who commit more serious crimes will hide more of their crime, they will still leave more incriminating evidence, in expected terms.[4] As a consequence, it can easily be verified that the results of the paper also holds if the agents can hide part of their crime to reduce the chance of leaving incriminating evidence.

The results in this paper hold for a wide class of distribution functions, as shown in Appendix A. Among them are the normal and the binominal distribution. No insight is lost by using the normal distribution to simplify the presentation of the results. Moreover, if the

[4] I do not discuss evidence destruction that is criminal, like threatening or killing a witness. Large scale drug dealing is an example of a crime that is sometimes hidden with another crime. While the threatening or killing of a witness may reduce the evidence of the drug dealing, however, it also leaves its own evidence and leads to considerably harsher punishment if the criminal is convicted. Hiding crime by committing another one raises several problems that are outside the scope of this paper. For example, when the criminal evidence destruction is costly to society, there may be a trade-off between deterring the "basic" crime and deterring the criminal evidence destruction.

crime can be described as a sum of many law violations with the same expected value c, the investigations made by the authorities often leads to an approximately normal distribution of the average of their observations X. Take the example where a firm underreports its incomes to evade taxes. The actual amount varies stochastically between periods (or projects), but the expected amount of underreporting in each period is c. A fraction of the periods are checked by the authorities. Consequently, the observations from these n periods X, X_2, ..., X_n are independent observations from the same probability distribution with expected value c. The central limit theorem then implies that the average value $X = (1/n)\sum_{i=1}^{n} X_i$ is approximately normally distributed.

The agent's gain from crime is an increasing, concave function of the level of crime, i.e. $g'(c) > 0$ and $g''(c) < 0$. The agent's moral concern, or opportunity cost of crime, is modelled as proportional to the magnitude of crime with proportionality factor m. However, any increasing function of c such that the net gain to the agent is concave in c would give the same results. Let $h(c)$ be the social cost of crime, where $h'(c) > 0$. We focus on crimes where the social cost exceeds the private gains for all levels of c. The latter assumption is reasonable for crimes such as price manipulation where the private gains from crime are at the expense of the victims.

I assume that observations of x are costless, and there is no cost of apprehension. Yet, the main results of the analysis do not change if we include cost of observing x and apprehending agents, as long as such enforcement costs cannot differ between agents. Including enforcement cost complicates the analysis without adding significant insight. When enforcement is costless, all crimes should be deterred if penalties were not limited. Since penalties are limited, however, it may not be feasible to deter all agents from committing crime. The question addressed below is how the penalty function should be designed in this case, and in particular what the optimal standard of proof is.

If the agent is convicted, he is given a penalty that depends on the assessed level of crime, which in turn depends on the observed incriminatory evidence x. Let $P(x)$ be the penalty function. The penalty may be limited by the agent's ability to pay or by a legal maximum penalty. Here, both limits are represented by a maximum penalty $\bar{P}$. Since more incriminatory evidence should never lead to lower punishment, $P(x)$ must be non-decreasing in x. This paper analyses the case where the penalty is a fine with negligible administrative costs. Since the penalty is then simply a transfer from the agent to the government, social welfare is not affected.[5]

As mentioned, the criminal standard of proof requires that the crime should be proven "beyond reasonable doubt", while the civil standard is "preponderance of evidence". A standard of proof can be defined as the level of certainty required to find the defendant guilty as charged. One interpretation is the following[6]: when the court is presented with evidence x, they should find the defendant guilty if the probability of finding x (or worse)

[5] Including socially costly penalties, such as jail sentences or the withdrawal of production licenses, complicates the analysis without adding significant insights.

[6] An alternative representation of the court's reasoning would be the Bayesian approach, where the defendant is convicted if the probability that he is guilty, given the evidence and the a priori beliefs, exceeds the standard of proof s. The Bayesian approach yields a similar decision rule, namely that the defendant should be convicted if the level of incriminatory evidence is above a certain threshold.

when the defendant is innocent is below the standard of proof s. Formally, the defendant is convicted if x is above a threshold x^{t} such that

$$1 - F(x^{\mathrm{t}}, 0) = s. \tag{1}$$

If the standard of proof is lowered, so is the threshold evidence x^{t} that leads to conviction. We can therefore write x^{t} as a function of s, $x(s)$, where $x'(s) > 0$.

The expected penalty of an agent is $\int_{-\infty}^{+\infty} P(X)\, f(x, c)\, \mathrm{d}x$, where $P(x)$ will be zero below the threshold level of evidence x^{t}. We want to find the penalty function that minimizes crime, when $0 \leq P(x) \leq \bar{P}$ and $P'(x) \geq 0$. An optimal evidence threshold, if there is one, should come out as a result of the optimization.[7] Since the penalty is a non-decreasing function of the incriminatory evidence, the expected penalty is an increasing, convex function of c.[8] Agents are assumed to be risk neutral; they maximize net expected gain from crime. An agent's net expected gain from crime is

$$\pi(c) = g(c) - mc - \int_{-\infty}^{+\infty} P(x) f(x, c)\, \mathrm{d}x \tag{2}$$

For each feasible penalty function $P(x)$, which the authorities might choose, there is an optimal level of crime by the agent. The agent chooses the level of crime that maximizes net gain $\pi(c)$. Since $g(c)$ is concave and the expected penalty is convex in c, the function $\pi(c)$ is concave. If $\pi'(0) \leq 0$, crime is unprofitable. In that case the firm chooses $c = 0$. If $\pi'(0) > 0$, the agent's choice of crime is an interior solution to his optimization problem, implicitly given by the first order condition:

$$g'(c) - m = \int_{-\infty}^{+\infty} P(x) f_c(x, c)\, \mathrm{d}x \tag{3}$$

The condition simply states that the net marginal gain from crime should equal the marginal cost from increased expected penalties.

The interesting case is when the maximum penalty $\bar{P}$ is too low to deter crime, i.e. when the agent will choose positive levels of crime for all feasible penalty functions. The aim of the enforcement policy is then to pick the penalty function that induces the lowest level of crime, when crime is given by Eq. (3). The optimal law enforcement can be characterized as follows:

Proposition 1. *To minimize the level of crime chosen by the agent, the penalty should be zero for incriminatory evidence below a threshold x^* and equal to its maximal level $\bar{P}$ for evidence levels above the threshold. The threshold x^* is a decreasing function of the moral concern (or opportunity cost) m and of the maximum penalty $\bar{P}$.*

The Proof of Proposition 1 is given in Appendix A.[9]

[7] Alternatively, we could formulate the problem as follows: Find the evidence threshold x^{t} and the penalty function $P(x)$ for $x > x^{\mathrm{t}}$ that minimizes crime when the agents' expected penalty is $\int_{x^t}^{\infty} P(x) f(x, c)\, \mathrm{d}x$.

[8] By taking the derivative of the expected penalty $\int_{-\infty}^{\infty} P(x) f(x, c)\, \mathrm{d}x$ twice and using partial integration, we obtain $\int_{-\infty}^{\infty} P(x) f_{cc}(x, c)\, \mathrm{d}x = -\int_{-\infty}^{\infty} P'(x) F_{cc}(x, c)\, \mathrm{d}x \geq 0$. Since $P'(x) \geq 0$ and $F_{cc} \leq 0$, it follows that the expected penalty is convex in c.

[9] It is straightforward to show that the second part of Proposition 1 holds even if the penalty function $P(x)$ is given, and we can only choose the evidence threshold x^{**}. The problem is then to choose the threshold x^{**} that

It follows that there is a crime minimizing standard of proof s^* given by $x^* = x(s^*)$. Hence, to reduce the standard of proof is the same as to reduce the threshold evidence, and vice versa. In the following, when I talk about an increase in the evidence threshold, it is implied that the standard of proof is changed such that $x = x(s)$ holds.

When X is normally distributed, it is easy to explain the results of Proposition 1 by inspecting the first order condition (3): the right-hand side is the marginal increase in the expected penalty from an increase in the magnitude of crime, hereafter called the marginal penalty. To maximize the marginal penalty, the penalty should be as low as possible for values of x that become less likely if crime is increased ($f_c < 0$) and as large as possible for values of x that become more likely as crime is increased ($f_c > 0$). When X is normally distributed, x-values below the expected value c become less likely as c is increased and x-values above c become more likely. Consequently, if c^* is the minimum crime level that can be induced, there should be no penalty when evidence below c^* is observed, and the penalty should be maximal for evidence above c^*. In other words, the penalty should be a threshold function that jumps from 0 to $\bar{P}$ at the threshold $x^* = c^*$. Since the minimum crime level that can be induced, c^*, is higher the lower the agent's opportunity cost (m), the optimal threshold is also higher the lower the opportunity cost.

Proposition 1 implies that when the magnitude of crime goes up because agents' opportunity cost or moral concern (m) goes down, it may be optimal to raise the standard of proof even though this lowers the expected penalty for all levels of crime. The reason is that even though the expected penalty goes down for all levels of crime when the standard of proof is raised, the expected penalty for serious violations of the law increases relative to more moderate violations. Hence, the marginal penalty for committing a serious violation of the law has increased. As long as agents are relatively law abiding (m is high), a low standard of proof is optimal, because it creates a high marginal penalty even for moderate violations, thus discouraging agents from anything more than minor violations. When agents become less law abiding (m becomes lower) and therefore choose to commit more serious violations, the low standard of proof is no longer optimal. The reason is that when an agent is punished even with weak incriminatory evidence, there is no extra penalty for causing high levels. Consequently, the increase in the expected penalty for committing a serious violation instead of a more moderate one is small. By raising the standard of proof, the marginal penalty and thereby marginal deterrence goes up for serious violations.

One implication of Proposition 1 is that it is not optimal to use a low standard of proof to compensate for a low penalty. On the contrary, the lower the maximum penalty is, the higher the standard of proof should be to create sufficient marginal deterrence of serious crimes.

The result of Proposition 1 is illustrated in Fig. 1. The two downward sloping curves depict the left-hand side of Eq. (3), i.e. the net marginal gain from crime, for two levels of moral concern, $m_A > m_B$. The two upward sloping curves depict the right-hand side of Eq. (3), i.e. the marginal penalty for two different evidence thresholds. The agent's

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maximizes the marginal penalty $\int_{x^{**}}^{+\infty} P(x) f_c(x, c)\,\mathrm{d}x$. It is easy to show that this yields the same condition as when $P(x)$ is chosen optimally, namely that x^{**} should be equal to the minimum crime level that can be induced, c^{**}. If the penalty function differs from the optimal one, however, the minimum feasible crime level c^{**} will be higher than under the optimal penalty function. Consequently, the evidence threshold should be higher.

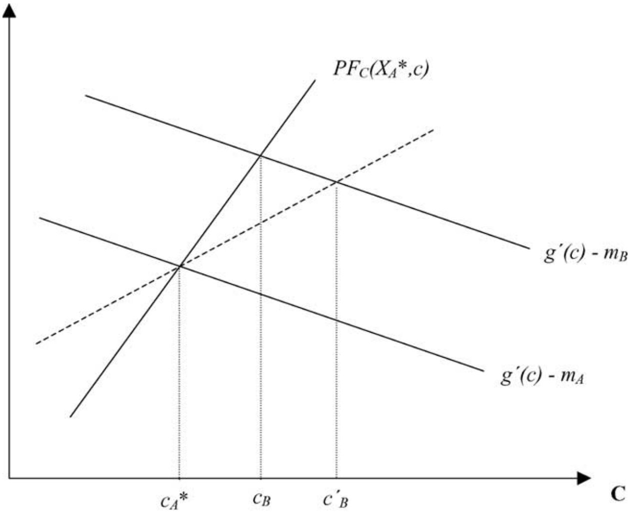

Fig. 1. Equating the marginal gain from crime, $g'(c) - m$, with the marginal penalty, $PF_c(x_A^*, c)$ gives the crime level c_A when the standard of evidence is x_A^*. If the moral concern is reduced from m_A to m_B, crime is increased from c_A^* to c_B^*. Lowering the standard of evidence gives a less steep marginal penalty curve, shown by the dotted line, which gives an even higher level of crime, c'_B.

optimal choice of crime is where the marginal gain from crime equals the marginal penalty. When agents have moral concern m_A, the crime minimizing evidence threshold is x_A^*. The corresponding marginal penalty is given by the solid upward sloping curve. The agent chooses the crime level c_A^*. If moral concern is reduced to m_B, while the evidence threshold is unchanged, the agent's optimal crime level is increased to c_B. However, if the evidence threshold is lowered in response to reduced moral concern the marginal penalty curve becomes less steep, as shown by the dotted line. As a consequence, the crime increasing effect of lower moral concern is alleviated. While crime was increased to c_B when the evidence threshold remained at x_A^*, it is increased further to c'_B when the evidence threshold is lowered.

The marginal penalty curve becomes less steep when x^* is lowered. This can be verified by differentiating the marginal penalty with respect to the evidence threshold. When X is normally distributed, we get

$$\frac{\mathrm{d}(-PF_c(x^*, c)}{-\mathrm{d}x^*} = Pf(x, c)\frac{x^* - c}{\sigma^2}$$

The marginal penalty does not change at $c = c_A^*$ since $x^* = c_A^*$, but is reduced for crime levels above c_A^*.

It is a common view that there is always a conflict between crime deterrence and protection against wrongful convictions, and that protection against wrongful convictions is the only reason why the standard of proof is not reduced. Proposition 1 implies that a high standard of proof may also be optimal to deter crime. Moreover, a crime minimizing standard of proof may even be higher than what we would find necessary to protect against wrongful convictions. This will typically be the case if agents have low opportunity costs of crime, or low moral concern, such that they cannot be deterred form crime but only induced to be more moderate by a high standard of proof.

3. The optimal standard of proof when agent's moral costs differ

To minimize the cost of crime, the standard of proof should ideally differ for agents with different moral costs, as shown above. The higher the moral concern (or opportunity cost) the lower is the optimal standard of proof. However, the principle of equal legal treatment implies that the standard of proof must be the same for all agents. As a consequence, it is too low for some agents and too high for others, and their reactions to changes in the standard of proof differ. In this section, I derive the optimal standard of proof when agents differ, and analyze how it should be changed as moral cost changes.

Appendix B demonstrates that with many types of agents, it is still optimal to use a threshold penalty function where the penalty is zero for evidence below a threshold x^* and equal to the maximum level P for evidence above x^*. We know from Proposition 1 that, with one type of agents, the crime minimizing evidence threshold is higher the lower the moral cost of the agents. Hence, the lower the common threshold the less crime in high-moral agents but the more serious is the crimes in the low-moral agents. The optimal, common threshold is determined as a tradeoff between these two concerns.

Fig. 2 illustrates the tradeoff between deterring low-crime and high-crime agents with a threshold penalty function: The two U-shaped curves, derived in Section A.2, depicts the

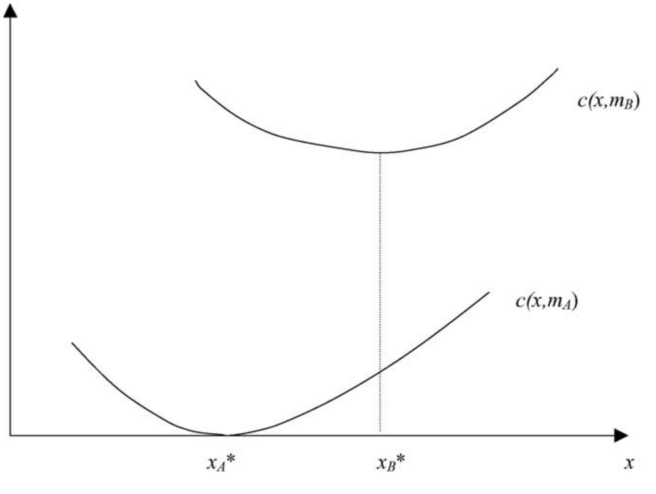

Fig. 2. The two curves, $c(x, m_A)$ and $c(x, m_B)$ depicts the optimal level of crime as a function of the threshold evidence x for agents of type A and B, respectively. Since $m_A > m_B$, type A agents choose lower levels of crime than type B agents for all evidence thresholds. Type A is chosen such that it can be deterred from crime, i.e., induced to choose $c = 0$, for threshold x^*_A. Agents of type B cannot be deterred from crime, but crime is minimized for threshold x^*_B.

optimal level of crime as a function of the threshold evidence for agents of type A and B, respectively. Since $m_A > m_B$, type A agents choose lower levels of crime than type B agents for all evidence thresholds. Type A is chosen such that it can be deterred from crime, i.e. induced to choose $c = 0$, for threshold x_A. Agents with higher moral costs than m_A can be deterred from crime for a range of evidence thresholds. Agents with lower moral costs than m_A, such as type B agents, cannot be deterred from crime for any threshold.

An evidence threshold below or equal to x_A is not optimal, since increasing the threshold would then reduce crime in all agents with $m < m_A$, while no agents would commit more crime. If m_B is the lowest moral cost parameter among the agents, a similar argument shows that a threshold above or equal to x_B is not optimal. Hence, the threshold should be between x_A and x_B. The location of the threshold between x_A and x_B depends on the tradeoff between reducing crime in low-morale and high-morale agents. By moving the evidence threshold closer to x_A, crime is reduced in high morale agents such as A, but increased in low morale agents such as B.

To find how the optimal evidence threshold varies with changes in distribution of types of agents, I consider the case with only two types of agents, A and B. The net social cost of crime in an agent of type i is $h(c(x, m_i))$ where $c(x; m_i)$ is the optimal choice of crime for an agent of type i. The superscript on x is omitted where it is clear that the symbol refers to the evidence threshold. The total social cost is the weighted sum of the cost of the two types of agents, with the share of each type as weight. Hence, if α is the share of the agents with the highest moral concern m_A, the total social cost is

$$S = \alpha h(c(x; m_A)) + (1 - \alpha)h(c(x; m_B)) \tag{4}$$

There is a trade-off between the social costs of violations from the two groups of agents. A threshold closer to x_B results in more crime and therefore more social harm from type A agents, but less crime and therefore less social harm from type B agents. When S is convex (see Appendix B) in x, the optimal evidence threshold is where the marginal harm from crime in A-agents equals the marginal cost of crime from B-agents, i.e. where

$$\frac{\mathrm{d}S}{\mathrm{d}x} = \alpha h'(c_A)c_x(x; m_A) + (1 - \alpha)h'(c_B)c_x(x; m_B) = 0 \tag{5}$$

If the share of type B agents (with low moral concern) increases, the cost of deviating from the ideal evidence threshold for B-agents becomes higher. As a consequence, the evidence threshold should be closer to x_B, as summarized in the following proposition.

Proposition 2. *The optimal common standard of proof is higher the higher the proportion of agents with low moral concern.*

The proof is given in Appendix B.

While Proposition 2 implies that the standard of proof should be lowered when there are more high moral agents, it does not imply that it should be lowered when high moral agents become even more morally concerned. Even if the ideal standard of proof for A-agents is lower as their moral concern (m_A) becomes higher, the optimal common standard of proof may actually be higher when A-agents become more morally concerned.

The reason for this paradoxical result is that lower moral concerns for either of the types of agents have two effects. First, agents that become more morally concerned reduce their crime for all standards of proof. This implies that the marginal gain from lower crime in these agents goes down, and more weight should be given to reducing crime in the agents that have not become more morally concerned. In other words, there is less need to deter the agents as they internalize more of the social cost of crime. As a consequence, the standard of proof should be closer to the optimal level for the agents where moral concern has not increased. The second effect is that higher moral concern may make crime either more or less responsive to changes in the standard of proof. If crime becomes more responsive, the standard of proof should be closer to the ideal level in the agents that have become more morally concerned. If effort becomes less responsive, the standard of evidence should be closer to the ideal level for the other type. Combining these two effects gives us the following result.

Proposition 3. *If higher moral concern in agents with high* (*low*) *moral makes their crime less responsive to changes in the standard of proof, the standard of proof should be set closer to the ideal level for agents with low* (*high*) *moral*.

The proof is given in Appendix B.

4. Concluding remarks

Illegal insider trading is an example of a crime that is difficult to prove because the evidence is circumstantial. To prove that a trader had access to precise and price-affecting confidential information, the prosecution usually has to make uncertain inferences from telephone calls, meetings, trading patterns, relationships between people and other circumstantial evidence. Such inferences seldom meet the standard of proof required in a criminal court. Hence, in countries that have only provided for criminal enforcement of insider trading, like the Netherlands and Norway, few people are convicted. The Netherlands had only one conviction in the period 1988–1998. Norway has had only one conviction since 1985. The question is if these countries should also use civil sanctions, like in the US, since this would lower the standard of proof for insider trading.

One implication of my model is that there is a trade-off between minor and large crimes. If one chooses a high standard of proof to deter serious crimes, the number of small violations is higher than if the standard of proof was reduced. Hence, if there are few convictions but many small violations, as is the case for illegal insider trading, this does not imply that the choice of the standard of proof is wrong. On the contrary, it may be that the agents with low moral concern (or a low opportunity cost of crime) are successfully induced to choose small crimes instead of serious crimes because the high standard of proof makes small crimes relatively profitable. If one reduces the standard of proof, the numbers of crimes will most likely decrease, but the total cost of insider crimes may well increase because the marginal deterrence of serious crimes is reduced.

When agents can choose the severity of the violation, the optimal standard of proof depends on the composition of the agents. For example, if agents with high opportunity costs of crime dominate, such that there are few serious criminals to deter, the standard of proof should be low to make the marginal costs for minor crimes high. Hence, if the main problem of insider trading is that a large proportion of the agents may be tempted to commit minor violations, access to further civil sanctions may help. However, if deterrence of serious violations is most important, the standard of proof should remain high.

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Appendix A

A.1. *Assumptions on F(x, c)*

The following four assumptions on $F(x, c)$ are sufficient conditions for Propositions 1–3 to hold:

(a1) The court cannot exclude any level of crime from their observation of x, that is, the support of $f(x, c)$ is the same for all c.
(a2) More serious crime increases the chance of high levels of incriminatory evidence x, and at an increasing rate. Formally, $F_c \leq 0$ for all c, with strict inequality for some c and $F_{cc} \leq 0$ for all c, with strict inequality for some c.
(a3) Higher levels of x signify more serious crime i.e. higher c. Formally, f_c/f is strictly increasing in x, which is equivalent to $f_{cx} - f_c\, f_x > 0$, sometimes called the monotone likelihood ratio condition.
(a4) As crime becomes more serious, high levels of incriminatory evidence x become more likely and low levels become less likely, as illustrated in Fig. 1. The x-value that is equally likely when c is increased is increasing in c. This condition holds if a3 holds and $f_{cc}(x, c) < 0$ for x and c such that $f_c(x, c) = 0$.

Proof of Proposition 1 *(The optimal penalty function)*. The agents' choice of crime is determined by Eq. (3). Since $g''(c) \leq 0$ the penalty function $P(x)$ that induces minimum crime is the one that maximizes the right hand side of (3). Let c^* denote the minimum crime level. The optimal penalty function is then:
$P(x) = 0$ for x-values where $f_c(x, c^*) < 0$ and $P(x) = \bar{P}$ for x-values where $f_c(x, c^*) \geq 0$.

The threshold x^* that triggers the maximum penalty is given by

$$f_c(x^*, c^*) = 0 \tag{A.1}$$

Since $f_{cx} - f_c f_x > 0$ for all x (from a3), it follows that $f_{cx}(x^*, c^*) > 0$. As a consequence, x^* is the unique x-value that satisfies (A.1). Since $f_c(x, c^*) < 0$ for $x < x^*$ and $f_c(x, c^*) > 0$ for $x > x^*$, it follows that the optimal penalty is zero for $x < x^*$ and $\bar{P}$ for $x \geq x^*$, which completes the proof. □

The next step of the proof is to determine the minimum feasible crime level c^*, such that x^* can be determined by (A.1). With the optimal penalty function described in Proposition 1, the agent's net expected gain may be written as:

$$\pi(c) = g(c) - mc - \bar{P}[1 - F(x^*, c)] \tag{A.2}$$

The first order condition (3) then becomes:

$$g'(c) - m = -\bar{P}F_c(x^*, c) \tag{A.3}$$

Eq. (A.3) determines the minimum feasible crime c^* as a function of the threshold x^*, the moral concern m, and the maximum penalty $\bar{P}$, i.e.

$$c^* = c(x^*; m, \bar{P}) \tag{A.4}$$

It can easily be verified by differentiating (A.3) that $\mathrm{d}c^*/\mathrm{d}m < 0$ and $\mathrm{d}c^*/\mathrm{d}\bar{P} < 0$. Inserting (A.4) into (A.1) gives us:

$$f_{\mathrm{c}}(x^*, c(x^*; m, \bar{P})) = 0 \tag{A.5}$$

Eq. (A.5) determines x^* as a function of the agent's moral concern m and the maximum penalty $\bar{P}$. Implicit differentiation with respect to m and $\bar{P}$ yields the following equations:

$$\frac{\mathrm{d}x^*}{\mathrm{d}m} = -\frac{f_{cc}(x^*, c^*)}{f_{cx}(x^*, c^*)}\frac{\mathrm{d}c^*}{\mathrm{d}m} \tag{A.6}$$

$$\frac{\mathrm{d}x^*}{\mathrm{d}\bar{P}} = -\frac{f_{cc}(x^*, c^*)}{f_{cx}(x^*, c^*)}\frac{\mathrm{d}c^*}{\mathrm{d}\bar{P}} \tag{A.7}$$

From (A.3) recall that $\mathrm{d}c^*/\mathrm{d}m < 0$ and $\mathrm{d}c^*/\mathrm{d}\bar{P} < 0$. It follows from assumptions a3 and a4 that $f_{cx}(x^*, c^*) > 0$ and $f_{cc}(x^*, c^*) < 0$. This implies that $\mathrm{d}x^*/\mathrm{d}m$ and $\mathrm{d}x^*/\mathrm{d}\bar{P}$ are negative, which completes the proof. □

A.2. *The choice of crime as a function of the evidence threshold*

For a threshold x^{t}, the agent's optimal choice of crime is given by Eq. (A.3) when x^* is substituted with x^{t}, i.e.

$$g'(c) - m = -\bar{P}F_{\mathrm{c}}(x^{\mathrm{t}}, c) \tag{A.8}$$

Hence, if c^0 denotes the agent's optimal crime level, c^0 is given by

$$c^0 = c(x^{\mathrm{t}}; m, \bar{P}) \tag{A.9}$$

Since x^* is the threshold that induces the minimum level of crime c^*, it follows that $c^0 > c^*$ for $x^{\mathrm{t}} \neq x^*$. Differentiating (A.1) with respect to x^{t} we obtain:

$$\frac{\mathrm{d}c}{\mathrm{d}x^{\mathrm{t}}} = -\frac{\bar{P}f_{\mathrm{c}}(x^{\mathrm{t}}, c)}{\pi''(c)} \tag{A.10}$$

where $\pi''(c^0) < 0$. Since x^* is the only x-value that satisfies $f_c(x, c(x; m, \bar{P})) = 0$, and $f_{cx} > 0$ for $f_c = 0$, it follows that $f_c < 0$ for $x^t < x^*$ and $f_c > 0$ for $x^t < x^*$. Hence,

$$\begin{aligned} \frac{dc^0}{dx^t} &< 0 \quad \text{for } x^t < x^* \\ \frac{dc^0}{dx^t} &= 0 \quad \text{for } x^t = x^* \\ \frac{dc^0}{dx^t} &> 0 \quad \text{for } x^t > x^* \end{aligned} \tag{A.11}$$

Differentiating dc/dx^t with respect to x^t yields

$$\frac{d^2c}{dx^2} = -\frac{\bar{P}}{\pi''(c)} \left\{ f_{cx} + f_{cc}\frac{dc}{dx} - f_c \frac{dc}{dx^t}\frac{\pi'''}{\pi''} \right\} \tag{A.12}$$

For $x^t = x^*$, $f_c = 0$ and $dc/dx^t = 0$ such that $(d^2c/dx^2 = -\bar{P} f_{cx}/\pi'') > 0$. Hence, c^0 is convex in x^t at the optimum, but it may not be convex for other values of x^t.

A.3. The distribution of incriminating evidence when evidence may be manipulated

I assume that the manipulation of evidence has the following effect: the offender can hide a part u of the crime such that the incriminating evidence will be as if the crime was of magnitude $c - u$. Let e denote the evidence-producing crime, i.e. $e \equiv c - u$. The cost of hiding crime is $w(u)$, where $w'(u) > 0$ and $w''(u) > 0$ is assumed. Hence, the net expected gain from crime is

$$\pi(c, u) = g(c) - mc - w(u) - \int_{-\infty}^{\infty} P(x) f(x, c - u)\, dx \tag{A.13}$$

Maximizing π with respect to c and u gives us the first order conditions

$$\frac{d\pi}{dc} = g'(c) - m - \int_{-\infty}^{\infty} P(x) f_e(x, c - u)\, dx = 0 \tag{A.14}$$

$$\frac{d\pi}{du} = -w'(u) + \int_{-\infty}^{\infty} P(x) f_e(x, c - u)\, dx = 0 \tag{A.15}$$

Differentiating with respect to m gives us

$$\frac{dc}{dm} = \frac{1}{D}\pi_{uu} = -\frac{1}{D}\left[w''(u) + \int_{-\infty}^{\infty} P(x) f_{ee}(x, c - u)\, dx \right] \tag{A.16}$$

$$\frac{du}{dm} = -\frac{1}{D}\pi_{cu} = -\frac{1}{D}\left[\int_{-\infty}^{\infty} P(x) f_{ee}(x, c - u)\, dx \right] \tag{A.17}$$

where $D = \pi_{cc}\pi_{uu} - (\pi_{cu})^2$. Since $e \equiv c - u$ we get

$$\frac{\mathrm{d}e}{\mathrm{d}m} = -\frac{1}{D}w''(u) \tag{A.18}$$

D is positive if the second order condition holds. By assumption $w''(u) > 0$, and by partial integration we obtain $\int_{-\infty}^{\infty} P(x) f_{ee}(x, e)\mathrm{d}x = \int_{-\infty}^{\infty} P'(x) F_{ee}(x, e)\mathrm{d}x \geq 0$. It follows that $\mathrm{d}c/\mathrm{d}m$, $\mathrm{d}u/\mathrm{d}m$ and $\mathrm{d}e/\mathrm{d}m$ are negative. If moral concern m becomes lower, crime goes up. The offender will hide more crime (u goes up), but the increased hiding will be less than the increase in crime such that he leaves more incriminating evidence (e goes up). Hence, even if the offender has the opportunity to hide some of his crime, it is optimal for him to leave more incriminating evidence the more serious the crime he commits. It is straightforward to show that, as a consequence, e and c move in tandem when the standard of evidence is changed. The results of the paper therefore hold whether or not evidence can be manipulated.

Appendix B

B.1. The optimal penalty function when firms differ

The moral concern parameter (or opportunity cost) m takes values between 0 and m_{B}, and is distributed between agents with a probability density function $z(m)$. As in Fig. 2 type A is defined such that all types with $m < m_{\mathrm{A}}$ cannot be deterred from crime for any feasible $P(x)$. The aim is to find the penalty function $P(x)$ that minimizes total social cost of crime

$$S = \int_0^{m_{\mathrm{B}}} h(c^{\mathrm{o}})\, z(m)\, \mathrm{d}m \tag{B.1}$$

where c^{o} is the optimal level of crime for an agent, determined by the first order condition in Eq. (3),

$$g'(c) - m - \int_{-\infty}^{\infty} P(x) f_c(x, c)\, \mathrm{d}x = 0 \tag{B.2}$$

Hence, c^{o} depends on m and on the penalty function $P(x)$. Differentiating (B.1) and (B.2) gives

$$\mathrm{d}S = \int_0^{m_{\mathrm{B}}} h'(c)\, \mathrm{d}c z(m)\, \mathrm{d}m \tag{B.3}$$

$$\pi''(c)\mathrm{d}c = \int_{-\infty}^{\infty} \mathrm{d}P_x\, f_c(x, c)\, \mathrm{d}x \tag{B.4}$$

where dP_x denotes a change in the penalty for observed evidence x. Inserting dc from (B.4) into (B.3) gives us

$$dS = \int_{-\infty}^{\infty}\left\{\int_0^{m_B}\frac{h'(c)f_c(x,c)}{\pi''(c)}z(m)\,dm\right\}dP_x\,dx \tag{B.5}$$

The sign of dS/dP_x depends on the sign of the term inside the bracket. For x-values such that the bracket is negative, $dS/dP_x > 0$, which implies that $P(x) = 0$ is optimal. For x-values such that the bracket is positive, $dS/dP_x < 0$, which implies that $P(x) = \bar{P}$ is optimal.

To prove that the optimal penalty function is a threshold function of the type described in Proposition 1, I proceed in two steps. (i) First, I show that $P(x) = \bar{P}$ is optimal for $x \geq x_B$, where x_B is given by $f_c(x_B, c_B) = 0$ and $P(x) = 0$ is optimal for $x \leq x_A$, where x_A is given by $f_c(x_A, c_A) = 0$. Hence, x_A is the optimal evidence threshold if the if all agents were of type A, and x_B is the optimal threshold if all agents were of type B. (ii) Second, I show that for $x_A < x < x_B$, the penalty must either be zero or maximal. Moreover, $P(x)$ jumps from zero to the maximal value $\bar{P}$ at a threshold level x^* between x_A and x_B.

(i) Since $h'(\underline{c}) > 0$ and $\pi''(c) \leq 0$, it follows that the bracket in (B.5) is positive, such that $P(x) = \bar{P}$ is optimal, for x values where $f_c > 0$ for all types of agents. Since x_B is a unique x-value that satisfies $f_c(x_B, c_B) = 0$, and $f_{cx}(x_B, c_B) > 0$ (from (A.3)) it follows that $f_c(x, c_B) > 0$ for $x > x_B$.) It follows from (A.3) that for $m < m_B$, i.e. for all other types, $f_c(x, c) > 0$ for $x \geq x_B$. Hence, $P(h) = \bar{P}$ is optimal for $x \geq x_B$. By the same reasoning, it is easily shown that $P(x) = 0$ is optimal for $x \leq x_A$, since $f_c < 0$ for all types of agents for $x \leq x_A$.

(ii) I have shown that $dS/dP_x > 0$ for $x \leq x_A$ and $dS/dP_x < 0$ for $x \geq x_B$. Hence, if $dS/dP_h = 0$ for one x-value only, x^*, it follows that the optimal penalty function changes from 0 to $\bar{P}$ at $x_A \leq x^* \leq x_B$.

B.2. Is S convex in h?

Total social cost S is a weighted sum of social cost from the two types of agents, as given by Eq. (4). A sufficient, but not necessary, condition for S to be convex in x is that $h(c(x, m_i))$ is convex in x. Differentiating $h(\cdot)$ twice with respect to x gives us

$$\frac{d^2h}{dx^2} = h''(c)(c_x)^2 + h'(c)c_{xx} \tag{B.6}$$

The first term is non-negative since $h''(c) \geq 0$. Hence, a sufficient but not necessary condition for s_i to be convex in x is that $c_{xx} > 0$, i.e. that $c(x; m)$ is convex in x. As shown in Appendix A, $c(x; m)$ is convex in x for x^*, but not necessarily for other x-values.

Proof of Proposition 2. Differentiating Eq. (4) with respect to α, and reorganizing, we obtain:

$$\frac{dx}{d\alpha} = \frac{h'(c_B)c_x(x; m_B) - h'(c_A)c_x(x; m_A)}{S_{xx}} \tag{B.7}$$

If S is convex in x, the denominator is positive. Moreover, since $c_x(x;\, m_\mathrm{A}) > 0$ and $c_x(x;\, m_\mathrm{B}) < 0$, the nominator is negative. This implies that $\mathrm{d}x/\mathrm{d}\alpha < 0$, which completes the proof. □

Proof of Proposition 3. Differentiating Eq. (5) with respect to m_i gives us:

$$\frac{\mathrm{d}x}{\mathrm{d}m_\mathrm{A}} = \frac{-\alpha\{h'(c^\mathrm{A})c^\mathrm{A}_{xm} + h''(c^\mathrm{A})c^\mathrm{A}_x c^\mathrm{A}_m\}}{S_{xx}} \tag{B.8}$$

$$\frac{\mathrm{d}x}{\mathrm{d}m_\mathrm{B}} = \frac{-(1-\alpha)\{h'(c^\mathrm{B})c^\mathrm{B}_{xm} + h''(c^\mathrm{B})c^\mathrm{B}_x c^\mathrm{B}_m\}}{S_{xx}} \tag{B.9}$$

where $c^i_x \equiv \mathrm{d}c(x, m_i)/\mathrm{d}x$ and $c^i_m \equiv dc(x; m_i)/dm_i$. We assume that $S_{xx} > 0$, i.e. that there is a unique internal solution to the optimization of x^*. Since $c^\mathrm{A}_x > 0$ (because $x^* > x^*_\mathrm{A}$) and $c^\mathrm{A}_m > 0$, the last term in the bracket of (B.8) is negative. Hence, $\mathrm{d}x/\mathrm{d}m_\mathrm{A}$ is positive if $c^\mathrm{A}_{xm} < 0$, i.e. if a type A agent becomes less responsive to changes in x^* when m_A is higher. If $c^\mathrm{A}_{xm} > 0$, the sign of $\mathrm{d}x^*/\mathrm{d}m_\mathrm{A}$ depends on the relative strength of the two opposite effects.

By similar arguments, we find that $\mathrm{d}x^*/\mathrm{d}m_\mathrm{B} < 0$ if $c^\mathrm{B}_{xm} > 0$. If $c^\mathrm{B}_{xm} < 0$, the sign of $\mathrm{d}x^*/\mathrm{d}m_\mathrm{B}$ depends on the relative strength of the two opposite effects. □

References

Davis, M. L. (1994). The value of truth and the optimal standard of proof in legal disputes. *Journal of Law, Economics and Organization*, *10*(2).

Kaplov, L., & Shavell, S. (1994). Accuracy in the determination of liability. *Journal of Law and Economics*, *XXXVII* (April).

Miceli, T. J. (1990). Optimal prosecution of defendants whose guilt is uncertain. *Journal of Law, Economics and Organization*, *6*(1).

Mookherjee, D., & Png, I. P. L. (1994). Marginal deterrence in enforcement of law. *Journal of Political Economy*, *102*, 1039–1066.

Rubinfeld, D. L., & Sappington, D. E. M. (1987). Efficient awards and standards of proof in judicial proceedings. *RAND Journal of Economics*, *81*(2), 308–315.

Schrag, J., & Scotchmer, S. (1994). Crime and prejudice: The use of character evidence in criminal trials. *Journal of Law Economics and Organization*, *10*(2), 319–342.

Shavell, S. (1992). A note on marginal deterrence. *International Review of Law and Economics*, *12*, 345–355.

Wilde, L. L. (1992). Criminal choice, nonmonetary sanctions and marginal deterrence: A normative analysis. *International Review of Law and Economics*, *12*, 333–344.

Williamson, J. (1995). *Manipulation on trial*. Cambridge University Press.