The Role of Experience in Deterring Crime:
A Theory of Specific versus General Deterrence

by

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Abstract: This paper examines the role of experience in determining the deterrent effect of criminal punishment. Economic models of crime typically assume potential offenders know the probability of apprehension. Thus, neither the individual's personal experience of being caught and punished nor the observation of someone else's punishment experience affects that individual's future behavior. This paper incorporates a role for experience in determining criminal activity, distinguishing between (1) how individuals form perceptions of the probability of punishment, including how those perceptions are influenced by what they experience or observe, and (2) how those perceptions, once formed, influence their decisions about criminal activity.

JEL codes: K14, K20, K42
Key words: Economics of crime, specific deterrence, general deterrence

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1. Introduction

The concept of deterrence lies at the core of economic models of crime dating back to the Becker (1968) model and its various precursors.[1] Deterrence represents the idea that people are discouraged from committing wrongful acts by the prospect of having to face some form of punishment. In the canonical economic model of crime,[2] individuals commit crimes when the benefit exceeds the expected penalty, where the latter depends on both the perceived likelihood of apprehension and the magnitude of the sanction. In this model, for any given benefit, as long as the probability of punishment and the associated sanction do not change over time, deterrence does not change either, and, hence, the crime rate stays constant. In other words, neither the individual's past *experience* of being caught and punished (or not) nor the observation of someone else's punishment experience in one period affects that individual's behavior in subsequent periods.

However, considerable evidence demonstrates that individuals, in fact, update their perceptions of the probability of apprehension based on experience (see Nagin (2013) and Apel (2022)). The fundamental question of interest in the current study is how direct and indirect experiences affect deterrence and the resulting crime rates. We emphasize two key factors affecting deterrence: (1) how individuals form perceptions of the probability of punishment, including how those perceptions are influenced by what the individuals experience or observe, and (2) how those perceptions, once formed, shape individuals' decisions about criminal activity. Economic models of deterrence typically consider only the latter feature, taking as settled the offender's perception of the probability of punishment. We construct an economic model of deterrence that explicitly incorporates both factors and then use the model to study their combined effects on deterrence.

We begin with the standard economic model of crime in which an individual contemplating commission of an illicit act has some pre-existing belief about the likelihood of apprehension and punishment. We then embed this framework in a dynamic (2-period) setting that links current experience or observation to future behavior by allowing for the possibility that an individual updates her perceptions of the likelihood of apprehension and punishment based on personal

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[1] See, for example, Bentham (1780), Beccaria (1764), and Montesquieu (1748).
[2] See Polinsky and Shavell (2000) for a survey.

experience or observation of others' experiences. We first use this dynamic model to formalize the impacts of an offender's own experience and the impact of an offender's knowledge about the experience of others. We highlight important similarities and differences between these two types of experience, as well as how they relate to deterrence in the canonical economic model. We then examine the model's implications for crime rates.

The criminology literature suggests that either type of experience reduces future crime rates. We show that, although this conventional wisdom is true in a narrow sense, it is not true in general. In particular, we demonstrate that overall crime rates can be higher or lower when individuals revise their perceptions based on their own experience or the experience of others. Our results have implications for the design of deterrence strategies, which often implicitly assume that the act of apprehending and punishing an individual in one period not only redresses the crime or wrongdoing associated with that activity but also helps deter future crimes. Our results also prove relevant for designing and interpreting empirical studies of enforcement that seeks to incorporate experience, often in the context of regulatory enforcement.

Finally, we hope that our model sheds some light on the meaning of the terms "specific deterrence" and "general deterrence", which are used (albeit somewhat differently) in the economics and the criminology literatures. In both literatures, specific deterrence refers to the impact of one's own experience on future deterrence. This impact reflects an inherently dynamic concept because it depends, by definition, on the offender's *own* past experience. However, the concept of general deterrence as typically used in the economics literature is a purely static concept, reflecting the fear of punishment based on a common belief among offenders about how enforcers will respond to a criminal act. In other words, the concept involves a one-time decision by offenders in the face of a fixed and known expected punishment. [3] The manner in which the expected punishment is learned by offenders, or how it might evolve over time, is not addressed in the economics literature. In contrast, the criminology literature uses the term "general deterrence" to refer to a dynamic concept based on the observations of the past experiences of others (Stafford and Warr, 1993). We adopt this explicitly dynamic notion of general deterrence to account for how an offender's initial beliefs, however they were formed, are affected by these

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[3] Several previous studies extend the standard model to allow for repeat offenses, but these models focus exclusively on how the expected punishment evolves in response to the *criminal history* of offenders, not on how offenders *update their beliefs* in response to their experiences. See Miceli (2013) for a survey of this literature.

observations. In doing so, we are able to provide a general framework for examining specific and general deterrence, which we believe provides a bridge between how these two concepts are understood in the economics of crime and criminology literatures.

The rest of our study is organized as follows. The next section reviews the theoretical and empirical literature related to the impact of experience on deterrence. Section 3 constructs the basic model and then Section 4 uses this model to formalize the conventional wisdom regarding how experience affects deterrence. Section 5 turns to the broader question of the implications for expected crimes rates. Section 6 illustrates the results with an example based on Bayesian updating. Section 7 discusses some implications of our analysis for optimal enforcement policy and empirical work on enforcement. Finally, Section 8 summarizes the results and offers concluding remarks.

2. Literature Review

Criminologists have long emphasized the impact of experience on deterrence, with a particular focus on the notions of specific and general deterrence (see, e.g., Stafford and Warr (1993)). For example, Meier and Johnson (1977, p. 294-295) note that "the deterrence literature differentiates threats that are communicated by the experience of others who suffer the consequences of violation ('general deterrence') from threats which are communicated through personal experience of the consequences at an earlier time ('specific deterrence')." In both cases, the presumption is that an individual will behave differently in the future when, in the present, she personally experiences punishment for a given crime or sees someone else being punished for a crime. This "demonstration effect" is often used as a rationale for the imposition of punishment for crimes already committed (which, by definition, cannot be deterred).[4]

The validity of this view hinges on the assumption that individuals update their perceptions of the risk of apprehension in response to experience. [5] A number of empirical studies offer

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[4] For example, according to Nagin (1978), punishing an individual who has committed a crime will "demonstrate to the rest of the public the expected costs of a criminal act, and thereby discourage criminal behavior in the general population" (p. 96). Similarly, as Oliver Wendell Holmes colorfully expresses in his classic treatise on the common law, if a person is observed committing a wrongful act, "the law would have to verify its threats [to impose punishment] in order that others might believe and tremble" (Holmes, 1881 [1963], p. 39).

[5] Other factors, including various biases, can also affect offenders' assessments of the probability of detection. Some of these factors are examined in the behavioral economics literature. As examples, Harel

evidence supporting this assumption. Nagin (2013) and Apel (2022) provide reviews of this literature, which includes studies from both economics and criminology. A notable economic study is Lochner (2007), who finds that individuals who experience an arrest subsequently increase their perceived probabilities of future arrest, while those who avoid arrest subsequently reduce their perceptions.[6] Similarly, in the criminology literature, Anwar and Loughran (2011) find that experiencing an arrest leads to a 6.3% increase in the perceived probability of apprehension.

Despite the strong evidence that individuals update perceived probabilities based on experience, few theoretical models explicitly incorporate the formation of deterrence-related perceptions.[7] We are aware of only three studies in the deterrence literature that model the formation and updating of perceptions of the likelihood or severity of punishment based on experience. The first study is Shavell's (2004, pp. 515-518) discussion of "individual deterrence", which includes a footnote (note 3, pp. 516-517) with a simple example of how individuals who do not know the true probability of punishment update their beliefs based on their personal experience using Bayesian updating. However, Shavell does not consider updating based on observed punishment of others or examine the implications of this updating for crime rates.

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and Segal (1999) and Horovitz and Segal (2007) observe that psychological evidence indicates that offenders "prefer" punishment schemes with greater certainty about the probability of detection. Thus, law enforcers can enhance deterrence by adopting policies that make the probability *less* uncertain. However, Teichman (2011) offers a survey of the behavioral economics of crime in which he notes that offsetting biases and unobservable risk preferences on the part of offenders lead to conflicting predictions regarding the impact of less certain punishment regimes. Moreover, Chopard and Obidzinsky (2021) examine the implications for law enforcement policy of the resulting "decisions under ambiguity" by criminal offenders. These types of psychological factors and biases can affect perceived probabilities of apprehension, as well as the updating of those perceptions in response to experience (Apel, 2022). Nonetheless, the evidence overall suggests that individuals update rationally (see, for example, Anwar and Loughran (2011), Coutts (2019), and Apel (2022)).

[6] Lochner (2007) finds, however, that individuals update primarily in response to their own experiences with crime and punishment, while being "largely unresponsive to outside influences" (p. 459). His results seem to provide support for a specific deterrence effect but less support for general deterrence.

[7] Several studies explore state-dependent enforcement strategies (e.g., Harrington, 1988) or, more specifically, increased scrutiny or higher penalties for repeat offenders (e.g., Polinksy and Shavell, 1998; Polinsky and Rubinfeld, 1991; Miceli, 2013). A few empirical studies examine the effects of entities' own experiences with actual punishment or regulatory interventions, such as inspections, guided by the associated theoretical framework (Helland, 1998a; Eckert, 2004; Kang and Lee, 2004). Since the increased scrutiny is specific to an entity, these studies perhaps capture a flavor of specific deterrence. However, our formulation of specific deterrence is conceptually different as it arises absent any actual upward ratcheting of enforcement. Some models, including those of Bebchuk and Kaplow (1992), Kaplow (1990), and Garoupa (1998), examine the implications for optimal enforcement policy when individuals are imperfectly informed about the probability of apprehension. However, these models do not examine how those "incorrect" perceptions are formed or change with experience.

A second study by Sah (1991) provides a more detailed analysis of how would-be offenders form their beliefs about the probability of apprehension. He specifically argues that individuals who are imperfectly informed about the probability of criminal punishment use information that they gather from their own experiences and from the experiences of acquaintances. He then examines the implications for crime participation rates, which vary across different social groups and over time. Although Sah's model accounts for information gathered from one's own experience and that of others, his interest focuses primarily on how criminality and actual probabilities of apprehension and punishment evolve endogenously over time, particularly in the presence of limited enforcement budgets and time-varying enforcement.

Finally, Maniloff (2019) develops a theoretical model of regulatory compliance that is similar to Sah's. However, this model focuses on how Bayesian updating diminishes over time as firms gain additional experience; i.e., as they observe additional signals about enforcement stringency.

Despite the limited theoretical and empirical work on the formation of deterrence-related perceptions, a large body of empirical literature in economics seeks to measure how specific and/or general deterrence (broadly conceived) affect the behavior of potential criminals or compliance with regulations (such as environmental and occupational health/safety regulations).[8] Studies of compliance behavior typically use information about enforcement actions (such as the number of inspections and the number or magnitude of sanctions) as possible explanatory variables.[9] Many of these studies focus primarily on specific deterrence; i.e., they include measures of actual punishment or regulatory interventions experienced by a particular entity as regressors explaining the specific entity's compliance

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[8] Although most of these empirical studies rely on micro-level data, a number of them use aggregate data, such as sector-level data, to examine the impacts of enforcement and monitoring on compliance outcomes (e.g., Viscusi, 1979; Viscusi, 1986). These studies are not able to distinguish between specific and general deterrence. As a notable exception, Rincke and Traxler (2001) creatively exploit municipality-level data on compliance with television license fees to isolate a general deterrence effect. Specifically, the study distinguishes between households that were subject to inspections and those that were not. The study finds a substantial response from households to increased monitoring in their vicinity. The authors describe this effect as an "enforcement spillover" or "externality in enforcement" rather than "general deterrence".

[9] A separate body of literature examines the deterrence effects of enforcement by exploiting variation in enforcement policy parameters. For example, Stafford (2002) examines the effect of the Environmental Protection Agency's dramatic 1991 increase in the penalties associated with violations of hazardous waste regulations on firm compliance. Similarly, Sigman (1998) examines the effect of variation in enforcement severity on the illegal dumping of waste material using state-level legal maxima on fine levels.

behavior.[10] Other studies examine only general deterrence; i.e., they include only measures of enforcement actions taken against other entities.[11] Finally, several studies explicitly examine both.[12] All of these studies, however, are challenged to distinguish between specific and general deterrence, as defined here, primarily because the studies must use imperfect proxies for the unobserved enforcement probabilities.[13]

In addition, most of the empirical studies reviewed above do not explore the relevant causal mechanisms through which specific and/or general deterrence operate. Exceptions include Scholz and Gray (1990), who test behavioral hypotheses based on the assumption that regulated firms have limited attention capacity; Shimshack and Ward (2005), who find evidence of both specific and general deterrence in the context of compliance with water quality regulations, which they attribute to regulator reputation building; Maniloff (2019), who finds suggestive evidence that firms update their beliefs about regulatory enforcement stringency as they gain experience in the industry; and Earnhart and Friesen (2013), who seek to separate the deterrence effects of learning from other causal mechanisms that might underlie deterrence decisions and find strong evidence for "experiential deterrence", which they suggest may be explained by salience rather than learning.[14] Salience is often linked to the "availability heuristic," whereby people judge the frequency of an event by how easy it is to recall such an instance; this heuristic represents one mechanism linking one's recent experiences to compliance-related behavior (Tversky and Kahneman, 1974).[15] Jolls, et al. (1998, p. 1537) note "that vivid and personal

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[10] See Magat and Viscusi (1990), Helland (1998b), Lanoie et al. (1998), Foulon et al. (2002), and Earnhart and Segerson (2012).

[11] See Helland and Whitford (2003), Gray and Shadbegian (2005), Thornton et al. (2005), and Earnhart et al. (2020).

[12] See Scholz and Gray (1990), Earnhart (2004a,b, 2009), Shimshack and Ward (2005, 2008), Gray and Shadbegian (2007), Earnhart and Glicksman (2011), Lim (2016), Earnhart and Friesen (2017), and Maniloff (2019).

[13] For some efforts to establish this distinction, see Laplante and Rilstone (1996), Nadeau (1997), and Gray and Shadbegian (2005).

[14] Studies in other contexts also find that experience itself can lead to changes in behavior even if the objective parameters are fully described. Haselhuhn et al. (2012) find that late returns of video rentals significantly decreased for patrons who had experienced previous fines for late returns despite no change in fine levels. Bigoni et al. (2008) find in their experimental study of antitrust programs that collusive behavior dropped following detection and punishment despite no change in the enforcement parameters. Alm et al. (2009) provide evidence from experimental tax compliance experiments suggesting that the salience mechanism can operate even when objective probabilities are known.

[15] Other studies explore salience but not in a deterrence setting. For example, Keller et al. (2006) find that perceptions of flood risk increased for those who had experienced flooding despite the inclusion of objectively expressed flood risk information. In a different context, Simonsohn et al. (2008) find that, in several game theory

information will often be more effective than statistical evidence" in changing behavior.

This literature review suggests that, although evidence demonstrates that individuals update their perceptions in response to experiences and experiences affect criminal and compliance behavior, neither the theoretical nor the empirical literature provides a clear understanding of the impact of experiences on behavior and resulting crime rates. This study addresses this gap by explicitly examining the role of experience in the formation of offenders' beliefs about enforcement and then suggesting how this examination helps inform both normative discussions about enforcement policy and the empirical studies assessing its effectiveness.

3. Basic Model

In modeling behavior within a given period, we follow the approach from the standard economic model of crime where a potential offender (hereinafter simply "offender") is a risk-neutral expected utility maximizer who commits a crime in a given period if and only if the realized gain exceeds the expected sanction. Let g be the offender's gain from committing a criminal act in that period. We can interpret g as reflecting the offender's circumstances or criminal opportunities in that period, which are drawn from a distribution function, $F(g)$, with the associated density function, $f(g) = F'(g)$.[16] Let $s>0$ be the dollar or monetary equivalent of the cost to an offender of the sanction imposed upon apprehension.[17,18] Finally, let $p>0$ be the (true)

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experiments, different sources of information are weighted differently, with a person's own experience weighted more, even when objectively all sources of information are equally informative.

[16] If we view g as the offender's "type", then $F(g)$ represents the distribution of possible types for a particular individual in a given time period. Under an alternative interpretation of the model, $F(g)$ could represent the distribution of types across a given population. In this case, the crime rates derived below represent proportions of the population that commit a crime (rather than the probability that a given individual commits a crime). However, since we take the distribution $F(g)$ as exogenously given and fixed over time, under this alternative interpretation, the case of specific deterrence considered below where an individual draws a new g each period no longer applies. Specifically, this case would require a change in a given individual's type, which alters the distribution of $F(g)$. Nonetheless, the case of general deterrence with perfect observability, which we show is analytically equivalent to specific deterrence with multiple draws, is still relevant under the alternative interpretation of g.

[17] We do not need to distinguish between penalties and prison since our primary concern is how the threat of a sanction affects the decision making of potential offenders, and, consequently, the crime rate.

[18] Individuals may not know with certainty the level of the sanction. For example, in some enforcement contexts, violators do not always receive fines especially for initial violations. For example, highway troopers commonly issue warnings to violators of speed limits. If the sanction level is uncertain, then s should be interpreted as the mean of the distribution of sanctions that the offender could face. However, to avoid confusion, we simply refer to s as the sanction and reserve the term "expected sanction" for ps.

probability of apprehension, which depends on the enforcement policy in place. In the standard economic model, individuals know both s and p, so they can calculate the expected sanction, ps. They thus commit a crime in a given period if and only if the realized net gain exceeds the expected sanction; i.e., if and only if $g > ps$.[19] The fact that the expected sanction is positive ($p > 0$ and $s > 0$) is what allows for a deterrent effect of punishment in this context, which is the key insight of the standard economic model.

While it seems reasonable to suppose that offenders know the sanction, s,[20] it is less reasonable to suppose that they know p. However, they can form a belief about p based on observations and/or experience. Further, as offenders gain knowledge over time, they can update their beliefs. As noted above, the literature suggests that the combination of new information and the corresponding updating of beliefs are key factors giving rise to specific and/or general deterrence effects (in the dynamic sense), depending on the source of the information.

To capture these factors, we consider a two-period time horizon where an offender can commit at most one offense in a given period. We examine two distinct scenarios. In the first, a single individual potentially commits a crime in each of the two periods. This scenario implies that the offender is the same person in both periods, and her first-period experience possibly affects her own decision making in the second period. In the second scenario, the offenders in the two periods are different individuals. In this scenario, the first-period experience of the first offender may affect the decision making of the second offender, depending on what aspects of the first offender's experience the second one observes and how she responds to it. The two scenarios are meant to capture the difference between specific and general deterrence, respectively, as these concepts were described above.

We assume that in Period 1, the distribution describing the offender's beliefs about the

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[19] This assumption is a standard but simplified way to model behavior in the law and economics literature (e.g., Shavell, 2004). It abstracts from a number of factors that have been considered in other work. For example, in a regulatory compliance context, the link between a firm-level decision and violation of a statute can be stochastic (e.g., Earnhart and Segerson, 2012) and compliance-related decisions can involve the level of production or activity (e.g., Segerson and Tietenberg, 1992; Shavell, 2009). We abstract from these real-world considerations in order to focus on the key features that drive our results, namely, how experience impacts the updating of beliefs and subsequent incentives to commit a crime.

[20] Even if offenders are not certain about s, apprehension should not shape the perceptions of s. Shavell (2004, p. 517) notes that offenders should not systematically raise (or lower) their estimates of s as a result of getting caught, assuming offenders' expectations about s are unbiased. In other words, getting caught *per se* does not imply a higher or lower s in the future.

probability of apprehension has a mean of $\hat{p}$, which may or may not coincide with the true p, and a variance of σ_0^2. (In the example presented in Section 6, we assume an unbiased prior, i.e., $\hat{p} = p$.) Thus, under risk neutrality, an offender in Period 1 commits a crime in that period if and only if $g > \hat{p}s$. As a result, the probability of a crime (or equivalently here the crime rate) equals $\left(1 - F(\hat{p}s)\right)$. Because of risk neutrality, the decision to commit a crime depends only on the mean $\hat{p}$ and not its variance.[21] For this reason, to simplify the exposition, we generally refer to $\hat{p}$ as the individual's belief or perception of p.

If the offender commits a crime, she is either caught and sanctioned or not.[22] This combination happens based on the true probability p. At the start of the second period, the second-period offender (who may be the same or a different person) forms her beliefs about the probability of apprehension. These beliefs may differ from the first-period offender's beliefs, depending on the decisions and experience of the first-period offender. Figure 1 depicts a generic game tree for this two-period world. Beginning at the top, the individual active in the first period either commits a crime or not. If she does, she is either caught or not. These pathways produce the three possible nodes shown at the start of Period 2 in Figure 1: (1) the individual committed a crime in Period 1 and was caught [Node X], (2) she committed a crime in Period 1 but was not caught [Node Y], and (3) she did not commit a crime in Period 1 [Node Z]. The choice of the second-period decision maker, whether she is the same or a different person, then depends on whether that person can distinguish among these three nodes, and if so, how she updates her beliefs about p in response to that knowledge.

[Figure 1 here]

We model the second-period decision maker's updating process as follows:[23] (1) if the first-period decision maker was observed being caught and punished, the second-period decision

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[21] We show below that the variance of beliefs can affect the magnitude of the updating (see Section 6). However, the general results derived in Sections 4 and 5 do not depend on the variance of beliefs.

[22] We assume away false apprehension; i.e., the only individuals who face possible apprehension are those people who commit crimes.

[23] Because the decision about whether to commit a crime depends only on the mean of beliefs and not on the variance, we focus here only on updating the mean. In general, however, the offender can also update her variance of beliefs. For example, Bayesian updating, which we consider explicitly in Section 6, modifies both the mean and the variance. See, for example, Greenberg (2012).

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maker updates her assessment of p, increasing it from $\hat{p}$ to $\hat{p}_c > \hat{p}$;[24] (2) if the first-period decision maker was observed committing the crime but was not caught and punished, the second-period decision maker updates her assessment of p to $\hat{p}_n < \hat{p}$; and (3) if the first-period decision maker was observed not committing a crime, the second-period decision maker does not update $\hat{p}$.

This updating process could, but need not, be based on Bayesian updating. Previous studies of specific and general deterrence often implicitly or explicitly assume Bayesian updating (see, for example, Stafford and Ward (1993), Shavell (2004, pp. 516-517), and Maniloff (2019)). We consider Bayesian updating explicitly in the example offered in Section 6. At this point, however, we leave the updating method as general as possible to allow for the broadest possible interpretation. For example, an alternative interpretation could be that the updating simply reflects changes in "salience." Under this interpretation, getting caught increases salience, and hence creates the perception that the event (apprehension) is more likely in the future, while not getting caught decreases salience by causing any previous apprehensions to fade (more) into the past, thereby creating a perception that the probability of apprehension is lower.[25]

Once the second-period offender has formed her beliefs about apprehension based on experience or observations in Period 1, she decides whether or not to commit a crime in Period 2.[26] We describe Period 2 decisions in more detail in Section 5. Before turning to that, in the next section we use the model above to formalize the sense in which the conventional belief regarding the impact of specific and general deterrence on crime is true. As we will show, this view stems from a comparison of conditional probabilities and as such is not, we believe, very useful for understanding the implications of experience. Nonetheless, we present it here both to provide a link to the conventional wisdom and to distinguish this view from what we believe is the more

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[24] It is possible that an individual could instead revise their assessment downward, reflecting a belief that, having been caught once, the likelihood of being "unlucky" a second time is low. However, while allowing for this "resetting effect" in their model, Anwar and Loughran (2011) find instead that individuals who have been arrested revise their assessments upward, consistent with the assumption we make here.

[25] Although the two-period (short run) model presented here and the results derived from it in Sections 4 and 5 apply under either a Bayesian or a salience interpretation of the model, the long run implications of these two behavioral assumptions can differ, since the magnitudes of adjustments in response to new information decline over time under Bayesian updating but not necessarily if they reflect salience.

[26] We assume that the sanction for a second-period offense remains fixed at *s*. A separate question, not posed here, is how *s* should be adjusted (if at all) for repeat offenders. See, for example, Miceli (2013).

appropriate basis for evaluating the impacts of specific and general deterrence, which we will examine in Section 5.

4. Specific and General Deterrence: Impacts Based on Conditional Probabilities of a Crime

4.1. Specific Deterrence

We consider first the case of specific deterrence, which relates to the case where the same individual acts in both periods. As noted, the person's perception of p in Period 1 is $\hat{p}$. Now suppose the individual commits a crime. If she is caught and punished, she updates the perceived probability of apprehension to $\hat{p}_c > \hat{p}$. In this case, her probability of committing a crime in Period 2 is $(1 - F(\hat{p}_c s))$. Alternatively, if the first-period offender is not caught and punished, she revises the perceived probability downward to $\hat{p}_n < \hat{p}$. Consequently, her probability of committing a crime in Period 2 is $(1 - F(\hat{p}_n s))$.

Result 1: *Given that $\hat{p}_c > \hat{p}_n$, the probability that a first-period offender who commits a crime in Period 1 commits a crime in Period 2 is lower if she is caught and punished for her first-period crime than if she is not caught and punished for that crime.*

This result provides the basis for the conventional wisdom that punishment for a crime committed in Period 1 reduces the probability of committing a crime in Period 2. We emphasize that this effect is *not* due to an exogenous escalation in the expected punishment (i.e., a higher p or s) based on an offender's criminal history, but only to her evolving beliefs. If we use this to define the reduction in crime attributable to specific deterrence, the magnitude of the reduction would be given by $(1 - F(\hat{p}_n s)) - (1 - F(\hat{p}_c s)) = F(\hat{p}_c s) - F(\hat{p}_n s) > 0$. This reduction clearly differs from the deterrence effect in the standard economic model that follows simply from a strictly positive apprehension probability (since without updating the two conditional probabilities would be identical and hence the reduction would be zero). [27]

Importantly, however, the reduction reflected in Result 1 captures only the difference in two *conditional* probabilities (i.e., two *conditional* crime rates). In terms of Figure 1, it is the difference between the probability of committing a Period 2 crime, *conditional on being at node Y,* and the probability of committing a Period 2 crime, *conditional on being at node X.* It does not

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[27] One might contend that even in the standard model punishment in Period 1 makes it "credible" that punishment will ensue in Period 2 and hence will affect the probability that a crime will be committed in that period. Since this interpretation of the standard model would include a kind of updating, it is consistent with our notion of specific (or general) deterrence.

capture the effect of specific deterrence on the overall *expected* crime rate in Period 2, which combines the probabilities of all three of the branches in Figure 1 that lead to a crime being committed in Period 2. The overall expected crime rate is presumably the key outcome of interest when designing policy at the start of Period 1. We consider how an individual's experience in Period 1 affects this crime rate in Section 5. Before turning to that issue, however, we show that the conventional wisdom regarding general deterrence can be characterized in a similar way.

4.2. General Deterrence

In contrast to the preceding scenario, general deterrence concerns a situation where the observation of what has happened to an individual in Period 1 impacts the probability that a *different* individual will commit a crime in Period 2. In this context, we need to consider two possible information scenarios. In the first scenario, the second-period offender can perfectly observe what the first-period offender has done. In particular, she observes whether the first-period offender committed a crime, and, if so, whether that offender was caught and punished or not. This scenario is most relevant when the second-period offender can observe if the first-period offender "got away with" a crime or violation, as, for example, when one individual sees another individual speeding without being apprehended by the police.

In the second scenario, the second-period offender simply observes whether the first-period offender was punished or not, but does not directly observe whether the first-period offender committed a criminal act. Thus, if no punishment is rendered in Period 1, the second-period offender cannot tell if the first-period offender committed a crime and was not caught, or if she simply did not commit a crime. In terms of Figure 1, the second-period offender cannot distinguish between Nodes Y and Z (i.e., both are part of the same information set).[28] This scenario is relevant when a second-period offender only hears about previous crimes when the criminal is apprehended and punished and is unaware of specific "unsolved" crimes and undetected or unpunished violations. Examples include shoplifting, fraud, and regulatory violations by other firms.

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[28] The model might alternatively assume that, if no punishment is rendered in Period 2, the second-period offender simply concludes that no crime was committed, i.e., she incorrectly concludes that all criminals are apprehended and punished with certainty. However, this assumption is irrational and ignores the important recognition of "avoided punishment" and its impact on subsequent behavior (see Stafford and Warr (1993)).

The first scenario, which involves perfect observability, is qualitatively similar to the scenario of a single individual acting in both periods where specific deterrence affects behavior.[29] Thus, conditional on observing the first-period individual commit a crime, the second-period individual commits a crime in Period 2 with probability $(1 - F(\hat{p}_c s))$ if the first-period individual is caught and punished, and with probability $(1 - F(\hat{p}_n s))$ if she is not caught and punished. Thus, in this setting, general deterrence and specific deterrence play an identical role. In particular, under either, the reduction in the probability of committing a crime in Period 2 given punishment (of oneself or someone else) in Period 1 is equal to $F(\hat{p}_c s) - F(\hat{p}_n s) > 0$ and implies the following result:

Result 2: *Given that $\hat{p}_c > \hat{p}_n$, when two different offenders act in Periods 1 and 2 but the second-period offender can perfectly observe the actions and the outcome of the first-period offender, then (i) specific and general deterrence have identical impacts, and, hence, (ii) the probability that the second-period offender commits a crime in Period 2 is lower if the first-period offender is caught and punished for that crime than if she is not caught and punished for that crime.*

Specific and general deterrence are not identical, however, in the second scenario where the second-period offender only observes whether the first-period offender is caught and punished. The question is how the second-period individual rationally updates her beliefs in this scenario. If she observes the Period-one offender being caught and punished, she revises her beliefs upward from $\hat{p}$ to $\hat{p}_c$ as before. In contrast, if she observes nothing, she rationally revises her beliefs downward. However, the key question is how exactly she implements this revision.

One way is to compute a weighted average of $\hat{p}_n$ and $\hat{p}$, where the weights are, respectively, the perceived probability that the first-period offender committed a crime and was not caught, and the perceived probability that she did not commit a crime at all, both conditional on the absence

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[29] One might contend that a person will react differently depending on whether she experienced punishment personally or observed someone else being punished under the same circumstances. This is obviously true in terms of the impact of punishment on one's own realized utility. However, the two experiences (seeing someone else being punished versus incurring punishment oneself) should generate the same consequences *in terms of the updating of beliefs,* provided the individual believes that the probability of punishment is the same for all individuals (including themselves).

of observed apprehension and punishment and the person's perception about p. Using Bayes Theorem, these probabilities are as follows:

$$\frac{[1-F(\hat{p}s)](1-\hat{p})}{1-\hat{p}[1-F(\hat{p}s)]}, \tag{1}$$

and

$$\frac{F(\hat{p}s)}{1-\hat{p}[1-F(\hat{p}s)]}. \tag{2}$$

The resulting updated belief based on the weighted average, denoted by $\bar{p}$, equals the following:

$$\bar{p} = \frac{[1-F(\hat{p}s)](1-\hat{p})}{1-\hat{p}[1-F(\hat{p}s)]}\hat{p}_n + \frac{F(\hat{p}s)}{1-\hat{p}[1-F(\hat{p}s)]}\hat{p}. \tag{3}$$

Since the weights are less than one, $\hat{p} > \bar{p} > \hat{p}_n$. Thus, the second-period offender revises her assessment of p downward, but not by as much as if she had observed the first-period offender committing a crime and escaping apprehension.[30]

Consider next the choices of the second-period offender. If she observes the first-period offender being caught, her probability of committing a crime in Period 2 is $(1 - F(\hat{p}_c s))$, whereas if she observes nothing, she commits a crime with probability $(1 - F(\bar{p}s))$. Thus, as before, the probability that she commits a crime in Period 2 is lower when she observes an offender being punished in Period 1 than when she does not observe an offender being punished in Period 1. Moreover, given $\hat{p} > \bar{p} > \hat{p}_n$, Result 3 follows immediately:

Result 3: *Given $\hat{p} > \bar{p} > \hat{p}_n$, when the second-period offender can only observe whether or not the first-period offender was caught and punished, (i) the probability that the second-period offender commits a crime in Period 2 is lower if she observes that a first-period offender was caught and punished for a crime than if she is unaware of whether the first-period offender commits a crime, and (ii) the reduction in the probability that the second-period offender commits a crime is smaller when the second-period offender can only observe whether or not the first-offender was caught and punished than when the second-period offender can perfectly observe both the action and outcome of the first-period offender.*

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[30] Although (3) represents one particular form of updating, this statement critically drives the results here and in Section 6.

In this scenario, the reduction in the probability of committing a crime in Period 2 is now given by this expression: $(1 - F(\bar{p}s)) - (1 - F(\hat{p}_c s)) = F(\hat{p}_c s) - F(\bar{p}s) > 0$. Again, however, this is the difference between two *conditional* probabilities. In terms of Figure 1, it is the probability of a crime in Period 2 conditional on the second-period offender being at Node X, minus the probability of a crime in Period 2 conditional on the second-period offender being at Node Y or Z. The reduction in the probability is smaller in this second information scenario than in the perfect-observability scenario because the second-period offender rationally realizes that the lack of observed punishment in Period 1 might simply mean that the first-period individual committed no crime, which dilutes the impact of general deterrence.

As in the previous cases, the result in Result 3(i) is consistent with conventional wisdom. However, again the impacts of specific and general deterrence that we have formalized in this section consider only the difference in conditional probabilities. As noted above, from a policy perspective, the more important question is how experience affects overall expected crime rates, which consider (and combine) all possible branches of the game tree in Figure 1; i.e., whether the expected Period-2 crime rate will be lower than the expected Period-1 crime rate as a result of specific or general deterrence. The impact on crime rates is the typical (sometimes implicit) rationale provided for the importance of specific or general deterrence. For example, enforcement officials commonly base their decisions to publicly announce apprehensions and punishments based on the rationale that such announcements will deter future crimes. We will now show, however, that our results only justify this rationale under certain conditions.

5. Specific and General Deterrence: Impacts on Crime Rates

The expected or unconditional crime rate (hereinafter simply the "crime rate") in any period is the total expected number of crimes committed in that period divided by the total population. We represent this number by the *unconditional* probability that a crime is committed by any given individual in a particular period. As noted above, the crime rate in Period 1 is simply the following:

$$R_1 = (1 - F(\hat{p}s)). \tag{4}$$

In contrast, in Period 2 the crime rate combines all three pathways in Figure 1 through which a crime could be committed in Period 2. In the standard economic model of crime, regardless of the realized outcomes in Period 1, and as long as the fundamental enforcement strategy does not

change (meaning the probability of apprehension, p, and sanction size, s, remain fixed), the crime rate in Period 2 will be the same as in Period 1; i.e., $R_2 = R_1$. Our model gives this result in the absence of updating; i.e., when $\hat{p}_c = \hat{p}_n = \hat{p}$. On the other hand, if experience leads to updating, and we use crime rates as the relevant basis for comparison, a claim that specific or general deterrence effects, as we have defined them, reduce the crime rate would be true only if $R_2 < R_1$. However, this section shows that this result only arises under certain circumstances. More generally, we show that the crime rate may either rise or fall as a consequence of offender updating in each of the scenarios we study.

5.1. Impact of Specific Deterrence

We examine the implications of specific deterrence under two alternative cases. Case 1 assumes that the offender takes a draw of g at the start of Period 1, denoted by g_1, and that draw defines her benefit from a crime in both periods. In Case 2, by contrast, the offender takes two independent draws of g, denoted by g_1 and g_2, at the beginning of the first and second periods, respectively. This case is relevant when an offender's circumstances that impact the net gain from committing a crime can change over time.[31] Of course, Case 1 is a special case of Case 2 where $g_2 = g_1$. However, because these two cases have qualitatively different implications (as we show below), we consider them separately.

5.1.1. Case 1: Specific Deterrence with No Change in Offender's Net Gain

In Case 1, where the offender's gain is the same in both periods (i.e., $g_2 = g_1$), the general expression for the second-period crime rate equals the following:

$$R_2 = \{[1-F(\hat{p}s)] \times [p \cdot \Pr(g_1{>}\hat{p}_c s \mid g_1{>}\hat{p}s) + (1-p) \cdot \Pr(g_1{>}\hat{p}_n s \mid g_1{>}\hat{p}s)]\} +$$
$$F(\hat{p}s) \cdot \Pr(g_1{>}\hat{p}s \mid g_1{<}\hat{p}s). \tag{5}$$

The first term (in curly brackets) is the probability that the offender commits a crime in Period 1, multiplied by the expected probability of committing a crime in Period 2, which depends on the probability that she was caught and punished for her first-period crime and the subsequent updating in response to this experience.[32] The second term is the probability that she did not commit a crime

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[31] As a specific example, in a regulatory enforcement context, a firm's benefit from violating a standard or costs of compliance with a standard can vary over time with market conditions. In a criminal context, a changing g could reflect learning-by-doing or declining ability with age.

[32] Note that, because this is an objective calculation of the expected crime rate, the true probability of apprehension, p, enters the formula.

in Period 1, multiplied by the probability of committing a crime in Period 2, given the revelation of no new information in Period 1. The expression in (5) takes the expectation in Period 1 (i.e., at the top of Figure 1). However, the expectation reflects the fact that the offender makes her commission decision in Period 2 *after* the realization of the outcome of the first-period decision. In other words, the expectation reflects the optimal *conditional* decisions in Period 2.[33]

Again, we use Bayes Theorem to derive the conditional probabilities in (5) as follows:

$$\Pr(g_1 > \hat{p}_c s \mid g_1 > \hat{p}s) = \frac{1 - F(\hat{p}_c s)}{1 - F(\hat{p}s)}, \tag{6}$$

$$\Pr(g_1 > \hat{p}_n s \mid g_1 > \hat{p}s) = 1, \text{ and} \tag{7}$$

$$\Pr(g_1 > \hat{p}s \mid g_1 < \hat{p}s) = 0. \tag{8}$$

Substituting these into (5) gives the following expression for the Period 2 crime rate:

$$R_2 = [1 - F(\hat{p}s)] \left[p \frac{1 - F(\hat{p}_c s)}{1 - F(\hat{p}s)} + (1 - p) \right]. \tag{9}$$

Simplifying this expression and making use of (4) yields the following:

$$R_2 = R_1 - p[F(\hat{p}_c s) - F(\hat{p}s)]. \tag{10}$$

If the offender does not update her beliefs (i.e., $\hat{p}_c = \hat{p}$), then $R_2 = R_1$, reflecting only the deterrence included in standard economic models of crime. However, if $\hat{p}_c > \hat{p}$, then $R_2 < R_1$; that is, the Period-two crime rate is less than the Period-one crime rate. Although this reduction in the crime rate reflects the upward adjustment of the offender's belief about p in the case where she is caught and punished in Period 1, the bracketed term in (10) is not the difference in the conditional probabilities of committing a crime defined in Section 4.1, which was given by $F(\hat{p}_c s) - F(\hat{p}_n s)$.

Note that, although specific deterrence can lead to revising probabilities both upward when caught and downward when not caught, in Case 1 the effect on the second-period crime rate stems only from the upward adjustment. The intuition for this result is the following. If an individual's net benefit from committing the crime in Period 1, g_1, is sufficiently high to induce her to commit the criminal act in the first period under the initial belief about probabilities ($\hat{p}$), then *a fortiori* that individual will find it worthwhile to commit the crime in the second period with *any* downward revision in the apprehension probability that results from not being caught and punished in the first

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[33] If the offender must make the commission decision for Period 2 prior to the realization of the Period 1 outcomes, then the offender simply bases her decision on the expected value of the updated probabilities, $\hat{p}\hat{p}_c + (1 - \hat{p})\hat{p}_n$ and decides to commit a crime in Period 2 if and only if $g_2 \geq [\hat{p}\hat{p}_c + (1 - \hat{p})\hat{p}_n]s$. If updating, on average, does not change mean beliefs, i.e., if $\hat{p}\hat{p}_c + (1 - \hat{p})\hat{p}_n = \hat{p}$, then, in Case 1, both specific and general deterrence are absent. Footnote 18 makes this same point regarding the absence of an impact of apprehension on beliefs about the sanction s.

period. (Formally, if $g_1 > \hat{p}s$, then $g_2 = g_1 > \hat{p}_n s$.) In other words, if the offender "gets away with" the crime in Period 1, she will commit the crime again *with certainty* in Period 2, as shown in (7). This conclusion turns critically on the constancy of g over the two periods. Thus, the downward adjustment in beliefs prompted when the offender is not caught in Period 1 plays no role in second-period deterrence because the expected sanction is smaller, while the gain remains the same.[34] Result 4 summarizes the implication of this result for the relative crime rates in the two periods.

Result 4: *When a single offender potentially commits crimes over two periods based on a single draw of g(i.e., without any change in her net gain over the two periods), then, due to specific deterrence, the crime rate in Period 2 is lower than the crime rate in Period 1 ($R_2 < R_1$).*

5.1.2. Case 2: Specific Deterrence with a Possible Change in Offender's Net Gain

In Case 2, we allow the gain to the individual from committing a crime to vary across the two periods. Specifically, we allow the individual to have different and independent realizations of g in the two periods, though we assume that the realizations are drawn from the same distribution. As noted above, different realizations can reflect changes in the individual's criminal opportunities, or different benefits or opportunity costs of a crime or violation over time. Although this case offers an example of specific deterrence because it is literally the same offender over the two periods, we show that the resulting implications are identical to those from general deterrence with perfect observability (Case 3 below) because the independent realization of g in Period 2 effectively makes the second-period offender a "different person" in terms of her criminal options.

The Period 2 crime rate in this case is the following:

$$R_2 = [1 - F(\hat{p}s)][p \cdot \Pr(g_2 > \hat{p}_c s \mid g_1 > \hat{p}s) + (1 - p) \cdot \Pr(g_2 > \hat{p}_n s \mid g_1 > \hat{p}s)] +$$
$$F(\hat{p}s) \cdot \Pr(g_s > \hat{p}s \mid g_1 < \hat{p}s) \quad . \tag{11}$$

This expression differs from (5) only by the inclusion of g_2 rather than g_1 in the three conditional probabilities. Given the independent draw of g_2 in Period 2, use of Bayes Theorem now identifies the following conditional probabilities:

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[34] Although the prediction of a decrease in the crime rate for repeat offenders is testable in theory, the escalating sanction for offenders with a criminal history in most circumstances would complicate efforts to isolate the impact of updating.

$$\Pr(g_2 > \hat{p}_c s \mid g_1 > \hat{p}s) = 1 - F(\hat{p}_c s) \,, \tag{12}$$

$$\Pr(g_2 > \hat{p}_n s \mid g_1 > \hat{p}s) = 1 - F(\hat{p}_n s) \,, \tag{13}$$

$$\Pr(g_2 > \hat{p}s \mid g_1 < \hat{p}s) = 1 - F(\hat{p}s). \tag{14}$$

Substituting these expressions into (11) and re-arranging yields this expression:

$$R_2 = R_1 - R_1 \{ p[F(\hat{p}_c s) - F(\hat{p}_n s)] - [F(\hat{p}s) - F(\hat{p}_n s)] \}. \tag{15}$$

Again, in the absence of updating, the crime rate remains unchanged between Periods 1 and 2. With updating, though, the crime rate generally differs in the second period. In contrast to Case 1, however, the second-period crime rate now depends on *both* the upward and downward revisions of the offender's beliefs. As a result, the crime rate in Period 2 can exceed the crime rate in Period 1, despite the existence of specific deterrence. Depending on the distribution function and the magnitudes of the updates, the expression shown in curly brackets in (15) can be positive or negative since $\hat{p}_c > \hat{p} > \hat{p}_n$. Thus, in contrast to Case 1, R_2 can be larger or smaller than R_1. This ambiguity does not hold in the absence of downward revisions to the subjective probability (i.e., if $\hat{p}_n = \hat{p}$).

Intuitively, if the individual commits a first-period crime and is caught and punished, she revises her subjective probability upward, reducing the likelihood that she will commit a crime in Period 2. However, if she commits a first-period crime and avoids punishment, she revises her beliefs downward, increasing the likelihood that she will commit a crime in Period 2. The overall impact on the expected crime rate in Period 2 therefore depends on the relative strengths of these two opposing effects. We summarize this conclusion as follows:

Result 5: *When a single offender potentially commits crimes over two periods based on independent draws of g, then, due to specific deterrence, the crime rate in Period 2 may be higher than, lower than, or the same as the crime rate in Period 1 (i.e., $R_2 \gtreqless R_1$).*

Note that, although the difference in the conditional probabilities of committing a crime under specific deterrence given above, $(F(\hat{p}_c s) - F(\hat{p}_n s))$, enters (15) and contributes to the conclusion in Result 5, it does not solely determine the difference between the crime rates in the two periods. The overall difference reflects not only the conventional notion of the impact of specific deterrence measured by the difference in conditional probabilities of committing a crime, but also the magnitude of the downward adjustment in beliefs that results when the individual

commits a crime in Period 1 and avoids punishment (which, in the current scenario, results in more crime). The relative magnitudes of the offsetting effects depend on the specific way in which beliefs are formed and updated, as well as the distribution function F. In Section 6, we provide a specific example using Bayesian updating and a uniform distribution for F.

5.2. Impact of General Deterrence

In the case of general deterrence (i.e., where the offenders are different people in Periods 1 and 2), the individuals necessarily have distinct draws of g. However, two cases are still possible depending on what the second offender can observe. In Case 3, the second-period offender knows with certainty whether the first-period offender committed a crime, and if so, whether the latter was caught and punished. In Case 4, by contrast, the second-period offender only observes apprehension and punishment in Period 1. We consider these cases in turn.

5.2.1. Case 3: General Deterrence with Perfect Observability

It should be apparent that Case 3 is logically equivalent to Case 2 under specific deterrence above. Thus, the Period-two crime rate is given by (15), which allows us to state immediately the following:

Result 6: *When different individuals potentially commit crimes over two periods and the second-period offender can perfectly observe whether the first-period offender commits a crime and whether or not she was apprehended and punished, then, due to general deterrence, the crime rate in Period 2 may be higher than, lower than, or the same as the crime rate in Period 1 (i.e., $R_2 \gtreqless R_1$).*

5.2.2. Case 4: General Deterrence with Imperfect Observability

In Case 4, where the second-period offender cannot observe the action of the first-period offender and can only observe whether that offender is punished for a crime, the Period 2 crime rate can be derived by replacing $\hat{p}_n$ with $\bar{p}$ in (15), which gives the following:

$$R_2 = R_1 - R_1\{p[F(\hat{p}_c s) - F(\bar{p}s)] - [F(\hat{p}s) - F(\bar{p}s)]\}. \text{[35]} \tag{16}$$

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[35] This expression for R_2 is based on the following underlying formulation: $R_2 = R_1 - [1 - F(\hat{p}s)]\{R_1 - p[1 - F(\hat{p}_c s)] - (1 - p)[1 - F(\bar{p}s)]\}$.

Since $\hat{p}_c > \hat{p} > \bar{p}$, the term in curly brackets may again be positive or negative, implying that R_2 may be greater or less than R_1. Further, a comparison of (15) and (16) gives the following:

Result 7: *(i) When different individuals commit crimes over two periods and the second-period offender can only observe whether or not the first-period offender was caught, then, due to general deterrence, the crime rate in Period 2 may be higher than, lower than, or the same as the crime rate in Period 1 (i.e., $R_2 \gtreqless R_1$). (ii) However, the second-period crime rate is lower under Case 4 than under Case 3.*

Result 7 implies that, while general deterrence does not necessarily reduce the second-period crime rate in this case (relative to the first-period rate), the second-period rate is lower than in Case 3 (all else equal). This result implies that revealing more information about "avoided" punishment in Period 1 can actually cause the crime rate to be higher than it otherwise would have been. We return to this point in Section 7. Table 1 summarizes the results for the various scenarios examined in this section.

[Table 1 here]

6. An Example with Bayesian Updating

To illustrate the implications of the above results more clearly, we consider a particular form of updating—namely, Bayesian updating—and employ specific functional forms for $F(g)$ and for the distribution of beliefs. The assumption of Bayesian updating allows us to derive explicit expressions for the crime rates in the two periods that we can then directly compare.[36] For simplicity, we will assume that the offender's net benefit from committing a crime, g, is distributed uniformly on $[0, G]$. Moreover, we assume that the offender starts with a prior belief about the probability of apprehension that is characterized by a beta distribution over p that is unbiased and has variance σ_0^2. The beta distribution is commonly used in Bayesian inference when the variable of interest is a binomial random variable. A key property of this distribution which makes it useful

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[36] Bayesian updating is a common assumption in economic models of updating. For a recent review of the literature on the validity of this assumption, see Coutts (2019). For discussions of the evidence supporting Bayesian updating specifically in the context of apprehension and sanctions, see Anwar and Loughran (2011) and the reviews by Nagin (2013) and Apel (2022).

in this context is that it is a conjugate prior for a binomial proportion. This property implies that, since the prior distribution is a beta distribution, the posterior distribution is a beta distribution as well (see Greenberg, 2012, Chapter 2).[37]

Given these assumptions, the Period 1 crime rate in (4) is:

$$R_1 = 1 - \frac{ps}{G} . \tag{17}$$

If the offender perfectly observes the first-period outcome, she updates her beliefs using Bayes Theorem, which yields the following:

$$\hat{p}_c = p + \frac{\sigma_0^2}{p} \qquad \text{and} \qquad \hat{p}_n = p - \frac{\sigma_0^2}{1-p} . \tag{18}$$

These probabilities represent the means of the posterior distributions, conditional on the first-period outcome.[38] Reassuringly, the expected value of these updated probabilities remains unbiased: $p \cdot \hat{p}_c + (1-p)\hat{p}_n = p$. (The appendix generalizes these expressions in order to allow for multiple observations, or signals, prior to the Period-2 decision.)

Using these expressions, we derive the Period 2 crime rates under the different cases described above.

6.1. Case 1: Specific Deterrence with No Change in Offender's Net Gain

In Case 1, the second-period crime rate in (10) becomes the following:

$$R_2 = \left(1 - \frac{ps}{G}\right) - \frac{ps}{G}(\hat{p}_c - p) = R_1 - \frac{\sigma_0^2 s}{G} , \tag{19}$$

which, consistent with Result 4, is less than R_1. The difference reflects specific deterrence. Furthermore, the reduction in the crime rate is proportional to the variance of the distribution over beliefs, σ_0^2, and the sanction size, s. Thus, the more dispersed are beliefs, the stronger is the effect of specific deterrence. Moreover, as expected, larger sanctions enhance this effect.

6.2. Cases 2 and 3: Specific Deterrence with a Possible Change in Offender's Net Gain and General Deterrence with Perfect Observability

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[37] Greenberg (2012, p. 18) states that "the beta prior is a 'natural' prior for Bernoulli data and the choice of the two parameters in the beta prior can capture a wide variety of prior beliefs." In particular, the uniform distribution is a special case of the beta distribution. Both the exponential and gamma distributions are limiting cases.
[38] The corresponding posterior variances are as follows:

$$\sigma_c^2 = \frac{\hat{p}_c(1-\hat{p}_c)\sigma_0^2}{p(1-p)+\sigma_0^2} \qquad \text{and} \qquad \sigma_n^2 = \frac{\hat{p}_n(1-\hat{p}_n)\sigma_0^2}{p(1-p)+\sigma_0^2} .$$

In Cases 2 and 3, the second-period crime rate is given by (15). Recall that the extra term in these cases is ambiguous in sign, reflecting the offsetting impacts of the upward adjustment in the offender's assessment of p if she was caught in Period 1, and the downward adjustment if she was not caught in Period 1. In the current example, (15) becomes the following:

$$R_2 = R_1 - R_1\left(\frac{s}{G}\right)[p(\hat{p}_c - \hat{p}_n) - (p - \hat{p}_n)] . \tag{20}$$

After substituting for $\hat{p}_c$ and $\hat{p}_n$ from (18), the extra term vanishes, implying that $R_2 = R_1$. Thus, the upward and downward adjustments exactly offset in these cases, leaving the crime rate constant over the two periods. As a result, neither specific nor general deterrence offer an additional deterrence effect on the crime rate, even though we showed in Section 4 that the conditional probability of committing a crime in Period 2 would be lower if the first-period offender (whether the same or a different person) is caught and punished. This apparent inconsistency highlights the importance of distinguishing between the impact of specific/general deterrence on conditional (as in Section 5); probabilities of committing a crime (as in Section 4) versus the impact on the resulting crime rate in this example, the former is strictly positive, while the latter is zero.

6.3. Case 4: General Deterrence with Imperfect Observability

In Case 4, the second-period crime rate is given by (16), which in this example becomes

$$R_2 = R_1 - R_1\left(\frac{s}{G}\right)[p(\hat{p}_c - \bar{p}) - (p - \bar{p})] . \tag{21}$$

Substituting from (18) for $\hat{p}_c$ and using our definition of $\bar{p}$ in (3), we obtain

$$R_2 = R_1 - R_1\left(A\frac{s\sigma_0^2}{G}\right), \tag{22}$$

where $A > 0$ is the conditional probability in (2) with $\hat{p} = p$, which reflects the probability that the second-period offender does not commit a crime conditional on no observed apprehension and punishment in Period 1. The expression in (22) implies that the second-period crime rate falls relative to the first-period rate. Although the offender updates her prior belief downward when she does not observe a first-period offender being punished, that adjustment is less than if she had observed the first-period offender commit a crime and avoid punishment (given that $\bar{p} > \hat{p}_n$). Thus, in contrast to Case 3, in Case 4 the downward adjustment is not enough to offset the upward adjustment, which causes the second-period crime rate to decline.

The impact of general deterrence on the crime rate in this case is again proportional to both the variance in the offender's beliefs and the sanction size, as in Case 1. However, the resulting reduction in the crime rate is smaller. This difference stems from the second-period offender's

imperfect observability of the first-period offender's experience.

6.4. Discussion Based on the Example

This example illustrates the general results from Sections 4 and 5; namely, that, even if observing the apprehension and punishment of crimes in Period 1 results in a lower *conditional* probability that the offender will commit a crime in Period 2, this reduction does not necessarily imply that the (unconditional) expected crime rate in Period 2 will be lower. In this example, the second-period crime rate is lower in some cases (Cases 1 and 4) but not necessarily in others (Cases 2 and 3).

The example also illustrates the role of the variance of beliefs in determining crime rates. Although the general expressions for the crime rates in Section 5 depend only on the means of prior and posterior beliefs, the example highlights the fact that the *updating* of those means depends on the prior variance. As illustrated, a greater variance leads to a larger change in beliefs about means because the updating process places more weight on experience and less weight on prior beliefs when these beliefs are more variable.

An important implication of this role for the variance in beliefs is its impact over time. We have presented a simple two-period model, which is relevant in contexts where an offender's criminal opportunities fall within a limited time period. In other contexts, however, offenders may face criminal opportunities repeatedly over a longer period of time, which gives the opportunity for repeated signals about apprehension. For example, in a context of regulatory compliance, Maniloff (2019) argues that firms learn about the stringency of regulatory enforcement by observing the regulator's behavior over time. Repeat criminal offenders may similarly learn about law enforcement practices. We can also apply our model to such a context by interpreting Period 1 as any arbitrary point in time and interpreting the prior distribution in Period 1 as the posterior distribution based on all experiences up to that time. As offenders accumulate experience (signals) over time and update their priors using Bayesian updating, the variance of their beliefs decreases and asymptotically approaches zero (Greenberg, 2012, Chapter 4). In other words, the variance at any given time t depends on the number of signals received through $t-1$, and σ_{t-1}^2 (the variance of beliefs in period t based on signals through $t-1$) goes to zero as $t \to \infty$. This pattern implies that, under Bayesian updating, in the long run specific and general deterrence (as defined) approach zero, and, hence, in the long run $R_1 = R_2$.

This outcome suggests that, starting with unbiased priors, to the extent that specific or general deterrence affect the crime rate through Bayesian updating, they do so only in the short

run. In the long run, therefore, we are only left with deterrence as captured in the standard economic model, where an individual's recent experience or knowledge regarding the recent experience of others does not affect deterrence. Consistent with this theoretical conclusion, using data on oil and gas producers, Maniloff (2019) empirically shows that the marginal deterrence effect of regulatory actions (general deterrence) decreases with the number of signals a firm has received. Anwar and Loughran (2011) find a similar result for juvenile offenders.

7. Implications of the Results

This section discusses the implications of the preceding results, first for law enforcement policy, and second for empirical analysis of the effects of enforcement policies on compliance with the law.

7.1. Implications for Enforcement Policy

How might the specific and general deterrence effects that we identify in Section 5 affect the design of law enforcement policy? We consider two possible avenues. The first relates to disclosure policy; that is, how much information about crime and punishment should the enforcement authority reveal to the public? This factor is, of course, only relevant for general deterrence since individual offenders obviously have full information about their own experiences.

We can distinguish between two possible disclosure policies: (i) disclose everything—that is, make public all available information about what crimes have been committed, whether the offenders were caught, and the extent of punishment; and (ii) disclose only instances where offenders were caught and punished, while concealing information about crimes that have gone unsolved and violations that did not lead to any sanctions. These scenarios correspond, respectively, to our Cases 3 and 4. A policy of full disclosure requires the enforcer to know about every crime that is committed, regardless of the outcome for the offender. This policy is easier to implement for high-profile or notorious crimes (e.g., murder), those that are routinely reported by the victims (e.g., theft or burglary), those committed openly (e.g., speeding), and self-reported violations of regulatory standards. In contrast, this policy would be harder to implement for crimes committed secretly (e.g., tax evasion or embezzlement). Our results suggest, however, that, even when authorities possess full information, they may want to keep crime rates hidden and only disclose arrests because full disclosure gives would-be offenders information about avoided punishment, and this additional information works against deterrence. By contrast, selectively

disclosing instances where someone is caught and punished creates uncertainty on the part of offenders, which dampens their downward adjustment to the subjective apprehension probability, thus strengthening general deterrence.

The other possible avenue along which our results might affect enforcement policy is through their implications for enforcement authorities' actual choices of p and s. The specific question is whether our conclusions regarding specific and general deterrence effects should prompt deviation of these choices from those arising from the standard economic model. Such a deviation, if warranted, must come through the extra deterrence effects created by offenders' updating their beliefs about p, where by "extra" we mean the marginal impact on crime rates caused by such updating (i.e., the dynamic version of general deterrence). One might conjecture, for example, that specific and/or general deterrence effects provide a rationale for increasing p relative to what would otherwise be optimal based on the idea that catching more offenders today would cause future offenders to revise upward their belief about p, thereby producing greater deterrence benefits tomorrow. This argument turns out to be unsupported by the model because it does not account for downward adjustments of p.

Focusing on the specific example involving Bayesian updating presented in Section 6,[39] we find that the marginal benefit of increasing p is not improved by specific or general deterrence in Cases 1-3. In Case 1, the effect of specific deterrence given by the final term in (19) is independent of p, while Cases 2 and 3 include no extra deterrent effect at all. In other words, the marginal benefit of an increase in p is the same with or without specific/general deterrence. Thus, if the optimal choice of p equates this marginal benefit to the corresponding marginal cost, that choice would also be the same. Finally, in Case 4, the impact of p on the effect of general deterrence, captured by the final term in (22), is ambiguous. Thus, the analysis offers no clear prediction about the impact on the marginal benefit of p and, hence, on its optimal value. Of course, the absence of a clear effect here is a consequence of the assumption of unbiased prior beliefs about p. However, even with unbiased prior beliefs, the variance of those beliefs *does* matter in Cases 1 and 4; in particular, it magnifies the extra deterrent effect in both cases. Again, this impact suggests that disclosure of less, rather than more, information about crime and punishment might have a salutary effect on deterrence.

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[39] Our inability to draw clear conclusions for the specific examples obviously carries over *a fortiori* to the general model.

As for the choice of sanction size, this factor magnifies the effect of specific deterrence in Case 1 (based on (19)), but plays no role in Cases 2 and 3 (again, because specific deterrence is absent), and generates an ambiguous effect in Case 4. Based on these conclusions, we do not find a strong case for increasing enforcement, either by raising p or s, in response to offender updating.

7.2. Implications for Empirical Analysis

Our theoretical analysis also has implications for the implementation of empirical studies aimed at exploring the effects of specific and/or general deterrence or deterrence broadly. We comment on these effects briefly here.

As noted in Section 2, most empirical studies of specific and/or general deterrence use measures of actual enforcement to proxy for the probability or severity of punishment. Yet, these studies purport to examine the impact of *real* or *actual* changes in these policy choices on compliance behavior, especially in the case of general deterrence (e.g., regulator's reputation of toughness).[40] However, as our theoretical model highlights, variation in observed or realized outcomes (such as the number of inspections) does not necessarily imply variation in the probability of enforcement. Similarly, the *absence* of actual punishment does not necessarily imply a zero *probability* of punishment. Empirical studies can only capture the effect of changes in the *actual probability* of apprehension or the severity of the sanction if they can measure actual variation in enforcement strategies over time and/or across space (as, for example, when a regulatory agency commits more resources to inspectors and actually conducts more inspections). Although a few empirical studies offer this analysis (see Footnote 8), most of the literature on specific and general deterrence, which measures enforcement using proxies based on realized outcomes rather than enforcement inputs, does not. Based on these measures, studies should not interpret a finding of no impact on behavior as evidence that enforcement is ineffective. Rather, the absence of any impact may simply indicate that, although realized outcomes varied over time and/or across space within some empirical sample, the offender's *perception* of the underlying *probability* of enforcement did not, leading compliance decisions not to vary either.[41]

Conversely, a statistically significant relationship between measures of enforcement outcomes and compliance should be interpreted as responses to changes in the *perception* of enforcement stringency. In other words, our model suggests that, in the absence of changes in

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[40] For example, Shimshack and Ward (2005) claim to examine a regulator's reputation of toughness.
[41] Maniloff (2019) also makes this point.

underlying enforcement strategies, the null hypothesis being tested in these models is not the existence of a response to a change in enforcement strategy but rather, conditional on that strategy, the existence of (and response to) updating based on experience.

Second, our focus on Bayesian updating implies that potential offenders learn over time. Consequently, although a particular enforcement strategy (i.e., choice of p) can have impacts in the long run, the effects of actual experience and hence specific and general deterrence should disappear in the long run. This conclusion suggests that empirical studies should control for variation in offender's time spent in the "system" and interact this control factor with the deterrence measures, as in Maniloff (2019). In contrast, if salience influences updating, then every time a potential offender is apprehended or not, the effects of specific and general deterrence should remain relevant, even in the long run. This alternative conclusion suggests that "time since last punishment" rather than "time in the system" is the relevant factor to include as an interaction term in empirical analysis. However, in contexts where enforcement opportunities are relatively infrequent, "time in the system" may poorly measure opportunities to learn. In these contexts, the two factors do not differ meaningfully. Consequently, it may be difficult to distinguish whether a long time since the last punishment implies a lack of salience or simply limited opportunity to learn.

8. Summary and Conclusion

This study has sought to explore the role of experience in deterring crime, whether based on personal experience (specific deterrence) or observation of the experience of others (general deterrence), in the context of an economic model of crime. We employed a two-period version of the standard model that clearly distinguished between (1) how individuals form perceptions of the probability of punishment, including how those perceptions are influenced by what the individuals experience or observe, and (2) how those perceptions, once formed, influence individuals' decisions about criminal activity. In this sense, our model offered a means of integrating the notion of deterrence embodied in the standard economic model of crime and the concepts of specific and general deterrence, which are often the focus of the criminology literature, as well as empirical work on the impacts of enforcement.

We used the model to ask whether experience necessarily reduces crime rates, a presumption that is often made in the deterrence literature. We specifically highlighted the

important distinction between the impact of experience on the conditional probability of committing a crime, which is always positive (see Section 4), and the impact on the resulting crime rate, which we showed can be positive or negative (see Section 5). Although the impact based on conditional probabilities comports more closely with conventional wisdom, we believe that the impact on crime rates is more relevant for understanding the deterrence-related implications of experience.

We examined the impact on crime rates under two scenarios: one in which a single offender acts over both periods, and one in which two different offenders act sequentially. In this context, we considered how the decision of the second mover depends on the experience of the first mover, assuming that the former engages in rational updating of her beliefs in response to the experience of the latter. The answer depended on what exactly the second mover knows or is able to observe. Obviously, in the case of a single, repeat offender (the specific deterrence scenario), the second mover knows the first-period outcome and updates her beliefs accordingly. The impact on the crime rate, however, also depends on whether the offender's criminal opportunities change from one period to the next. We showed that if they do not change, the crime rate unambiguously falls in the second period; that is, there is a clear effect of specific deterrence. However, when those opportunities can change over time, the impact on the crime rate depends on whether the offender was or was not caught in the first period. The expected effect on the crime rate is, therefore, ambiguous.

When two different offenders act sequentially (the general deterrence scenario), the outcome in the second period depends on what the second offender is able to observe. If she can perfectly observe the first offender's experience, then the outcome is identical to that under the specific deterrence scenario when the offender's opportunities change. Thus, the change in the crime rate is again ambiguous. More realistically for many contexts, if the second-period offender can only observe when the first-period offender is caught and punished, the impact on the second-period crime rate is again ambiguous, but the crime rate is lower than in the preceding scenario— that is, the rate falls by more or rises by less. In this sense, the incompleteness of information known by the second-period offender enhances deterrence.

Generally speaking, our results revealed that the conventional view that experience leads to a lower crime rate in the future as a result of the punishment of current offenders narrowly focuses on those outcomes in which a first-period offender is actually caught and punished,

whereas our broader focus accounts for the effect of all possible first-period outcomes. Although the probability of committing a crime in the future is lower when current offenders experience or are observed being apprehended and punished (relative to what they would have been if the offending individual were not apprehended and punished), the opposite is true when first-period offenders are not apprehended. The resulting effect on the average crime rate—what we believe is the more relevant meaning of deterrence—is therefore ambiguous, depending on what information is available to offenders.

Our results have implications for law enforcement policy and for the design of empirical studies of deterrence. Regarding law enforcement, the results imply that disclosure of less rather than more information about crime and punishment might actually be a desirable policy. This implication follows because perfect information about crime and apprehension rates gives potential offenders information about avoided punishment, which mitigates deterrence, whereas disclosing successful apprehensions enhances deterrence. As for particular enforcement policies (i.e., choices over the underlying probability of apprehension, p, and sanction size, s), the model offered no clear prescription. Although one might have expected that catching more offenders today would enhance deterrence tomorrow by inducing offenders to update their beliefs upward, our model shows that such an "extra" benefit does not generally exist, given unbiased prior beliefs by offenders. Since the upward and downward adjustments work in opposition to each other, the overall impact remains ambiguous.

Finally, we pointed out various implications of our analysis for empirical studies aimed at distinguishing specific and general deterrence effects. The key lessons are twofold. First, *ex post* variation in observed or realized outcomes does not necessarily reflect variation in the underlying probability of apprehension, nor does absence of punishment imply a zero probability of apprehension. Empirical studies can only discern these causal effects by employing data on actual enforcement inputs. Absent this information, the lack of observed effects does not necessarily imply that the threat of punishment fails to deter potential offenders, while observed effects may simply reflect updated beliefs by offenders. Second, if perceptions are based on Bayesian learning (rather than salience), both specific and general deterrence effects should wane over time with repeated experience, holding constant the underlying enforcement variables. To capture this effect, empirical studies need to control for the amount of time an offender has been "in the system" and/or the frequency of contact with enforcement authorities.

References

Alm, James, Betty Jackson, and Michael McKee (2009), "Getting the Word Out: Enforcement Information Dissemination and Compliance Behavior," *Journal of Public Economics*, 93, pp. 392-402.

Anwar, Shamena, and Thomas A. Loughran (2011), "Testing a Bayesian Learning Theory of Deterrence among Serious Juvenile Offenders," *Criminology*, 49(3), pp. 667-698.

Apel, Robert (2022), "Sanctions, Perceptions, and Crime," *Annual Review of Criminology*, 5, pp. 16.1-16.23.

Bebchuk, Lucian and Louis Kaplow (1992), "Optimal Sanctions When Individuals Are Imperfectly Informed About the Probability of Apprehension," *Journal of Legal Studies*, 21, pp. 365-370.

Beccaria, Cesar (1764 [1986]) *On Crimes and Punishments*, Indianapolis, IN: Hackett Publishing Co.

Becker, Gary (1968), "Crime and Punishment: An Economic Approach," *Journal of Political Economy*, 76, pp. 169-217.

Bentham, Jeremy (1780 [1970]) *An Introduction to the Principles of Morals and Legislation*, New York: Oxford Univ. Press.

Bigoni, Maria, Sven-Olaf Fridolfsson,, Chloe Le Coq, and Giancarlo Spagnolo (2008), "Risk Aversion, Prospect Theory, and Strategic Risk in Law Enforcement: Evidence from an Antitrust Experiment," SSE/EFI Working Paper Series in Economics and Finance No 696.

Chopard, Bertrand and Marie Obidzinski (2021), "Public Law Enforcement Under Ambiguity," *International Review of Law and Economics*, 66, forthcoming.

Coutts, Alexander (2019), "Good News or Bad News are Still News: Experimental Evidence on Belief Updating," *Experimental Economics*, 22, pp. 369-395.

Earnhart, Dietrich (2004a), "Regulatory Factors Shaping Environmental Performance at Publicly-Owned Treatment Plants," *Journal of Environmental Economics and Management*, 48 (1), pp. 655-681.

_____ (2004b), "Panel Data Analysis of Regulatory Factors Shaping Environmental Performance," *Review of Economics and Statistics*, 86 (1), pp. 391-401.

_____ (2009), "The Influence of Facility Characteristics and Permit Conditions on the Effects of Environmental Regulatory Deterrence," *Journal of Regulatory Economics*, 36 (3), pp. 247-273.

Earnhart, Dietrich and Lana Friesen (2013), "Can Punishment Generate Specific Deterrence without Updating? Analysis of a Stated Choice Scenario," *Environmental and Resource Economics*, 56 (3), pp. 379-397.

_____ (2017), "The Role of Regulated Facilities' Perceptions of the Effectiveness of Regulatory Monitoring and Enforcement: Compliance with the Clean Water Act," *Ecological Economics*, 142, pp. 282-294.

Earnhart, Dietrich and Robert Glicksman (2011), *Pollution Limits and Polluters' Efforts to Comply: The Role of Government Monitoring and Enforcement*, Palo Alto, CA: Stanford University Press.

Earnhart, Dietrich, Donna Ramirez Harrington, and Robert Glicksman (2020), "The Effects of Enforcement on Corporate Environmental Performance: The Role of Fairness," *Review of Law and Economics*, published online on January 24, 2020, DOI: https://doi.org/10.1515/rle-2019-0012.

Earnhart, Dietrich and Kathleen Segerson (2012), "The Influence of Financial Status on the Effectiveness of Environmental Enforcement," *Journal of Public Economics*, 96, pp. 670-684.

Eckert, Heather (2004), "Inspections, Warnings, and Compliance: The Case of Petroleum Storage Regulation," *Journal of Environmental Economics and Management*, 47 (2), pp. 232-259.

Foulon, Jérôme, Paul Lanoie and Benôit Laplante (2002), "Incentives for Pollution Control: Regulation or Information," *Journal of Environmental Economics and Management*, 44 (1), pp. 169-187.

Garoupa, Nuno (1998), "Optimal Law Enforcement and Imperfect Information When Wealth Varies Among Individuals," *Economica*, 65, pp. 479-490.

Gray, Wayne and Ronald Shadbegian (2005), "When and Why Do Plants Comply? Paper Mills in the 1980s," *Law and Policy*, 27, pp. 238-261.

_____ (2007), "The Environmental Performance of Polluting Plants: A Spatial Analysis," *Journal of Regional Science*, 47 (1), pp. 63-84.

Greenberg, Edward (2012), *Introduction to Bayesian Econometrics*, Cambridge, UK: Cambridge University Press.

Harel, Alon and Uzi Segal (1999), "Criminal Law and Behavioral Law and Economics: Observations on the Neglected Role of Uncertainty in Deterring Crime," *American Law and Economics Review,* 1, pp. 276-312.

Harrington, Winston (1988), "Enforcement Leverage When Penalties Are Restricted," *Journal of Public Economics*, 37, pp. 29-53.

Haselhuhn, Michael, Devin Pope, Maurice Schweitzer, and Peter Fishman (2012), "The Impact of Personal Experience on Behavior: Evidence from Video-Rental Fines," *Management Science*, 58, pp. 52-61.

Helland, Eric (1998a), "The Enforcement of Pollution Control Laws: Inspections, Violations and Self-Reporting," *The Review of Economics and Statistics*, 80 (1), pp. 141-153.

_____ (1998b), "The Revealed Preferences of State EPAs: Stringency, Enforcement, and Substitution," *Journal of Environmental Economics and Management*, 35 (3), pp. 242-261.

Helland, Eric and Andrew Whitford (2003), "Pollution Incidence and Political Jurisdiction: Evidence from the TRI," *Journal of Environmental Economics and Management*, 46, pp. 403-424.

Holmes, Oliver W. (1881 [1963]), *The Common Law,* Boston: Little-Brown.

Horovitz, Anat and Uzi Segal (2007), "The Ambiguous Nature of Ambiguity and Crime Control," *NYU Journal of Law and Liberty,* 2, pp. 541-556.

Jolls, Christine, Cass Sunstein, and Richard Thaler (1998), "A Behavioral Approach to Law and Economics," *Stanford Law Review*, 50, pp. 1471-1550.

Kang, Sang Mok and Myunghun Lee (2004), "An Empirical Study on Effective Pollution Enforcement in Korea," *Environment and Development Economics*, 9, pp. 353-365.

Kaplow, Louis (1990), "Optimal Deterrence, Uninformed Individuals, and Acquiring Information About Whether Acts Are Subject to Sanctions," *Journal of Law, Economics, & Organization*, 6, pp. 93-128.

Keller, Carmen, Michael Siegrist, and Heinz Gutscher (2006), "The Role of the Affect and Availability Heuristics in Risk Communication," *Risk Analysis*, 26, pp. 631-639.

Lanoie, Paul, Mark Thomas, and Joan Fearnley (1998), "Firms responses to effluent regulations: pulp and paper in Ontario, 1985-1989," *Journal of Regulatory Economics*, 13 (2), pp. 103-120.

Laplante, Benoit, and Paul Rilstone (1996), "Environmental inspections and emissions of the pulp and paper industry in Quebec," *Journal of Environmental Economics and Management*, 31 (1), pp. 19-36.

Lim, Jinghui (2016), "The Impact of Monitoring and Enforcement on Air Pollutant Emissions," *Journal of Regulatory Economics*, 49 (2), pp. 203-222.

Lochner, Lance (2007), "Individual Perceptions of the Criminal Justice System," *American Economic Review*, 97, pp. 444-460.

Magat, Wesley A. and W. Kip Viscusi (1990), "Effectiveness of the EPA's Regulatory Enforcement: The Case of Industrial Effluent Standards," *J. of Law and Economics*, 33 (2), pp. 331-360.

Malik, Arun (1990), "Markets for Pollution Control When Firms Are Noncompliant," *Journal of Environmental Economics and Management*, 18, pp. 97-106.

Maniloff, Peter (2019), "Can Learning Explain Deterrence? Evidence from Oil and Gas Production," *Journal of the Association of Environmental and Resource Economists*, 6(5), pp. 853-81.

Meier, Robert F. and Weldon T. Johnson (1977), "Deterrence as Social Control: The Legal and Extralegal Production of Conformity," *American Sociological Review*, 42(2), pp. 292-304.

Miceli, Thomas (2013), "Escalating Penalties for Repeat Offenders: Why are They so Hard to Explain? *Journal of Institutional and Theoretical Economics*, 169, pp. 587-604.

Montesquieu, Charles-Louis (1748 [1977]) *The Spirit of Law*, Berkeley, CA: Univ. of California Press.

Nadeau, Louis (1997), "EPA Effectiveness at Reducing the Duration of Plant-Level Noncompliance," *Journal of Environmental Economics and Management*, 34 (1), pp. 54-78.

Nagin, Daniel (1978), "General Deterrence: A Review and Critique of the Empirical Evidence," pp. 95-139 in A. Blumstein, J Cohen, and D. Nagin, eds., *Deterrence and Incapacitation: Estimating the Effects of Criminal Sanctions on Crime Rates*, Washington, D.C.: National Academy of Sciences.

Nagin, Daniel S. (2013), "Deterrence: A Review of the Evidence by a Criminologist for Economists," *Annual Review of Economics*, 5, pp. 83-105.

Polinsky, A. Mitchell and Daniel Rubinfeld (1991), "A Model of Optimal Fines for Repeat Offenders," *Journal of Public Economics*, 46, pp. 291-306.

Polinsky, A. Mitchell and Steven Shavell (1998), "On Offense History and the Theory of Deterrence," *International Review of Law and Economics*, 18, pp. 305-324.

_____ (2000), "The Economic Theory of Public Enforcement of Law," *Journal of Economic Literature*, 38, pp. 45-76.

Rincke, Johannes and Christian Traxler (2001), "Enforcement Spillovers," The Review of Economics and Statistics, 93 (4), pp. 1224-1234.

Sah, Raj (1991), "Social Osmosis and Patterns of Crime," *Journal of Political Economy*, 99, pp. 1272-1295.

Scholz, John and Wayne Gray (1990), "OSHA Enforcement and Workplace Injuries: A Behavioral Approach to Risk Assessment," *Journal of Risk and Uncertainty*, 3, pp. 283- 305.

Segerson, Kathleen and Tom Tietenberg (1992), "The structure of penalties in environmental enforcement: an economic analysis," *Journal of Environmental Economics and Management*, 23 (2), p. 179-200.

Shavell, Steven (2004) *Foundations of Economic Analysis of Law*, Cambridge, MA: Belknap Press.

Shavell, Steven (2009), *Economic analysis of accident law*, Cambridge, MA: Harvard University Press.

Shimshack, Jay and Michael Ward (2005), "Regulator Reputation, Enforcement, and Environmental Compliance," *Journal of Environmental Economics and Management*, 50, p. 519-540.

_____ (2008), "Enforcement and over-Compliance," *Journal of Environmental Economics and Management*, 55, pp. 90-105.

Sigman, Hilary (1998), "Midnight Dumping: Public Policies and Illegal Disposal of Used Oil," *RAND Journal of Economics*, 29 (Spring), pp. 157–178.

Simonsohn, Uri, Niklas Karlsson, George Loewenstein, and Dan Ariely (2008), "The tree of experience in the forest of information: Overweighing experienced relative to observed information," *Games and Economic Behavior*, 62 (1), pp. 263-286.

Stafford, Sarah (2002), "The effect of punishment on firm compliance with hazardous waste regulations," *Journal of Environmental Economics and Management*, 44 (2), pp. 290-308.

Stafford, Mark and Mark Warr (1993) "A Reconceptualization of General and Specific Deterrence," *Journal of Research in Crime and Delinquency* 30, pp. 123-135.

Teichman, Doron (2011), "The Optimism Bias of the Behavioral Analysis of Crime Control," *Univ. of Illinois Law Review*, 2011, pp. 1697-1712.

Thorton, Dorothy, Neil Gunningham, and Robert Kagan (2005), "General Deterrence and Corporate Environmental Behaviour," *Law & Policy*, 27 (2), pp. 262-288.

Tversky, Amos and Daniel Kahneman (1974), "Judgment under Uncertainty: Heuristics and Biases," *Science*, 185, pp. 1124-1131.

Viscusi, W. Kip (1979), "The Impact of Occupational Safety and Health Regulation," *Bell Journal of Economics*, 10 (1), pp. 117-140.

Viscusi, W. Kip (1986), "The impact of occupational safety and health regulation, 1973-1983," *The RAND Journal of Economics*, 17 (4), pp. 567-580.
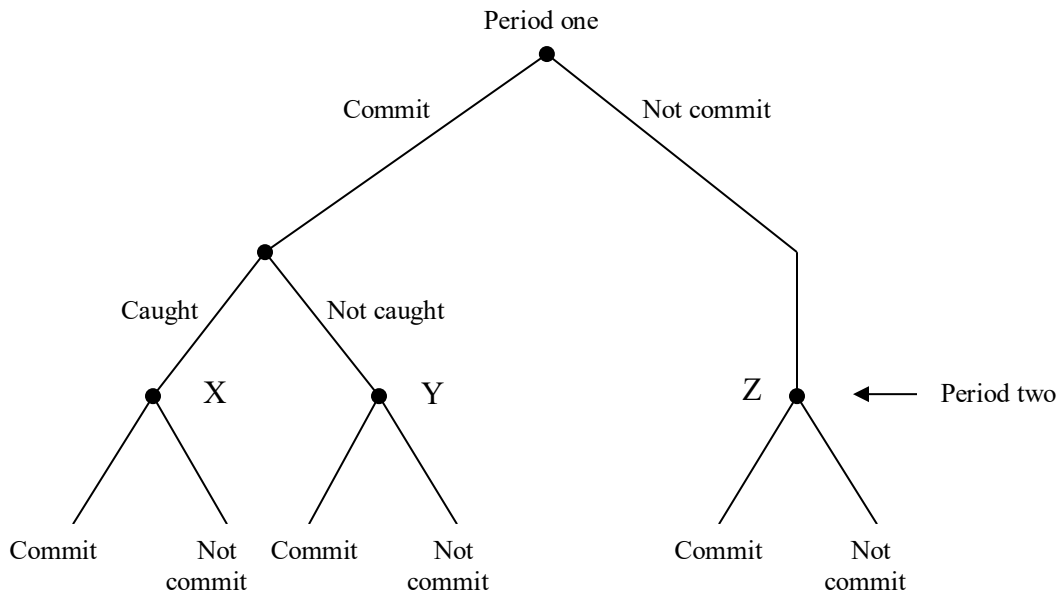
Figure 1. Game tree for the two-period crime model.

Table 1: Impact of Specific and General Deterrence on Crime Rates

Scenario	Comparison of (Expected) Crime Rates
Specific Deterrence (single offender):	
No change in circumstances/gain over time	$R_2 < R_1$
Different circumstances/gain over time	$R_2 \gtreqless R_1$
General Deterrence (different offenders):	
Perfect observability (of crime and enforcement)	$R_2 \gtreqless R_1$
Imperfect observability	$R_2 \gtreqless R_1$

Appendix

Generalized Expressions of Subjective Apprehension Probabilities and the Evolution of Beliefs

This appendix generalizes the updated subjective apprehension probabilities constructed in Section 6. This generalization allows our analysis to explore the evolution of beliefs. Specifically, this generalization permits the possibility that the second-period offender has multiple observations (signals) prior to making her crime commission choice in Period 2.

Consider an offender at any point in time with an initial unbiased prior with variance σ_0^2. This offender perfectly observes $n > 1$ crimes. Let $x \leq n$ denote the number of times the offender is caught and punished. Given an (unbiased) prior belief of p, the mean of the posterior distribution is as follows:

$$\hat{p}(n,x) = \frac{(x-p)\sigma^2 + p^2(1-p)}{(n-1)\sigma^2 + p(1-p)} = p + \sigma_0^2 \left[\frac{x-np}{(n-1)\sigma^2 + p(1-p)} \right].$$

The expressions in (18) are a special case of this formulation for $n = 1$. Specifically, $\hat{p}_c = \hat{p}(1,1) = p + \frac{\sigma^2}{p}$ if the offender is caught ($x = 1$), and $\hat{p}_n = \hat{p}(1,0) = p - \frac{\sigma^2}{1-p}$ if the offender is not caught ($x = 0$). The general expression here implies that $\hat{p}(n,x) > (<)p$ as $\frac{x}{n} > (<)p$. Furthermore, $E[\hat{p}(n,x)] = \sum_{x=0}^{n} \binom{n}{x} p^x (1-p)^{n-x} \hat{p}(n,x) = p$, and as $n \to \infty$, $x \to pn$, which implies $\hat{p}(n,x) \to p$.