TESTING A BAYESIAN LEARNING THEORY OF DETERRENCE AMONG SERIOUS JUVENILE OFFENDERS

SHAMENA ANWAR
School of Public Policy & Management at Heinz College
Carnegie Mellon University

THOMAS A. LOUGHRAN
Department of Criminology and Criminal Justice
University of Maryland–College Park

KEYWORDS: deterrence, rational choice, Bayesian updating, juvenile offenders

The effect of criminal experience on risk perceptions is of central importance to deterrence theory but has been vastly understudied. This article develops a realistic Bayesian learning model of how individuals will update their risk perceptions over time in response to the signals they receive during their offending experiences. This model implies a simple function that we estimate to determine the deterrent effect of an arrest. We find that an individual who commits one crime and is arrested will increase his or her perceived probability of being caught by 6.3 percent compared with if he or she had not been arrested. We also find evidence that the more informative the signal received by an individual is, the more he or she will respond to it, which is consistent with more experienced offenders responding less to an arrest than less experienced...
offenders do. Parsing our results out by type of crime indicates that an individual who is arrested for an aggressive crime will increase both his or her aggressive crime risk perception as well as his or her income-generating crime risk perception, although the magnitude of the former may be slightly larger. This implies that risk perception updating, and thus potentially deterrence, may be partially, although not completely, crime specific.

Standard economic theory assumes that individuals make rational decisions when choosing to commit crimes, meaning that if the expected costs to committing a crime are outweighed by the expected benefits, the rational individual will choose to offend. According to the seminal model outlined by Becker (1968), the expected cost of committing a crime is defined as the probability of getting caught, $p$, multiplied by the utility cost, $C$, of being punished, whereas the expected benefit is defined as the probability of getting away with the crime, $(1 - p)$, multiplied by the utility benefit, $B$, of committing the crime. This expected utility calculus, as used by offenders, is central to the tenets of deterrence theory, which assumes that sanctions should ultimately work to increase risk and cost perceptions, which in turn should reduce crime (Clarke and Cornish, 1985; Gibbs, 1975; Tittle, 1975; Zimring and Hawkins, 1972). An important implication of this offender rational choice calculus is that if an individual’s perceptions of $p$, $B$, and $C$ do not change over time, the individual who offends once will find it optimal to continue offending at every future opportunity. However, if through offending an individual increases his or her perception of $p$ or $C$, or decreases his or her perception of $B$, an individual that offended in the past can be deterred from offending again.

As it is difficult to define precisely the somewhat abstract utility benefits and costs of committing crimes, this article focuses on how an individual’s offending experiences affect his or her risk perception, $p$. In fact, substantial empirical evidence suggests that the deterrent effect of the certainty of punishment is much greater than that of the severity of punishment (e.g., Klepper and Nagin, 1989; Paternoster, 1987). The risk of getting caught is specifically tied to the importance of using arrests to deter individuals from committing crimes. Arresting individuals for a crime will only deter them if two necessary things happen: First, an individual’s risk perception $p$ of

---

1. The utility cost of crime may include any number of items, such as penalties associated with formal sanctions (Schmidt and Witte, 1984), opportunity cost from loss of legitimate income (Grogger, 1991, 1998; Pezzin, 1995), as well as less quantifiable costs such as stigmas and labeling (Smith and Paternoster, 1990). Similarly, the utility benefit to crime likely includes the economic incentives as well as the social rewards (Nagin, 1998; Williams and Hawkins, 1986).
getting caught must *increase*, and second, an individual must commit fewer crimes *in response to this increase* in risk perception.

There has been an abundance of research, mainly using nonoffending samples, which supports this second point by showing that individuals’ criminal actions do reflect their current perceptions of risk certainty. For instance, Nagin’s (1998: 7) review of the literature on perceptual deterrence found that it “points overwhelmingly to the conclusion that behavior is influenced by sanction risk perceptions—those who perceive that sanctions are more certain are less likely to commit crime.” In contrast, however, there has been a relative dearth of literature examining the just as important first point—the link between an individual’s offending experiences and his or her subsequent risk perceptions (Pogarsky, Piquero, and Paternoster, 2004).

Our measure of an individual’s offending experience is whether or not that person was arrested for the crimes committed. Specifically, the primary question addressed in this article is as follows: If an individual commits a crime and is arrested for it, how much, and in what direction, will it change the individual’s risk perception? From a policy perspective, this is an extremely important question, as arrests can be very costly. If an arrest can materially increase an individual’s risk perception, and thus potentially act to deter him or her from offending again in the future, the cost might well be beneficial.

THEORIES OF HOW ARRESTS AFFECT RISK PERCEPTIONS

Theoretically, the link between arresting an individual and his or her future risk perception is ambiguous. For instance, Pogarsky and Piquero (2003) put forth the notion of “resetting,” which is rooted in the concept of the gambler’s fallacy. The idea is that individuals who are arrested believe that it would be extremely improbable that they would be arrested again and, thus, “reset” their perceived risk to a lower level. This results in an

---

2. For complete reviews of this line of research, see Nagin (1998), Pratt et al. (2006), and Wikström (2007).
3. Throughout this article, we often refer to determining the effect of being arrested on an individual’s risk perception as the potential deterrent effect of an arrest. We term this as a “potential” effect because even if getting arrested increases an individual’s risk perception, it will not deter him or her unless the individual responds to this increase by committing less crime (which is something we do not directly examine in this article).
4. Even if arrests do not increase individuals’ risk perceptions (and, thus, potentially deter them), they are still important because the underlying arrest rate in a society will deter many individuals from ever choosing to offend. Furthermore, if arrests lead to incarceration, they can also have an incapacitation effect.
arrest being negatively related to an individual’s risk perception. In this scenario, not only are arrests not a deterrent, but also they encourage individuals to commit more crimes. Indeed, in some instances, punishment has been found to be associated with lower risk and costs to offending (Piquero and Pogarsky, 2002; Sherman, 1993).

Bayesian learning theory, which describes a manner for individuals to incorporate newly learned information from observation to update subjective prior beliefs, based on the logic of Bayes’ probability theorem, predicts a different result, however. The basic premise of this theory is that individuals begin their criminal careers unsure about what their actual arrest rate will be (i.e., their true probability of getting caught). They thus form a subjective belief about this probability, termed their prior perception. As individuals begin to commit crimes, they will observe their arrest rate during this time frame, which can be thought of as a noisy signal of their “true” arrest rate. Individuals will use this information to revise their prior belief and form their updated, or posterior, belief. This posterior belief, which is more informed, yet still subjective, can be thought of as a weighted average of the prior perception and the signal.

The Bayesian updating model is consistent with either a positive or a zero weight on this signal. For instance, individuals who are still unsure about their true arrest rate will continue to value the signal and, thus, put a positive weight on it. This results in an individual’s experiences having an effect on his or her perceptions—specifically, if an individual is arrested, that individual’s risk perception should increase. Alternatively, if the individual offends but is not arrested, his or her risk perception should decrease. This downward revision is based on the concept of “punishment avoidance” where individuals may offend yet not incur any punishment, which may have an emboldening effect (Stafford and Warr, 1993). Some empirical evidence suggests that individuals who experience such punishment avoidance may in fact have smaller perceptions of both risk and cost later on (Paternoster and Piquero, 1995).

Conversely, the model of Bayesian updating is consistent with individuals putting zero weight on their signal. That is, individuals who are far along in their offending careers may be sure about their true arrest rate and no longer update their risk perceptions based on their new experiences. In this

---

5. Bayes’ theorem provides a formula for the conditional probability some event \( A \) occurs given that another event \( B \) has already occurred, which can be written as
\[
P(A | B) = \frac{P(A \cap B)}{P(B)}.
\] Intuitively, Bayes’ theorem can be thought of as a way in which subjective beliefs about \( A \) can be updated after observing \( B \).

6. This signal (i.e., the ratio of arrests to offenses committed) has been used before in empirical studies of perceptual deterrence (Horney and Marshall, 1992; Matsueda, Kreager, and Huizinga, 2006).
situation, arresting an individual has absolutely no effect on his or her risk perceptions, implying a deterrent effect no longer exists. In fact, elements of the deterrence process may vary by degree of offending experience (Decker and Wright, 1994; Loughran et al., 2011; Paternoster, 1987; Paternoster et al., 1985; Saltzman et al., 1982), and sanctions threats only may be able to influence certain subsets of the total population (Parker and Grasmick, 1979; Pogarsky, 2002). Thus, theoretically, it is unclear whether an arrest should encourage individuals to commit more crimes, deter them from committing more crimes, or have absolutely no effect on their future offending behavior.\(^7\)

**BAYESIAN UPDATING AND OFFENDING**

Because theory produces ambiguous results, one needs to examine this question empirically. Previous studies by Pogarsky, Piquero, and Paternoster (2004), Lochner (2007), and Matsueda, Kreager, and Huizinga (2006) each have shown solid evidence that an arrest will increase an individual’s risk perception. All three studies use panel data sets that include information in each time period on an individual’s perceived risk of arrest, as well as the number of crimes committed and the number of times arrested. Also, each study estimates a variant of the same model, whereby the risk perception at the end of the period is regressed on the prior risk perception, the number of arrests, and the number of crimes. All three find positive coefficients on the number of arrests, implying that getting caught for a crime will increase an individual’s risk perception. Each also finds negative coefficients on the number of crimes committed, implying that committing a crime that goes unpunished will lessen an individual’s risk perception.

Although it is important to recognize the contributions made by Pogarsky, Piquero, and Paternoster (2004), Lochner (2007), and Matsueda, Kreager, and Huizinga (2006), namely providing key evidence that individuals update their perceptions in response to experiences in such a

\(^7\) We should note that, in contrast to those studies that have demonstrated changes in perceptions in reaction to offending, some others have flatly concluded that sanction perceptions are not influenced by the actions taken by the criminal justice system. For instance Kleck et al. (2005) analyzed individual perceptions of punishment and actual punishment levels in 54 urban counties using hierarchical linear modeling and found there to be no association between the two. Kleck and Barnes (2011) also showed that aggregate perceptions within counties also were not generally related to actual county levels of the punishment. These papers employ a different empirical strategy than studies that examine how individual offending experience affects perceptions—specifically they estimate the association between sanction perceptions and macrolevel arrest clearance rates. Still, the null results reported in these papers are inconsistent with the above literature arguing that perceptions and offending are indeed dependent.
way that an arrest is a deterrent, there are several important ways in which this extant literature on crime risk updating can be advanced to expand the findings to broader interpretability and generalizability. For instance, the previous studies that have examined this question have used data sets that are primarily composed of nonoffending individuals, and those that do offend commit minor crimes such as petty shoplifting or marijuana use. Because we are trying to determine how risk perceptions respond to offenses and subsequent arrests, the analyses use only the individuals that do offend, resulting in small effective sample sizes. More importantly, however, individuals considered more serious in both the nature and the frequency of their offending (e.g., those who engage in fighting or armed robbery) might respond differently to arrests. In terms of policy relevance, we are most interested in the effect among more serious offenders because that is the primary group we want to deter.

A second limitation of the previous literature is that because the empirical models treat arrests and crimes independently, it is difficult to obtain an accurate measure of how much risk perceptions change in response to an arrest. As mentioned, the posterior risk perception for a time period is regressed on the prior risk perception, the number of arrests incurred in the time period, and the number of crimes committed in the time period. The coefficient on arrest is interpreted as the amount the risk perception changes when an additional arrest is incurred. Yet this effect is assumed to be linear, which is unrealistic—the effect of an arrest must also depend on the number of crimes committed. Furthermore, the effect of an arrest and the effect of an unpunished crime on risk perceptions are not separate entities to be estimated. These effects are essentially the opposite of one another, as the effect of an unpunished crime should be the negative of the effect of an arrest. Thus, although the extant literature does suggest individuals are perhaps deterred by arrests—at least as far as updating their risk perceptions—the degree of this evidence is somewhat limited.

**CURRENT FOCUS**

This article builds on the prior theoretical and empirical literature on the linkage between offending and sanction risk perceptions in several ways.
important ways. The primary goal is to resolve the issues discussed earlier with prior empirical studies of risk belief updating to obtain a more accurate measure of the effect an arrest has on an individual’s risk perception. Specifically, we first address the issue of sample relevance by using data from a longitudinal sample of serious juvenile offenders. By using this highly relevant sample of individuals, all of whom have had interaction with the legal system for serious offenses, we can precisely target a group at whom policies pointed at deterring crime are most pertinent (Apospori, Alpert, and Paternoster, 1992). Second, we develop a theoretical model of Bayesian updating that allows the posterior risk perception to depend explicitly on the prior risk perception and the observed arrest rate. This allows us to test whether offenders update their perceptions in a manner consistent with Bayesian theory. Furthermore, by using the arrest rate as a regressor, as opposed to separately including the number of arrests and the number of crimes committed, we can estimate the potential effect of arrest on future perceptions, which is not constrained to be linear but rather dependent on the number of crimes an individual has committed.

Like previous studies, our overall results support the theoretical model of Bayesian updating that arrest will have a positive effect on risk perceptions and, thus, can potentially act as a deterrent even among active, serious offenders. However, we also build on the previous literature by addressing two other more nuanced questions to offender risk updating. First, we consider the prediction of Bayesian updating models that individuals should place more weight on more informative signals than they do on noisier signals. Specifically, the weight an individual puts on a signal should not depend solely on current crimes but also on the accumulated number of past crimes. As developed in the subsequent discussion, we show how this notion could be consistent with an “experience effect,” where arrests have less of an effect on risk perception as accumulated experience increases, resulting in the potential deterrent effect of arrests decreasing later on in one’s criminal career. We find evidence that less weight is put on an arrest as the ratio of an individual’s current period crimes committed to total crimes committed decreases, which suggests arresting individuals at points early in their criminal careers can potentially have a much larger effect than arresting them once they are further along.

A second important extension addresses whether risk perception updating is crime specific. In other words, does getting arrested for one type of offense affect future perceptions associated with only that class of offenses or does it affect perceptions for all crime types? Rational choice models of criminal behavior typically assume potential offenders have crime-specific risk perceptions that vary independently of one another, although not much empirical research supports this (Nagin, 1998). From a policy perspective, this is important—if risk updating is crime specific, then police cracking
down on one type of crime will not have a deterrent effect on other crimes (and could even encourage other crimes if police shift limited resources away from detecting certain crimes or by inducing a substitution effect). Yet, if the nature of the updating is not crime specific, then cracking down on a specific crime will have a global deterrent effect for all crimes.

Although this has not been extensively studied before, the richness of the data set allows us to examine this directly. Specifically, we have information on the specific crimes individuals commit, which we classify as either aggressive crimes (e.g., fighting or shooting someone) or income-generating crimes (e.g., selling drugs or stealing). This can be matched to detailed information on an individual’s risk perceptions for committing various crimes, allowing us to determine separately an individual’s aggressive crime risk perception and his or her income-generating crime risk perception. We find evidence suggesting that the nature of updating is not entirely crime specific; yet the level of updating may be larger for the specific crime for which one is arrested.

The organization of this article is as follows: The next section outlines both the general and the crime-specific Bayesian updating models we estimate, followed by a description of the data, the empirical results, and finally a conclusion and discussion.

MODEL OF BAYESIAN UPDATING

This section specifies a tractable model that will allow us to estimate the increase in risk perception that is associated with an arrest. As outlined, previous research has implied that individual offending experiences affect their risk perceptions in a manner that is consistent with a Bayesian updating model. Using this as a point of departure, we develop a Bayesian model of how individuals form perceptions over time and show that this model is consistent with our data. We then show how this model can be used to estimate the effect of an arrest on an individual’s risk perception. This section begins with the general model, where we determine how the overall risk perception responds to overall criminal experience. We then parse this model out further to determine whether an individual’s risk perception response to an arrest is crime specific.

GENERAL UPDATING MODEL

Denote $z_i \in [0,1]$ as person $i$’s true arrest rate. This can be thought of as the proportion of times individual $i$ would be arrested if he or she committed an infinite (or relatively large) number of crimes. Rates are allowed to differ across persons to reflect the fact that individuals commit different types of crimes and have a different adeptness at committing these crimes. Early on in an offender’s career, he or she will have committed relatively
few crimes and, thus, not know his or her true arrest rate. Consequently, the offender must form a subjective risk perception about $z_i$. This section provides an intuitive explanation for what the Bayesian updating process predicts perceptions at time $t$ will be, as this is what is relevant for our estimation procedure.

At the start of period $t$, individual $i$’s risk perception will simply be his or her risk perception at the end of the previous period, denoted as $p_{i,t-1}$. This is the individual’s prior perception at time $t$. As by now individuals will have some information about their true arrest rate, but will still not know it with certainty, this prior can be thought of as a noisy measure of $z_i$. During time period $t$, individuals will each interact with the criminal justice system and receive a noisy signal of their true arrest rate, denoted as $\theta_{it} \in [0, 1]$. This signal is a function of the individual’s arrest rate during that period, as well as any other factors that might affect the perception of his or her arrest rate, such as family and friends’ arrest experiences, the individual’s ongoing maturity, and city-level trends in policing. We directly observe the individual’s arrest rate, whereas the latter factors will be unobservable to us. Denote $s_{it} \in (0,1)$ as a weighted average of these unobservable variables. The overall signal $\theta_{it}$ can then be written as a weighted average of the observable and unobservable information:

$$
\theta_{it} = \delta_{it} \left( \frac{A_{it}}{C_{it}} \right) + (1 - \delta_{it}) s_{it}
$$

where $A_{it}$ denotes the number of arrests individual $i$ had in period $t$ and $C_{it}$ denotes the total number of crimes individual $i$ committed in period $t$. The weight individuals put on each factor will depend on which factor is more informative to the individual. As this will differ by both individuals and across time periods, the weight $\delta$ is subscripted by $it$.12

As the individual’s prior perception and signal are both informative about his or her true $z_i$, the Bayesian model predicts individuals will form a new posterior perception $p_{i,t}$ that is a weighted average of the two:

$$
p_{i,t} = \alpha_{i,t} \theta_{it} + (1 - \alpha_{i,t}) p_{i,t-1}
$$

---

10. Each time period $t$ corresponds to a period of 6 months because we observe individuals in the data set in 6-month intervals.

11. For example, suppose that as individuals get older, they perceive the arrest rate to be higher. This will get incorporated into the signal by including a rate in the weighted average that is higher than $p_{i,t-1}$.

12. For example, if an individual in period $t$ commits a lot of crimes, but no one in his or her social network has much criminal activity during period $t$, the individual should view his or her own arrest rate signal as being more informative about his or her true arrest rate and should weight that more heavily.
where $\alpha_{i,t} \in (0,1)$ denotes the relative weight on the signal for individual $i$ in period $t$. If individuals perceive their prior perception is more informative about the true arrest rate than the signal is, they will put relatively more weight on the prior, and $\alpha_{i,t}$ will be relatively low. Likewise, if individuals perceive their signal to be more informative about the true arrest rate, $\alpha_{i,t}$ will be relatively high. The weight $\alpha_{i,t}$ will be individual specific because individuals will differ in the informativeness of the signals they receive. For example, an individual that observes his or her arrest rate after committing one crime in a period will not gain as much information as an individual that observes his or her arrest rate after committing ten crimes in a period. The weight $\alpha_{i,t}$ will also be time specific because over time one would expect individuals to put increasing weight on their prior perception (and less weight on the signal they receive). The prior perception $p_{i,t-1}$ in equation 2 can be shown to be a function of the individual’s initial perception at time period $t = 1$, and all of the signals the individual has received up through period $t – 1$. Thus, over time, more and more information becomes incorporated into the prior perception, making it a more informative measure of the true $z_i$ over time.\(^{13}\)

Plugging equation 1 into equation 2 yields the following expression:

$$p_{it} = \alpha_{it} \delta_{it} (A_{it}/C_{it}) + (1 - \alpha_{it}) p_{i,t-1} + \alpha_{it}(1 - \delta_{it}) s_{it}$$

(3)

Recall that $\delta_{it}$ depends on how informative $A_{it}/C_{it}$ is relative to $s_{it}$ and that $\alpha_{it}$ depends on how informative the combination of $A_{it}/C_{it}$ and $s_{it}$ is relative to $p_{i,t-1}$. To test whether individuals update their perceptions using a Bayesian framework, one would need to regress $p_{it}$ on $A_{it}/C_{it}$, $p_{i,t-1}$, and $s_{it}$ and to determine whether the weights (coefficients) depended on how informative $A_{it}/C_{it}$ was relative to $s_{it}$ and how informative $p_{i,t-1}$ was relative to both $A_{it}/C_{it}$ and $s_{it}$ combined. As we do not observe $s_{it}$, this equation is impossible for us to estimate. Furthermore, even if we did observe $s_{it}$, it

---

13. The following example should make clear why the weight on the signal should decline as time goes on. Consider an individual that has not committed any crimes who goes out and commits five crimes in one time period. As this is his first interaction with the system, he will be very unsure about what his true arrest rate is, and we might expect him to put a substantial amount of weight on the signal he receives. Now suppose this individual continues to commit crimes, so that by several time periods later, he has committed 100 crimes. If he again goes out and commits five crimes, the experience from this will not be nearly as informative as the experience he has already gained from committing the previous 100 crimes, and he should thus not put as much weight on this signal as he did when he had not committed any crimes. Thus, one can see that as time goes on and as individuals gain more and more experience with the system, the new experiences they have in a time period will be dwarfed by the sum of all their past experiences, resulting in the weight put on their signal declining over time.
Bayesian Learning and Deterrence 677

would be difficult to determine objectively which part of the signal (\(s_{it}\) or \(A_{it}/C_{it}\)) should be more informative to the individual in a given time period, as it is measured on such different scales.

As we cannot explicitly test whether individuals are Bayesian, we will instead modify equation 3 to determine whether individuals update in a manner that is consistent with Bayesian theory. In particular, we aim to test two main implications here. First, we wish to determine whether the average individual’s posterior perception of his or her arrest rate is formed as a weighted average of his or her learned arrest rate in period \(t\) and prior perception coming into period \(t\). If so, then individuals who get arrested will respond by increasing their risk perceptions. Second, we test whether individuals respond more to more informative arrest signals, where the informativeness of the arrest signal depends on the number of past crimes an individual has committed and on the number of current crimes. Specifically, the less crimes an individual has committed in the past, the less certain the individual should be about his or her arrest rate, and the more informative the current arrest rate signal should be. Likewise, the more crimes an individual commits in the current period, the more informative the arrest rate signal should be. As such, individuals with low previous crimes and/or high current crimes should respond by putting more weight on their arrest signal. Finding evidence of this implies that as individuals commit more crimes over time, they will respond less to being arrested. This would also suggest arrests will have less of a potential deterrent effect for those farther along in their criminal careers.

As \(s_{it}\) is unobservable in equation 3, \(\alpha_{it}(1 – \delta_{it})s_{it}\) can be considered an error term. This term will not have mean zero [because \(s_{it} \in (0, 1)\)], so a constant is included in the regression specification to fix this. Rewriting equation 3 in terms of what we can estimate yields:

\[
p_{it} = \beta_0 + \beta_{1, it}(A_{it}/C_{it}) + \beta_{2, it}p_{i,t-1} + v_{it}
\]

where \(\beta_0\) represents the average of \(\alpha_{it}(1 – \delta_{it})s_{it}\), \(\beta_{1, it} = \alpha_{it}\delta_{it}\), \(\beta_{2, it} = (1 – \alpha_{it})\) and \(v_{it}\) is the demeaned value of \(\alpha_{it}(1 – \delta_{it})s_{it}\). Notice that the coefficients \(\beta_1\) and \(\beta_2\) are both subscripted by \(it\), reflecting that the relative weight put on the arrest rate and the prior perception will be individual and time specific (as discussed). If we remove the \(it\) subscripts, the \(\beta_1\) and \(\beta_2\) we estimate will be the average of these weights across all individuals and time periods. This will allow us to determine whether the average individual’s posterior perception of his or her arrest rate is formed as a weighted average of his or her arrest rate in period \(t\) and prior perception coming into period \(t\), which is the first implication we wanted to test. We thus estimate the following model using ordinary least
squares (OLS):

\[ p_{it} = \beta_0 + \beta_1 (A_{it}/C_{it}) + \beta_2 p_{i,t-1} + \epsilon_{it} \]  

(5)

where \( \epsilon_{it} = (\beta_{1,it} - \beta_1) (A_{it}/C_{it}) + (\beta_{2,it} - \beta_2) p_{i,t-1} + v_{it} \)

For our data to be consistent with the Bayesian updating model, we should find \( \beta_0, \beta_1, \beta_2 \in (0,1) \). In the Results section, we show that we find this to be true without putting any constraints on the parameters.\(^{14}\) As such, we can then use this model to determine what the effect of an arrest is on the average person’s risk perception. Specifically, the effect of an arrest on the risk perception is the derivative of \( p_{it} \) with respect to \( A_{it} \):

\[ \frac{\partial p_{it}}{\partial A_{it}} = \beta_1 (1/C_{it}) \]  

(6)

This means committing one crime and getting arrested for it will raise an individual’s risk perception by \( \beta_1 \).\(^{15}\) One can see that as the number of crimes increases, the effect of an arrest on risk perception will decrease.

To test the second implication of Bayesian updating, we return to equation 4 and specifically acknowledge that the \( \beta \) coefficients are individual and time specific. This reflects the fact that the informativeness of the arrest signal will vary across individuals and across time. The more past crimes an individual has in a given period, the more he or she should be certain about his or her arrest rate probability and should, thus, update less in response to any new information (from his or her own arrest rate signal or from other unobserved signals). In terms of the model, as the number of past crimes

---

14. Note that even though we are estimating a model that is derived from Bayesian theory, we are not putting constraints on the parameters. Thus, we are not requiring the updating process to be Bayesian but testing that it is consistent with such a process. For example, if the gambler’s fallacy theory was true, we would find that \( \beta_1 < 0 \), so that an individual’s risk perception would decline as his or her arrest rate increased.

15. To interpret the \( \beta_1 \) coefficient in this manner, it must be the case that \( \epsilon_{it} \) is uncorrelated with \( (A_{u}/C_{u}) \). As fluctuations in the peer arrest rate variable are present in \( \epsilon_{it} \) (through the \( v_{it} \) term), this requires that an individual’s arrest rate be uncorrelated with his or her peer’s arrest rate. Early on in an individual’s criminal career, the unobservable signal \( s_u \) will not be correlated with \( p_u \) or \( (A_{u}/C_{u}) \) because both are noisy measures of \( z \), and this noise is likely uncorrelated. Further along, however, as \( p_u \) becomes a more accurate reflection of \( z \), they may become correlated. Although it is highly likely that the number of crimes that individuals and their peers commit are correlated, we believe it is plausible that their arrest rates are uncorrelated because it is somewhat random whether individuals get arrested. However, if individuals were committing all of their crimes with their friends and both they and their friends were always arrested together, then the \( \beta_1 \) could overstate the deterrent effect of an arrest because it would pick up the effect of both the individual’s arrest rate and his or her peer’s arrest rate.
increases, we would expect $\alpha$ to increase, whereas $\delta$ should remain the same. This implies that the weight put on the arrest rate signal should increase. The amount of crimes an individual commits in a given period (his or her current crimes) tells us something about the amount of new information the individual is getting from his or her arrest rate signal (relative to other current unobserved signals and past signals) and, thus, will also affect the weight placed on the signal. Specifically, as the number of current crimes rises, one would expect both $\alpha$ and $\delta$ to increase, implying the weight put on the current arrest rate signal should increase.

Thus, the signal informativeness should depend on both how extensive the individual’s past criminal behavior is as well as how extensive his or her current criminal behavior is. As we do not observe the individual’s criminal behavior until a year before he or she enters our data sample, we proxy for the individual’s past criminal behavior with the total number of crimes he or she commits from one year before they enter our sample up through period $t - 1$. The extent of current criminal behavior is given by the number of crimes committed in period $t$.

To test whether individuals update their risk perceptions in a manner consistent with Bayesian theory, we stratify the sample into four groups, which are defined by whether the number of current crimes an individual commits in a given period is above or below the median amount, and by whether the number of past crimes an individual has committed is above or below the median amount. We then estimate equation 5 separately for each of these different groups. This will allow us to compare the weights the different groups put on the arrest rate signal, and to determine whether this pattern is consistent with Bayesian theory.

Thus, although we cannot explicitly determine whether individuals update using a Bayesian framework, we can test whether individuals update in a manner that is consistent with the two most important implications of Bayesian updating from a policy perspective. We should again differentiate how the model we estimate compares with the ones previously estimated by Pogarsky, Piquero, and Paternoster (2004) and Lochner (2007). The main difference is that these studies both include $A_{it}$ and $C_{it}$ separately as two regressors instead of combining them into an arrest rate as we do here. This is essentially saying the individual views the information in $A_{it}$ and $C_{it}$ as two independent signals as opposed to a rate. By using the rate as a regressor, we are allowing the effect of an arrest to depend on the number of crimes an individual commits. Furthermore, previous literature did not allow the weight put on current criminal interactions to depend on

---

16. When individuals enter the data sample, they are asked about their criminal activity over the previous year.
the previous criminal experience the individual has had. The second part of our analysis explicitly recognizes that the weight placed on these signals should depend not only on the individual’s current number of crimes but also on his or her past number of crimes.

CRIME-SPECIFIC UPDATING MODEL

The model specified in equation 5 makes no distinction between aggressive and income crimes, and thus, inherently assumes that individuals have the same aggressive and income-generating crime risk perceptions, and places the same weight on their aggressive and income-generating crime experience when forming those perceptions. Empirically, we find that individuals do have different aggressive and income-generating crime risk perceptions, which suggests we should estimate these updating processes separately for the two different types of crimes.\(^\text{17}\)

To test whether individuals update their risk perceptions in a crime-specific way, we need to estimate separately the processes for forming aggressive and income-generating crime risk perceptions, and we need to allow an individual’s income and aggressive crime experience to be weighted differently in these respective processes. An empirical issue that occurs when attempting to do this is that we cannot separately identify an individual’s aggressive crime experience from his or her income-generating crime experience because our data do not identify what specific crimes individuals were arrested for. However, if we restrict our analysis to individuals that only committed aggressive crimes in a given period, then it is reasonable to assume that any arrest they had corresponded to an aggressive crime. To determine whether updating is crime specific, we can then test whether an individual’s aggressive crime experience has exactly the same effect on his or her aggressive crime perception as on his or her income crime perception, using the following two equations:

\[
p_{it}^A = \beta_0 + \beta_1 (A_{it}^A/C_{it}^A) + \beta_2 p_{i,t-1}^A + \epsilon_{it}^A \tag{7}
\]

\[
p_{it}^I = \gamma_0 + \gamma_1 (A_{it}^A/C_{it}^A) + \gamma_2 p_{i,t-1}^I + \epsilon_{it}^I \tag{8}
\]

where \(p_{it}^A\) (\(p_{it}^I\)) denotes an individual’s aggressive (income) crime perception in period \(t\) and \(p_{i,t-1}^A\) (\(p_{i,t-1}^I\)) denotes an individual’s aggressive (income) crime perception in period \(t-1\). \(A_{it}^A/C_{it}^A\) is the percent of aggressive crimes individual \(i\) is arrested for in period \(t\). Note that an individual’s

\(^\text{17}\). Table 2 shows that the average aggressive crime risk perception is lower than the average income-generating crime risk perception.
income-generating crime experience does not enter into these equations because we are examining individuals that did not commit any income-generating crimes during period $t$.

If the Bayesian updating is not crime specific, we should find that $\beta_1 = \gamma_1$. This means that an individual's aggressive crime experience has exactly the same effect on his or her aggressive risk perception as on his or her income risk perception. However, if crime-specific updating does occur, one would expect that an individual’s aggressive crime experience would have a larger effect on his or her aggressive crime risk perception than on his or her income-generating risk perception. Thus, $\beta_1 > \gamma_1$. Another interesting distinction is to determine whether $\gamma_1 = 0$ or whether $\gamma_1 > 0$. If $\gamma_1 = 0$, it will imply that aggressive crime experience has absolutely no effect on income-generating crime risk perceptions. This would indicate that if policies were enacted to increase the arrests of individuals committing aggressive crimes, it would have absolutely no effect on individuals committing income-generating crimes. However if $\beta_1 > \gamma_1 > 0$, this policy will still have a deterrent effect with respect to income-generating crimes, although it would not be as large as the deterrent effect for aggressive crimes.

Estimation of equations 7 and 8, and comparison of $\beta_1$ with $\gamma_1$, can be done jointly as a system of Seemingly Unrelated Regressions (SUR; Zellner, 1962). This procedure uses a generalized least-squares (GLS) estimator to estimate $\beta_1$ and $\gamma_1$ jointly, as well as the variance–covariance matrix of the parameters that allows them to be dependent on one another. This dependence is likely because the same data were used to estimate both equations, and both $\varepsilon_{it}^A$ and $\varepsilon_{it}^I$ will be correlated with each other because they contain similar information. Note that we cannot estimate the analog of these equations for individuals that only committed income-generating crimes as there are not sufficient data to perform this analysis.

DATA

This article uses data from a subset of the participants enrolled in the Pathways to Desistance Study, a longitudinal investigation of the transition from adolescence to young adulthood in serious adolescent offenders. Participants in the Pathways to Desistance Study are adolescents who were found guilty of a serious offense (almost entirely felony offenses) in the juvenile or adult court systems in Maricopa County, AZ, or Philadelphia County, PA. These youth were ages 14 to 17 years at the time of the study. A total of 1,354 adolescents are enrolled in the study, representing approximately one in three adolescents adjudicated on the enumerated charges in each locale during the recruitment period (November 2000 through January 2003). Information regarding the rationale and overall design of the study
Table 1. Sample Demographic Descriptive Statistics (N = 1,354)

<table>
<thead>
<tr>
<th></th>
<th>Mean</th>
<th>Median</th>
<th>Standard Deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Site (percent)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Philadelphia</td>
<td>51.7</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Phoenix</td>
<td>48.3</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Gender (percent)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Male</td>
<td>86.4</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Female</td>
<td>13.6</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Race (percent)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>White</td>
<td>20.2</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Black</td>
<td>41.4</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Hispanic</td>
<td>33.5</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Other</td>
<td>4.8</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Age at Baseline (years)</td>
<td>16.5</td>
<td>16.6</td>
<td>1.1</td>
</tr>
<tr>
<td>Age at First Arrest (years)</td>
<td>13.8</td>
<td>14.0</td>
<td>2.0</td>
</tr>
<tr>
<td>Number of Prior Arrests</td>
<td>4.3</td>
<td>3.0</td>
<td>4.8</td>
</tr>
</tbody>
</table>

Data were collected at seven consecutive 6-month observational periods—baseline (defined as when individuals first entered the sample) plus six additional follow-up interviews over 36 months (defined as periods 1 through 6). After that, individuals were interviewed at yearly intervals for 2 more years (defined as periods 7 and 8). Thus, we use data on individuals observed for a total of 60 months, which is broken down into eight periods. In each of these eight periods, we have information about individuals’ perceived risk, the number and types of crimes they committed, and the number of times they were arrested.

MEASURES

PERCEIVED RISK

An individual’s perceived risk is measured in each period by asking the individual how likely it is he or she would be caught and arrested for the following seven crimes: fighting, robbery with gun, stabbing someone, breaking into a store or home, stealing clothes from a store, vandalism, and auto theft. Response options ranged from 0 (no chance) to 10 (absolutely certain to be caught). These scores were then divided by 10 (absolutely certain to be caught). These scores were then divided by 10 (absolutely certain to be caught). These scores were then divided by 10 (absolutely certain to be caught). These scores were then divided by 10 (absolutely certain to be caught). These scores were then divided by 10 (absolutely certain to be caught). These scores were then divided by 10 (absolutely certain to be caught). These scores were then divided by 10 (absolutely certain to be caught). These scores were then divided by 10 (absolutely certain to be caught). These scores were then divided by 10 (absolutely certain to be caught). These scores were then divided by 10 (absolutely certain to be caught). These scores were then divided by 10 (absolutely certain to be caught). These scores were then divided by 10 (absolutely certain to be caught). These scores were then divided by 10 (absolutely certain to be caught). These scores were then divided by 10 (absolutely certain to be caught). These scores were then divided by 10 (absolutely certain to be caught). These scores were then divided by 10 (absolutely certain to be caught). These scores were then divided by 10 (absolutely certain to be caught). These scores were then divided by 10 (absolutely certain to be caught). These scores were then divided by 10 (absolutely certain to be caught). These scores were then divided by 10 (absolutely certain to be caught). These scores were then divided by 10 (absolutely certain to be caught). These scores were then divided by 10 (absolutely certain to be caught). These scores were then divided by 10 (absolutely certain to be caught). These scores were then divided by 10 (absolutely certain to be caught). These scores were then divided by 10 (absolutely certain to be caught).
Table 2. Variation in Risk Perceptions Over Time

<table>
<thead>
<tr>
<th>Crime Perception</th>
<th>Baseline</th>
<th>Period 4</th>
<th>Period 8</th>
<th>Average Standard Deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average Risk Perception</td>
<td>.528 (.290)</td>
<td>.555 (.290)</td>
<td>.576 (.302)</td>
<td>.202 (.095)</td>
</tr>
<tr>
<td>Aggressive Crimes</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Fighting</td>
<td>.287 (.341)</td>
<td>.340 (.354)</td>
<td>.411 (.376)</td>
<td>.089 (.070)</td>
</tr>
<tr>
<td>Stabbing someone</td>
<td>.648 (.374)</td>
<td>.657 (.343)</td>
<td>.659 (.340)</td>
<td>.079 (.066)</td>
</tr>
<tr>
<td>Vandalism</td>
<td>.409 (.382)</td>
<td>.449 (.377)</td>
<td>.471 (.381)</td>
<td>.089 (.069)</td>
</tr>
<tr>
<td>Income-Generating Crimes</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Robbery</td>
<td>.639 (.381)</td>
<td>.648 (.347)</td>
<td>.658 (.339)</td>
<td>.079 (.067)</td>
</tr>
<tr>
<td>Breaking in to a store/home</td>
<td>.600 (.370)</td>
<td>.617 (.343)</td>
<td>.628 (.341)</td>
<td>.081 (.065)</td>
</tr>
<tr>
<td>Stealing clothes from a store</td>
<td>.530 (.375)</td>
<td>.564 (.356)</td>
<td>.577 (.356)</td>
<td>.087 (.067)</td>
</tr>
<tr>
<td>Auto theft</td>
<td>.584 (.378)</td>
<td>.615 (.354)</td>
<td>.621 (.360)</td>
<td>.087 (.070)</td>
</tr>
<tr>
<td>Sample Size</td>
<td>1,352</td>
<td>1,201</td>
<td>1,197</td>
<td></td>
</tr>
</tbody>
</table>

NOTE: Standard errors are in parentheses.

to individuals’ risk perceptions averaged over all seven crime categories. When individuals first enter the sample, on average, they feel the probability they will get caught is .528, and this increases to .576 over the time they are in the sample. Even though the average is trending slowly upward, examining the data at the individual level shows a lot of these individuals have risk perceptions that fluctuate quite a bit, both up and down. This is shown in the last column of the table, which identifies the average of the standard deviations of each individual’s perceptions. It is computed by first finding the standard deviation of each individual’s perceptions from baseline through period 8, and then finding the average of these standard deviations. The average standard deviation of .202 is large and implies that individuals are doing significant revising of their risk perceptions over time.

Rows 2–10 of table 2 report time trends in risk perceptions for each of the seven different crime categories, grouped by aggressive or income generating. One can see the trends for each of these individual crimes is the same slow uptrend that the overall average showed.

Self-Reported Offending

The number of crimes an individual commits is the self-reported offenses (SROs) recorded in each period. This measure is a revised version of a common delinquency measure (Huizinga, Esbensen, and Weihar, 1991). For the purposes of the Pathways study, the self-report scale commonly used in much delinquency research was trimmed to include only the most serious 22 offenses listed. These 22 offenses are delineated in table 3. In each period, an individual is asked whether he or she committed each of these 22 crimes and, if so, how many times. Table 3 summarizes these results for the first 6-month period (which is representative of all the periods). The first row shows the results for all crimes aggregated together, and the rest
Table 3. Summary of Criminal Offending Behavior

<table>
<thead>
<tr>
<th>Criminal Behavior</th>
<th>Proportion Committing Crime</th>
<th>Average</th>
<th>Range</th>
</tr>
</thead>
<tbody>
<tr>
<td>Any Crime</td>
<td>.584 (.494)</td>
<td>34.70</td>
<td>(194.40)</td>
</tr>
<tr>
<td>Aggressive Crimes</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Destroyed or damaged property</td>
<td>.145 (.353)</td>
<td>5.53</td>
<td>(16.90)</td>
</tr>
<tr>
<td>Set fire to house, building, etc.</td>
<td>.013 (.115)</td>
<td>1.59</td>
<td>(1.33)</td>
</tr>
<tr>
<td>Rape</td>
<td>.000 (.000)</td>
<td>–</td>
<td>–</td>
</tr>
<tr>
<td>Murder</td>
<td>.001 (.028)</td>
<td>1.00</td>
<td>(.00)</td>
</tr>
<tr>
<td>Shot someone</td>
<td>.010 (.101)</td>
<td>2.23</td>
<td>(1.42)</td>
</tr>
<tr>
<td>Shot at someone</td>
<td>.045 (.208)</td>
<td>2.67</td>
<td>(2.65)</td>
</tr>
<tr>
<td>Beaten up someone badly</td>
<td>.106 (.308)</td>
<td>1.90</td>
<td>(1.71)</td>
</tr>
<tr>
<td>Been in a fight</td>
<td>.472 (.499)</td>
<td>3.34</td>
<td>(4.18)</td>
</tr>
<tr>
<td>Beaten up, threatened, or attacked someone as part of a gang</td>
<td>.083 (.275)</td>
<td>2.83</td>
<td>(2.81)</td>
</tr>
<tr>
<td>Income-Generating Crimes</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Entered/broken into a building to steal</td>
<td>.035 (.184)</td>
<td>3.84</td>
<td>(7.35)</td>
</tr>
<tr>
<td>Stolen something from a store</td>
<td>.082 (.274)</td>
<td>10.50</td>
<td>(23.10)</td>
</tr>
<tr>
<td>Used checks/credit cards illegally</td>
<td>.020 (.139)</td>
<td>3.84</td>
<td>(4.92)</td>
</tr>
<tr>
<td>Stolen a car/motorcycle to keep or sell</td>
<td>.030 (.171)</td>
<td>28.40</td>
<td>(121.70)</td>
</tr>
<tr>
<td>Bought, received, or sold something stolen</td>
<td>.172 (.378)</td>
<td>11.50</td>
<td>(69.00)</td>
</tr>
<tr>
<td>Prostitution</td>
<td>.007 (.084)</td>
<td>127.75</td>
<td>(350.40)</td>
</tr>
<tr>
<td>Aggressive and Income-Generating Crimes</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Carjacked someone</td>
<td>.012 (.108)</td>
<td>2.53</td>
<td>(2.47)</td>
</tr>
<tr>
<td>Taken something from another by force (with weapon)</td>
<td>.044 (.204)</td>
<td>2.51</td>
<td>(2.05)</td>
</tr>
<tr>
<td>Taken something from another by force (without weapon)</td>
<td>.113 (.316)</td>
<td>4.44</td>
<td>(9.91)</td>
</tr>
<tr>
<td>Dropped Crimes</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sold marijuana</td>
<td>.120 (.325)</td>
<td>89.20</td>
<td>(208.60)</td>
</tr>
<tr>
<td>Sold other illegal drugs</td>
<td>.102 (.302)</td>
<td>97.10</td>
<td>(233.60)</td>
</tr>
<tr>
<td>Carried a gun</td>
<td>.120 (.325)</td>
<td>43.30</td>
<td>(99.10)</td>
</tr>
<tr>
<td>Driven while you were drunk or high</td>
<td>.124 (.329)</td>
<td>13.40</td>
<td>(23.30)</td>
</tr>
<tr>
<td>Arrests</td>
<td>.157 (.363)</td>
<td>1.23</td>
<td>(.57)</td>
</tr>
</tbody>
</table>

**NOTE:** The sample size is 1,261 individuals. Standard errors are in parentheses.

of the rows correspond to the individual crimes. From the first row, one can see that 58.4 percent of the sample committed a crime during this time period. Among those individuals who committed a crime, the mean number of crimes committed is 34.7. Of particular importance to note is the range of crimes—during this 6-month time period, some individuals committed anywhere from 1 to 3,250 crimes.

The 22 crimes were grouped into four different categories: aggressive crimes, income-generating crimes, crimes that are both aggressive and income generating, and dropped crimes. The crimes in this latter category were deemed to not have a direct relationship with the risk perception.
variable. As we are interested in looking at how risk perceptions regarding specific crimes respond to people’s experiences committing those crimes, we only include individuals that committed crimes that are reflected in those risk perceptions. The crimes that are in the dropped category include all crimes that we felt did not meet these criteria. Because these crimes are not directly reflected in the risk perception variable, we set them equal to zero.

Arrests

The measure of an individual’s arrests in each period he or she is less than 18 years of age are based on reports of petitions to juvenile court recorded in the Juvenile Online Legal Tracking System (JOLTS) used in Maricopa County and the juvenile court database in Philadelphia County. Probation violations before the age of 18 years were excluded because they do not necessarily represent a new offense, and they may indicate local practices as much as adolescent behavior. Arrests after the age of 18 years were based on merging the court record information from each jurisdiction with nationwide Federal Bureau of Investigation arrest records. We match the arrests to the specific period in which they occurred. The last row of table 3 shows that 15.7 percent of the individuals are arrested at least once during the first 6-month period in the sample.

RESULTS

To estimate equation 5, a few sample modifications were necessary. As mentioned in the Data section, we disregard all crimes that are part of the dropped category by setting them equal to zero for everyone. Furthermore, because one regressor is $A_t/C_t$, we cannot include anyone that did not commit a crime during this period, or where this information is missing.

18. For instance, the first three of these crimes (pertaining to selling drugs or carrying a gun) all represent crimes that are repeated numerous times during a particular period. The sheer number of crimes individuals commit in these categories indicate their risk perception of getting caught is almost zero. The risk perceptions shown in table 2 for the various crimes are all around .5, implying these crimes are not reflected in the risk perceptions being measured. Furthermore, these crimes are continuous in nature (as opposed to episodic) because individuals that carry a gun or sell drugs usually do this continuously, and thus, it is hard to quantify the actual number of times an individual engages in this behavior. The last crime, driving while drunk or high, is neither an aggressive or income-generating crime, and thus, it also does not fit with the measured risk perceptions.

19. We also ran specifications where instead of setting these dropped crimes equal to zero, we dropped individuals from the sample in time periods where they committed these crimes. The results did not change appreciably.
(Note that the model specified in equation 5 would not be accurate for nonoffenders as they must put more weight on their prior perception and their unobserved signal, because all weights will still sum to 1.) We thus dropped the individual’s observations in time periods where they did not commit any crimes or this information was missing. Another issue is that we do not observe every individual for all eight time periods, nor do we have information on all individuals about the crimes they have committed at baseline. Technically, for us to stratify the results according to how many previous crimes the individual has committed, we would need to observe all of this information. Restricting our sample only to individuals for which we have complete information would result in dropping too many individuals. Thus, we ended up dropping individuals for whom we did not have crimes at baseline, but we kept in individuals that had missing observations over their time period in the sample. In calculating their previous crimes, we impute individuals’ missing observations with the average crimes they committed over all other periods.

One final issue is the outliers associated with the self-reporting of offenses. Table 3 shows that for many crimes, the number of offenses individuals report is high. For instance, someone reports destroying or damaging property 200 times in a 6-month time period. We think these extremely high values are unrealistic, and thus, we top-code at the 99th percentile the number of crimes.

Panel A of table 4 shows the results from estimating the general model of Bayesian updating specified in equation 5. The standard errors are clustered at the individual level because as each individual contributes multiple observations, his or her error terms are likely correlated over time. The results we find are consistent with a model of Bayesian updating. The coefficients indicate that an individual’s perception of getting arrested is a weighted average of his or her prior perception and new information. Overall, 47 percent of the weight is put on the prior perception, 21 6 percent is put on the arrest rate, and the remaining 47 percent is put on the unobservable part of the signal (which has an average value of .53). These results are all statistically significant at $\alpha = .01$.

20. Dropping individuals with missing crimes at baseline only resulted in 46 individuals being dropped. There were 432 individuals who had missing information at one or more periods during their time in the sample, which made it infeasible to drop them.

21. As a reviewer pointed out to us, any measurement error in perceptions will bias the coefficient on the prior perceptions downward, and that such measurement error is perhaps possible because the risk perception for the observation period is measured at a single time, whereas offending may occur at anytime within the observation period. Thus, we note the weight we show being put on the prior should perhaps be thought of as a lower bound estimate.
## Table 4. OLS Results for General Updating Model

<table>
<thead>
<tr>
<th>Panels</th>
<th>Coefficients</th>
<th>N</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Panel A</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Full sample</td>
<td></td>
<td>4,335</td>
</tr>
<tr>
<td><strong>Panel B</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1. High past crime, high current crime</td>
<td></td>
<td>1,144</td>
</tr>
<tr>
<td>2. High past crime, low current crime</td>
<td></td>
<td>1,051</td>
</tr>
<tr>
<td>3. Low past crime, high current crime</td>
<td></td>
<td>516</td>
</tr>
<tr>
<td>4. Low past crime, low current crime</td>
<td></td>
<td>1,624</td>
</tr>
<tr>
<td><strong>Panel C</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Ratio ≥ .100</td>
<td>.236** (.012)</td>
<td>2,607</td>
</tr>
<tr>
<td>Ratio &lt; .100</td>
<td>.268** (.015)</td>
<td>1,728</td>
</tr>
<tr>
<td><strong>Panel D</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Ratio ≥ .330</td>
<td>.245** (.019)</td>
<td>1,078</td>
</tr>
<tr>
<td>.140 ≤ Ratio &lt; .330</td>
<td>.240** (.017)</td>
<td>1,116</td>
</tr>
<tr>
<td>.052 ≤ Ratio &lt; .140</td>
<td>.237** (.016)</td>
<td>1,067</td>
</tr>
<tr>
<td>Ratio &lt; .052</td>
<td>.273** (.018)</td>
<td>1,074</td>
</tr>
</tbody>
</table>

*Notes: The ratio in panels C and D is (crimes individual i commits in period t)/ (crimes i commits from 1 year before entering sample up through period t). Standard errors (in parentheses) are clustered by individual.*

Recall equation 6 shows how the coefficient on the arrest rate can be used to determine the deterrent effect of an arrest. This implies the estimated effect of an arrest on an individual’s risk perception is \(0.063/C_{it}\). This means that if an individual commits one crime, his or her posterior risk perception will be 6.3 percent higher if arrested for the crime than if not arrested. As the number of crimes increases, one can see the effect of an arrest on risk perceptions will decline (although it will always be positive).

Panels B–D stratify these baseline regression results in different ways to determine whether individuals that receive more informative signals do indeed place more weight on them, as the Bayesian model would predict. In panel B, we stratify the sample into four groups, depending on the individual’s current and previous crimes in a given period. Individuals are coded as having a high amount of past crimes in a given period if their past crimes exceed the median number of past crimes in period 8 for all individuals. If their past crimes are less than or equal to this median amount (20 crimes), the individual is coded as having a low amount of past crimes for the given period. The median number of current crimes among all individuals for the majority of time periods is 3, and thus, we coded an
ANWAR & LOUGHRAN

individual in a given period as having a high amount of current crime if they committed more than three crimes in the period. If they committed three or less, the individual was classified as having low current crime.  

Groups 1 and 2 have the same previous criminal experience, as do groups 3 and 4, but groups 1 and 3 have a higher amount of current experience than groups 2 and 4, respectively. Given the same previous experience, the more extensive an individual's interactions with the criminal justice system in the current period, the more informative his or her arrest rate signal should be, and thus, the more weight he or she should place on the arrest signal. This is exactly what we observe, as individuals in group 1 place statistically significantly more weight on their signal than individuals in group 2 (.175 vs. .027; \( p < .001 \)), and individuals in group 3 place more weight on their signal than individuals in group 4 (.133 vs. .031; \( p = .061 \)).

If we compare the groups in a different manner, we can determine what the effect of increasing previous criminal experience is on the weight placed on the signal. Groups 1 and 3 and groups 2 and 4 have the same current experience, but groups 1 and 2 have a higher amount of past experience than groups 3 and 4, respectively. Given the same current experience, the less extensive an individual's past interactions with the criminal justice system, the more weight he or she should place on the current signal. Although this barely holds in magnitude when we compare groups 2 and 4, it does not hold when we compare groups 1 and 3. In neither comparison, though, do the differences approach even marginal statistical significance. However, one caveat to stratifying the results in this way is that each of these groups actually consists of people that are likely to be systematically different from each other. Ideally, one would like to compare identical groups, where one group randomly happens to have more previous criminal experience. Instead, in this analysis, we are comparing people who have consciously decided to commit many previous crimes with people who consciously decided to commit very few previous crimes. Even if both groups do update in a Bayesian manner, they might naturally place different weights on their signal, which makes it difficult to back out the effect of past experience.

An alternative way to examine whether individuals respond more to more informative signals is to code an individual's arrest rate signal in a given period as informative if the ratio of the individual's current crimes in period \( t \) to his or her total crimes (committed from one year before he

22. Note that the same individual can end up in different groups in different time periods.

23. To be clear, the model also generates predictions about the coefficients on both constant and the prior, as well as those placed on the signal; yet in the interest of space and clarity, we do not discuss these in the text.
or she enters the sample up through period $t$) is large. Intuitively, if this ratio is large, individual $i$ committed a large portion of his or her total crimes in period $t$, meaning the arrest rate signal he or she receives during period $t$ should be relatively informative. The advantage this strategy has over the previous stratification is that people that have high ratios are not necessarily systematically different than people with low ratios. For example, a ratio of $1/3$ can include individuals with both high and low previous criminal experiences. The downside is that we cannot isolate the effect of increasing previous criminal experience versus increasing current criminal experience because as the ratio increases, both of these factors can change simultaneously.

In panels C and D of table 4, we stratify the sample in different ways according to the ratio of current crime to total crime. In panel C, we compare individuals who have a ratio at or greater than .1 (i.e., they commit 10.0 percent or more of their total crimes in the current period) with individuals who have a ratio less than .1. Notice that for those individuals at or greater than the .1 ratio, the coefficient of an arrest is nearly double what it is for the group less than .1. Furthermore, we can reject the null hypothesis that these two coefficients are equivalent ($p = .023$). In panel D, we stratify the sample based on (approximate) quartiles of the ratio, yielding four groups: those with a ratio that is less than .052, those with a ratio between .052 and .140, those with a ratio between .140 and .330, and those with a ratio that is greater than or equal to .330. Again, notice that the coefficients on the arrest rate are ordered by increasing magnitude as the ratio increases, implying that the less experienced the offender, the more he or she is responding to an arrest by updating. In summary, the results from panels C and D suggest strong evidence of an “experience effect,” or in other words, the level of risk updating in response to an arrest, as well as the potential deterrent effect of an arrest, decreases as offenders accumulate more offending experience.

TESTING CRIME-SPECIFIC UPDATING

To test for crime specific updating, we estimate equations 7 and 8 using an SUR framework. We only used individual-time period observations if offenders committed either aggressive-only crimes or income-generating-only crimes (as defined in table 3). We thus drop individuals who committed both types of crimes in a period, or that committed crimes in the joint category of table 3. Because most of the income-generating crimes committed by individuals were drug crimes (which were set to zero), we did not have enough “exclusive” income offenders to do the analysis with them. Thus, we restrict our analysis to aggressive-only offenders when estimating equations 7 and 8.
Table 5. GLS Estimates for Crime-Specific Updating

<table>
<thead>
<tr>
<th></th>
<th>Aggressive Risk Perception</th>
<th>Income Risk Perception</th>
</tr>
</thead>
<tbody>
<tr>
<td>$A_{it}^{A}/C_{it}^{A}$</td>
<td>.050** (.019)</td>
<td>.040* (.015)</td>
</tr>
<tr>
<td>$p_{A,I,t-1}$</td>
<td>.400** (.015)</td>
<td>—</td>
</tr>
<tr>
<td>$p_{I,I,t-1}$</td>
<td>—</td>
<td>.390** (.016)</td>
</tr>
<tr>
<td>Constant</td>
<td>.258** (.010)</td>
<td>.354** (.011)</td>
</tr>
<tr>
<td>Sample size</td>
<td>1,951</td>
<td>1,951</td>
</tr>
</tbody>
</table>

NOTE: Standard errors are in parentheses.
*p < .05; **p < .01.

Table 5 reports the GLS estimates of the SUR system. Notice that an arrest for aggressive offending is associated with a 5 percent increase in risk associated with aggressive offending, and this effect is statistically significant at $\alpha = .01$. The same arrest is also associated with a statistically significant 4 percent increase in income offending ($p = .050$) or, in other words, slightly less than the change in perceived risk for aggressive crimes. These results imply that, at a minimum, an arrest for an aggressive crime is affecting both aggressive and income-generating crime perceptions. This finding is important, as it implies that individuals are not updating in a way that is not entirely crime specific. However, although we cannot formally reject the null hypothesis that the aggressive coefficient is larger at conventional levels of statistical significance using a basic chi-squared test ($p = .230$), we should point out that in terms of magnitude of the respective point estimates, the arrest coefficient for aggressive perceptions is 25 percent larger than the arrest coefficient for income-generating crimes. This result would imply that although an arrest for an aggressive crime is seemingly affecting both aggressive and income-generating risk perceptions, the effect is greater for aggressive crime perceptions. This result, although by no means definitive, offers at least preliminary evidence that there may be a dimension of crime specificity to the updating process. However, given the totality of these results, we may safely infer from that the process is not entirely crime specific.

24. A reviewer posited a potential alternative explanation to crime-specific updating from the model specification, noting that it could simply be the case that with income-generating crimes, the prior is just stronger (i.e., the individual is better informed); therefore, all observed signals would carry less weight. Thus, we could observe the aggressive signal carrying less weight in the income-generating perception equation, not because of crime-specific updating, but just because overall signal weight is weighted less here. However, empirically we find this to likely not be the case here, as it seems as though the weights on the two prior are basically the same (i.e., .40 for aggressive crimes vs. .39 for income-generating crimes) as reported in table 5.
DISCUSSION

This article offers a theoretical model and empirical test of Bayesian updating of subjective risk perceptions among a sample of serious juvenile offenders. Our results suggest that individuals do update rationally in accordance with Bayesian theory. Specifically, we find that if an individual commits a crime and is arrested for it, his or her risk perception will be 6.3 percent higher than an equivalent individual who was not arrested. Furthermore, we find evidence that this updating process may also be dependent on the level of prior offending information (i.e., past crimes) an individual has accumulated, with an experience effect suggesting that less informed offenders tend to update their risk perceptions more in response to acquiring new information than more seasoned offenders.

These results suggest that risk perceptions are in fact both dynamic and malleable, and that the process of the formation of perceptions is experience specific. By showing these results among a sample of policy-relevant serious juvenile offenders, several important policy implications can be noted. First of all, it seems that even among serious offending juveniles, an arrest still has a potential deterrent effect, at least as far as increasing risk perceptions. However, among more experienced or frequent offenders, this gain from deterrence may be reduced or, in some cases, lost all together. Furthermore, these results directly address what Nagin (1998: 18) outlined as a chief criticism made by those skeptical of the deterrent effect of official sanctions—namely, that even if criminal behavior is influenced by perceptions, in the absence of some forward linkage between sanctions and perceptions, criminal behavior is immune to policy changes, “not because individuals fail to weigh perceived costs and benefits, but because the sanction risk perceptions are not anchored in reality.” Our results present some evidence that such a latter linkage between policy and perceptions is active.

Finally, our results support the idea that risk updating is not limited to the specific crime perceptions for which one is arrested (i.e., it is not strictly crime specific). Still, however, we do detect some evidence that the effect of an arrest may at least be greater for the risk perceptions associated with that specific crime than for other perceptions, at least at the aggregation of income-generating offending versus aggressive crimes. Given the lack of statistical significance linked to our finding on this latter point, we stress the need to interpret it cautiously. Yet this distinction is crucial for the policy implications of deterrence, as it suggests that although there may be a global deterrent effect for any arrest, policies targeting specific types of offending may be marginally more effective at curbing these offenses than general polices aimed at reducing crime across the board. However, these types of crime-specific reduction policies can also be problematic in a sense if they
induce a substitution effect (Nagin, 1998); yet our results suggest such an effect will perhaps be less pronounced because all perceptions are seemingly updated to some degree in response to an arrest. Our findings particular to the topic of crime-specific updating are both preliminary and exploratory, and thus, we offer this topic as a fruitful area for future research, including further understanding as to the role of substitution effects.

It is important to point out that although we do find evidence that arrests are potentially a deterrent, it is still difficult to determine how large of an actual deterrent effect they produce. To determine this, we need to know two things: 1) by how much does an arrest increase an individual’s risk perception? and 2) by how much does this increase in risk perception in turn change his or her criminal activity level? We present evidence attempting to answer the first question in this article, but we have not addressed the second. In a previous study, Lochner (2007) found that a 10 percentage point increase in an individual’s risk perception resulted in major thefts being reduced by 3 percent and auto thefts being reduced by more than 8 percent. Applying this finding to our results implies that an individual that gets arrested for a crime will reduce these behaviors by 1.2 percent and 3.2 percent, respectively. However, as mentioned, Lochner (2007) used a primarily nonoffending sample from the National Longitudinal Survey of Youth, so these estimates might not be as relevant for the offenders in our sample. Furthermore, our results suggest that there may be important interactions between experience level and within-individual changes in perception. Thus, a more formal analysis addressing these questions with a group of serious offenders is an important topic for future work.

Finally, it is important to note that the effectiveness of arrests in reducing crime goes far beyond the deterrent effect we have tried to estimate here. Besides deterring individuals, arrests also can have an incapacitation effect if they lead to individuals getting incarcerated, which will reduce crime. Moreover, we find evidence that individuals put a substantial amount of weight on the unobserved portion of the signal they receive compared with their own arrest rate. Specifically, individuals on average put a weight of .06 on their own arrest rate and .47 on their unobserved signal. The sheer weight that is put on the unobserved signal (as opposed to the arrest rate) implicates the components of this as being highly important. Although

---

25. There has been a multitude of literature that has tried to examine the link between an individual’s perceptions and his or her criminal behavior. Most of this prior research is plagued by both simultaneity and selection problems. Furthermore, these studies typically just examine how the individual’s average perception is correlated with his or her criminal activity, whereas we want to know how the individual’s change in criminal activity is related to his or her change in perceptions. Lochner’s (2007) study is one of the few that examined this directly and deals with the simultaneity issues.
we cannot parse out exactly what factors are in this unobserved signal, undoubtedly the arrest rate of their peers is included in this signal. Thus, not only will an individual’s own arrests have a deterrent effect, it is likely that the arrests of his or her peers also will have a deterrent effect. Thus, the effect of an arrest we find may very well be a conservative estimate of the true deterrent effect of arrest. Others have attempted to quantify the role of peers in the learning process, (e.g., Matthews and Agnew, 2008; Pogarsky, Piquero, and Paternoster, 2004; Sirakaya, 2006), but as of yet, it remains unclear how the roles of personal experience and peer experiences reconcile. More work needs to be done, both theoretically and empirically, to determine what systematic factors are included in this unobserved signal, as these could potentially have much larger deterrent effects than what we observe for arrests.

Although these results have important implications for perceptual deterrence and rational choice research, we must stress that risk updating is merely one component of a complicated decision-making calculus that is generally still not well understood. Thus, although the evidence of updating demonstrated in this article by the group of serious offenders is encouraging, it is still wholly insufficient to infer that the decision to engage in offending is driven primarily by perceived risk for this class of serious offenders. With this limitation in mind, we envision several future directions for research on perception updating, rational choice, and offender decision making worth pursuing.

First, it is likely that updating, as well as the degree to which updated perceptions are ultimately a deterrent, widely overlaps with criminal propensity, typically operationalized in terms of self-control. Findings from the literature dealing with this interaction of criminal propensity are mixed, with some studies concluding that those with low self-control are perhaps less deterrable by increased sanction threats (Nagin and Paternoster, 1993; Nagin and Pogarsky, 2004; Piquero and Tibbetts, 1996) whereas others conclude the opposite (i.e., that lower self-control may make one more deterrable; Pogarsky, 2002; Tittle and Botchkovar, 2005; Wright et al., 2004). Thus, we believe that similar amounts of perception updating across individuals may yield different deterrent effects ultimately and advocate future research on this topic.

Second, our results suggest that these individuals are rationally updating their subjective perceptions on average, but individually there may be great variability among the offending population as to both the level of updating in response to new information. Assuming experience can only explain part of this incongruity, then it is critical to improve understanding of individual-level factors that are linked to both willingness and/or ability to update perceptions, especially if these factors are relevant legal factors, which can be used for policy. For example, if certain mental health diagnoses are associated with a lack of updating of one’s risk perceptions, then certain
institutional treatment services aimed at stressing consideration of cost/risk in these individuals may prove beneficial.

Finally, although risk is arguably the most important element of rational choice, it is merely one component of expected utility; for instance, some prior literature suggests perceived rewards may ultimately be the most important element in driving rational choice (e.g., Matsueda, Kreager, and Huizinga, 2006). Also, the decision-making process stemming from the compiling of each of these different cost–benefit elements likely varies both between individuals, as well as within an individual over time (McCarthy, 2002; Paternoster and Pogarsky, 2009). Therefore, the degrees to which other rational choice perceptions such as costs and rewards are updated, as well as the way changes in these components are internalized over time, are topics worthy of future scholarship. Furthermore, standard rational choice models of crime assume that individuals are all utility-maximizing agents; yet substantial evidence from behavioral economics is available to suggest that this is likely not the case (cf. Camerer and Loewenstein, 2004). Understanding how elements of the expected utility calculus may systematically break down with respect to criminal involvement is potentially indispensable for crafting future policies aimed at deterrence. Ultimately, this is the necessary future direction of the study of perceptual deterrence.

REFERENCES


Shamena Anwar is an assistant professor of economics and public policy at Carnegie Mellon University. Her research interests include deterrence and examining the critical role of race in jury decisions, criminal sentencing, and health care outcomes.

Thomas A. Loughran is an assistant professor of criminology and criminal justice at the University of Maryland–College Park. His research interests include deterrence and offender decision making, individuals’ responses to sanctions, and methods to infer treatment effects from non-experimental data.