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Offender Decision-Making in Criminology: Contributions from Behavioral Economics

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Abstract

If there is agency and some decision-making process entailed in criminal behavior, then what are the incentives for crime and for conformity, and what is their role in offending decisions? Incentives have long been the province of economics, which has wide influence in criminology (e.g., Becker 1968). However, economics has evolved considerably since Becker's influential model. An important development has been the advent of behavioral economics, which some consider a branch of economics on par with macroeconomics or econometrics (Dhami 2016). Behavioral economics integrates empirical departures from traditional microeconomic theories into a rigorous and more descriptively accurate economic model of choice. This review explains how behavioral economic applications on offender decision-making can help refine criminological theories of choice and identify innovative possibilities for improving crime-control policies.

The errors of a theory are rarely found in what it asserts explicitly;
they hide in what it ignores or tacitly assumes.

—Kahneman 2011, pp. 274–75

INTRODUCTION

Agency and choice have been fundamental to criminology since its inception. The Enlightenment philosophers Cesare Beccaria and Jeremy Bentham broke from religious dogma by positing human behavior was voluntary. The determinism of phrenology in the nineteenth century reflected a denial of agency and choice; instead, physical attributes of the brain and body determined involvement in crime (Gould 1996, Rafter 2004). Crime discourse also deemphasized choice during the "Golden Age of Theory" from 1930 to 1960 (Laub 2004) but for different reasons. The ecological perspective of the Chicago School then focused on the causal capacities of social structure and physical environment in producing deviance. This even led to arguments of pure macrocausation or emergence, where collective phenomena are synergistic and unexplainable solely with respect to individuals (Sawyer 2001). However, emphasis subsequently shifted back toward choice. Parsons (1937) and then Homans (1964) argued that any theory of crime causation requires an explanation for reasoned action. Laub & Sampson (2003) considered human agency the "missing link" in our understanding of desistance. And Nagin (2007, p. 259) advocated "moving choice to center stage in criminological research and theory."

But human agency necessitates some "decision-making process, however crude or faulty, that reflects the benefits, costs, and risks of alternative courses of action" (Nagin 2007, p. 262). Thus, the point of departure for this review is how incentives toward crime or conformity influence offending decisions. It happens that responsiveness to incentives is a signature notion in economics, which has had wide influence in criminology, particularly on theories of offender decision-making. Actors in economic models seek to maximize their personal well-being. Thus, disincentives such as threatened or actual punishments should discourage crime. Yet as Dhami & al-Nowaihi (2012, p. 299) observed: "Traditional economics is based on the assumptions of fully rational and self-interested behavior. A very large body of evidence casts serious doubts on both these assumptions."

One potential conclusion is that incentives have little role in crime decisions. But this does not square with the empirical evidence either. Incentive-driven behavior is evident, for example, in target selection for property or personal victimization (e.g., Wright & Decker 1997) and in the updating of sanction risk perceptions based on offending and punishment experiences (Anwar & Loughran 2011, Wilson et al. 2017). It may also be that criminological research does not fully reflect recent theoretical advancements on choice. The same microeconomic principles that once produced incomplete accounts of decision-making in health, finance, and public policy also produce underdeveloped theories of criminal decision-making. This premise underlies behavioral economics, which has been described by Thaler (2015, p. 23) as "economics that is based on realistic assumptions and descriptions of human behavior. It is just economics with more explanatory power because the models are a better fit with the data."

Because behavioral economics derives directly from economics, we first explain several microeconomic principles. Thereafter, we review criminological applications of behavioral economic principles to better understand offender decision-making. The review is organized according to the following three aspects of behavioral economics: (*a*) prospect theory, (*b*) dual-process decision-making, and (*c*) heuristics and biases.

MICROECONOMIC PRINCIPLES AND OFFENDER DECISION-MAKING

Scholars have been studying decision-making for a long time [e.g., Bernoulli 1738, Pascal 1995 (1670)]. In the mid-twentieth century, von Neumann & Morgenstern (1944; see also Savage 1954)

pioneered insights that led to Expected Utility Theory, which Kahneman (2011, p. 270) considered "to this day the most important theory in the social sciences." Becker (1968) extended expected utility principles in his rational choice model of crime, which remains influential in contemporary research on offender decision-making (e.g., Loughran et al. 2016a, Dugan & Chenoweth 2012, Kreager & Matsueda 2014).[1] Before proceeding, it is worth emphasizing the purposes of microeconomic theories. As Dhami (2016, p. 2) puts it, "economics provides a coherent and internally consistent body of theory that offers rigorous, parsimonious, and falsifiable models of human behavior." Thaler (2015) emphasized that economic theories were normative, in that they logically demonstrate how self-interested actors can maximize their well-being.

In a straightforward version of this rational choice model, the actor chooses between a specific crime opportunity or remaining with the status quo. Economic actors assess their well-being with a utility function, $U(*)$, which recalibrates dissimilar consequences (e.g., jail versus money) into like units (utiles) for evaluative and comparative purposes. Refraining from a specific crime opportunity yields U(status quo). In contrast, offending is an uncertain route. Three variables help capture this uncertainty: p, the probability of detection and punishment; Y, the benefits the actor anticipates from committing the offense; and f, the punishment if caught. With probability $(1-p)$, the actor will evade capture and experience $U(Y)$. With probability p, the actor is caught and punished. In this case, a punishment of f is subtracted from the benefits of offending, y. The actor therefore experiences $U(Y-f)$. The expected utility from crime is a global assessment (weighted average) of the risks and consequences. In sum, an individual should offend if

$$EU_{crime} = pU(Y - f) + (1 - p)U(Y) > U(\text{status quo}) \qquad 1.$$

Notice that the expected utility from crime decreases as both p, the certainty, and f, the severity of punishment, increase. This reflects the familiar deterrence notions of certainty and severity effects. This rational choice model also readily captures other criminological notions such as extralegal deterrents (e.g., stigma and shame), self-regulation and time preference, and the updating of sanction certainty perceptions (see Loughran et al. 2012, 2016a; Nagin & Pogarsky 2001; Wilson et al. 2017). Below, we highlight two aspects of the model that are essential to behavioral economics.

Utility

The mathematical form of the utility function reflects several core features of choice. **Figure 1** presents a prototypical concave utility function [$U(x) = \sqrt{x}$]. Its slope decreases asymptotically toward zero, meaning that the more one already has of something, the less marginal utility nominally equivalent increments of that thing add. This is the principle of diminishing sensitivity and, in the extreme, satiation. In plain terms, for someone with $1,000 to their name, another $1,000 should seem huge. For someone with $1,000,000, another $1,000 may go unnoticed (see also Lattimore & Witte 1986, Thomas & Loughran 2014).

The shape of a utility function reflects the corresponding actor's risk preference. A prevalent conception in criminology is that risk-taking constitutes one of six elements of low self-control (Gottfredson & Hirschi 1990). To illustrate the economic conception of risk, imagine that an actor with the concave utility function in **Figure 1** faces a choice. One option is to flip a fair coin and receive $10,000 if it lands heads, but nothing if it lands tails. Or alternatively, the actor can receive the average outcome of the gamble for sure: 0.5($10,000) + 0.5(0) = $5,000. Individuals who

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[1]Readers might recall Becker's (1968, p. 170) pronouncement: "a useful theory of criminal behavior can dispense with special theories of anomie, psychological inadequacies, or inheritance of special traits and simply extend the economist's usual analysis of choice."
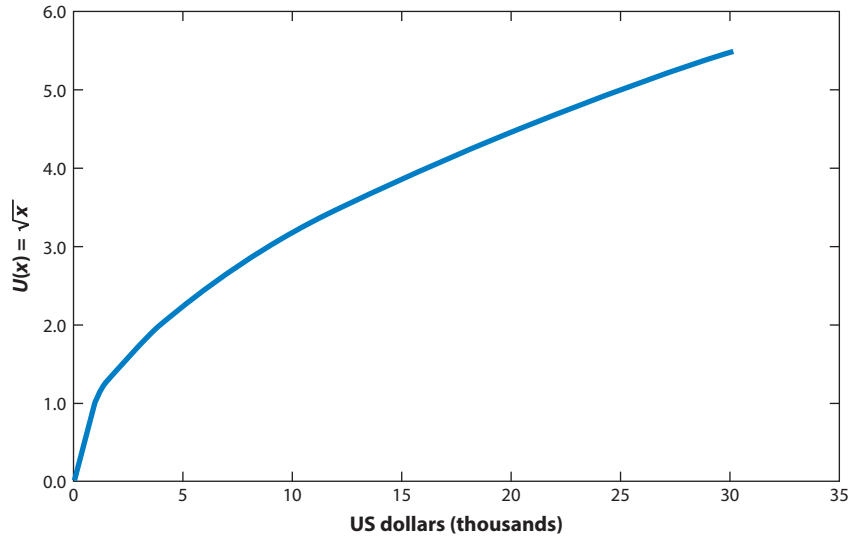
Figure 1

Standard concave utility function.

are indifferent between these two options are risk neutral, i.e., they can take the gamble or leave it. However, a common instinct is to prefer the $5,000 sure thing, which in economics reflects risk aversion. More generally, an actor is risk averse if he or she would accept an amount less than the average monetary value of a gamble rather than take that gamble. Notice in **Figure 1** that if the coin lands on heads, the actor experiences $U(x) = \sqrt{10,000} = 100$ utiles of well-being. Thus, the expected utility of the gamble is $0.5(100) + 0.5(0) = 50$ utiles. But this actor should certainly prefer $5,000 in lieu of the gamble because $U(x) = \sqrt{5,000} = 70.7$ utiles. A comparable demonstration is possible that someone with the convex utility function, $U(x) = x^2$, is risk seeking and would prefer a gamble over an amount equal to the expected dollar value of that gamble.

Probability

Offending decisions entail considerable uncertainty. The potential consequences from crime range from instrumental and psychic inducements to legal and extralegal punishments. Yet each of these potential consequences has its own perceived likelihood. Economics relies on Bayesian principles to quantify this form of uncertainty with probabilities that range from 0 to 1 and reflect the likelihood of specified events (Cyert & DeGroot 1974). The probability that an event will occur is the ratio of the number of ways the event can occur to the total number of things that can occur. But economic theorists cautioned that numeric probability may not be sufficiently versatile to capture all forms of uncertainty (Keynes 1921).[2] Nonetheless, utility and probability became staple constructs in Becker's (1968) model. Probability is often the default metric for quantifying uncertainty in studies of offender decision-making.

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[2] Compare this, for example, to a five- or seven-point Likert scale ranging from very uncertain to very certain.

PROSPECT THEORY AND OFFENDER DECISION-MAKING

Unlike microeconomics, behavioral economics is not simply normative. Rather, it aims to develop "descriptive economic models that accurately portray human behavior" (Thaler 2015, p. 30). This is well illustrated by prospect theory, the first of three areas of behavioral economics we address in this review.

Central Features of Prospect Theory

Below we explain the two central features of Prospect Theory, value and probability weighting. Thereafter, we review criminological contributions on offender decision-making that apply these principles.

Value versus utility. In prospect theory, decision-making is reference dependent. Gächter et al. (2009) illustrated this with a study that randomly divided potential conference attendees into two groups. One group was instructed by email: "We take this opportunity to remind you that the discounted conference fee for early registration is available until 10 July 2006." The second group received an alternative email: "We take this opportunity to remind you that the conference fee will include a penalty for late registration after 10 July 2006." Among junior participants, the entire penalty group registered on time, whereas one-third of junior faculty in the discount group registered late. Economically, the frames are equivalent. The conference fee is higher for people who register after the deadline. But the discount frame characterizes the consequences of late registration as a foregone gain, whereas the penalty frame treats the price increase as a loss. Thus, the value an individual places on an outcome appears to depend on whether that person perceives the outcome as a gain or a loss.

Prospect theory replaces the utility function with the value function in **Figure 2**, which is concave in the domain of gains but convex for losses. Thus, as in expected utility theory, decision-making for gains tends to reflect diminishing sensitivity and risk aversion. However, prospect theory treats losses differently. First, the theory explicitly represents diminishing sensitivity for perceived losses, as reflected by the flattening of the value function at more negative amounts. Second, the value function also reflects asymmetric risk preference according to framing, i.e., people tend to be risk averse for gains, but risk seeking when facing losses. This is most often illustrated with a public health problem posed by Tversky & Kahneman (1981). Respondents
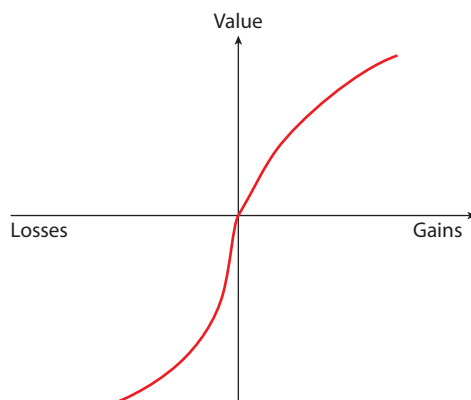

Figure 2

Prospect theory value function. Adapted from Kahneman & Tversky (1979) with permission.

were more likely to favor a policy intervention against a life threatening contagious disease when it was framed positively (e.g., lives saved), rather than negatively (e.g., lives lost). Prospect theory is essential to future research on offender decision-making because such an integral part of the crime decision is a potential criminal penalty (a loss).

Note as well that the value function is steeper in losses than it is in gains. This reflects the behavioral economic notion of loss aversion, which is often expressed rhetorically as "losses loom larger than gains" (Thaler 2015). This is mathematically evident from the value function; for any $x > 0$, $V(-x) > V(x)$ in absolute magnitude. Recall the earlier study (Gächter et al. 2009) that tested differences between a discount and penalty frame for attendees of an academic conference. The penalty frame prompted respondents to treat the higher fee as a loss in the amount of the penalty. This can feel particularly aversive. The discount frame conveys an economically equivalent message but with a different psychological impact. There, registering late costs participants more, and if this occurs they merely fail to benefit from the saved penalty.

Probability weighting. Finally, prospect theory also extends the treatment of probability in decision-making. Consider the following example, adapted from Gonzalez & Wu (1999). Suppose a researcher must decide whether to improve a manuscript submission with a month more of analysis or submit it as is. The contemplated analyses are expected to improve the chance of acceptance by 10 percentage points. Would the researcher be any more willing to do the additional work if they believed the probability of success without the extra analyses was 90% than if they believed that probability was 40%, or what about 0% versus 40%? Intuition suggests the additional work should be more likely for increments at the ends of the continuum than for nominally equivalent increments in the middle. When the current chances are 90%, the 10% increment yields a certain publication, and when the current chances are 0%, the 10% increment avoids a certain rejection. Each of these scenarios seems intuitively more impactful than the nominally equivalent increase from 40% to 50%.

Thus, rather than treat probabilities as given, prospect theory converts them with a nonlinear probability weighting function, such as that in **Figure 3**. The prospect theory weighting function embodies several empirical regularities regarding probability that emerged from empirical disconfirmations of expected utility models. First, individuals tend to overweight very small probabilities and underweight very large ones. Second, and relatedly, increments of probability at the endpoints of the continuum tend to influence decisions more than nominally equivalent increments toward the middle of the continuum do (Kahneman & Tversky 1979).

Applications of Prospect Theory

We divide our discussion of the criminological applications of prospect theory into the two aspects of the theory just presented, value and probability weighting.

Value function: reference dependence, diminishing sensitivity, and risk. A growing criminological literature reports investigations of offender decision-making from the standpoint of prospect theory. Bushway & Owens (2013) investigated the possibility of reference dependence in the deterrent capacity of prison sentences. The authors analyzed sentencing and matched criminal history data from Maryland, where judges may depart from advisory sentencing guidelines. The legislature monitors such departures and periodically updates the guidelines to better correspond to judges' actual sentences. These periodic adjustments to recommended sentences provide exogenous variation to estimate how any disparity between expected and actual sentences affects recidivism.
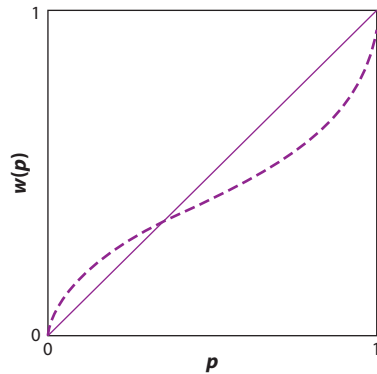
Figure 3

Prospect theory weighting function. Adapted from Kahneman & Tversky (1979) with permission.

Drawing on prospect theory, the authors posited that the aversiveness, and thus the specific deterrent capacity, of a punishment should depend on the punishment the offender expected to receive. Imagine two defendants: The first expects an eight-year sentence but only receives four, whereas the second receives four years as expected. The first defendant may perceive greater relief, but hence less aversion, from the same four-year sentence than the second defendant does. Consistent with this premise, Bushway & Owens (2013) found that, controlling for the actual sentence, a wider divergence between threatened and actual sentences (threatened sentences are typically greater) produced more recidivism.

Criminological research also reflects the principle of diminishing sensitivity, or the declining impact of additional gains or losses with movement away from a reference point or status quo (Thaler 2015). For example, this notion may help explain why the severity of formal sanctions appears far less consequential for deterring crime than the certainty of apprehension (Apel 2013, Pratt et al. 2006, Raaijmakers et al. 2017). In Klepper & Nagin's (1989) study of perceptual deterrence and tax compliance, punishment severity was measured as the perceived probability of prosecution, whereas certainty was measured as perceived probability of detection by the IRS. They found no evidence that a continuous measure of severity was associated with offending but found strong evidence of deterrent effects when severity was measured dichotomously as a nonzero chance of criminal prosecution. They explained that "if a nonzero chance of criminal prosecution is an absolute deterrent, marginal increases in the perceived risk of criminal prosecution above the zero threshold should be inconsequential to behavior" (Klepper & Nagin 1989, p. 239). The effect is diminishing sensitivity to losses as outlined in prospect theory, and it is germane to all potential costs of crime. It suggests that after a certain threshold, which may vary by crime type and across individuals (based on reference points), additional increases in punishment severity may have little deterrent value, even if increases in severity before that threshold have large deterrent effects (e.g., Weisburd et al. 2008).

Framing effects based on asymmetric risk preference are particularly relevant in tax compliance. Here, the offending decision, the amount of income, if any, to underreport, has an additional contextual feature, i.e., the amount withheld or provisionally paid during the year. From an economic perspective, the offending decision should be invariant to how much money, if any, is withheld or prepaid. Instead, the question is simply "How much of my gross income should the government receive/keep?" But this economic expectation is unsupported. For example, Clotfelter (1983) found evidence for a "withholding phenomenon," in which underpayment of taxes varied negatively with

the portion of the year-end tax obligation that was withheld. This empirical pattern follows from prospect theory. The taxpayer's end-of-year withholding position appears to fix a reference point for compliance. With less prepayment or withholding, the taxpayer is more apt to evaluate the potential tax obligation as a loss (i.e., How much will I pay?). By contrast, for all funds that have been prepaid or withheld, the compliance decision involves a foregone gain (i.e., How much should they keep?). This suggests the empirically supported correspondence between the sum that is prepaid or withheld and tax compliance. Further evidence is found in Schepanski & Shearer (1995) that current asset position rather than the expected position (or some stable personal attribute) fixes the frame and helps shape taxpayer risk attitudes (see also Delaney Thomas 2013).

Whichard & Felson (2016) sought to extend this reasoning to why inmates resist arrest. They began by observing how improbable it is to successfully resist arrest and, moreover, how serious the repercussions can be. Thus, the decision to resist arrest seems unsupportable by any reasoned cost-benefit analysis. However, reference dependence may contribute to the incidence of resisting arrest despite the long odds against success. Once a police encounter reaches a point at which the suspects perceive they will be arrested, this realization can shift the offender's reference point, such that the impending arrest is a loss thereby triggering the type of risk-seeking behavior that resisting arrest entails. In analyses of inmate data from the 2004 Survey of State and Federal Correctional Facilities, the authors found some evidence consistent with this hypothesis. Suspects were more likely to resist arrest if they were on probation or parole or were in possession of some illegal contraband. These findings, however, seem most consistent with diminishing sensitivity to risk, but overall the study represents an innovative application of behavioral economic principles in crime research.

Nonlinear probability weighting. For decades, criminological deterrence research had focused mostly on disputing the very existence, rather than the nature or functional form, of deterrent effects. This hindered the identification of contextual features of deterrence. An exception involves the notion of a tipping effect. Some of these studies identify a threshold level of certainty ($p \approx 0.3$) below which changes in detection probability do not influence offending behavior (e.g., Tittle & Rowe 1974).

More generally, Loughran et al. (2012) tested the various implications of nonlinear probability weighting for deterrence and offender decision-making. Using data from a sample of serious adolescent offenders, they found strong evidence for a nonlinear certainty effect. To start, they too reported a tipping effect at $p = 0.3$. Moreover, above the threshold, the significant negative association between the perceived probability of arrest and offending grew stronger at the upper end of the risk continuum (0 and higher). These findings reinforce a recurrent theme about context dependence. Here, the association of changes in perceived risk and changes in offending depends squarely on the starting point within the probability continuum.

Behavioral economics also addresses potential ambiguity beyond simply the level of detection probabilities. In economics, an actor's certainty estimate is thought to summarize a subjective distribution of detection probabilities. But beyond the point estimate typifying this distribution, consequential information also comes from its variance or spread. More plainly, ambiguity reflects the level of clarity or assuredness with which an individual holds a certainty estimate (see Camerer & Weber 1992).

Research has found that individuals tend to be ambiguity averse. That is, all things being equal, given a choice between two options people prefer the less ambiguous one (Ellsberg 1961, Kahn & Sarin 1988). The implication is that two offenders may treat identical subjective probabilities of arrest differently (e.g., 40%), depending on how accurately they believe their estimate captures the true probability of arrest. Related to this, Ellsberg (1961) conducted an experiment in which

respondents select one of two urns from which they will draw one ball. If the ball is red, they win a cash prize. The first urn contains 50 red balls and 50 black balls. The second contains 100 red or black balls, but in unknown proportions. In this case, the number of red balls is uniformly distributed from 0 to 100, and hence, $E[x] = 50$. Yet although the probability of selecting a red ball and winning is identical across urns, individuals routinely prefer the first urn, thus demonstrating ambiguity aversion.[3]

Sherman (1990) extended these principles in his review on police crackdowns. He observed that deterrent effects often exhibited two characteristics. There was evidence of residual deterrence, which persists after the crackdown ends. As well, there was deterrence decay, which refers to the diminution of deterrent effects as the crackdown persists. Sherman considered both findings consistent with ambiguity aversion. Deterrence decay can occur as any initial ambiguity about enforcement during the newly instituted crackdown subsides. In contrast, residual deterrence can persist after the crackdown ends because it takes time for people to learn it has ended and thus have their ambiguity correspondingly reduced. Sherman advocated for short, rotating crackdowns to maximize residual deterrence and minimize deterrence decay and thus improve the net crime-control benefits from the intervention (see also Nagin 1998).

Criminological research has investigated several further dimensions of ambiguity. One follows from the behavioral economic finding that decisions depend on whether the actor perceives the choice involves a loss or a gain. Most research on ambiguity and choice has involved gains. But because the offending decision centers around potential penalties, it has fallen to crime researchers to explore ambiguity in the domain of losses. Moreover, such research has also investigated whether the role of ambiguity depends on location in the probability continuum. Specifically, the effect of ambiguity may vary depending on initial probability level, such that people may actually be ambiguity seeking when probabilities are low for gains, and vice versa for losses (Einhorn & Hogarth 1985, Ellsberg 1961).

Several studies investigated these issues in the context of offender decision-making. In a series of experiments, Casey & Scholz (1991a,b) found that ambiguity (or vagueness of detection risk) reduced college students' willingness to commit tax noncompliance when detection risk was low but had the opposite effect when detection risk was high. They termed this a boundary effect. Such individuals behaved as if ambiguity prompted them to revise their point estimate away from the nearest boundary and toward the middle of the probability continuum. In their experiments, ambiguity was built into hypothetical scenarios by varying the hypothetical accountant's assuredness "about how likely it is that your return will be spot-checked [by the IRS]" (Casey & Scholz 1991a, p. 838). Loughran et al. (2011) also produced similar findings. These authors measured ambiguity as the variance in perceptions of arrest risk for similar offenses. They found a deterrent effect of perceived ambiguity but only at low levels of probability (<0.30).[4] By contrast, Pickett et al. (2016) measured ambiguity in perceived arrest risk using respondent's self-reported assuredness (1 = very sure, 6 = very unsure) in their risk perceptions. They found no evidence of a deterrent effect of ambiguity on intentions to commit white-collar offenses. However, the authors did not consider the possibility that the deterrent effects of ambiguity might be conditional on whether the perceived probability of arrest is low or high.

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[3]A recent study suggests the ambiguity aversion observed in laboratory studies may be a methodological artifact, reflecting aversion to unfamiliar experimental procedures more than aversion to ambiguity per se (Mislavsky & Simonsohn 2016).

[4]In the study by Loughran et al. (2011), the deterrent effects of ambiguity were observed only for no-one-around (NOA) crimes (i.e., breaking in, stealing, theft, and vandalism). Notably, Casey & Scholz (1991a,b) also focused on a NOA crime—tax noncompliance.

Interestingly, some evidence suggests that self-reported ambiguity (or lack of assuredness) may be less sensitive than risk perceptions to new information. In one experiment, respondents provided with information about objective arrest rates updated their perceptions of the probability of arrest and did so by a substantial amount (by an average of 7–10 percentage points on a 0–100 scale) (Pickett et al. 2016). However, the new information did not have a statistically significant effect on ambiguity. Other studies found evidence that self-reported ambiguity may be more strongly associated than risk perceptions with relatively stable individual traits, like ambiguity intolerance and self-efficacy (Pickett & Bushway 2015, Pickett et al. 2015b). Even still, evidence on the sources of ambiguity in perceived risk remains thin.

Certainly, further research is needed that explores alternative predictors of ambiguity in perceived risk. There is also a need for additional investigations of the potential deterrent effects of ambiguity, which leverage alternative measures of ambiguity. Not least, an especially promising direction for future studies would be to explore whether the deterrent effects of ambiguity vary across individuals and processing modes. For example, ambiguity in perceived risk might exert larger deterrent effects among persons who are intolerant of ambiguity or who are using a more logical/reasoned, rather than intuitive, processing mode.

DUAL-PROCESS OFFENDER DECISION-MAKING

Dual-Process Aspects of Behavioral Economics

Although prospect theory is the seminal, early statement of behavioral economics (Kahneman & Tversky 1979), three works exemplify some more recent advancements (Dhami 2016, Kahneman 2011, Thaler 2015). One in particular, *Thinking, Fast and Slow* by Kahneman (2011), elaborates the dual-process nature of behavioral economics. System 2 typifies the kind of reasoning envisioned under models of rational choice and Bayesian updating and is conscious, deliberative, and slow. In contrast, System 1 is intuitive, automatic, and fast. It provides constant and near instantaneous answers to the questions in daily life (Kahneman 2011). This includes questions about the risk of future events (Johnson & Tversky 1983, 1984; Slovic 2010), such as the probability of apprehension and sanction after committing a crime. System 1 is able to provide these answers through the use of mental shortcuts, also known as cognitive heuristics. However, System 2 has the capacity to reject the heuristic answers of System 1 and work through to its own conclusions. This type of systematic, reasoned thinking is also a staple of daily life. However, the behavioral economics literature suggests that System 2 deliberation governs less human decision-making than one might initially think. For various reasons (e.g., preoccupation, depletion, individual differences in reasoning styles, or simple ambiguity), System 2 often accepts the heuristic answer, which then becomes the basis for a person's judgment or belief (Kahneman 2011).

Criminological research on choice has typically modeled offending decisions with System 2 processes, such as the formulation and weighing of consequences and likelihoods. But dual-process thinking is quite consistent with formative notions about the nature of crime. Consider the depiction of crime by Gottfredson & Hirschi (1990, p. 16): "It is easy to be misled about the nature of crime in American society . . .The fact of the matter is that the vast majority of criminal acts are trivial and mundane affairs that result in little loss and less gain. These are events. . .that require little preparation, leave few lasting consequences, and often do not produce the result intended by the offender." This influential description of the nature of crime leaves ample room for offhand-edness, automaticity, and a general absence of close contemplation. These are all conditions leading to heuristic decision-making, the topic of the section on Heuristics, Biases, and Offender Decision-Making. First, we discuss research on dual-process reasoning and criminal choice.

Criminological Applications of Dual-Process Principles

Although prospect theory focuses on System 2 operations, there has been growing interest in applying principles of dual-process reasoning to better understand offender decision-making (e.g., Mamayek et al. 2015, Pickett & Roche 2016, Thomas & McGloin 2013). Below, we highlight two contributions along these lines: (*a*) Paternoster & Pogarsky's (2009) delineation and assessment of thoughtfully reflective decision-making (TRDM) and (*b*) van Gelder & de Vries's (2012, 2014) theoretical and empirical work on the hot/cool perspective.

Highlighting the distinction in behavioral economics between systematic and intuitive reasoning processes, Paternoster & Pogarsky (2009) conceptualized systematic reasoning as TRDM. They explained that TRDM consists of the tendency to be thoughtful and logical at each separate stage of the decision-making process: before (gathering information), during (carefully deliberating), and after (revisiting and critiquing) a decision is made. Per their arguments, TRDM captures the essence of agency and rationality in decision-making and should have indirect effects on offending through several mechanisms, including the accumulation of social capital. They characterized TRDM as a trait that varies both between and within individuals over time but that is not always engaged in every situation.

Most studies to date have focused on between-individual variation in TRDM. This research has provided strong support for the role of TRDM in offender decision-making. Using longitudinal data from the National Longitudinal Study of Adolescence Health, Paternoster & Pogarsky (2009) found that TRDM was negatively associated with general delinquency, illegal drug use, and heavy drinking. In a follow-up study using the same data, Paternoster et al. (2011) found that TRDM was, in fact, strongly associated with the accumulation of social capital (e.g., school and parental attachment). In turn, TRDM had indirect effects on both negative (e.g., delinquency and drug use) and positive (e.g., community and civic participation, health) adult outcomes through the accumulation of social capital. By contrast, studies that have used college samples have reported mixed evidence that TRDM is related to intentions to offend (Kamerdze et al. 2014, Mamayek et al. 2015).

Far less evidence is available on whether the effects of TRDM vary across contexts. Two notable exceptions are recent studies by Maimon et al. (2012) and Louderback & Antonaccio (2017). Maimon et al. (2012) found that in the school context, the relationship between TRDM and both violence and in-school intoxication was strongest in schools with more lenient sanctions. The implication is cognitive style and agency may be more important in the most criminogenic settings, i.e., those with weaker deterrence cues. Louderback & Antonaccio (2017) found higher TRDM is associated with lower levels of both cybercrime involvement and victimization across measures and samples of both college employees and students. Still, additional studies are needed to further investigate how TRDM influences decision-making in different contexts. One promising strategy might be to use virtual reality to simulate criminal opportunities to examine how TRDM influences decisions in action within specific criminal situations (see van Gelder et al. 2017). An equally important direction for future research is to explore how TRDM varies within individuals. Changes in TRDM over time may help to explain intermittency and desistance from crime.

Separate from the TRDM literature, van Gelder & de Vries (2012, 2014) developed a hot/cool perspective of criminal decision-making. Like scholarship on TRDM, the hot/cool perspective focuses on the distinction between intuitive and systematic reasoning processes. However, this perspective draws more heavily on evidence that suggests the two reasoning modes can best be understood, respectively, as affect-based versus cognition-based processing (van Gelder 2013), i.e., risk as feelings versus risk as analysis (Slovic et al. 2004). The hot mode of processing is largely affective, intuitive, and nonvolitional. Hot choices are based on emotions, such as fear and anger,

rather than probabilistic inferences. Information processing occurs automatically and thus involves little agency. By contrast, the cool mode of processing involves the agency and cognitive reasoning typically assumed by rational choice theories of crime. It entails thoughtful reflection and logic, is under conscious control, is responsive to probabilistic information, and is well-suited for weighing the costs and benefits of behaviors. Theoretically, the hot and cool modes of processing may help to account for the influence of both situational factors and traits on offender decision-making (van Gelder & de Vries 2012, 2014).

In a series of innovative studies, van Gelder and colleagues found support for each of the core tenets of the hot/cool perspective of criminal decision-making (van Gelder & de Vries 2012, 2014; van Gelder et al. 2009). First, this research has documented that both affect and cognition influence criminal decisions (see also Pickett et al. 2017). Second, these researchers have shown emotional priming activities, such as having participants unscramble words like mood or feeling, activates the hot mode of processing, increasing the responsiveness of offender decision-making to affect. By contrast, activating a cognitive mode increases the importance of risk perceptions for criminal choice. Finally, this work has revealed that certain traits, such as self-control, exert indirect influences on offender decision-making by increasing the experience of negative emotions and/or amplifying risk perceptions when individuals are faced with criminal opportunities.

Extant research on the hot/cool perspective has relied exclusively on hypothetical vignettes to study offending. Therefore, it remains unclear how various situational factors in the real world activate hot versus cool processing. For example, sexual arousal seems likely to activate hot processing for certain offenses and thus increase the importance of affect over cognition, even if it has little influence on risk perceptions (Loewenstein et al. 1997). However, there is insufficient evidence to draw firm conclusions. It is also possible the role of hot versus cool processing varies by crime type. If so, the important risk perceptions for deterrence may also vary by crime type. To illustrate, white-collar offenses may be particularly likely to involve cool processing. This may, in part, explain the meta-analytic finding that the deterrent effects of sanction perceptions are largest in the case of white-collar crimes (Pratt et al. 2006).

Interestingly, studies have not examined whether TRDM influences hot versus cool processing. Plausibly, TRDM may increase cool processing and thus the salience of cognitive judgments about risk. Prior research has generally found TRDM is not associated with the level of perceived risk (Mamayek et al. 2015, Pickett & Bushway 2015). Nonetheless, net of the level of perceived risk, TRDM may influence individuals' sensitivity to a given level of perceived risk and thus their deterrability (see Jacobs 2010).

HEURISTICS, BIASES, AND OFFENDER DECISION-MAKING

Heuristic Decision-Making Generally

One of the foremost insights from behavioral economics has been to highlight that individuals frequently make judgments and decisions intuitively with the aid of cognitive heuristics, in turn making humans prone to systemic biases (Kahneman 2011, Thaler 2015). In rare cases, heuristics can both save effort and improve accuracy, a less-is-more effect (Gigerenzer & Gassmeier 2011). Wübben & Wangenheim (2008) studied how managers distinguish between active and inactive customers for purposes of outreach and marketing. The researchers evaluated how well a full statistical model using the considerable background information at the company's disposal predicted time to next purchase versus a decision heuristic. The decision heuristic was the hiatus heuristic, which simply identified active customers as those who made a purchase within a specified period of months (e.g., six or nine months). Despite ignoring considerable information relative to the full

statistical model, the hiatus heuristic predicted consumer-purchasing behavior more accurately than the full model did.

Many heuristics save effort but diminish accuracy. Yet this might not make the heuristic faulty or undesirable, a less-is–roughly equivalent effect. For residential burglars, environmental cues—for instance, the lighting or conspicuousness of the target—constitute rules of thumb for intuitive cost-benefit perceptions. These types of shortcuts deal with inherently uncertain environments where expertise is difficult to gather (Kahneman 2011). Here, the heuristic provides a short form of the decision under economic theory. It facilitates a snap judgment of risk and reward and a yes-or-no burglary decision. In this context, swiftness and efficiency are likely to minimize the burglar's exposure to detection risk at critical junctures in the process. More details are certainly ascertainable but at what cost in detection risk? Swiftness might also allow the burglar to better manage visceral feelings of fear or nervousness, which may themselves contribute to being detected (Jacobs & Cherbonneau 2017).

Finally, there are well-known decision heuristics with attendant biases. One example is the availability heuristic, in which the psychological salience of an event influences assessments of its probability. The problem is that availability to memory is a highly error prone proxy for statistical likelihood. We discuss below how availability bias may be exploitable for policy interventions to curb crime and transgression. This involves enhancing the salience to memory of adverse consequences (e.g., perp walking a white-collar criminal from his or her office during business hours) to inflate perceptions of the certainty of punishment and enhance deterrence.

Another heuristic with important implications for crime control is the affect heuristic. Behavioral economics provides evidence that suggests the level of a person's affect pool influences his or her perceptions, including those pertaining to the costs and benefits of crime. Positive affect prompts people to place greater emphasis on the net benefits to them from crime. This suggests that circumstances producing temporary variations in affect—e.g., intoxication, drug use, and exposure to violence—can produce commensurately temporary variations in offending propensity.

Heuristic Principles and Offender Judgment Processes

In the past few years, criminologists have begun to assemble evidence for how heuristics affect criminal choice. Pogarsky et al. (2017) recently investigated whether and how several cognitive heuristics influence sanction risk perceptions. Beyond confirming the applicability of heuristic thinking for crime risk perception, Pogarsky et al. (2017) situated the work within the Bayesian updating perspective of rational choice theory to encourage further theoretical advancements. The authors empirically investigated (*a*) how well a subjective numeric probability performs in capturing human judgment and choice and (*b*) whether there are specific cognitive heuristics that potentially bias offender decision-making.

On the first question, they found evidence for intuitive risk perception, specifically that subjective probabilities may overlook relevant features of choice. Consider the behavioral economic heuristic of intensity matching. There is ample evidence from the domain of civil litigation that certain judgments are not well captured with a numeric scale (Sunstein et al. 1998). This is particularly true of judgments with an affective component, such as crime risk perceptions, which commonly occur while individuals feel emotions such as fear (Pickett et al. 2017) or thrill (Katz 1988). The shortcut in this case is that individuals substitute a simpler question (e.g., How do I feel about this?) for the question at hand (e.g., How likely is it that I will be punished if I offend?).

Pogarsky et al. (2017) tested this by manipulating the response scale for a probabilistic question (e.g., How much more likely would you be to get arrested for committing a burglary during the day versus at night?). If individuals truly used numeric probability as it is conceived, they should

provide the same estimate regardless of the response scale. But this does not occur. Instead, the distribution of responses is no different whether the five responses range from no more likely to five times as likely or more versus from no more likely to twenty times as likely or more. Relatedly, individuals who were randomly assigned to receive the lower scale produced an average estimate of 2.17 times as likely, compared to 6.5 times as likely for the higher response scale.

Pogarsky et al. (2017) provided further evidence for intuitive risk perception with their demonstration of a conjunction fallacy. One group of respondents was instructed to estimate the chances of being arrested for stealing a purse out of a parked car at night. A second group of respondents was instructed to make the same estimate but under the assumption that the police tracked an iPhone in the purse with GPS. Logically, the latter scenario must be less probable than the first because it is a more specific instance, requiring the confluence of more events (iPhone and GPS). Nonetheless, the mean estimated chance of arrest for the second group was double that for the first (42% versus 21%). This is attributable to the salience and imaginability the greater detail in the second scenario provides. But as the results demonstrate, it risks error to treat salience as a direct reflection of likelihood. On the second question above, Pogarsky et al. (2017) found evidence for several biases in crime decision-making. For example, asking respondents to evaluate the probability of arrest risk in light of a high or low number greatly impacted their estimates of arrest risk, demonstrating strong effects for anchoring by adjustment. To a lesser extent, providing participants with affect-laden information influenced the perceived costs of offending, consistent with an affect heuristic.

Subsequently, Thomas et al. (2017) reported findings from a series of experiments that further supported the use of anchoring to judge sanction risk. Specifically, they found providing participants with an anchor, informative or uninformative, before eliciting their sanction perceptions significantly influenced their perceptions of arrest risk, as did varying the order in which crimes with different risk levels were presented. They also found evidence of coherent arbitrariness (Ariely et al. 2003). Although arbitrary anchoring shaped the absolute level of perceived risk, there was consistent rank ordering of crime types by arrest risk. This suggested the presence of local coherence within persons, and the possibility an individual's rank ordering of different crimes by perceived risk may determine their relative likelihood of committing those crimes.

Beyond these two experimental studies, which have directly tested the effects of specific heuristics on sanction perceptions, some research also provides indirect evidence about the use of heuristics in offender judgment processes. For instance, Pogarsky & Piquero (2003) found some offenders, particularly those with little offending experience, tended to reduce their perceived arrest risk after experiencing punishment. This would reflect the gambler's fallacy, in which potential crime actors impute interdependencies among chance events. In this view, the offender perceives that since a rare event has occurred, that rare event is unlikely to recur because things even out.

More recently, Loughran et al. (2016b) analyzed longitudinal data from a sample of young felons and found gun-carrying actually reduced perceived arrest risk. Objectively, however, gun carrying should increase a felon's actual risk of arrest. Gun possession, much less carrying, is by itself an arrestable offense for felons, and the presence of a gun during crimes greatly increases the likelihood victims will notify police (Baumer & Lauritsen 2010). Still, possessing a gun during a crime almost assuredly increases the likelihood of victim compliance. Loughran et al.'s (2016b) findings may thus suggest offenders use what could be termed a completion heuristic or power heuristic to judge arrest risk, substituting assessments of the likelihood of successfully carrying out a crime, or feelings of security or power, for the likelihood of being arrested during or after the offense.

In another experimental study, McGloin & Thomas (2016) evaluated the causal effect of the presence of accomplices on perceptions of the risk, costs, and rewards of collective crime. They

found as the number of accomplices increased, participants judged the risk of arrest and the informal costs of participating (e.g., perceived responsibility, family disappointment) to be lower but the rewards (e.g., fun and excitement) from offending to be higher. McGloin & Thomas's (2016) findings may reflect participants' knowledge about the true effects of the presence of accomplices on the objective incentives of crime, especially the fun and excitement of offending. Alternatively, their findings may suggest individuals use what could be characterized as an accomplice heuristic to judge the risks and costs of offending. Specifically, participants may have relied on the number of accomplices to judge intuitively the likelihood of being singled out personally by the police, and the moral wrongfulness of the offense (see Cialdini 2009).

Other studies used alternative methods to assess the effect of heuristics on criminal judgment processes. Pickett & Bushway (2015), for example, identified several personality traits— trait-positive and -negative affect, TRDM, cognitive reflection, ambiguity intolerance, and self-efficacy—that, theoretically, should influence the extent to which individuals rely on intuitive reasoning processes and cognitive heuristics to judge sanction risk. Premised on evidence that the use of heuristics means "[p]eople overestimate the probabilities of unlikely events" (Kahneman 2011, p. 324), Pickett & Bushway (2015) posited that intuitive sanction perceptions would tend to be larger, reflecting greater overestimates of objective risk. Overall, their results were mixed. However, consistent with their hypotheses, trait-positive affect and intolerance of ambiguity were positively associated with perceived risk. These findings would be expected if respondents used intuitive reasoning to judge arrest risk.

Although most research on heuristics and biases in offender decision-making is relatively recent, the available evidence strongly suggests offenders use intuitive reasoning to judge the risk, costs, and rewards of offending. Still, much remains unknown. For instance, it is unclear which specific situational factors most influence sanction perceptions in heuristic judgment processes. Although additional studies are needed to measure sanction perceptions and randomize the presence of situational factors to further test for perceptual effects, a crucial next step is to find evidence of heuristic decision-making occurring organically in criminal contexts.

The literature on situational crime prevention provides many insights on this issue, suggesting factors such as lighting and symbols of surveillance (e.g., cameras) influence offending through deterrence processes (Clarke 1997, Guerette & Bowers 2009). Situational crime prevention has traditionally relied on the assumption that physical changes to an environment can alter the objective (and to some extent, perceived) costs and benefits of criminal activity in that environment. This remains a powerful insight, but behavioral economics suggests an equally powerful pathway to altering offender behavior, environmental changes may directly influence subjective perceptions by way of heuristic decision-making. Teasing out this distinction will require finding natural examples of situational characteristics that do not alter the objective costs and benefits of a crime but present enticing or repelling subjective characteristics to would-be offenders.

Research is also needed to explore how various trait and situational factors, by activating hot versus cool information processing, influence individuals' reliance on heuristics to judge criminal incentives in different contexts. Kamerdze and colleagues (2014) found that extreme trait-positive affect is negatively related to offending, and Pickett & Bushway (2015) also found that positive affect led to high perceptions of sanction risk. Meanwhile, there is a significant amount of psychological research suggesting that positive affect increases intuitive and heuristic decision making (Blanchette & Richards 2010). Thus, individuals who feel positively may be more likely to refrain from crime: (*a*) to avoid jeopardizing their positive mental state, but also because (*b*) state positive affect leads to intuitive hot processing, which can produce heuristic overestimation of the certainty, celerity, and severity of punishment. Future research should examine this possibility as well as the possible interplay with durable personal traits related to situational affect.

CONCLUDING OBSERVATIONS

This section addresses the implications for theory and policy of behavioral economics research on offender decision-making. To start, we recommend revisiting the economic underpinnings of criminology in light of behavioral economic advancements. As Thaler (2015, p. 22) argues, "we don't have to stop inventing abstract models that describe the behavior of imaginary econs. We do, however, have to stop assuming that those models are accurate descriptions of behavior, and stop basing policy decisions on such flawed analysis."

Consider the criminological treatment of risk. Among the hallmark findings of behavioral economics are framing effects that reflect asymmetric risk preference, i.e., risk aversion in gains yet risk seeking in losses. The traditional economic perspective on criminal choice considers risk preference invariant to the actor's perception of whether the choice involves a loss or a gain. And some criminological theories of decision-making do not recognize risk preference as a stand-alone theoretical construct at all. Yet from a policy standpoint, behavioral economic principles suggest that something as straightforward as changing the framing of how an individual perceives the crime decision may increase deterrence. Future research should more regularly appeal to these core behavioral economic findings as standard features of future theoretical models and as regular control variables to strengthen analyses of other dimensions of choice.[5]

Several aspects of criminological theory merit further attention in light of recent behavioral economics research. The first involves the precision and breadth of theoretical constructs representing personal attributes. We discuss this in the context of self-control, but our reasoning applies to composite personal traits generally. The general theory of crime aggregates various personal decision tendencies into an omnibus self-control construct that is theorized to be unidimensional (Gottfredson & Hirschi 1990). However, recent research suggests it may be more fruitful to treat the constituent elements of self-control individually. For example, Mamayek et al. (2015) argued with supporting evidence that although the propensity to act impulsively and the capacity to regulate impulses are treated as elements of self-control under the general theory of crime (Gottfredson & Hirschi 1990), they are distinct and separable constructs, each with unique implications for choice (see also Mamayek et al. 2016, Piquero et al. 2011).

Recently, Burt et al. (2014) investigated the dimensionality of self-control by estimating group-based trajectory models of self-control from ages 10–25 among participants in the Family and Community Health Study, a multiwave panel study of African-American youths in Iowa and Georgia. The authors discussed how research in personality psychology "contradicts Gottfredson and Hirschi's assertions that the elements of self-control come together in the same people to compose a unidimensional personality trait" (Burt et al. 2014, p. 457). Instead, the authors defined two distinct aspects of adolescent development, impulsivity, and sensation seeking, which are often theorized to be elements of self-control. Theoretically, insights from behavioral economics on risk preferences may help to further illuminate the processes underlying changes over time in sensation seeking and impulsivity. Consistent with Mamayek et al. (2015; see also Vazsonyi & Ksinan 2017), Burt et al. (2014) found that these attributes constituted distinct explanatory factors, each with unique growth trajectories and unique implications for adolescent development and offending.

The assumption of unidimensionality has further conceptual implications. It implies, for example, that attitudes toward risk, with emphases on immediacy, cognitive deficits, and self-absorption, are not sufficiently distinguishable from one another to merit independent treatment. The implication from the general theory is that more can be learned from the omnibus approach than from

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[5]Ironically, behavioral economics recognizes a status quo bias representing an inordinate preference for the current state of affairs (Samuelson & Zeckhauser 1988).

treating constituent elements individually. But behavioral economics offers an advanced conception of risk preference, complete with framing effects and asymmetries depending on context (gains versus losses). Moreover, although beyond the scope of this review, behavior economics insights on time preference suggest that aggregating distinct decision attributes into omnibus traits may be counterproductive for theoretical advancement. One of the many manifestations of low self-control is said to be a "concrete here and now orientation" (Gottfredson & Hirschi 1990, p. 26). But as with risk preference, behavioral economics offers rich and well-developed conceptions of how various aspects of the timing of consequences affect crime decisions. There is the exponential time discounting model of Nagin & Pogarsky (2001) and its recent extension to hyperbolic discounting (Loughran et al. 2012). Frederick et al. (2002) even question the meaningfulness of a single numeric discount rate to capture time preference at all. Instead, they argue that distinct psychological attributes (e.g., consumption norms, the disutility of delay, the capacity to regulate impulses) combine to determine how timing and delay affect decision-making. Thus, as behavioral economics elaborates these constituent details of choice, it further erodes the conceptual basis for treating these features as subcomponents of an aggregate trait.

A second theoretical front pertains to the distinctions between cognition and emotion and between generalized assessments (e.g., Agnew & Messner 2015) and situation-specific perceptions. Pickett et al. (2017) recently developed a model that more explicitly emphasizes the contextual aspects of offender decision-making. The authors' framework extends deterrence theory in several ways. The first is to explicitly distinguish emotional fear from cognitive perceptions of risk. Traditional economic perspectives on crime focus exclusively on cognitions in decision-making (Becker 1968). By contrast, behavioral economics research shows that emotions exert a strong influence on choice and mediate the effect of cognitions (Loewenstein et al. 2001). Although fear was prominent in formative discourse on deterrence [e.g., Hobbes 1957 (1651)], attention to the emotional aspects of offending decisions has mostly been displaced by economic models that do not recognize emotions as theoretical constructs. But Pickett et al. (2017) argue, with supporting empirical evidence, that the emotional fear a would-be offender feels over what might happen to him or her if caught is quite distinguishable from cognitive assessments of the likelihood of various consequences if caught. Dual-process theorizing further underscores the fear/risk distinction. Fear seems more likely the province of System 1's fast and intuitive processes, whereas assessments of cognitive risk reflect the more contemplative System 2's domain.

Moreover, Pickett et al. (2017) explicitly model each of these constructs (risk and fear) at both the generalized and situational level. We consider this distinction critical for future research to more explicitly identify situational, contextual, and heuristic influences on offending decisions. Current offender decision-making work tends to focus on either generalized or situation-specific perceptions but not both.[6] The theoretical model of Pickett et al. (2017) not only explicitly recognizes both general and situational versions of risk and fear but also facilitates testing for the independent and interrelated influences that perceptions of risk and fear exert on offending.

Behavioral economic findings also have implications for crime-control policy. A heuristic can either assist or impede purposeful action. For example, residential burglars employ cues about the lighting and location of a target home as successful shortcuts in furtherance of crime. In turn, knowledge of these environmental cues can help potential victims protect against victimization (e.g., lights on means someone is home). In contrast, heuristics like anchoring, for example, can

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[6]An example of the former is perceptual updating work that estimates the effects of punishment and offending experiences on perceptions of sanction risk at various points in time (i.e., the waves of a longitudinal study, as in Anwar & Loughran 2011). Alternatively, the vast body of perceptual deterrence work following the hypothetical vignette approach focuses on sanction risk perception grounded in a specified context (e.g., Nagin & Pogarsky 2001).

hinder purposeful action when they bias judgments and perceptions. But in this case, the bias is potentially exploitable for crime-control purposes. This is particularly true when recalling Geerken & Gove's (1975) original conception of deterrence as message communication (see also Pickett et al. 2016).

Jolls et al. (1998) addressed the possible exploitation of decision biases to discourage transgression. They (Jolls et al. 1998, p. 1,538) suggested that rather than use beige-colored parking tickets as many municipalities do, it might be beneficial to use "brightly colored tickets that read 'VIOLATION' in large letters on the drivers' side window, where they are particularly noticeable to drivers and passersby." Earlier we explained how salience and imaginability can unduly influence perceptions of likelihood. The strategy of Jolls et al. (1998), therefore, is to heighten public awareness of parking tickets to elevate perceptions about the likelihood of being ticketed via the availability heuristic.

Rather than exploit heuristics for crime-control benefits, policies may also debias people in the hopes of reducing transgression. This involves helping would-be offenders focus more on deliberative (System 2) decision-making to help them appreciate the full weight of the consequences of crime. Much automatic behavior is helpful (e.g., flinching), but some may be maladaptive. Heller et al. (2017) recently conducted an evaluation of several randomized controlled trials of programs in Chicago to reduce the automaticity of decision-making for socioeconomically disadvantaged youth. They found the Becoming a Man (BAM) program, which uses cognitive behavioral therapy to counsel youth to slow down and resist automatic impulses when making decisions, caused reductions in both crime and school dropout.

Our suggestions here to better integrate key behavioral economic principles into criminological theory follow from the interdisciplinary nature of our field. Many disciplinary perspectives have enriched criminological thought; among these are sociology, psychology, law, economics, political science, geography, and, more recently, behavioral economics. This review has shown how further progress on crime as choice is possible at the confluence of three fields of study: criminology, economics, and behavioral economics. But the utility of insights from fields like behavioral economics may ultimately depend on how carefully those lessons are situated within the existing theoretical landscape of criminology.

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