HEURISTICS AND BIASES, RATIONAL CHOICE, AND SANCTION PERCEPTIONS*

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The relevance of several cognitive heuristics and related biases for rational choice perspectives on crime, and for perceptions of sanction risk, were investigated. We present findings from a series of randomized experiments, embedded in two nationwide surveys of American adults (18 and older) in 2015 (N = 1,004 and 623). The results reveal that offender estimates of detection risk are less probabilistically precise and more situationally variable than under prevailing criminological perspectives, most notably, rational choice and Bayesian learning theories. This, in turn, allows various decision-making heuristics—such as anchoring and availability—to influence and potentially bias the perceptual updating process.

"One point should be set immediately outside dispute. Everyone agrees that people have reasons for what they do. They have motivations, and they use reason (well or badly) to respond to these motivations, and reach their goals. Even much, or most, of the behavior that is called abnormal involves the exercise of thought and reason."—Simon, 1986.

Agency and choice often play an integral role in criminal transgression. Residential burglars routinely consider the lighting and conspicuousness of potential targets to reduce the likelihood of detection (Cromwell, Olson, and Avary, 1991; Wright and Decker, 1994). Armed robbers often victimize other offenders to reduce the likelihood that the victimization gets reported to authorities (Wright and Decker, 1997). Street-level drug dealers sometimes store inventory in their mouths (in balloons), so they can readily swallow the evidence if they encounter law enforcement (Jacobs, 1999). The results of longitudinal studies of panel data have revealed that offending is negatively related to the perceived certainty of punishment (Lochner, 2007; Loughran, Paternoster, et al., 2016), and perceptions of sanction certainty are responsive to whether an actor has been punished

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for past offending experiences (Anwar and Loughran, 2011; Horney and Marshall, 1992; Matsueda, Kreager, and Huizinga, 2006). Moreover, the results of randomized experiments have shown that rule breaking is reducible by clearly communicating an elevated risk of punishment to potential offenders (Nagin and Pogarsky, 2003; Weisburd, Einat, and Kowalski, 2008).

Among criminological perspectives, rational choice most directly addresses agency and decision-making (McCarthy, 2002). Other theoretical perspectives, such as strain, learning, and life course, also address how perceptions of reality guide volitional conduct (Agnew and Messner, 2015). Yet, perhaps because basic versions of the perspective are so tractable, rational choice theory typically frames research on offender decision-making. This persists despite fundamental critiques of the perspective, which include 1) assailable assumptions, particularly about crime actors; 2) little explained variance in key outcomes; 3) a focus on mostly instrumental rather than expressive offending; and 4) the frequent exclusion of known predictors of crime (Paternoster, 2010; Pickett and Roche, 2016; Pratt, 2008; Tonry, 2008). Such critiques are often well founded.

Thus, rational choice applications in criminology seem incomplete, and sometimes inaccurate, regarding crime actors and offending decisions. We argue that principles of heuristic decision-making, drawn from behavioral economics and psychology, can improve the descriptive accuracy of rational choice accounts of crime decisions (Pickett and Roche, 2016).[1] We examine this possibility with respect to one of the primary inputs into crime decisions—the actor's perception of arrest risk.

Existing research on crime risk perceptions from the standpoint of Bayesian learning theory has produced valuable insights (Anwar and Loughran, 2011; Kreager and Matsueda, 2014; Pickett, Loughran, and Bushway, 2016; Wilson, Paternoster, and Loughran, 2016), but it has only managed to account for a small portion of variation in sanction risk perceptions. Moreover, the results of several studies have shown no correlation between sanction perceptions and broader measures of objective punishment risk (Kleck and Barnes, 2013, 2014; Kleck et al., 2005; Lochner, 2007). And researchers examining young felons have reported that some factors that should *increase* objective arrest risk, such as carrying a gun, may reduce perceived arrest risk (Loughran, Reid, et al., 2016).[2] Paternoster (2010: 808) characterized how much remains unknown about sanction perception formation and updating as a "dirty little secret in deterrence research." Furthermore, variability exists among rational choice perspectives within criminology. For example, the situational crime prevention perspective, which is also grounded in rational choice principles (Clarke and Cornish, 1985), connects offending decisions primarily to the characteristics of specific *opportunities* and *situations*.

Within this context, we seek to advance understanding of crime decision-making. Our objective is to expand the theoretical and empirical scope of research on crime decisions and perceptions of risk. We begin by identifying elements of rational choice discourse that are compatible with heuristic choice. Ensuing empirical results show that several cognitive heuristics from the behavioral economics and psychology literatures influence how individuals form, modify, and use sanction perceptions in crime decisions.

1. For instance, priming effects have already been studied for the extent to which they impact crime survey methodologies (see Bouffard, Exum, and Collins, 2010).
2. Not only are felony offenders susceptible to arrest simply for possessing a gun, but also the presence of a gun during crimes greatly increases the likelihood of victims notifying police (Baumer and Lauritsen, 2010).

RATIONAL CHOICE AND OFFENDING DECISIONS

Under the rational choice perspective, individuals wish to experience pleasure and avoid pain (Bentham, 1789). In so doing, they integrate information into perceptions about key dimensions of the different consequences from offending, and they weigh these perceptions in some decision-making process. Individuals pursue crime opportunities they expect will provide a net benefit (Becker, 1968; Cornish and Clarke, 2003; McCarthy, 2002).

Crime decisions can be multidimensional. The benefits to the offender from crime can be both pecuniary (i.e., cash or other loot) and nonpecuniary (e.g., status or thrill). Calculating the benefits *net* of *opportunity costs* from foregone legal alternatives lends further nuance. The potential costs from offending are divisible into legal (e.g., criminal justice system custody, financial costs of defense, and possible conviction) and extralegal (e.g., stigma from others and labeling impacts) consequences from crime. In theory, individuals maintain and update perceptions about the *certainty*, *severity*, and *celerity* of each potential consequence and integrate these considerations into decisions about whether to pursue specific offending opportunities (e.g., Klepper and Nagin, 1989; Paternoster and Simpson, 1996). Even core features of what some criminologists recognize as self-control are readily captured by the interrelated, economic concepts of risk and time preference.[3]

Nevertheless, rational choice theory has undergone considerable scrutiny by researchers, particularly with respect to its characterization of the decision-maker. In neoclassical economics, actors use unbounded information, patience, and computational abilities to maximize their personal welfare or *utility* (Thaler, 2015; Thaler and Sunstein, 2008). On this point, criminological rational choice frameworks vary. Bayesian learning theory, which is part of the expected utility paradigm (Becker, 1968), gains theoretical and mathematical precision from its depiction of a central actor that rigidly adheres to a set of mathematical axioms representing the fundamentals of human behavior (Hauser, 1978). Other rational choice approaches are less rigid about the nature of crime actors. For example, the aim of Clarke and Cornish's situational crime prevention model (2001: 25) is to endorse a broad formulation of rational choice (see Clarke and Cornish, 1985; Opp, 1997) that posits self-interested choice but with a central actor who has ordinary human flaws, limitations, and idiosyncrasies, reflecting an imperfect (or bounded) rationality.

Thus, theoretical heterogeneity exists *within* criminological rational choice discourse. Situational crime prevention takes the criminal opportunity as its unit of analysis. The perspective focuses on crime reduction outcomes, but it assumes they are mediated by situation-specific changes in sanction perceptions. Importantly, it is compatible with notions of bounded rationality and cognitive heuristics, but it is nonspecific about the situational or "heuristic updating" of perceived risk. That is, Cornish and Clarke (2001) do not elaborate *how*, *why*, or *which* heuristics might affect sanction perceptions. Meanwhile, Bayesian learning theory takes the criminal actor as the unit of analysis. The approach

3. In rational choice models that descend most directly from Becker (1968) and are therefore grounded in expected utility theory (von Neumann and Morgenstern, 1944), the curvature of the utility function reflects *preference for risk* (Lattimore and Witte, 1986). Moreover, such models include a parameter for time preference, to capture among other things, the moderating role of attitudes toward delay (e.g., present orientation) on the evaluation of consequences for contemporaneous decision-making (Loughran, Paternoster, and Weiss, 2012; Nagin and Pogarsky, 2001).

focuses on changes in sanction perceptions over time, from the standpoint of a strictly and formally rational actor.[4] The Bayesian updating model does not account for situational changes in sanction risk perceptions that may also be salient to the offending decision. Thus, to connect these variants of rational choice thought, we analyze how cognitive heuristics affect the Bayesian updating of sanction risk perceptions.

SANCTION RISK PERCEPTIONS AS THE OUTCOME VARIABLE

Under the rational choice perspective, an actor's perceptions of the certainty, celerity, and severity of punishment for a given criminal opportunity should drive the decision of whether to engage in that crime. The lower the perceived certainty, celerity, or severity, the more likely the crime will be committed. Indeed, a preeminent finding in criminology is that, of these three risk perceptions, the deterrent capacity of perceived sanction *certainty* is paramount (Matseuda, Kreager, and Huizinga, 2006; Nagin, 2013; Paternoster and Simpson, 1996).

Research conducted on the formation and modification of sanction certainty perceptions follows one of several paths. One tests the relationship between sanctioning in a place, typically reflected by the arrest clearance rate in a county, and residents' perceptions of sanctioning in that place, typically captured by the perceived certainty of punishment. The results of these studies find no evidence that sanction risk perceptions are responsive to variation in arrest clearance rates (Kleck and Barnes, 2013, 2014; Kleck et al., 2005; Lochner, 2007). Another avenue suggests that data on judgments of risk and offending decisions should be most meaningful if set within the situational context in which offending opportunities realistically unfold. Thus, hypothetical vignettes are used by researchers to provide survey respondents with reasonably familiar settings—for example, drinking and driving or marijuana use for college student respondents (e.g., Nagin and Paternoster, 1993).

Lastly, research has been conducted to examine the impact (or lack thereof) of an individual's personal or vicarious experiences of past offending on the perceived certainty of punishment. The results of these studies reveal that sanction risk perceptions *are* responsive to whether an actor has been punished for past offending experiences (Anwar and Loughran, 2011; Horney and Marshall, 1992; Matsueda, Kreager, and Huizinga, 2006; Pogarsky and Piquero, 2003). Nonetheless, there is also evidence of counterintuitive effects (Loughran, Reid, et al., 2016), such as resetting after punishment (e.g., the "gambler's fallacy"; see Pogarsky and Piquero, 2003). Moreover, the findings from all such studies only explain a small portion of the variation in sanction risk perceptions.

BAYESIAN LEARNING THEORY AND PERCEPTUAL CHANGE

The rational choice framework of Bayesian updating has provided a useful structure and direction for investigations of crime risk perceptions.[5] Actors maintain a running *prior* estimate of arrest risk based on all information available to the actor up to that

4. See McCarthy (2002) for a mathematical presentation of "strict rationality" as it relates to crime decisions.
5. For mathematical models of the Bayesian updating of crime risk perceptions, see Anwar and Loughran (2011) and Kreager and Matsueda (2014).

point in time. Periodically thereafter, actors may revise their *priors* based on new pieces of information, referred to as *signals.* In revising a *prior*, the actor integrates a *signal* into the prevailing stock of information, decides how much to *weight* the *signal* relative to the existing information, and produces a new, *posterior* risk estimate.

Signals

Research thus far has been focused on past offending experience, especially whether the actor was punished for past crimes (Anwar and Loughran, 2011; Lochner, 2007; Matsueda, Kreager, and Huizinga, 2006). In existing studies, *signals* are necessary but not sufficient conditions for perceptual updating. Instead, updating is cyclical. Persons collect information (*signals*) between designated instances of updating and the process repeats. Thus, updating is *period based.* Potential between-period *signals* are assumed to be available for influence when updating next occurs.

An alternative conception of updating, which is more amenable to other variants of criminological rational choice theory such as situational crime prevention, is *event based.* In this alternative perspective, actors revise *priors*, perhaps only temporarily, based on situational *signals* in the context of an offending opportunity. Unfortunately, the scope of existing empirical and theoretical approaches has not included signal-to-signal perceptual updating.

Moreover, it is unclear what constitutes a *signal* for updating purposes. Beyond the actor's personal arrest ratio during the reference period, Anwar and Loughran (2011: 675) suggested *signals* include "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." Nonetheless, they do not identify the situational characteristics related to a given criminal opportunity. However, as Nagin, Solow, and Lum (2015: 81) explain, situational factors matter a great deal, stating that any "discussion of the probability of apprehension without reference to the characteristics of the criminal opportunity is ill posed." The suggestion that knowledge about the arrest ratio of others during the updating period affects perceptions reflects the dual concepts of vicarious punishment and vicarious punishment avoidance (Piquero and Pogarsky, 2002; Stafford and Warr, 1993). Both the actor's and others' arrest ratios are mathematical probabilities that are readily integrated into the *prior.*

Yet, nonprobabilistic *signals* come in a variety of forms. For example, Apel (2013) and Pogarsky (2009) identified the need to address how attributes of places in which actors develop perceptions and make decisions influence perceptual updating. Such aspects might involve, for example, indicia of disorganization and/or social cohesion, which could well bear on detection risk. Environmental modifications consistent with situational crime prevention also constitute likely candidates for nonprobabilistic *signals* (Clarke, 1997; Guerette and Bowers, 2009). For instance, the presence of closed-circuit television (CCTV) cameras or multiple cashiers can *signal* to an actor to update his or her perceived arrest risk.

Weighting

In integrating the new information, the actor must decide how much *weight* to afford the *signal* relative to the *prior.* Logically, the *weight* given the *signal* should depend, among other things, on how extensive the information is underlying the *prior* (Anwar and

Loughran, 2011). A person who has a healthy stock of past offending experience should consider new pieces of information less influential than should a person whose stock of past information is sparse. Or, alternatively, such an offender may be better able to judge the value of new information. Likewise, a personal punishment experience will likely be weighted more heavily than a friend's vicarious punishment experience. Finally, the output from each instance of Bayesian updating is a *posterior* certainty estimate, which is a weighted average of the *signal* and *prior*.[6]

OPEN QUESTIONS REGARDING BAYESIAN UPDATING IN CRIMINOLOGY

The Bayesian updating approach merits further scrutiny on several grounds. First, partly because of its assumption of *period-based* updating, the Bayesian model generally conceptualizes change in sanction risk perceptions as meaningful and durable. The *posterior* of updating instance 1 seamlessly becomes the *prior* of updating instance 2, which after it is updated to *posterior* 2, then becomes *prior* 3, ad infinitum. Risk estimates are assumed to neither change nor degrade between instances of updating. Relatedly, the Bayesian model conceptualizes the *prior* as a point estimate, rather than as a bounded distribution of possible values (e.g., a "ballpark" idea). The results of research on ambiguity in survey responses casts doubt on the notion that *priors* are always, or even often, precise point estimates (Loughran et al., 2011; Pickett, Loughran, and Bushway, 2015).

Second, research effort has not yet been directed toward a broader range of theoretically relevant candidate *signals*, particularly situational ones. Rational choice discourse offers little guidance on this point, and partly as a consequence of this, current data and empirical approaches include a limited set of empirically testable sources for sanction risk perceptions. Thus, perceptual updating research has been restricted to a narrow interpretation of the *signal*, defining it solely as a new arrest (or lack thereof), and presuming there is just one *signal* (a composite one) for each instance of updating.

We distinguish two primary types of sanction perception updating: person specific (or period based) and situation specific (or event based). The Bayesian updating model addresses person-specific updating. This process is independent of any specific criminal opportunity, and it involves durable change in someone's general perception of personal arrest risk for broad categories of crime (e.g., violent vs. nonviolent or solitary vs. group crimes; Anwar and Loughran, 2011; Loughran et al., 2011). The existence of person-specific updating is reflected not only by evidence of the effects of offending and arrest experiences but also by the sizable correlation between survey respondents' prior and current sanction perceptions (Lochner, 2007; Matsueda, Kreager, and Huizinga, 2006; Thomas, Loughran, and Piquero, 2013). By contrast, situation-specific updating occurs in reference to a given criminal opportunity. It involves generating a situation-specific risk perception by adjusting one's person-specific perception to account for the particular context and specific offense, the characteristics

6. Here, two polar extremes are instructive. Someone who is intractably stubborn might not weight the signal at all. For this person, the signal is irrelevant and the posterior certainty estimate precisely equals the prior. Alternatively, an amnesiac would not remember the past stock of information. In this case, the prior is irrelevant, and there is complete weight on the signal such that the signal becomes the new posterior certainty estimate.

of which are *signals*. It is here that we expect cognitive heuristics to be particularly influential.

HEURISTICS AND THE PERCEPTION OF SANCTION RISK

Skepticism about the rational actor assumption dates back to the inception of rational choice models in social science (e.g. Allais, 1953; Ellsberg, 1961; Tversky and Kahneman, 1974; Yamagishi et al., 2014). Most people do not routinely possess the capacity or inclination to approach nuanced and multifaceted decisions (criminal or otherwise) in accord with formal rationality. That said, unsystematic deviations from core assumptions should compromise at most the precision but not the accuracy of empirical estimation. On average and over time, such deviations tend to cancel one another out. They are random sources of error or imprecision that become subsumed by error terms in multivariate empirical models. Yet decades of published results from psychological research have shown that individuals reliably deviate from strict rational choice formulations in *predictable* ways (Kahneman, 2011).

As part of this "bounded rationality," individuals use experience-based shortcuts—heuristics—to assist decision-making. As Simon (1990: 6, emphasis added) explained:

> If the game of chess, limited to its 64 squares and six kind of pieces, is beyond exact [human] computation, then we may expect the same of almost any real-world problem, including almost any problem of everyday life. From this simple fact, we derive one of the most important laws of qualitative structure. ... Because of the limits on their computing speeds and power, intelligent systems must use *approximate methods* to handle most tasks.

Consider the choice of whether to commit or refrain from a specific crime opportunity. Such decisions often occur when actors are intoxicated and/or viscerally aroused (Loewenstein, Nagin, and Paternoster, 1997; Pridemore, 2002), with incomplete information, and under conditions of chaos and/or time-sensitivity. Moreover, there is wide heterogeneity in the capacity and inclination for abstract and otherwise effortful thinking (Pickett and Bushway, 2015; Thomas, Loughran, and Piquero, 2013). For example, individuals with low *cognitive reflection* are less likely to persevere past an impulsive but incorrect conclusion to obtain the correct one with added cognitive effort (Frederick, 2005). And individuals with low *thoughtfully reflective decision-making* are less able to collect information, contemplate alternatives, deliberate, and retrospect when problem solving (Loughran et al., 2011; Paternoster and Pogarsky, 2009). Thus, crime decisions seem particularly amenable to approximation in estimating sanction risk and making offending decisions.

HEURISTIC DECISION-MAKING

According to Gigerenzer and Gaissmaier (2011: 454): "A heuristic is a strategy that ignores part of the information, with the goal of making decisions more quickly, frugally, and/or accurately than more complex methods." Heuristics can be beneficial for the decision-maker. Psychologists have identified decision rules that produce "less-is-more" effects (Lee, 2010; Smithson, 2010). That is, heuristics that save effort and promote efficiency can also *improve* predictive accuracy (Brighton and Gigerenzer, 2012). Heuristics may also decrease accuracy but yield reductions in time and effort that justify their use. Nevertheless, heuristics can also bias the decision-making process. In this case, any reductions in time and effort provide negligible benefits and may instead lead decision-makers astray. This is the thrust of the heuristics and biases program of behavioral economics and social psychology. We argue that the use of heuristics is often what connects situational characteristics to sanction perceptions within the context of a given criminal opportunity; this is true even though potential offenders enter the situation with different baseline levels of perceived arrest risk.

SPECIFIC HEURISTICS AND PERCEPTUAL UPDATING

Question Substitution and Intensity Matching

If indeed there is situation-specific, decision-making activity that current rational choice perspectives fail to capture, the operation of several additional heuristics could confirm this is the case. Apel and Nagin (2011: 424) posited that, "Rather than forming crime-specific estimates of the certainty, severity, and celerity of punishment, the average individual (but not necessarily the average offender) might instead rely on an omnibus assessment or some generalized conception of punishment risk." These generalized conceptions may be non-numerical assessments of likelihood (e.g., gut feelings). If so, in surveys, persons may simply map those feelings onto whatever scale is provided, such that their answers "look the part"—numeric, probabilistic—even though there is no genuine correspondence between their mental representations and the objective units of measurement that the scale represents (Slovic, 2010). This heuristic process is called *question substitution* and *intensity matching* (Kahneman, 2011).

The Bayesian updating model assumes that the *prior* and *posterior* are stable, well-formed, numeric estimates—for example, "there is a 28 percent chance I will be arrested if I commit this crime." If some people in certain circumstances judge sanction risk heuristically, then the Bayesian conceptualization of both the *prior* and the *posterior* as well-formed numeric information is unnecessarily rigid. Rather, within the context of criminal opportunities, people may have, at least temporarily, diffuse feelings of likelihood, which are non-numeric, general, and fleeting.[7] Although there should be between-person variability in these gut feelings, these feelings may receive unwarranted numerical credence from survey researchers.

The Conjunction Fallacy

Next, consider the *conjunction fallacy*, which occurs when a person uncritically substitutes "plausibility for probability" (Kahneman, 2011: 159). Rather than having stable and precise numerical knowledge, people often derive an intuitive sense of the likelihood of events from the coherence of descriptive details. Objectively, the more detailed a hypothetical future is, the less probable it becomes because its occurrence requires the confluence of more circumstances. Nevertheless, this is not always what occurs perceptually.

7. Kahneman (2011: 150) explained that for laypeople, "probability ... is a vague notion, related to uncertainty, propensity, plausibility, and surprise"; they "do not try to judge probability as statisticians and philosophers use the word."

When more details enhance the vividness and seeming realism of a scenario, it can prompt the actor to overestimate the likelihood of the compound occurrence.[8] The implication is that situational characteristics or information that influence the detail of potential offenders' imagined offending scenarios may impact their sanction perceptions.

The nuclear detonation scenario is a good example. One group must estimate the probability that a nuclear weapon will be detonated in a war or an act of terrorism during the next 5 years, whereas another group must estimate the probability that a specific nation (Iran) will provide nuclear weapons to a terrorist group, who will use them against specific countries (Israel or the United States) in the next 5 years. Formal logic dictates that the probability of the second scenario *must* be smaller than that of the first because the second scenario is just one instance of the first scenario's broader set of possibilities. Nevertheless, the vividness of the second scenario prompts people to consider it *more* likely on average (Pinker, 2011: 369).

The Availability Heuristic

To generate probability judgments about future events, such as judgments about arrest risk, a person may rely on the *availability* heuristic (Tversky and Kahneman, 1973). Here, people estimate an event's probability based on whether they can either 1) quickly recall relevant examples or 2) easily imagine a scenario where the event would occur (Breakwell, 2014; Kahneman, 2011). They then substitute the heuristic answer (i.e., ease of recall or imaginability) in place of an answer to the more difficult question about event probability. A person, thus, can conflate great speed and fluency in recalling a result with the greater probability of an event (e.g., arrest) occurring (MacLeod and Campbell, 1992; Tversky and Kahneman, 1973). For example, a person may temporarily rate the risk of car accidents to be higher after witnessing a particularly bad wreck on the side of the road (Tversky and Kahneman, 1973: 178). In the context of crime decisions, any situational feature or information that makes it easier to recall or imagine getting away versus getting caught should influence perceived arrest risk (Pickett and Bushway, 2015).

The Affect Heuristic

The *affect* heuristic is a mental shortcut in which an actor's "affect pool" influences assessments of the costs, benefits, and risks of certain conduct (Slovic et al., 2004, 2007). Here, if a person's "feelings toward an activity are favorable, they are moved toward judging the risks as low and the benefits as high," which leads perceived risk and benefit to be "negatively correlated in people's minds (and judgments)," even though they are often positively correlated in reality (Slovic et al., 2004: 315). Put differently, people are often resistant to the concept of true high-risk, high-reward scenarios, and they will rely on their emotions to make a simpler judgment: for instance, giving people information about the benefits of nuclear power plants trends to reduce the perception of nuclear power's risks (Finucane et al., 2000). Therefore, for crime decisions, situational characteristics or information that alters potential offenders' feelings toward a criminal activity may influence their assessments of its costs and benefits.

8. Kahneman (2000: 708) has also called this phenomenon a type of *extension neglect*—an inability to focus on the size of a set during an evaluation where set size is logically relevant.

Anchoring

Lastly, *anchoring* suggests that initial exposure to a numerical value can influence people to use that value as a reference point in turn influencing subsequent value judgments. This heuristic is well illustrated by an experiment in which subjects were instructed to estimate the percentage of African countries in the United Nations (Tversky and Kahneman, 1974). Before subjects answered this question, the authors spun a wheel numbered 1 to 100, which was rigged to land on 10 for half the subjects and 65 for the other half. After the spin, the experimenters asked subjects whether their estimate was higher or lower than the result of the spin. Then they asked subjects to estimate the percentage of African nations. Subjects for whom the wheel landed on 10 gave an average estimate of 25 percent, whereas subjects for whom the wheel landed on 65 gave an average estimate of 45 percent (Tversky and Kahneman, 1974). Under comparable logic, any situational *signal* that leads potential offenders to consider first a specific level of arrest risk before offending should affect both their sanction perceptions and their likelihood of committing the crime.

Theoretical Summary

Clearly, if any of these cognitive heuristics, or other heuristics, influence sanction risk perceptions, then the current Bayesian updating model should be broadened. Furthermore, it would illuminate how those situational characteristics identified as important by the results of situational crime prevention literature may affect sanctions perceptions. Specifically, any situational characteristic that leads to anchoring or that impacts the affect pool (affect) or recall of relevant memories (availability) would constitute a signal. By contrast, the current Bayesian updating model only considers an arrest, or lack thereof, after a crime to be a signal. Even though it may be a potent and durable signal, an arrest (whether personal or vicarious) is invariably just one in a slew of possible signals preceding the decision to offend. Although heuristics may only temporarily influence the would-be offender's sanction risk perceptions, they may nonetheless influence behavior. The remainder of this article investigates whether and how these specific heuristics influence the perceptual updating process.

DATA

The data for our study derive from a series of randomized experiments embedded in two surveys that were administered in 2015 to separate nationwide samples of adult (18 and older) residents of the United States. Both surveys were conducted by "workers" from a leading online crowdsourcing website—Amazon's Mechanical Turk (MTurk; Amazon, Inc., Seattle, WA). These workers voluntarily joined MTurk to participate in various human intelligence tasks (HITs; e.g., editing a book, writing product descriptions, or rating websites) for money. There are currently several hundred thousand MTurk workers.

MTurk samples are widely used in studies across academic disciplines (e.g., Dowling and Wichowsky, 2014; Ratner et al., 2014; Stern et al., 2014). Collective findings from a large amount of literature have demonstrated the suitability of MTurk surveys for academic research (Buhrmester, Kwang, and Gosling, 2011; Mason and Suri, 2012; Paolacci and Chandler, 2014; Shapiro, Chandler, and Mueller, 2013; Simons and Chabris, 2012). Most importantly, there is now evidence that experimental findings obtained with MTurk and probability samples have "considerable similarity" (Mullinix et al., 2015). Weinberg, Freese, and McElhattan (2014), for example, showed that similar experimental results were obtained by a sample of MTurk workers versus a national probability sample. Furthermore, they found that MTurk workers provided higher quality responses than did the probability sample, being less likely to fail comprehension checks, speed through the questionnaire at an unrealistic pace, have item-nonresponse, or engage in stylistic responding (i.e., response nondifferentiation).

In administering the surveys, we followed the current best practices for research with MTurk samples. First, we limited participation to workers with an approval rating on prior HITs of at least 95 percent. Peer, Vosgerau, and Acquisti (2013) found that this approach improves response quality. Second, to minimize as much as possible issues with non-naiveté (see Chandler, Mueller, and Paolacci, 2014), we allowed respondents with a brief MTurk history to participate. Specifically, we set the experience threshold at only 50 prior HITs, which is the lowest possible threshold other than having none at all.

As with all MTurk surveys, the links to the surveys were posted as HITs on the MTurk website, and workers were offered a small payment to participate. We chose the payment amount based on the estimated completion time for each survey and payment norms in prior research. Scholars using MTurk often pay participants between $0.15 and $0.75 to participate, depending on survey length (Berinsky, Huber, and Lenz, 2012; Mullinix et al., 2015). Weinberg, Freese, and McElhattan (2014: 298) paid respondents $3.00 for a survey taking 1 hour. We aimed for a similar hourly pay rate. We estimated that survey A would take approximately 10 minutes to complete; on average, it took 11 minutes and 47 seconds to complete. We estimated that survey B would take around 5 minutes to complete; on average, it took 5 minutes and 23 seconds to complete. For survey A, we offered workers $0.75 to participate. For survey B, we offered $0.30. Consistent with Weinberg, Freese, and McElhattan (2014), the effectively hourly pay rate for the two surveys was approximately $4 and $3, respectively.

The surveys were advertised as the "2015 National Survey on Criminal Justice Risk" (survey A) and "2015 National Survey on Criminal Risk" (survey B). Survey A was fielded first, and followed 6 days later by survey B. Participants to survey A were blocked from participating in survey B. Overall, 1,015 respondents began survey A, and 629 began survey B. Of these persons, 1,004 (99 percent) finished survey A and 623 (99 percent) finished survey B. Thus, there were essentially no breakoffs in either survey. Nonetheless, because of item nonresponse, the sample sizes vary slightly across the experiments.

Table 1 presents the descriptive statistics and prior personal and vicarious arrest histories for all respondents in both surveys with complete data on the respective questions. The results of prior research consistently have revealed that MTurk workers tend to be Whiter, younger, better educated, with lower incomes than the general public (Levay, Freese, and Druckman, 2016; Shank, 2016; Weinberg, Freese, and McElhattan, 2014). This is precisely what is observed in both of our surveys. The findings from some studies have shown that females make up a slight majority of MTurk workers (Berinsky, Huber, and Lenz, 2012), but others have shown the opposite (Levay, Freese, and

Table 1. Descriptive Statistics for Both Samples

	Survey A		Survey B		
Variables	**Mean or %**	**SD**	**Mean or %**	**SD**	**Range**
Male	50.85	—	49.60	—	0–1
White	81.44	—	75.85	—	0–1
Age	36.01	11.35	33.25	10.43	18–76
Education	3.08	1.26	3.13	1.27	1–5
High school or less	12.79	—	9.82	—	0–1
Some college	25.57	—	30.27	—	0–1
Associate's degree	13.39	—	11.92	—	0–1
Bachelor's degree	36.96	—	33.17	—	0–1
Graduate degree	11.29	—	14.81	—	0–1
Income	2.43	1.01	2.41	1.06	1–5
Less than $25K	20.26	—	23.99	—	0–1
$25–49.9K	32.24	—	27.38	—	0–1
$50–99.9K	34.53	—	35.91	—	0–1
$100–149.9K	10.28	—	9.02	—	0–1
$150K or more	2.69	—	3.70	—	0–1
Prior arrest	17.81	—	19.74	—	0–1
Vicarious arrest	44.02	—	46.31	—	0–1
Days a week—drink alcohol	1.31	1.69	—	—	0–7
Days a week—speed	1.82	2.16	—	—	0–7
Days a week—text and drive	.61	1.39	—	—	0–7

ABBREVIATIONS: SD = standard deviation.

Druckman, 2016).[9] In both of our samples, there is almost an even split of males and females. In both samples, approximately 20 percent of respondents reported having a prior arrest, and more than 40 percent reported having a family member or close friend who had been arrested. These figures are nearly identical to those that have been reported by researchers in prior studies analyzing data from MTurk samples and samples from other online opt-in panels (Pickett and Bushway, 2015).

Randomization was carried out independently for each experiment. The exception was the intensity matching experiment, which required random assignment to one of two sets of three questions. Here respondents were randomly assigned to one of the two sets of questions with the "birthday technique" (Reips, 2002).[10] The experiments primarily involved what Mutz (2011: 37) has characterized as "indirect treatments," where participants are unaware either of the presence of manipulations or that they have anything to do with subsequent questions. Thus, we never informed respondents that they were participating in experiments but instead only asked them to complete the survey. Specifically, along with institutional review board (IRB) information, the description of each survey included the following information: "This is a short non-profit survey being conducted

9. For example, Berinsky, Huber, and Lenz's (2012: 356) MTurk sample was only 40 percent male, 84 percent White, with a mean age of 32 years. By contrast, Levay, Freese, and Druckman's (2016: 5) MTurk sample was 54 percent male, 72 percent White, with a mean age of 32 years.

10. Specifically, respondents born in January, April, June, July, September, or December were assigned to receive the questions with a high scale, and those born in February, March, May, August, October, or November were assigned to receive the low scale. This technique for online randomization is similar to the next- and last-birthday methods that are commonly included in random-digit dialing surveys for within-household respondent selection, and it shares the same assumption that the assignment of birthdays is a random process (see Salmon and Nichols, 1983).

on behalf of researchers at the [University]. It asks individuals to provide their opinions about criminal justice issues here in America."

We discuss the respective method and findings for each specific experiment concurrently. To avoid repetition, all experiments were focused on sanction perceptions for a different type of offense. With the exception of one experiment (intensity matching), all were designed to maximize their relevance to the persons in our samples [e.g., speeding, driving under the influence (DUI), or texting-while driving]. This required focusing on less serious offenses. The exact question wording for the measures in each experiment is provided in appendices A (for survey A) and B (for survey B) in the online supporting information.[11]

FINDINGS

All experiments had randomized post-test–only designs. If we assume initial equality between groups (via randomization), observed group differences in sanction risk perceptions are considered evidence of situational updating based on the information provided.

WELL-FORMED VERSUS DIFFUSE PRIORS

We first investigate the possibility that rather than having precise numerical crime-specific *priors*, persons may instead have only an intuitive sense of the general level of arrest risk. Such a general feeling about arrest risk might then be adjusted to take into account the particular characteristics of a given criminal opportunity. It might also be scaled to fit with specific types of survey questions and response scales. We explored this by testing the sensitivity of risk estimates to different descriptions of crimes and response scales. Precise numerical *priors* should vary in logically consistent ways across circumstances and response formats and should not violate the laws of probability.

Conjunction Fallacy

In one experiment embedded in survey A we asked participants to estimate the arrest risk for the "typical driver" in their hometowns who drove drunk. We randomized whether the question asked 1) simply about the overall chance of being arrested; 2) about the chance of running a stoplight and then being arrested; or 3) about the chance of running a stoplight, causing a car accident, and then being arrested (see table A.4 in appendix A in the online supporting information). Mathematically, the overall arrest risk must be higher than the risk of arrest through specific events. Intuitively, however, the more detailed scenarios can seem more plausible because causal information often increases imaginability (Kahneman, 2011). Therefore, if sanction risk perceptions represent diffuse intuitive judgments, we may observe comparatively high estimates of arrest risk in the more detailed (but less probable) scenarios. Instead, the mean perceived arrest risk was similar for all three situations: 32 percent for arrest ($N = 328$); 27 percent for stoplight and arrest ($N = 331$); and 29 percent for stoplight, accident, and arrest ($N = 319$). A one-way analysis of variance revealed the difference in estimated risk across groups was not significant ($F = 2.77$, $p = .063$). Even though

11. Additional supporting information can be found in the listing for this article in the Wiley Online Library at http://onlinelibrary.wiley.com/doi/10.1111/crim.2017.55.issue-1/issuetoc.

this does not strictly conform to our prediction, participants' perceptions of arrest risk are still inconsistent with the laws of probability. The objective probability of the first event occurring is necessarily much higher than that of either the second or the third, and the objective probability of the second event occurring is higher than that of the third.

In a second experiment embedded in survey A, we asked participants to estimate the arrest risk for stealing a purse (containing $100 and an Apple iPhone; Apple, Inc., Cupertino, CA) out of a parked car at night. We randomized whether the question asked 1) about the overall chance of arrest in this scenario or 2) about the chance of arrest specifically because of police tracking the iPhone (see table A.4 in appendix A in the online supporting information). The causal information in the latter of these two questions would be expected to increase its imaginability. Nonetheless, the chance of arrest by iPhone tracking is mathematically less probable than is the overall chance of arrest. But, as would be expected if sanction risk perceptions represent intuitive judgments, the mean perceived chance of arrest was 21 percent ($N = 321$) in the less detailed condition, but it was 42 percent ($N = 316$) among participants who estimated their perceived chance of arrest specifically by iPhone tracking, fully 21 percentage points (or 100 percent) higher. This difference, which is in the *opposite direction* than that consistent with the laws of probability, is highly significant ($t = 10.27, p < .001$).

Intensity Matching

In another experiment embedded in survey A, we explored the nature of participants' *priors* using an alternative method. Here three questions asked participants to compare the level of arrest risk for different sets of offenses. We included three separate comparisons: 1) burglarizing a house during the day versus night; 2) buying cocaine from a stranger versus friend; and 3) robbing a bank versus a convenience store (see table A.5 in appendix A in the online supporting information). These questions require participants to compare their *priors* for each of the two respective offenses to determine the extent to which those offenses differ in arrest risk. This should be a straightforward quantitative exercise if participants have precise numerical *priors* by crime type. It would be akin to asking them to compare their age with somebody else's age and then to report the difference in years. By contrast, if participants' *priors* instead represent more diffuse feelings about the general level of arrest risk, they should use intuitive reasoning to estimate the difference in arrest risk, and they should do so without regard to any true underlying numerical scale (Kahneman, 2011; Slovic, 2010). In turn, we would expect them to match their intuitive judgments to whatever numerical scale we provide them, through what Kahneman (2011: 93) termed "intensity matching."

In the experiment, the questions were identical. Nevertheless, we randomized whether participants received a five-point response scale that was low (ending with "5 times as likely or more") or high (ending with "20 times as likely or more"). The last response option in the low scale entirely encompassed the last three options in the high scale (see table 2). Slovic (2010: 104) used a similar method to test whether smokers' estimates of lung cancer risk represented reliable quantitative knowledge or intuitive judgments. The results of our experiment are presented in table 2. The distribution of responses to the three questions is almost identical, regardless of the specific response scale provided. To illustrate, among participants receiving the low (vs. high) scale, 6 percent (9 percent),

Table 2. Experiment Testing Intensity Matching for Arrest Risk Perceptions: Alternative Response Scales

Experimental Group and Scale	Burglary Arrest Risk: Day vs. Night n	(%)	Drug Arrest Risk: Stranger vs. Friend n	(%)	Robbery Arrest Risk: Bank vs. Store n	(%)
Group A (Received Low Scale)						
No more likely	108	(22%)	82	(17%)	57	(12%)
Twice as likely	177	(36%)	118	(24%)	81	(17%)
3 times as likely	123	(25%)	122	(25%)	114	(23%)
4 times as likely	49	(10%)	80	(16%)	98	(20%)
5 times as likely or more	31	(6%)	86	(18%)	138	(28%)
N	488		488		488	
Group B (Received High Scale)						
No more likely	92	(19%)	40	(8%)	45	(9%)
2 to 5 times as likely	172	(35%)	131	(27%)	69	(14%)
6 to 10 times as likely	139	(29%)	145	(30%)	129	(27%)
11 to 19 times as likely	37	(8%)	86	(18%)	85	(17%)
20 times as likely or more	46	(9%)	84	(17%)	158	(33%)
N	486		486		486	

NOTE: The boxed category in the low scale includes the boxed categories in the high scale.

18 percent (17 percent), and 28 percent (33 percent) chose the highest option for the burglary, buying drugs, and robbery comparisons, respectively. In each comparison, the difference between the means on the five-point scales across the groups receiving the low- versus high-response options was statistically nonsignificant ($p > .05$, two-tailed). These findings strongly suggest to us that the participants simply matched the intensity of their intuitive risk perception to whatever numerical scale we gave them.

HEURISTIC SIGNALS

Thus, we find some support for our earlier expectation that the current Bayesian learning theory conception of the *prior* as a specific numerical point estimate is overly narrow in consequential ways. Most importantly, the *prior* may instead constitute a less precise intuitive "sense" of risk or likelihood that is, therefore, more susceptible to cognitive biases than current rational choice theory acknowledges. We next examine whether several specific cognitive heuristics—anchoring, affect, and availability—seem to produce situational perceptual updating.

ANCHORING

As elaborated by Kahneman (2011), we explore *both* anchoring by *adjustment* (survey B) and by *priming* (survey A). In both surveys, participants were asked to estimate the percent chance (0–100 percent) they would be apprehended by police if they drove off from an accident (hit-and-run).

In survey B, consistent with findings from prior research, we tested anchoring by adjustment by first asking the participants whether their apprehension risk was higher or lower than a specific number, which we randomized either to be low ("19 percent") or high ("79 percent"). They were then asked to estimate the actual level of risk (see table B.1 in appendix B in the online supporting information). The resulting difference between the two experimental groups in perceived apprehension risk was dramatic. Participants who received the low number reported a mean perceived apprehension risk of 32 percent (N = 327). Those who received the high number reported a mean perceived risk of 49 percent (N = 296), a full 17 percentage points (or 53 percent) higher ($t = 7.89$, $p < .001$). Thus, situational information or cues can dramatically affect an individual's perception of risk at a given time—what we term "situational updating."

In survey A, we tested anchoring by priming. The goal was to investigate whether exposure to an unrelated number can affect subsequent estimates of apprehension risk. Nonetheless, it was necessary to ensure that respondents did, in fact, pay attention to the number we gave them. We devised a novel method to do this. Directly before the hit-and-run risk question, participants answered an unrelated instructional manipulation check (IMC, see Berinsky, Margolis, and Sances, 2014). IMCs comprise a requirement that respondents prove that they are paying attention by following a precise set of instructions when responding. We used an IMC that involved asking participants how often they ate out, but instructing them to select "other" and type in a specific number (see table A.4 in appendix A in the online supporting information). The number was randomized to be either low ("20") or high ("80").[12] On the next question, participants who received the low number reported a mean perceived apprehension risk of 31 percent (N = 457). Yet, those who received the high number also reported a mean perceived risk of 31 percent ($N = 518$). Therefore, although we find strong evidence that considering a specific level of apprehension risk before estimating risk is impactful (see earlier discussion), exposure to an unrelated number is not.

Affect Heuristic

Next we test for situational updating via the affect heuristic. Our theoretical concern is whether situational factors that influence an individual's feelings (or "affect pool") toward a criminal behavior may, in turn, impact his or her intuitive judgments of its risks and benefits (Finucane et al., 2000). We tested the affect heuristic among participants in survey A, and we did so in the context of texting-while-driving (TWD). Two questions measured participants' perceptions of the costs and benefits of TWD in states where it is illegal (see table A.2 in appendix A in the online supporting information). We operationalized the costs of TWD as the percent chance of being pulled over by the police. We operationalized the benefits as the degree to which TWD helps drivers communicate with family and friends (1 = none, 5 = a great deal). Few participants perceived benefits to TWD, and thus, we recoded responses such that those who perceived some benefit were scored "1" and everyone else was scored "0".[13] As would be expected if participants used the affect heuristic to make these judgments intuitively (see Slovic et al., 2004), there

12. Only 25 participants (or 2.5 percent of the sample) failed the IMC. These individuals were excluded from the analyses.

13. The response breakdown for the perceived benefits of TWD was 1) none (49 percent), 2) very little (39 percent), 3) only some (9 percent), 4) a good amount (2 percent), and 5) a great deal (1 percent).

was a significant negative correlation in the full sample between the perceived costs and benefits of TWD ($r = -.14, p < .001, N = 976$).

To test the role of the affect heuristic in perceptual updating, we provided participants with information designed to manipulate their emotions toward TWD (see table A.2 in appendix A in the online supporting information). The information appeared immediately before the two questions about the costs and benefits of TWD (see earlier), and it was presented as an empirical finding (i.e., "A new study shows…"). We randomized whether the information was negative (TWD is a leading cause of teen deaths), neutral (most cell phone users text daily), or positive (couples who text regularly stay together). We would expect the perceived costs to be highest among participants who received the negative information and lowest among those who received the positive information. This is exactly what we observed. The mean perceived chance of being stopped by police was 26 percent ($N = 330$) in the negative information group, 23 percent in the neutral information group ($N = 305$), and 21 percent in the positive information group ($N = 341$). A one-way analysis of variance revealed a significant difference in estimated risk across the groups ($F = 3.55, p = .029$).

By contrast, we would expect the perceived benefits to vary in the opposite direction, being lowest in the negative information group and highest in the positive information group. We did not observe this pattern. Rather, the proportion of participants perceiving benefits to TWP was lowest in the positive information group (46 percent) and identical in the negative and neutral information groups (54 percent). Although a global chi-squared test applied to all three groups was only marginally significant ($\chi^2 = 5.89, p = .053$), separate equality of proportions tests revealed the positive information group was significantly ($p < .05$) less likely to perceive benefits of TWD than either the negative or the neutral information group. In sum, then, we find evidence that exposure to emotion-laden information causes changes in perceptions of formal sanction risk that are consistent with the use of the affect heuristic, but we do not find this to be the case for perceived benefits.

Availability Heuristic

Finally, we explore situational updating based on the availability heuristic, for which recall speed or fluency influences probability estimates (Kahneman, 2011; Tversky and Kahneman, 1973). We tested this heuristic with participants in survey A, and we did so in the context of both DUI and speeding. Two questions asked participants to estimate the percent chance (0–100 percent) that they would be pulled over by the police if they committed each offense (see table A.3 in appendix A in the online supporting information). Directly before each of these questions, however, participants were randomly asked about their vicarious experiences with either punishment avoidance or punishment for the offense (see table A.3 in appendix A in the online supporting information). Doing so should, theoretically, influence recall fluency by priming specific types of relevant experiences (see Kahneman, 2011). For DUI, we randomized whether participants were asked if they knew someone who had gotten away with driving drunk (avoidance prime) or knew someone who had received a DUI ticket (punishment prime). In both cases, most participants said yes (84 percent and 63 percent, respectively). For speeding, we randomized whether participants were asked if they knew anyone who always speeds (avoidance prime) or if they had witnessed a police officer pull someone over for speeding in the past year (punishment prime). Again, in both cases, most participants said yes (83 percent and 86 percent, respectively).

Participants receiving the DUI avoidance prime reported a mean perceived apprehension risk for the offense of 33 percent ($N = 480$), whereas the average risk estimate was 32 percent among those receiving the punishment prime ($N = 496$). Substantively identical results were obtained when we restricted the sample to participants who answered "yes" to the priming question (mean risk = 30 percent in both groups). The findings were similar for speeding risk estimates. The mean perceived risk of being pulled over for speeding was 19 percent for participants receiving the speeding avoidance prime ($N = 491$) and 20 percent for those receiving the punishment prime ($N = 486$). When we restricted the sample to participants answering "yes" to the priming questions, the respective risk estimates were 18 percent versus 19 percent. In neither case was the difference significant. Therefore, the evidence is not consistent with participants using the availability heuristic to judge sanction risk for these offenses. Of course, this could simply mean that the primes were not effective for enhancing recall fluency for experiences with punishment avoidance versus punishment.

CONCLUSION

In this article, we investigated the implications of cognitive heuristics for criminal decision-making. Although our research is set within the rational choice paradigm, our findings implicate a range of criminological discourses concerned with agency and choice. Our findings suggest perceptions of sanction risk are neither as durable nor as numerically precise as rational choice or Bayesian learning theory suggest. This invites deviations from strict rational choice norms in the form of *situational* and sometimes *biased* perceptual updating. It also coincides with the emphasis in situational crime prevention on bounded rationality and how the features of the immediate environment affect criminal decision-making. At the same time, a key finding in the literature is that some variability in sanction perceptions is independent of any given situation and is correlated with over time changes in punishment experience; this is consistent with Bayesian updating models (Anwar and Loughran, 2011; Matsueda, Kreager, and Huizinga, 2006).

Heuristic principles help bridge the divide between situational crime prevention approaches (Clarke, 1997; Cornish and Clarke, 2003) and more formal rational choice approaches such as the Bayesian updating model (Anwar and Loughran, 2011; Wilson, Paternoster, and Loughran, 2016) and, in so doing, provide a more accurate understanding of criminal decision-making (Pickett and Roche, 2016). Our central argument is that individuals enter situations that present an opportunity for offending with some preexisting, but generalized, conception of sanction risk, which is well depicted by Bayesian updating models. Then, primarily through heuristic reasoning processes, individuals use the available situational information and environmental features to update their baseline perception on a temporary basis. Some of our findings support this depiction. An important next step is to explore how specific situational characteristics known to sometimes reduce crime, such as street lighting or the presence of CCTV cameras (Farrington and Welsh, 2002; Welsh and Farrington, 2009), influence sanction perceptions through heuristic reasoning processes.

There is considerable policy importance to examining heuristics and biases in offender decision-making. Because the Bayesian updating framework only includes probabilistic signals, specifically arrest and offending experiences, its policy relevance is largely limited to efforts to increase actual arrest rates. Unfortunately, for many offenses, it is not clear that the police have much influence over the arrest rate (Braga et al., 2011). By contrast, the heuristic perspective suggests that a wide range of nonprobabilistic signals may have deterrent value. Policies that influence the prevalence of such signals—for example, by increasing police sentinel activity (Nagin, Solow, and Lum, 2015)—may deter crime even without affecting arrest rates. To illustrate, the results of recent work have shown that public communications about arrest rates exert a casual effect on sanction perceptions but *lower* perceived risk because individuals tend to overestimate arrest rates initially (Pickett, Loughran, and Bushway, 2016). By contrast, it may be possible to *increase* perceived arrest risk by using public communications that target heuristic updating. These might provide details increasing the imaginability of arrest (e.g., listing the many ways to get caught) or information triggering negative emotional feelings toward a criminal behavior (e.g., commercials on harms to the victims of DUI accidents). Not least, environmental modifications that make it easier to imagine getting caught, strengthen the coherence of any considered apprehension scenarios, or detail specific routes to arrest (e.g., CCTV cameras or cell phone tracking) may all increase perceived arrest risk through heuristic reasoning. Indeed, our findings on anchoring suggest that large deterrent effects might be achievable simply by leveraging situational factors or information to cause offenders to consider first a high level of arrest risk before estimating their arrest risk.

Our findings also have broad theoretical implications. For example, the cognitive heuristics examined herein may help explain the well-documented effects of dispositional factors on sanction perceptions. Neither the literature on situational crime prevention nor Bayesian learning theory is well suited for explaining how individuals' dispositions or personalities influence their sanction perceptions. Nevertheless, the results of studies have shown that several personality traits are strongly associated with perceived punishment risk (Pickett and Bushway, 2015; van Gelder and de Vries, 2012, 2014) and influence sanction perception updating (Thomas, Loughran, and Piquero, 2013). In a seminal study, van Gelder and de Vries (2012) found that honesty-humility, agreeableness, extraversion, conscientiousness, and self-control were all associated with perceived sanction risk. Such personality traits may influence individuals' propensity to judge sanction risk using cognitive heuristics, and they may shape the outcomes of intuitive reasoning processes (Pickett and Bushway, 2015). Testing this possibility seems like a particularly promising line of inquiry for future research.

Additionally, further theoretical and empirical attention is warranted to understand the language of choice in offender decision-making. The predictable deviations from rational choice principles observed herein produce logical inconsistencies fundamental enough to violate the laws of probability. They may also produce cognitive misapprehension, not unlike an optical illusion, which can be difficult to accept even after one has learned the "trick" (Escher, 1986). Current theorizing and data collection continue to treat probability as "the language of choice" (Joel and Putnam, 2015). This is not unreasonable as much crime decision-making discourse has focused on arrest risk, and probability is the standard metric for risk. But it should be increasingly evident that exclusive reliance on conventional probabilistic principles can leave key gaps in our understanding of crime decisions.

Consider behavioral economic-based critiques of the process for assessing monetary punitive damage awards in civil trials. A jury can award punitive damages, over and above compensatory damages, when they find the defendant's conduct is particularly egregious, and additional monetary damages are needed for retribution and/or deterrence (Huang, 2014). Specifically, jurors express how "outraged" they are in dollar terms. The research program inspired by this work shows how mapping punitive intent onto a dollar scale is fraught with error, and how it can produce erratic and unpredictable damage awards (Rhee, 2012; Sunstein, Kahneman, and Schkade, 1998).

From here we can make an analogy to the prominent role of probability in current crime decision-making scholarship. As with punitive damage assessments, there have been strong qualitative, even emotional, aspects to the deterrence perspective since its inception. This is evident from the pain and pleasure principle of Bentham (1789), through Geerken and Gove's (1975) conception of deterrence as a process of "threat communication," and finally from the many formative contributions to criminological rational choice and deterrence thinking by Nagin (1998, 2013). Thus, crime discourse has long envisioned an emotive component to deterrence that probabilistic assessment may not fully capture (van Gelder and de Vries, 2012, 2014). Developing a better understanding of the language and metrics people use to evaluate costs, benefits, and risk, as well as identifying the emotive components of these concepts, should be a priority for future rational choice and deterrence research.

Nonetheless, our analyses have several limitations. First, we used conventional samples (only 18–20 percent had ever been arrested). The question remains whether an offender sample would yield comparable findings. At the same time, the results of previous studies often have revealed that the correlates of sanction perceptions are similar among offender and nonoffender samples (see Pickett and Roche, 2016). Still, future work is needed to replicate our findings with active criminals.

Second, most of our experiments focus on minor offending. Thus, it is possible that different results would emerge if we focused instead on perceived arrest risk for serious crimes. We know of no theoretical reason to expect that the use of heuristics to judge arrest risk would vary by the seriousness of the offense. Regardless, exploring this possibility would help establish the generality of heuristic choice for crime decisions.

Third, we did not include a manipulation check in the experiment testing the affect heuristic. As a result, we cannot be sure that the observed effect of the treatment was mediated by changes in affect. Our theoretical model leads us to anticipate that this is true. At the same time, other potential theoretical explanations for our findings exist, and research is needed to adjudicate between these different accounts. Regardless of the specific mediating mechanism, however, what is most notable, and most relevant to policy-making, is that the information provided to respondents about texting-while driving seemed to exert a causal effect on sanction perceptions. Determining exactly why this occurred is tremendously important for future research.

To conclude, although there has been recent progress in demonstrating the full breadth of criminological rational choice models, this progress has been bounded by a failure to embrace the possibility that crime decisions are more nuanced, situational, and idiosyncratic than current rational choice discourse suggests. We hope we have illustrated one way to learn more about how decisions to commit or refrain from crime are made. Enduring progress, however, will require further theoretical refinement and correspondingly novel data collection strategies.

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SUPPORTING INFORMATION

Additional Supporting Information may be found in the online version of this article at the publisher's web site:

Appendix A. Question Wording for Survey A
Table A.1. Anchoring by Priming—Experimental Manipulation and Survey Item Measuring Perceived Apprehension Risk
Table A.2. Affect Heuristic—Experimental Manipulation and Survey Items Measuring Perceived Risk and Benefit
Table A.3. Availability Heuristic—Experimental Manipulation and Survey Items Measuring Perceived Risk
Table A.4. Fallacies in Probabilistic Reasoning—Experimental Manipulation
Table A.5. Intensity Matching—Experimental Manipulation and Survey Items Measuring Comparative Perceived Risk

Appendix B. Question Wording for Survey B
Table B.1. Anchoring by Adjustment—Experimental Manipulation and Survey Item Measuring Perceived Apprehension Risk