

Ambiguity and legal compliance

Timothy C. Barnum¹  | Daniel S. Nagin² 

¹ Department of Criminology, Max Planck Institute for the Study of Crime, Security and Law, Freiburg im Breisgau, Germany

² Heinz College, Carnegie Mellon University, Pittsburgh, Pennsylvania, USA

Correspondence

Timothy C. Barnum, Department of Criminology, Max Planck Institute for the Study of Crime, Security and Law, Günterstalstraße 73, 79100 Freiburg im Breisgau, Germany.

Email: t.barnum@csl.mpg.de

Research Summary: This study examines the independent and joint effect of ambiguity and perceived certainty of apprehension on law-breaking decision-making. Data come from a survey of experienced drivers ($N = 1147$) who viewed videos depicting a car speeding on an interstate highway under experimentally manipulated circumstances. The sampled drivers were generally ambiguity averse, opting to reduce speeding as ambiguity about the perceived certainty of apprehension increased. However, perceived ambiguity interacted with perceived certainty such that increases in ambiguity increased the deterrent effect of ambiguity for low certainty probabilities and decreased the effect for high probabilities.

Policy Implications: Ambiguity may serve as a valuable tool for increasing the efficacy of crime-prevention strategies, especially for crimes with naturally low levels of risk. However, researchers should think carefully about the effects of ambiguity when analyzing the efficacy of certainty-based policies because the injection of ambiguity can both increase and decrease legal compliance. Also, discussed are the implications for a key function of policing—traffic safety.

KEYWORDS

ambiguity aversion, ambiguity seeking, deterrence, idiosyncratically coherent risk perceptions

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Nearly three centuries ago, Beccaria (1764) postulated that the certainty of punishment is a more effective deterrent than the severity of the ensuing punishment. Decades of perceptual deterrence research have consistently confirmed Beccaria's postulate (e.g., Apel & Nagin, 2011; Nagin, 2013; Paternoster, 2010). This evidence has motivated a range of crime prevention policies aimed at increasing the certainty of detection, such as hot spot policing (Braga & Apel, 2016; MacDonald et al., 2016; Rosenfeld et al., 2014), which have consistently been demonstrated to be effective. By preventing crime from occurring in the first place, certainty-based prevention strategies have the benefit of averting not only the social cost of crime but also the social cost of punishment.

Sherman (1990), however, interjected a caution that remains valid in contemporary United States as it was 30 years ago: "in modern America there is too much crime and too little law enforcement to make punishment very certain" (p. 3). To this point, Sherman (1990) and, subsequently, Nagin (1998) theorized that law-breaking behavior could be further deterred by increasing the level of equivocation or *ambiguity* about the likelihood of sanction certainty. For example, Sherman (1990, p. 7) suggested that by increasing police presence unpredictably, ambiguity would be increased without sacrificing certainty averaged over time and across place.

The hypothesis that an aversion to ambiguity might be a deterrent independent of sanction certainty originates with what is now referred to as the "Ellsberg Paradox" (Ellsberg, 1961). Stripped to its essentials, the Ellsberg Paradox is that people prefer simple gambles compared to compound gambles with equivalent expected value. Compound gambles are a form of decision making under uncertainty in which there is not a single probability specifying the chances of an outcome. Instead, there is a distribution of probabilities each with its own probability of occurring. By way of example, consider the following simple and compound gambles with equal expected values. In the case of the simple gamble, you are presented with an urn that conceals 50 red and 50 blue balls. You win \$50 if a red ball is chosen but lose \$40 if a blue ball is chosen. The expected value of this simple gamble is \$5 ($= 0.5 \times \$50 - 0.5 \times \40). In the compound version of the gamble, you are told that the urn conceals between 0 and 100 red and blue balls and all 100 possible mixtures of red and blue balls are equally likely. If unknown to you there are no red balls, then you are certain to lose \$40. On the other hand, if the urn is all red balls, you are certain to win \$50. Thus, for each 100 possible mixtures of red and blue balls the expected value for that *simple* gamble ranges from $-\$40$ to $+\$50$. Because each possible mixture is equally likely, the expect value of the *compound* gamble is \$5, the same as the expected value for the simple gamble where it is known that the urn contains 50 red ball and 50 blue balls. Yet experimental evidence overwhelmingly shows that people prefer the simple gamble (even if they must pay for that option; see Becker & Brownson, 1964).

To date, however, evidence on the relationship between ambiguity and decision making primarily comes from laboratory-based experiments involving choices between differently structured gambles. By contrast, crime is a real-world phenomenon in which would-be offenders must consider benefits and/or costs that generally are not denominated in monetary terms (e.g., exacting revenge, arrest, confinement, stigma, etc.). Moreover, as developed below and also in prior research, ambiguity in some circumstances can increase deterrence as suggested by the Ellsberg Paradox, but, in other circumstances, evidence and theory suggests ambiguity may actually "diminish" it (Ellsberg, 2011). Consequently, it remains unclear how and to what extent ambiguity influences the decision to take advantage of real-life offending opportunities.

This paper extends the nascent criminology literature on ambiguity by generalizing a model of idiosyncratically coherent decision making set out in Barnum et al. (2021) to account for the joint effect of perceived certainty of apprehension and ambiguity in law-breaking decisions. In short, this model describes two separate but interrelated components that contribute to the formation of

sanction risk perceptions: (1) a person-specific component composed of cognitive biases, personality characteristics, and private information, and (2) a coherence component defined by observable features of a criminal opportunity. The authors focused on the theoretical underpinnings of the coherence component, demonstrating people coherently define and adjust risk perceptions based on the objective features of an offending opportunity net of idiosyncratic differences in their overall ability to assess risk. The current study adds to this line of thought by incorporating the role of ambiguity in criminal decision making, a potentially salient person-specific factor that has important implications for deterrence research, crime-prevention policy, and in the context of the experimental results reported below, the traffic safety function of policing.

In doing so, we formalize the notion of boundary effects first advanced by Casey and Scholz (1991a) and later expanded on by Loughran et al. (2011) to show how ambiguity not only serves as an independent deterrent, but that its effect on offending also changes in magnitude and direction depending on how risky a would-be lawbreaker perceives a specific opportunity to be. We test our theoretical extension using a form of lawbreaking that is familiar to anyone who drives: speeding on an interstate highway. Although speeding is not a form of lawbreaking that is typically the focus of perceptual deterrence research, it is nonetheless an illegal behavior that results in (sometimes deadly) traffic accidents, which makes it a significant challenge to public safety and a top priority for many law enforcement agencies. By various estimates, traffic-related issues often make up more officer-involved time on the job and generate more calls for service than other crime categories (e.g., violent crimes, property crimes, disturbances; see Lum et al., 2021; Terrill et al., 2014). Moreover, its familiarity makes it ideal for testing our generalization of the model to account for the effects of ambiguity—a generalization that is applicable to research on risk perceptions and their influence on lawbreaking more generally.

Our point of departure begins with the observation that the objective probability of apprehension for “any” crime is highly dependent on circumstances. For speeding, one of the most important factors affecting apprehension risk is the amount over the speed limit—the probability of apprehension for speeding when traveling at 71 mph on an interstate highway with a 70-mph speed limit is negligible but is near certain for a driver overtaking a police vehicle at 90 mph. Lest there be any doubt about the proposition that the amount over the speed limit affects the probability of apprehension, Barnum et al. (2021) report a near-identical correspondence between citizens’ perceptions that risk of apprehension increases with the amount over the speed limit and the perceptions of individuals charged with enforcing speed limits, namely, highway patrol officers.¹ Likewise, decades of research from environmental criminology tell us that the probability of apprehension for robbing a lone elderly person on a deserted street at night is small, whereas that same probability is near 1 if the target is extremely well protected, such as a high-end jewelry store like Tiffany’s in New York City (see, e.g., Nagin et al., 2015).

The dependence of sanction risk on circumstances, whatever the form of lawbreaking, sets the stage for our generalization of the Barnum et al. (2021) model. Specifically, the extension adds to the model the apparatus for examining how varying assessments across individuals of their confidence in their perception of objective risk under specified circumstances affects decision making. Interpersonal variation in such confidence is the essence of interpersonal variation in ambiguity perceptions and its multifaceted impact on criminal decision making.

Using an elicitation method advanced in Pickett et al. (2015; see also Loughran et al., 2011, p. 1045), we directly measure ambiguity by asking participants to report their level of “sureness” about their probabilistic estimates of being ticketed. We then assess the extent to which ambiguity effects the decision to offend by querying 1147 American adult drivers about the likelihood of being ticketed for speeding based on three experimental videos depicting a car speeding on the

highway. The videos allowed us to randomly manipulate and control for salient contextual factors that define the objective certainty of being pulled over for speeding. We find a highly significant general aversion to ambiguity net of also statistically significant perceptions of sanction certainty. However, we also find an interactive effect between ambiguity and the perceived certainty of being ticketed on the decision to speed that is consistent with the boundary effects hypothesis of Casey and Scholz (1991a, 1991b). We discuss how our generalized model of idiosyncratically coherent risk perceptions can inform various crime-prevention strategies across a range of objectively low- and high-risk crimes to effectively leverage the deterrent effects of ambiguity.

1 | AMBIGUITY AND LEGAL COMPLIANCE

As discussed, ambiguity aversion is the tendency for people to prefer prospects with known risks as opposed to unknown risks that can only be specified in terms of a distribution of risks, even when in expectation these prospects yield the same value. Concerning this preference, Camerer and Weber (1992, p. 325) observed “it is hard to think of an important natural decision for which probabilities are objectively known” and by implication, ambiguity may be a contributing factor to most real-world decision making that requires the consideration of sureness. This conclusion resonates with research on the decision to engage in crime as mounting evidence suggests people typically misestimate the objective likelihood of getting caught, instead relying on various decision heuristics (Apel, 2013; Pogarsky et al., 2017, 2018). As such, it is reasonable to expect that ambiguity about sanction risk perceptions influences the decision to offend. To date, however, research on the association between ambiguity and legal compliance has been mixed, challenging the hypothesis that ambiguity serves as an independent influence.

Pickett and Bushway (2015) examined the measurement and sources of ambiguity for a range of risky and criminal behaviors (see also Pickett et al., 2015). They found that dispositional attributes (e.g., positive affect, cognitive reflection) influence perceptions of arrest risk, and importantly, the level of ambiguity in such perceptions. In a follow-up study, Pickett et al. (2016) also directly tested the hypothesis that ambiguity exerts an independent deterrent effect on offending. They found no evidence that ambiguity produced a statistically significant deterrent effect, even though perceived certainty did.

It is important to point out that like Sherman (1990) and Nagin (1998), Pickett et al. (2016) assumed that *ambiguity aversion* would persist regardless of how risky actors perceived the behavior to be. This assumption has important implications for the role of ambiguity as an independent deterrent because, as Ellsberg (2011) points out, the effect of ambiguity may manifest differently if the probability of the outcome occurring is low versus high. Specifically, decision makers may optimistically hope that ambiguity offers “better” odds than a known-risk alternative when the perceived likelihood of a loss is near certain—a phenomenon known as *ambiguity seeking* (see Midgette et al., 2021).

The phenomenon of ambiguity seeking implies that ambiguity’s impact on decision making depends on the location of the decision makers’ point estimate of risk on the 0–1 probability continuum. To this point, Casey and Scholz (1991b) investigated ambiguity, sanction risk, and deterrence related to tax evasion. In a lab-based experiment, the authors varied the ambiguity of the certainty of being caught for tax cheating. Consistent with deterrence theory, they found that the expressed preference for noncompliance with tax rules decreased with the certainty of punishment penalty. However, when the information about the risk of being caught was ambiguous and that probability was near the upper end of the probability range (0.90), noncompliance was “higher.” Conversely, noncompliance was “lower” when the risk of being caught was ambiguous

and that probability was near the lower end (0.10). Casey and Scholz (1991b) termed this interaction “boundary effects.”

Loughran et al. (2011) tested for boundary effects using data from The Pathways to Desistance Study. They found that for crime types with a more ambiguous perceived certainty of punishment, the deterrent effect of certainty was greater than for crime types with a nominally equivalent but less ambiguous certainty. The effect of ambiguity, however, depended on the level of perceived certainty. Specifically, ambiguity served as deterrent for lower probabilities but “reversed” for higher risks. Returning to the arguments by Sherman (1990) and Nagin (1998), this finding implies that injecting ambiguity into crime-control policy may enhance deterrence for crimes with a naturally low certainty of apprehension (e.g., drunk driving) but could have the opposite effect for crimes with naturally greater risk (e.g., bank robbery).

The findings of Loughran et al. (2011) provide a point of departure for the current work. Due to limitations in the Pathways data, the authors were unable to directly measure ambiguity.² Furthermore, their analyses were restricted to decontextualized measures of risk perceptions based on information gathered between 6- and 12-month periods. These data limitations potentially confound important contextual and situational information that defines risk as being low, high, or somewhere in-between.

2 | UNPACKING THE INTERACTION BETWEEN AMBIGUITY AND PERCEIVED RISK

The findings of Loughran et al. (2011) and Casey and Scholz (1991b) suggest a complicated relationship between perceived sanction certainty, ambiguity, and law-breaking behavior. To advance the role of ambiguity in models of choice, and to highlight its relevance for crime-control policy, it is important to identify the mechanisms linking uncertainty and decision processes. We draw on Barnum et al. (2021) model of idiosyncratically coherent risk perceptions and on a model of target choice selection set out by Nagin, Solow, and Lum (2015) (NSL) to propose such a mechanism.

In a nutshell, the model of idiosyncratically coherent risk perceptions is as follows: Let $p(c)$ denote the probability of apprehension for a set of circumstances described by a vector c and let $PR_i(c)$ denote individual i 's subjective estimate of the probability of apprehension in circumstances c . Prior research on sanction risk perceptions finds large variations in the level of $PR_i(c)$ across individuals, which implies $PR_i(c)$ does not equal objective risk $p(c)$ at least for most individuals. To allow for the level of risk to vary across individuals yet still be grounded in $p(c)$, Barnum et al. (2021) model $PR_i(c)$ as a function of two components—a person-specific component, denoted by γ_i , and $p(c)$. One possible model of this relationship is the linear probability model whereby $PR_i(c)$ is the sum of the two components: $PR_i(c) = \gamma_i + p(c)$. More general than this additive functional form, $PR_i(c)$ is assumed to increase monotonically in the individual-level parameter, γ_i , and with the objective, situation-dependent risk, $p(c)$.

We turn now to generalizing the Barnum et al. (2021) specification of idiosyncratically coherent risk perceptions by drawing on a model of target selection set out in NSL. A key parameter of the NSL model is $PR(c)_i^*$, the maximum risk of apprehension specific would-be lawbreaker i is willing to tolerate holding constant other choice relevant characteristics captured by c . For speeding, $PR(c)_i^*$ specifies the maximum risk of being ticketed for speeding that a would-be speeder is “willing to accept” holding constant other relevant considerations to the speeding decision such as perceived safety. To illustrate, suppose an individual's $PR(c)_i^* = 0.3$ for a given set of circumstances defined by road and weather conditions, schedule urgency, and so on as measured in c . The individual will speed under these circumstances if their perceived risk of being ticketed,

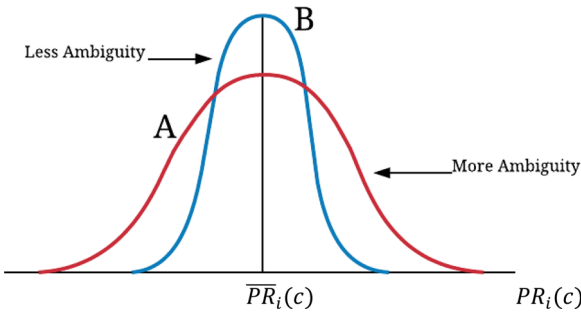


FIGURE 1 Ambiguity about probability of apprehension ($PR_i(c)$) [Color figure can be viewed at wileyonlinelibrary.com]

$PR_i(c)$, is less than 0.3, but if higher the individual will choose not to speed. Note that a key characteristic of the specified circumstances in the determination of $PR_i(c)$ is the amount over the speed limit. Thus, while an individual may be unwilling to speed, for example, at 10 mph or more over the speed limit, they may be willing to speed at, for example, 6 mph or less over the speed limit because in the former condition they perceive that $PR_i(c) > PR(c)_i^*$, whereas in the latter $PR_i(c) > PR(c)_i^*$.

To account for ambiguity aversion, we allow for the possibility that individuals do not have a single estimate of $PR_i(c)$ but instead have what is called a subjective distribution of possible estimates in which some may be perceived more likely than others (e.g., Manski, 2004). Formally, the subjective distribution is itself a probability density function in which more likely subjective estimates have higher density. Figure 1 shows two such subjective distributions of $PR_i(c)$ both with the same mean, $\overline{PR}_i(c)$. The quantity $\overline{PR}_i(c)$ should be thought of as an individual's mean, or possibly median or modal estimate of the probability of sanction. For the speeding experiment, we treat $\overline{PR}_i(c)$ as the survey participant's response to the question asking for their estimate of the certainty of being ticketed under the circumstance depicted in the video. The variance of the distributions about $\overline{PR}_i(c)$ characterizes the degree of ambiguity about $PR_i(c)$, with greater variance of that distribution corresponding to greater ambiguity. Accordingly, distribution B corresponds to less ambiguity than A.

This characterization of ambiguity comports with two competing conceptualizations of ambiguity. The first is a Bayesian conceptualization, which predicts individuals' levels of ambiguity should be directly determined by the nature of the information they have about the probability of a specific event (Manski, 2004). Under this conceptualization, the variance should decline as he or she gains more information about that particular risk. By contrast, the dispositional conceptualization of ambiguity suggests that trait-based assuredness in risk estimates should be largely unrelated to event-specific information (Kleitman & Stankov, 2007). For a detailed discussion of the differences of these conceptualizations, see Pickett and Bushway (2015).

The current conceptualization of ambiguity as the variance of subjective risk estimates around $\overline{PR}_i(c)$ allows for the possibility of both informational and trait-based sources of ambiguity to exist, thereby allowing us to isolate the independent effect of ambiguity on decision outcomes regardless of its source. Although it is outside of the current scope to test specific sources of ambiguity, we discuss the importance of these sources for the current findings in the conclusion.

Returning to the context of the NSL model, Figure 2 offers a theoretical explanation for the interaction between ambiguity and certainty. The top panel of Figure 2 corresponds to the situation where $\overline{PR}_i(c) < PR(c)_i^*$, which we anticipate will most frequently occur when the respondent's estimate of $\overline{PR}_i(c)$ is low, reinforcing offending. Superimposed on $\overline{PR}_i(c)$ are the two subjective distributions of $PR_i(c)$ about $\overline{PR}_i(c)$ with A corresponding to high ambiguity and B to low ambiguity. For much of the low ambiguity distribution, it is still the case that

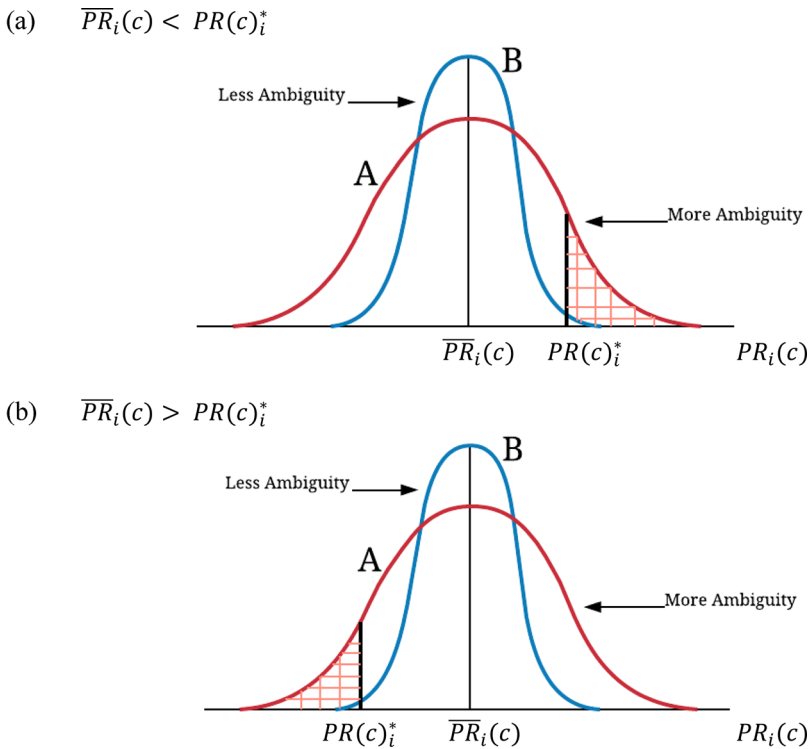


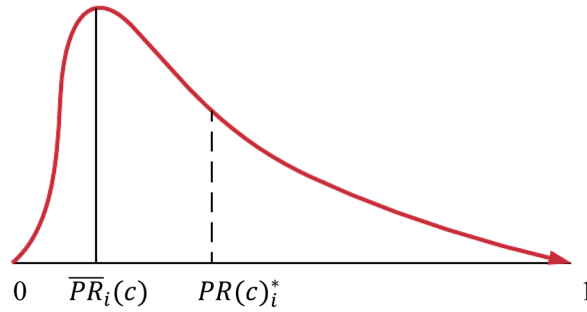
FIGURE 2 The interaction of ambiguity with $PR(c)_i^*$ and $PR_i(c)$ [Color figure can be viewed at wileyonlinelibrary.com]

$PR_i(c) < PR(c)_i^*$, whereas for the high ambiguity distribution, much more of the subjective distribution of $PR_i(c)$ exceeds $PR(c)_i^*$. For these instances, speeding is deterred. For this reason, we anticipate for that for low estimates of $\overline{PR}_i(c)$ more ambiguity about $PR_i(c)$ will “increase” deterrence.

Consider next the situation depicted in the lower panel where $\overline{PR}_i(c) < PR(c)_i^*$, which would typically indicate the actor perceives speeding as being too risky, reinforcing legal compliance. However, as the level of ambiguity increases (as with distribution A), it produces the reverse effect than in the above panel. Relative to low ambiguity (distribution B), more of the subjective probabilities is below the $PR(c)_i^*$ threshold, which has the effect of increasing not decreasing the likelihood of speeding. Stated differently, when $\overline{PR}_i(c) < PR(c)_i^*$ actors with high ambiguity will have more doubts about whether he or she can successfully speed without being ticketed than a low-ambiguity person with the same $\overline{PR}_i(c)$. On the other hand, when $\overline{PR}_i(c) > PR(c)_i^*$ the reverse of this reasoning may occur—the high-ambiguity person will have more optimism about the prospects of successfully avoiding a speeding ticket than a low-ambiguity person with the same $\overline{PR}_i(c)$. This process reflects Casey and Scholz’s (1991b) boundary effect.

Figure 3 contextualizes the boundary effect prediction by specifying an asymmetrical distribution of ambiguity around $\overline{PR}_i(c)$ for values of $\overline{PR}_i(c)$ close to the probability boundaries. Specifically, probabilities near the lower (0) or upper (1) bounds in the probability distribution restrict the direction of the subjective distribution. When $\overline{PR}_i(c) < PR(c)_i^*$ and $\overline{PR}_i(c)$ approaches 0, increased ambiguity can only produce a positive skew, which can result in the belief that the behavior is “riskier” than originally conceived. Conversely, when $\overline{PR}_i(c) > PR(c)_i^*$ and $\overline{PR}_i(c)$

(a) Right Skew of Ambiguity from Lower Bound



(b) Left Skew of Ambiguity from Upper Bound

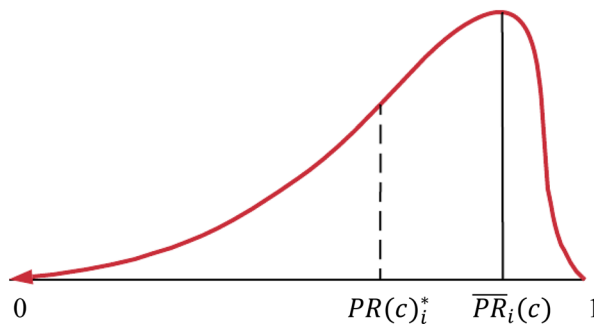


FIGURE 3 Boundary effects of ambiguity on decision to offend [Color figure can be viewed at wileyonlinelibrary.com]

approaches 1, increased ambiguity about $\overline{PR}_i(c)$ produces a left skew, effectively making the behavior appear “less” risky. Put differently, would-be offenders who perceive $\overline{PR}_i(c)$ to be either very low or very high but are highly ambiguous about these beliefs may act in seemingly irrational ways—choosing not to offend when the risk of detection is low, whereas choosing to offend when sanctioning is near certain.

3 | METHODS

3.1 | Data

We administered an online survey during the summer of 2020 to a nationwide sample of adult (18 and over) U.S. residents. The participants for the current study were recruited from Amazon’s Mechanical Turk (MTurk). MTurk samples are widely used in academic research (e.g., Barnum & Solomon, 2019; Dowling & Wichowsky, 2015; Herman & Pogarsky, 2020; Pickett et al., 2018; Pogarsky, Roche, & Pickett, 2017). Although there are some concerns about the generalizability of findings from MTurk and other opt-in online samples (e.g., Graham, Pickett, & Cullen, 2021; Thomas & Pickett, 2020), Coppock et al. (2018) showed that a lack of effect heterogeneity explained why experimental findings from MTurk samples usually generalize to experiments using population-based samples (see also Mullinix et al., 2015; Weinberg et al., 2014). We followed

standard practices for using MTurk samples (Levay, Freese, & Druckman, 2016; Peer et al., 2013; Shank, 2016).

In total, 1271 respondents began the survey with 1213 complete responses recorded. We excluded 45 cases with item nonresponse on key variables. We removed an additional 21 cases without a valid driver's license to increase the internal validity of the experimental videos. Our final analytic sample consists of 1147 participants. Consistent with other MTurk studies, our sample is 56% male, 67% non-Hispanic White, 80% employed, and has an average age of about 38 ($SD = 12.47$; range = 18–78).

3.2 | Experimental speeding videos

As already discussed, a strong test of the effects of ambiguity on crime decisions should utilize a methodology that presents study participants with rich, contextual information beyond that of short written scenarios, which may introduce imputation error (see van Gelder et al., 2019). Toward this end, we employed experimental videos depicting a car speeding on an interstate highway during the middle of the day (see Barnum et al., 2021). Importantly, the videos control for contextual risk factors that undoubtedly influence the decision to speed (e.g., time of day, lighting, physical surroundings like trees, traffic density and flow, weather conditions, etc.).³

In total, there are three versions of the scenario, each filmed from the vantage point of the driver and account for four factors related to speeding risk: (1) personal driving speed and style, (2) the speed and driving style of others on the road, (3) environmental features of the road (e.g., winding road, overpasses), and (4) perceived police strategies in the area (e.g., a speeding crackdown is underway). Version 1 depicts the driver getting passed by traffic in the right lane. Version 2 depicts the driver going with traffic in the left lane, and version 3 depicts the driver passing traffic in the left lane. All three versions showed the driver passing a 70-mph speed limit sign and were 15-s long. Respondents viewed all three traffic condition videos in random order, which allows for both between- and within-persons comparisons.⁴

In addition to the three traffic flow variants, two additional factors were manipulated. First, each video showed a speedometer in the lower left-hand corner displaying one of three randomly assigned driving speeds that was the same in all three traffic flow videos: 76, 82, or 86 mph (all of which are over the 70-mph speed limit depicted in the video). Second, an informational manipulation regarding the intensity level of policing was randomly assigned and then held constant in all three viewed traffic flow videos. Specifically, preceding each video, respondents were told: (1) "Imagine there have been recent budget cuts that has significantly REDUCED police patrol activity in this area" or (2) "Imagine a newly elected governor has committed to significantly INCREASING police patrol activity in this area."

The manipulations (traffic flow, speed, and police information) are intended to shape sanction certainty perceptions so that they range from low (e.g., 76 mph, getting passed, reduced police) to high (e.g., 86 mph, passing traffic, increased police). This allows us to test whether ambiguity about perceived sanction risk operates as an independent deterrent and, importantly, whether the effect of ambiguity on speeding intentions operates differently at different levels of perceived risk.⁵

The videos were embedded into a survey with a total of 2 (informational cue) \times 3 (speed condition) = 6 possible experimental conditions.⁶ Respondents first viewed the videos and rated risk, ambiguity, safety concerns, and intentions to speed after each video. Respondents then provided information on driving background and demographics.

3.3 | Measuring ambiguity

There is no widely agreed upon measure of ambiguity. Manski and colleagues (Manski, 2004; Manski & Molinari, 2010) measure ambiguity by asking survey respondents to provide a range of probabilities for the event of interest (e.g., chances of getting a disease) that the respondent is confident contains the actual probability of the event. Wider intervals are interpreted as implying more ambiguity than narrower intervals. The advantage of this elicitation method is that it measures ambiguity in the same metric as the quantity being elicited—that is, units of probability. Its main disadvantage is that in instances in which an interval range of the quantity being elicited is also obtained, the original point estimate may fall outside this ambiguity interval. This, for example, occurred for 30% of respondents in a pretest of this elicitation approach for this project. This inconsistency may occur because it is cognitively burdensome for some to express such an interval of confidence (see Pickett et al., 2015).

A second approach tested in Pickett et al. (2015) follows a recommendation in Loughran et al. (2011, p. 1045) to first ask “how likely is it that you will be caught and arrested for crime X?” followed by the question, “how sure are you about this answer?” Pickett et al. (2015) concluded “these two methods produce measures that have more similarities than differences” (p. 636). The “sureness” question is also consistent with the suggestions for measuring ambiguity by Apel (2013) and Kleitman and Stankov (2007). Because of its ease of implementation, we use Pickett et al.’s (2015) “sureness” measurement question. Specifically, after participants rated the probability of getting pulled over for speeding under the conditions of the videos, we immediately followed up by asking: “How SURE or UNSURE are you about this answer?” The response categories for this item ranged from 1 = *Very sure* to 6 = *Very unsure*, thus higher scores represent greater levels of ambiguity.

3.4 | Perceived risks, cost, and intentions to speed

We measured *perceived certainty of being ticketed* by tasking participants to “Imagine you have been driving for approximately half an hour under the same conditions as in the video presented above. What is the PERCENT CHANCE (or CHANCES OUT OF 100) you would get caught by the police for speeding?” Participants were presented with this question on the survey immediately following all three video vignettes. We converted percentages into probabilities by dividing participants’ estimates by 100 so that scores ranged from 0 to 1.

Barnum et al. (2021) demonstrated that net of perceived certainty, safety is another relevant consideration in the decision to speed. To measure safety concerns, we asked participants “How SAFE or UNSAFE would it be for you if you drove like the car in the video under these conditions?” Responses range from 1 = *Extremely safe* to 5 = *Extremely unsafe*. This was measured after all three videos and henceforth we refer to this variable as *perceived danger* due to the coding of the variable.

In addition to certainty and safety concerns, we captured *perceived fine of a speeding ticket* with the question “how much do you think the fine is in DOLLARS for driving [6/12/16, depending on their assignment] mph over the speed limit?” Participants were posed this question only once after they viewed all three videos.

Finally, *intention to speed* was measured by respondents’ answer to, “Now, thinking about the scenario above, if you were actually driving in these conditions, what is the percent CHANCE (or CHANCES OUT OF 100) you would actually drive at the same speed or greater as the car in the

TABLE 1 Driver characteristics ($N = 1147$)

Variable	Mean	SD	Min	Max
Speeding frequency	2.562	1.096	1	5
Highway driving frequency	3.520	0.977	1	5
Prior speeding tickets	1.601	0.972	1	5
Use of any police detector	0.271	0.445	0	1
Texting while driving	1.774	1.104	1	5
Aggressive driving	1.722	0.687	1	3
Impulsivity	2.443	1.030	1	5

scenario?" Respondents provided an intention estimate between 0 and 100, and responses were divided by 100 to reflect probabilities.

3.5 | Driver characteristics

We captured several driver characteristics to assess overall driving experience (see Table A1 for details). Driver characteristics are reported in Table 1 and show that on average, our sample consists of experienced drivers, who drive between 11 and 15 miles per day, drive on an interstate highway at least weekly, and speed on the interstate highway about half of the time. We interpret this to mean the current sample is well suited to rate speeding risk, and the attendant ambiguity about these risks based on our videos.

4 | RESULTS

As a prelude to the discussion of the influence of ambiguity on the decision to speed, we summarize the impact the experimental manipulations have on perceived certainty, danger, and intent. These analyses provide an important initial step in testing our generalized model of idiosyncratically coherent risk perceptions. The results presented in Table 2 replicate the findings by Barnum et al. (2021) and confirm that within the present sample perceptions are coherently anchored in the objective features of the videos.

On average, the assigned speed condition had a large and highly significant impact on perceived risk of being ticketed that increased from 0.26 in the 76-mph condition to 0.56 in the 86-mph condition. The traffic flow condition also had a similarly large and highly significant impact on risk perceptions: the mean level of perceived certainty increased from 0.30 in the being passed video to 0.48 in the passing scenario. The assigned enforcement condition also had a material and highly significant impact on perceived risk with perceived risk of participants assigned to the increased enforcement condition being nearly 30% larger than those assigned to the reduced enforcement condition. Results in Table 2 also confirm that perceived danger, perceived ticket cost, and intentions to speed are also grounded in the objective features of the videos.⁷

Table 2 includes perceptions of ambiguity about the certainty of getting pulled over. Our theory of ambiguity makes no predictions that ambiguity will systematically vary across the experimental conditions. Although there are some statistically significant differences, no discernable patterns

TABLE 2 Summary statistics for situational perceptions and intentions by experimental conditions (N = 1147)

Variable	Full sample			Speed condition			Police enforcement condition		
	Mean	SD		76	82	86	Reduced	Increased	p-value
Perceived certainty									
Getting passed	0.305	0.296	0	0.262	0.304	0.350	0.278	0.334	**
Going with	0.376	0.290	0	0.321	0.373	0.434	0.333	0.420	***
Passing	0.485	0.285	0	0.418	0.484	0.555	0.414	0.559	***
Perceived ambiguity									
Getting passed	2.228	1.067	1	2.091	2.245	2.349	2.230	2.226	ns
Going with	2.503	1.085	1	2.348	2.562	2.601	2.471	2.537	ns
Passing	2.525	1.054	1	2.491	2.546	2.539	2.591	2.457	*
Perceived danger									
Getting passed	2.562	1.074	1	2.236	2.615	2.836	2.620	2.502	ns
Going with	2.648	1.081	1	2.323	2.657	2.969	2.677	2.620	ns
Passing	3.064	1.148	1	2.657	3.116	3.419	3.079	3.048	ns
Perceived fine	213.958	481.481	0	150.656	258.673	233.292	238.672	188.545	ns
Intention to speed									
Getting passed	0.541	0.339	0	0.635	0.519	0.469	0.538	0.544	ns
Going with	0.500	0.341	0	0.612	0.477	0.412	0.497	0.503	ns
Passing	0.407	0.332	0	0.516	0.374	0.329	0.418	0.395	ns

Abbreviation: ns, not statistically significant.
^ap-values from one-way ANOVA.
^bp-values from two-sample t-tests.
 *p < 0.05; **p < 0.01; ***p < 0.001.

TABLE 3 OLS and fixed effects regressions predicting ambiguity

Variables	Getting passed <i>b</i> (<i>SE</i>)	Going with <i>b</i> (<i>SE</i>)	Passing <i>b</i> (<i>SE</i>)	Fixed effects <i>b</i> (<i>SE</i>)
Perceived certainty	3.716* (0.356)	3.168* (0.380)	1.624* (0.404)	5.121* (0.232)
Perceived certainty ²	-4.265* (0.417)	-4.122* (0.424)	-2.954* (0.412)	-5.196* (0.245)
Perceived danger	0.258* (0.027)	0.237* (0.028)	0.159* (0.025)	-0.000 (0.021)
Intercept	1.204* (0.078)	1.611* (0.087)	2.185* (0.102)	1.679* (0.055)

Note: Standard errors in parentheses. Cross-sectional $N = 1147$; fixed effects observations $N = 3441$ (three observations nested in each person).

* $p < 0.001$.

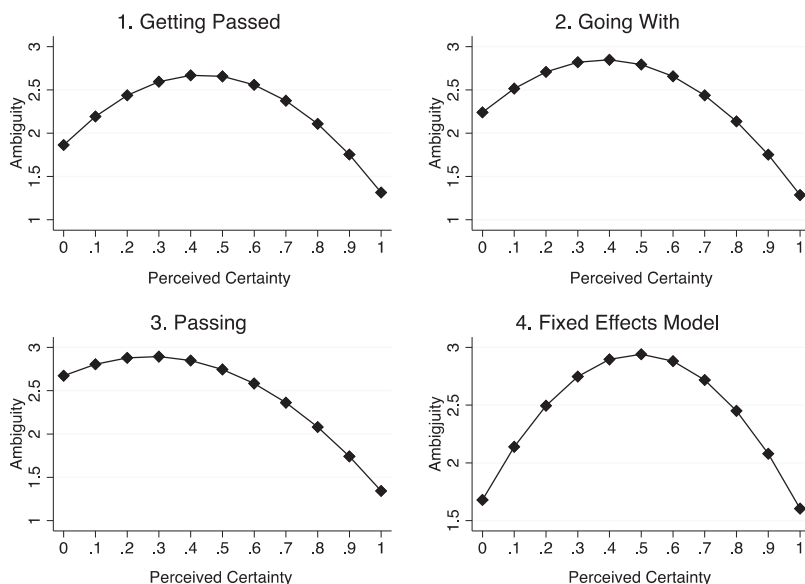


FIGURE 4 Predicted ambiguity across point estimates of perceived certainty

emerge across the speed and traffic condition manipulations and, interestingly, perceived ambiguity is unrelated to the police information manipulation—a finding that appears most consistent with trait-based predictions about ambiguity sources.

Next, we explore the interrelationship between ambiguity and certainty perceptions as identified in prior works. Specifically, we test whether in our data we find the same inverted U-shaped relationship between ambiguity and certainty that maximizes at or around 0.5 previously identified in Manski (2004) and Pickett et al. (2015, 2016). Table 3 reports regressions of perceived ambiguity as a quadratic function of certainty and dangerousness as a main effect only. Four versions of this basic regression are reported. Ordinary least squared (OLS) regressions are produced for each of three traffic videos and a person fixed effect model that combines data across the three videos watched. All regressions find highly significant quadratic like relationships between ambiguity and certainty. Figure 4 displays plots of the four quadratic functions. All maximize around

0.5, thereby replicating prior research findings and further suggesting the effect of ambiguity on offending may also depend on how risky a person perceives an offending opportunity to be in the first place.

We also note that ambiguity has a significant negative association with danger in the traffic condition equations. The only individual baseline characteristic that is significantly associated with ambiguity is driving frequency. That association is negative, which implies that driving experience reduces ambiguity about certainty, a finding consistent with Bayesian-based theory of the source of ambiguity.

4.1 | Ambiguity and intentions to speed

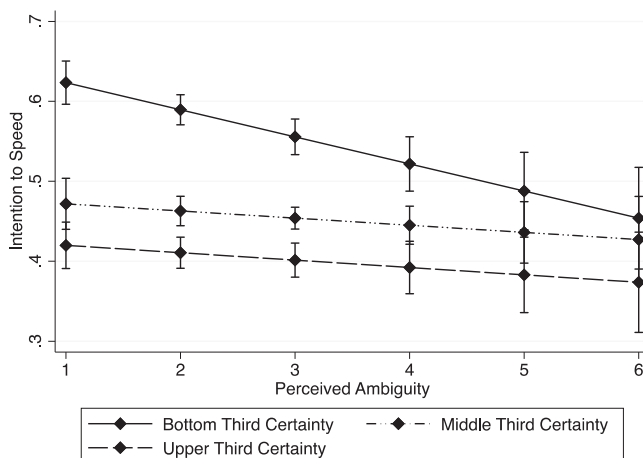
We turn now to testing the main predictions of our generalized model concerning the joint and interactive effects of ambiguity and perceived certainty on the intention to speed. Linear fixed-effects models were estimated for this purpose. Intent was regressed on perceived certainty, ambiguity, and danger for all three viewed videos while controlling for traffic conditions and video viewing order and a person-specific fixed effect. Results are presented in Table 4.

TABLE 4 Fixed effects regressions predicting intentions to speed

Variables	Model 1: Reduced model				Model 2: Full model with interactions			
	<i>b</i>	<i>SE</i>	95% CI		<i>b</i>	<i>SE</i>	95% CI	
Perceived certainty	-0.291	0.025	-0.339	-0.241	-	-	-	-
Perceived ambiguity	-0.025	0.005	-0.035	-0.014	-0.034	0.008	-0.050	-0.018
Perceived danger	-0.071	0.006	-0.083	-0.060	-0.076	0.006	-0.087	-0.065
Situational controls								
Getting passed (ref.)	-	-	-	-	-	-	-	-
Going with	-0.008	0.008	-0.022	0.007	-0.007	0.008	-0.022	0.008
Passing	-0.039	0.008	-0.056	-0.023	-0.045	0.008	-0.061	-0.028
First viewed (ref.)	-	-	-	-	-	-	-	-
Second viewed	-0.000	0.007	-0.015	0.014	-0.001	0.007	-0.015	0.013
Third viewed	-0.004	0.007	-0.019	0.010	-0.004	0.007	-0.019	0.01
Intercept	0.869	0.019	0.832	0.905	0.886	0.023	0.942	0.931
Ambiguity interactions								
Ambiguity × Low risk (ref.)	-	-	-	-	-	-	-	-
Ambiguity × Mid risk	-	-	-	-	0.025	0.010	0.005	0.045
Ambiguity × High risk	-	-	-	-	0.025	0.011	0.003	0.047
Perceived certainty								
Low risk (ref.)	-	-	-	-	-	-	-	-
Mid risk	-	-	-	-	-0.178	0.029	-0.234	-0.119
High risk	-	-	-	-	-0.228	0.011	-0.289	-0.167

Note: 95% confidence intervals presented. Cross-sectional $N = 1147$; fixed effects observations $N = 3441$ (three observations nested in each person). Bold = $p < 0.05$ or less.

FIGURE 5 Marginal effects for the interaction of ambiguity and perceived certainty



Model 1 includes only main effects with the aim of identifying the effects of ambiguity on intent net of the two other relevant rational choice considerations: certainty and danger. The result is consistent with the prediction that ambiguity has a negative and highly significant association with intentions to speed ($p < 0.001$), net of the highly significant negative associations of perceived certainty and danger (both significant at the 0.001 level). The findings imply that respondents are generally ambiguity averse even after accounting for ticketing risk and safety considerations. We note, however, that effect size and elasticity calculations suggest that the magnitude of ambiguity's impact on intentions is half or less of the magnitudes of certainty and danger impacts.

We turn now to testing the prediction concerning the interaction of the deterrent effect of certainty with ambiguity. In the context of the NSL model, we expect that lower probabilistic estimates of certainty that have high levels of ambiguity will serve to increase the deterrent effect, whereas the opposite will occur for higher probabilistic estimates. To construct this test, indicator variables were constructed binning respondent risk estimates into the bottom third ($\leq 18\%$), middle third ($>18\%$ but $\leq 50\%$), and top third ($>50\%$) of the sample's risk estimate distribution. The indicator variable was then interacted with perceived ambiguity.

Results for this moderation analysis are reported in Model 2. Consistent with the boundary effects hypothesis, the effect of ambiguity on intent depended on the point estimate of certainty such that increases in ambiguity around point estimates of 18% or lower resulted in significant reduction in intentions to speed. On the other hand, increased ambiguity about estimates in the middle and upper third of the probability continuum (i.e., 19% and greater) reversed the effect of ambiguity on intentions to offend so that participants reported a greater willingness to speed. This finding implies that the presence of ambiguity enhances the deterrent effect of certainty at low probabilities, but as perceived certainty increases the deterrence enhancement diminishes in magnitude and eventually reverses itself to mitigate deterrent effects at higher probabilities. It never, however, reverses the sign of the deterrent effect of certainty. A graphical depiction of the interaction is presented in Figure 5. It is important to note, however, there are no statistically significant differences between the interactive effects of being in the mid or upper tier of risk on intent suggesting that effect is largely driven by low probabilities.

We tested the robustness of this interaction by both increasing and decreasing the "threshold" for being in the low-probability group. Specifically, we compared people with estimates equal to or less than 25% to the rest of the sample, as well as people with estimates equal to 10% or less, and results were substantively similar to the results discussed above.⁸

5 | DISCUSSION AND CONCLUSIONS

The underlying assumption of offender decision-making theory is that benefits and costs are weighed and that an action will be chosen if anticipated benefits exceed anticipated costs. From a deterrence standpoint, the probability and severity of punishment serve to offset anticipated gains from law-breaking behavior. Thus, would-be offenders should take advantage of a criminal opportunity when the threat of sanction is perceived to be low and refrain when it is perceived to be high. This logic has motivated several “certainty-based” sanction policies aimed at reducing crime in specific areas (Apel & Nagin, 2011; Braga et al., 2014; Midgette et al., 2021; Sherman & Weisburd, 1995). Notwithstanding empirical support from deterrence-based studies, evidence from other decision domains and from within criminology shows that decision makers deviate from the axiomatic expectations of rational choice theory in predictable ways (e.g., Pickett, 2018; Pogarsky et al., 2017; Thaler & Ganser, 2015; Thomas et al., 2018; Tversky & Kahneman, 1992; see also Loughran, 2019; Pogarsky et al., 2018).

The aim of this study was to examine the effect on law-breaking decisions of one set of deviations from standard axiomatic model of decision making under uncertainty—ambiguity aversion and ambiguity seeking. Our central findings build on the Barnum et al. (2021) model of idiosyncratically coherent risk perceptions by integrating aspects of NSL’s model of target selection with recent insights on ambiguity and offending. We extended the Barnum et al. model to show how individual differences in ambiguity around perceptions of risk—which contributes to the idiosyncratic component—can deter behavior net of other traditional decision-making variables (e.g., risk and safety perceptions). Importantly, our findings also show that ambiguity has an asymmetric effect on intentions to offend depending on whether participants perceive an offending opportunity to be very low or high in sanction risk as defined by important situational determinants. That is, drivers in low-risk circumstances, such as driving only a few miles per hour over the speed limit consistent with other traffic, who are unsure about whether they will encounter a police officer, may in turn focus their attention on the prospect of getting caught and opt to further reduce their speed. However, as the circumstances change, and it becomes increasingly clear that the behavior is risky (e.g., driving well over the speed limit while passing other traffic), ambiguity about whether the driver will encounter a police officer opens for the possibility of success, which can increase the desirability of noncompliance. Thus, the impact of ambiguity on decision making can help make sense of counterintuitive deterrence outcomes (or lack thereof) under extreme circumstances, such as instances where certainty of detection is near certain, yet noncompliance is the result (e.g., Cherbonneau & Jacobs, 2019).

Our model extension serves to translate the logic of ambiguity aversion and ambiguity seeking into real-world offending opportunities in which offenders are attuned to observable contextual information. In so doing, it provides a theoretical lens for enhancing the effectiveness of routine deterrence tactics. The results have direct implications for police efforts to reduce speeding and reckless driving. Though often viewed as minor offenses, these behaviors contribute substantially to vehicle crashes, which cause far more injuries and deaths in the United States than does criminal violence (Wu et al., 2021). Indeed, traffic safety is the leading public safety concern for police in many jurisdictions and is one of the most frequent problems that police must manage daily (Terrill et al., 2014). Thus, leveraging ambiguity can be a useful tool for reducing reckless driving, that is, with an important caveat—sporadic enforcement of speed limit violations may serve to mute perceptions that “modest” speed limit violations can be done with impunity; however, ambiguity around more “severe” violations may perpetuate speeding.

In a recent study, Wu, Lum, and Koper (2021) found routine patrol levels, such as proactive and targeted policing, produce short-term reductions in crashes at the most serious crash hot spots but have less impact elsewhere. Extending our generalized model, these efforts may benefit from increasing ambiguity through sporadic and randomized enforcement in areas where the rate of accidents is “low” (e.g., long stretches of highway) (see also Wu & Lum, 2020). In low-risk situations, static approaches to speeding may be ineffective because they merely signal to a driver when to slowdown and subsequently speed up again, whereas randomized approaches disrupt this process forcing drivers to be more cautious about their driving for extended periods (see also Braga, 2007; Braga & Weisburd, 2010; Telep et al., 2014; Weisburd & Braga, 2006). Conversely, in situations where the rate of accidents is “high,” such as heavily traveled expressways, routine and continued enforcement is preferred. Here, consistent patrol and/or the use of automated enforcement practices (e.g., speed cameras) provides unambiguous signals to reduce speed throughout these high-risk areas (see Graham et al., 2019).

Policy makers in general may consider increasing perceptions of ambiguity around sanction threats for crimes that are normally difficult to enforce and consequently have lower rates of detection (which is the case for many crime types; see Apel, 2013). By way of example, consider another traffic safety concern aimed at deterring alcohol-impaired driving (DUI), which is an exemplar low-risk offending opportunity. Efforts to limit impaired driving in the United States are a costly endeavor, typically involving many police officers who are usually on overtime status. As such, implementation of these polices is rare in most communities, often limited to a few national holidays—consequently, the objective risk for a DUI arrest at any given moment is inherently low. Nevertheless, when implemented, evidence suggests that both directed patrols and sobriety checkpoints can effectively reduce impaired driving, as well as other alcohol-related outcomes such as crashes (Lacey et al., 2006; Shults et al., 2001; Stuster & Blowers, 1995; Voas et al., 1985).

Although not directly pertaining to DUI policy specifically, our findings offer insights for enhancing deterrence of DUI by increasing ambiguity. For example, randomizing sobriety checks by location, time of day, and day of the week should increase ambiguity about encountering checkpoints. This coupled with clear public announcements about the implementation of the checkpoints could increase the deterrent effect of such enforcement strategies without necessarily increasing the resources required for implementation. Indeed, Homel and colleagues (Homel, 1990; Homel et al., 1995) demonstrated the effectiveness of Random Breath Test (RBT) operations in Australia, which has more recently proven to be effective in the United States (Lacey et al., 2006).

Although prevention policies aimed at deterring “low-risk” crimes can benefit from the injection of ambiguity, there are several offending situations where the perceived certainty of detection is already high in which prevention policies should aim to remove as much ambiguity as possible. Consider the null effect findings of recent randomized experiments of swift, certain, and fair (SCF) punishment regimes compared to probation as usual (PAU) (e.g., Kleiman et al., 2014; Lattimore et al., 2016; O’Connell et al., 2016). One possible explanation is that the random component of drug tests introduces ambiguity for participants. By randomizing drug tests, participants do not know when or how often they will be tested. Furthermore, there appears to be heterogeneity across sites of these programs, even within replication sites that foster ambiguity. Humphreys and Kilmer (2020) note that the program design in the field experiments was less than stellar, and that the impacts reported might be explained at least in part by implementation fidelity. When a program is run differently than its design, each point of deviation can be a source of uncertainty or ambiguity for

participants. Thus, it is possible ambiguity serves as a mechanism for the lack of efficacy of these SCF programs.

Returning to our model extension, the more ambiguity a would-be offender perceives about the certainty of failing a drug test, the more they may reason that they are able to avoid detection despite the naturally high level of certainty. That is, increased ambiguity about perceived certainty, $\overline{PR}_i(c)$, skews the subjective distribution of $PR_i(c)$ such that part of the distribution falls below an actor's threshold, $PR(c)_i^*$, prompting law-breaking behavior. This point is bolstered by evidence from South Dakota's 24/7 Sobriety Project, which compared to programs like HOPE implements very frequent and regimented testing. Indeed, several studies have indicated that, at the county level, the program is associated with a 9%–12% reduction in substance-impaired driving arrests (e.g., for Online Early Unpaginated; Midgette et al., 2021).

Given the asymmetric influence of ambiguity on crime decisions, a specific focus of future research should be identifying individual traits and circumstantial factors that influence the variance of the subjective distribution of $PR_i(c)$. Understanding the sources of ambiguity will allow policy makers to more effectively take advantage of this variance thereby increasing deterrence for crimes that occur under low-risk circumstances as suggested by Sherman (1990) while further increasing deterrence by decreasing variance in high-risk situations such as in the types of policy implementations described in Midgette et al. (2021).

Although we did not directly test the sources of ambiguity aversion or seeking, our results do provide some insights for future research. Notably, the impact of ambiguity was “certainty dependent” such that ambiguity was greatest around risk estimates near 50%. This suggests that people treat low and high probabilistic estimates differently than mid-range estimates in the probability continuum (e.g., 40% to 60%), which may be interpreted more as a “50/50” guess rather than a linear ratio-level likelihood (see Pickett et al., 2015). Moreover, our results suggest the possibility of two different but complimentary sources of ambiguity in sanction risk perceptions. On the one hand, and in line with Pickett et al. (2016), we find no evidence that the law enforcement manipulation influenced perceived ambiguity. This is consistent with theoretical scholarship on dispositional ambiguity (Brim, 1955; Kleitman & Stankov, 2007) and might be suggestive of either an underlying general self-confidence trait or individual differences in ambiguity intolerance. Although participants lacking self-confidence might be disposed to overreport mid-range estimates of risk, those who are ambiguity intolerant may instead overestimate and/or underestimate risk by reporting very high or very low estimates (Pickett et al., 2015, 2016). On the other hand, we found a negative correlation between driving frequency and perceived levels of ambiguity about risk. This experiential effect is consistent with the Bayesian conceptualization of ambiguity suggesting that ambiguity diminishes as decision makers acquire new and relevant information (Manski, 2004). Given the potential theoretical and policy advancements, more work is needed to identify the sources of ambiguity about sanction certainty perceptions, and, importantly, how ambiguity factors into decisions to engage in a range of violent and nonviolent crimes.

Our experimental videos were advantageous for depicting realistic opportunities to speed by controlling for several environmental features that define an actor's risk-tolerance threshold, $PR(c)_i^*$. A useful next step would be to examine the effect of ambiguity on the decision to offend in other natural settings such as in neighborhoods in which randomized police presence is being monitored. Researchers could survey residents with instruments that measure both subjective expectations about getting arrested and the perceived ambiguity about this estimate (see, e.g., Haberman & Ratcliffe, 2015; Ratcliffe et al., 2015; Weisburd et al., 2011). This would also allow researchers to explore the effects of ambiguity on other types of lawbreaking more typically examined in deterrence research.

In summary, our results depict a complex relationship between ambiguity, perceived sanction certainty, and intentions to offend. Although people generally appear to be aversive toward ambiguity when deciding whether to speed, in situations in which the probability of getting ticketed is perceived to be low—as when driving only 6 mph over the speed limit while getting passed by other cars—increased ambiguity enhances deterrence and encourages (seemingly irrational) legal compliance in the absence of risk. As such, researchers should think carefully about the effects of ambiguity when analyzing the efficacy of certainty-based policies, because as we and others have shown, the injection of ambiguity can both increase and decrease legal compliance.

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CONFLICT OF INTEREST

The authors confirm that they have no conflict of interest to declare.

ORCID

Timothy C. Barnum  <https://orcid.org/0000-0001-7843-4579>

Daniel S. Nagin  <https://orcid.org/0000-0003-0075-1851>

ENDNOTES

- ¹ There was also a strong correspondence in perceptions of apprehension risk based on traffic conditions (i.e., getting passed, going with, or passing other cars on the road) between citizens and police officers, further demonstrating the coherent grounding of sanction risk perceptions for speeding in the operant conditions of the offending opportunity.
- ² The authors treated the variance of an individual's subjective risk distribution, across two types of crime class, as an empirical approximation of that individual's subjective distribution of risk, or ambiguity, rather than directly querying about respondent's perceived level of ambiguity about each probability.
- ³ The videos were filmed on the same 1-mile stretch of highway that had a speed limit of 70 mph and was moderately traveled. The videos were filmed in a natural setting over the course of about 1 h.
- ⁴ Note we also estimated the experimental analyses presented in Table 2 using information from the "first-viewed" video to ensure between-subjects analysis. The results from these analyses were substantively similar to those presented below. Furthermore, we included "video order" variables in the fixed-effects analyses, which were not statistically related to our speeding outcome. These analyses provide confidence that ordering as well as joint evaluation of the videos had little effect on our interpretations.
- ⁵ Although it is difficult to determine the extent to which online survey respondents engage in other activities at the time of the task, the consistency of results presented below, and with prior experiments using similar designs (e.g., Barnum et al., 2021), suggests respondents actively viewed the content of the videos.
- ⁶ This results in nearly 200 participants per experimental condition providing adequate statistical power to detect treatment effects (e.g., Auspurg & Hinz, 2014; Mutz, 2011).
- ⁷ Importantly, safety and ticket cost perceptions are unaffected by the enforcement condition, a situational factor that, unlike risk of detection, is objectively unrelated to safety concerns.
- ⁸ Specifically, as ambiguity increases, estimates of certainty at 25% or lower, compared to larger estimates, were associated with a unit decrease in intentions to speed of -0.043 ($SE = 0.009$; $p < 0.001$), and estimates of certainty at 10% or lower resulted in a -0.023 ($SE = 0.009$; $p < 0.05$) unit decrease in intent.

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APPENDIX

TABLE A1 Driver characteristic measurement description

Variable	Question wording	Measurement
Speeding frequency	When driving on an interstate highway with a speed limit of 70 mph, how often do you speed?	1 = <i>Never</i> to 5 = <i>Always</i>
Highway driving frequency	How frequently do you drive on interstate highways?	1 = <i>Never</i> to 5 = <i>Daily</i>
Prior speeding tickets	In the past 5 years, how many speeding tickets have you received?	1 = <i>None</i> to 5 = <i>Four or more</i>
Use of any police detector	Do you use a radar detector or navigation app (e.g., Waze) to detect police in your area?	0 = <i>No</i> ; 1 = <i>Yes</i>
Texting while driving	How often do you read email or text messages while driving?	1 = <i>Never</i> to 5 = <i>Always</i>
Aggressive driving	Would you describe yourself as MORE or LESS aggressive than the average driver?	1 = <i>More aggressive</i> to 3 = <i>Less aggressive</i>
Impulsivity scale	Thinking about yourself, how much do you AGREE or DISAGREE with the following statements?	1 = <i>Strongly agree</i> to 5 = <i>Strongly disagree</i> (reverse coded)
	(1) act on the spur of the moment without stopping to think; (2) don't devote much thought and effort to preparing for the future; (3) do whatever brings me pleasure here and now, even at the cost of some distance goal; and (4) more concerned with what happens to me in the short run than in the long run ($\alpha = 0.863$; Grasmick et al., 1993).	