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ARTICLE

Can the group disincentivize offending? Considering opt-out thresholds and decision reversals*

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Abstract

Scholars generally agree that offending decisions occur in social context, with some suggesting that choice models should explicitly integrate the notion that the deviant actions of others can incentivize offending. In this study, we investigate whether group settings can also disincentivize deviant action via reverse bandwagon effects, where individuals reverse their offending decision and express an intention to opt out of the criminal act. Based on survey data from three universities using hypothetical scenarios about theft and fighting, we find evidence of opt-out thresholds. Our findings indicate that deviant groups can serve as both an incentive and a disincentive, and that the relationship between group size and the perceived utility of crime is more complicated than prior work has suggested. Moreover, we find that these self-reported opt-out thresholds vary across scenarios, indicating that socially interdependent decision-making processes may be situation specific. In the end, the study underscores the importance of acknowledging the social context in offending decisions and highlights that group effects may be more complex and nuanced than previously discussed.

KEYWORDS

decision making, group effect, thresholds

Researchers in both psychology and sociology increasingly recognize that decision-making models should account for the fundamental ways social context shapes choice (Bruch & Feinberg, 2017; Larrick, 2016). Some criminologists have taken the same stance (Hoeben & Thomas, 2019), with Hochstetler (2001, p. 756) asserting that "the immediate allure of crime is incomprehensible without considering … enabling and constraining action by others." The idea that group settings can incentivize the decision to offend resonates in many descriptions of offending (e.g., Short & Strodtbeck, 1965), including Warr's (2002) contention that people who would otherwise not offend when alone can be tempted to do so in a group setting. Likewise, Osgood et al. (1996) called attention to group dynamics in their routine activities theory, arguing that when youth are around fellow adolescents in unstructured and unsupervised settings, it can make offending both easier (i.e., less risky) and more rewarding. More recently, McGloin and Rowan (2015) offered an interdependent decision model of offending by translating the basic tenets of Granovetter's (1978) threshold model of collective behavior to a criminological context.

Granovetter (1978) argued that the perceived utility of a behavior at least partly depends on how many other people are engaged in the act. Consistent with this view, McGloin and Rowan (2015) found that 40 percent of their undergraduate sample reported they would be willing to damage property or steal *only if other people started doing so first*. Thus, a substantial portion of the sample's willingness to offend would have been obscured if they had adopted an asocial view of choice and only asked subjects about situations in which they would offend alone. Therefore, the threshold model might offer insight on the social interdependencies that shape offending decisions (see also Gardner & Steinberg, 2005; O'Brien et al., 2011), broadening the consideration of how the group can serve as an incentive for crime (McGloin & Thomas, 2016). Yet, this may be a narrow and incomplete view of how the group shapes offending choices.

In an expansion of the threshold model, Granovetter and Soong (1986) incorporated the notion of a *reverse bandwagon* effect, proposing there is both a minimum opt-in threshold, at which enough people join to shift one's decision to act (i.e., Granovetter's initial proposition), as well as a maximum opt-out threshold, at which enough additional people join to shift one's decision back to nonaction (i.e., a decision reversal). If this is empirically true in an offending context, it would have notable consequences for our understanding of offending decisions. Deviant group settings have consistently been framed as inducements for offending, yet the notion of an opt-out threshold suggests they can also function as a *disincentive* for criminal action. Furthermore, although decision-making theories in criminology allow for individuals to change their mind about offending (e.g., Paternoster & Bushway, 2009), situational-based reversals have received minimal attention and the notion that the same factor may shift from incentivizing the decision to offend to disincentivizing such action is unique. Investigating "opt-out" thresholds can therefore expand our understanding of the interdependencies associated with the decision to offend, help clarify the ways in which situational elements shape offending decisions (Matsueda, 2017), and comment on the broader interplay between choice and peer influence (Hoeben & Thomas, 2019).

The current study considers whether others' deviant actions can prompt individuals to opt out of offending. That is, we examine the extent to which individuals reverse their offending intentions based on the increasing size of an offending group. Drawing on contemporary work highlighting the crime-specific nature of rational choice models of offending (Clark & Cornish, 1985; Shover, 1985; Thomas et al., 2020), we explore the prevalence and nature of opt-out thresholds for two different criminal scenarios. Taking a cue from prior work measuring opt-in thresholds, we use hypothetical vignettes with a sample of students from three different universities to identify opt-out thresholds for fighting and theft. In the end, this study expands our understanding of the interdependent nature of offending decisions and suggests that the discipline may need to be more nuanced in discussing how the offending behavior of others shapes choice.

1 | THRESHOLDS AND THE DECISION TO OFFEND

A core tenet of the social sciences is that the actions of others can fundamentally change decision-making and behavior. For such reasons, psychologists and sociologists observe that "asocial" models of choice are underdeveloped and fail to reflect reality (Bruch & Feinberg, 2017, p. 210; Larrick, 2016). In most cases, scholars discuss how the actions of others can promote conformity with the group. Perhaps the most well-known example comes from Asch's (1951) "vision test," in which individuals were asked to identify a match for a line with one of three other lines that were clearly not of the same length. Despite the correct answer being obvious, most participants who took the test with confederates that identified an incorrect match showed evidence of group conformity by likewise endorsing the wrong response. Research documents that the rate of conformity increases in more uncertain situations (Asch, 1952; Deutsch & Gerard, 1955), as well as when the confederate group increases in size (Asch, 1956).

There are also decision models describing "herding" in financial investments and market decisions. One leading explanation of why investors tend to make the same decision they see others make, and thereby converge around the same action, is what is known as a "cascading effect" (Bikhchandani et al., 1992; Welch, 1992). Information cascades occur when individuals make decisions based primarily on the actions of other people—for example, deciding to sell short on a stock—even when their own personal information does not support (or even contradicts) such decisions. The general idea is that people assume, based on observed behavior, that others must know some information they do not and update their decision calculus accordingly, resulting in sequential adoption of the same behavior. Such tendencies have contributed to seemingly unexpected crashes in the stock market because investors, observing large firms and others selling stocks in large quantities, begin "dumping" stocks even further en masse (Bernhardt, 1987). Put simply, investors' subjective beliefs of the costs and benefits of an investment decision may shift based solely on what they observe others doing.

Another seminal perspective on bandwagon effects rooted in expected utility theory was inspired by Schelling's (1971, 1972) residential segregation model, which argued that people make decisions about whether to move out of their neighborhoods based on how many same-race people have migrated out and/or other-race people have moved in. Granovetter (1978) expanded this argument to collective action more broadly, arguing that behavioral choices are interdependent and at least partly based on the behavior of others.[1] He stated that, when deciding whether to engage in an action, individuals have a "threshold" ranging from 0 (i.e., individuals with a high propensity for the behavior under consideration who do not need others to participate first to see acting as having utility) to 1 (i.e., individuals who join once 100 percent of others participate first). In Granovetter's (1978) model, a threshold represents the point at which the perceived utility of an action is great enough to spur participation: For example, if a person has a threshold of .2, then once 20 percent of people present in the situation have participated in some action, he or she will view the utility of engaging in the act as greater than the disutility. If fewer than 20 percent of the present people participate, however, then this person will not have an intention to act because their utility threshold has not been met. When presenting his model, Granovetter

[1] Readers are likely familiar with another interdependent approach to decision-making: game theory. But the models discussed here (bandwagon, herding, threshold) argue decisions are made in sequence, whereas game theory focuses on decisions made in parallel (Macy, 1991). Threshold models also acknowledge that people do not always know the "rules" in interdependent decision-making (i.e., how others' behavior shapes their outcomes and vice versa), rather than assuming a known outcome set and stable preferences.

(1978) argued that it was applicable to a range of collective behaviors, including voting, consumer demand, strikes, and migration; indeed, the threshold concept has been integrated into models and empirical studies across such actions (Macy & Evtushenko, 2020).

McGloin and Rowan (2015) proposed the threshold model could provide insight on the decision to offend. They suggested individuals might be incentivized to offend as others joined in the act, given that this could lower the perceived risk of arrest (Granovetter, 1978); make crime both psychologically (through processes such as the diffusion of responsibility; Darley & Latané, 1968) and practically easier (Wright & Decker, 1994); and offer valued benefits such as heightened excitement and a sense of belonging (Katz, 1988; Osgood et al., 1996; Short & Strodtbeck, 1965). Research findings confirm that as the number of criminal accomplices increases (within a specified range set by researchers), the perceived formal and informal risks/costs associated with offending decline while anticipated rewards increase (McGloin & Thomas, 2016). This underscores the idea that decisions about offending can be socially interdependent (Hoeben & Thomas, 2019), and it aligns nicely with the broad literature affirming that exposure to deviant peers facilitates offending (McGloin & Thomas, 2019).

Importantly, however, if one takes the bandwagon, herding, and threshold models to their logical conclusion, they would suggest an infinite cascade in which group action grows unabatedly (Nelson, 2002)—that is, the portion of potential actors who ultimately decide to take part in an action should be strictly increasing. Baseline models about herding in investment decisions and bandwagon effects in voting assume such effects would be continual and monotonic—for example, once the information cascading process begins, only the lack of availability of buyers should interrupt the process. Yet, empirical observations do not bear this out (Hodgson & Maloney, 2013; Nelson, 2002). Instead, there may be a tendency for bandwagons to slow or even reverse. Indeed, Asch (1956) himself found that although conformity generally increased as group size increased, this effect plateaued at more than three confederates (see also Rosenberg, 1961; Stang, 1976). Latane and Wolf (1981) hypothesized that initially more sources of information increase the impact of a group, but eventually too many sources lead to diminishing and declining effects. Game theorists have also found countervailing effects of increasing group size, suggesting intermediate group sizes alter the utility in a way that evokes the most cooperation (Barcelo & Carpraro, 2015; Carpraro & Barcelo, 2015). Granovetter and Soong (1986) explicitly addressed this issue of decelerating and reversal effects in their expansion of the threshold model by appealing to the documented "snob" effect in studies of consumer demand (Leibenstein, 1950).

1.1 | Opting out and decision reversals

In his initial presentation of the threshold model, Granovetter (1978, p. 1439) used the example of dining at a restaurant to allude to the idea that increasing numbers of people joining an act may encourage individuals to opt in to a behavior but also, at a certain point, prompt decisions to opt out: "[I]f the place is nearly empty, it is probably a bad sign-without some minimal number of diners, one would probably try another place. But the curve will cross the x-axis again at a later point-where the restaurant is so crowded that the waiting time would be unbearable." Later, Granovetter and Soong (1986, 1988) explicitly incorporated the idea of decision reversals by acknowledging that collective behavior of others can also lead to a *reverse bandwagon effect*. Leibenstein (1950, p. 196) defined a reverse bandwagon, or "snob" effect, as a negative relationship between an individual's consumer demand and the overall market demand. Whereas some people are more likely to consume a product as the number of others who do so increases (bandwagon effect), others are *less* likely to consume a product as it becomes more popular (reverse bandwagon). In most cases, bandwagon and reverse bandwagon effects are seen as a function of between-person differences (Kuwashima, 2016; Vigneron & Johnson, 1999). That is, when individuals are aware of the popularity of a product, some of them will respond by joining the bandwagon and purchasing the product whereas others (e.g., hipsters) may derive utility from uniqueness and avoid the purchase altogether (see Niankara, 2009).

Granovetter and Soong (1986, 1988) took a somewhat novel view in arguing that a person could sequentially engage in both a bandwagon and a reverse bandwagon. In providing a consumer demand example, they stated "there may be many products that people are unwilling to purchase until some minimum number of others has, but that also becomes less appealing once some maximum number is exceeded" (Granovetter & Soong, 1986, p. 85). Thus, they assumed that individuals act because their initial thresholds are met, but that "if a group exceeds some still *higher* proportion, they might change their mind" (Granovetter & Soong, 1988, p. 86, emphasis in original).[2] Accordingly, any attempt to understand the broader relationship between group size and the perceived utility of a behavior must consider both the initial decision to act *and* possible decision reversals. Consider a case where there is a bandwagon effect in intentions to vote for a particular political candidate, such that individuals begin to endorse her as she gains support from others. As support increases, however, some of her backers may change their mind, now viewing the candidate to be "too mainstream" (for related research, see Hodgson & Maloney, 2013). This means that if one were to only consider initial opt-in decisions for voting, it would give an inflated sense of the candidate's election chances as some of her initial base of support drops away. Instead, current snapshots of intended voting action for this candidate would inherently reflect both those still on the bandwagon and those who changed their mind.

Granovetter (1978) leveraged rioting behavior as an example when presenting his initial opt-in threshold model, but he shifted focus to consumer demand when expanding the model to include opt-out decisions (Granovetter & Soong, 1986); this raises the question of whether reverse bandwagons translate to an offending context. If opt-out thresholds do exist for offending decisions, it would suggest that the perceived utility of a criminal act can reverse based on situational factors and that, counter to the framing of group effects in criminology, the deviant behavior of others can induce a decision to *stop offending*. From our view, there is reason to suspect that perceived risks, costs, and rewards may shift in meaningful ways such that increasing participation by others in a criminal act can lead individuals to see the action as having disutility rather than perpetual utility.

1.2 | Situational reversals in the decision to commit crime: The role of increasing group size

There is a broad literature on the decision to stop offending when framed as desistance (Bersani & Doherty, 2018), but a smaller research base on specific situational decisions to stop offending. Still, there is clear evidence of such changes, reflecting offenders' awareness of and responsiveness to factors such as alarm systems, lighting, security cameras, and police presence that impact

[2] It is important to recognize that simply stopping a behavior, or changing course, does not in and of itself suggest a reverse bandwagon. It could reflect a second bandwagon effect in which individuals follow the behavior of others who have already decided to change course (e.g., Hodgson & Maloney, 2013; Leibenstein, 1950; Sandell, 1999). In contrast, a reverse bandwagon involves people changing their mind because of the rising number of people who are engaging in the behavior, as opposed to following the example of others who may have already stopped.

perceptions of arrest risk (Apel, 2013).[3] As Cusson (1993, p. 62) argued, “it seems that fear of situational danger does lead to an abandonment of criminal projects.” For example, Grandjean (1988) observed that when people attempting to rob banks in Switzerland heard an alarm sound, most of them (nearly 70 percent) ran away. Furthermore, Wright and Decker (1994, p. 104) argued, “[Offender] decision making does not end with the selection of a target; indeed, the decision to commit a residential burglary is itself subject to reversal, at least in theory, until the offender has actually completed the process of getting into that target.”

Such research suggests that if new information emerges in a situation (e.g., the activation of an alarm), it can affect the decision calculus so that continuing to participate in a deviant act no longer has utility. Thus, there is evidence that certain situational factors may promote offending (including peers; Gardner & Steinberg, 2005) and other—different—situational factors may discourage offending (e.g., a capable guardian). But Granovetter and Soong’s (1986, 1988) argument departs from these studies in a crucial way. They do not suggest that opt-out decisions are only informed by the emergence of some new factor (e.g., the arrival of a police officer or motion-detected lights going on) but instead that it could be shaped by the same situational factor that can also incentivize action. Rational choice literature in criminology frames variables as either incentives *or* disincentives for offending; if factors serve as both, it is assumed this is only because the impact differs across people (i.e., some people may find the physical rush that comes with risky behavior to be pleasing, whereas others find it aversive; Deitzer et al., 2021). Yet Granovetter and Soong’s (1986) arguments also account for the possibility that the same person may view the group context as both an incentive *and* a disincentive depending on its dosage. Moreover, framing the group as a possible disincentive shifts the portrayal of group effects and offending decisions in fundamental ways.

Researchers have considered nonlinear peer effects on offending, which has been crucial in helping the discipline understand that the deviant behavior of others does not universally and infinitely amplify the decision to offend. For example, Rees and Zimmerman (2016) found evidence of a “satiation effect,” in which the incremental effect of one additional deviant friend on the respondent’s own deviance diminishes as the proportion of the friend group that is deviant increases (see also Zimmerman & Messner, 2011). Zimmerman and Messner (2011) identified a nonlinear effect of violent peer exposure on violent offending, where the impact decreases at higher levels of violent peer exposure (see also Vásquez et al., 2015); this same nonlinear form has been identified for the relationship between peer and one’s own substance use (Zimmerman & Vasquez, 2011). Such findings align with Tittle’s (1995) criticism of models like social learning theory, which hypothesized that the impact of criminogenic factors would be linear; instead, he argued that the more common something becomes, the more it becomes banal and ineffectual.[4] Yet the argument here goes further than these studies as it proposes an inversion in the relationship rather than simply diminishing returns. The key question then becomes: Why might an increasing number of people involved in a criminal act prompt a (reversal) decision to opt out of offending?

The perceived costs and rewards associated with offending could change in this way. Consider the following apparent paradox: Some evidence indicates that the perceived risk of arrest declines

[3] Nagin et al.’s (2015) model of choice likewise acknowledges individual thresholds—in this case, the degree to which the gains must exceed the risk in order for the individual to act on a criminal opportunity—producing variation in responses to features of the situation. Not all will be (de)incentivized by an opportunity the same way, depending on their threshold.

[4] To be fair, both Sutherland (1947) and Burgess and Akers (1966) allowed for the possibility of uncertain or diminished effects at a saturated level of deviant peer exposure.

as more people become involved in a crime (McGloin & Thomas, 2016), but at the same time, some evidence also indicates an objective "group hazard," such that group crime is more likely to come to the attention of police (Erikson, 1971; Hindelang, 1976). Tillyer and Tillyer (2015) found that the likelihood of arrest was significantly higher for robberies that involved multiple offenders, and Lantz (2020) found a hazard of arrest for robbery and homicide that generally increased as the group size also increased. Although speculative, perhaps people initially believe a group provides protection from individual sanctioning, but then they come to acknowledge a possible group hazard as larger numbers of people become involved in the criminal act and the likelihood of drawing attention increases. Additionally, individuals may come to see an offense as increasingly risky and uncertain as more people are involved, given the growing chance that accomplices may turn people into the authorities or that the situation could heighten the risk of physical danger (McCarthy et al., 1998). For example, Lantz (2018) documented with NIBRS data that the presence of multiple offenders exacerbated violence during an offense, increasing the likelihood of serious injury and weapon use.

In our view, a proper consideration of such potential mechanisms requires an acknowledgment that these will be situationally based decisions—that is, the calculus of risk and reward will be tied to how increasing group size affects anticipated outcomes associated with a particular crime in a specific situational context (Granovetter, 1978; McGloin & Rowan, 2015). As Thomas et al. (2020, p. 485) stated, "a central component of mathematical rational choice theory is … that responsivity to incentives [and disincentives] will be crime specific." Different types of crimes, and the different situations in which they are embedded, carry different risks and rewards (Clarke & Cornish, 1985; Shover, 1985), and these may change in particular ways as the number of other people involved increases. To be sure, from a neutralization perspective, the ability to rationalize deviance varies across situations and there is within-individual variation in offending tendencies as a result (Thomas, 2019; see also Matza, 1964).

Still, considerations of criminal "situations" tend to overlook the social nature of crime and, when the group context is considered, often view it as static in nature. Crime is an emergent phenomenon that unfolds, and when others are present, the "incremental signaling" that alters momentum toward crime may be an equally important signal used to infer when to disengage from criminal behavior (e.g., Hochstetler, 2001; McGloin et al., 2011). Distinct changes may occur in outcome expectancies for different offending situations as group size grows, but many of these changes in risks and rewards coalesce around the notion that additional participants will eventually diminish the offense's utility. For example, individuals may come to view a robbery as increasingly costly as more people become involved because of potential harm to both the victim and the offender. Although one may perceive the risk of personal danger from victim resistance to be low if one to two co-offenders are present, thereby promoting an intention to offend, as more people join in the act, uncertainty increases and raises the potential risk of injury to involved parties if things get out of hand (Lantz, 2018; McCarthy et al., 1998). Shifting to theft, the perceived harm element may not resonate strongly; a few co-offenders may increase the expected monetary reward, but the calculation of diminishing financial gain as more people participate in stealing some fixed set of goods may well lead individuals to decide participation is no longer worthwhile when the offending group is large. Next, having other people involved in damaging or burglarizing a property may incentivize criminal action because perceived risks and costs (e.g., perceived responsibility) decline as perceived rewards increase (McGloin & Thomas, 2016); yet, if the involved offenders grow to a notable and obvious crowd, then one may come to believe a law enforcement response is increasingly likely. Thus, although these criminal situations hold unique considerations, they may similarly have an inflection point whereby the probability of (continuing) offending diminishes, albeit for different reasons and at different group sizes. These are hypothetical considerations, to be sure, but they draw on prior work and speak to the notion that it would be sensible to assume that opt-out thresholds and the decision reversals they prompt vary across criminal situations in meaningful ways.

2 | CURRENT STUDY

Existing research documents that peers provide situational benefits, intrinsic rewards, and shifts in the tolerance of risk, which incentivize the decision to offend (e.g., Gardner & Steinberg, 2005; Osgood et al., 1996). Even so, the utility derived from any situation may not be stable as the set of conditions that first prompted the decision to act changes. This introduces a possible second form of interdependency: Those who decide offending has utility may revert to perceiving it as having disutility as more people continue to join in the act (Granovetter & Soong, 1986). This study investigates opt-out thresholds using hypothetical vignettes that capture offending intentions for both fighting and theft. Documenting reverse bandwagon effects (e.g., opt-out thresholds) would run counter to the typical portrayal of how the deviant behavior of others can induce offending, but we nonetheless anticipate that some individuals will report decision reversals in both scenarios. We also anticipate there may be differences in these opt-out thresholds across the two offending situations, given that risk and reward perceptions are specific to the context at hand.

If this study finds that Granovetter and Soong's (1986, 1988) arguments have empirical support in an offending context, it will have compelling implications for both rational choice and the portrayal of peer effects in criminology. Rational choice models generally approach decision-making as an independent process, but evidence of thresholds will affirm how it has some dependency on social context (Hoeben & Thomas, 2019). Moreover, if our data reveal that the same factor can both encourage and discourage crime, it underscores the localized, situational nature of risk and reward updating (e.g., Briar & Piliavin, 1965; Wright & Decker, 1994). Such findings would also prompt new discussions in the peer influence literature, as it would suggest that deviant actions of others may not always encourage offending, but instead may become a disincentive at some point.

3 | DATA AND METHOD

3.1 | Sample

Data for this study come from surveys of undergraduate students at three different universities. Some scholars have argued that we should move beyond the "science of sophomores" when studying offender decision-making (Bouffard et al., 2008), but the threshold model explicitly aims to explain decision-making even among those individuals who do not have a preference for the behavior under consideration—indeed, the model is meant to capture people who might otherwise not offend if they were alone. In this way, the model embraces Osgood and colleagues' (1996) argument that situational factors can be influential enough to tempt even individuals with little to no propensity for crime. As they stated, "we reject a categorical distinction between offenders and nonoffenders. Instead, we assume that people vary widely in their susceptibility to deviance, that this variation is continuous … and that most people have the potential for at least occasionally succumbing to an opportunity for deviant behavior" (Osgood et al., 1996, p. 639). Of course, this does not mean that using a student sample captures the general population and it does run the risk of being biased toward the lower end of the criminal propensity spectrum.

In an attempt to broaden our student sample, we surveyed undergraduates at three universities across different regions: an East Coast U.S. state, a Western U.S. state, and a Canadian province. All three universities are public research institutions with large undergraduate enrollments (approximately 30,000 at each university) located in or near major cities. Researchers received permission to offer students enrolled in large sociology and criminology courses the opportunity to take a survey. The courses were selected based on the instructor's willingness to set aside class time for their students to take the survey (i.e., it was not a random selection). Researchers would visit a particular class and explain that the study was about decision-making, participation was voluntary, participants could choose to not answer any questions, and it would be anonymous. The survey, which was web-based via Qualtrics software, was completed while in class at that time and the researcher was available to answer any questions. Students accessed the survey via their smartphones, tablets, or laptops. A pilot study revealed that all students had access to such technology and were able to easily log onto the survey; furthermore, there were no indications during data collection that any students had barriers to accessing the survey. Using an online survey provided three key benefits: It randomized the order of the scenarios we used to measure thresholds; it activated relevant skip patterns based on respondent answers; and it used answers on prior questions to properly frame subsequent questions. In total, 2,057 students were given the opportunity to take the survey (i.e., they were present in classes on the days the researchers offered the survey) and 1,966 who were at least 18 years old consented to take the survey, resulting in a response rate of 95.6 percent (University 1 $n = 1{,}106$, University 2 $n = 289$,[5] University 3 $n = 571$). The overall sample is 35.5 percent male, with an average age of 19.4 [standard deviation (SD) = 2.05]. Furthermore, 55.2 percent of the sample self-identifies as White, 20.7 percent as Asian, 7.1 percent as Black/African American, 5.6 percent as Hispanic, and 11.4 percent as bi-/multirace or "other".[6] Compared with general samples in the United States, the sample is notably younger, more female and Asian, and less Hispanic. Moreover, as a university-based sample, it is not consistent with the demographic patterns typically observed in offender-based samples. Thus, it is important that readers appropriately bound the inferences drawn from our analysis and view this study as an initial exploration.

3.2 | Measures

This study uses scenarios to capture both the intention to offend (opt-in threshold) and, conditional on having that threshold, the intention to stop offending (opt-out threshold). Scholars have questioned the validity of behavioral intention measures when used as a proxy for actual behavior (Apel, 2013; Exum & Layana, 2018; Exum et al., 2012). Like Schelling's (1971, 1972) tipping point model, however, Granovetter's (1978) threshold model explicitly aims to explain when behavioral *intentions* change—that is, when the perceived utility of an act changes. Accordingly, both

[5] Data collection at University 2 ended earlier than anticipated as a result of Covid-19 closures and restrictions.

[6] A breakdown of the sample demographics by University, as well as comparisons of the sample demographics with University data if available, are in appendix A in the online supporting information. The most notable departure from the overall university demographics is that our subjects are notably more likely to be female, which likely reflects our decision to sample students in social sciences courses. Additional supporting information can be found in the full text tab for this article in the Wiley Online Library at http://onlinelibrary.wiley.com/doi/10.1111/crim.2021.59.issue-4/issuetoc.

Granovetter and Schelling argued that one straightforward way to capture thresholds is to provide respondents with a scenario that describes an opportunity for a particular behavior and then directly ask about the point at which they would decide to act (Granovetter & Soong, 1983, 1988; Schelling, 1972; see also McGloin & Rowan, 2015; Taylor, 1984). Granovetter and Soong (1988, p. 99) argued that if the research interest is in accurately measuring these opt-in and opt-out thresholds specifically, it is better to measure the intentions directly, rather than infer them from behavior: "[B]ecause it is direct, it does not suffer from the censoring and lag problems of revealed preference measures, and it appears empirically that respondents have no difficulty answering questions of this kind." Thus, we used hypothetical vignettes to query respondents about their thresholds for both a violent (fighting) and a property (theft) offense. The survey randomized the order of these scenarios, which are provided below:

Fighting Scenario: After attending a show in [the city named depended on university location], you walk back to a small parking garage with a group of about ten other people (some are your friends, and some are friends of your friends who you had not met before). You see that a stranger is sitting on the garage floor right near your cars and smoking a cigarette. As you get closer, you say, "Excuse me, can you move? We need to get to our cars." This stranger looks at all of you and says, "I will move when I'm done smoking. Until then, fuck off." A person behind you steps in and says, "Look, no one is looking for trouble, but it's time to move along, ok?" The stranger stands, says, "I said you can wait until I'm done smoking", flicks the cigarette at your face and then shoves one of your friends.

Theft Scenario: You attend an outdoor concert festival in [the city named depended on university location] that is supposed to feature several performers over the course of the afternoon and evening. About halfway through the festival, just before the headlining acts are supposed to start, the concert promoters get on the microphone and say that the concert festival is over and that everyone must exit the park. They do not give a reason for the cancellation but say that absolutely no refunds will be given for the tickets. As you start to leave the concert in a group of about 100 people, which includes your friends and other concertgoers, you hear someone say that people should take food and drinks from the promoters' concession stands in order to make up for the money spent on the tickets.

Note that the group sizes are different across different crime types to make the situations more realistic (e.g., it is unrealistic to assume a fight would involve 100 people), yet still allow for intuitive conversions to thresholds (i.e., threshold values easily reduce to proportions between 0 and 1). After reading the scenario, respondents were told to imagine themselves in this situation and were asked "if other people in the group started fighting/taking food and drinks, would you join in fighting him/taking some too?"[7] Subjects had three response options: 1) even if no one else did it first, I would do it; 2) if other people started doing it first, I would join; and 3) even if all 10/100 people starting doing it first,[8] I would not join in. If subjects selected the second option, they were then prompted to write in how many people would have to engage in the behavior first before they joined in.

Respondents who provided an opt-in threshold that was below the maximum number of possible people (i.e., fewer than 10 for the fighting scenario and fewer than 100 for the theft scenario)

[7] Respondents were told that "fighting" could include things like pushing, slapping, grabbing, or hitting.

[8] Whether the question specified "10" or "100" here depended on which scenario was in play (i.e., 10 for the fighting scenario and 100 for the theft scenario).

were then queried about their *opt-out threshold*. They were asked to imagine that their opt-in threshold was met (i.e., the number of people they said would need to act before they participated in the fight or theft; the survey reminded them of their opt-in threshold by specifying the number of people) and were asked if they would change their mind and stop fighting/stealing if more people joined in and started to fight/steal too. Response options included the following: 1) "Yes, I might change my mind and stop fighting/stealing depending on how many people joined in"; and 2) "No, I would not change my mind—I would still fight/steal even if all 10/100 people did it too." If the subject selected the first response option, they were prompted to provide the number of people who would have to take part in the act before they would change their mind and stop (subjects were reminded that this value should be greater than their opt-in threshold and would max out at 10 or 100, depending on the scenario).[9] Thirty two responses (across both scenarios) to the opt-out threshold value were either equal to or less than their opt-in threshold. Because these responses indicate a possible misunderstanding of the questions under consideration, these cases were coded as missing.

The survey also queried respondents about several items we use as covariates in part of our analyses. First, given that prior work has documented that impulsivity is related to opt-in thresholds (McGloin & Rowan, 2015), we include a measure based on the average response to the four items that comprise the impulsivity section of the Grasmick et al. (1993) self-control scale[10] (scale ranges from 1 to 6, with higher values indicating more impulsivity; mean = 2.90, SD = .86). Second, sensitivity to peer influence may relate to one's tendency to make decisions based on the behavior of others, so we measured resistance to peer influence as the average response to three items adapted from the Steinberg and Monahan (2007) resistance to peer influence scale[11] (scale ranges from 1 to 6, with answers coded so that higher values reflected greater resistance to peers; mean = 3.11, SD = .71). We also account for male, race, and age in these models, given that some prior work has documented differences in the group crime across these attributes (Reiss, 1988; van Mastrigt & Farrington, 2011).

3.3 | Analytic plan

Our analysis proceeds in stages. First, we investigate the presence of opt-out thresholds in our sample. This initially consists of graphing the cumulative distribution function of opt-out thresholds and then simultaneously considering intended movement in *and* out of offending by graphing the

[9] With few exceptions, subjects provided a single number when asked to identify the value of their opt-in and/or opt-out threshold. When individuals did provide a range (e.g., 5–6 people, 4+ people), we coded the threshold as the lower bound of the given range.

[10] The four items assessed agreement with the following statements: "I often act spur of the moment without stopping to think," "I don't devote much thought and effort to preparing for the future," "I often do whatever brings me pleasure here and now, even at the cost of some distance goal," and "I'm more concerned with what happens to me in the short run than in the long run." The alpha for the scale was .68.

[11] Subjects were asked to report how much they agreed with the following statements: "I think it's more important to be an individual than to fit in with a crowd"; "I sometimes go along with my friends just to keep them happy"; "I sometimes say things I don't really believe because I think it will make my friends respect me more." The alpha for the scale was low (.45), so as a sensitivity check we ran the regression model(s) with the individual items instead and the substantive results were the same.

difference in the opt-in and opt-out cumulative distribution functions for both fighting and theft. This will speak to whether the overall relationship between the number of other people involved in the criminal act and the subjects' intention to offend is different than what only considering opt-in thresholds would suggest.

Second, because the above-mentioned approach provides only an aggregate description of decision reversals in the sample, we conduct a group-based trajectory analysis to capture potential heterogeneity in threshold patterns across individuals, by scenario. Specifically, we estimate group-based trajectory models (GBTMs) using a logit link function to estimate individual differences in one's intention to engage in both fighting and theft conditional on the size of the deviant group. Mathematically, the estimated equations are the analog to the GBTM commonly employed in life-course criminology (see Nagin & Land, 1993), but rather than estimating the likelihood of criminal behavior over time, we estimate whether an individual intends to offend based on increasing numbers of others being involved. When estimating the GBTM, we follow Nagin's (2005, p. 61) suggestion that determination of the optimal number of groups is based on an interplay between "formal statistical criteria and subjective judgment." That is, we use a two-stage model selection process beginning first with using the Bayesian Information Criterion (BIC) as the basis for determining the optimal number of groups (D'Unger et al., 1998). Nonetheless, because the BIC is not the only metric by which to evaluate the optimal number of groups, we follow the recommendations of Nagin (2005) and balance the information provided by the BIC with model parsimony and rely on a model selection strategy that both fits the data well and reports informative and distinctive patterns in the data (see also Loughran & Nagin, 2006).

We then turn to a more formal assessment of whether self-reported opt-out thresholds differ across the two offending scenarios. Specifically, we estimate a Tobit regression (estimated in Stata) predicting the opt-out thresholds given their censored nature (Greene, 1997; Long, 1997; Tobin, 1958). Logically, this analysis focuses only on those individuals who *could* have an opt-out threshold: that is, individuals who reported an opt-in threshold and whose threshold value was lower than the maximum (i.e., an opt-in threshold < 1.0). Within this subsample, we set all respondents who indicated that they would not cease offending even if all 10/100 others joined in (i.e., those who are eligible to have an opt-out threshold but do not report one) at a value of 1.1, so that the model considers them right-censored observations. The model accounts for the aforementioned covariates and for the clustering of observations within the three different university settings, as well as for the fact that responses are nested within persons. Using a Tobit model assumes agreement with the proportionality assumption that the process producing variation in the censoring outcome is the same process that produces variation in the noncensored cases (Schmidt & Witte, 1984; Smith & Brame, 2003). This assumption aligns with the threshold model, as Granovetter (1978) viewed not having a threshold value in a particular situation (i.e., not opting in or not opting out) as part of the same choice distribution that includes other threshold values and, therefore, also suggested the same factors that affect an individual's threshold value likewise influence whether an individual identifies a threshold or not (i.e., whether an observation is censored). A likelihood ratio test of the proportionality hypothesis of the Tobit model (see Greene, 1997) indicated that we fail to reject this assumption (our chi-square test statistic was 9.30 with 12 degrees of freedom), which led us to conclude that the Tobit was appropriate for our analysis. Even so, we did estimate a Cragg (1971) double hurdle model as a sensitivity check and the opt-out threshold differences across scenarios were consistent with the Tobit model.

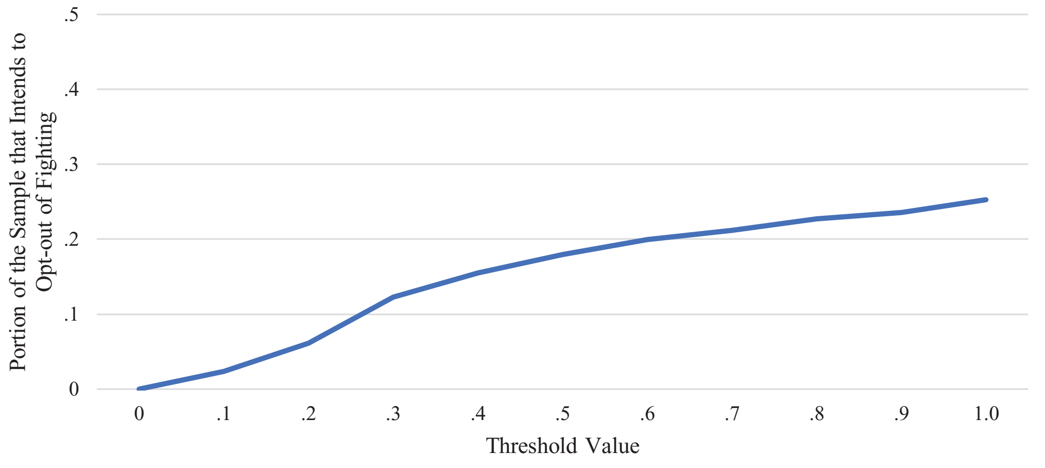

FIGURE 1 Opt-out threshold cumulative distribution function for the fighting scenario (N = 1,852) [Color figure can be viewed at wileyonlinelibrary.com]

4 | RESULTS

4.1 | Is there evidence of opt-out thresholds?

Among the cases with valid information on the opt-in threshold items for the fighting scenario (N = 1,852), 62.5 percent of subjects indicated that they would not offend even if all 10 people joined in fighting the stranger, 18.2 percent indicated they would fight the stranger even if no one else did (i.e., a threshold of 0), and 19.3 percent indicated that they would fight *only* if some number of other people did so first. Thus, nearly 38 percent of the sample has an opt-in threshold ranging from 0 to 1.0 for fighting under the specified conditions (mean = .19, SD = .27). Among those subjects who expressed an intention to fight, the clear majority indicated they would change their mind if more people continued to join in fighting the stranger—that is, they show evidence of a reverse bandwagon effect. Specifically, 68 percent of subjects who reported a fighting opt-in threshold also had an opt-out threshold, with the average respondent saying they would stop fighting at an opt-out threshold of .44 (i.e., once four to five people were involved in the fight; SD = .26).[12] Figure 1 provides the cumulative distribution function (cdf) of the opt-out thresholds for fighting for the whole sample: As Granovetter and Soong (1986) predicted, it is increasing and monotonic.

In turning attention to responses for the theft scenario (N = 1,847), 52.4 percent of subjects indicated that they would not steal food and drinks even if all 100 did so, 4.2 percent indicated they would steal even if no one else did (i.e., a threshold of 0), and 43.4 percent indicated that they would steal *only* if some number of other people did so first.[13] Therefore, nearly half of the sample has an opt-in threshold for theft under the conditions specified in the scenario

[12] Note that for both scenarios, subjects who have an opt-in threshold but not an opt-out threshold include those who expressly reported that they would not change their mind, as well as those whose opt-in threshold meant they could not have an opt-out threshold (i.e., opt-in threshold = 1.0).

[13] Although the majority of *responses* to each scenario was that the subject did not have an intention to offend, the majority of *respondents* did report an opt-in threshold for at least one scenario. To be clear, approximately 68 percent of subjects reported an opt-in threshold for at least one scenario.

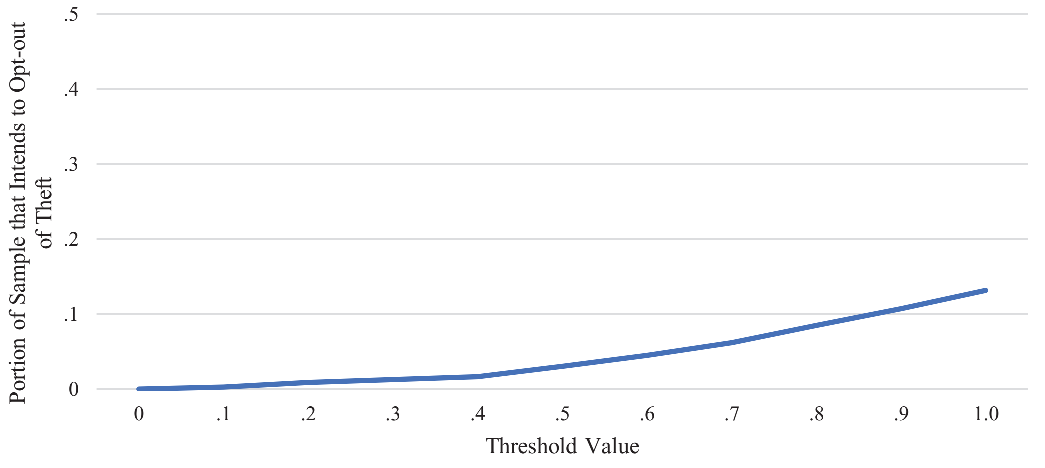

FIGURE 2 Opt-out threshold cumulative distribution function for the theft scenario ($N = 1{,}847$) [Color figure can be viewed at wileyonlinelibrary.com]

(mean = .43, SD = .29), and for most of them, intentions to offend depend on the actions of others (i.e., they show evidence of a bandwagon effect by having a threshold > 0). We likewise find evidence of opt-out thresholds, but decision reversals are not the modal response for this scenario. Among those subjects who had an opt-in threshold for stealing, approximately 27.8 percent indicated they would reverse their decision if more people continued to join the act. For these individuals who show a decision reversal, the average opt-out threshold was .72 (SD = .24), which translates into a decision to stop stealing once approximately 70 people were participating in the theft. Figure 2 provides the cdf of opt-out thresholds for the theft scenario, which is also increasing and monotonic.

Taking guidance from Granovetter and Soong (1986), we investigate the overall relationship between group size and the perceived utility of offending by considering the difference in the opt-in and opt-out cumulative distribution functions. Again, taking the difference means that one is simultaneously considering individuals' intentions to join and leave over increasing threshold values. For example, imagine an opt-in cumulative distribution function that indicates that 50 percent of people would intend to act at an opt-in threshold of .4, but a complementary opt-out cumulative distribution function that indicates that 15 percent of people would no longer engage in the act at this point. By taking stock of the individuals who would flow in *and* out of action, one realizes that the accurate portion of the sample that would intend to be engaged in the behavior at a .4 threshold is 35 percent. In this way, the difference between the two cumulative distribution functions provides a more comprehensive overview of the relationship between the range of threshold values and the intention to act. We plot this relationship alongside the opt-in threshold cdf to provide a sense of how (not) considering opt-out thresholds might provide a much different sense of the relationship between group size and the intention to offend.

Figure 3 focuses on the fighting scenario and provides both the opt-in cdf and the overall relationship between the intention to fight and the portion of others involved in the act (i.e., the difference between the opt-in and opt-out cdfs). Looking at that line, we see that approximately 18 percent of subjects said they would fight alone, and as threshold values grow, this portion increases to 21 percent, where it stabilizes for a bit around threshold values of .1–.2, and then downturns as more individuals' opt-out thresholds are taken into account, until it eventually stabilizes

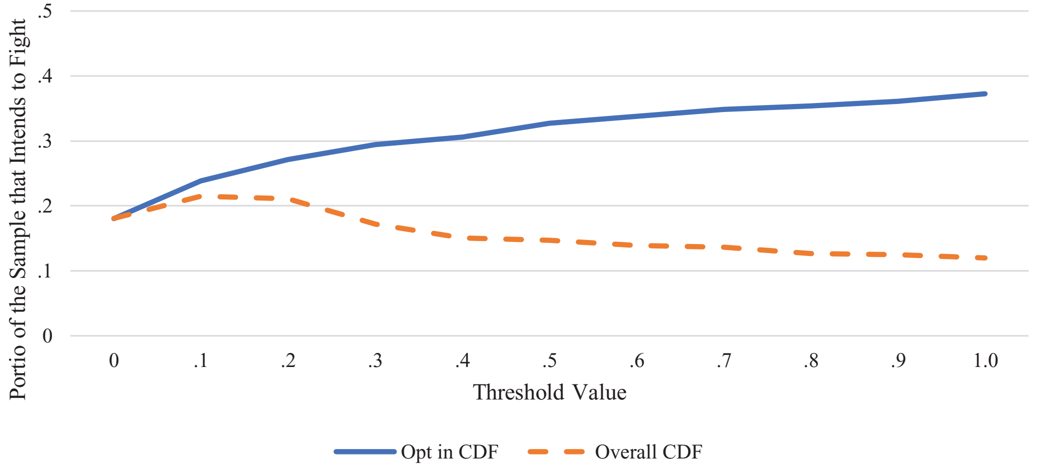

FIGURE 3 Opt-in threshold cumulative distribution function and the overall relationship between intention to offend and group size for the fighting scenario (i.e., the difference in the opt-in and opt-out cumulative distribution functions; $N = 1{,}852$) [Color figure can be viewed at wileyonlinelibrary.com]

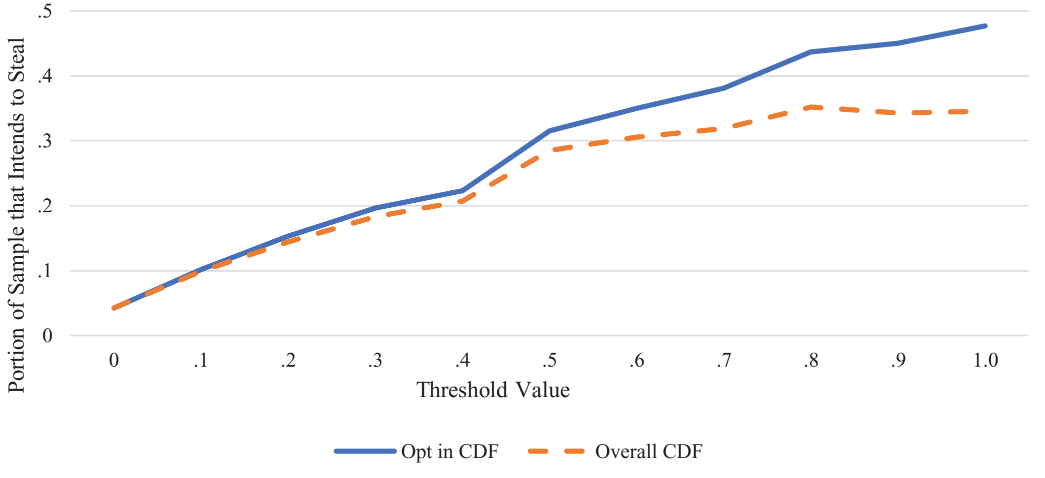

FIGURE 4 Opt-in threshold cumulative distribution function and the overall relationship between intention to offend and group size for the theft scenario (i.e., the difference in the opt-in and opt-out cumulative distribution functions; $N = 1{,}847$) [Color figure can be viewed at wileyonlinelibrary.com]

again around 12 percent starting around a .8 threshold value. Figure 3 confirms that, whereas the opt-in cumulative distribution function suggests that an increasing number of individuals would intend to fight as the number of other people involved continued to increase, accounting for the opt-out thresholds makes it clear that our sample, on average, appears to have a higher likelihood of deciding to fight when only a few others are involved as opposed to larger numbers of participants. For example, considering only opt-in thresholds would give the impression that 36 percent of subjects would act once a threshold of .9 was met; yet, when incorporating the opt-out thresholds, only ~12 percent of subjects would intend to still be fighting at that point.

Turning to the theft scenario, figure 4 demonstrates that the overall relationship between perceived utility of theft and the number of other people involved in the act generally remains

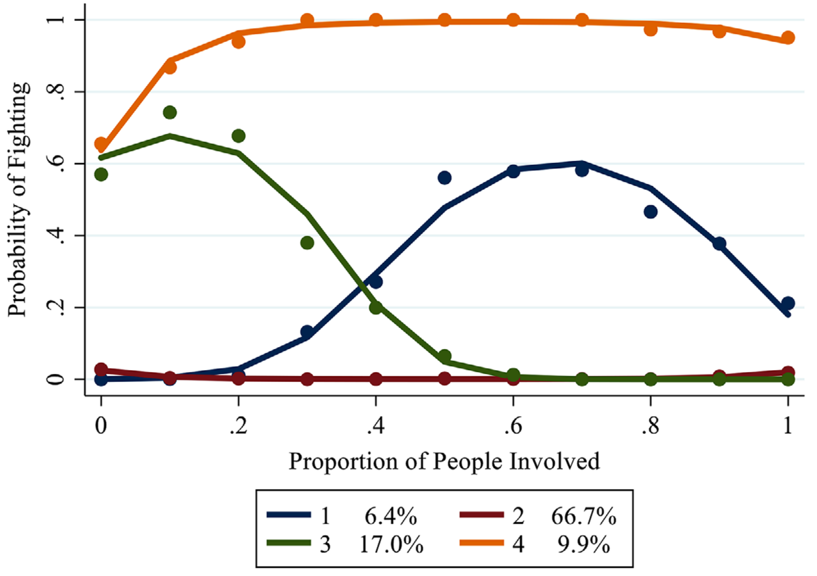

FIGURE 5 Group-based trajectories of the perceived utility of fighting by group size (N = 1,852) [Color figure can be viewed at wileyonlinelibrary.com]

positive. There is a very slight dip in the portion of the sample that views theft as having utility when the threshold value increases from .8 to .9, but this seems more reflective of a plateau rather than a negative turn. For responses to this scenario then, only considering the opt-in thresholds is not as misleading as it would be for the fighting scenario. For example, considering only the opt-in thresholds would give the impression that 45 percent of the sample would intend to steal at a threshold of .9, but when incorporating opt-out thresholds, this portion is closer to 34 percent. Appendix B in the online supporting information provides the range of cdfs discussed here when considering only those cases for which the subjects expressed an intention to offend (i.e., for those subjects with an opt-in threshold).

4.2 | Group-based trajectories of offending utility and group size

The cdfs offer a description of the aggregate patterns in the perceived utility of offending conditional on group size, yet there may be important variability across individuals. We identify subgroup differences in perceived utility by employing group-based trajectory models for both scenarios and present the findings in figures 5 and 6. Focusing first on fighting (figure 5), we identified four subgroups of individuals (BIC = −4,164.48; AIC = −4,123.05). Unsurprisingly, the most common group (~67 percent of the sample) are individuals who have a consistently low probability of expressing an intention to fight, regardless of the group size. The remaining individuals—those who at some point in the distribution are predicted to have a high probability of deciding to fight—demonstrate considerable differences in the conditional influence of the group. Two groups show a high probability of reporting intentions to fight either alone or when the number of people involved is very low, but they diverge as the number of people involved increases. One group (making up ~10 percent of the sample) has a high probability of deciding to fight alone and continues to have a high probability of fighting even as the proportion of others

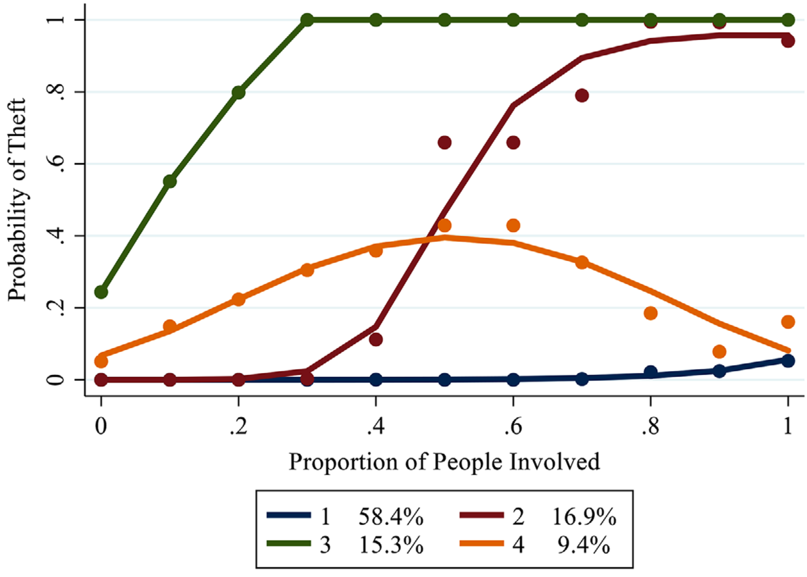

FIGURE 6 Group-based trajectories of the perceived utility of theft by group size ($N = 1{,}847$) [Color figure can be viewed at wileyonlinelibrary.com]

involved approaches 1. Another group (~17 percent of the sample), on the other hand, has a high probability of reporting an intention to fight when the number of people involved is low but a substantial decrease in such intentions after the threshold exceeds .2. The final group (~6 percent of the sample) reflects individuals who report an intention to fight only after around 40 percent of the group has already joined, but then they begin to demonstrate a sharp decline in their intentions to fight once threshold exceeds .7. Put simply, there appears to be important differences across individuals in the perceived utility of fighting based on the number of other people involved, with some groups showing evidence of the group becoming a disincentive.

Turning to the theft scenario, we again identified four subgroups of intentions to steal BIC = −4,839.58; AIC = −4,798.17), but the trajectories of these groups differ considerably from those for the fighting scenario. Almost everyone in the sample has a low probability of reporting an intention to steal when no one or only a few others have done so first. From there, the largest estimated subgroup comprises individuals who report a low intention to steal across the full range of threshold values (~58 percent of the total sample). Two additional subgroups differ in their initial opt-in thresholds, with one (~15 percent of the sample) showing sharp increases in the intention to steal when the number of people involved is small (after a threshold of approximately .1) and another (~17 percent of the sample) sharply increasing their intention to steal after a threshold value of about .4. What these two subgroups have in common is that once they opt-in, their probability of reporting an intention to steal remains persistently high even as the proportion of people involved approaches 1—that is, while demonstrating clear evidence of having an opt-in threshold, they do not appear to have a high probability of subsequently opting out. In fact, in the theft scenario, only one estimated group (~9 percent of the total sample) shows clear evidence of having an opt-out threshold. The trajectory of this group demonstrates an initial early increase in the intentions to steal (at a threshold of about .20) with a subsequent decrease in such intentions at a threshold of around .65. Thus, the trajectory analyses suggest there are differential patterns in the interdependencies of offending decisions across situations, though both affirm that at least some subjects reverse their intentions to offend because they come to view the group as a disincentive.

4.3 | Situational differences in opt-out decisions

The descriptive patterns in the data suggest there may be differences in opt-out threshold and decision reversals across scenarios, which we further explore by estimating a Tobit regression.[14] This model includes the aforementioned controls for impulsivity, resistance to peer influence, gender, race, and age.[15] The model accounts for nesting within the three universities by including university dummy indicators. Finally, the model also accounts for nesting of observations within persons by using Stata's (StataCorp, College Station, TX) vce(cluster) option. This is a modified version of the Huber/White sandwich estimator, relaxing the assumption of independent error terms (Froot, 1989; Rogers, 1993; Williams, 2000; Wooldridge, 2002).

As table 1 indicates, the findings suggest there is a statistically significant relationship between the scenario type and self-reported opt-out thresholds, net of controls [b = .571, standard error (SE) = .026, p < .001]. The coefficient produced by the Tobit model is difficult to interpret on its own, however, because it combines two effects into a single estimate (Roncek, 1992). We therefore decomposed the marginal effects of the predictor variables on their impact on the probability of having an opt-out threshold in the observed data (i.e., not being censored) and on the predicted value of the threshold given that they report a tendency to opt-out (using Stata commands *margins, dydx(*) predict (pr(0,1.01))* and *margins, dydx(*) predict (e(0,1.01)))*. These estimates are reported in the two right-hand columns of the table.

From these decomposed effects, we see that when responding to the theft scenario, subjects had about a 33 percent lower probability in the likelihood of having an opt-out threshold when compared with the fighting scenario (marginal effect = –.330, suggesting a higher probability of being censored). We also find that the decomposed marginal effect of the situation is related to the expected value of the threshold, if they report one. Specifically, the expected change in the opt-out threshold is .157 (or ~16 percent) higher in the theft scenario than in the fighting scenario, net of controls. In other words, if a subject reports an opt-out threshold, it is likely to be higher in the theft scenario compared with the fighting scenario. These results align with the descriptive information discussed earlier and highlight that, in our data, the group was more likely to be perceived as a disincentive in relation to the fighting scenario and that subjects tended to view it as such at a lower threshold value.

Three controls variables have a statistically significant relationship with the self-reported opt-out thresholds. Individuals with higher levels of impulsivity (b = .050, SE = .017, p < .01) are less likely to report an opt-out threshold (marginal effect = –.029), and if they do, the threshold value tends to be (slightly) higher (marginal effect = .014), net of covariates. That is, people with

[14] Given our article's focus, we do not have opt-in thresholds as an additional dependent variable. For readers interested in this question, McGloin and Rowan (2015) provided preliminary indications that situational variables, impulsivity, and moral beliefs were associated with differences in opt-out thresholds.

[15] We considered including the opt-in threshold value as a covariate. It is highly related to the scenario condition and other covariates, however. We are concerned that its inclusion could affect the overall model and make interpretations more complex and challenging. When estimating our tobit regression model with this covariate, the situational effect is consistent with what we report in the main text, but we still believe the prudent choice is to focus on the model presented here. We also note that when including this covariate in Cragg specification, the primary situational difference is with the probability of having an opt-out threshold.

TABLE 1 Tobit regression model predicting self-reported opt-out thresholds ($N = 1{,}484$)

Variables	Coefficient	Robust SE	Expected Probability	Conditional Expected Threshold Value
Situation (Theft = 1)	.571***	.026	−.330	.157
Impulsivity	.050**	.017	−.029	.014
Resistance to Peers	.010	.021	−.006	.003
Age	−.020*	.010	.012	−.005
Male	.021	.029	−.013	.006
Race (Reference = Other)				
White	.018	.048	−.010	.005
Black	.033	.069	−.019	.009
Asian	.021	.053	−.012	.006
Hispanic	−.037	.067	.022	−.010
University (Reference = University 1)				
University 2	−.068	.041	.039	−.019
University 3	−.073*	.036	.042	−.020

Notes: The sample size reflects the 1,507 cases in which subjects were eligible to have an opt-out threshold (i.e., they had an opt-in threshold and it was less than 1.0), excluding 19 cases with missing information on the opt-out value and 4 cases with missing information on the impulsivity covariate.
*$p < .05$; **$p < .01$; ***$p < .001$.

higher levels of impulsivity appear to be more likely to retain their intention to offend rather than reverse their decision, and if they do reverse their decision, it tends to occur toward the higher end of the threshold distribution. In our data, there is also a relationship between age and self-reported opt-out thresholds. ($b = -.020$, SE = .010; $p < .05$), although the substantive effect is small. When decomposed into the two effects, it suggests that older subjects are slightly more likely to have an opt-out threshold (marginal effect = .012) and that, when they do report an opt-out threshold, it tends to be minimally lower (marginal effect = −.005). Finally, the model indicates that respondents from one university (University 3 compared with University 1; $b = -.073$, SE = .036, $p < .05$) were more likely to report opt-out thresholds (marginal effect = .042), and when they did, it tended be lower in value (marginal effect = −.020). Being male, the various racial identities, and the resistance to peers measure do not have statistically significant associations with self-reported opt-out thresholds in our data.

5 DISCUSSION

In both academic and public discourse, the group context is often framed as a situational incentive to participate in risky behavior. For instance, investigations of the 2011 Stanley Cup Riot explicitly identified the crowd as an important explanation of violence and property crime committed after the event (e.g., Vancouver Police Department, 2011). As one rioter stated, "For reasons I can't really explain, I went from being a spectator to becoming part of the mob mentality that swept through many members of the crowd" (Kotylak, 2011, para. 4). This aligns with empirical work documenting that the criminal behavior of others can entice people to offend as it reduces perceived sanction risks and informal costs while amplifying anticipated rewards (McGloin & Thomas, 2016). Yet the social context of decision-making may be notably more complex, such that the group might also serve as a *disincentive* for offending. By applying Granovetter and Soong's (1986, 1988) extension of the threshold model to offending situations, we proposed individuals may have an "opt-out" threshold at which they will reverse their intention to offend. This view embraces the socially interdependent nature of choice (Hoeben & Thomas, 2019) and aligns with the view that, just as individuals update their perceived utility of crime across events (e.g., Anwar & Loughran, 2011; Thomas et al., 2013), they may also engage in localized updating *within* criminal events that can cause them to alter or reverse course (e.g., Wright & Decker, 1994). It underscores the idea that engaging in a criminal act is not simply the result of a static binary choice made at a single moment in a social vacuum, but instead it is a dynamic decision that is sensitive to social context and continues to unfold during the criminal event.

Our study offers preliminary evidence of decision reversals by documenting that, under certain conditions, the group can also serve as an offending disincentive. To be fair, some people in our data appear to only view the group as an incentive as they indicate an intention to offend only after some number of others do so first and do not change their mind even as increasing numbers of participants join. Yet our data also identified individuals who report they would change their mind and stop offending once a certain number of additional people joined in the act. Indeed, in nearly half of cases where subjects expressed an intention to offend, they also reported having an opt-out threshold. Within this group, we identified some situations where it appeared the group was *only* a disincentive, such that individuals indicated they would offend alone but then demonstrated a reverse bandwagon effect. And, we also observed situations where people endorsed both a bandwagon and a reverse bandwagon effect—that is, the group appears to have promoted and then deterred offending intentions for the same decision maker. This finding aligns most closely with Granovetter and Soong's (1986, 1988) argument that the behavior of others can shift from incentivizing action to disincentivizing action within individuals. Both cases of documented decision reversals suggest people use evolving situational cues to update the perceived utility of criminal action, which can lead them to abandon an offense.

Prior work outside of criminology has documented opt-out processes triggered by following others who have decided to change course (e.g., Sandell, 1999). This may be a part of how the behavior of others influences the decision to stop criminal behavior, but our data point to a decidedly different phenomenon. We uncovered evidence of a reverse bandwagon effect, which points to important nuances in the way that social interdependencies shape offending and urges scholars to reconsider the idea that criminal groups/others are always an offending risk (e.g., McGloin, 2009). It also indicates that only considering how the behavior of others can prompt decisions to offend gives a misleading sense of the relationship between group size and offending decisions as it predicts ever-increasing numbers of people are likely to join criminal acts.

Of course, this naturally raises the question of *why* some individuals demonstrate a reverse bandwagon effect. In broad terms, the underlying threshold model assumes that some portion of the cost–reward calculus shifts such that other people engaging in the offense no longer incentivizes action (Granovetter & Soong, 1986, 1988). But, as discussed earlier, a more thorough understanding likely rests in a micro-level, situational focus. As with prior work on the group nature of offending decisions (Granovetter, 1978; McGloin & Nguyen, 2012; McGloin & Rowan, 2015), we argued that a careful consideration of these interdependent choices must be rooted in situational, social context. For this reason, we anticipated that patterns of opt-out thresholds might differ across criminal situations. In our data, subjects were more likely to report opt-out thresholds when responding to our fighting scenario compared with our theft scenario and these threshold values tended to be lower.

Importantly, our scenarios differ both with regard to crime type and several other situational elements. For example, our fighting vignette involved a hypothetical situation in which the subject was confronted by a single aggressor in a way that could elicit an urge to defend oneself or one's friends. This offers clear temptations to offend, but the perceived costs and rewards may quickly change as more people join a fight. Individuals may become more attuned to the potential harm (to themselves or to others) as the number of involved participants in a crime increases (see also McCarthy & Hagan, 2005) and the perceived reward of protecting one's social reputation may shift to a social cost of being seen as part of a "pile on" as more people join in the fight. It may be easy to deny responsibility or avoid guilt when fighting someone who was an initial aggressor by oneself or with another person, but these anticipated social costs may be notably more salient if this aggressor becomes a target of seven or eight people fighting him. This view aligns with Thomas and McCuddy's (2020) recent finding that when perceived guilt is high, deviant peers are less likely to promote conformity.

In comparison, the potential harm to involved parties may seem less salient in our scenario about stealing from vendors. For example, vendors may have enough goods to provide something of value to even large numbers of people—that is, the idea that increasing numbers of offenders can reduce individual gains may not become an issue until large numbers of people are involved. If our theft scenario instead involved a smaller finite set of goods—perhaps money from a cash register or one person's valuables—then the perceived risk/reward calculus may change differently (Tillyer & Tillyer, 2015). Moreover, it may take dozens or even hundreds of people to produce profound enough property damage or loss to make it difficult to ignore (financial) harm to a victim. If we had described a situation in which the crowd size was much larger, thereby allowing for even more people to be involved, perhaps we would have observed a greater tendency for people to opt out (e.g., perhaps the functional form of the relationship between the portion of others involved in the act and the perceived utility of the act would have looked more similar to the flighting scenario). Even so, we do observe a reverse bandwagon for some individuals in the theft scenario. In this case, perhaps it speaks to a growing perception of a group sanction hazard; ten or twenty people stealing from vendors may prompt a perception that an individual has a lower probability of arrest compared with offending alone, but a very large-scale looting event will almost certainly invite a more intense and aggressive law enforcement response. This is all speculative, to be sure, but it rests on strong theoretical and empirical arguments that perceived costs and rewards vary in meaningful ways across criminal situations and should be studied at this level (Thomas et al., 2020). We view our findings as building on prior work documenting how such costs and rewards vary as more people become involved in crime (McGloin & Thomas, 2016) and setting the stage for work that sheds insight on the precise mechanisms whereby increasing numbers of co-offenders can reverse the perceived utility of an act.

Of course, some skeptics may question whether our findings about the complex interdependent nature of decision-making and the role of opt-out thresholds truly warrants attention, given that almost one third of subjects in our data did not even express an intention to offend across either scenario, which means it was not possible for them to demonstrate opt-out thresholds. However, the idea that particular situational factors may be salient for some individuals and not others is not novel in criminology, nor does it diminish the importance of understanding the role of independency in decisions about offending. For example, the premise of deterrence is at the cornerstone of decision models in our discipline, and it is the foundational construct in most rational choice studies of crime. Yet Pogarsky (2002; see also Herman & Pogarsky, 2020; Jacobs, 2010) suggested that not everyone is "deterrable." In his work, he identified three groups that responded to (dis)incentives in different ways: 1) acute conformists, for whom intentions to offend are not responsive to legal threats as their sense of morality and social bonds already preclude their involvement in crime; 2) deterrables, who are neither always criminal nor conforming; and 3) incorrigibles, the most committed offenders, for whom sanctions have little preventive impact (Pogarsky, 2002). From his view, sanction threats and their prominence in decision-making is of primary relevance only to the second group of individuals. Pogarsky's work moved the discipline toward a better, more nuanced, understanding of decision-making; it did not suggest that deterrence is a less important construct because it does not guide offending choices for all people. Similar to Pogarsky (2002), we observe situations in which people are disinclined to offend despite a supposedly tempting group context, and we observe situations where people seem committed to offending even if others are not acting, as they identify an opt-in threshold of 0 (i.e., they express an intention to offend alone). Importantly, however, we also observe that some portion of this latter group is still susceptible to social context as they report opt-out thresholds in the same situation (i.e., a reverse bandwagon effect). The absence of a universal effect does not mean social context is unimportant, but it invites additional empirical and theoretical attention to make sense of such variation.

Indeed, we would argue that our findings add insight into how situational contexts can influence offending decisions. There has been considerable research in criminology at the macro- (e.g., neighborhoods) and meso-levels (e.g., peer groups) highlighting the salient role that context plays in influencing behavior (see McGloin & Thomas, 2019; Sampson, 2012, for reviews), and an equally impressive set of scholarship finding that individuals are responsive to the risks, costs, and rewards associated with crime when making decisions to offend (Loughran et al., 2016; Matsueda, 2006; Piliavin et al., 1986; Thomas et al., 2020). Yet, as Short (1998) noted over two decades ago, scholars often act as "ships that pass in the night" who acknowledge each other without attempting to integrate insights into a cohesive explanatory model (see also Coleman, 1990). Not surprisingly, several scholars have called for earnest efforts to assess contextual and situational interdependencies of offender decision-making. As Granovetter and Soong (1983) argued, a particularly important component of threshold models is the relationship between individual thresholds (i.e., opting in and out) in any given situation and the equilibrium that is achieved for that particular event. This offers one way for researchers to connect micro-level processes to macro-level outcomes (Matsueda, 2017). Within an offending context, there may be an equilibrium at which the group size is unlikely to increase because people joining are offset by people leaving and opt-in thresholds for some are not being met. Given the different opt-in/opt-out patterns we identified in our trajectory analysis, it is important to remember that small shifts in the distribution of individuals present and in the nature of the situational context can result in drastically different criminal outcomes (Granovetter, 1978). And, just as better understanding these micro-level patterns can shed insight on macro-level patterns, it is also probable that macro-level context shapes these threshold decisions. For example, Schaefer et al. (2014) found that neighborhood characteristics affected co-offending patterns, such that juveniles were more likely to offend with others in neighborhoods with less disadvantage, higher levels of residential mobility, and peers of similar race/ethnicity. From their view, these factors promoted trust among potential accomplices. In transitioning research from hypothetical vignettes to real-world situations, it will be important to incorporate how neighborhood context could shape both individuals' opt-in and opt-out thresholds, as well as the likelihood of bringing potential accomplices together in time and space (Felson, 2003).

Of course, any inferences drawn from our study must be bound by its inherent limitations. Chief among these constraints are the characteristics of the sample we used, which relied on university students. Student samples have been employed by many scholars interested in offender decision-making (Bouffard & Exum, 2013; Nagin & Paternoster, 1994; Paternoster & Simpson, 1996), and the insights gained from these studies have generally been found to be applicable to more representative populations (Apel, 2013). Nevertheless, we recognize the concerns over the use of college student samples (see Bouffard et al., 2008) and the demographics of our sample are not fully consistent with the U.S. general population or with the typical profile of offenders/arrestees. As such, our results are bounded by our particular sample and best viewed as preliminary, inviting replication and expansion. In moving forward on this front, research should extend to older samples, given that young adults may be more responsive to how the presence of peers impacts decisions compared to older adults: Prior studies have shown that as individuals enter their mid-to-late 20s they become less responsive to peer processes and the social rewards associated with crime (e.g., Gardner & Steinberg, 2005; Thomas & Vogel, 2019). In other words, the age profile of our sample may mean that subjects were particularly likely to make socially interdependent decisions about offending.

The second important area for future work is broadening the criminal situations under study. We queried people about their offending intentions with regard to two specific and unique scenarios—it is only by incorporating different crime types and situational conditions within those crime types that we can discern whether there are predictable differential patterns of opt-out thresholds in ways that can shed insight on how the perceived utility of crime is (partly) conditional on group size. This expansion will also test the boundaries of the theoretical arguments offered here and in the threshold model more broadly. For instance, it is tempting to think that this model is applicable only to crimes with an inherent or stereotypical "collective" element, such as rioting or looting [though, to be fair, Matseuda (2006, p. 27) argued "most crime falls under the rubric of collective action"]. But this model is not so narrow—the overall argument is that people consider the actions of others as one element in offending choice more generally. Indeed, following the logic of the threshold model, a solo crime may represent a situation in which one person has a threshold of 0 (i.e., they do not require others to act first) and others present did not have their thresholds met (Granovetter, 1978). This model can also explain that person reversing course if others join in (i.e., if their opt-out threshold was now met), which may eventually lead to the cessation of the criminal act if the others now deem that not enough people have opted in in order for the act to have utility. Thus, this type of model would offer theoretical insight into a wide array of criminal situations, including solo offenses, uncompleted offenses, and those less likely to devolve into crowd behavior. Future expanded work can test the premise that this truly is a window into the interdependent nature of decision making more broadly.

Over the last few decades, scholars have sought to demonstrate the salient role that peers and groups have in explaining involvement in criminal behavior. As such, researchers were motivated to demonstrate that the presence of others (invariably) increases the probability of engaging in crime. Although some work has shown variation in the importance of peers as the proportion of criminogenic peers rises (e.g., Rees & Zimmerman, 2016; Thomas & McCuddy, 2020), the current study shifts the focus toward a more nuanced consideration of the impact of the deviant behavior of others. The inclusion of opt-out thresholds in the current study acknowledges the dynamic, interdependent nature of decision-making and bookends the group context as both an incentive and a disincentive for criminal behavior. In doing so, this framework offers insight into the unique effects of the group and supports additional opportunities to study other situational contributors to offending decisions and reversals.

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SUPPORTING INFORMATION

Additional supporting information may be found online in the Supporting Information section at the end of the article.

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