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Marginal Deterrence: The Association between the Certainty of Arrest and Monetary Reward on Robbery Escalation

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MARGINAL DETERRENCE: THE ASSOCIATION BETWEEN THE CERTAINTY OF ARREST AND MONETARY REWARD ON ROBBERY ESCALATION

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Christopher E. Torres

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To: Dean John F. Stack, Jr.
Steven J. Green School of International and Public Affairs

This dissertation, written by Christopher E. Torres, and entitled Marginal Deterrence: The Association Between the Certainty of Arrest and Monetary Reward on Robbery Escalation, having been approved in respect to style and intellectual content, is referred to you for judgment.

We have read the dissertation and recommend that it be approved.

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The dissertation of Christopher E. Torres is approved.

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DEDICATION

I dedicate this dissertation to my mother and Vanessa Hudgings.

Mom, without your love and support, I would never have been able to tap into my true potential.

Vanessa, I dedicate this dissertation to you, knowing that you will change the world with your heart and mind when you grow up.

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ABSTRACT OF THE DISSERTATION

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This dissertation serves as the seminal large-scale empirical analysis of the marginal deterrence principle. The extant literature on deterrence suffers from a great deal of controversy for two distinct reasons. First, prior research adheres to a myopic view of criminal offender decision-making because it focuses solely on the binary “yes” or “no” decision to commit a crime. It is thus plausible that prior work suppressed deterrent effects to some degree because the use of a binary outcome ignores any intermediate decision made by the criminal offender. Second, while the determination to perpetrate a crime is dependent on the sum of risk and reward, prior empirical work exclusively investigates the concept of risk and neglects the potential pleasure/reward an individual derives from partaking in criminal activity. Consequently, it remains unknown how criminal offenders respond to the coalescence of the concepts of pain and pleasure.

The marginal deterrence principle maintains that criminal offenders choose to perpetrate less severe forms of crime when the risk exceeds the potential reward, reducing the overall harm imposed on society. Using multilevel data and an ordinal dependent variable that includes six possible intermediate outcomes, I examine a robbery offender's complete utility calculus with an illicit incentive independent variable comprised of risk and monetary reward. After nesting 29,297 robbery incidents within 98 cities, results from a multilevel ordinal regression equation reveal evidence of an illicit incitement effect. Specifically, a one-unit increase in the illicit incentive amplifies the odds that offenders will escalate the severity of their robbery by a factor of one. These findings support the view that pleasure rooted in monetary incentives engenders the commission of more severe forms of robbery. The observed salience of monetary incentives is important for advancing interventions that seek to combat violent forms of robbery through the marginal deterrence framework.

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ABBREVIATIONS AND ACRONYMS

Autoregressive integrated moving average	ARIMA
Bureau of Justice Statistics	BJS
Expected utility	EU
Federal Bureau of Investigation	FBI
Generalized linear model	GLM
Hierarchical generalized linear model	HGLM
Hawaii's Opportunity with Enforcement Program	HOPE
Marginal quasi-likelihood	MQL
National Incident-Based Reporting System	NIBRS
Offense gravity score	OGS
Ordinary least squares regression	OLS
Principal component analysis	PCA
Penalized quasi-likelihood	PQL
Robbery category	RC
Rational Choice Theory	RCT
Social isolation index	SII
Uniform Crime Report	UCR
Vehicular homicide law	VHL

CHAPTER I

INTRODUCTION

The concept of deterrence is ancient and dates to fourth-century Platonic thinking. When Plato wrote the *Protagoras* (a dialogue between Socrates and Protagoras) in 380 BCE, his primary focus was comprehending the forces of human virtue, wickedness, and the teachability of the two.[1] Plato's dialogue sparked the initial genesis of criminal deterrence when he wrote:

> In punishing wrongdoers, no one concentrates on the fact that a man has done wrong in the past, or punishes him on that account, unless taking blind vengeance like a beast. No, punishment is not inflicted by a rational man for the sake of the crime that has been committed (after all one cannot undo what is past), but for the sake of the future, to prevent either the same man or, by the spectacle of his punishment, someone else from doing wrong again. But to hold such a view amounts to holding that virtue can be instilled by education; at all events the punishment is inflicted as a deterrent. (Plato, [380 BCE] 1956, pp. 55-56)

Since the prevention of criminal behavior is one of the foundational pillars of criminology, Plato's writings still indirectly resonate within modern academic circles today. For example, Protagoras believed that virtue is learned like all matters comprehensible to the human mind (Stalley, 1995). Through this lens, the philosophers viewed criminal behavior as a curable disease whereby offenders learn virtue through the

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[1] It is important to note that Protagoras is both the title and the name of one of the key philosophers in Plato's dialogue.

suffering induced by punishment (Plato, [380 B.C.E.] 1956). This concept, commonly known as specific deterrence, works only for the individual who experiences the treatment (Andenaes, 1974).

In contrast, Socrates believed that punishment served the interests of society rather than the individual (Stalley, 1995). Socrates' stance insinuates that virtue is unlearnable; thus, the threat of punishment should extend to the population on a grand scale to prevent others from committing similar crimes.[2] This concept in contemporary criminology is known as general deterrence, which can be defined formally as "the imposition of sanctions on one person [to] demonstrate to the rest of the public the expected costs of a criminal act, and thereby discourage criminal behavior in the general population" (Nagin, 1978, p. 96).

Moreover, while Plato's discourse hinted that criminal behavior was voluntary, he did not articulate how human intellect could drive the commission of a crime (Stalley, 1995). Most archaic philosophies argued that crime derived from inherent evil or educational misalignment. It was not until the enlightenment era that a naturalistic theory of criminal deterrence emerged to explain the rationality behind criminal behavior (Bernard et al., 2010).

[2] Socrates' contrasting perspective to Protagoras on the learnability of virtue hints at the first conceptualization of the undeterrable criminal. This concept was not fully recognized in the criminological literature until many centuries later.

Classical Theory & Rationality

Deterrence theory drastically expanded in the wake of 18th-century utilitarian thought. The intellectual paradigm dominant during this era was concentric around reason and human happiness. Henceforth, early philosophers used human pleasure and pain as a conceptual measure to gauge the morality of an individual's actions. For example, a deed was moral if it maximized pleasure for the greatest number of people, whereas an action that begets an equal amount of pain would be immoral (Braybooke, 2004).

The link between utilitarianism and the concept of criminal deterrence did not appear until the publication of *On Crimes and Punishment* by Cesare Beccaria ([1764] 1963). Beccaria explicitly articulates that laws (and not just individuals) should produce the greatest happiness for the largest number of people. Therefore, the deterrence of criminal behavior (a potent source of pain) became the task of chief import to uphold society's enduring happiness (Bruinsma, 2018). However, crime prevention during the 18th-century was based solely on the state's harsh and often disreputable punishment.

After observing the cruel and ineffective punishments imposed on prisoners, Beccaria developed three theoretical elements that, when used in conjunction, would augment the effectiveness of criminal deterrence. First, the certainty of punishment maintains that offenders fully understand that their illegal actions will reap harmful and uncomfortable consequences (Yu & Liska, 1993). The second element, the severity of punishment, postulates that offenders receive a punishment that exceeds the harm they enacted on society (Friesen, 2012). Last, the immediacy of punishment must follow the judgment, or else hope of escape will negate the fear intended by the imposed punishment (Bruinsma, 2018).

Jeremy Bentham expanded Beccaria's work by conceptualizing the rational criminal and the hedonistic calculus (Bentham, [1780] 1823). Until Bentham began his work on utilitarianism and criminal deterrence, philosophers of the 18th-century assumed that all criminals were hedonistic pleasure-seekers and that crime was a mindless outlet for said pleasure. Bentham theorized that while all individuals seek some form of pleasure, the outcome of this desire is relative. Thus, on the perennial quest to attain relative satisfaction, individuals will rationally weigh their actions based on a calculus of pain and pleasure and decide whether they must break the law to actualize their desires (Bentham, [1780] 1823; Bruinsma, 2018).

The suggestion that humans naturally gravitate towards pleasure and away from pain helped pave the way for the conceptual development of the criminal decision-making process (de Lazari-Radek & Singer, 2017). However, within the confines of the 18th-century, Bentham's concept of the rational offender remained theoretical and never underwent scientific testing. As noted by Archambeault (1984), "Bentham’s armchair philosophical approach failed to provide him with a mechanism for actually measuring pain and pleasure or moral guilt” (p. 231). The operational mechanism to test the rational calculus of pain and pleasure would not appear for another two hundred years.

Modern Deterrence Theory

The seemingly simplistic view of rationality makes the theory of deterrence a viable and reflexive conceptual foundation for explaining criminal behavior (Nagin,

1998) and a promising solution to crime (Pratt et al., 2006). The principle of deterrence adheres to three basic assumptions: (1) a message is relayed to a target group [e.g., it is wrong to murder, and if you take another's life, you could go to prison or receive the death penalty]; (2) the target group receives the message and perceives it as a threat; and (3) the target group makes rational choices based on the information received (Tomlinson, 2016, p. 33). The first assumption is generally engrained in most individuals because punishment is a looming shadow over all illicit behavior. Geerken and Gove (1975) differentiated between two specific types of message transmission engendered by either formal or informal sanctions. The primary purpose of identifying and understanding these forms of communication is to provide threatening signals to potential offenders.

Formal sanctions represent actions shaped by official agents of social control such as police officers, corrections officers, and lawmakers (Paternoster, 2018). The threat generated by these agents can manifest from increased police presence (Evans & Owens, 2007), increases in the severity of punishment (Stolzenberg & D'Alessio, 1997), or focused enforcement strategies (Kennedy, 1997). On the other hand, informal sanctions refer to the interpersonal transmission of threats through media outlets, movies, word of mouth, and social media (Paternoster, 2018). Informal sanctions tend to rely on the potential offender's social environment, wherein they garner information through interactions with other offenders or any other means of socialization (Geerken & Gove, 1975).

The second premise is more complicated and has developed an entire body of literature known as perceptual deterrence. The efficacy of perceptual deterrence theory hinges on a negative relationship between any given individual's acuity of punishment and their involvement in criminal activity (Paternoster, 2018). Though the conceptualization of perceptual deterrence theory shows some promise in understanding the elements that thwart criminal activity (Apel, 2013; Apel et al., 2009; Pogarsky et al., 2004), little is known about the determinants of how such perceptions manifest (Apospori & Alpert, 1993; McClelland & Alpert, 1985). Additionally, perceptual deterrence theory requires individual-level qualitative indicators often unavailable on a large scale to provide accurate policy recommendations (Kleck & Barnes, 2013; Kleck et al., 2005).[3]

Lastly, the third assumption of deterrence theory dictates that a potential offender must make some form of rational calculation after weighing the potential risks engendered by either formal or informal sanctions. As the threat of apprehension or punishment increases, the decision to commit a crime should become less appealing to the individual. With this assumption, modern deterrence theory directly links to the archaic Platonic principles of virtue/shame (Plato, [380 B.C.E.] 1956) and the utilitarian ideals of pain/pleasure (Beccaria, [1764] 1963; Bentham, [1780] 1823). The notion of a rational criminal calculus thus leads to a more direct focus on Beccaria’s elements of certainty, severity, and the celerity of punishment as explanatory factors. Specifically, these crucial elements of deterrence theory allow researchers to analyze a measurable

[3] For example, many perceptual deterrence studies rely on hypothetical simulations (Paternoster, 2018).

criminal decision apparatus to observe potential deterrent effects. Before delving into a dialogue of the operational form and measurement of deterrence theory, the elements of certainty, severity, and celerity take the spotlight to provide a context for this discussion.

Certainty

Although one may presume that the severity of punishment is the ineffable force behind deterring criminal behavior, the element of "certainty" serves as the impetus for garnering deterrent effects. Dating back to the enlightenment era and from a strictly conceptual standpoint, Beccaria ([1764] 1963) stated that:

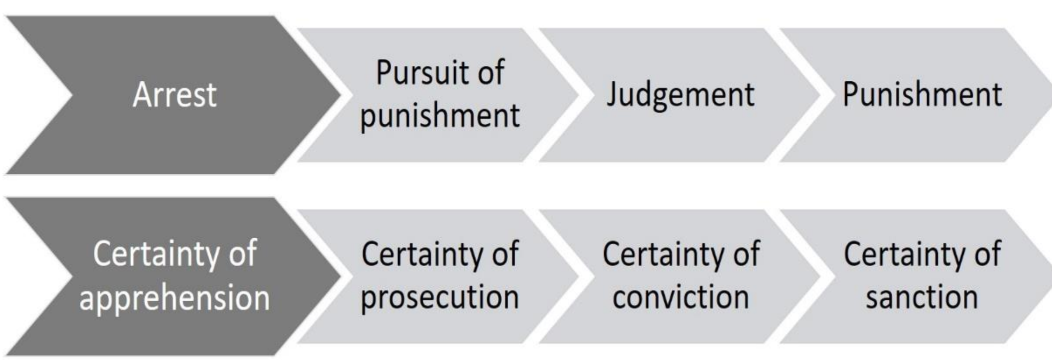
> One of the greatest curbs on crimes is not the cruelty of punishments, but their infallibility, and, consequently, the vigilance of magistrates, and that severity of an inexorable judge which, to be a useful virtue, must be accompanied by a mild legislation. The certainty of a punishment, even if it be moderate, will always make a stronger impression than the fear of another which is more terrible but combined with the hope of impunity; even the least evils, when they are certain, always terrify men's minds, and hope, that heavenly gift which is often our sole recompense for everything, tends to keep the thought of greater evils remote from us, especially when its strength is increased by the idea of impunity which avarice and weakness only too often afford. (p.58)

Current empirical research echoes Beccaria's sentiment as the certainty of punishment is considered to be the most effective at yielding deterrent effects from a multitude of different perspectives (Corman & Mocan, 2000, 2005; D'Alessio & Stolzenberg, 1998; DeAngelo & Hansen, 2014; Draca et al., 2011; Evans & Owens, 2007; Klick & Tabarrok, 2005; Lin, 2009). The certainty element refers to an offender's probability of apprehension, identification, branding, or punishment for committing a criminal act (Becker, 1968; Chalfin & Tahamont, 2018).

Since the late 20th century, criminological research has consistently found that crime is a multifaceted event (Verma & Lodha, 2002) and that individuals have various tipping points during the decision-making process (Loughran et al., 2012; Tittle & Rowe, 1974; Yu & Liska, 1993). These multiple dimensions reveal that the certainty element can stratify into several operational measures contingent upon where an offender falls on the criminal procedural timeline. After deciding to commit a crime, an offender must first undergo apprehension. The state's pursuit of punishment then ensues, judgment decreed, and finally, the offender receives a punitive sentence. Therefore, the certainty element encompasses the certainty of apprehension, certainty of prosecution, the certainty of conviction, and the certainty of sanction (Nagin, 2018). See Figure 1 for an overview.

Figure 1

Procedural Criminal Timeline and Certainty Stratum



The certainty measure is associated directly with assumption one of deterrence theory, which relays a threatening message to a target group of potential offenders (Tomlinson, 2016). Still, it can affect them at different points in the procedural timeline, as depicted in Figure 1. Official agents of social control thus serve as the first point of contact with the potential offender during any crime event. A potential offender must first become seized by law enforcement before prosecution and punishment. Though the certainty element of deterrence logically splits into four major categories, including the certainty of prosecution, conviction, and sanction, all the strata refer to punishment. In contrast, the certainty of arrest exclusively refers to "getting caught" or apprehended by police and is the most critical element in preventing criminal behavior (Nagin, 2018).

While policing is highly decentralized and institutional practices vary by jurisdiction (Lowatcharin & Stallmann, 2020; Wasco, 2020), one common thread that unifies all law enforcement agencies across the country is the detection and prevention of crime for the public good. Hence, in any developed country with a sanction regime, all decisions made by potential offenders must yield and consider the probability of apprehension by law enforcement officers. The certainty of apprehension is also multidimensional in its operationalization. It can range from proxy measures such as arrest frequency (Jacob & Rich, 1981) to ratio measures of arrests and reported crime (Wilson & Boland, 1978). Previous empirical analyses decree that the frequency of arrest and police presence/resources remain the most salient causal predictors of the relationship between the certainty element and deterrent effects (D'Alessio & Stolzenberg, 1998; Nagin, 2018). More precisely, the certainty of apprehension is the most potent when the crime under investigation relies on a mundane decision apparatus with a short time horizon (Braga et al., 2011; Cornish & Clarke, 1987; Cook, 1987).

Severity

Dovetailing the certainty of apprehension is the concept of punishment severity. In theory, one might assume that longer prison sentences (harsh punishment) will discourage individuals from committing a crime (Beccaria, [1764] 1963). Empirical findings, however, do not match this belief. According to Nagin (2018), "the theory of deterrence is predicated on the idea that if state-imposed sanction costs are sufficiently severe, criminal activity will be discouraged, at least for some … Severity alone, however, cannot deter" (p. 160). Findings derived from the general body of research on deterrence theory postulate that the certainty element is more effective at garnering deterrent effects overall (Eide, 1994; Nagin, 2013a). Punishment severity, however, still plays a salient role once the certainty of arrest is high because the impending punishment after apprehension must remain distasteful (Weisburd et al., 2008).

The interplay between the certainty and severity elements leads to a widespread debate on the empirical relevance of analyzing the severity of punishment. Because of this disagreement, Mendes (2004) proffers an interesting tripartite division among deterrence perspectives. On one end of the argument, researchers promote the idea that the severity element is of little empirical use when testing deterrence theory (Decker & Kohfeld, 1990; Eide, 1994). In the mid-ground, scientists argue that the severity element is relevant but often reliant on the certainty element for success (Becker, 1968; Ehrlich, 1973). Lastly, there lies the opinion that the certainty and the severity element should maintain equal relevance in empirical analyses (Chambliss, 1966; Gibbs, 1968; Mendes & McDonald, 2001; Tittle, 1969). Some examples of manipulations to the severity element include California's three-strikes law (Helland & Tabarrok, 2007; Stolzenberg & D'Alessio, 1997; Zimring et al., 2001), sentence enhancements (Raphael & Ludwig, 2003; Zimring, 1975), and capital punishment (Cook, 2009; Nagin, 2018).

Celerity

Celerity, also known as "swiftness" or the timing between apprehension and punishment (Beccaria, [1764] 1963), is the least studied of the three key elements. However, some regard this dearth of empirical research on the celerity element to be inconsequential in evaluating the effectiveness of deterrence theory (Nagin, 2013b). The modern criminal justice system is not designed for speed but rather for preserving the fundamental principles of the constitution, thus making the certainty and severity elements more practical predictors of deterrent effects.

It is important to note that it is challenging to examine the timing of punishment directly because it intertwines with the certainty element. For example, Project HOPE (Hawaii's Opportunity with Enforcement program) was developed and implemented by a judge who was disgruntled with defendants' noncompliance with their conditions of probation, failing their drug tests, and failing to appear in court hearings (Alm, 2011). Therefore, short jail sentences followed immediately after any delinquent behaviors that violated their probation. The program's goal was to avoid severe reprimands and engage in swift and sure punishment. Although promising in design, the deterrent effects associated with the celerity element in Project HOPE diminished when offenders concluded their jail sentences (Cullen et al., 2018). Pratt and Turanovic (2018) comment directly on this issue in the following manner:

> Right at the outset it is important to note that failing a probationer on a urine test is not the same thing as catching them in the act—it is highly unlikely that an offender will partake in their drug of choice while sitting in the probation officer's presence. Instead, the scenario is more likely to look like this: an offender smokes his stash of heroin on a Monday, tests positive for opiates on a Friday, and is incarcerated on the spot for his offense. In this instance, his punishment is only swift by criminal justice standards—a place where the bar is already set pretty low. (p.194)

Research from applied developmental psychology also suggests that punishment should be immediate for the celerity element to be practical. Specifically, findings show that deterrent effects begin to deteriorate if punishment is delayed anywhere from ten seconds to two minutes (Abramowitz & O'Leary, 1990; Banks & Vogel-Sprott, 1965; Trenholme & Baron, 1975). Due to this inherently sensitive and short timeframe, the immediacy of punishment (aside from the deprivation of liberty) is impossible to impose in contemporary criminal justice processing (Pratt & Turanovic, 2018). The only way to resolve this problem would be to formally punish offenders at the point of apprehension, which would be unconstitutional since they are innocent until proven guilty.

The Measurement of Criminal Deterrence

Though deterrence theory is conceptually easy to understand, scientific analysis becomes multidimensional and somewhat nuanced when considering the measurement of the theory's critical elements. Hypothetically, one should measure punishment's certainty, severity, and celerity concurrently to encapsulate actual deterrent effects. Unfortunately, due to the immense quality of data required to make this empirical determination, the analysis of the three at once is very challenging. Practical examinations of deterrence theory underwent several waves of development beginning in the 1960s. Studies were initially theoretical (Armstrong, 1961; Boulding, 1963) as there was no operational framework to model the criminal decision-making process. Drawing on the Benthic concepts of pleasure and pain (Bentham, [1780] 1823), Gary Becker revolutionized criminal deterrence theory and utilitarian thinking by introducing the economic model of crime and the concept of utility.

The Economic Model of Crime, the Function of Utility, and Deterrence

Becker (1968) defines utility as the pleasure garnered from participating in criminal activities, and the utility function is the operationalized term applied for statistical analysis. An offender's decision to commit a criminal offense at the most basic level is contingent on the relative utility gained from each of the following possibilities (Becker, 1968; Chalfin & Tahamont, 2018).[4]

1. The utility associated with the reward from the successful completion of the crime (U_{C1})
2. The utility associated with committing the crime and being apprehended and punished (U_{C2})

[4] All the formulations are derived from Becker (1968) and adapted from Chalfin and Tahamont's (2018) review of evidence and economic theory for ease of interpretation.

3. The utility associated with not committing the crime (U_{NC})

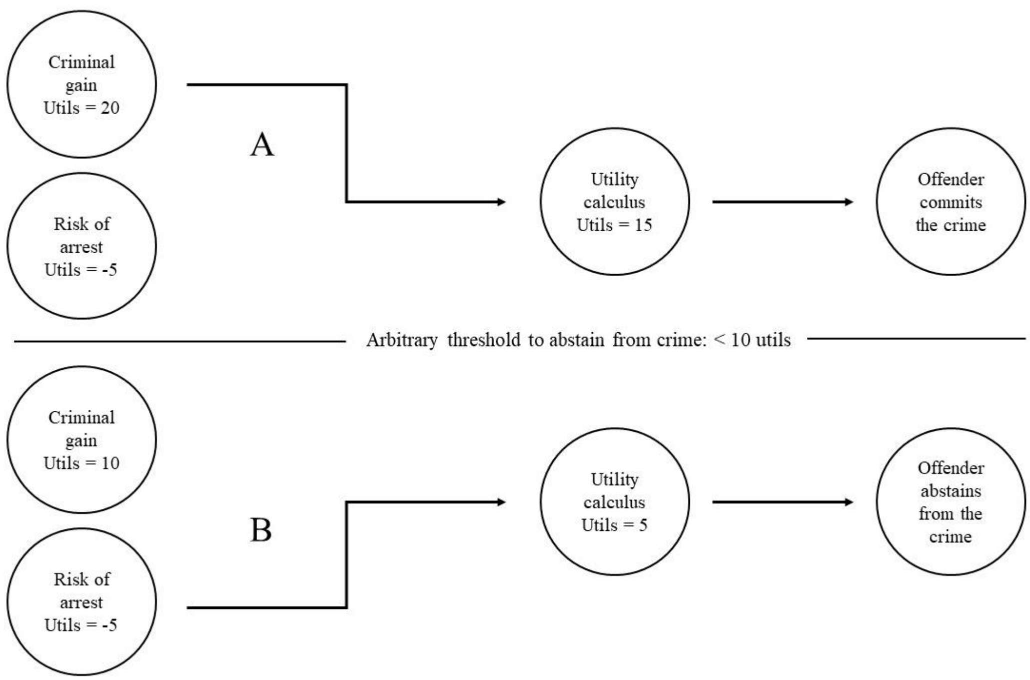
$$U_{C1} + U_{C2} > U_{NC} \tag{1}$$

Though simple in design, the above formulation is the most fundamental principle of the rational criminal decision-making process. To further expand on this rational model of offending, Becker (1968) widened Beccaria's ([1764] 1963) concepts of the certainty, severity, and celerity of punishment. In a unique operationalization of these concepts, Becker (1968) identified the probability of apprehension (certainty), outcomes after arrest (severity), and the timing between the two (celerity). Additionally, Chalfin and Tahamont (2018) classify these three crucial variables as operating externally from the potential offender's thought process; therefore, the rational model must calculate the functional utility generated from a potential criminal act by including these exogenous factors.

For further clarification, I will deduce an example that delineates the criminal decision-making process related to Becker's (1968) baseline economic model by using the functional form of utility, the "util." A util is a hypothetical currency representing a unit of measurement that allows researchers to weigh the potential decision outcomes of a macro cost-benefit analysis (Chand, 2013). Figure 2 details the example using simple quantitative properties by assigning positive and negative numbers to *UC1*, *UC2,* and *UNC* from (1). A hypothetical threshold is also set in Figure 2 to visually display the tilting point between committing or abstaining from crime.

Figure 2

The Economic Criminal Decision-Making Process



In Figure 2 (A), the maximum utils are higher for criminal gain relative to the risk of arrest; therefore, the offender will commit the crime. In Figure 2 (B), the utils are negative by an elevated level of risk, so the offender will abstain from committing the crime altogether. Although (1) and Figure 2 may seem overly simplistic, they are the building blocks for the economic perspective of crime and the underlying theoretical foundation for the current study.

Though a utility calculus can theoretically forecast the occurrence of all crime types, its predictive deterrent value is far more salient for instrumental crimes in comparison to expressive crimes (Chambliss, 1967; Parker & Smith, 1979; Zimring & Hawkins, 1973). The differentiation between expressive and instrumental crimes is key to making accurate scientific predictions, quantitative calculations, and generalizations about offending patterns associated with econometric decision-making. As noted by Willison and Warkentin (2013):

> The instrumental/expressive distinction has been used by criminologists to address a diverse range of crimes including terrorism (Amir, 1988), rape (Rosenberg et al., 1988), vandalism (Whittingham, 1981), workplace violence (Swanton, 1989), intra-family violence (Dawson, 2006; Gelles & Straus, 1987), arson (Fritzon, 2001; Hakkanen et al., 2004), and violent street crime (Bennett & Brookman, 2008). (p. 9)

Though rationality is grounded in instrumental and expressive crimes, the incentive to commit these offenses scales by either tangible gain (instrumental) or intense emotional proclamation (expressive). For context, the following two sub-sections outline the differences between instrumental and expressive crimes.

Instrumental Crimes

It is important to note that committing instrumental crimes such as robbery, fraud, or burglary yields a direct tangible acquisition of criminal gain (Chambliss, 1967). Moreover, the offender is concerned with achieving a goal that stems from a constant attraction, such as an easy and high financial payout (Burek, 2006). Due to this continuous pull, individuals pondering the commission of an instrumental offense will undergo a similar rational cost-benefit analysis to those contemplating legitimate decisions. For example, individuals seeking legitimate forms of income will either apply for jobs or ply a trade skill. Within this framework, monetary success is the primary pursuit to build or fortify a life that conforms to contemporary social values (Cooper & Stewart, 2015).

Throughout the journey to monetary success, these individuals will face many decisions to increase their overall profits guided by a relentless financial pull. Some examples would include acquiring a more prestigious position, pursuing higher education, or investing resources to enhance their business prospects. In contrast, a potential offender will choose to engage in an instrumental crime as they offer the possibility of a quick payout that requires little to no skills or training (Reuter et al., 1990). A qualitative study conducted by Deakin et al. (2007) shows that offenders decided to commit a robbery based on situational conditions that made the crime easy to complete. For example, the researchers found that robbers chose victims who were either distracted or known to carry excess cash on their persons for a quick illicit payout. Therefore, the constant in all instrumental crimes is the potential criminal gain that offenders prioritize as a means to an end (Burek, 2006; Chambliss, 1967). An underlying assumption associated with committing an instrumental crime is that a potential offender is always willing and able (Becker, 1968; Ehrlich, 1973).

Expressive Crimes

In stark contrast to instrumental crimes, expressive crimes tend to assuage intense emotions such as anger, annoyance, or anguish (Leroch, 2014). A critical factor differentiating an expressive crime from an instrumental one is that the offender's motive is rooted in the specific crime or the event being an end in itself (Burek, 2006; Willison & Warkentin, 2013). Examples of expressive crimes are murder, aggravated assault, domestic violence, rape, or stalking (Leroch, 2014; Weller et al., 2013). Though the nomenclature of crime between instrumental and expressive may seem straightforward, certain crimes such as homicide straddle the line (Block & Christakos, 1995; Polk, 1994). Whether or not expressive crimes are less preventable than instrumental crimes remains an unanswered theoretical question (Nagin, 1998). However, one can deduce that it would be far more difficult for researchers to effectively analyze deterrent effects from expressive crimes because such an investigation would require detailed qualitative data and *a priori* individual-level knowledge.

The First Wave of Deterrence Research

In the wake of the economic model of crime, interest in deterrence research spiked as Becker finally ushered in a quantitative apparatus to test Bentham's hedonistic calculus. As a result, two distinct waves of deterrence research surfaced. The first wave of statistical analyses emerged in the late 1960s and early 1970s. These studies were primarily ecological as they investigated aggregate units such as states and were typically cross-sectional in design (Chiricos & Waldo, 1970; Gibbs, 1968; Glaser & Zeigler, 1974; Tittle, 1969).

Jack Gibbs conducted the first empirical analysis attempting to test the deterrence thesis in 1968. Gibbs' goal was to explain the variation between the homicide rate and the certainty and severity elements. He defined the certainty element as the number of persons admitted to prison (on a criminal homicide charge) divided by the reported criminal homicides; similarly, he operationalized the severity element as the mean prison months sentenced in a state (see Gibbs, 1968, pp. 519-521). Chi-squared analyses allowed Gibbs to reject his null hypothesis and conclude that both elements played a crucial role in deterring criminal homicide. However, based on his results, the certainty element was twice more potent than the severity element.

Moving forward, Tittle (1969) operationalizes the certainty and severity elements similarly and uses the total enumeration of U.S. states as the unit of analysis. Tittle expanded Gibbs' research further as he did not only investigate the crime of homicide. He specifically included sex offenses, assault, larceny, robbery, burglary, and auto theft, along with the crime of homicide. Tittle's analysis revealed that all seven index crimes decreased as certainty increased. However, the associations for homicide and auto theft were not statistically significant, directly contradicting Gibbs' results on the certainty-homicide relationship (see Table 1 in Tittle, 1969, p. 415).[5]

Dovetailing Tittle's (1969) research while also critiquing Gibbs' (1968) findings, Glaser and Zeigler (1974) observed that in states that employed the death penalty, homicide rates were higher on average. Their conclusion postulated that the severity of the sentence (in length) meant very little to deter criminal behavior. Prisoners who committed homicide and were sentenced to death but not executed served shorter sentences than those imprisoned for the same crime in non-death penalty states. Due to the shorter length of prison sentences, the findings proffered by Glaser and Zeigler

[5] See also Chiricos and Waldo (1970) for a contrasting opinion on Tittle’s results from a quantitative perspective.

suggest incapacitation rather than the elements of deterrence theory as the primary form of crime reduction observed in the earlier studies.

Due to the inconsistent results generated in these initial studies coupled with the growing popularity of the theory, a divide emerged between policy and theoretical developments on criminal deterrence. Because of this divide, the National Academy of Sciences commissioned an extensive systematic review to determine the effectiveness of the results garnered from these first-generation deterrence studies. Though informative and pivotal to developing empirical deterrence research, Blumstein et al.'s (1978) comprehensive review found that these studies were inaccurate and suffered from methodological flaws.

The Second Wave of Deterrence Research

The 1990s ushered in the second wave of criminal deterrence research (D'Alessio & Stolzenberg, 1998; Kessler & Levitt, 1999; Levitt, 1996; Marvell & Moody, 1994; Piquero & Rengert, 1999; Stevens & Payne, 1999). This new surge of empirical analyses superseded the earlier studies as they added a longitudinal element into their research designs and attempted to control for time ordering and causality. Blumstein et al. (1978) lamented that one of the major problems with early studies on deterrence was the inability of researchers to measure the reciprocal relationship between formal sanctions and crime. Is crime declining because of increased formal sanctions? Or is the crime itself causing an increase in the number of formal sanctions applied?

It is also possible that proxy measures of the critical elements of deterrence may not be entirely exogenous (Corman & Mocan, 2000, 2005; Evans & Owens, 2007).

Blumstein et al. (1978) dictate that the effect of incapacitation may interfere with a researcher's ability to observe actual deterrent effects. Incapacitation effects refer to the attenuation in crime due to the physical constraint of criminal offenders. In an attempt to identify causality, previous longitudinal research has taken several unique methodological steps to deal with endogeneity. These fixes have included lagged variables (Corman & Mocan, 2000), instrumental variables (Levitt, 1996, 2002), and Granger-causation tests (Marvell & Moody, 1996; D'Alessio & Stolzenberg, 1998).

Much like the first wave of deterrence research, the current literature is extensive and riddled with contrasting methodological and theoretical paradigms. Consequently, the asymmetry that has emerged among the body of contemporary deterrence research makes it very difficult for policymakers to develop theory-informed interventions. The following chapter defines the convoluted findings, identifies the problem with prior studies, and provides two unique explanatory avenues that may resolve the controversy.

CHAPTER II

LITERATURE REVIEW

A large body of empirical research has accrued over the last several decades that examines the impact of deterrence on criminal offending. Though the second wave of deterrence research ushered in more statistically reliable quantitative procedures, results have become convoluted and oversaturated. The criminological literature on deterrence theory generally details three unique outcomes. First, many studies find evidence of a deterrent effect (Braga & Weisburd, 2012; Dolling et al., 2009; Rebellon et al., 2010). Second, some studies observe that when any of the quintessential elements of deterrence theory amplify, the propensity to offend also rises, known as a brutalization effect (Pogarsky & Piquero, 2003; Shepard, 2005). Third, several studies find no statistically significant effects between the certainty (Greenberg & Kessler, 1982; Loftin & McDowall, 1982), severity (Briscoe, 2004; Worral, 2004; Zimring et al., 2001), or celerity (Cullen et al., 2018; O'Connell et al., 2011) of punishment on criminal behavior.

Part I. Understanding the Controversy

The current study attempts to resolve some of the controversies in the criminal deterrence literature by considering two untested specifications to the economic model of crime. The first considers a stratified decision outcome guided by the theoretical principle of marginal deterrence. The second relates to the illicit incentive, which may propel individuals to commit more severe forms of an offense by discounting the risk of apprehension/punishment. Part I of the literature review describes and synthesizes the three confounding outcomes listed above that fuel the controversy. Subsequently, Part II of the review details the current study's two novel contributions to the criminological literature and how they may add to the debate.

Deterrent Effects

As mentioned previously in Chapter 1, most studies use the certainty of apprehension as their critical explanatory variable in measuring deterrence. It is important to note that despite the varied nature of prior research, one common consensus is that the criminal decision-making process (and the interweaving effects of certainty, severity, and celerity) plays a salient role in whether a deterrent effect will actualize (Apel & Nagin, 2011; Nagin, 2013a; Paternoster, 2010). Since an offender's decision apparatus is relatively mundane, they are more receptive to changes in the frequency of arrest (D'Alessio & Stolzenberg, 1998) or the visibility of more police officers (Levitt, 1996, 2002; Nagin, 2018).

For example, D'Alessio and Stolzenberg (1998) test the deterrence thesis by explicitly using the arrest frequency as a surrogate measure for the certainty element. Using a vector autoregressive moving average and using days (24-hours) as the time-unit, they demonstrated causal evidence for deterrent effects even after controlling for possible incapacitation effects and a reciprocal relationship. Specifically, they found that as arrest frequency increased, criminal activity declined. However, it took one day for the deterrent effect to actualize. This short lag suggests that the message diffusion of the arrests spread quickly to the public, thus preventing criminal behavior. Historical meta-analyses show that, on average, message diffusion of hot topics often occurs in 24-hour cycles (Basil & Brown, 1994). However, this timeframe may have condensed in recent years with the advent of social media, which provides instantaneous message transmissions (Shin et al., 2018).

In a similar vein, Lin (2009) estimated a series of two-stage least squares regression models on both property and violent crime. Lin found consistent statistically significant adverse effects between the elasticity of crime concerning local police strength and arrest frequency for property crimes. Her results skewed when considering the overall violent crime rate, with only two of her five models achieving statistical significance.[6] For example, the crime of robbery was near statistical significance in her primary model, but it reached the .05 significance threshold in a sensitivity analysis, thereby making it a salient predictor.

Using data drawn from the New York Police Department and a time-series analytical strategy, Corman and Mocan (2000) found a deterrent effect for the crime of robbery after making a distinction between expressive and instrumental violent crimes. Using the frequency of arrest as a proxy for the certainty element, Corman and Mocan (2000) reported that "a 10-percent increase in robbery arrests brings about a 7.1 to 9.4-percent decrease in robberies" (p. 601). Lastly, the researchers unveiled a consistent negative relationship for the elasticities of crime between the law enforcement variables

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[6] It is important to note that Lin (2009) uses the 90% level as a threshold for statistical significance. The reader will note that the current study only acknowledges the two models that exceed the universally accepted 95% threshold for statistical significance for inclusion in the literature review. Lin details only one model that she accepted at the 90% level.

(frequency of arrest and number of police officers) for murder, robbery, burglary, and motor vehicle theft.

In a parallel study, Corman and Mocan (2005) expanded on their previous work by combining deterrent effects with broken windows theory in New York City. The main goal of their study was to decipher whether the certainty of arrest for misdemeanor offenses (broken windows policing) or police force drove the commission of a crime. The results produced from the time-series analysis revealed that after controlling for economic factors and police numbers, misdemeanor arrests and robbery decreased by approximately three percent, motor vehicle thefts by two percent, and grand larcenies by half a percent.

Pivoting slightly, Klick and Tabarrok (2005) garnered further support for deterrent effects stimulated by the abrupt allocation of resources. The researchers used a series of longitudinal regressions to investigate the impact of terror alert levels developed by the Department of Homeland Security on street crime in the District of Colombia. The results garnered from their analysis showed that as the Metropolitan Police went on high alert by physically increasing their presence in District 1 (National Mall area), street crime decreased substantially. In contrast, the other districts showed no significant effect of the reallocation of police personnel on crime. After disaggregating by crime type, auto theft and theft from an automobile continued to maintain a statistically significant negative relationship with the amplification of police presence in District 1. However, violent crimes, burglary, and theft showed no change. This latter finding suggests that criminal opportunities diminish for robbery and burglary during high terror alert periods because potential victims tend to remain indoors and off the street. On the other hand, opportunities for the theft of automobiles and the theft from automobiles remain static. Klick and Tabarrok (2005) concluded "… that an increase in police presence of about 50 percent leads to a statistically and economically significant decrease in the level of crime on the order of 15 percent, or an elasticity of .3" (p.277).

To this point, the narrative has focused exclusively on the certainty of apprehension (the most potent predictor of deterrent effects). However, some studies find suggestive evidence of deterrent effects that stem from manipulating the severity element in criminal deterrence theory. Take California's three-strikes law as an example. The law developed a nomenclature of "strike" offenses which included severe/violent crimes such as robbery, rape, murder, and attempted murder, to list just a few (Ardaiz, 2000). According to Helland and Tabarrok (2007):

> A criminal with one strike who is convicted of any subsequent felony (not necessarily a strike) faces an automatic doubling of the sentence length on that conviction and cannot be released prior to serving at least 80 percent of the sentence length. A criminal with two strikes who is convicted of any subsequent felony faces a prison sentence of 25 years to life and cannot be released prior to serving at least 80 percent of the 25-year term. (pp. 309-310)

Therefore, the law intends to threaten would-be offenders with progressively severe punishment and incapacitate chronic career lawbreakers who otherwise would continue offending.

Helland and Tabarrok (2007) observe a marginal decrease in offending the closer offenders get to the third strike. Following a cohort of ex-offenders released from prison in 1994, the researchers specifically parse out a causal effect of the severity of punishment on both two and three-strikes imposed upon a recidivating offender. The researchers found that “California's three-strike legislation reduces felony arrest rates among the class of criminals with two strikes by 15-20 percent per year with some estimates as high as 30 percent depending on sample and specification" (Helland & Tabarrok, 2007, p. 326). Though a specific deterrent effect is associated with the third strike, it still requires the commission of two serious crimes. However, it is essential to note that most studies find little or no general deterrent effect when analyzing the overall impact of the three-strikes law on crime (Helland & Tabarrok, 2007; Stolzenberg & D'Alessio, 1997; Zimring et al., 2001).[7]

Brutalization Effects

The brutalization effect, which is the antithesis of a deterrent effect, represents a positive relationship between the key elements of deterrence theory and the decision to commit a crime. Most research on brutalization effects focuses on the severity and certainty of punishment. For example, as the severity of crime increases, the propensity/severity of offending is also theorized to increase. Brutalization effects most likely appear in situations where the most severe forms of punishment are under investigation, such as punishment for murder. It is natural to assume that the threat of

[7] This concept is discussed in detail in the sub-section that explains the null effects in deterrence research.

death, and the subsequent loss of a future, would deter any rational-minded would-be offender from committing a capital crime. However, contemporary criminological research paints a different picture (National Research Council, 2012).

In one of the most prominently cited studies on capital punishment and deterrence theory, Bowers and Pierce (1980) use data from 1907-1963, which accounted for 5,706 executions to test for a brutalization effect. Restricted to the City of New York, the researchers implemented a longitudinal regression equation targeted at observing how the number of homicides per month was affected by the occurrence of executions from the following year. After controlling for seasonal changes and population displacement from major wars, the results generated in their analysis revealed that two additional homicides occurred in the month directly after an execution. The commonly adduced explanation for this effect is that when the state executes individuals, it deteriorates the respect for human life and thus signifies to potential offenders that it is acceptable to kill. Bowers and Pierce (1980) explain this phenomenon by writing that "the lesson of the execution, then, maybe to devalue life by the example of human sacrifice. Executions demonstrate that it is correct and appropriate to kill those who have gravely offended us” (p. 456).

In a later study, Cochran et al. (1994) obtained similar results when analyzing an execution carried out via lethal injection in Oklahoma. Using weekly data drawn from the UCR Supplementary Homicide Report, Cochran et al. (1994) used an interrupted time-series procedure to model the effect of the execution on crime. The researchers found a statistically significant positive effect on stranger homicides during the post-intervention observations. Specifically, Cochran et al. (1994) state that the execution “led to an increase in approximately one additional stranger-related homicide incident per month" (p. 129). Bailey (1990) further strengthened the brutalization thesis by replicating the analysis conducted by Cochran and his colleagues. He found that the brutalization effect appeared for both stranger and non-stranger killings and suggested that executions from other states may have influenced the uptick in murders in Oklahoma.

As mentioned previously, most studies that find evidence of crime increasing in the wake of criminal deterrence efforts concentrate on the severity of punishment. As previously mentioned, the certainty element divides into the certainty of apprehension and punishment. For example, Pogarsky and Piquero (2003) investigated the relationship between the certainty of punishment and increased offending for the crime of drunk driving. By analyzing a sample of college students, they found a partial positive offending pattern. Pogarsky and Piquero (2003) found evidence of "resetting for low-risk subjects, among whom sanction-certainty estimates were lower for individuals who had been punished" (p. 112). Ultimately, as the certainty of experiencing punishment increased, the odds of an offender committing a drunk-driving offense also increased as they updated their view of punishment. While the study only investigated one minor crime and lacks generalizability because of the focus on college students, it hints at a possible relationship between the certainty element and a positive offending pattern, thus adding to the controversy in the current body of deterrence research.[8]

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[8] A similar brutalization effect is observed when considering the severity of punishment and drunk driving (Briscoe, 2004).

Null Effects

Debate persists on the validity of observed deterrent effects due to the antithetical results garnered from prior deterrence-based analyses. As noted by Pratt and Turanovic (2018), "few ideas are afforded as much simultaneous allegiance and skepticism as deterrence theory" (p. 187). For example, while researchers find support for deterrent effects, others, using similar methodologies, garner null results. This section will review these empirical works, emphasizing the effect of police numbers, arrests, and California's three-strikes law. Since deterrence research is voluminous, the discussion is constrained to the three topics mentioned above for the sake of brevity.[9]

The economic model of crime is the leading operational framework used to explain the criminal decision-making process. Loftin and McDowall (1982) take the stance that the economic framework is relatively weak because it does not consider public organizational or political variables. Using 51 years of data drawn from Detroit, the researchers failed to reveal a substantive effect between police size and crime. Commenting on their time-series analysis, Loftin and McDowall (1982) state that "within the empirical bounds of variation in police strength in Detroit, police strength and crime are not systematically related and that the tightly coordinated adjustments envisioned in economic theory are not characteristic of the real world" (p. 399).

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[9] It is important to note that the asymmetry in criminal deterrence research is vast and voluminous. These three topics are discussed as they are the most relevant to the current discussion and are present in the section entitled *Deterrent Effects*. It falls outside the scope of the current study to provide an exhaustive contrasting narrative.

In another often-cited study, Greenberg and Kessler (1982) used a stratified random sample of 98 cities with a population of 25,000 or more over six years and a three-wave panel model to assess the relationship between arrest and crime rates. Their results revealed that deterrent effects were minor across all index crimes but then became inconsistent over time, and this irregularity negated any sense of statistical integrity. Similarly, their analysis on clearance rates also produced null results. Greenberg and Kessler (1982) concluded that “our failure to find evidence for a crime-prevention effect contrasts with the econometric studies based on cross-sectional or time-series data, which have found evidence consistent with a crime-prevention effect” (p. 784).

California’s three-strikes law also adds to the conversation on null results. Despite early exploratory analyses of the three-strikes law (Greenwood et al., 1996), most evaluation-based studies find little to no general deterrent effects (Helland & Tabarrok, 2007; Stolzenberg & D'Alessio, 1997; Zimring et al., 2001). For example, Stolzenberg and D'Alessio (1997) observed that crime was already declining in California immediately before the implementation of the three-strikes law. Therefore, any analysis that simply compared pre-and post-intervention rates would be biased to a certain degree. Stolzenberg and D'Alessio (1997) conducted a longitudinal intervention analysis using an auto-regressive integrated moving average (ARIMA) technique to control for this unique ecological situation. They modeled the implementation of the three-strikes law as a step function in their analysis. An examination of ten major cities in California showed that the three-strikes law had a deterrent effect in only one city, Anaheim. The researchers concluded that the deterrent effect of California’s three-strikes law was minimal at best.

Part II. Attempting to Resolve the Controversy in Criminal Deterrence Research: Marginal Deterrence & Monetary Incitement

The observed controversy in empirical deterrence research is vast and confounds the knowledge used to develop crime-control policies. One of the most significant issues with the economic model of crime is the assumption that a potential offender's decision outcome is binary (see Figure 2). For example, while most studies on criminal deterrence assume a dichotomous response to a shift in the certainty or severity elements (Corman & Mocan, 2005; DeAngelo & Hansen, 2014), the actual outcome is naturally an ordered stratiform. Specifically, offenders may dynamically choose to commit a less severe offense in the wake of an increase in the critical elements of deterrence. Therefore, subsequent regressions that do not control for any intermediate options other than a binary yes/no response to the criminal decision-making process will overlook potential deterrent effects.

Another issue relating to empirical analyses that attempt to measure deterrent effects is the general failure among social scientists to consider an illicit incentive. In a more complex version of his original formulation, Becker (1968) created an expected utility function (EU), where the criminal gain is a salient portion of the criminal decision-making process. The EU is as follows where i is a specific individual, j is a specific crime, Y is the potential criminal gain, and F is a crucial element of deterrence theory (certainty/severity):

$$EU_{ij} = P_{ij}U_{ij}\,(Y_{ij} - F_{ij}) + (1 - P)U_{ij}\,(Y_{ij}) \tag{2}$$

Within this formulation, the expected utility garnered by an offender when committing a crime is more significant when the right side of the equation [$(1 - P)U_{ij} (Y_{ij})$] outweighs the left [$P_{ij}U_{ij} (Y_{ij} - F_{ij})$] (Chalfin & Tahamont, 2018).

While studies attempt to measure the relative criminal gain (Akers, 1973; Gottfredson & Hirschi, 1990; Hirschi, 1969; Levitt, 2004; Shaw et al., 2015; Toby, 1957), they do not accurately account for the illicit incentive. For example, the economics literature postulates that when the motivation to take a course of action outweighs the cost, an individual is more likely to discount any of the consequences associated with the action. This flouting of costs, commonly referred to as the discount rate, mirrors Bentham's conceptualization of ‘pleasure-chasing’ in his hedonistic calculus. If the relative incentive is high within a given geography, an individual should be more likely to offend even when the risk is moderate. Therefore, any study that does not correctly control for such an incentive is likely to be misspecified.

The current study expands the breadth of deterrence theory and the economic model of crime by accounting for all intermediate criminal decision outcomes and a discount rate. Specifically, through the lens of marginal deterrence, I proffer that if the criminal incentive increases relative to risk, a potential offender will rebate the deterrent effects imposed by getting caught by committing a more severe offense. I label this novel theoretical concept the “monetary incitement principle.”

The Erroneous Dichotomy of Previous Research

While prior research on criminal deterrent effects is informative and helpful in generating actionable crime-control policies, it generally suffers from a logical fallacy.

While many of the most sophisticated studies implement a continuous outcome variable representing a crime rate (DeAngelo & Hansen, 2014; Evans & Owens, 2007; Klick & Tabarrok, 2005), the results only indicate whether crime increases or decreases in the wake of the critical elements of deterrence. The outcome of the criminal decision-making process is limited in empirical observation to either a macro-level shift in the decision to commit a crime or to abstain from crime altogether.

Although complex in methodological design, this situation creates a neatly designed dichotomy that oversimplifies the study of the criminal decision-making process. This issue, known as a false dichotomy, is a fallacy wherein the outcome of a situation is assumed to be one of two bifurcated contrary predicates, and no intermediate states exist between the two predicates (Govier, 2010). The fallacy of the false dichotomy is present in an array of sociological and epistemological research studies in an attempt "… to create a workable and simplified view of the world that is amenable to scientific testing" (Saad, 2020, p. 24). Because of the operational bifurcation of the outcome measure in deterrence research, empirical results may be erroneous to a certain degree as the categorical disjunct between an increase or decrease in crime negates the possibility of detecting any other possible logical outcomes (Govier, 2010). Dichotomization is problematic in deterrence research because it severely limits the criminal decision-making process down to a simple yes or no action. For example, the contrary predicates that previous research implicitly assumes are: "if you abstain from offense x (observed through a decrease in the crime rate), no other crime has occurred."[10]

The above assertion creates a false disjunctive statement because it is common criminological knowledge that many offenders are extremely difficult to deter (Shavell, 1992) and will often continue to offend in the aftermath of manipulations to the key elements of deterrence. That said, criminals may continue to commit crimes but reduce the severity of their offending to avoid either apprehension or stricter punishment. This situation would be undetectable in regressions that use a ratio outcome variable to measure linear increases or decreases in crime. Although outcome measures that are naturally continuous or fall into a Gaussian distribution yield very sophisticated statistical analyses, they are only equipped to observe two mutually exclusive outcomes (an increase or a decrease in crime), which are exhaustive due to model specification.[11]

For example, a common goal of deterrence research and practices is to attenuate harm to society caused by the commission of crime through absolute or marginal deterrence. With the advent of a crime control strategy, absolute deterrence dictates that criminal offending and the harm associated with the offending are both effectively eliminated. In reality, because it is impossible to stop crime entirely, many police

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[10] In contrast, a statement with complementary predicates would be “if you abstain from crime x, crime x was not committed.” This situation then ushers in the possibility of a less severe version of crime x, or a different crime altogether.

[11] This is not to say that an ordinary least squares regression analysis cannot capture marginally decreasing fluctuations in the decision to commit a crime. However, it is incumbent on the researcher to design controls in a manner that encapsulates such a theoretical possibility. Only a handful of studies have attempted to empirically measure this phenomenon (Crino et al., 2019), and none of the major studies that inform policy have directly addressed the issue.

departments, policymakers, and researchers strive to lessen the harm engendered by offending as much as possible. In the case of marginal deterrence, as punitive sanctions rise, there should be a marginal decrease in both the occurrence of crime and the damage to society caused by the illicit acts. This situation is fallacious to a certain degree. If crime increased for a less severe offense but decreased for a more severe violation, the harm would attenuate because more severe offenses tend to produce more damage to society (Shavell, 1992). Therefore, any policy that attempts to reduce harm to society, such as amplifying the likelihood of apprehension, will be ineffective if crime increases overall.

Although an increase in a lesser crime engendered by marginal deterrence results in less harm to society, studies that neglect to control for the stratification of crime severity in the potential offender's choice structuring may overlook potential deterrent effects. An array of studies attempt to address this conundrum by analyzing various types of crime in the aggregate to detect variations in offending patterns (Evans & Owens, 2007; Lin, 2009). The issue, however, is that the underlying motivations for the commission of a robbery, murder, and selling illicit narcotics all fluctuate vastly. Although a complex undertaking, it would be more appropriate for marginal deterrence studies to investigate the various severity levels for each crime where the crime itself is stratified.[12]

[12] The concept of choice structuring elements is expanded on in a proceeding section.

The Deductive Validity of the Economic Model of Crime

It should be noted that deterrence scholars are not making these binary conceptualizations of reality without knowledgeable intention. Instead, the root of the false dichotomy lies in the implicit operationalization and model specification laid out in Becker's (1968) economic model of crime. Becker's framework, which also guides the current study, is rooted in deductive propositional logic and remains valid (Govier, 2010; Tomic, 2013). Becker's economic model of crime lays the rational groundwork for criminal decision-making into an "*if-then*" econometric paradigm based on a series of conditional formulations. For example, in Becker's most simplistic equation, *if* the utility associated with the reward from committing the crime outweighs the costs, *then* the potential offender will choose to commit the crime (see Equation 1 and Figure 2 for clarity).

Though criticized in the above section, I will provide a visual example of how previous econometric deterrence research is rooted in logic and guides the current study. Lending support from the literature on logic and philosophy, I will provide an "*if-then*" truth table to supplement the present discussion. Truth tables are static diagrams that provide the basis for testing and appraising the validity of conditional statements in the study of propositional logic (Govier, 2010).[13]

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[13] According to Govier (2010, p. 216), "propositional logic deals with the relationships holding between simple propositions and their compounds. In propositional logic, the basic logical terms are *not, or, and, if,* and, *then.*"

In the economic model of crime, the conditional statement dictates that *if* all conditions are met in a formulation to make crime less appealing (via the analysis of relevant exogenous variables), *then* crime will decrease (Chalfin & Tahamont, 2018).[14] The following equation represents the basis for the truth table that tests the above conditional statement.

$$E \supset C \tag{3}$$

Where ⊃ represents *if E then C*, *E* represents the conditions of the economic formulation, and *C* represents a decrease in crime. Table 1 represents the deductive validity of the above conditional statement provided by Becker (1968) that previous studies follow in the procurement and discussion of their results. Within the table, *T* represents *true,* and *F* represents *false.*

Table 1

If-then Truth Table Testing the Validity and Logic of the Economic Model of Crime

	E	**C**	**E ⊃ C**
1	T	T	T
2	T	F	F
3	F	T	T
4	F	F	T

[14] When referring to "formulations," it can include any of the augmentations to Becker's (1968) seminal economic model of crime.

Line (1) represents if all conditions of the formulation are met (true) and crime decreases (true), then E $\supset$ C is accurate, and deterrent effects are observed (though based on a binary outcome). Line (2) represents if all conditions of the formulation are met (true) and crime does not decrease (false), then E $\supset$ C is false, and a brutalization effect or null result is observed.[15] Line (3) represents if all conditions of the formulation are not met in the analysis (false), but crime decreases (true), then E $\supset$ C is true and deterrent effects are observed (perhaps due to an unobserved exogenous variable). Line (4) represents if all formulation conditions are not met in the analysis and crime does not decrease, then E $\supset$ C is true.

As displayed above, previous research on the economic model of crime is deductively valid but examines empirical reality through a bifurcated lens. Commenting on truth tables, Ragin (2005) writes that "one limitation of the truth table approach is that it is designed for causal conditions [that] are simple presence/absence dichotomies . . . Many of the causal conditions that interest social scientists, however, vary by level or degree" (p. 1). Therefore, criminological research would greatly benefit by expanding the criminal decision-making process to include a multidimensional approach that considers all intermediate decision-making possibilities. To date, two bodies of literature have attempted to broach this issue and expand knowledge on undeterrable offenders. These two fields of study are marginal deterrence and restrictive deterrence. It is important to note that the two concepts bear similar definitions and are often used interchangeably.

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[15] It is important to note that just because "C" is false in line 2 does not mean that crime increases (contrary predicate). No effects may have been observed in this situation.

The difference between the concepts is that while marginal deterrence refers to the offender's prevalence to choose various levels of a given crime (Shavell, 1992), restrictive deterrence refers to the frequency an offender commits a crime (Jacobs, 2010).

Marginal Deterrence

Though the principle of marginal deterrence became recognized over the past three decades (Shavell, 1992), traces of the concept date back to the writings of Jeremy Bentham during the enlightenment era. According to Bentham ([1780] 1823):

> To induce a man to choose always the least mischievous of two offenses; therefore, where two offenses come in competition, the punishment for the greater offense must be sufficient to induce a man to prefer the less. (p. 171)

To concretize the marginal deterrence thesis, Shavell (1992) developed a hypothetical model wherein a given individual chooses between three ordered outcomes that produce various levels of harm. The choices in the template are crime two (high-harm), crime one (low-harm), or the decision to abstain from crime altogether. If criminal sanctions are not severe enough for the commission of crime two and private benefits are high (Becker, 1968; Kramer, 1990), the potential criminal will, hypothetically, be more likely to commit this crime (thus transferring the most harm to society).

Most of the literature to date that discusses marginal deterrence follows Shavell's (1992) model and is concentric around the development of optimal sentencing policies (Crino et al., 2019; Friedman & Sjostrom, 1993; Kramer, 1990; Lundberg, 2019; Mookherjee & Png, 1994). Hence, the analytical spotlight has remained on the severity element as these studies attempt to develop a sentencing structure that progressively shifts punishment to match the amount of harm imposed on society. Due to the complexity of operationalizing stratified decision outcomes (Gau, 2019), most studies remain hypothetical rather than empirical at this point (Lundberg, 2019). Mookherjee and Png (1994) recognize this and lay the operational groundwork for social scientists to test the principle of marginal deterrence.

Much like Becker (1968), Mookherjee and Png (1994) strongly believe that all individuals are not identical in the specification of their utility calculus, and the assumption that all offenders deter equally is erroneous. This view suggests that empirical tests of the marginal deterrence thesis should control for, to a certain extent, the motivations for committing the offense relative to an increase in any of the critical elements of deterrence theory. For example, to effectively observe a marginal deterrent effect for an instrumental crime, the equation should factor in the criminal gain/reward. In contrast, a study investigating expressive crimes should control for private psychic benefits.

In their hypothetical model, Mookherjee and Png (1994) argue that potential offenders will choose a crime that maximizes the difference between the criminal benefits and the expected penalty for the act. According to their model, those who highly benefit from a more harmful act cannot hypothetically choose a less severe crime. Crino et al. (2019) calculated a series of regressions to test for a marginal deterrent effect stemming from a punishment scale that progressively increased with more harmful acts to verify this theoretical proposition empirically. The researchers attempted to differentiate between crime types of various offense levels while controlling for sentence length and the harshness of the sanction regime in the U.S. They found that "cross-state variation in the steepness of the punishment-severity schedules is not random, but correlates with maximum punishment and monitoring cost in accordance with the predictions of the marginal deterrence framework" (Crino et al., 2019, p. 609).

Their results postulate suggestive evidence that marginal deterrence is at work in the wake of a progressively increasing sanction scale even after controlling for individual private benefits. This study suggests that marginal deterrence and the illicit incentive are intertwined because most offenders are undeterrable.[16] The study's main weakness is that their surrogate measure for an individual's benefit is income inequality, which may be too broad of a variable to encapsulate an operational utility calculus. Additionally, they investigate various crimes that draw on different motivating factors. Therefore, it is challenging to discern which crime is more susceptible to marginal deterrent effects.

Basili and Belloc (2020) conducted another empirical test of the marginal deterrence thesis. The researchers analyzed the relationship between a severity-scaling vehicular homicide law (VHL) and marginal deterrence in Italy. The law introduced new penalties for careless driving that scaled upward in severity based on the harm caused by an accident or accidental death. Specifically, they used a series of generalized linear regression models to test whether the severity-oriented law marginally reduced negligent/reckless driving. They found that "whilst increasing the entire range of sanctions for all the possible levels of harm caused by an accident, Italian VHL had a

[16] This concept is discussed in detail in the proceeding section.

negligible marginal deterrent effect on the most serious dangerous driving" (Basili and Belloc, 2020, p. 7). Before moving forward, it is essential to note that though a sanction regime can progressively decrease the severity of offense chosen by potential criminals, it is also the best equipped to observe a brutalization effect.

To clarify, Friedman and Sjostrom (1993) postulate that marginal deterrence can progressively increase harm rather than decrease it. In their article, the authors provide a metaphor wherein a thief has the opportunity to steal several farm animals. However, the severity of the penalty (death) is equal regardless of which animal the thief steals. If the thief is hung for stealing either a sheep or a lamb, the thief will steal the animal that garners the most value (the lamb).

Ekelund et al. (2006) displayed quantitative support for the sheep-lamb theoretical conundrum. They claimed that since the death penalty is the most severe form of punishment, it may negate any subsequent marginal deterrent effects once the offender has initially committed a murder. Using the Supplementary Homicide Report, the researchers estimated a series of Poisson regression models to test whether offenders were more or less likely to commit multiple murders after the initial homicide. After controlling for variables such as poverty, race, and unemployment, Ekelund et al. (2006) found that "multiple murders are not deterred by execution in any form, quite possibly because the marginal cost of murders after the first is approximately zero" (p. 522). Put simply, if the punishment remains the same for murdering one individual or three, why would the offender abstain from murdering all of the individuals? Such a situation is also advantageous because no witnesses are left behind.

As articulated in the studies mentioned above, the theory of marginal deterrence primarily builds on manipulating criminal sanctions/punishment (Shavell, 1992; Stigler, 1970). However, while all extant research on marginal deterrence implements a scaling severity element, the general body of deterrence literature dictates that crime is unquestionably more responsive to the certainty element (Corman & Mocan, 2000, 2005; D'Alessio & Stolzenberg, 1998; Evans & Owens, 2007; Klick & Tabarrok, 2005). One explanation for the robust certainty of punishment effect is that an arrest record, even without a criminal conviction, is problematic for most individuals. Therefore, a significant gap in the criminological literature exists on how crime reacts to marginal fluctuations in the certainty element rather than the severity of a sanction regime. Though the marginal deterrence principle holds criminal gain as an essential element of its functioning, a more detailed review is required to understand its salience. Previous econometric research indicates that the criminal incentive plays a notable role in how likely an offender is to commit a crime as the potential payout may discount/negate the imposed threat of arrest and punishment (Agnew, 1994; Becker, 1968; Cullen et al., 1985; Ehrlich, 1973).

The Discount Rate & Illicit Incentives

The concept of pleasure depicted in Bentham's hedonistic calculus directly represents the attraction/incentive to commit a crime. In Becker's (1968) economic model of crime, when the pleasure (utility/incentive) outweighs the pain (risk), then an individual is more inclined to engage in criminal activity even when risk is moderate. Economists and criminologists alike implement operational measures known as discount rates to control for this unique factor in the criminal decision-making process (Mamayek et al., 2017). The discount rate is crucial to understanding marginal fluctuations in criminal decision-making as many potential offenders are undeterrable to a certain extent (Shavell, 1992). Thus, their utility calculus is driven by a reward relative to the threat of sanction imposed by the state (either the certainty or severity elements).

As mentioned previously, the pleasure garnered from committing a crime is relative and can manifest in instrumental or expressive outcomes. Due to this definitional ambiguity, various theoretical works have emerged to help explain how this pleasure (benefit/payout) acts as a force that propels the commission of a crime (Akers, 1973; Gottfredson & Hirschi, 1990; Hirschi, 1969). Though preceding works are informative, there remains a dearth of methodologically valid illicit incentive measures. As a result, the general failure by social scientists to account for the illicit incentive may contribute to the asymmetry in deterrence research. Draca and Machin (2015) elaborate on this issue as follows:

> . . . [the illicit incentive] seems to be the most understudied element of crime determinants that arise from the basic economic model of crime, as it is an area in which there is less of an evidence to draw general conclusions. That said, research in the area is active, despite the conceptual and measurement difficulties that tend to be associated with obtaining good data on the returns to crime for individuals. (pp. 399-400)

The small but growing body of empirical research on illicit incentives shows that the most salient surrogate measures for the pleasure/utility element relate to monetary returns (Draca & Machin 2015; Harbaugh et al., 2013; Shaw et al., 2015). These quantitative analyses of illicit incentives branch out into two distinct works of economic literature. The first and the most equipped to inform large-scale policy examines the value of the loot stolen. As it relates to the economic model of crime, Draca and Machin (2015) operationally define this concept as "the cash flow or return generated by a criminal project, holding the probability of detection or other costs fixed" (p. 401). The second body of literature examines the role of the legal wage.

Empirical works on the value of stolen items have two main focuses. One is the relationship between crime and the fluctuating prices of goods, and the second is how participation in crime correlates to loot value. With the advent of improving technology, the value of various goods has increased drastically (Shaw et al., 2015). Under the assumption that crime follows a pattern of potential gains to illegal activity, Draca et al. (2019) found evidence of an increase in crime following a change in the structure of the pricing of goods. More specifically, they used panel data to test the elasticity of crime to the pricing of forty-four unique consumer goods. After controlling for endogeneity issues in the pricing structure, they found statistically significant elasticity coefficients ranging between .3 and .4. As the pricing of consumer goods decreased, the odds of offenders stealing these same goods also decreased. According to Draca et al. (2019), "the finding that the positive crime–price elasticity holds across a range of goods implies that part of any crime drop could be explained by a falling real value of goods that were traditionally stolen by criminals" (p. 1252).

Under the idea that economic returns matter as a form of pleasure/incentive, a branch of experimental research also delves into the relationship between participation in crime and loot value. Harbaugh et al. (2013) conducted a hypothetical simulation whereby college and high school students could steal from each other after weighing the payout, the probability of getting caught, and the severity of the fine if apprehended. They found “that a $1 increase in the amount of money that is available to steal (loot) increases the probability of theft by 3 percentage points [with an elasticity of .32]” (Harbaugh et al., 2013, p. 9). Though the study is hypothetical because it is laboratory-based, it still allows for the certainty of apprehension and the severity of punishment to be controlled. The findings generated in their study strongly suggest that the value of loot as a pleasure/reward measure is a direct and logical proxy for the illicit incentive.

It is critical to point out that the concept of a criminal “earning” differs from the value of items stolen. Though criminal earnings are still a proxy for the incentive to commit a crime, they are likely only accurate for career criminals who have accumulated a valid illicit salary. Additionally, data on criminal earnings are often skewed and require specialized fieldwork that accounts for only some crimes like drug-dealing or crimes that maintain a criminal enterprise (Draca & Machin, 2015; Levitt & Venkatesh, 2000; Reuter et al., 1990).

The second body of literature that endeavors to measure the pleasure garnered from a crime relates to the labor market. Suppose unskilled individuals are unemployed or do not earn a meaningful salary to actualize their goals in life. In this situation, they may turn to instrumental crimes to supplement their legitimate income. Studies conducted at both the individual and aggregate levels support the notion that low wages and unemployment motivate individuals to commit instrumental crimes (Freeman, 1995; Gould et al., 2002). As aptly noted by Draca and Machin (2005):

> … the economic model of crime suggests that, on the margin, participation in criminal activity is the result of the potential earnings from successful crime exceeding the value of legitimate work, in which the earnings from crime are discounted according to the risk of apprehension and subsequent sanctions. (pp. 392-393)

In another study, Lin (2008) used a series of two-step least squares regression equations to test whether unemployment propels the commission of instrumental offenses. Results showed that "a 1.0 percentage point increase in unemployment can increase property crime by around 1.1 to 1.8 percent" (Lin, 2008, p. 420). While the unemployment rate continues as a surrogate for the illicit incentive, many studies find that it fails to be substantive in predicting violent offending. For example, using longitudinal data, Grogger (1998) reported that many individuals who engage in criminal activity also actively participate in the legitimate labor market. However, despite earning a legal wage, these individuals' legitimate income was typically trivial and impeded their ability to achieve relative pleasure. Crime, therefore, offers a quick fix and increases the overall resources that can effectively be employed to actualize their desires. Gould et al. (2002) further showed that when unemployment and indicators of financial struggle are measured together, more accurate results emerge.

Income inequality is another popular topic when discussing contemporary matters related to the hedonistic calculus. Unfair pay, which differs from marginal income and poverty, restricts specific individuals from the pleasure that they desire out of life. In return, instrumental crimes offer an escape from the disproportionate salaries offered to these individuals. Rufrancos et al. (2013) posit empirical evidence of this assertion through a time-series systematic review. They find that as income inequality increases over time, there is also a notable rise in instrumental offenses. Like empirical research examining the unemployment rate, income inequality fails to predict violent expressive crimes.

Significance & Hypotheses

The current study aims to remedy the problematic controversy among results in empirical deterrence research in two novel ways. First, the illicit monetary incentive relative to risk is added directly to an econometric formulation to gauge whether offenders discount risk when the pleasure garnered from an offense is fixed. Prior research may have overlooked actual deterrent effects by neglecting to account for this possibility by failing to measure the coalescence of pain and pleasure. Second, the current study conducts the first large-scale empirical test of the marginal deterrence thesis. Prior research tests the marginal deterrence principle using surrogate measures of the severity element from deterrence theory. In this study, for the first time, I use the certainty element as the risk factor in the criminal utility calculus that considers a stratified marginal outcome.

To effectively test for marginal deterrence, the current study uses a dependent variable that represents an ordered decision outcome. As previously mentioned, most of the notable studies on criminal deterrence focus specifically on a bifurcated response to shifts in either the certainty (Draca et al., 2011; Klick & Tabarrok, 2005; Lin, 2009) or severity elements (Helland & Tabarrok, 2007; Zimring et al., 2001). Although previous research on marginal deterrence attempts to differentiate between criminal decision-making and specific crime types (Crino et al., 2019; Gibbs, 1968; Jacobs, 2010; Lin, 2009), studies fail to parse out the intermediate decision outcomes an offender may have nested within one crime. Instead, they implicitly assume offenders will bounce from one crime type to another when all crimes maintain different incentives. The current study focuses singularly on the crime of robbery to develop a more nuanced empirical investigation of the marginal deterrence principle.

Methodological Significance of Studying Robbery

Robbery provides a conceptually unique decision-making process ideal for detecting marginal deterrent effects quantitatively because the crime can functionally decrease in severity. For example, suppose the certainty of arrest for an armed robbery is higher than the illicit payout gained from committing the crime. The offender may still choose to commit the robbery but in a less severe form, such as holding someone up with the threat of violence rather than with a firearm. It is also methodologically beneficial to analyze robbery as it is an instrumental offense driven by the desire for monetary gain (Reppetto, 1974; Wright & Decker, 1997). Moreover, when offenders primarily seek a pecuniary reward, they become difficult to deter and may continue to offend by committing less severe offenses (Shavell, 1992).

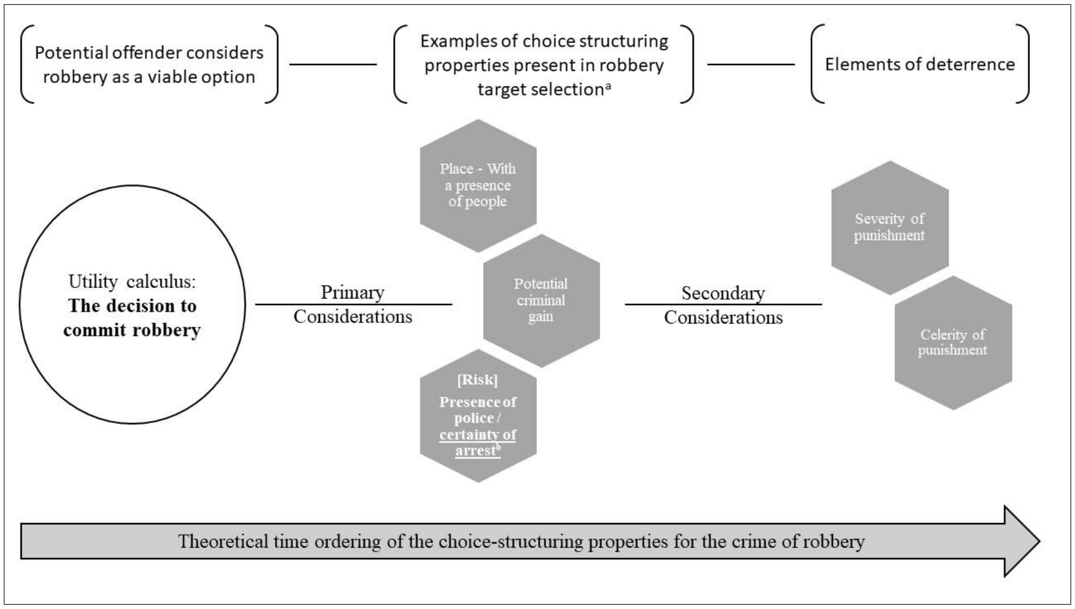
Robbery also provides a quantitative advantage as the certainty of arrest (risk factor) is embedded directly in the crime's choice structuring properties. Though the current analysis uses Becker's (1968) economic model of crime and deterrence/marginal deterrence theory as the guiding conceptual foundation, a brief discussion on Rational Choice Theory's (RCT) choice structuring elements is warranted. The current study does not test RCT in any capacity, but rather the theory illustrates the relevance of analyzing the certainty of arrest rather than the severity of punishment for robbery.

As an extension of RCT, Cornish and Clarke (1987) set forth the conceptualization of choice structuring properties within each crime type to understand why an offender commits a specific crime. Due to the simplistic decision-making process for the crime of robbery, the choice structuring properties are relatively direct and not overly influenced by exogenous variables (Braga et al., 2011; Cornish & Clarke, 1987; Cook, 1987). Prior research on RCT suggests that the decision to commit a robbery occurs relatively quickly after the potential gain and the risks involved are appraised (Block & Davis, 1996; Sampson et al., 1997; St. Jean, 2007; Wright & Decker, 1997).

When contemplating risk in the decision-making process for robbery, it almost exclusively refers to the visible presence of the police, cameras, or security guards in the location the crime would occur (Braga et al., 2011; Erickson, 1996; Wright & Decker, 1997). One unifying element of these visible risk factors is that they all increase the certainty of apprehension. Therefore, when potential robbers conduct their rational appraisal, they directly include a crucial element of deterrence theory as a primary choice-structuring consideration. Figure 3 provides a visual example of the primary (choice structuring properties) and secondary concerns of a potential offender when pondering the decision to perpetrate a robbery.

Figure 3

Theoretical Choice-structuring Considerations for a Potential Robbery Offender



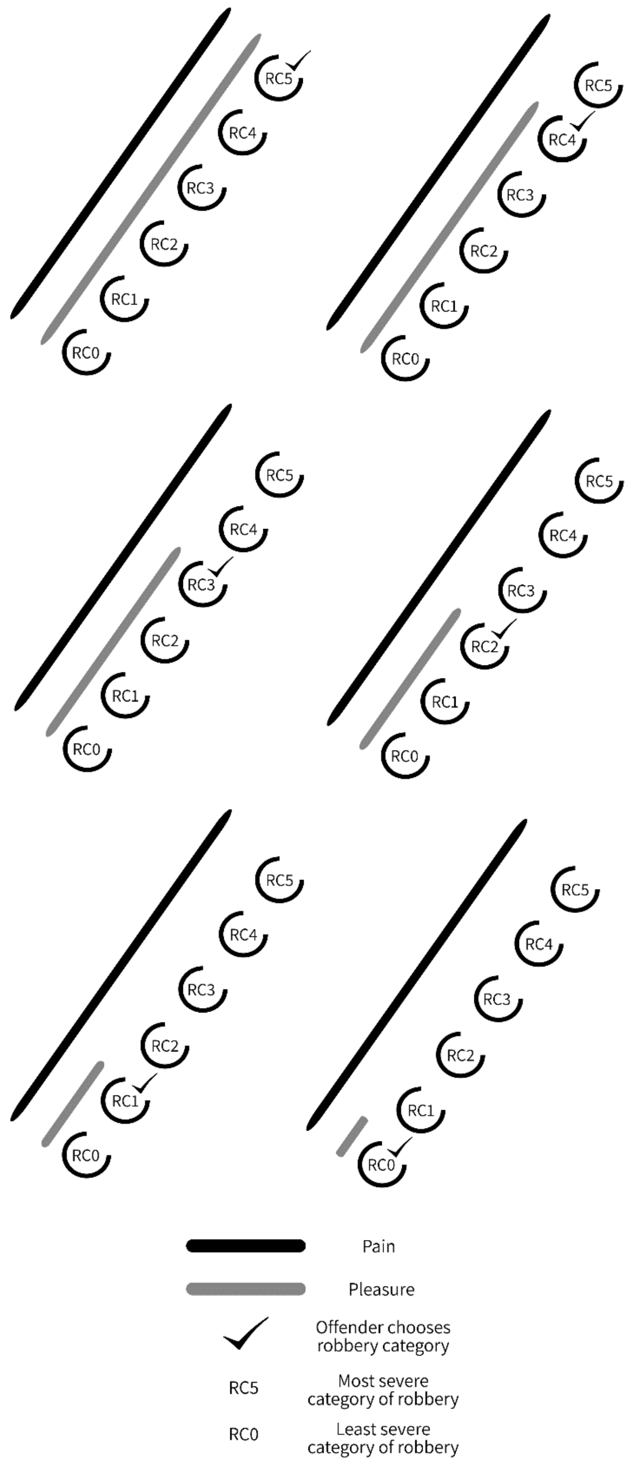
Note. [a]The choice structuring elements in the figure are not exhaustive and are an adaptation of the conceptualization made by Cornish and Clarke (1987). [b]The certainty of apprehension is a key element of deterrence theory. Since this element is directly connected to a potential offender's decision-making process, there is an assumption that increasing the certainty of arrest will directly decrease robbery occurrences to some degree (Nagin, 2013a). This circumstance gives the study of robbery a unique operational advantage.

Consequently, deterrence scholars tend to agree that individuals who commit crimes differ in their decision-making processes from those who do not commit crimes. From an econometric perspective, criminals are more impulsive, have high discount rates, and are more present-oriented. Mamayek et al. (2017) define discounting as the rational and deliberate devaluation of the future (see p. 214 to compare discounting and impulsivity). Regarding marginal deterrence, offenders rebate any potential risks with a high discount rate. Conversely, the marginal deterrence thesis dictates that as the discount rate increases, a potential offender should be more inclined to commit a more severe crime (Mastrobuoni & Rivers, 2016; Polinsky & Shavell, 1999).

To illustrate, Figure 4 fuses the certainty element, the discount rate, and the ordered decision scheme to display the conceptual foundation for the empirical test of marginal deterrence in the current study. The figure represents a theoretical visualization of how the discount rate applies to the operationalization of marginal deterrence. If the illicit reward increases relative to the certainty of arrest, several possible outcomes may materialize past the dichotomous decision to commit a crime or abstain completely. Within the figure, six sub-categories of robbery (*RC)* appear as *RC0* – *RC5* and represent the ranked decision outcomes a potential offender may choose. Chapter 3 defines these categories in detail. The current analysis aims to test the marginal deterrence thesis by empirically evaluating the interaction of pain and pleasure. More specifically, as the illicit monetary incentive (pleasure) increases relative to the certainty of arrest (pain), there should be an increase in the likelihood that offenders will commit a more severe form of robbery. In contrast, if the illicit incentive decreases, the severity of robbery should follow suit.

Figure 4

The Marginal Deterrence Principal



CHAPTER III

DATA & METHODOLOGY

To date, the few existing empirical studies on marginal deterrence exclusively focus on the aggregate level of analysis (Basili & Belloc, 2020; Ekelund et al., 2006). Macro-level research has the unique advantage in that it provides accurate measurements of the ecological dynamics that may affect criminal behavior. For example, surrogate measures of the critical elements of deterrence naturally occur on the city or county level (e.g., frequency of arrest or mean prison sentence in months). However, while intuitive, these studies cannot fully capture a marginal deterrent effect because the decision to deescalate the severity of a crime occurs on the individual level (Shavell, 1992). That said, the current study explicitly tests the marginal deterrence hypothesis by implementing a multilevel dataset and methodology.

Data

The present study concurrently analyzes two unique units of analysis to test the marginal deterrence hypothesis. Specifically, different types of robbery incidents (micro-level) are nested within 98 cities (macro-level) with a population of 50,000 or more for 2015 and 2016.[17] Consistent with prior criminological research, cities serve as a robust unit of analysis to measure deterrent effects (Nagin, 1998). Figure 5 provides an overview of the geographic dispersion of the cities used in the current analysis.

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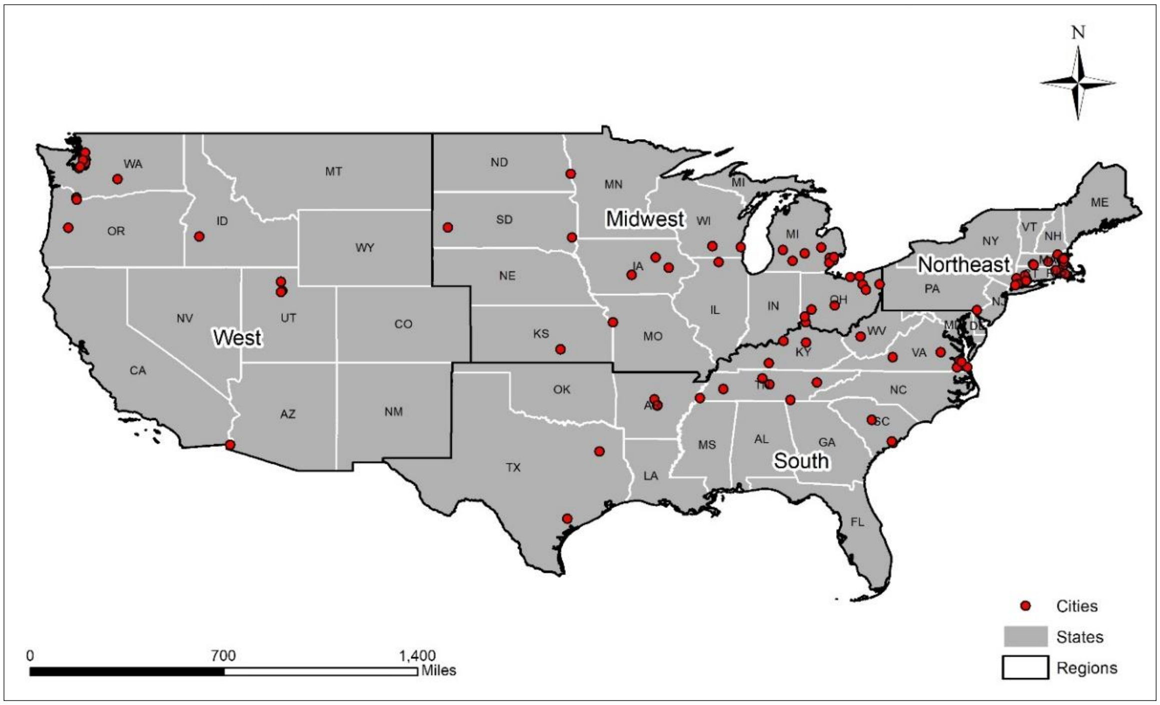
[17] Furthermore, the individual-level unit of analysis is referred to as "micro-level" and the aggregate-level unit of analysis is referred to as the "macro-level."

Figure 5

Geographic Delimitations of the Study



The micro-level data derive from the National Incident-Based Reporting System (NIBRS) and represents 29,297 robbery incidents (National Archive of Criminal Justice Data, 2018). The NIBRS was born of the Federal Bureau of Investigation's (FBI) Uniform Crime Report (UCR), which provides aggregate counts and crime rates throughout the U.S. The NIBRS, however, collects an array of detailed and sophisticated indicators on the incident, offense, victim, known offender, and arrestee level (Federal Bureau of Investigation, 2013).

For example, the NIBRS harbors information such as the value of property stolen, drug type and quantity, type of victim, bias motivation, and types of physical injury, to list just a few. The recording of these data elements originates from the responding police officer at the crime scene and then undergoes extensive quality-control procedures. While not all police departments report to the NIBRS, enough do to sufficiently consider it nationally representative. Pattavina et al. (2017) conducted an evaluation-based scientific analysis on the representativeness of the NIBRS in comparison to the UCR. They found that the distribution of arrests across crime types was similar, save for trivial differences in demographics. This finding led them to two unique conclusions about the NIBRS. The first was that the NIBRS was more representative of the arrest rate overall, and the second was that the NIBRS provided more contextual precision than the UCR.

Dependent Variable

In stark contrast to previous research that neglects to consider any intermediate decision outcomes (Corman & Mocan, 2000; Lin, 2009), the dependent variable in the current study represents the stratified types of robbery an offender may choose. Specifically, the micro-level outcome measure stratifies down to a six-level severity index originating from the NIBRS. The strata include attempted robbery (encoded 0), robbery with no weapon (encoded 1), robbery with bodily force (hands, feet, teeth, etc.) (encoded 2), robbery with a knife, cutting instrument, or blunt object (encoded 3), robbery with a firearm (encoded 4), and robbery where a victim was seriously injured or killed (encoded 5).

Figure 6 displays a breakdown of the distribution of the dependent variable. Upon visual examination of Figure 6, it is apparent that the dependent variable falls into a non-linear categorical logistic distribution. Categorical distributions appear when *k* is greater than 2 for the outcome variable, and each category is discrete (Murphy, 2006).[18] This logistic distribution can represent ordered or unranked multinomial outcomes (Long, 1997; McCullagh & Nelder, 1989). Whether or not the echelons of the outcome measure represent a ranked or unranked encoding scheme lies within the research hypothesis outlined in the study. McCullagh and Nelder (1989) drive this point by using the same logistic distribution in an example that includes a ranked scale of colors (electromagnetic spectrum) and the unranked colors of automobiles. For example, Long (1997) expresses that even though:

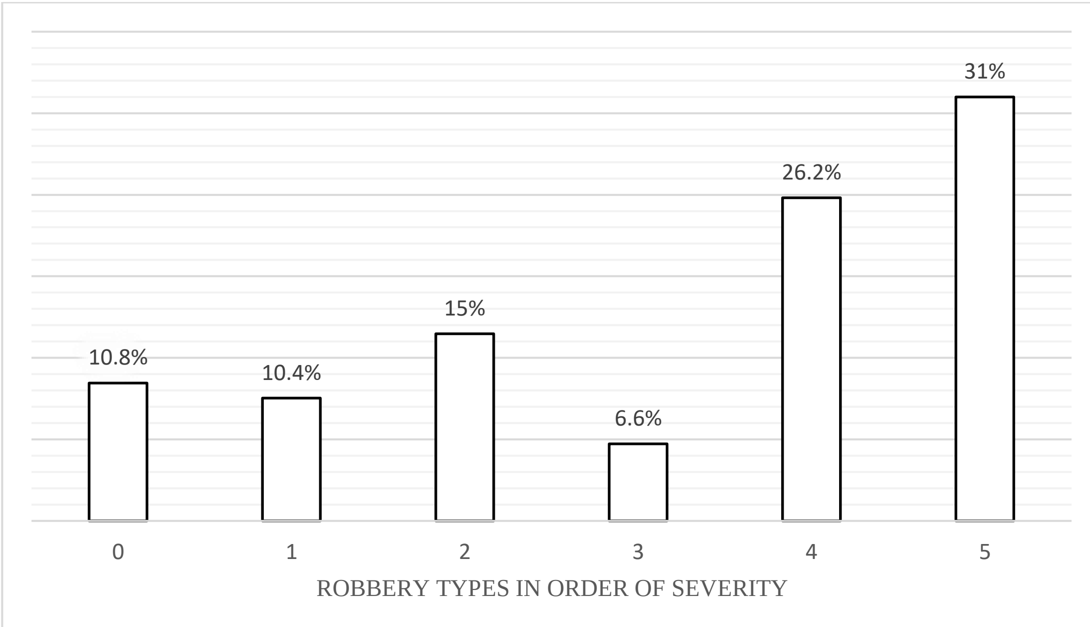
> . . . the values of a variable *can* be ordered does not imply that the variable *should* be analyzed as ordinal. A variable might be ordered when considered for one purpose, but be unordered or ordered differently when used for another purpose. (p. 115)

Therefore, the outcome measure should have a naturally occurring severity scale underlying its operationalization to classify the variable's distribution as ordinal. If the categories of the outcome measure are ambiguous or purposefully viewed as unranked, then the categorical logistic distribution takes on the operations of a Bernoulli/multinomial distribution (Dey & Raheem, 2016; Murphy, 2006). In the current analysis, the robbery categories naturally increase in severity through each variable attribute as they progressively impose more harm.

[18] The character *k* generally represents a category. If k=6, then there are six categories.

Figure 6

Histogram of the Dependent Variable



Note. 0 = attempted robbery, 1 = robbery with no weapon, 2 = robbery with bodily force (hands, feet, teeth, etc.), 3 = robbery with knife or cutting instrument or blunt object, 4 = robbery with a firearm, and 5 = robbery where a victim was seriously injured or killed.

Macro-level Incentive Measure

As previously discussed, the monetary payout is a driving incentive for the commission of robbery (Agnew, 1994; Becker, 1968; Ehrlich, 1973). In a similar vein, the incentive that stems from the criminal payout directly fits into a robber's choice structuring elements, making it a direct motive (Cornish & Clarke, 1987). Since this incentive drives the rational process, I intend to measure a complete utility calculus by accounting for both pleasure (incentive) and pain (frequency of arrest).

The criminal incentive variable operationalizes as the average take (in dollars) per arrest in robbery incidents. Mathematically, it is the quotient of the estimated value stolen divided by the frequency of arrest, weighted by the robbery severity scale, and converted to a mean incentive score per city. The value stolen per arrest was derived by dividing the estimated value by the arrest frequency for each category of the dependent variable. Since no property is stolen in an attempted robbery, a 0 score was assigned to each city in this category. The calculated scores were converted to a percent distribution by dividing each score by the sum of the six scores and multiplying by 100. Then, the computed percentages were weighted by the robbery severity scale. Category 1 was multiplied by 1, category 2 was multiplied by 2, category 3 was multiplied by 3, category 4 was multiplied by 4, and category 5 was multiplied by 5. Category 0 (attempted robbery) remained a constant 0. The weighted scores were summed and divided by 6 to produce a mean criminal incentive score per city.

Consequently, as the variable increases, the offenders' incentive also increases relative to the certainty of apprehension. This variable serves as a direct proxy for the relative pleasure gained from committing a robbery after offsetting the potential pain. For clarity, the descriptive analysis in Chapter 4 provides an in-depth explanation of the operational function of the macro-level incentive variable.

Though debate persists in the extant literature on how to best analyze the certainty element (Chalfin & Tahamont, 2018; Jacob & Rich, 1982; Wilson & Boland, 1982), the frequency of arrest is the most logical outcome for this specific investigation (D'Alessio & Stolzenberg, 1998). As mentioned previously, offenders rely on a crude and often extemporaneous decision apparatus (Braga et al., 2011; Cornish & Clarke, 1987; Cook, 1987). Thus, making them more sensitive to the raw number of arrests (D'Alessio &

Stolzenberg, 1998). The frequency of arrest and illicit payout measures originated from the NIBRS and were aggregated upwards to all the macro-level units in the sample. The NIBRS provides a unique geographic identifier for each crime incident, thus enabling the data to link to the macro-level units in the sample.

Drawing on Becker's (1968) concept of the utility function and the theoretical currency of the util, I posit the following formulations to describe how the primary variable of theoretical interest should react with the outcome measure as it relates to the marginal deterrence hypothesis. The formulations dictate that the amount of expected utility/pleasure (U) associated with the incentive relative to risk (PR) for any given outcome ($_{ox}$) will result in a marginal choice to commit a form of robbery (O_x) with a lower severity ($_{-PR}$) or a higher severity ($_{PR}$).

$$(1-PR_{ox})U_{ox} + PR_{ox}U_{ox} = O_x(_{-PR}) \tag{4}$$

The left side of the equation represents the risk associated with committing any given form of robbery. The right side of the equation represents the utility associated with the incentive relative to risk. In (4), if the left side of the equation results in more utils than the right, a potential offender should progressively commit less severe forms of robbery, as denoted by $O_x(_{-PR})$.

$$(1-PR_{ox})U_{ox} + PR_{ox}U_{ox} = O_x(_{PR}) \tag{5}$$

While nearly identical, (5) represents the inverse of (4) and signifies the monetary incitement effect. In this case, if the right side of the equation (pleasure) results in more utils than the left side (pain), a potential offender's discount rate should be higher. They will thus choose a more severe form of robbery, denoted by $O_x(_{PR})$, as the pain/risk discounts.

Macro-level Control Variables

Several macro-level control variables are included in the analysis to control for the excess variation in the stratified decision to commit a robbery. These variables include the population density, whether a city is considered northern or southern, percent of males 15-24, percent of individuals attending college, income inequality, residential segregation, and a community disadvantage index. All the macro-level control variables listed above are ratio measures except for the northern/southern city variable, which is nominal. This custom variable denotes whether a city falls north or south of the Mason-Dixon line. Cities below the Mason-Dixon line represent southern cities (coded 1), and those above the line are northern (coded 0). This differentiation is relevant because previous work finds that individuals in southern cities tend to act more aggressively (Erlanger, 1975), and the cities themselves garner higher violent crime rates (Snell, 2010). Controlling for geographic variations in aggressive behavior is exceedingly relevant due to the violent nature of robbery (Federal Bureau of Investigation, 2016).

The population density variable controls for the number of individuals per square mile of land within a city. The research on the effect of population density on crime is inconsistent. Some researchers argue that areas with denser populations offer more criminogenic opportunities (Sampson, 1983), while others maintain that these same areas offer more natural surveillance (Silva, 2014). As a result, conflicting results have emerged due to the stratification of crime types (Christens & Speer, 2005; Li &

Rainwater, 2000). Sampson's (1983) analysis provides strong support for the opportunity thesis despite the inconsistent findings. Specifically, he finds a positive relationship between population density and the occurrence of robbery.

The age-crime curve remains one of the most salient relationships in the study of ecological associations and crime (Hirschi & Gottfredson, 1983). Expressly, individuals aged 15 to 24 represent a small portion of the U.S. population but accounted for approximately 52 percent of robberies in 2015 (Federal Bureau of Investigation, 2015b). In a similar vein, males account for roughly half of the U.S. population (United States Census Bureau, 2010) but are responsible for 85 percent of the robberies (Federal Bureau of Investigation, 2015a). Due to this statistical overrepresentation, a control variable representative of the percentage of males aged 15-24 appears in the analysis.

In conjunction with the macro-level age/sex variable, I include a control variable for emerging adulthood productivity that may reduce the chances of criminal behavior. The pursuit of higher education has long been a defining element for individuals aging out of (Hirschi & Gottfredson, 1983) or desisting from crime in general (Sampson & Laub, 1995; Walters, 2018). Prior research shows that individuals who lack education, concentrated skills, or a specialization tend to commit instrumental crimes (Schnepel, 2013). Data for the population density, percent male 15 to 24, and percent attending college, derive from the 2010 decennial census (United States Census Bureau, 2010).

Moving forward, Becker (1968) emphasizes that an ecological incentive to commit instrumental crimes extends to those who experience low returns from the legitimate market. This situation is especially relevant when those who experience income inequality reside close to those who experience high returns and thus possess items of value/wealth. While using Becker's theoretical framework as a backdrop, Kelly (2000) finds that "the high elasticity of violent crime with respect to inequality is generated by the strong impact of inequality on assault and robbery" (p. 535). Though several unique quantitative approaches exist for calculating income inequality, the Gini coefficient is one of the most standardized and appropriate measures (Haughton & Khandker, 2009). The functioning of the Gini coefficient determines a cumulative frequency that compares the distribution of one variable to a uniform distribution representative of equality (Haughton & Khandker, 2009). The coefficient ranges from 0 to 1, where 0 represents perfect equality, and 1 signifies absolute inequality. Data for the Gini coefficient come from the U.S. Census Bureau (2010).

Similarly, Black segregation remains a chronic issue within cities throughout the U.S. (Emerson et al., 2001; Massey & Denton, 1993). While these areas tend to suffer a myriad of adverse social conditions (Collins & Williams, 1999; Massey et al., 1994), the most problematic is the excess of crime (Akins, 2003; Peterson & Krivo, 1993; Shihadeh & Flynn, 1996). The Black segregation variable is measured using the social isolation index (SII), which controls for the lack of meaningful legitimate opportunities within a city that have historically led individuals to the commission of robbery (Shihadeh & Flynn, 1996). It also controls for race-based patterns of violence. For example, prior research shows that as Black isolation increases, violence tends to become intraracial rather than interracial (O'Flaherty & Sethi, 2007). O’Flaherty and Sethi (2007) state that Blacks are more likely to rob other Blacks when isolation increases. The robbery incident becomes more violent as disadvantaged Blacks are less willing to part with their valuables.

Data for the SII came from the 2010 decennial census and was calculated with the formula below.

$$B_{bw} = \sum (n_{ib}/ N_b)\ (n_{iw}/n_i) \tag{6}$$

Within (6), n_{ib} refers to the number of Blacks within the block group, N_b is the number of Blacks in the city, n_{iw} is the number of Whites in the block group, and n_i is the total population of the block group. The SII is constructed so that as the index ascends, segregation increases. Prior research shows that the SII targeted at Black isolation is a more potent predictor of robbery incidents than are other segregation measures such as the dissimilarity index (Shihadeh & Flynn, 1996).

Lastly, community disadvantage is a composite measure calculated from a principal component analysis (PCA) of several variables predictive of robbery. The variables that comprise the measure include the percent of families below the poverty line in 2009, the percent of households headed by a single female with children, and the percent of the civilian labor force that is unemployed (see Table 2). If the composite variable falls within a high range, it represents an elevated level of community disadvantage for a city. The data for the community disadvantage measure originated from the U.S. Census Bureau (2010) for poverty and the female head of household measures, while the Bureau of Labor Statistics (2010) was used for the unemployment measure.

Table 2

Principal Component Analysis for Community Disadvantage

	Percent of variance	Component
Percent of population living below the poverty line in 2009	82.432	.887
Percent of households headed by a single female with children	10.419	.920
Percent of civilian labor force that is unemployed	7.149	.917

Note. N = 98 cities.

Micro-level Control Variables

Several relevant micro-level control variables are added to the analysis, as they may be associated with the decision to commit a more or less severe form of robbery. Namely, these variables include the race and sex of the victim and offender, the ethnicity and age of the victim, and whether the victim was a juvenile. All the micro-level control variables follow a nominal encoding scheme except for age, which is a ratio variable. See Table 3 for the encoding of these dichotomous variables. All data for the micro-level measures originate from the NIBRS.

As previously discussed, age is a quintessential control variable in criminal deterrence research (Chalfin & McCrary, 2017). On the individual level, the victim's age controls for the enhanced proclivity of robbers to disproportionately victimize older individuals, believing they will exude less resistance (Wright & Decker, 1997). Congruently, biological sex for victims and offenders appears on the micro-level in the analysis. Though prior studies suggest that biological sex is not a salient indicator of robbery perpetration (Rennison & Melde, 2014), it may still yield some explanatory power about victim selection. Prior research suggests that females are disproportionately targeted as robbery victims because they appear more compliant and less intimidating (Miller, 1998).

In a similar vein, juveniles tend to suffer from violent victimization stemming from a robbery at a rate of approximately 3 per 1,000 for the crime of robbery (Hullenaar & Ruback, 2020). While deterrence studies often overlook juveniles, they may hold explanatory power for the fluctuating level of violence within a robbery incident. Much like the perception that females represent a minor threat, juveniles may be more compliant with an offender during a robbery.

In a similar vein, race plays a functional role in the perpetration and victimization of robbery (Bureau of Justice Statistics, 2019; Lochner & Moretti, 2004), though variation exists from city to city (Velez et al., 2015). Hipp et al. (2020) found that as the percent Black increased in the proximity to their geographical unit of analysis (street segment), the odds of a robbery occurring increased by approximately 15 percent. Additionally, it is essential to note that most violent crimes in the U.S. are intraracial rather than interracial (Morgan, 2017). However, for robbery, Whites bear 63 percent of the prevalence of robbery victimization while Blacks and Hispanics experience approximately 15 percent for 2015 (Truman & Morgan, 2018). According to O'Flaherty and Sethi (2007), robbers disproportionately target Whites as they seem more affluent. Similarly, Akins (2007) states that "since the income of a potential robbery victim may not be visually apparent to a potential offender, race is thought to be used as a proxy for wealth" (p. 86).

Table 3

Descriptive Statistics and Encoding of Variables in the Analysis

	Proportion (Mean/SD)	Coding
Robbery severity scale	(3.27/1.74)	0=attempted robbery, 1=robbery without weapon, 2=robbery with personal weapons (hands, feet, teeth, etc.), 3=robbery with knife/cutting instrument or blunt object, 4=robbery with firearm, 5=robbery resulting in victim injury or death (homicide)
Black offender	.79	1=black, 0=white
White victim	.53	1=white, 0=black
Hispanic victim	.13	1=Hispanic, 0=non-Hispanic
Male offender	.93	1=male, 0=female
Female victim	.65	1=female, 0=male
Victim age	(35.75/15.62)	Years
Victim juvenile	.08	1=juvenile, 0=adult
Incident year	.52	1=2016, 0=2015
Black offender indicator	.31	1=missing data, 0=valid
Hispanic victim indicator	.25	1=missing data, 0=valid
Male offender indicator	.27	1=missing data, 0=valid
Criminal incentive	(71.49/10.77)	Measures incentive to commit a more serious robbery; higher scores indicate greater incentive.
Population density	(3,026.56/2,128.91)	Population per square mile of land area.
Southern city	.31	1=Southern city, 0=no; controls for possibility of southern subculture of violence and crime

	Proportion (Mean/SD)	Coding
Percent male 15-24	(8.02/1.86)	Percent of population prone to criminal activity (ages 15-24)
Income inequality	(.47/.04)	Measures distribution of household income for all residents (Gini coefficient); ranges from 0=perfect equality to 1=total inequality
Social isolation index	(.56/.21)	Measures residential racial segregation; higher scores indicate greater segregation.
Percent some college	(23.51/3.49)	Percent of population with some college or associate degree.
Community disadvantage	(.00/1.00)	Factor scores from principal component analysis of 3 variables: (a) % of population below poverty line in 2009, (b) % of households headed by a single female with children, and (c) % of civilian labor force that is unemployed; higher scores indicate greater disadvantage

Note. N = 29,297 incidents in 98 cities.

Missing Data

It is important to note that three variables in the current analysis are missing about 20% of their cases. These variables include Black offenders, male offenders, and whether the victim was Hispanic. The pattern of missing values suggests that the data are absent due to systematic variations in reporting practices among the different law enforcement agencies. Therefore, to maximize available information, a statistically sound missing data technique is required to include these variables. Cohen and Cohen (1983) introduce a mean substitution method for systemically missing data, commonly known as the indicator variable technique. This novel stratagem reduces excessive bias introduced by the often-used traditional mean substitution method.

The first step requires creating a nominally encoded variable where 1 = missing data values and 0 = valid values. The second step is to assign a constant to each missing value. Stolzenberg and D'Alessio (1993) write that "this number is not an estimate for the missing value but is assigned so that all calculations in the regression analysis are generated from the same sample size" (p. 188). The constant itself should equate to the mean of the missing values generated by the dichotomous indicator variable. This procedure ensures that any problematic correlations between the missing values and the missing data indicator equal zero (Cohen & Cohen, 1983). If statistically significant, the data are genuinely missing systematically. The coefficient of the original variable then maintains a reliable interpretation as Stolzenberg and D'Alessio (1993) display that "the bias is mitigated by the indicator variable" (p. 188).

Analytical Strategy

Due to the multilevel nature of the data and the violation of the Gaus-Markov assumptions by the dependent variable (Larocca, 2005), I employ a series of two-level generalized linear regression models to test the marginal deterrence hypothesis. Traditionally, non-linear outcome variables undergo empirical transformation to fit into an orthogonal Gaussian distribution for direct linear investigation (Kirk, 1982; Mosteller & Tukey, 1977). Hox (2010) states that "empirical transformations have the disadvantage that they are ad hoc, and may encounter problems in specific situations" (p. 113). Generalized linear models (GLM) provide a more accurate apparatus for investigating ordered categorical data. They directly include the transformation and stipulate an appropriate error distribution as part of the statistical model without manual manipulation of the outcome variable (Gill, 2000; McCullagh & Nelder, 1989).

GLMs require three unique conditions to produce accurate parameter estimates (see Hox, 2010, p. 113; McCullagh & Nelder, 1989, p. 27). First, there must be an outcome variable (y) with a specific error distribution that can produce a mean and variance statistic. Second, a linear additive regression equation that produces a latent predictor in the outcome variable must be present. Third, a link function connects the expected values of the outcome variable to the predicted values. As mentioned previously, the dependent variable in the current analysis falls into a categorical logistic distribution and is naturally ordinal (Ling et al., 2018; Long, 1997). In the logistic distribution, the mean is 0, and the variance is $\pi^2/3$ (3.29) (Hox, 2010; Long, 1997). Since the error distribution is non-linear, the GLM also produces robust standard errors for the parameter estimates. The robust standard errors pave the way for higher performance statistical models because they elucidate whether the standard errors produced by the regression coefficients are unbiased (Beck & Katz, 1997).

On the basis thereof, the current analysis uses multilevel cumulative ordered logistic regression (a hierarchical generalized linear model – HGLM) to test the marginal deterrence hypothesis. Ordinal outcome variables such as Likert scales are often analyzed using ordinary least squares regression (OLS) when the categories are seven or higher, and the researchers can show that the distribution is symmetrical (Hox, 2010). In the case of the current outcome measure, there are only six categories. A Kolmogorov-Smirnoff test (K-S test) also indicated that the logistic distribution was not orthogonal ($p < .001$).

The cumulative ordered regression model undergoes a unique iterative process to generate parameter estimates. Specifically, it computes a threshold for each echelon of the outcome measure (Long, 1997). The thresholds represent the cutoff point between each intermediate decision outcome for the crime of robbery. It is important to note that the multilevel ordinal regression model in the current analysis will only display four thresholds even though there are six categories. The sixth threshold represents the reference category (k-1), and the first serves as an overall intercept for the two levels of analysis.

Traditionally, single-level ordinal regression does not generate a general intercept as the thresholds represent the variables set to zero for each category of the outcome measure. A single intercept is required when adding a second level of analysis because each threshold in the equation can randomly vary from one macro-level unit to another (Hox, 2010). To effectively observe fixed effects, the first threshold is subtracted from all the others so that it equates to zero and randomly varies across the macro-level units. This way, the other thresholds are constrained only to represent the fixed effects of the exogenous predictors in the model. The result of these cumulative probabilities is one coefficient that suggests the relationship's direction and magnitude based on a unique comparison of each threshold to the reference category. Equation 7 visually represents the thresholds where (*i*) represents an individual nested within a city (*j*), ϕ^*_{0ij} represents attempted robbery, and ϕ^*_{5ij} represents a robbery where the victim was seriously injured or killed.

$$\textit{Threshold 1: } Prob\left[Y_{ij} \leq 0 \middle| \beta_j\right] = \phi^*_{0ij} = \phi_{0ij} \tag{7}$$
$$\textit{Threshold 2: } Prob\left[Y_{ij} \leq 1 \middle| \beta_j\right] = \phi^*_{1ij} = \phi_{0ij} + \phi_{1ij}$$
$$\textit{Threshold 3: } Prob\left[Y_{ij} \leq 2 \middle| \beta_j\right] = \phi^*_{2ij} = \phi_{0ij} + \phi_{1ij} + \phi_{2ij}$$
$$\textit{Threshold 4: } Prob\left[Y_{ij} \leq 3 \middle| \beta_j\right] = \phi^*_{3ij} = \phi_{0ij} + \phi_{1ij} + \phi_{2ij} + \phi_{3ij}$$
$$\textit{Threshold 5: } Prob\left[Y_{ij} \leq 4 \middle| \beta_j\right] = \phi^*_{4ij} = \phi_{0ij} + \phi_{1ij} + \phi_{2ij} + \phi_{3ij} + \phi_{4ij}$$
$$\textit{Threshold 6: } Prob\left[Y_{ij} \leq 5 \middle| \beta_j\right] = \phi^*_{5ij} = 1.0$$

Since the most severe form of robbery (threshold 6) is the reference category, it is redundant in (7). Intuitively, the most severe form of robbery serves as a salient reference category as any observation made would be modeled at or below the decision to kill or seriously injure a victim. For example, a salient positive relationship between the illicit incentive and the outcome measure would show that given every possible iteration displayed in (7), an offender has an enhanced proclivity to choose a more severe form of robbery (monetary incitement effect). For a negative relationship, the same would apply, but the offender would be more likely to choose a less severe form of robbery (deterrent effect).

Lastly, for the HGLM to perform correctly, it must have a unique link function to tether the expected values to the predicted values in the outcome variable. A specific canonical link function exists for each error distribution to generate sound operational transformations of the outcome variable under analysis (Hox, 2010). The logit link function is the most appropriate for implementing ordinal regression when a logistic error distribution is present (McCullagh & Nelder, 1989). Additionally, the logit link function yields exponentiated beta regression coefficients (odds ratios), which allow for palatable interpretations (Breslow & Clayton, 1993). The logit link function is written below and adapted from Hox (2010, pp. 142-143):

$$Log\left(\frac{p^{*}_{kij\leq\phi_5}}{1-p^{*}_{k\leq\,\phi_5}}\right) = \beta_{0j} + \beta_{1j}X_{ij} + e \qquad (8)$$

Where β_{0j} is the randomly varying intercept and represents the mean log odds of an offender choosing an offense type at or below the most severe strata of the outcome measure with all independent variables set to zero; $p^{*}_{kij\leq\phi_5}$ represents the repeated cumulative probability of an offender (*i*) nested within a city (*j*) choosing an offense type (*k)* at or below the most severe form of robbery (ϕ^{*}_{5ij}); $1 - p^{*}_{k\leq\,\phi_5}$ represents the non-repeated cumulative probability of an offender nested within a city choosing an offense type at or below the most severe form of robbery; β_{1j} represents the micro-level predictors with X_{ij} as the numerical change in the probability of an offender choosing one type of robbery over the other; and *e* represents the error term.

It is important to note that the above formulation of the logit transformation only shows the micro-level predictors. However, the intercept randomly varies from one macro-level unit to another while all exogenous variables remain fixed. Therefore, the two-level model is as follows, where y_0 represents the city-level variables and μ_0 signifies the error term.

$$\beta_{0j} = y_{00} + y_{01} + \mu_0 \qquad (9)$$

An independent fixed observation computes for each macro and micro-level variable on the outcome measure with this model specification.

CHAPTER IV

MULTILEVEL REGRESSION ANALYSIS

To effectively test the associations between the illicit incentive and a stratified decision-making apparatus, the current study employs a series of HGLM regression equations. Multilevel modeling procedures are exceedingly appropriate to test hypotheses on criminal deterrence. The incentive element, which is the sum of an offender's risk and reward (utility calculus), functions at the aggregate level in the current analysis. Conversely, the decision to commit the various degrees of robbery (outcome measure) manifests at the individual level. Therefore, a two-level regression model accurately calculates the interplay between an increase in the illicit incentive and the individual offender's decision to commit a more or less severe form of robbery.

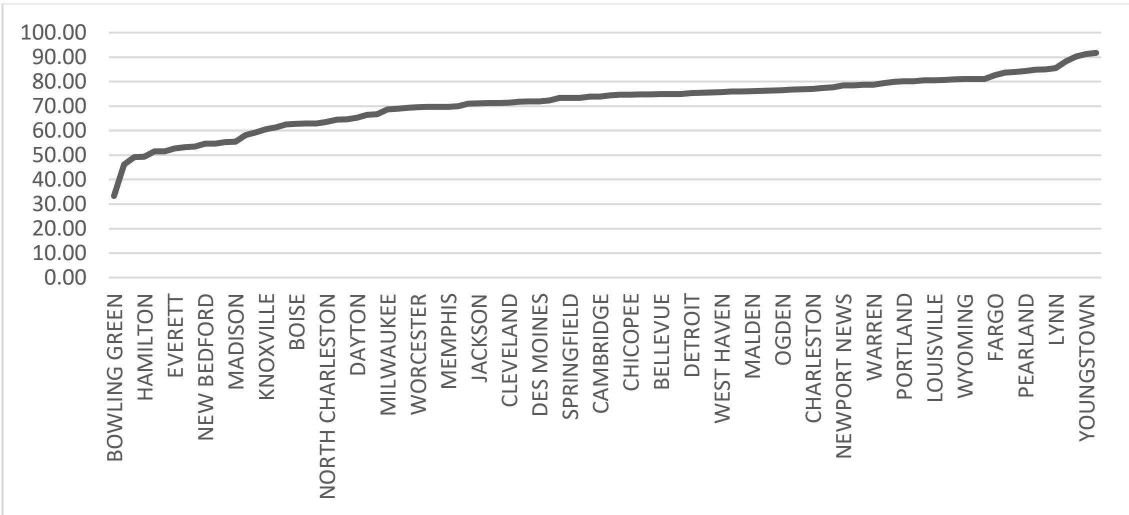
The analysis employs the HLM7 software to model the multilevel regression equations. The use of HLM7 helps to reduce type I error among the covariates by controlling for the natural clustering caused by the level two units (Hox, 2010). The remainder of the chapter details the analyses in the current study. First, a descriptive analysis provides context on the bivariate relationship of the illicit incentive and the severity of robbery. Second, a within-city fixed-effects analysis is conducted that excludes all contextual macro-level variables. The within-city model examines the impact of the individual-level explanatory variables to ascertain the relevance of using both levels of analysis. Lastly, a between-city fixed-effects model calculates the association of the ecological variables and tests the research hypothesis illustrated in Chapter 2 with the standard alpha threshold of .05. All explanatory variables in the within and between-city analysis utilize grand mean centering to ensure the mean of each variable is zero across all cases.

Descriptive Analysis

Due to the complexity of the variables and methodology in the current study, a descriptive analysis helps provide clarity. I begin the analysis by sorting the cities in ascending order by the weighted illicit incentive measure. Figure 7 displays the cities used in the analysis based on their percent distribution. A visual inspection of the trendline shows that the illicit incentive measure varies considerably among the cities and does not concentrate under any specific values on the Y-axis. For example, a robber in the city of Bowling Green has a 33 percent incentive to commit a more severe form of robbery. In contrast, a robber in Youngstown has a 91 percent incentive to escalate the severity of a robbery.

Figure 7

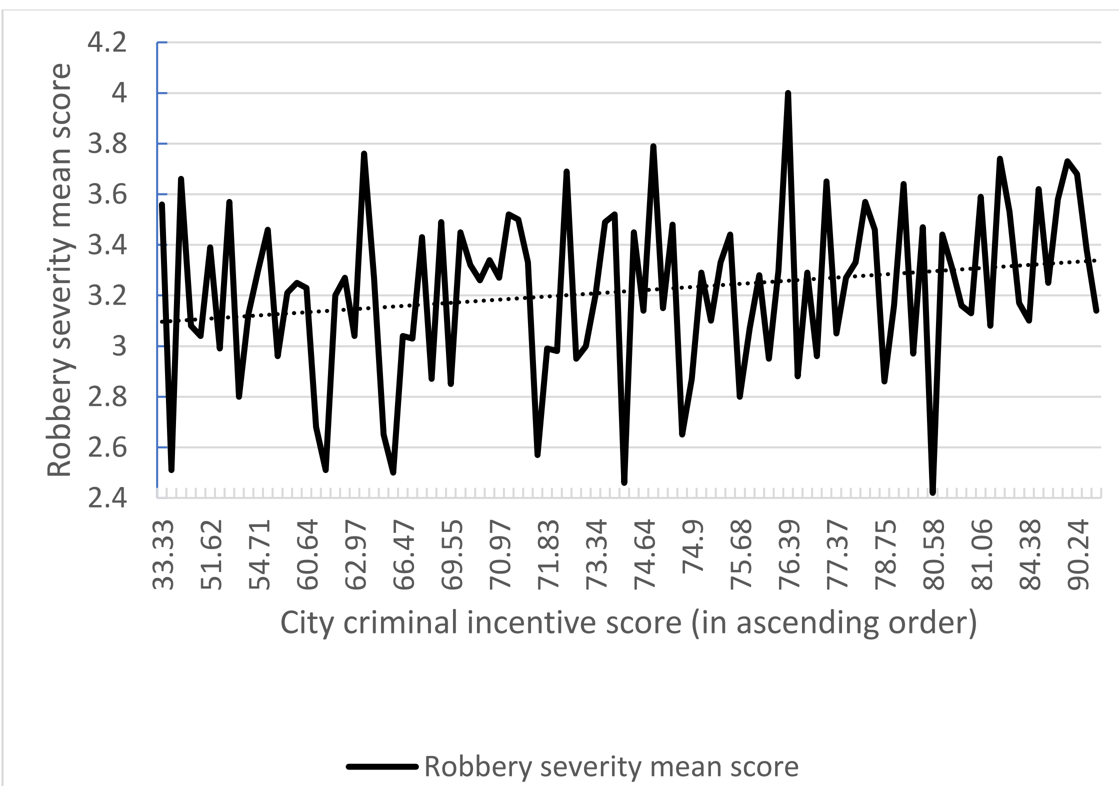
Variation Accounted for by the Illicit Incentive Variable



Next, the severity of robbery appears on the Y-axis to show the general interaction between the primary independent variable of theoretical interest and the outcome measure. Since the type of robbery an offender commits is at the micro-level, I summed the variable upwards to the city. Then, each macro-level unit had an average calculated for it that represented the mean level of robbery severity committed in each city. Upon visual examination of Figure 8, it is apparent that a notable positive relationship exists between the two variables. As the illicit incentive progressively ascends through the cities in the study sample, offenders are marginally choosing to commit more severe forms of robbery based on the city average.

Figure 8

Robbery Severity Mean Score by City Levels of Criminal Incentive



Though intuitive, these figures only represent a descriptive overview of what the data represent. To formally test the research hypothesis in the current study, I run a series of HGLMs. Before illustrating the within and between-city analyses, a brief discussion on the estimation method explains how the effect sizes and coefficients compute in the following regression equations.

Estimation Method

Maximum likelihood methods are often used for estimating parameters with GLMs (Hox, 2010). However, when implementing a multilevel specification, the estimation of model parameters becomes rather complex as both the micro and macro iterations lead to convergence errors. Therefore, many social scientists implement quasi-likelihood estimation procedures to ensure the most accurate approximations for their regression outputs. In HGLMs, there are two main quasi-likelihood estimation procedures appropriate for ordered data. They are the marginal quasi-likelihood (MQL) and penalized quasi-likelihood (PQL) estimation procedures. According to simulation studies, the MQL procedure performs best when the multilevel sample size is relatively small, and the PQL procedure is more accurate for larger datasets (Goldstein, 2003). The current study uses PQL to accurately estimate the relationship between the illicit incentive measure and the odds of an offender escalating the severity of robbery as the sample is relatively large.

Within-city Results

The preliminary ordinal regression equation only includes the individual offenders nested within the 98 cities. The within-city cumulative ordered regression equation is as follows: *i* represents the individual offender, *j* represents the city wherein they are nested, and β_{ij} represents the coefficients for the offender variables.[19]

(10)

$$\log[\phi^*_{0ij}/(1 - \phi^*_{0ij})] = \beta_{0j} + \beta_{1j}*(OBLACK_{ij}) + \beta_{2j}*(VWHITE_{ij}) + \beta_{3j}*(VHISP_{ij}) + \beta_{4j}*(OMALE_{ij}) + \beta_{5j}*(VFEMALE_{ij}) + \beta_{6j}*(VAGE_{ij}) + \beta_{7j}*(VJUVE_{ij}) + \beta_{8j}*(Y2016_{ij}) + \beta_{9j}*(INDOB_{ij}) + \beta_{10j}*(INDVH_{ij}) + \beta_{11j}*(INDOM_{ij})$$

$$\log[\phi^*_{1ij}/(1 - \phi^*_{1ij})] = \beta_{0j} + \beta_{1j}*(OBLACK_{ij}) + \beta_{2j}*(VWHITE_{ij}) + \beta_{3j}*(VHISP_{ij}) + \beta_{4j}*(OMALE_{ij}) + \beta_{5j}*(VFEMALE_{ij}) + \beta_{6j}*(VAGE_{ij}) + \beta_{7j}*(VJUVE_{ij}) + \beta_{8j}*(Y2016_{ij}) + \beta_{9j}*(INDOB_{ij}) + \beta_{10j}*(INDVH_{ij}) + \beta_{11j}*(INDOM_{ij})$$

$$\log[\phi^*_{2ij}/(1 - \phi^*_{2ij})] = \beta_{0j} + \beta_{1j}*(OBLACK_{ij}) + \beta_{2j}*(VWHITE_{ij}) + \beta_{3j}*(VHISP_{ij}) + \beta_{4j}*(OMALE_{ij}) + \beta_{5j}*(VFEMALE_{ij}) + \beta_{6j}*(VAGE_{ij}) + \beta_{7j}*(VJUVE_{ij}) + \beta_{8j}*(Y2016_{ij}) + \beta_{9j}*(INDOB_{ij}) + \beta_{10j}*(INDVH_{ij}) + \beta_{11j}*(INDOM_{ij})$$

$$\log[\phi^*_{3ij}/(1 - \phi^*_{3ij})] = \beta_{0j} + \beta_{1j}*(OBLACK_{ij}) + \beta_{2j}*(VWHITE_{ij}) + \beta_{3j}*(VHISP_{ij}) + \beta_{4j}*(OMALE_{ij}) + \beta_{5j}*(VFEMALE_{ij}) + \beta_{6j}*(VAGE_{ij}) + \beta_{7j}*(VJUVE_{ij}) + \beta_{8j}*(Y2016_{ij}) + \beta_{9j}*(INDOB_{ij}) + \beta_{10j}*(INDVH_{ij}) + \beta_{11j}*(INDOM_{ij})$$

$$\log[\phi^*_{4ij}/(1 - \phi^*_{4ij})] = \beta_{0j} + \beta_{1j}*(OBLACK_{ij}) + \beta_{2j}*(VWHITE_{ij}) + \beta_{3j}*(VHISP_{ij}) + \beta_{4j}*(OMALE_{ij}) + \beta_{5j}*(VFEMALE_{ij}) + \beta_{6j}*(VAGE_{ij}) + \beta_{7j}*(VJUVE_{ij}) + \beta_{8j}*(Y2016_{ij}) + \beta_{9j}*(INDOB_{ij}) + \beta_{10j}*(INDVH_{ij}) + \beta_{11j}*(INDOM_{ij})$$

All explanatory variables remain fixed within the preliminary analysis, while the intercept varies randomly to generate a variance statistic. Based on the size of the variance ($\tau = 0.063$) and a statistically significant chi-square test ($p < .001$), the explanatory variables in the within-city model are not enough to adequately measure the

[19] Φ represents each threshold in the analysis. Refer to (7) for thresholds and (8) for the logit link function. In (10), OBLACK = offender Black; VWHITE= victim White; VHISP = victim Hispanic; OMALE = offender male; VFEMALE = victim female; VAGE = victim age; VJUVE = victim a juvenile; Y2016 = year 2016; INDOB = missing data indicator for offender Black; INDVH = missing data indicator for victim Hispanic; INDOM = missing data indicator for offender male.

variation in the outcome measure. Thus, the between-city model is appropriate to test the research hypothesis.

The results of the within-city analysis appear in Table 4. The preliminary findings show that four of the explanatory and one of the missing data indicators maintain a statistically significant relationship with a robbery incident's severity. Since the ordinal regression equation implements the logit canonical link function, the regression output yields exponentiated beta coefficients.

The noteworthy relationships interpret as follows. When the offender is male, the odds of a robbery incident increasing in violence decrease by approximately 23 percent compared to female offenders. Similarly, when the victim is female, the odds of a robbery incident escalating in violence decreases by approximately 21 percent. A one-unit increase (year) in the victim age variable leads to a robbery incident decreasing in violence by approximately .3 percent. When the victim is a juvenile, the odds of a robbery escalating in violence decreases by about 34 percent. Lastly, the male offender missing data indicator returns statistically significant. This relationship suggests a non-random pattern to the missing values. A detailed discussion on this relationship appears in the between-city analysis section.

Table 4

Within-city Estimation of Fixed Effects with Robust Standard Errors

	Coefficient	Standard error	Odds ratio
Intercept	-2.233***	.175	.107
Black offender	-.079	.047	.924
White victim	.042	.032	1.042
Hispanic victim	.011	.048	1.011
Male offender	.267***	.057	1.306
Female victim	.263***	.059	1.301
Victim age	.003***	.001	1.003
Victim juvenile	.409***	.048	1.505
Incident year	.113	.133	1.119
Black offender indicator	.058	.067	1.060
Hispanic victim indicator	.077	.059	1.080
Male offender indicator	-.292***	.059	.746
Threshold 2	.761**	.250	2.141
Threshold 3	1.542***	.223	4.675
Threshold 4	1.801***	.208	6.055
Threshold 5	2.896***	.158	18.100

Note. *p $\leq$ .05; **p $\leq$ .01; ***p $\leq$ .001 (two-tailed tests). N = 29,297 robbery incidents in 98 cities.

Between-city Analysis

The between-city analysis accounts for variation in the individual outcome measure by including the city-level explanatory and control variables. The chief goal of the analysis is to perform the first large-scale empirical test of the marginal deterrence principle. The equation measures the interaction of pain and pleasure on the probability that an offender selects a more or less severe form of robbery. Using Figure 7 as an example, if the illicit incentive increases (pleasure) relative to the certainty of arrest (pain), there should be an increase in the likelihood that an offender will commit a more severe form of robbery. In contrast, if the incentive to commit severe robbery decreases, the severity of the robbery should also decrease. In the between-city ordinal regression equation, *j* represents each city, β_0 represents the randomly varying intercept, $\gamma_{0\text{-}11}$ represents the city-level explanatory variables, and *u* is the error term.[20]

$$\beta_{0j} = \gamma_{00} + \gamma_{01}*(GINI_j) + \gamma_{02}*(SII_j) + \gamma_{03}*(PM1524_j) + \gamma_{04}*(PCOLLEGE_j) + \gamma_{05}*(DENSITY_j) + \gamma_{06}*(SOUTHERN_j) + \gamma_{07}*(MINCENTI_j) + \gamma_{08}*(COMDIS_j) + u_{0j} \tag{11}$$

Table 5 displays the estimates concerning the illicit incentive and the probability that an offender will choose a more severe form of robbery. A visual examination of Table 5 reveals a statistically significant relationship between the incentive measure and the ranked decision outcomes for the crime of robbery. More precisely, at its grand mean, a one-unit increase in the illicit incentive amplifies the odds that an offender will escalate the severity of their robbery by a factor of one. Such a finding gives the impression that an increased financial incentive stimulates an incitement effect among offenders. Specifically, as the monetary illicit incentive increases, offenders rebate the potential risk associated with the crime and marginally increase the severity of their offending.

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[20] For brevity, the level one model is not re-listed. Equation 11 plugs directly into (10) where β_0 recurrs. In (11), GINI = Gini coefficient; SII = social isolation index; PM1524 = percent male aged 15-24; PCOLLEGE = percent some college; DENSITY = population density; SOUTHERN = cities below the Mason-Dixon line; MINCENTI = illicit incentive measure; COMDIS = community disadvantage index.

The results gleaned from the between-city analysis buttress the untested notion that incentives play a notable role in criminal deterrence research (Mookherjee & Png, 1994). As previously mentioned in Chapter 2, most contemporary empirical analyses on criminal deterrence adhere to the theoretical blueprints laid out by Bentham's hedonistic calculus. Bentham's core theoretical tenants dictate that a criminogenic decision results from the sum of pain and pleasure. The issue, however, is that previous deterrence research explicitly focuses on the stimulus of pain and neglects the element of pleasure. For example, studies tend to measure the association between a risk factor (certainty or severity of punishment) and the decision to commit a crime but fail to control for any variables that measure an incentive (Basili & Belloc, 2020; Corman & Mocan, 2000).

By proxy, studies that only measure pain investigate a partial utility calculus and assume that all offenders will be deterred equally by the risk factor under investigation (Mookherjee & Png, 1994). The results furnished here, representing a theoretically complete utility calculus, directly support that an incentive can offset the intended pain stimulated by the certainty of arrest. Therefore, any studies that do not consider the dimension of pleasure may overlook actual deterrent effects, ultimately adding to the controversy among the results in deterrence research.

Additionally, it is essential to note that previous theoretical works state that Bentham's concept of pleasure is relative and may vary from crime to crime (Becker, 1968; Mookherjee & Png, 1994). Though it may seem logically intuitive, the salient relationship between the illicit incentive and the ordered outcome variable strongly suggests that higher pecuniary returns stimulate more violent forms of robbery. Simply put, if an offender's incentive is high, they may choose a more violent form of robbery to ensure a quick, easy, and high payout. It is important to note that victims of more violent forms of robbery tend to be more compliant for fear of bodily harm (Wright & Decker, 1997).

Prior empirical studies on other forms of instrumental offenses point to a similar pattern of incentive-based behavior that fortifies the findings in the current analysis. Torres et al. (2020b) show that low-level, first-time drug dealers rush to replace those recently arrested for selling illicit drugs in hopes of garnering a fortune. Though not directly measured, the pecuniary incentive is so strong that it drives these offenders to commit acts of systemic violence to penetrate the illicit drug market due to the high payouts and simplicity associated with selling narcotics (Torres et al., 2020a).

Despite the salience of the primary explanatory variable of theoretical interest, several other contextual variables warrant attention. The SII returns a statistically significant relationship with the outcome measure. As Black isolation increases in a city, the odds of a robbery escalating into violence increases by approximately 51 percent. The Black isolation variable not only includes factors such as multiple disadvantages, segregation, and inequality, but it also controls for the geographic concentrations of these social detriments within a city (Shihadeh & Flynn, 1996). Isolated Black communities tend to lock in low-skill jobs, joblessness, and push out businesses that uphold the tax base (Blackley, 1990). Such a situation stimulates the commission of instrumental crimes and the escalation of violence overall (Shihadeh & Flynn, 1996). Measuring segregation not only controls for economic disadvantages but also helps to account for racial differences in the decision to commit a more or less severe form of robbery.

The SII represents the probability that a Black individual will interact with a White individual within a city. Therefore, it also controls for a unique opportunity structure based on the physical interaction between Blacks and Whites. To date, a robust and diverse literature explores the incentives and unique opportunities Black and White victims provide to offenders. For example, O'Flaherty and Sethi (2007) state that when faced with the choice of robbing a White or Black individual (assuming no segregation existed), the offender would choose to rob the White victim due to the racial stereotypes associated with robbery. These stereotypes include race-based incentives and the various degrees of violence implemented during the commission of the crime. More precisely, Whites represent wealth and are thus more valuable robbery targets to offenders as they may yield a higher payout and are less likely to resist during the robbery incident (O'Flaherty & Sethi, 2007). Since Whites are pliant in the eyes of a robber, less violence is required to garner the payout.

As segregation increases, however, Blacks are more likely to rob other Blacks as the pool of potential victims is limited and locked in. O'Flaherty and Sethi (2007) state that Blacks in socially isolated areas tend to earn less and are more protective of their belongings, thus making them more likely to resist during the commission of a robbery. Due to the enhanced probability of physical resistance, robbers are believed to escalate levels of violence to secure their payout in segregated areas. The results furnished in the current analysis provide ancillary support for this theoretical assertion.

Lastly, the other contextual control variables return a null relationship with the severity outcomes of a robbery incident. These variables include the population density of the city, whether the city was below the Mason-Dixon line, income inequality, community disadvantage, the percent of males aged 15-24, and percent some college. Three micro-level variables from the within-city model, however, remain statistically significant in the between-city analysis. Additionally, their effect sizes remain approximately the same. After adding the contextual city-level variables, the differences in biological sex remain consistent with prior research. In an almost identical fashion to the within-city analysis, the severity of robbery substantially decreases when the offender is male. More specifically, when an offender is male, the odds of the robbery increasing in violence decreases by approximately 23 percent. Prior research dictates that women appear less physically intimidating compared to men, thus making them more likely to escalate violence during a robbery incident (Miller, 1998).

Previous empirical analyses dictate that as victims get older, the amount of violence required to force compliance substantially decreases (Wright & Decker, 1997). The negative statistically significant relationship between the victim age variable and the ordinal robbery types buttress this assertation. Lastly, when a victim is a juvenile, the odds of a robbery escalating in violence decreases by approximately 34 percent. This finding indirectly supports that juveniles are valid targets for potential robbers but require less violence to secure the payout. While juveniles tend to possess less wealth, they may serve as an incentive to rob because they openly carry expensive devices such as smart watches and top-of-the-line cell phones.

The other individual-level control variables returned a null relationship with the severity of robbery outcomes. It is important to note that the male offender missing data indicator returns a statistically significant effect with the outcome measure. Since these effects maintain a p-value of .001, it indicates that the data are not missing at random. Instead, they reflect the systematic reporting practices of the law enforcement agencies within the 98 cities. Some police departments are less likely to report the biological sex of offenders than are others (Cohen & Cohen, 1983).

Table 5

Between-city Estimation of Fixed Effects with Robust Standard Errors

	Coefficient	Standard Error	Odds ratio
Intercept	-2.244***	.179	.106
Criminal incentive	-.005*	.002	.995
Population density	.033e-3	.019e-3	1.000
Southern city	-.049	.086	.952
Percent male 15-24	-.021	.018	.979
Income inequality	-2.293	.886	.746
Social isolation index	-.409*	.207	.665
Percent some college	.002	.011	1.002
Community disadvantage	-.011	.035	.989
Black offender	-.082	.048	.921
White victim	.046	.032	1.047
Hispanic victim	.005	.049	1.005
Male offender	.266***	.057	1.305
Female victim	.262	.059	1.299
Victim age	.003***	.001	1.003
Victim juvenile	.408***	.048	1.503
Incident year	.113	.133	1.119
Black offender indicator	.059	.067	1.061
Hispanic victim indicator	.071	.061	1.074
Male offender indicator	-.296***	.059	.744
Threshold 2	.762***	.250	2.142
Threshold 3	1.543**	.223	4.677
Threshold 4	1.801***	.208	6.059
Threshold 5	2.897***	.158	18.119

Note. *p ≤ .05; **p ≤ .01; ***p ≤ .001 (two-tailed tests). N = 29,297 incidents in 98 cities.

CHAPTER V

CONCLUSION

A voluminous amount of scientific research has accrued on criminal deterrence over the past sixty years. The pertinent literature that tests the effects of punishment's certainty, severity, and celerity on criminal behavior tends to follow a similar econometric orientation. This theoretical framework, known as the economic model of crime (Becker, 1968), suggests that criminals are rational and make decisions much like law-abiding citizens. Rooted in Bentham's hedonistic calculus, Becker's (1968) model made it possible to quantify the concepts of pain and pleasure through implementing a series of conditional formulations. In short, when an offender calculates more utils on the side of pleasure, they will choose to commit a crime. In stark contrast, if the offender calculates more utils on the side of pain, they should abstain from committing the crime altogether. This simplistic quantitative approach has catalyzed the testing of contemporary hypotheses related to criminal deterrence.

Nevertheless, the results furnished by econometric deterrence studies remain controversial. Some studies find a deterrent effect (Braga & Weisburd, 2012; Dolling et al., 2009; Rebellon et al., 2010), while others find a brutalization effect (Pogarsky & Piquero, 2003; Shepard, 2005). Still, others produce a mixed or null relationship (Briscoe, 2004; Greenberg & Kessler, 1982; Loftin & McDowall, 1982; Worral, 2004; Zimring et al., 2001). The controversial results regarding criminal deterrence research remain an issue for two distinct reasons. First, prior empirical studies implicitly assume that the criminal decision-making process adheres only to a binary yes/no outcome. Simply put, these studies neglect the possibility of any intermediate decision outcomes that may transpire between yes and no (Corman & Mocan, 2005; DeAngelo & Hansen, 2014; Evans & Owens, 2007; Klick & Tabarrok, 2005). Even when analyses employ sophisticated dependent variables that attempt to observe a linear increase or decrease in the crime rate as a proxy for deterrent effects, they are generally only equipped to observe two mutually exclusive outcomes. For example, if the risk of apprehension increases, an offender may commit a less severe form of the crime rather than abstaining altogether.

Second, while Becker (1968) and Ehrlich (1973) explicitly state that the decision to commit a crime is the sum of both risk and reward, prior empirical works exclusively investigate the concept of risk and neglect reward/pleasure. As a result, they only observe a partial utility calculus, and thus, it remains unknown how offenders respond to the coalescence of both theoretical concepts. I endeavor in this study to remedy the controversy in the current body of deterrence research induced by these two problematic gaps in the literature. Through the lens of marginal deterrence, I regress an illicit incentive (utility calculus) from an ordinally ranked outcome variable representative of six possible forms of robbery. The operational specifications of the variables allow the empirical model to control for an offender's complete utility calculus, which accounts for both pain and pleasure.

The results furnished from the multilevel analysis display that as the illicit incentive (pleasure) increases after controlling for risk (pain), the odds of a robbery escalating in violence substantially increase. This finding is particularly telling when considering all notable deterrence research studies neglect intermediate decision outcomes. This conclusive chapter discusses the unique areas where my research donates to the theoretical and practical knowledge on the economic model of crime, marginal deterrence, and criminal motivations. Peppered through these sections, I provide theoretical contributions, policy implications, limitations, and avenues for future research. Finally, in the concluding remarks, I delineate how my results help disentangle the controversy in criminal deterrence research while providing actionable advice to policymakers.

The Economic Model of Crime and Dynamic Outcomes

Due to the unidimensionality of Becker's (1968) economic model of crime, it has undergone several tenable extensions to expand knowledge on the criminal decision-making process. Such extensions include the allocation of leisure time (Ehrlich, 1973), changes in the criminal wage (Block & Heineke, 1975), and illegal consumption activities (Witte, 1980). Up to this point, the narrative of the current study has been concentric on the limitations of the economic model of crime (and the above-listed extensions) in that it posits a bifurcated decision outcome. Not only does this severely limit criminological knowledge on illicit decision-making, but it also paints only a partial picture of known phenomena related to criminal deterrent effects. More specifically, any static quantitative formulations that only investigate an increase/decrease in crime or a yes/no decision outcome will identify deterrent effects but fail to measure and explain their magnitude.

From an economic perspective, when a predictive formulation is static, it is fixed in place or position (Kuznets, 1930). An example would be a cross-sectional analysis that implements a continuous variable representing a crime rate. Since the continuous variable is locked in position by only producing two exclusive outcomes, it suppresses any unexpected changes or stratified oscillations in the criminal decision-making process. Consequently, the inability to accurately measure the magnitude of deterrent effects with Becker's original static model may be why meta-analyses find weak support for deterrence-based theories of crime (Pratt & Cullen, 2005). They specifically ignore the possibility that offenders may adjust when deciding to commit a crime.

Since static formulations dilute deterrent effects, a small but growing body of literature has emerged that conceives a dynamic posture for the econometric measurement of crime (McCrary, 2010). The analysis conducted here provides two novel extensions to the economic model of crime relating to dynamic decision outcomes. First, my results dictate that intermediate decision outcomes between the options to abstain or commit a crime play a salient role in observing actual deterrent effects. Therefore, I provide suggestive evidence that prior deterrence research that operationalizes static/binary decision outcomes is implicitly fallacious to a certain degree. Based on this evidence, researchers should focus their efforts on accounting for the possibility of intermediate decision options (based on crime type). However, it is essential to note that not all crimes have neatly designed categorical outcomes like robbery and that an individual may escalate the severity of offending by jumping from crime to crime. It is entirely possible that as the risk of apprehension lessens, a potential offender may choose to shift from larceny to robbery or any other instrumental crime when the monetary incentive outweighs the risk.

The second way the current study extends the economic model of crime is by using a single variable to measure the utility calculus of the criminal offender. All research predicated on Becker's (1968) seminal model centers on a criminal who conducts a rational appraisal of risk and rewards through the implementation of a utility calculus. Becker's operational models are directly rooted in Bentham's hedonistic viewpoint on crime. Bentham argues that an individual's decision outcomes derive from the sum of pain and pleasure. Therefore, when an individual's calculations emerge with a higher value supporting their criminogenic pleasure, they will choose to take action and commit a crime.

As mentioned in Chapter 4, most deterrence research is based on a partial criminal utility calculus because prior research measures risk but ignores illicit incentives. Although a few studies attempt to measure incentives by adding some form of criminal gain (Draca et al., 2019) or legitimate wage variable (Machin & Meghir, 2004), the researchers measure the incentives separately from the risk indicator. Becker (1968) maintains explicitly that both risks and incentives must be weighed simultaneously for an offender to make a rational decision about committing a crime. For example, Machin and Meghir (2004) attempted to measure the incentive to commit property crime by analyzing an hourly wage predictor. Within their regressions, the researchers independently observed the functioning of the incentive variable and their measure of risk (conviction rate and the average sentence length). While informative, their study's proposed utility calculus is incomplete because it remains unknown how the incentive reacts with the risk involved with the crime under investigation. Suppose that the observed incentive to commit a crime and the observed risk level were high. In this situation, there is no way to disentangle which quantitative value holds more weight in association with the outcome of the criminal decision-making process.

Another example manifests in studies that attempt to measure criminal gains by investigating price elasticities. Draca et al. (2019) attempted to measure the magnitude that crime responds to the fluctuating value of goods that offenders are most likely to steal. Though their analysis is compelling, it only explains how offenders react to the pleasure facet of the utility calculus. According to Draca et al. (2019), "the empirical analysis suggests that the returns to illegal activity are an important input into criminal decision-making" (p. 1255). Still, they neglect to include any measure of risk in the analysis. Based on these two illustrations of prior research, modeling an offender's decision would be more reliable if risk and reward appeared in one variable.

In the case of the current study, I observe a complete utility calculus because Becker's conceptualization of criminal gain and risk are combined into one measure (see "PR" in Equations 4 and 5). Therefore, the interpretation of model parameters includes the coalescence of pain and pleasure and produces an illicit incentive. This finding suggests that criminals discount risk when the monetary payout remains high. Lee and McCrary (2009) state that discounting factors are crucial elements for expanding econometric models of crime that focus on testing deterrence theory. The extant literature postulates that crime will increase when criminals discount risk and see more value in committing a crime (McCrary, 2010).

The results of the current study not only contribute to a theoretical discussion on dynamic perspectives of criminal deterrence, but they also provide sound policy-relevant advice as it relates to the degree of harm imposed by crime. Harm indices are an emerging metric used by urban policymakers to assess community development initiatives and calculate the negative side-effects associated with various social vicissitudes (Curtis-Ham & Walton, 2018). Despite the relevance of other ecological variables, crime surfaces as one of the most weighted indicators of harm. The issue, however, is that many indices that attempt to quantify harm do so by using a broad nomenclature. According to Ratcliffe (2015), the "costs of crime are generally calculated for sweeping categories (such as robbery or homicide) and are limited by not being able to distinguish between types of crime within these large categories" (p. 166). In the current analysis, the salient relationship between the illicit incentive and the six ordinal degrees of robbery stands in marked contrast to what previous CHIs have done in the past when disaggregating the weights of the different strata of robbery.

For context, the Pennsylvania Offense Gravity Score (OGS) is one of the leading econometric scales of general harm. The index assigns a weight or "gravity" to each crime listed in Pennsylvania's commonwealth that serves as a general proxy for the degree of harm imposed. The scale runs from 1 to 15, where robbery accounts for three unique categories. The crime is broken down by "robbery involving serious bodily injury" (gravity of 12), "robbery" (gravity of 9), and "robbery with threat of bodily injury" (gravity of 7). As displayed in the current analysis, limiting the stratification to only three sub-categories will severely dilute the range of measurable harm imposed by robbery within a city. Therefore, it would benefit future indices to include all strata in operationalizing a crime. It would even be advantageous to weigh attempted robbery as an independent category because the media stimulates gender-based fear of this crime

(Callanan & Rosenberger, 2015). Lastly, it is essential to note that the OGS relies on state statutes, which may be why its robbery categories are limited. The discussion here also adds to the debate on the quantification of harm indices by displaying that such metrics should stem from empirical research rather than the statutes' broad and limited definitions.

Marginal Deterrence

Research on criminal deterrence has typically taken a theoretical and speculative stance on the functioning of marginal deterrence (Lundberg, 2019; Shavell, 1992). The current study serves as the seminal large-scale empirical assessment of the marginal deterrence principle and makes two significant theoretical contributions to the criminological literature. First, prior research maintains a myopic focus on the effect of the severity of sanctions and marginal criminal decision-making regardless of the severity element's weakness at producing deterrent effects. The current study is the first to directly investigate the certainty element's impact on the margin of an offender's stratified decision outcome. The second contribution refers to the differentiation between marginal and restrictive forms of deterrence. Due to their conceptual definitions, prior empirical research tends to convolute the two terms. I provide here a novel categorization between marginal and restrictive deterrence by drawing a line in the sand between the frequency of offending and the prevalence of an offender choosing one crime over the other.

The principle of marginal deterrence arose to extend criminological knowledge on the notion that not all offenders consider one illicit act (Reinganum & Wilde, 1986). Instead, they may consider several acts of the same crime that vary in degree of severity. One of the main issues with the theoretical studies on marginal deterrence is that they are all predicated on the severity of punishment and the development of optimal sentencing policies (Basili & Belloc, 2020; Crino et al., 2019). For example, if an offender robs an individual and kills them during the incident, the punishment should be more severe than if the offender simply threatened the victim. This scaling punishment schedule intends to deter offenders progressively who are contemplating more severe criminal acts.

As with most research on criminal deterrence, the marginal deterrence principle assumes a rational process with the caveat that offenders weigh the risk and reward before deciding which margin to offend on (Shavell, 1992). The issue, however, is that the reliance on severity scales of punishment as a measure of risk severely dilutes any potential deterrent effects because of the disconnect in time between the criminal act and the prescribed punishment (Nagin, 2018). Empirical research from the field of developmental psychology shows that if punishment lags by up to only ten seconds, the effects of behavioral manipulation begin to deteriorate significantly (Banks & Vogel-Sprott, 1965; Trenholme & Baron, 1975). Therefore, if the marginal deterrence principle effectively decreases the severity of offending, the punishment would need to be immediate to skew an offender's utility calculus (Abramowitz & O'Leary, 1990). Though instantaneous punishment is possible by the immediate deprivation of liberty, previous works have shown that it resides in the background of an offender's decision-making process (Chalfin & Tahamont, 2018). In contrast, the certainty element remains in the foreground; therefore, the current study provides a novel alternative to measuring marginal deterrent effects.

Measuring the certainty element over the severity element is relevant because the criminal decision-making process is a relatively unsophisticated procedure and offenders rarely plan out their actions in detail (Cornish & Clarke, 1987). Additionally, offenders tend to maintain mundane and short time horizons on the turnaround of their initial decision to commit a crime (Nagin, 2018). To clarify, suppose committing a crime is the same as an investment that yields a quick payout due to the high risk involved in the act. An individual who has a short time horizon is more likely to dismiss the threat of a distant punishment because they are more focused on imminent threats such as the possibility of getting caught (certainty of apprehension). On the other hand, individuals with long time horizons may hold their investment indefinitely and never decide to offend because future consequences hold more weight to them (e.g., deprivation of liberty or severity of sanctions). McCrary (2010) makes an interesting distinction on offenders with long time horizons and criminal benefits by stating that ". . . all future draws are likely to be better than they otherwise would be . . . Hence, committing crime next period puts the agent at risk of being imprisoned [punished] and hence unable to avail himself of criminal opportunities two periods hence, three periods hence, and so on" (p. 22).

Though measuring the certainty over the severity element adds a new dimension to marginal deterrence research, it also ushers in a conversation on how alternative forms of punishment may influence the criminal decision-making process. For instance, some informal social control mechanisms may weigh into the risk portion of the utility calculus for some offenders. Such internal mechanisms include guilt, shame, or humiliation induced by getting arrested (Kornhauser, 1978). Since informal social controls are said to make "norms and rules more effective" (Reiss, 1951, p. 196), a buffering effect may exist between informal punishment and the certainty of apprehension. For example, individuals may weigh the certainty of arrest more heavily because they fear the shame of being arrested or humiliating their family, which is an internal form of punishment with varying levels of severity.

It should be noted that no empirical analysis has attempted to investigate the aggregate interactions between informal social control and a marginal criminal decision apparatus. Much like criminal deterrence research, analyses on informal social control are shifting into multilevel specifications. According to Groff (2015), "researchers [who study informal social control] have begun to acknowledge the existence of theoretical mechanisms operating at different levels of analysis" (p. 90). Due to the limitations of the dataset used in the current study, I could not control for any of these exogenous predictors. Future deterrence research should consider these punitive elements because they may appear in an offender's more immediate risk calculation rather than existing in the periphery. While this direction for future research would be fruitful for understanding marginal deterrence, the data required to test such a buffering effect would be challenging to acquire. Since informal social controls can be real or imagined in the mind of each offender, quantifying the variable is near impossible on a generalizable scale (Kornhauser, 1978).

Nevertheless, the results here solidify the salience of the deterrence doctrine through a rational choice framework which allows for econometric predictions that include dynamic decision outcomes (Moeller et al., 2016). The issue, however, is that the observable stratified effects can divide down into either marginal or restrictive deterrents. Marginal deterrent effects represent the prevalence an offender will choose one form of a crime over the other (Shavell, 1992), while restrictive deterrent effects refer to the frequency an individual offends (Gibbs, 1975; Jacobs, 1996). Gibbs (1975) defines restrictive deterrence as:

> The curtailment of a certain type of criminal activity by an individual during some period because, in whole or in part, the curtailment is perceived by the individual as reducing the risk that someone will be punished as a response to the activity. (p. 33)

To date, researchers have erroneously used the terms analogously because more contemporary theoretical works on restrictive deterrence allude to "crime switching," but have no empirical observations to buttress the notion (Moeller et al., 2016).

Moreover, due to the lack of empirical research on stratified decision-making, the definitional breadth of restrictive deterrence has crept into the domain of marginal deterrence. To clarify, Jacobs (1996) explicitly states the following when discussing restrictive deterrence:

> The offender commits crimes of lesser seriousness than the contemplated act, believing that punishment will not be as severe for a "more minor" infraction (thus, an offender shoplifts a $100 pair of jeans instead of robbing a convenient store for the same monetary reward). (p. 433)

The current analysis opens a new chapter in the criminal deterrence literature by displaying that marginal criminal decision-making is at play among offenders and should be classified appropriately. In contrast, restrictive decision-making should only include provisional tactics such as the temporary aggregate shifting of offenses from one place to another, tactics to reduce chances of detection, and advanced planning (Moeller et al., 2016). A prime example of restrictive deterrence is temporal and spatial crime displacement. McCrary (2010) uses "hot spots" policing as an example of how offenders dynamically bide their time until the probability of apprehension decreases so that they may amplify their offending patterns once again. As a result, crime temporarily decreases and then spikes when the certainty of apprehension fades. Crimes such as drug dealing, prostitution, and auto theft are more susceptible to restrictive shifts (Moeller et al., 2016) because they ebb and flow to structured market principles (Torres et al., 2020a).

Though I provide here a novel differentiation between restrictive and marginal criminal decision-making, it is not to say that any interplay between the two concepts does not exist. As postulated by previous conceptualizations of restrictive deterrence (Jacobs, 1996), an individual may choose to increase or decrease the severity of their offending temporarily until the coast is clear. Given that the term "restrictive" stems from a temporary behavior change, it is incumbent upon the researcher to control for marginal shifts in decision-making that may be interim. The results of my multilevel model suggest that the observed marginal shift in offending is relatively permanent since I control for the illicit incentive. The incentive to commit a robbery remains fixed while the certainty element (risk) depends on police presence and resources, which vastly fluctuate. Therefore, my generalizations do not appeal to temporary restrictive shifts in offending severity. So long as the incentive (pleasure) weighs heavier than the certainty of apprehension (pain/risk), then the outcome of the robbery under contemplation should increase in severity.

Carrots & Sticks

I previously explained how pain was the primary variable of interest in previous deterrence research while aspects of pleasure remain neglected. I take the stand that to garner deterrent effects truly, both aspects of pain and pleasure should be measured in conjunction with each other. Past research has failed to account for a complete utility calculus; thus, the positive relationship garnered from my analysis helps to distill knowledge on deterrent effects in the criminological literature. At first glance, the monetary incitement effect observed in the results seems logically intuitive as individuals theoretically chase pleasure and avoid pain at all costs (Bentham, [1780] 1823). Since the monetary reward outweighs the risk, my results align with past research on hedonistic motivations for committing crime and decision-making in general (Braybooke, 2004; de Lazari-Radek & Singer, 2017). However, one contradictory element to the monetary incitement effect is that prior empirical research in evolutionary psychology and neuroscience dictates that pain is a more powerful motivator than pleasure (Atkinson, 1964; Redgrave et al., 2008). This section discusses the mechanisms behind carrots, sticks, and criminal motivation related to the monetary incitement effect and marginal decision-making.

Suppose an individual is face-to-face with a hungry lion. A suitcase filled with enough cash to give a person complete financial freedom rests between the lion and the individual. As the lion begins to charge at the person, the instinct to avoid pain outweighs the pleasure garnered from the comfortable life the cash would provide. It is important to note that in this simplistic hypothetical simulation, the pleasure acquired from the suitcase is at the maximum threshold in the individual's utility calculus. Yet, no reasonable individual would run towards the lion, which would likely rip them to shreds; the motivation to avoid pain/death is always more significant than acquiring maximum pleasure.

To this point, the review of the literature and subsequent discussions have revolved around the sociological explanations and understanding of decision-making structures that include licit and criminogenic outcomes. Neurological research shows that the brains of both humans and animals are primitively wired to release certain chemical compounds in response to threatening or pleasant situations, such as cortisol, adrenaline, and dopamine (Navratilova & Porreca, 2014). For example, nociceptors (sensory receptors for pain) become activated by noxious stimuli imposed by a threat upon the individual, which triggers biologically promoted avoidance behaviors (Fields, 2006). Individuals who then perceive this threat and release the chemical compounds of cortisol and adrenaline go to great lengths to bypass the experience (Craig, 2003). In contrast, chasing pleasure is relatively linear and does not require much motivation or effort.

These neurological processes operant within individuals promote an evolutionary trial-and-error learning experience. Painful tribulations then cause the decision-maker to update their knowledge to survive better and perceive future threatening situations. According to Navratilova and Porreca (2014), "the evolutionary role of negative (pain) and positive (relief) affective states is to elicit motivations, respectively resulting in escape/avoidance and approach behaviors and to allow learning of how to predict dangerous or rewarding situations in the future" (p. 1305). Fanselow (1986) simplifies this concept by differentiating between perceptions of predator-driven pain and learned/conditioned pain. This situation is a crucial bifurcation because most individuals are not living in a constant state of primitive survival.

Simply put, our archaic predecessors experienced an opioid release that would block pain and engage their innate survival tactics in the face of imminent death

(Fanselow, 1986). Today, offenders are under constant threat from the criminal justice system. However, the threat is only triggered when the offender chooses to commit a crime. The perception of pain is thus contingent on the potential offender's conditioned experiences with the criminal justice system, offending, and punishment.

With this said, if the "lion" of the criminal justice system is so ferocious (pain), why then do individuals increase the severity of their offending in the wake of a higher illicit incentive (pleasure)? Especially when the payout cannot be as valuable as the suitcase in the above simulation. One likely answer is that most individuals who engage in crime are repeat offenders and perceive threats differently than first-time/potential offenders. According to statisticians from the Bureau of Justice Statistics (BJS), "about 66% of prisoners released across 24 states in 2008 were arrested within 3 years, and 82% were arrested within 10 years" (Antenangeli & Durose, 2021, p. 1). More specific to the crime under investigation in the current analysis, 40.2 percent of offenders arrested for robbery recidivated after the first year, 75.7 percent were rearrested after year five, and 82.5 percent were rearrested after year ten (Antenangeli & Durose, 2021). As a consequence of such a high recidivism rate, most offenders have had first-hand experience with the punishment from the criminal justice system, "survived" it, and then updated their knowledge and perceptions about risk and pain. Metaphorically speaking, the lion did not rip them to shreds but instead licked them.

With this updated knowledge and enhanced perception of pain, offenders are more likely to respond to incentive/pleasure rather than the potential risk, even though pain is a more powerful motivator for decision outcomes. This situation may also be why repeat offenders commit more severe forms of crime (commit a robbery with a firearm rather than with the threat of violence) than first-time offenders. There is a greater chance of payout/reward in more serious crimes as individuals are more likely to comply; thus, repeat offenders have less fear of the potential pain imposed upon them by the criminal justice system. Commenting on the neurological pathways of pain, relief, and motivation, Navratilova and Porreca (2014) state that "decision-making depends on previous experience and current options" (p. 1305). Due to data restrictions, the current analysis could not control for whether the individuals included in the study were repeat or first-time offenders.

Future research on the associations between pain, pleasure, and criminal behavior should focus on two distinct avenues. First, statistically controlling for criminal history will buttress the discussion on whether individuals with prior experience with the criminal justice system will discount risk at a higher rate than newbie offenders. Second, researchers should attempt to control for whether the individual acted alone or with co-offenders who possess previous criminogenic experience. Paternoster and Piquero (1995) argue that experience with criminal offending or punishment from delinquent peers can vicariously transfer to potential offenders, thus reducing pain perception. Additionally, several studies have linked peer behavior to the perceived threat of sanction and offending risk (Matsueda et al., 2006; Pogarsky et al., 2004).

Concluding Remarks

A large body of empirical research has accumulated over the past six decades on criminal deterrence theory. Though advancements in analytical knowledge have bolstered the reliability of published works, the results in the literature remain convoluted, oversaturated, and only observe condensed decision outcomes. These adverse results become controversial because policymakers rely on these findings in developing interventions to deter crime. My regression results help to disentangle this controversy because they provide practical advancements to the theoretical mechanisms behind criminal decision-making. First, the operationalization of the outcome measure makes it possible to observe all intermediate outcomes between the binary decision to commit or abstain from crime. The principle of marginal deterrence stems from the idea that not all offenders are deterrable, nor do they consider the commission of only a singular crime (Shavell, 1992). The salient ordinal relationship observed in the analysis suggests that future research should consider dynamic decision outcomes or actual deterrent effects may be suppressed. It also allows for an assessment of deterrent effects and paints a general picture of the harm imposed on society by robbery.

Second, prior criminal deterrence studies generally fail to consider an offender's complete utility calculus. While the analysis of criminal deterrence and the decision-making process is premised mainly on Bentham's hedonistic calculus, previous studies on deterrence ignore the element of pleasure because they base their results only on the reaction of crime to the exposure of pain (e.g., the certainty or severity elements). As done here, analyzing the coalescence of pain and pleasure in one illicit incentive variable will help to paint a more detailed picture of the social phenomenon of preventing criminal behavior. Third, until this study, marginal deterrence was discussed solely through the lens of the severity element, and its definition was intermingled with restrictive forms of deterrence. With a clear differentiation between restrictive and marginal deterrent effects, researchers can parse out temporary and consistent deterrent effects.

In conclusion, I have provided throughout this chapter theoretical and policy implications for marginal deterrence, my novel extensions of the economic model of crime, and the debate on criminal motivation related to carrots and sticks. More broadly speaking, the research presented here takes us closer to understanding illicit incentives, offending patterns, and how to analyze criminal deterrent effects more fully. The main goal of this dissertation was to disentangle the convoluted knowledge within the domain of econometric decision-making so that policymakers can establish practical theory-informed deterrence interventions more accurately. Based on my results, the foundation for marginally deterring offenders is for society to ensure that the certainty of apprehension surpasses the illicit incentive. However, because most offenders have prior experience with the criminal justice system, they may be more inclined to discount risk at a higher rate. This situation suggests that criminals adhere to the same neurological processes that control knowledge updating and enhance survivability (Fanselow, 1986; Navratilova & Porreca, 2014). Once apprehension and punishment have been experienced, offenders tend to add a negative weight to future forms of pain (Sullivan & Lugo, 2018).

One policy intervention that may be appropriate based on the results of this study and that mirrors the theoretical mechanisms of knowledge updating and decision-making is pulling levers policing. Pulling levers policing is rooted in the work of Goldstein's (1979) problem-oriented policing framework, which implements the philosophy of specific deterrence. Since an individualized approach is a prerequisite for pulling levers to be effective (Kennedy, 1997), chronic/repeat offenders must be identified for the theoretical application to garner success. The concept of "pulling levers" boils down to increasing police presence and functionally transmitting the message to offenders that every resource available will reallocate to their apprehension and punishment should their offending continue (Kennedy, 2009). The intention is to artificially augment and enhance the perception of pain (through the certainty element) an offender appraises by directly updating their knowledge and skewing their utility calculi. Realistically, knowing that many repeat offenders are undeterrable and may not consider only one crime, then altering the severity of the crime chosen rather than deterring crime altogether may be possible. This ordinal reduction of crime would come about by reducing the amount of pain these offenders are willing to discount, ultimately plummeting the amount of harm they impose. Sullivan and Lugo (2018) complement this discussion by stating that:

> … given the serious offender populations often targeted in such [pulling levers] programs, this notification of sanctions for further offending may be undermined by prior experience with the system. Therefore, leveraging group pressures, ensuring certainty and swiftness of consequences, and providing alternatives to offending in pulling levers are essential to preventing crime. (p. 128)

The downside to implementing pulling levers strategies is that they do not produce general deterrent effects. Instead, it requires specific knowledge about a criminal group or individual and exploits the weaknesses in the composition of their decision-making. Sullivan and Lugo's (2018) meta-analysis suggests that evaluations of pulling levers policing have returned with medium effect sizes with variations in effects across studies. For example, Papachristos et al. (2007) estimate several longitudinal growth curve models and find deterrent effects produced from offender notification meetings. These meetings directly manipulated the certainty of apprehension and led to an approximate 37 percent decrease in violent crime (Papachristos et al., 2007). Raphael and Ludwig (2003) find consistent decreases in city-wide gun crimes in Richmond, Virginia, due to a pulling levers strategy. The strategy under examination in Raphael and Ludwig's (2003) evaluation included augmentations of both the certainty and severity elements. Finally, Levchak (2021) found a consistent decrease in firearm robberies due to several pulling levers interventions that predated the program under evaluation in his ARIMA analysis.

Though there are some challenges and limitations to using pulling levers interventions, the renewed clarification on marginal deterrence theory and the criminal decision-making process produced in this dissertation provide sound advice for policymakers who aim to reduce violent forms of robbery. Sullivan and Lugo (2018) explicitly state that:

> "… this work [referring to pulling levers interventions] would most definitely pay dividends in understanding the practical effects of marginal deterrence efforts as it can help to illuminate how individuals who are likely to have had some prior view of the risk of engaging in criminal activity update those beliefs with additional information." (p.129)

One major challenge related to this discussion is that pulling levers interventions overlook restrictive deterrent effects. While offenders may attenuate their offending in response to updated knowledge, deterrent effects may only be temporary contingent upon the crime type. For example, in the case of more organized violent crimes such as selling illicit narcotics, dealers may contain excess market capacity that allows them to halt sales until the certainty of apprehension decreases (Torres et al., 2020b). Other more spontaneous crimes such as robbery do not have this luxury, and deterrent effects may remain more consistent. Based on the theoretical knowledge advanced in the current study, the differentiation between marginal and restrictive deterrent effects may better inform what specific levers are salient at reducing the severity of opportunistic instrumental offenses.

To conclude the dissertation, I have disentangled some of the controversies among the results in the criminal deterrence literature by extending knowledge on marginal deterrence theory, dynamic outcomes to the economic model of crime, and the debate on illicit motivations. Through these novel contributions, I have provided logical suggestions for policymakers to develop a theory-based intervention strategy that coalesces productively with the results gleaned from my multilevel analysis.

Though the knowledge I have generated brings us closer to a more nuanced understanding of criminal deterrence and illicit decision-making, the study does not come without limitations. First and foremost, while offenders may choose to jump from one instrumental crime to another, I only account for the crime of robbery. It would benefit the study of marginal deterrence to include several regressions that included different crimes that offenders may externally jump to or internally fluctuate within. For example, if it becomes too risky to commit the crime of robbery, there may be a threshold where an offender will then choose to commit a crime such as a burglary. Prior empirical work shows that offenders tend to be generalists rather than specialists who commit various crime types (Simon, 1997).

Second, the illicit incentive in the current study solely focuses on the monetary payout. Though the criminal gain is the most relevant incentivizing factor in commissioning an instrumental offense (Agnew, 1994; Becker, 1968; Ehrlich, 1973), other variables may work in tandem to increase the motivation for committing a crime. For example, as the price of goods increases at the ecological level, crime tends to follow an upward trend (Draca et al., 2019). In contrast, specific offenders at the individual level of analysis commit crimes to assuage intense negative emotions (Leroch, 2014). Though challenging, it would be beneficial to control for individual differences in the psychic incentives that may weigh on an offender's utility calculus. As a final note, it would also be interesting to see how several different incentivizing factors interact with each other. For example, if the monetary payout were low, but the psychic benefit was high, would an offender increase the severity of their crime to assuage an emotion and acquire a quick and easy (but lower) payout as a byproduct?

As commonly expressed in many criminological works, perception is key to understanding the criminal decision-making process (Paternoster, 2018). Unfortunately, the only way to collect data on the perceptions of risk and reward is through individual-level qualitative surveys. The main problem with such surveys is that they focus exclusively on minor crime types and lack information on chronic offenders (Barnum et al., 2021). Nevertheless, future researchers should attempt to fill the gap in criminological knowledge on how perceptual risk scales are associated with marginal decision outcomes.

Lastly, while a large portion of the dissertation's narrative discusses dynamic outcomes to the economic model of crime, it is not a full dynamic specification. I measure dynamic elements, but to truly test a formal specification delineated by this branch of the literature, a time element is required (McCrary, 2010). In economics, a dynamic model includes an intertemporal element that may cause an individual to weigh certain variables differently (Kuznets, 1930). Some examples include an offender experiencing diminished capacity, temporary income shocks, and their ability/willingness to save or borrow (McCrary, 2010). While I provide a canvas for future research to measure the magnitude of marginal deterrent effects, it is only a starting point and requires more rigorous testing. Future marginal deterrence research should implement longitudinal designs and focus on intertemporal variables that may affect the illicit incentive. For example, suppose the illicit incentive is low, and the offender is currently experiencing diminished earnings from losing their job. In that case, they may escalate the severity of the crime they choose to commit.

Despite these limitations, the work presented here brings us considerably closer to a clearer understanding of marginal deterrence and illicit decision-making. The noteworthy relationship between the illicit incentive measure and the six strata of robbery suggests that more attention should focus on multidimensional decision structures rather than simple binary outcomes. My study's theoretical and practical implications may help create a more dynamic understanding of pain, pleasure, and the illicit motivations that drive the commission of a crime. In the words of Jeremy Bentham ([1780] 1823), "nature has placed mankind under the governance of two sovereign masters, pain and pleasure. It is for them alone to point out what we ought to do, as well as to determine what we shall do" (p. 1).

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