PANOPTIC CONTROL IN THE DIGITAL AGE: EXAMINING THE EFFECT OF REQUIRED LIFETIME ELECTRONIC MONITORING ON REPORTED FORCIBLE RAPE

by

Rick Dierenfeldt

An Abstract
of a thesis submitted in partial fulfillment of the requirements for the degree of Master of Science in the Department of Criminal Justice University of Central Missouri April, 2013
ABSTRACT

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Sex offenses remain a pervasive problem in the United States. In response, several state legislatures have mandated lifetime electronic monitoring of convicted sex offenders. The impact of this legislation as it applies to forcible rape remains unexplored. Applying a routine activity framework, this study applies interrupted time-series analysis in the form of autoregressive integrated moving average (ARIMA) to monthly UCR reports of reported forcible rape from all states requiring lifetime electronic monitoring of convicted sex offenders between 2000 and 2009 (n= 120). Results indicate that lifetime electronic monitoring fails to act as a guardian capable of reducing the frequency of reported forcible rape at the aggregate level. Suggestions for future research include evaluation include micro-level, longitudinal studies of offender behavior.
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Introduction

It is well established among criminal justice professionals and academics alike that sex crimes and sex offenders generate a great amount of anxiety and fear in American culture (Critcher, 2005; Lees & Tewksbury, 2006; Levenson, Letourneau, Armstrong, & Zgoba, 2010). In response to this fear, lawmakers nationwide have enacted a wide variety of aggressive legislative measures aimed at deterring sexual re-offending and sexual victimization (Cohen & Jeglic, 2007; Craun, Simmon, & Reeves, 2011; Duwe & Donnay, 2008; Lees & Tewksbury, 2006; Lussier, Deslauriers-Varin, & Ratel, 2010; Petrunik, 2002). This trend has coincided with the general ‘get tough’ approach to crime adopted by U.S. policymakers in recent years (Martin, Hanrahan, & Bowers, 2009). Prominent examples include Megan’s Law and the Adam Walsh Act, which implemented sex offender registries, tiered sex offender classification systems, and requisite reporting by sex offenders of their whereabouts (Craun et al., 2011). In 2005, the Florida state government enacted legislation requiring the lifetime electronic monitoring of certain sex offenders in response to the sexual assault and murder of a nine-year-old girl by a convicted child molester (Padgett, Bales, & Blomberg, 2006). Similar legislation has since been enacted in nine other states (State Statutes Related to Jessica’s Law, 2008), demonstrating the fervent interest in monitoring the activities of convicted sex offenders after they have been released from prison (Langan, Schmitt, & Durose, 2003).

At face value, the need for such legislation seems logical. Despite increased efforts at incarcerating sex offenders, the majority of those convicted of these crimes return to the community (Cohen & Jeglic, 2007; Greenfeld, 1997; Langan et al., 2003; Meloy, 2005), resulting in the probation or parole supervision of more than 120,000 convicted sex offenders nationwide (Bureau of Justice Assistance, 2008). Of these parolees, 75 percent will have
received no treatment while incarcerated (Turner, Bingham, & Andrasik, 2000), equating to the release of approximately 11,000 untreated sex offender each year (Meloy, 2005). Furthermore, incidents of sexual victimization, especially violent acts perpetrated by convicted sex offenders, are often highly publicized (Craun et al., 2011; Vasquez, Maddan, & Walker, 2008). This fact has led some researchers to posit that sex offender legislation is primarily a response to media attention to such events (Craun et al., 2011; Critcher, 2005), which in turn bolsters misconceptions of sex offenders held by the public (Levenson, Brannon, Fortney, & Baker, 2007; Mercado & Ogloff, 2007; Scheela, 2001; Vasquez et al., 2008).

To this end, the crime of rape and the behavior of rapists are of particular interest. Dickey, Nussbaum, Chevolleau and Davidson (2002) conceptualize rapists as those who commit their offenses “because of a lack of internalization of societal rights and norms, disinhibition (most commonly through substance abuse), or situational factors, including misinterpretation of cues from the victim” (p. 212). The most sadistic of these offenders exhibit a predilection for inflicting physical and/or psychological suffering on their victims (Dickey et al., 2002). As stated by Taylor and Gassner (2010), “Among crimes against the person, sexual violence is the most severe traumatic crime that can be inflicted” (p. 241). Although researchers have acknowledged the severe, long-term costs to victims and the pervasive problem it poses to society (Abbey & Jacques-Tiura, 2011; Button, DeMichele, & Payne, 2009; Payne & Gainey, 2005; Pazzani, 2007; Schwartz, DeKeserdey, Tait, & Alvi, 2001), existing literature has largely ignored the crime of rape (McCabe & Wauchope, 2005). Moreover, attitudes toward rape represent the need for a dramatic shift in research perspective from examination of victim behaviors to those of rapists. The former, at best, does little to dispel the rape myths that seem to persist in popular culture, academia, and the criminal justice system. This assertion is evidenced
by the lack of credence given to cases in which no physical force is used (Abbey & Jacques-Tiura, 2011), as well as the abundance of victim-centered studies of rape that perpetuate victim blaming. Equally concerning has been the prevailing attitude toward rape prevention. As noted by Schwartz et al. (2001), women have been encouraged to “provide self-guardianship by staying home at night, never going out alone, avoiding public transportation, and never trusting strangers” (p. 632). While such practices would likely inhibit many forms of victimization, they are hardly practical.

Research on rapist behaviors appears to conflict with traditional dogma that “a person may be simply too busy doing conventional things to find time to engage in deviant behavior” (Hirschi, 1969, p. 22). In their seminal re-conceptualization of routine activity theory, Osgood, Wilson, O’Malley, Bachman and Johnston (1996), posited that ordinary activities are the source of variation in deviance. Simply stated, those who spend more time in situations conducive to deviance should exhibit higher rates of deviance (Osgood et al., 1996). This assertion is consistent with results of studies on rapist behavior, as conventional activities appear to be used to identify, stalk, and victimize suitable targets (McCabe & Wauchope, 2005). The sum of these findings supports the application of routine activity theory to examination of rapist behavior.

Even as academics dispute the nature of the inception of sex offender legislation, determining its effectiveness has proven to be an even more difficult task (Cohen & Jeglic, 2007; Meloy, 2005). There is a paucity of empirical research examining the effect of sex offender legislation, including lifetime electronic monitoring, on sexual victimization and recidivism (Cohen & Jeglic, 2007; Craun et al., 2011; Levenson et al., 2007; Meloy, 2005; Vasquez et al., 2008). This has translated into a dearth of knowledge and guidance for criminal justice professionals in the sanctioning and monitoring of convicted sex offenders (Meloy, 2005). As a
consequence, while empirical justification remains wanting, the financial costs of implementing and maintaining programs established by legislation continue to mount, adding to already swelling corrections expenditures (Martin et al., 2009; Pastore & Maguire, n.d.). The initial implementation costs associated with the Sex Offender Registration and Notification Act (SORNA), for example, were estimated to be in excess of $481 million nationwide (Justice Policy Institute, n.d.). Compliance with SORNA is compulsory unless state governments are prepared to forfeit ten percent of their respective Byrne Grant funds (Justice Policy Institute, n.d.).

While little is known of the overall impact of recent sex offender legislation, even less is known of the relationship between sex offender legislation and rape. Specifically, the relationship between required lifetime electronic monitoring and reported rape, as well as the application of criminological theory to this relationship have been neglected in the academic literature. In order to fill a gap in cumulative knowledge, the present study utilizes a routine activity framework to answer the research question: Does required lifetime electronic monitoring serve as a capable guardian responsible for reducing the frequency of reported forcible rape?
Literature Review

As was discussed in the introduction, the relationship between reported forcible rape and lifetime electronic monitoring remains unknown. In order to fill this gap in academic literature, the present study endeavors to examine a number of issues explored in previous studies. Specifically, studies that examined rapist behavior and recidivism, the impact of previous forms of sex offender legislation, and the effects of electronic monitoring as a post-conviction sanction among general offending populations will be reviewed. Examination of these efforts allows for consideration of their respective methodologies and theoretical frameworks in relation to those of the present study. This approach also allows for comparisons of the effectiveness of various post-conviction sanctions in comparison to lifetime electronic monitoring upon completion of statistical analyses.

Theoretical Framework of Previous Studies

A review of the extant literature reveals the application of criminological theory to sexual offending and victimization has historically been dominated by individual rather than sociological theories of criminology. Indeed, the theoretical framework guiding the great preponderance of previous studies examining sex offender legislation, sexual offenders, and sexual victimization (especially rape) has traditionally fallen into two categories: rational choice theory and deterrence theory (for examples see Beauregard, Rebocho, & Rossmo, 2010; Duwe & Donnay, 2008; Meloy, 2005). As stated by Meloy (2005), specific deterrence sex offender policies are aimed at convicted offenders. The efficacy of these policies is measured in terms of sexual recidivism (Meloy, 2005). In contrast, general deterrence sex offender laws target
potential offenders and are deemed successful if these individuals are deterred from sexual offending in response to the observed punishments of convicted sex offenders (Meloy, 2005).

Applying rational choice theory, Duwe and Donnay (2008) described the relationship between community notification and decreased sexual recidivism as one of ‘panoptic control.’ Succinctly, as community members keep a watchful eye on the activities of sex offenders residing within their respective neighborhoods, offenders are less likely to recidivate as a result of perceived surveillance (Duwe & Donnay, 2008). Duwe and Donnay (2008) reasoned that the critical explanatory factor for behavior modification ‘was not that prisoners were actually being observed at all times, but that they thought they were’ (p. 415). This reference draws inspiration from the Panopticon, or ‘all-seeing,’ prison conceived by Bentham (1791), which allowed one person to monitor the activities of any offender at any moment in time while remaining unseen. While monitoring was unverifiable, offenders began to modify their own behavior in response to the perceived constant surveillance (Bentham, 1791; Lyon, 1993; Roth, 2006). With the advent of computers and the internet, panoptic control has both permeated discussions on electronic surveillance and become the focal point of studies of issues ranging from criminal justice to private consumers (Lyon, 1993).

Similar to Duwe and Donnay’s (2008) likening of community notification laws, lifetime electronic monitoring may be viewed as a method of panoptic control in the digital age. Furthermore, the present study will not make a significant departure from the theoretical foundation guiding past research. Like rational choice and deterrence theories, the contemporary routine activity perspective can be conceptualized as an individual level criminological theory.
Routine Activity Theory and Rapist Behavior

Originally conceived by Cohen and Felson (1979), routine activity theory (RAT) has since been re-conceptualized and is now recognized for its ability to explain a wide range of individual, deviant behaviors (Osgood et al., 1996; Popp & Peguero, 2011; Schwartz et al., 2001). Both its popularity and explanatory power may be explained by its relatively parsimonious theoretical assumptions. Examining post-World War II increases in predatory crime despite decreases in traditionally accepted causal factors, Cohen and Felson (1979) asserted that predatory crime was the inevitable result of increased legal activities outside the home that exposed potential victims to potential offenders. According to RAT, a convergence in space and time of motivated offenders, suitable targets and the absence of capable guardians promotes victimization (Cohen & Felson, 1979). These assumptions strongly promote situational crime prevention (Lilly, Cullen, & Ball, 2011). The bulk of criminological theory has traditionally focused on the examination of factors motivating offenders to commit crime (Lilly et al., 2011). RAT, in contrast, departed from popular criminological focus on the personal histories of offenders, instead maintaining a theoretical interest in crime as a product of the relationship between conventional and illegal activities (Lilly et al., 2011; Meier & Miethe, 1993; Osgood et al., 1996). Succinctly, RAT has traditionally assumed that criminals are motivated to commit crime, but does not concern itself with how one becomes motivated to offend (Chan, Heide, & Beauregard, 2011; Cohen & Felson, 1979; Lilly et al., 2011; Osgood et al., 1996).

Accordingly, a number of researchers who have utilized a routine activity framework often exhibit preference for examining how the activities of victims contribute to their victimization, ignoring the variables which influence the motivated offender (Andresen, 2006;
Chan et al., 2011; Sasse, 2005). Thus, according to Osgood et al. (1996), application of RAT has frequently been limited to victimization and ignores crime as a function of the routine activities of the offender. As a result, the scope of application of RAT has historically been unnecessarily narrow. Indeed, RAT’s failure to address offender motivation was, perhaps, its primary criticism (Schwartz, et al., 2001). This shortcoming, according to Chan et al. (2011), undermined its effective versatility and ability to explain offender behavior.

As noted by Andresen (2006), the most consistent and powerful predictors of victimization within a routine activity framework are age, ethnicity, and marital status; however, such characteristics vary greatly across neighborhoods, cities, states and regions. Thus, different geographical areas (i.e. neighborhoods) have different routine activities (Andresen, 2006). One must also be cognizant that the contention that crime depends on routine activities also applies to offenders (Osgood et al., 1996). In the interest of crime prevention, then, it may be more prudent to focus efforts on the routine activities of offenders. As noted by Osgood et al. (1996), the situational factors that motivate an individual to commit crime should be considered in such analysis. In the context of predatory crime, suitable targets provide a situational motivation to offend (Osgood et al., 1996). In contrast to the conceptualization of a motivated offender advanced by Cohen and Felson (1979), Osgood et al. (1996) posited that the motivation to offend rests in deviant activity itself. These amendments reconcile the concerns expressed by multiple criminologists regarding RAT's previous inabilities to explain offender motivations.

Despite its potential for providing insight into sexual assault (Jackson, Gilliland, & Veneziano, 2006), RAT has been infrequently applied to the crime of rape (Belknap, 1987; Schwartz et al., 2001). As noted by Belknap (1987), this trend is likely influenced by the results of early studies which suggested that many sex offenses, including rape, are most often
perpetrated by family members, intimate partners, or friends of the victim (see Russell, 1984 and Estrich, 1987 for examples). In these cases, those who would otherwise serve as capable guardians offend against immediately available targets. Other studies, however, have revealed that rape perpetrated by strangers, acquaintances or work colleagues occurs with relative frequency (Amir, 1971; Belknap, 1987; McCabe & Wauchope, 2005; Sanders, 1980; Tjaden & Thoennes, 1999). The latter, according to McCabe and Wauchope (2005), may be the result of the offender’s knowledge of the victim’s habits and working patterns. Researchers caution, however, that their findings may have been influenced by the fact that stranger/acquaintance rape, in comparison to rape committed by an intimate partner, friend or relative, is much more likely to be reported to law enforcement as a result of heightened shame and embarrassment associated with the latter (McCabe & Wauchope, 2005; Schwartz et al., 2001).

Routine activity theory has been further criticized as being much better suited as a theoretical explanation for property crime rather than violent offending (Bennett, 1991). In particular, expressive crimes have proven difficult to predict using a routine activity framework, perhaps due to their spontaneous nature (Bennett, 1991). However, as noted by Sasse (2005), violent offending does not always occur spontaneously, an assertion that proves especially salient in cases of sex offenses. Rape, in particular, appears to be an exception to trends identified by Bennett (1991), as a number of offenders meticulously plan and prepare for their attacks. In certain cases, violent sexual offending appears to involve highly organized and tedious planning, defined by reconnaissance of the intended victims and their activities, as well as patience for the most opportune moment to attack (Chan et al., 2011; Knight, 1999; McCabe & Wauchope, 2005). A full third of rapists examined by Marshal (1988) used pornography as an
instrument in preparation for committing their offenses, illustrating that rape is often a planned event.

Researchers have long speculated about the motivations behind rape, offering varied explanations for this type of offending (McCabe & Wauchope, 2005). Power, pervasive anger, sexual gratification and opportunity have been cited as the most common motives for rape (Knight, 1999; McCabe & Wauchope, 2005). Additional motivations include feelings of social or sexual inadequacy (Prentky & Knight, 1991). Examining the behaviors and thought processes exhibited by rapists, multiple researchers suggest that motivated offenders use a multi-stage decision process used to identify suitable targets positioned in time and space (Brantingham & Brantingham, 1978; Beauregard, Rebocho, & Rossmo, 2010). This process allows for the construction of templates or scripts for offending which influence future behavior (Brantingham & Brantingham, 1978; Beauregard et al., 2010). Furthermore, the development of preferred criteria, combined with target vulnerability (i.e. the potential level of resistance offered by the target) and accessibility, appear to be key determinants in victim suitability and selection (Bennett, 1991; Boudreaux, Lord, & Jarvis, 2001; Chan et al., 2011; Hough, 1987).

In addition, results of studies conducted by Canter and Larkin (1993), Rossmo (2000), and Beauregard et al. (2010), suggest that sex offenders vary in their geographic and ‘hunting’ behaviors and preferences. These observations strongly support a typological classification of sex offenders (Dickey et al., 2002). An appreciable number of rapists appear to engage in or adopt highly ritualized, routine activities that assist them in not only identifying and stalking suitable targets, but spaces in which they are comfortable offending (Abbey & Jacques-Tiura, 2011; Beauregard et al., 2010; Canter & Larkin, 1993; Dickey et al., 2002). Aspects of variation appear in the preferred method of approaching the victim (e.g. subterfuge vs. surprise attack) and
type of location selected by the offender for commission of the offense (see Beauregard et al., 2010; Rossmo, 1997; 2000).

Rape and Recidivism

Rapist behavior has served as the focus of a scant few academic studies (McCabe & Wauchope, 2005). Instead, extant research endeavors appear to have assumed a blanket approach to examining sex offenders (Dickey et al., 2002; Vasquez et al., 2008). Furthermore, a cursory review of applied methodologies indicates that most studies that have used recidivism as a proxy for the success or failure of sex offender treatment and legislation. These approaches present several methodological concerns that will soon be discussed.

A great number of researchers have argued that as a group sex offenders exhibit relatively low rates of recidivism and are often less likely to re-offend upon release than non-sex offenders (Ducat, Thomas, & Blood, 2009; Langevin et al., 2004; Levenson et al., 2007; Levenson et al., 2010; Lussier, Deslauriers-Varin, & Ratel, 2010; Mercado & Ogloff, 2007; Vess & Skelton, 2010). The results of these studies lend support to the arguments of Levenson et al. (2007), Mercado and Ogloff (2007) and Scheela (2001) that fear of sex offenders is unwarranted or exaggerated. One must be cognizant, however, of methodological shortcomings common to sex offender research, including short follow-up periods, failure to separate sex offenders by offense type, and failure to consider risk classification. For example, several studies utilized follow-up periods of as little as three to five years (see Levenson et al., 2010 for an example).

According to Stadtland et al. (2005), recidivism rates among sexual offenders are likely underestimated because of short follow-up periods. This assertion is corroborated by longitudinal studies which indicate that recidivism rates among sex offenders rise considerably
over time (Beauregard, 2010; Langevin et al., 2004; Lussier et al., 2010; Vess & Skelton, 2010). Indeed, sexual re-offending rates tend to range from 4 to 10 percent in five-year follow-up studies (see Lussier, Proulx, & Leblanc, 2005; Meloy, 2005), but consistently increase to between 20 and 40 percent in studies utilizing 10 to 25-year follow-up periods (see Alexander, 1999; Greenberg, 1998; Hanson & Bussiere, 1998; Hanson & Morton-Bourgon, 2005; Harris & Hanson, 2004; Langevin et al., 2004; Prentky, Lee, Knight, & Cerce, 1997). Considered in conjunction with contemporary conceptualizations of the capable guardian (see Felson 1986), these trends may indicate high levels of self-control among sex offenders while under post-confinement probation and parole supervision. While speculative, this assertion suggests that parole officers may serve as capable guardians while monitoring their clients’ activities. Unfortunately, this scenario also supports Lyon’s (1993) assertion that the failure of panoptic control is that it produces “docile deviant populations” rather than “good citizens” (p. 666).

Interestingly, risk classification and age may possess comparable explanatory power. Lussier et al. (2010) noted that when sex offenders were categorized by low, low to medium, medium to high, and high risk, they exhibited respective five-year recidivism rates of 5-6, 9-12, 26-33, and 39 percent. Similarly, Dickey et al. (2002) found significant differences in sexual recidivism when differentiating by age and typology (rapists, pedophiles, or sexual sadists). Among young adults, offending groups were virtually equivalent (Dickey et al., 2002). Offending among adults aged 26-40 varied in comparison, with 41 percent of the sample classified as rapists, 31.3 percent as pedophiles, and 27.7 percent as sadists (Dickey et al., 2002). Interestingly, significant changes were observed in the type of sexual recidivism of older adults aged 40 to 70 (Dickey et al., 2002). Within this sample, 10 percent were classified as rapists, 60 percent as pedophiles, and 30 percent as sadists (Dickey et al., 2002).
These results suggest that rapists may begin to ‘age out’ of offending after age 40. A more disturbing possibility is that they adapt their victim preferences in order to compensate for their physical inability to victimize adults. Blanchard et al. (1999) assert that those who sexually victimize adults tend to be younger than those who commit similar offenses against children. Dickey et al. (2002) posit that this is likely related to changing motivations and physical capabilities required to complete acts of forcible rape. Specifically, the inverse relationship between age and offending may be explained by increased sexual dysfunction and decreased sexual performance, sex drive, levels of testosterone, muscle mass and physical ability (Buvat & Lemaire, 1997; Dickey et al., 2002; Panser, Rhodes, Girman, & Guess, 1995). It may be inferred, then, that physical characteristics and abilities of motivated offenders, and in particular rapists, influence offender decisions regarding target suitability.

Although multiple studies suggest that sex offenders should not be studied as a homogeneous group (Dickey et al., 2002; Hanson & Bussiere, 1998; Meloy, 2005; Vasquez et al., 2008), the literature often fails to make a typological distinction between sex offenders (Dickey et al., 2002), which may produce inaccurate results (Buttell, 2002; English, Pullen, & Jones, 1997; Hanson & Bussiere, 1998; Meloy, 2005). This academic oversight is mirrored in society’s response to sexual offending. As noted by Vasquez et al. (2008), “Sex offender legislation implies similarity across all types of sex offenders and offenses regardless of type of offense, age of victim, or age of offender in relation to victim” (p. 178).

Indeed, when sex offenders are further delineated by offense type, the prolific recidivism among rapists becomes immediately apparent. Studies by Doren (1998), Prentky et al. (1997) and Quinsey, Lalumiere, Rice, and Harris (1995), each suggest that between 23 and 39 percent of rapists will re-offend sexually. These results are supported by those of Vess & Skelton (2010),
in which approximately 46 percent of those who had a history of offending sexually against adults recidivated either sexually or violently. Equally disturbing is the affinity for sexual polymorphism exclusively exhibited by rapists. This phenomenon may be defined as the ability to adapt behaviors and victim preferences, often on the basis of opportunity (Beauregard, 2010; Lussier et al., 2007; Lussier et al., 2005). However, the diminished physical abilities that negatively impact the ability to victimize adult females must also be considered as an explanatory factor (see Buvat & Lemaire, 1997; Dickey et al., 2002; Panser et al., 1995). Of those recidivist rapists in their sample, Vess and Skelton (2010) determined that a full 37 percent re-offended against children following release from prison. Cumulatively, these studies suggest that rapists represent a particularly voracious, adaptive type of offender at increased risk of sexual re-offending (Vess & Skelton, 2010; Levenson et al., 2007; Greenberg, 1998).

Post-Conviction Sanctions

Recent legislative measures aimed at deterring sexual victimization and re-offending have included mandatory sentences, civil commitment, community notification, sex offender registries and electronic monitoring (Cohen & Jeglic, 2007; Craun et al., 2011). Anecdotally, such endeavors limit opportunities for sexual offending by publicly exposing offenders and limiting their abilities to form relationships with suitable targets (Duwe & Donnay, 2008; Petrosino & Petrosino, 1999). Although popular, the effectiveness of these measures remains, at best, speculative (Craun et al., 2011).

Empirical evidence suggests that sex offender registration has been ineffective in reducing victimization and re-offending (Levenson et al., 2010; Cohen & Jeglic, 2007; Craun et al., 2011; Sandler, Freeman, & Socia, 2008; Schram & Milloy, 1995; Vasquez et al., 2008;
Researchers have been quick to point out, however, that those authorities responsible for maintaining sex offender registries appear to have been inconsistent in enforcing and maintaining them (Cohen & Jeglic, 2007; Petrunik, 2002). Such apathy arguably renders sex offender legislation innocuous to deterrence (Cohen & Jeglic, 2007; Petrunik, 2002). It has also been suggested that the majority of sex offenses are committed by first-time offenders, effectively limiting the utility of sex offender registration (Sandler, Freeman, & Socia, 2008).

The efficacy of sex offender treatment is also in dispute. For example, while research by Stadtland et al. (2005) indicates that incarceration and treatment have been ineffective methods in curbing sexual offending, several other studies indicate that successful completion of treatment was correlated with a decrease in sexual re-offending (Alexander, 1999; Mailloux, Abracen, Serin, Cousineau, & Looman, 2003; Marshall, Anderson, & Fernandez, 1999). The results of these studies suggest that the motivations behind sexual offending may be addressed and successfully treated.

Finally, some studies suggest that community notification efforts successfully reduce sexual victimization (Duwe & Donnay, 2008; Simpson-Beck & Travis, 2004). These results are particularly interesting if examined through the lens of routine activity theory, as it strongly suggests that community notification promotes an increase in the number of capable guardians. This increase, in turn, effectively reduces sexual victimization. Additional research, however, counters that community notification may prevent a scant few cases of sexual victimization (Craun et al., 2011; Vasquez et al., 2008). For example, utilizing time-series analysis, Vasquez et al. (2008) examined the relationship between rape and sex offender registration and community notification laws in ten states. They reported significant decreases in only three
states while five states actually exhibited increased frequency of rape (Vasquez et al., 2008). The latter, as suggested by Vasquez et al. (2008) may be indicative of increased cooperation between communities and law enforcement, resulting in a higher number of arrests. However, a large number of sex offenses committed by registered offenders are against acquaintances, friends or family members (Craun et al., 2011). Sex offender registration and community notification offer little in the way of protection in these cases (Craun et al., 2011). Furthermore, such crimes defy the tenets of routine activity theory, as the person who would otherwise serve as a capable guardian is actually engaged in the victimization.

The cumulative failure of post-conviction initiatives has prompted some scholars to postulate that “it is crucial to maintain focus on stopping the offending at the source rather than retrospectively punishing those have already fulfilled a sentence set down by the courts” (Ducat et al., 2009, p. 164). Considering the strong support for sex offender legislation, however, such assertions are likely destined to be limited to the realm of theory rather than practice. Perhaps less pessimistic of post-conviction sanctions, Craun et al. (2011) and Meloy (2005) suggest that the utilization of multiple sanctions may precipitate a decrease sexual re-offending.

*Electronic Monitoring as a Capable Guardian*

Tendencies to conjoin routine activity theory and victimology have translated into guardianship generally being examined as a component of victimization (see Fisher, Daigle, & Cullen, 2010; Sasse, 2005; Spano & Nagy, 2011). Thus, a capable guardian is often defined as “formal or informal social control mechanism that restricts the availability and accessibility of an attractive target” (Chan et al., 2011, p. 232). Amending his original conceptualization of capable guardian, however, Felson (1986) posited that the presence of a handler capable of exerting
social control over a potential offender would reduce the likelihood of offending. Guardianship has since been operationalized in terms of formal and informal social controls, as well as devices or methods of target hardening (Bennett, 1991). The most effective of these, according to Bennett (1991), appear to be target hardening activities and informal social control capable of providing surveillance and intervention. These strategies effectively increase the risk to the motivated offender (Lilly et al., 2011). Lifetime electronic monitoring (LEM), then, appears well-suited to fulfill these functions as a capable guardian. As noted by Kilgore (2012), offenders often perceive electronic monitoring devices as proxies for their probation or parole officers.

The exponentially increasing use of electronic monitoring in the United States has coincided with burgeoning populations of incarcerated offenders in correctional institutions (Kilgore, 2012; Padgett et al., 2006). This should come as little surprise considering that it is a relatively low-cost alternative to incarceration (Martin et al., 2009; National Law Enforcement Corrections Technology Center, 1999). Such markedly rapid growth has not, however, been matched by evaluative research (Gainey, Payne, & O’Toole, 2000; Padgett et al., 2006), leaving scholars and policy makers alike to ponder its effectiveness (Padgett et al., 2006). This proves particularly salient when applied specifically to sex offenders (Armstrong & Freeman, 2011; Button et al., 2009; Payne & DeMichele, 2011), as the bulk of empirical research on the effectiveness of electronic monitoring has focused on non-sex offenders. This fact has not precluded the electronic monitoring of sex offenders under the anecdotal assumption that sex offenses may be prevented through knowledge or control of the offender’s location (Button et al., 2009; Payne & DeMichele, 2011). Although this presumption has not been tied to a particular criminological theory, it appears that electronic monitoring has been popularly interpreted as a
capable guardian. Thus, presumptions surrounding the capabilities of electronic monitoring are oriented toward a routine activities approach. The single study exclusive to sex offenders asserts that states requiring electronic monitoring of sex offenders were no more likely than states that did not to have offense rates below the U.S. average (Button et al., 2009). However, this study did not measure the effect of electronic monitoring within each state.

Despite this noticeable paucity, the results of studies on the use of electronic monitoring among non-sex offender populations offer some promise. Indeed, the social restrictions and monetary burden associated with electronic monitoring have been determined significant (Martin et al., 2009) to the extent that many offenders consider electronic monitoring to be more punitive than incarceration (Spelman, 1995; Wood & Grasmick, 1999). Simultaneously, the use of post-incarceration electronic monitoring has been viewed as a method of conveying to offenders society’s interest in reintegrating them into the community (Gainey et al., 2000; Payne & Gainey, 2004). Perhaps most importantly, research also suggests that the use of electronic monitoring fosters a reduction in re-offending (Bonta, Wallace-Capretta, & Rooney, 2000; Courtright, Berg, and Mutchnick, 2000; Gainey et al., 2000; Padgett et al., 2006). While not exclusive to sex offenders, Padgett et al.’s (2006) five-year study on the effects of electronic monitoring revealed that while under electronic supervision sex offenders were the least likely to recidivate or abscond, results supported by those of Finn and Muirhead-Steves (2002). Considered in sum, these studies suggest that the use of electronic monitoring may facilitate both punitive and re-integrative strategies, as well as the societal protection goals of the criminal justice process (Payne & Gainey, 2000; 2004). Thus, examination of the ability of electronic monitoring to serve in the capacity of a capable guardian is warranted.
Jessica’s Law

A review of the various versions of Jessica’s Law revealed that they vary by state. Florida House Bill 1877 (2005) provides that individuals whose sexual offenses, including forcible rape, were committed against victims under 15 years of age are subject to lifetime electronic monitoring. Similarly, Missouri statutes 217.735.1 (2005) and 559.106.1 (2005) provide that lifetime electronic monitoring applies to prior sex offenders whose crimes, including forcible rape, were committed against victims under 14 years of age. These examples serve as the most conservative of those states that have adopted Jessica’s Law. In contrast, California’s Proposition 83 (2006) demands that every offender convicted of a felony sex offense be subject to lifetime electronic monitoring. Similarly, North Carolina House Bill 1896 (2005) instructs criminal justice agencies to apply lifetime electronic monitoring devices in felony cases ranging from forcible rape to indecent exposure. Remaining states have adopted provisions for the application of lifetime electronic monitoring to ‘sexually dangerous’ and ‘sexually violent’ offenders, including those convicted of forcible rape (see GA HB 1059, 2006; LA HB 572, 2006; OR §§ 144.103 for examples). The summary legislative intent of these measures in California’s Proposition 83 (2006), which insists that lifetime electronic monitoring will “prevent (sex offenders) from committing other crimes” while placing citizens “in a better position to keep themselves, their children, and their communities safe from the threat posed by sex offenders” (p. 127). It is surmised, then, that the application of lifetime electronic monitoring will reduce sexual victimization.
Current Study

While the cumulative number of states requiring lifetime electronic monitoring of sex offenders continues to increase, this growth has not been matched by academic research. No study could be located which examined the relationship between lifetime electronic monitoring and reported forcible rape. In addition and as previously noted, routine activity theory has been applied infrequently to the crime of rape. The analysis of the relationship between lifetime electronic monitoring and the frequency of reported forcible rape will allow for preliminary conclusions of the viability of lifetime electronic monitoring as a capable guardian in reducing sexual victimization.

Reviewing extant literature, methodological and statistical concerns also became apparent. For example, in Button et al.’s (2009) examination of the relationship between electronic monitoring and reported forcible rape, independent t-tests were used to compare the mean rates of reported rape in states utilizing electronic monitoring against those that did not, as well as the U.S. average. Unfortunately, as a comparative study between states, their efforts did not allow for a determination of the effect of electronic monitoring on reported forcible rape within each sample state. Likewise, while Vasquez et al. (2008) adopted a methodology similar to that of the present study in their examination of the impact of community notification and sex offender registration on reported forcible rape, they did not control for other exogenous variables. Together, these studies provided a foundation for the present research endeavor.

As was also previously noted, recidivism rather than reported victimization has served as the traditional benchmark for measuring success in criminal justice research. When examining sex offenses, especially rape, this presents a particular issue of concern as recidivism is highly
erratic in terms of definition and measurement (Doren, 1998; Meloy, 2005). This shortcoming is accompanied by a myriad of other concerns, including under-reporting (Greenberg, 1998; Hanson & Bussiere, 1998), victim blaming (Beauregard, 2010) and plea bargaining (Cohen & Jeglic, 2007; Vess & Skelton, 2010). As noted by Langevin et al. (2004), sex crimes are often reclassified as non-sexual offenses in the course of plea agreements, which may produce artificially low recidivism rates. While issues such as victim blaming and underreporting may hinder studies using either unit of analysis, it may be more appropriate to measure reported crime rather than recidivism when examining the effect of sex offender legislation. As was discussed in the introduction, sex offender legislation is often advertised as a shield that protects the general public from victimization (Craun et al., 2011; Critcher, 2005; Levenson et al., 2007; Vasquez et al., 2008). If legislative measures are successful in this regard then one should expect to find observable decreases in reported sexual victimization. This outcome is also consistent with the tenets of routine activity theory. Therefore, the present study will examine reported crime in order to ascertain the relationship between lifetime electronic monitoring and reported forcible rape.
Methodology

Overview

The present research consists of a quasi-experimental design utilizing data from the Uniform Crime Reports. The goal of the study was to answer the research question: Does required lifetime electronic monitoring of convicted sex offenders reduce the frequency of reported forcible rape? The analyses were performed using aggregate counts of reported forcible rape in each of the ten states that require lifetime electronic monitoring of convicted sex offenders.

Sample

The target population of this study was that of states requiring lifetime electronic monitoring of convicted sex offenders. Due to the small size of the target population, a purposive sampling technique was utilized. Thus, the entire population of states requiring the lifetime electronic monitoring of convicted sex offenders was examined. The population, as well as the sample, included the following states: California, Florida, Georgia, Kansas, Louisiana, Missouri, North Carolina, Oregon, Rhode Island, and Wisconsin\(^1\). It was anticipated that inclusion of all states utilizing lifetime electronic monitoring in statistical analysis would reduce potential preclusions or limitations of generalizability. The use of purposive sampling also ensured reasonable confidence in results, as the sample was representative of the population being examined.

\(^1\) Florida, Kansas, and Rhode Island were excluded from the final sample due to reporting deficiencies that will be discussed in the data section.
The primary focus of this research was to determine the effect of lifetime electronic monitoring as a capable guardian on reported forcible rape, an endeavor that could best described as evaluative. As previously noted, however, the role of electronic monitoring of sex offenders and lifetime electronic monitoring, in particular, in reducing victimization remains an area of neglect in academic research. Thus, the present study also exhibits characteristics inherently exploratory in nature.

Data

The use of agency records published in the FBI’s Uniform Crime Reports (UCR) was well-suited for the research goal of the present study, considering that one of the established goals of lifetime electronic monitoring legislation is to reduce sexual victimization. As a publicly available summary-based measure of crime, this information was readily accessible and uniform in publication. Each of the ten states included in the sample enacted required lifetime electronic monitoring between 2005 and 2006, followed by implementation between 2006 and 2008. Yearly rates were available from the years 2002-2009 on the FBI’s official website (see Table 1.). A cursory examination of these data suggested that California, Florida, Oregon, Rhode Island, and Wisconsin experienced generally downward trends in reported forcible rape during this period. In contrast, Kansas and Missouri appeared to experience upward trends. No observable trend could be discerned in Georgia, North Carolina, or Louisiana.

Rather than yearly rates, advanced statistical analysis in the form of interrupted time-series analysis would require monthly counts of reported rape in each state. Monthly data, compared to yearly, is superior as a unit of analysis for the purposes of measuring change (D’Alessio & Stolzenburg, 1995; McDowall, McCleary, Meidinger, & May, 1980). The
increased number of observations also permits the application of more highly sophisticated statistical analysis (D’Allesio & Stolzenburg, 1995). As this data was not available via the official website, a request for monthly reports was submitted to the FBI. In order to guarantee an appreciable number of observations \( n=120 \), the request included monthly totals of reported rape for each of the ten sample states from 2000 to 2009. Data that could be used in the operationalization of appropriate controls, including population and number of reporting agencies, was also requested.

Upon receipt, data for each state were reviewed in order to ensure compatibility with the selected statistical method. Florida, Kansas, and Rhode Island were excluded from further analysis due to reporting deficiencies. These included reporting crime on a quarterly basis and deviation from quarterly to monthly reporting in the midst of the series. Data from each of the remaining sample states, which were reported by jurisdiction, were then totaled as statewide aggregates. These manipulations were performed for counts of reported forcible rape, reporting agencies, and population. Each data set was then visually inspected for normality using stem-and-leaf plots and histograms, followed by statistical tests for normality in the form of skewness-kurtosis tests. Both visual inspection and statistical tests confirmed that skewness and kurtosis were not significantly different than 0 and 3 in California, Louisiana, Missouri, North Carolina or Wisconsin. Thus, each was accepted as a normal distribution. In contrast, skewness and kurtosis were found to be significant in both Georgia \( (\tau = 2.238, \kappa = 16.183) \) and Oregon \( (\tau = 1.312, \kappa = 8.248) \). In order to ensure regression was not unduly influenced by one or a select few elements in the distribution, the data were logarithmically transformed, creating a new variable (natural log plus one) which was used in the statistical analysis.
Analyses

The present study utilized a quasi-experimental, longitudinal design. Previous research has relied on cross-sectional designs to compare rates of reported forcible rape of states utilizing electronic monitoring against those who have yet to implement such measures. Considering the research problem, this is a flawed methodological approach because it does not allow for a reasonable determination of the ability of electronic monitoring to reduce sexual victimization over time within individual states.

In contrast, the present study employed interrupted time-series analysis. An observed time series is the realization of a random process; one of many that might have been generated. (McDowall et al., 1980). Time-series designs are commonly employed in longitudinal studies within criminal justice research (Dugan, 2010; Dugan, 2011; Jang, Hoover, & Joo, 2010; Pratt & Lowenkamp, 2002; Vasquez et al., 2008), offering effective means of assessing the impact of a discrete intervention on a social process (Dugan, 2010; McDowall et al., 1980). Interrupted time-series, in particular, allows researchers to determine the effect of social policy on crime through comparison of observations (i.e. aggregate reported crime) before and after the introduction of an intervention (Dugan, n.d.; Dugan, 2010; Jang et al., 2010; McDowall et al., 1980). Analyses generally test the null hypothesis by comparing pre- and post-intervention segments of a time series (Dugan, 2010; McDowall et al., 1980). Appropriate application ensures that serial dependence, which often emerges in social science research, is modeled and statistically controlled (Dugan, n.d.; Dugan, 2010; McDowall et al., 1980).

Three sources of noise may obscure an intervention: trend, seasonality, and random error (McDowell et al., 1980). Autoregressive Integrated Moving Average (ARIMA) models, which
account for all three types of noise (Dugan, n.d.; McDowell et al., 1980), were utilized in the present study. As described by McDowall et al. (1980), an ARIMA model “is simply a model of the stochastic process which generated the observed time series” (p. 15). The three structural parameters of an ARIMA model (p,d,q) describe the relationships between random shocks and the time series (McDowall et al., 1980). The term “random shock” is used to describe a unit with a zero-mean and constant variance that is randomly drawn from the normal distribution of a time series (McDowall et al., 1980). Each random shock is an input that enters the filters (p,d,q) of an ARIMA model and emerges as an observation (McDowall et al., 1980). Structural parameter p denotes the number of autoregressive structures in the model, which occurs when the current time series observation \( Y_t \) is composed of a portion of the preceding observation \( Y_{t-1} \) and a random shock \( a_t \) (Dugan, n.d.; McDowall et al., 1980). An ARIMA (1,0,0) process is demonstrated in Equation (1).

\[
Y_t = \phi Y_{t-1} + a_t
\]  

(1)

Meanwhile, parameter q denotes the number of moving average structures in the model (Dugan, n.d.; McDowall et al., 1980). Moving average is a common form of serial dependency whereby the current observation \( Y_t \) is a product of the current random shock \( a_t \) and portions of the preceding random shock \( a_{t-1} \) (Dugan, n.d.; McDowall et al., 1980). An ARIMA (0,0,1) process is demonstrated in Equation (2) and is identifiable because of a significant correlation in the autocorrelation in the first lag (Dugan, n.d.; McDowall et al., 1980). Put more simply, an ACF (1) is the correlation coefficient estimated between the current observation and the preceding observation. Subsequent correlations are expected to drop to zero (Dugan, n.d.; McDowall et al., 1980).
\[ Y_t = a_t - \theta_1 a_{t-1} \]  

Parameter \( d \) indicates that the time series model was differenced, which “amounts to subtracting the first observation of the series from the second, the second from the third, and so on” (McDowall et al., 1980, p. 16). Differencing is a solution to a unit root symptomatic of a non-stationary process in the series (Dugan, n.d.; Dugan, 2010). An ARIMA \((0,1,0)\) process is demonstrated in Equation (3).

\[ Y_t = Y_{t-1} + a_t \]  

Non-stationary processes include random walk with drift and trending (Dugan, n.d.; McDowall et al., 1980). In cases where trend is manifest, the time-series will move either upward or downward (McDowall et al., 1980). In contrast, a time-series that exhibits drift will move upward then downward or downward then upward (McDowall et al., 1980). These processes occur when the random shocks of a time-series are integrated, producing observations \( Y_t \) that are composed of all past random shocks \( Y_{t-1} + a_t \) (McDowall et al., 1980). In cases of non-stationarity, it is critical to difference the time-series prior to assessing the impact of the intervention component. If this step is not performed, change in the series may be inappropriately attributed to the intervention (Dugan, n.d.). The augmented Dickey-Fuller test, which addresses forms of serial correlation common to time-series and determines the presence of a unit root, was applied to each series (Dugan, n.d.; Dugan, 2010). In each case, \( z \)-scores were insignificant and critical values were smaller in magnitude than the test statistic. This result indicated the absence of a unit root and that differencing was not required (Dugan, n.d.; Dugan, 2010). The null was rejected in all cases, as the series were considered without trend or drift. (McDowall et al., 1980).
The auto-correlation function (ACF) and partial auto-correlation function (PACF) for each series were then examined for evidence of autoregressive and moving average processes as well as seasonality, which is often encountered in social science research (Dugan, n.d.; McDowall et al., 1980). Seasonality is defined by a cyclical pattern in the time series (Dugan, n.d.; McDowall et al., 1980). Consistent with a routine activity framework, one might expect reported forcible rape to increase during the summer months as individuals leave their respective residences to engage in extracurricular activities. McDowall et al. (1980) also posit that aggregated events, such as those examined in the present study, are likely to exhibit seasonality because some months are shorter or longer than others. While an ARIMA (p,d,q) model describes relationships between adjacent observations in a series, seasonal autoregressive, integrated, and moving average structures are denoted by P,D, and Q (Dugan, n.d.; McDowall et al., 1980). Seasonal nonstationarity within monthly data is characterized by annual drift or trending and must be differenced seasonally (McDowall et al., 1980). For monthly data, this process is demonstrated in Equation (4).

\[ Y_t - Y_{t-12} = \theta_0 \]  

(4)

Seasonal auto-regression is characterized by dependence of the current observation upon the corresponding observation from the preceding year (Dugan, n.d.; McDowall et al., 1980). For monthly data, this process is demonstrated in Equation (5).

\[ Y_t = \phi_{12} Y_{t-12} + a_t \]  

(5)

Seasonal moving averages are characterized by dependence of the current observation upon the random shock from the preceding year (Dugan, n.d.; McDowall et al., 1980). For monthly data, this process is demonstrated in Equation (6).
\[ Y_t = a_t - \theta_{12}a_{t-12} \]  \hspace{1cm} (6)

**Model Building**

Examination of the ACF and PACF in the California and North Carolina series resulted in the identification of first order autoregressive processes whereby the current value had a direct relationship with a portion of the preceding value (McDowall et al., 1980). Second order autoregressive processes were observed from seasonal lag to seasonal lag. Thus, examination of the ACF and PACF were used to tentatively identify ARIMA \((1,0,0)(2,0,0)_{12}\) models for California and North Carolina (see Table 2.). When parameters for each model were estimated, each autoregressive (AR) achieved statistical significance, validating an ARIMA \((1,0,0)(2,0,0)_{12}\) process (see Table 3. and Table 7.). Examination of the ACF and PACF residuals provided further evidence that they were not different than white noise. This multiplicative model is also more powerful than alternative additive models because it offers a better representation of seasonality (Dugan, n.d.; McDowall et al., 1980).

Examination of the ACF and PACF in the Georgia series resulted in the identification of a first order moving average process, as only the first correlation of the ACF was significant (Dugan, n.d.; McDowall et al., 1980). No seasonal autoregressive or moving average processes were discerned. Thus, an ARIMA \((0,0,1)(0,0,0)_{12}\) was identified. Parameters for the model were then estimated. The moving average (MA) achieved statistical significance, validating an ARIMA \((0,0,1)(0,0,0)_{12}\) model. Examination of the ACF and PACF residuals provided evidence that they were not different than white noise.

Examination of the ACF and PACF in the Louisiana and Missouri series resulted in the identification of second order autoregressive processes whereby the current value had direct
relationships with portions of the two preceding values (McDowall et al., 1980). A first order autoregressive process was observed from seasonal lag to seasonal lag. These observations were used to tentatively identify an ARIMA $2,0,0(1,0,0)_{12}$ model (see Tables 5. And 6.). When parameters for the model were estimated, each AR achieved statistical significance, validating an ARIMA $2,0,0(1,0,0)_{12}$ process. Examination of the ACF and PACF residuals indicated that they were not different than white noise.

Examination of the ACF and PACF in the Oregon series resulted in the identification of no autoregressive or moving average processes. Nor could any seasonal autoregressive or moving average process be discerned. This resulted in the tentative identification of an ARIMA $(0,0,0)(0,0,0)_{12}$ process, which is indicative of a time-series that “fluctuates noisily” about a nonzero constant (McDowall et al., 1980, p. 18). It is noteworthy that an ARIMA $(0,0,0)(0,0,0)_{12}$ is rarely encountered in the social sciences because it suggests the absence of serial dependency (McDowall et al., 1980). Estimation of the model revealed that the constant reached statistical significance (see Table 8.). Examination of the ACF and PACF residuals indicated that they were not different than white noise, validating an ARIMA $(0,0,0)(0,0,0)_{12}$ process.

Examination of the ACF and PACF in the Wisconsin series resulted in the identification of no autoregressive or moving average processes in adjacent observations. However, a first order autoregressive process was observed from seasonal lag to seasonal lag. Thus an ARIMA $(0,0,0)(1,0,0)_{12}$ process was tentatively identified. Estimation of model parameters revealed that the seasonal AR achieved statistical significance (see Table 9.). Subsequent examination of the ACF and PACF residuals indicated that they were not different from white noise. The ARIMA $(0,0,0)(1,0,0)_{12}$ was accepted.
Dependent Variable

As previously noted, recidivism has served as the traditional benchmark for success when examining the effectiveness of sex offender legislation. Such narrow exclusivity, however, ignores a principal goal of sex offender legislation: reducing sexual victimization. California, for example, describes the primary objective of lifetime electronic monitoring as “the enhancement of public safety through the reduction in the number of people being victimized by crimes committed by persons on parole” (Ca. Rev. Stat. §§ 3010, 2006).

An examination of UCR data revealed that forcible rape is the only sex offense published as a Part I offense. Forcible rape was selected as the dependent variable and defined in accordance with the pre-2012 definition provided by the FBI: the carnal knowledge of a female forcibly and against her will. Attempts or assaults to commit rape by force or threat of force were also included; however, statutory rape (without force) and other sex offenses were excluded (Uniform Crime Report, 2009). The dependent variable was operationalized as monthly aggregate counts of reported forcible rape obtained from raw UCR records between 2000 and 2009. Reporting occurred by jurisdiction and required tabulation for statewide monthly totals.

Use of the FBI’s definition ensured uniformity in aggregation, as definitions vary by state. Missouri, for example, defines rape as sexual intercourse by forcible compulsion and/or without the consent of the victim (MO §§ 566.030), while Wisconsin defines the same as sexual assault (WI §§ 940.225). While there have been recent attempts to reconcile statute with the revised federal definition in multiple states, a review did not reveal any changes to rape laws in

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2 On January 6, 2012, the FBI amended this definition to include the penetration of the vagina with any body part or object, or oral penetration by a sex organ of another person, without the consent of the victim.
any of the sample states during the series. Oregon House Bill 2343 (2009) amended the elements of rape to include cases of voluntary intoxication on the part of the victim, but the law did not take effect until January, 2010.

Independent Variables

Once each model is specified and tested, control variables may be added, resulting in the development of ARMAX (Autoregressive Moving Average with Exogenous Inputs) models. In this study, ARMAX models were designed to control for temporary effects that ceased following the first, second, and third months of legislative enactment, as well as permanent effect of legislation. Permanent effect was operationalized as a dichotomous variable (0 = absence of intervention, 1 = intervention in place). Temporary effects (temp1, temp2, temp3) were operationalized as pulse functions in accordance with the recommendation of McDowall et al. (1980). Additional controls were also utilized in the development of ARMAX models, including population and number of reporting agencies. These data, like monthly counts of reported forcible rape, were procured from official UCR reports obtained from the FBI and required tabulation for statewide totals. Number of reporting agencies was operationalized as the aggregate measure of all law enforcement agencies reporting to the UCR within each state. The independent variable population was operationalized as the aggregate measure of all residents within the jurisdictions of law enforcement agencies reporting to the UCR within each state. It should be noted, however, that the latter two variables varied yearly rather than monthly. This was incidental to the manner in which they were reported in the UCR.
Hypothesis

The results of studies examining the effectiveness of sex offender legislation generally point toward the failure of such efforts to inhibit sexual re-offending and sexual victimization. This fact may be the product of varied methodological approaches used in previous studies. Extant literature does, however, reveal that rapists represent a particularly motivated type of sexual offender. The noted successes of electronic monitoring of non-sex offenders and, to some extent, sex offender community notification as a method of panoptic control offer promise that sex offenders may perceive electronic monitoring devices as omnipresent capable guardians. In turn, such perceptions may moderate the number of occurrences in which they come into close proximity to suitable targets, thereby reducing victimization. In accordance with routine activity theory, it is hypothesized that the introduction of required lifetime electronic monitoring will cause a decrease in reported forcible rape in each of the sample states.

Summary

The quantitative data collection process, research question, and hypothesis have each been described. The manner in which time-series modeling will test the research question and conceptualization and operationalization of inclusive variables has also been discussed. Next, the findings from the research question, which endeavors to determine the abilities of LEM as a guardian capable of reducing the frequency of reported forcible rape and the applicability of routine activity theory to this relationship, will be presented.
Results

Once parameter estimations and diagnoses for the ARIMA models were completed, the effects of the intervention or impact assessment could be measured (see Figures 1 through 7). This is accomplished by adding the intervention component to the specified noise model (McDowall et al., 1980) and is demonstrated in Equation (7). Here, $N_t$ represents the ARIMA $(p,d,q)(P,D,Q)_s$ model and $f(I_t)$ is the intervention component.

$$Y_t = f(I_t) + N_t$$ \hspace{1cm} (7)

In practice, one of three distinct patterns could be expected (Dugan, 2010; McDowall et al., 1980; Pridemore, Chamline, & Trahan, 2008). The patterns may be abrupt and permanent, gradual and permanent, or abrupt and temporary (Dugan, n.d.; Dugan, 2010; McDowall et al., 1980; Pridemore et al., 2008). A fourth pattern, gradual and temporary, occurs with less frequency and is much more difficult to model (Dugan, n.d.; Dugan, 2010; McDowall et al., 1980).

McDowall et al. (1980) suggest first modeling interventions with abrupt, temporary change because the significance and magnitude of the slope often provide researchers with an indication of the likelihood of permanent change. Specifically, if while modeling abrupt, temporary effects the slope is near one and significant then the effects are likely permanent (McDowall et al., 1980). In the case of abrupt and temporary change, those affected by lifetime electronic monitoring (LEM) may have immediately ceased committing forcible rape upon receiving the sanction, but re-engaged in such behaviors in response to situational motivation(s) or lack of perceived guardianship provided by LEM. An abrupt, temporary effect is demonstrated in Equation (8). Here, $\delta$ represents the slope of the change resulting from the
intervention while $\omega$ represents an estimate of the difference between pre and post intervention process levels (McDowall et al., 1980). The term $P_t$ represents the intervention component as a pulse function. Put more simply, $P_t$ is equal to one at the moment of intervention, but equal to zero both before and after. In this study, sensitivity analysis included testing of 1, 2, and 3 month temporary effects.

$$Y_t = \delta Y_{t-1} + \omega P_t + N$$  \hspace{1cm} (8)

Modeling for gradual, permanent effects is the next step suggested by McDowall et al. (1980). This effect is suggested to be the most prevalent in social sciences (Dugan, n.d.; McDowall et al., 1980). In relevance to the present study, LEM would likely affect larger numbers of offenders over months and years as they were released from confinement. Therefore, a gradual but permanent decrease in reported forcible rape might be expected. This effect is demonstrated in Equation (9), where the pulse function has been replaced by the step function $\omega I_t$.

$$Y_t = \delta Y_{t-1} + \omega I_t + N$$  \hspace{1cm} (9)

Finally, if the slope is small and insignificant when modeling a gradual, permanent effect then this may indicate that the effect is abrupt and permanent (Dugan, n.d.; McDowall et al., 1980). In relation to the present study, the introduction of LEM would cause an immediate and permanent reduction in reported forcible rape. This effect is demonstrated in Equation (10) where the slope component has been removed.

$$Y_t = \omega I_t + N$$  \hspace{1cm} (10)
California

Following the recommendations of McDowall et al. (1980), abrupt, temporary effects were the first to be modeled. The slope at the first lag was both near one (δ = .644) and significant (p = .000), indicating the effect of the intervention was likely permanent (see Table 3.). The one-month effect was insignificant (z = 0.04, p = .971). Results for two-month (z = -0.08, p = .935) and three-month effects (z = -0.12, p = .902) were similarly insignificant. Gradual, permanent effects were then modeled. The resulting slope was both near one (δ = .565) and significant (p = .000), suggesting that the effect was gradual and permanent. However, gradual and permanent effects were insignificant (z = -1.52, p = .129). In response, the research hypothesis was rejected for California.

Georgia

Modeling of abrupt, temporary effects revealed a slope at the first lag that was (δ = .524) statistically insignificant (p = .054) (see Table 4.), indicating that any intervention effect was more likely temporary than permanent. The one month effect was insignificant (z = -.005, p = .963). Results for two-month (z = -0.14, p = .891) and three-month effects (z = -.006, p = .955) were similar, indicating the absence of a temporary intervention effect. Gradual, permanent effects were then modeled but failed to achieve statistical significance (z = 0.31, p = .273). The research hypothesis was thus rejected for Georgia.

Louisiana

Modeling of abrupt, temporary effects revealed a slope that was both near one (δ = .746) and significant (p = .000) (see Table 5.), indicating an increased likelihood of permanent effects. Temporary effects at one month (z = 0.41, p = .682), two months (z = 0.68, p = .495) and three
months (z = 0.87, p = .383) failed to reach statistical significance. Gradual, permanent effects were then modeled. The resulting slope was near one (δ = .724) and achieved statistical significance (p = .000), which indicated a gradual, permanent effect. However, further examination revealed that the gradual, permanent effect of the intervention was not statistically significant (z = -1.39, p = .165). The research hypothesis was rejected for Louisiana.

Missouri

Modeling of abrupt, temporary effects revealed a slope that was both near one (δ = .757) and significant (p = .000) (see Table 6.), indicating that any intervention effect was likely permanent. Results of sensitivity analysis at one month (z = 0.49, p = .625), two months (z = 0.96, p = .335), and three months (z = 0.42, p = .676) failed to approach statistical significance. Gradual, permanent effects were then modeled resulting in a slope that was near one and statistically significant (δ = .738, p = .000), suggesting that the effect was likely gradual and permanent. However, the gradual and permanent effects of LEM failed to achieve statistical significance (z = 1.05, p = .292). This result prompted rejection of the research hypothesis for Missouri.

North Carolina

Modeling of abrupt, temporary effects revealed a slope that was both near one (δ = .539) and significant (p = .000) (see Table 7.), indicating that any intervention effect was likely permanent rather than temporary. Results for one-month (z = -.70, p = .482), two-month (z = -.20, p = .841), and three-month effects (z = -.76, p = .448) failed to achieve statistical significance. Modeling of gradual and permanent effects resulted in a slope both near one (δ = .505) and significant (p = .000). However, the gradual and permanent effects of LEM failed to achieve
statistical significance ($z = -1.13, p= .260$). The research hypothesis was rejected for North Carolina.

**Oregon**

Modeling of abrupt, temporary effects revealed a negative slope that was both small ($\delta = -.074$) and insignificant ($p= .343$) (see Table 8.), indicating that any intervention effect was temporary rather than permanent. One-month effects were statistically insignificant ($z= -.077, p= .468$). Two-month ($z = -.53, p=.594$) and three-month effects ($z = -.57, p= .570$) were also insignificant, indicating the absence of abrupt, temporary effects. Gradual, permanent effects were then modeled, but failed to achieve statistical significance ($z= -0.31, p= .348$). These results prompted rejection of the research hypothesis for Oregon.

**Wisconsin**

Modeling of abrupt, temporary effects revealed a negative slope that was both small ($\delta = .054$) and insignificant ($p= .615$) (see Table 9.), indicating that any intervention effect was temporary rather than permanent. One-month effects were statistically insignificant ($z = -.03, p= .973$). Two-month ($z = -.56, p=.575$) and three-month effects ($z = -.62, p= .533$) were also insignificant, indicating the absence of abrupt, temporary effects. Gradual, permanent effects were then modeled, but failed to achieve statistical significance ($z= -1.63, p= .102$). These results prompted rejection of the research hypothesis for Wisconsin.
Discussion

The cumulative failure of lifetime electronic monitoring suggests a null effect and prompts rejection of the research hypothesis. ARIMA models for each state failed to achieve statistical significance, effectively precluding the need to apply additional controls in the ARMAX models. At face value, this result is supportive of previous research on the relationship between guardianship and violent crime, which indicate a null effect (Bennett, 1991; Stahura & Sloan, 1988). These results are interesting when compared to those of Vasquez et al. (2008) who, in their examination of the effects of sex offender registration and community notification, were unable to draw clear conclusions.

It is acknowledged that the methodological approach adopted in the present study is somewhat unorthodox. Examination of aggregate measures of crime cannot generally be relied upon to provide explanations for individual offending. However, as was noted throughout this study, lifetime electronic monitoring of individual offenders has been conceptualized and presented by state legislatures as a key to reducing aggregate victimization. This conceptualization served as the impetus for the adopted criminological framework, data set, and statistical method adopted in the present study. While the temptation may exist to simply conclude that lifetime electronic monitoring fails to reduce victimization, other factors must be considered.

First, Kilgore (2012) suggests that electronic monitoring creates numerous inconveniences for the wearer, including disrupting one’s ability to secure employment and develop positive social relationships. These assumptions moved Kilgore (2012) to further posit that electronic monitoring does little to dissuade criminal offending. The results of the present
study offer some support for such assertions, especially when considered in conjunction with the results of studies examining rapist motivation. Issues related to power, pervasive anger, social inadequacy and vindictiveness have been cited as common motivations for committing forcible rape (Knight, 1999; McCabe & Wauchope, 2005; Prentky & Knight, 1991). Furthermore, social isolation, loneliness, and a lack of healthy intimate relationships have been correlated with violent sexual offending, most notably sexual homicide (Chan et al., 2011). If lifetime electronic monitoring inhibits one’s ability to secure employment and develop positive social capital, motivation for committing such acts may be fuelled. Unfortunately, the data set utilized in the present study did not allow for examination of these concerns.

These considerations suggest that effective offender-based rape prevention measures must target the motivations of the offender if they are to be successful. As noted by Stahura and Sloan (1998), violent crime is more strongly correlated with offender motivation than the presence of capable guardians. Like sex offender registration and community notification, lifetime electronic monitoring fails in this regard. Here, the assertion of Ducat et al. (2009) that retrospective punishment is a fruitless endeavor proves particularly applicable. In their totality, post-conviction initiatives including lifetime electronic monitoring appear wholly ineffective in reducing reported forcible rape.

Offender age is an additional variable that the present research design could not statistically control. Protected targets may increase the thrill of offending, particularly among younger offenders (Miethe, 1991). As noted by Averdijk (2011), any reduction in offending among older, more experienced offenders in response to the intervention of guardianship may be offset by increased offending among younger offenders. This concern is of particular interest considering the inverse relationship between forcible rape and offender age noted by Dickey et
al. (2002) and Heilbrun and Cross (1979). It is possible that the utility of lifetime electronic monitoring among convicted rapists may be limited to older offenders who already exhibit a decreased propensity for committing forcible rape in comparison to their more youthful peers (Dickey et al., 2002). Here, however, the potential for sexual polymorphism amongst rapists detailed in the literature review merits additional discussion. Researchers have posited that decreased physical abilities (i.e. decreasing strength and muscle mass, increasing sexual dysfunction) that accompany age likely inhibit an offender’s ability to consummate the crime of forcible rape against an adult victim (Buvat & Lemaire, 1997; Dickey et al., 2002; Panser et al., 1995). This natural phenomenon may explain the tendency of many convicted rapists to sexually re-offend against children noted by Vess and Skelton (2010) once they are released from prison. Of interest, then, is the possibility that lifetime electronic monitoring may prevent the sexual victimization of children by convicted rapists.

Sandler et al. (2008) suggested that the utility of sex offender legislation may be effectively limited because the majority of sex offenses are committed by first time offenders. One must concede that the efficacy of lifetime electronic monitoring may suffer the same limitation. Moreover, the non-retroactive nature of lifetime electronic monitoring precludes application to offenders whose crimes were committed prior to legislative enactment. If this fact is considered in conjunction with the recent introduction of lifetime electronic monitoring, it becomes apparent that LEM likely affects relatively few offenders. Even in the absence of these acknowledgments, the results of the present study can be reconciled with those of examinations of rapist recidivism, which indicate that relatively few re-offend in the first few years following release. It is conceivable, then, that the impact of lifetime electronic monitoring as a capable guardian cannot yet be adequately quantified. Indeed, the effects of lifetime electronic
monitoring may not be realized until fifteen to twenty years after inception- a time frame that coincides with higher recidivism rates among convicted rapists. Interestingly, this conclusion stands in conflict with the immediate impact suggested by proponents of sex offender legislation.
Conclusion

The results of the present study indicate that lifetime electronic monitoring fails to serve as a guardian capable of reducing reported forcible rape at an aggregate level. While this study builds a foundation for other researchers, it also suffered a number of limitations. The reasoning for measuring change in aggregate data in response to individual sanctions and the adoption of a routine activity framework have already been discussed. Next, threats to internal and external validity must be addressed. The only states included in the present study were those states requiring lifetime electronic monitoring. States in which electronic monitoring of sex offenders terminated upon completion of probation or parole, as well as states which have not implemented electronic monitoring programs, were excluded from analysis. This methodological approach precluded random assignment as well as examination of control groups. This may be interpreted as a form of selection bias. Regrettably, this approach also precludes generalizability of results beyond the sample. However, considering the results of previous studies reporting tendencies of increased rapist recidivism over time, as well as the non-retroactive nature of this particular type of sex offender legislation, the adopted methodology seemed the more logical approach. Moreover, the sample included the entire population under study.

The selected method of statistical analysis also possessed inherent weaknesses. As noted by Dugan (2011), interrupted time-series designs using aggregate data are limited because the “precise timing of the events and interventions are obscured during aggregation” (p. 382). As a result causality, or lack thereof, may be difficult to correctly identify (Dugan, 2011). The use of monthly aggregates may also have concealed the influence of one event over proceeding events within the same monthly reporting period (Dugan, 2011). For example, a highly publicized completed rape, series of rapes, or the apprehension of a rape suspect may have served as
impetus for varying self-protective measures adopted by civilians as well as police tactics and resource allocation. In turn, these factors may influence an increase or decrease in forcible rapes during a monthly reporting period. The use of monthly aggregates also created difficulties regarding the use of covariates in ARMAX models. As noted by Dugan (2011), exogenous become exceedingly difficult to obtain at monthly aggregations. The use of yearly aggregations of population and reporting agencies as monthly counts would have violated the requirement that covariates be measured at the same temporal unit as the dependent variable had they been used (Dugan, 2011). An additional weakness, time-series designs maintain focus on temporal dependence of events rather than the context specific dependence (Dugan, 2011). Unfortunately, the lack of incident-based data precluded the use of more sophisticated statistical analysis (i.e. series hazard modeling) that is capable of controlling for this dependence (Dugan, 2011).

Finally, the greatest threat to reliability and validity may very well have been the use of UCR data itself. As noted by Maxfield and Babbie (2011), agency records are often plagued by social production of data and duplicate reporting as a consequence of either inconsistency or the discretion available to reporting authorities. Furthermore, clerical errors inevitably occur and increase as the amount of data increases in volume. This poses a legitimate concern considering the sheer volume of data reported in the UCR. These threats are compounded by the FBI’s use of the hierarchy rule in tabulating reported crime in the UCR (Maxfield & Babbie, 2011). Considering the methodological approach adopted by the present study, however, there was little that could be done to control for UCR reporting methods beyond acknowledging their shortcomings.

Rather than depend on aggregated data, it is recommended that future research efforts utilize longitudinal, micro-level designs which incorporate offending cohorts who are subject to
lifetime electronic monitoring. This methodological approach would enable researchers to control for a number of variables which were not inclusive to the present study, such as offender age, employment, social capital, criminal history, offender motivation, and sexual polymorphism. This approach also lends itself to integration of quantitative and qualitative methodologies. Furthermore, beyond simple regression analysis, access to incident-based data will allow future researchers to apply more sophisticated statistical methods, such as series hazard modeling, which is capable of overcoming the deficiencies inherent to ARIMA and ARMAX modeling (Dugan, 2011). It is also recommended that future studies engage in modeling of incident-based data at the community level. In this vein, the continued development of the National Incident Based Reported System (NIBRS) may offer some relief. Such analyses would allow for comparisons between communities, perhaps allowing researchers to draw conclusions regarding the viability of LEM’s guardianship in rural versus urban environments.

Unfortunately, few conclusions can be drawn from this study beyond suggestions for future research. Although legislation that promises to “keep tabs” on sexual offenders is likely to receive overwhelming support from legislators and communities alike, reason dictates that concepts should be scientifically tested before they become social policy. However, the premature implementation of lifetime electronic monitoring may yet bear fruit. Micro-level studies of individual offenders may be conducted in cooperation with state corrections agencies and then compared to examinations of aggregate crime in order to determine the true effectiveness of lifetime electronic monitoring.
Figures

Figure 1.

California Reported Forcible Rape with LEM Intervention
Figure 2.

Georgia Reported Forcible Rape with LEM Intervention
Figure 3.

Louisiana Reported Forcible Rape with LEM Intervention
Missouri Reported Forcible Rape with LEM Intervention

Figure 4.
Figure 5.

North Carolina Reported Forcible Rape with LEM Intervention
Figure 6.

Oregon Reported Forcible Rape with LEM Intervention
Figure 7.

Wisconsin Reported Forcible Rape with LEM Intervention
Table 1.

Rate of Reported Forcible Rape per 100,000 Population

<table>
<thead>
<tr>
<th>State</th>
<th>2002</th>
<th>2003</th>
<th>2004</th>
<th>2005</th>
<th>2006</th>
<th>2007</th>
<th>2008</th>
<th>2009</th>
</tr>
</thead>
<tbody>
<tr>
<td>California</td>
<td>29</td>
<td>28.2</td>
<td>26.8</td>
<td>26</td>
<td>25.3</td>
<td>24.7</td>
<td>24.2</td>
<td>23.6</td>
</tr>
<tr>
<td>Florida</td>
<td>40.4</td>
<td>39.5</td>
<td>38</td>
<td>37.1</td>
<td>35.8</td>
<td>33.7</td>
<td>32.6</td>
<td>29.7</td>
</tr>
<tr>
<td>Georgia</td>
<td>24.6</td>
<td>25.7</td>
<td>27</td>
<td>23.6</td>
<td>23.2</td>
<td>22.8</td>
<td>22.7</td>
<td>23.4</td>
</tr>
<tr>
<td>Kansas</td>
<td>38.1</td>
<td>38.3</td>
<td>40.4</td>
<td>38.4</td>
<td>44.8</td>
<td>44.3</td>
<td>42.5</td>
<td>38.9</td>
</tr>
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<td>Louisiana</td>
<td>34.1</td>
<td>41.1</td>
<td>35.8</td>
<td>31.4</td>
<td>36.4</td>
<td>32.4</td>
<td>27.9</td>
<td>30.3</td>
</tr>
<tr>
<td>Missouri</td>
<td>25.8</td>
<td>24.4</td>
<td>25.7</td>
<td>28</td>
<td>30.2</td>
<td>29.2</td>
<td>27.3</td>
<td>26.8</td>
</tr>
<tr>
<td>North Carolina</td>
<td>26.4</td>
<td>25.4</td>
<td>27.4</td>
<td>26.5</td>
<td>28.2</td>
<td>26.3</td>
<td>24.8</td>
<td>24.6</td>
</tr>
<tr>
<td>Oregon</td>
<td>35.2</td>
<td>34.2</td>
<td>35.7</td>
<td>34.8</td>
<td>32.3</td>
<td>33.5</td>
<td>30.5</td>
<td>30.5</td>
</tr>
<tr>
<td>Rhode Island</td>
<td>36.9</td>
<td>46.9</td>
<td>29.6</td>
<td>29.8</td>
<td>26.7</td>
<td>24.2</td>
<td>26.4</td>
<td>27.3</td>
</tr>
<tr>
<td>Wisconsin</td>
<td>22.7</td>
<td>21.9</td>
<td>20.6</td>
<td>20.6</td>
<td>20.4</td>
<td>21.8</td>
<td>19.9</td>
<td>19.6</td>
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</table>
Table 2.
Univariate Statistics of States Included in Analyses

<table>
<thead>
<tr>
<th>State</th>
<th>Noise Model</th>
<th>Sample Size</th>
<th>Intervention Month/Year</th>
</tr>
</thead>
<tbody>
<tr>
<td>California</td>
<td>ARIMA (1,0,0)(2,0,0)₁₂</td>
<td>n=120</td>
<td>11/2006</td>
</tr>
<tr>
<td>Georgia^</td>
<td>ARIMA (0,0,1)(0,0,0)₁₂</td>
<td>n=120</td>
<td>10/2006</td>
</tr>
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<td>Louisiana</td>
<td>ARIMA (2,0,0)(1,0,0)₁₂</td>
<td>n=120</td>
<td>08/2006</td>
</tr>
<tr>
<td>Missouri</td>
<td>ARIMA (2,0,0)(1,0,0)₁₂</td>
<td>n=120</td>
<td>08/2006</td>
</tr>
<tr>
<td>North Carolina</td>
<td>ARIMA (1,0,0)(2,0,0)₁₂</td>
<td>n=120</td>
<td>01/2007</td>
</tr>
<tr>
<td>Oregon^</td>
<td>ARIMA (0,0,0)(0,0,0)₁₂</td>
<td>n=120</td>
<td>04/2006</td>
</tr>
<tr>
<td>Wisconsin</td>
<td>ARIMA (0,0,0)(1,0,0)₁₂</td>
<td>n=120</td>
<td>01/2008</td>
</tr>
</tbody>
</table>

^Indicates that the data have been logarithmically transformed
Table 3.
California Model of Forcible Rape by Month

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>Standard Error</th>
<th>Z</th>
<th>P</th>
</tr>
</thead>
<tbody>
<tr>
<td>Model 1</td>
<td>AR(1)</td>
<td>.460</td>
<td>.098</td>
<td>4.69</td>
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<tr>
<td></td>
<td>AR(1)</td>
<td>.441</td>
<td>.095</td>
<td>4.63</td>
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<tr>
<td></td>
<td>AR(2)</td>
<td>.252</td>
<td>.098</td>
<td>2.57</td>
</tr>
<tr>
<td></td>
<td>Intercept</td>
<td>776.599</td>
<td>20.253</td>
<td>38.35</td>
</tr>
<tr>
<td>Model 2</td>
<td>δ</td>
<td>.644</td>
<td>.110</td>
<td>5.84</td>
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<tr>
<td></td>
<td>Month 1</td>
<td>2.674</td>
<td>73.394</td>
<td>0.04</td>
</tr>
<tr>
<td></td>
<td>Intercept</td>
<td>273.984</td>
<td>86.534</td>
<td>3.17</td>
</tr>
<tr>
<td>Model 3</td>
<td>δ</td>
<td>.643</td>
<td>.110</td>
<td>5.83</td>
</tr>
<tr>
<td></td>
<td>Month 2</td>
<td>-5.138</td>
<td>62.608</td>
<td>-0.08</td>
</tr>
<tr>
<td></td>
<td>Intercept</td>
<td>274.833</td>
<td>86.571</td>
<td>3.17</td>
</tr>
<tr>
<td>Model 4</td>
<td>δ</td>
<td>.642</td>
<td>.110</td>
<td>5.82</td>
</tr>
<tr>
<td></td>
<td>Month 3</td>
<td>-4.320</td>
<td>35.084</td>
<td>-0.12</td>
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<tr>
<td></td>
<td>Intercept</td>
<td>275.397</td>
<td>86.754</td>
<td>3.17</td>
</tr>
<tr>
<td>Model 5</td>
<td>δ</td>
<td>.565</td>
<td>.128</td>
<td>4.41</td>
</tr>
<tr>
<td></td>
<td>LEM</td>
<td>-25.183</td>
<td>16.603</td>
<td>-1.52</td>
</tr>
<tr>
<td></td>
<td>Intercept</td>
<td>345.507</td>
<td>102.502</td>
<td>3.37</td>
</tr>
</tbody>
</table>

***significant at p< .001    **significant at p< .01    *significant at p< .05

NOTE: “LEM” is the designation for the permanent intervention of lifetime electronic monitoring legislation. “Month 1-3” is the designation for the 1, 2, and 3 month effect following the introduction of LEM. “Agencies” is the designation for number of reporting agencies.
Table 4.

Georgia Model of Forcible Rape by Month

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>Standard Error</th>
<th>Z</th>
<th>P</th>
</tr>
</thead>
<tbody>
<tr>
<td>Model 1</td>
<td>MA(1)</td>
<td>.246</td>
<td>.073</td>
<td>3.40</td>
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<td></td>
<td>Intercept</td>
<td>6.145</td>
<td>.018</td>
<td>335.42</td>
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<td>Model 2</td>
<td>δ</td>
<td>.524</td>
<td>.272</td>
<td>1.92</td>
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<tr>
<td></td>
<td>Month 1</td>
<td>-0.031</td>
<td>.677</td>
<td>-0.05</td>
</tr>
<tr>
<td></td>
<td>Intercept</td>
<td>2.930</td>
<td>1.674</td>
<td>1.75</td>
</tr>
<tr>
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<td>δ</td>
<td>.518</td>
<td>.270</td>
<td>1.92</td>
</tr>
<tr>
<td></td>
<td>Month 2</td>
<td>-0.038</td>
<td>.279</td>
<td>-0.14</td>
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<tr>
<td></td>
<td>Intercept</td>
<td>2.964</td>
<td>1.664</td>
<td>1.78</td>
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<tr>
<td>Model 4</td>
<td>δ</td>
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<td>.272</td>
<td>1.92</td>
</tr>
<tr>
<td></td>
<td>Month 3</td>
<td>-0.006</td>
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<td>-0.06</td>
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<tr>
<td></td>
<td>Intercept</td>
<td>2.947</td>
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<td>δ</td>
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<td>.312</td>
<td>1.49</td>
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<td></td>
<td>LEM</td>
<td>.034</td>
<td>.031</td>
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<tr>
<td></td>
<td>Intercept</td>
<td>3.278</td>
<td>1.916</td>
<td>1.71</td>
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</table>

***significant at $p \leq .001$  **significant at $p \leq .01$  *significant at $p \leq .05$
Table 5.

Louisiana Model of Forcible Rape by Month

<table>
<thead>
<tr>
<th></th>
<th>Variable</th>
<th>Coefficient</th>
<th>Standard Error</th>
<th>Z</th>
<th>P</th>
</tr>
</thead>
<tbody>
<tr>
<td>Model 1</td>
<td>AR(1)</td>
<td>.353</td>
<td>.107</td>
<td>3.30</td>
<td>.001***</td>
</tr>
<tr>
<td></td>
<td>AR(2)</td>
<td>.231</td>
<td>.090</td>
<td>2.57</td>
<td>.010**</td>
</tr>
<tr>
<td></td>
<td>AR(1)_{12}</td>
<td>.301</td>
<td>.099</td>
<td>3.04</td>
<td>.002**</td>
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<tr>
<td></td>
<td>Intercept</td>
<td>114.390</td>
<td>4.542</td>
<td>25.18</td>
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</tr>
<tr>
<td>Model 2</td>
<td>δ</td>
<td>.746</td>
<td>.074</td>
<td>10.69</td>
<td>.000***</td>
</tr>
<tr>
<td></td>
<td>Month 1</td>
<td>15.303</td>
<td>37.318</td>
<td>0.41</td>
<td>.682</td>
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<tr>
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<tr>
<td>Model 3</td>
<td>δ</td>
<td>.741</td>
<td>.076</td>
<td>9.71</td>
<td>.000***</td>
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<td></td>
<td>Month 2</td>
<td>8.130</td>
<td>11.909</td>
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<td>10.002</td>
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***significant at p ≤ .001  **significant at p ≤ .01  *significant at p ≤ .05
Table 6.
Missouri Model of Forcible Rape by Month

<table>
<thead>
<tr>
<th>Model</th>
<th>Variable</th>
<th>Coefficient</th>
<th>Standard Error</th>
<th>Z</th>
<th>P</th>
</tr>
</thead>
<tbody>
<tr>
<td>Model 1</td>
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<tr>
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<td>AR(2)</td>
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<td>2.97</td>
<td>.003**</td>
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<tr>
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<td>AR(1)_{12}</td>
<td>.396</td>
<td>.102</td>
<td>3.89</td>
<td>.000***</td>
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<tr>
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<td>Intercept</td>
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<td>5.788</td>
<td>21.98</td>
<td>.000***</td>
</tr>
<tr>
<td>Model 2</td>
<td>δ</td>
<td>.757</td>
<td>.077</td>
<td>9.76</td>
<td>.000***</td>
</tr>
<tr>
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<td>5.061</td>
<td>10.351</td>
<td>0.49</td>
<td>.625</td>
</tr>
<tr>
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<td>21.289</td>
<td>1.26</td>
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<tr>
<td>Model 3</td>
<td>δ</td>
<td>.761</td>
<td>.078</td>
<td>9.76</td>
<td>.000***</td>
</tr>
<tr>
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<td>Month 2</td>
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<td>7.650</td>
<td>0.96</td>
<td>.335</td>
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<tr>
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<td>Intercept</td>
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<td>9.742</td>
<td>3.12</td>
<td>.002**</td>
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<td>.085</td>
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***significant at p<.001  **significant at p<.01  *significant at p<.05
Table 7.
North Carolina Model of Forcible Rape by Month

<table>
<thead>
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<th>Model</th>
<th>Variable</th>
<th>Coefficient</th>
<th>Standard Error</th>
<th>Z</th>
<th>P</th>
</tr>
</thead>
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<td>.085</td>
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<td>.000***</td>
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<td></td>
<td>AR (2)_{12}</td>
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<td>.088</td>
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<tr>
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<td>.115</td>
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<td>3.89</td>
<td>.000***</td>
</tr>
<tr>
<td>Model 3</td>
<td>δ</td>
<td>.536</td>
<td>.116</td>
<td>4.64</td>
<td>.000***</td>
</tr>
<tr>
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<td>Month 2</td>
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<td>9.455</td>
<td>-0.20</td>
<td>.841</td>
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<td>Intercept</td>
<td>83.464</td>
<td>21.513</td>
<td>3.88</td>
<td>.000***</td>
</tr>
<tr>
<td>Model 4</td>
<td>δ</td>
<td>.534</td>
<td>.116</td>
<td>4.62</td>
<td>.000***</td>
</tr>
<tr>
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<td>Month 3</td>
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<td>.505</td>
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<td>3.584</td>
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</table>

***significant at p≤.001   **significant at p≤.01   *significant at p≤.05
Table 8.
Oregon Model of Forcible Rape by Month

<table>
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<th>Model</th>
<th>Variable</th>
<th>Coefficient</th>
<th>Standard Error</th>
<th>Z</th>
<th>P</th>
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<td>.014</td>
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<td>.509</td>
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<td>.078</td>
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***significant at $p \leq .001$   **significant at $p \leq .01$   *significant at $p \leq .05$
Table 9.
Wisconsin Model of Forcible Rape by Month

<table>
<thead>
<tr>
<th>Model</th>
<th>Variable</th>
<th>Coefficient</th>
<th>Standard Error</th>
<th>Z</th>
<th>P</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
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<td></td>
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</tr>
<tr>
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<td>.000***</td>
</tr>
</tbody>
</table>

***significant at p≤.001    **significant at p≤.01    *significant at p≤.05


Boudreaux, M.C., Lord, W.D., & Jarvis, J.P. (2001). Behavioral perspectives on child homicide: The role of access, vulnerability, and routine activities theory. *Trauma, Violence, and Abuse, 2*(1), 56-78. ISSN: 15248380


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