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**An Evaluation of the Stearns County Domestic Violence Court:
In Relation to Recidivism**

By

Kristopher Michael Kunde

A Thesis

Submitted to the Graduate Faculty of

St. Cloud State University

in Partial Fulfillment of the Requirements

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Abstract

Stearns County, Minnesota implemented a new court system to only handle domestic violence cases. It started in 2008 and its sole purpose is to reduce recidivism. This is the latest policy in a long list to try and curb the epidemic that is domestic violence. The purpose of this research is to analyze how effective the court has been in its goal. The data used in this research is from 2008 to when it was collected in October of 2014. The analysis will include descriptive statistics, t-tests, logistic regression and ARIMA modelling for its analysis and will analyze on characteristic variables such as, race, sex and age, as well as legal variables such as number of violations, sentencing date, if the offender recidivated or not and etc.. The findings from the analysis show that the court is more than likely not reducing recidivism.

An Evaluation of the Stearns County Domestic Violence Court: In Relation to Recidivism

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Chapter 1: INTRODUCTION

Statement of Problem

The Center for Disease Control (CDC) estimated in 2003 that the physical and mental health care costs from interpersonal violence was close to \$4.1 billion and the productivity that was lost caused by this violence was estimated at \$858.6 million (Buzawa, Buzawa & Stark, 2012). If the CDC's estimate is adjusted for rate of inflation, the cost of interpersonal violence for physical and mental health services in 2014 would be \$5.27 billion and the productivity that was lost would be a little over \$1.1 billion dollars. However, these costs do not take into account the cost of the entire criminal justice system: law enforcement, courts, and corrections. The United States is spending billions and billions of dollars every year combating the problem of domestic violence and yet, the government is reluctant include certain definitions of domestic violence into the law.

Many legal definitions of domestic violence only include the threat of and acts of physical violence. For example, in the state of Minnesota, its domestic violence statute, §609.2242, clearly states that someone is guilty of a misdemeanor domestic assault charge if either there is a threat of, intent or actual physical violence (Domestic Violence, 2013). The legal definitions ignore, what could be considered by some domestic violence victims, as the worst part of the abuse which is the verbal abuse that causes emotional and psychological damage. Some victims of domestic violence would rather be physically assaulted versus having to undergo verbal abuse (Lyon, 2003).

The feminist movement and other recent events or developments have made domestic violence a public problem for law enforcement and the courts. Unfortunately, making it a problem for law enforcement and the courts created many other problems. Prosecuting offenders

results in the need to punish them. The courts punishment options are disruptive to families and results in many unexpected consequences. Unlike other crimes, domestic violence occurs between people who love each other or may have loved each other. These same individuals may share interest and responsibility for children. By punishing one person, it may further complicate these problems.

Domestic violence is also a unique crime because in most cases, both parties play an active role in the conflict and may share responsibility for the violence, even if one of them is considered the aggressor. From these complications, many judges and courts have thought of alternative solutions to the traditional trials, convictions and sentencing in dealing with domestic violence cases, when such alternatives are appropriate. The 7th Judicial District in Minnesota has developed what it calls a “Domestic Violence Court” (DVC) as an innovative approach to holding offenders accountable and reducing recidivism.

The purpose of this research proposal is to examine whether offenders, who participate in the Stearns County Domestic Violence Court, are being held accountable for their actions and therefore are less likely to recidivate than offenders who go through the regular criminal justice process for domestic violence. Offenders that go through the domestic violence court have more access to alcohol and drug treatment programs. They are closely monitored to ensure that the offenders do not break any conditions of release. If he does violate one condition, the individual is more likely to get caught and the person is in front of a judge within a week to get further punishment. Whereas, domestic violence offenders in the traditional court system, do not have such easy access to or not mandated to take alcohol or drug treatment programs. “Greater judicial oversight of perpetrator behavior and imposition of significant sanctions for violations of court

orders should be the hallmark of a domestic violence court,” from Karan, Keilitz, and Denaro (1999).

Stearns County Domestic Violence Court has many goals but there are only two main goals, holding the offender accountable for their actions and reducing recidivism. This researcher will focus on whether or not the participants in this court are less likely to reoffend. It is possible to hold an offender accountable without reducing recidivism and vice versa. Therefore, this goal was chosen to be the focus of this research because the criminal justice system’s overall goal is to make sure that criminals do not recidivate. To reduce recidivism, the court employs intensive supervision and swift punishment for the participant’s actions. Recidivism will be defined as committing a new domestic violence crime as defined by Minnesota State Statute § 609.2242 during or after the completion of the domestic violence court.

Domestic violence costs the government and private institutions billions of dollars every year. However, the legal definition of domestic violence is very narrow and leaves out sometimes the worst part of the abuse; the verbal abuse that can cause severe emotional and psychological harm to society. Stearns County is trying to stop the worst offenders from recidivating through the use of a domestic violence court. There are many goals for the domestic violence court but the main question this research will try to answer is; is the court reducing recidivism?

Chapter 2: LITERATURE REVIEW

A Review of Domestic Violence History & Corresponding Theories

To understand how the Stearns County Domestic Violence Court was developed, domestic violence itself first needs to be understood. This chapter will examine domestic violence's long history, early attempts to stop it, what led to the adaptation of domestic violence courts and a summary of the previous evaluations on recidivism in problem solving courts. The use of criminological theories and scientific research will be helpful to understand the guiding theory behind the Stearns County Domestic Violence Court.

Domestic Violence History

Domestic violence has a long history, not only in modern history but ancient times as well. "From the earliest record, most societies to varying extents have given the male patriarch of a family the right to use force against women and children under his control" (Buzawa, Buzawa & Stark, 2012). Society has been very much patriarchal and women were not seen as human beings but as property. This was very clearly evident in the English common law system and was well known that, "the concept of male property rights over women and the right of men to beat 'their women' if needed" (Buzawa, Buzawa & Stark, 2012). As it is commonly known, the English common law system was the precursor for the American criminal justice system.

The Puritans in Massachusetts, in 1641, were the first to make domestic violence illegal (Buzawa, Buzawa & Stark, 2012). This was the first time in history to outlaw domestic violence but there was a clear problem with it. The Puritans did not oppose religious law in that moderate levels of domestic violence were accepted (Buzawa, Buzawa & Stark, 2012). Thus, it was still understood from the English common law that a man could beat his wife with a rod no thicker than his thumb.

The first real movement to stop domestic violence was in the middle of the 19th century. The state of Alabama was the first to revoke the husband's right to physically punish his wife (Barner & Carney, 2011). Soon after, several other states followed Alabama's example. However, this progress was slowed by other historical events, World War I and the Great Depression. Society turned its focus away from domestic violence to focus on these more pertinent events.

It was not until the 1960's and 1970's when the women's rights movement began that people started focusing on domestic violence again. Before the 1960's, domestic violence was only a misdemeanor level offense, but with increased attention during the women's rights movement, states started moving domestic violence cases to civil or family courts (Barner & Carney, 2011). This was a step forward in that domestic violence was receiving recognition by the government but it was not until Lenore Walker's study of domestic violence that would increase the women's rights movement and draw significant attention to domestic violence issues.

Lenore Walker in the 1970's coined the term "Battered Woman Syndrome" (BWS). She stated that women in abusive relationships were trapped in a three stage cycle. The first stage is the tension building phase where the woman receives many minor verbal and physical attacks and she often blames herself for this abuse (Coleman, 2009). The second stage is the battering stage where the minor incidents become more frequent and the woman cannot stop the attacks no matter what she tries (Coleman, 2009). She is very much in fear of major physical pain at this stage. The third and final stage is the honeymoon stage. Coleman describes it as, "begins almost immediately following the battering incident, and is characterized by the batterer's lack of violence and exhibition of what Walker calls 'contrite loving behavior'" (2009). After this third

stage the cycle would start all over. Lenore Walker's theory became so popular that by 1977, the media began calling women's rights movement as the "Battered Women's Movement" (Barner & Carney, 2011). Although BWS gained in popularity, not everyone was on board with this new theory.

Initially, BWS had success as a great theory and became a defense for women who were charged with crimes such as murdering their husbands. However, BWS has never been validated through empirical research (Dixon, 2007). The problem lies with, "...there is no reliable means to differentiate those women who merely claim a history of battering from those who have actually been battered" (Dixon, 2007). Women, who have actually been severely battered, show similar symptoms of people with Post-Traumatic Stress Disorder (PTSD) (Buzawa, Buzawa & Stark, 2012). However, BWS has played a big part with changing how the criminal justice system views domestic violence cases. The term "battered woman" itself symbolizes a woman in a severely abusive relationship. BWS might not be the prevailing theory today but it offers one explanation on how women cannot get out of domestic violence relationships.

The Battered Women's Movement culminated in one court case that would change how the criminal justice system dealt with domestic violence forever. In the court case of *Thurman v. City of Torrington* in 1984, a battered woman, Tracey Thurman, was separated from her husband Charles Thurman. Over the course of eight months, Charles was threatening viciously and frequently upon Tracey and their son Charles Junior's life (Saccuzzo, 1999). The police did not respond to any of the numerous calls made by Tracey or her family and friends. Things quickly escalated and he attacked her in a friend's home to get to Charles Jr. and in a separate incident Charles Thurman also kicked in Tracey's windshield while sitting in her car (Saccuzzo, 1999). Finally, the violence culminated and Charles stabbed Tracey in the neck, throat and chest and

when the police arrived, they watched him kick her while she was on the ground bleeding and then dropped Charles Jr. on her (Saccuzzo, 1999).

Thurman v. City of Torrington led to several changes across the country in the 1980's and 1990's. The most significant of these changes is that courts moved away from civil proceedings to criminal ones and it empowered the district attorneys by moving forward with prosecuting domestic violence crimes without regard as to what the victims wanted (Barner & Carney, 2011). With this movement towards where the offender is the center of domestic violence, the criminal justice system enacted mandatory arrest laws and no drop policies for the prosecution.

Mandatory arrest laws first came about in the 1980's. The goal of these laws were to limit the discretion the police officers had at the scene of a domestic violence and it was to empower the victims by affirming them that they are victims (Buzawa, Buzawa & Stark, 2012). It was also believed that the victim would want retribution and by placing the burden of arrest on the officer that there would be less stress on an already traumatized victim. At first, mandatory arrest policies were given praise and they were even backed by research in the Minneapolis Domestic Violence Experiment (MDVE).

MDVE was looking at the best way that a police officer could handle a domestic violence situation. They were analyzing three different ways of handling the dispute; separation of the parties, advise them of alternative solutions and arrest the offender (Buzawa, Buzawa & Stark, 2012). The outcome of this experiment reaffirmed the belief and theory of mandatory arrests. The researchers found that arresting the offender had the strongest effect on recidivism. This report made national attention and changed public policies regarding domestic violence. However, MDVE had no internal validity because of the way police officers were choosing the best course of action. The officers were not following the research methodology that was put into

practice by the researchers. When MDVE was replicated in five further studies, their findings suggested that there were no differences between whether the parties were separated, advised on alternative solutions or arresting the offender. This research was not the only thing that led to the downfall of mandatory arrest policies.

There were some unintended consequences that the theorists did not expect with mandatory arrests. The most surprising one was that there were large increases in the number of women being arrested for domestic violence. Under these laws, the police officers were required to arrest individual parties based upon a single act, even though it might be defensive in nature (Buzawa, Buzawa & Stark, 2012). Therefore, with the unintended consequences and the failure to show that arrest was the best course of action, the mandatory arrest law has been replaced with officer discretion.

From the ancient times when women were the property of men to when men could only beat their wives with a stick no bigger than their thumb to now where there are laws dedicated to domestic violence, there has been a significant increase and attention to domestic violence issues. The greatest influence was from the woman's rights movement starting in the 1960's. One of the milestones was the introduction of the concept of battered woman. It changed the way the criminal justice system viewed these instances and the laws to handle these situations. Mandatory arrest had some minor success but once researchers saw that it did not increase the arrest rates for men but women, they changed the policies to give the discretion back to law enforcement. Since mandatory laws, researchers have been looking at other ways to solve this epidemic.

Domestic Violence Courts

Domestic violence courts are an innovative approach to help ensure the safety of victims and try to stop offenders from recidivating. Many of these courts apply community coordinated responses to solve domestic violence issues. The very first to use this was the Duluth Model which began in 1981 (Barner & Carney, 2011). This model was innovative in that it was the first that combined resources, departments and organizations to stop the abuse. The Duluth Model uses what is called the “power and control wheel” to explain how men batterer women and it suggests that the violence is from patriarchal society and not caused by emotional or situational prompts (Barner & Carney, 2011). Great emphasis is placed on judicial punishments in response to actions that the offenders have made. However, the Duluth Model is an innovative approach at solving an epidemic level problem but it is not a domestic violence court.

The Duluth Model focuses more on education of the offenders to change their behavior and the courts are used more as punitive measures; whereas, domestic violence courts have been defined as “those hearing criminal domestic violence cases on a separate calendar or by a dedicated judge or judicial officer” (Labriola, Bradley O’Sullivan, Remepel, & Moore, 2010). This means that there are certain judge(s) designated to domestic violence courts which takes place at a set time, only hears domestic violence cases and the courts are the center of the coordinated community response. Whereas, the Duluth model does not have a separate schedule for domestic violence cases or dedicated judges and it is not the center of coordinated community response. The domestic violence court started coming about more after the Violence Against Women Act (VAWA) was signed into law in 1994. The act strengthens many federal laws and provides financial support to women’s shelters but most importantly it requires a coordinated community approach to domestic violence which further allowed the establishment

of domestic violence courts (U.S. Department of Justice, Office on Violence Against Women, 2009). Domestic violence courts are a specialized court that came from the problem solving courts in the 1990's such as drug courts.

Most problem solving courts function under the assumption that the offender's behavior comes from problems that treatment or services can solve (Labriola et al., 2010). In regard to domestic violence courts, it is disputable whether the underlying problem is the offender's behavior but of societal values which is the basis for the Duluth model. There are a few key aspects that make domestic violence courts different from other problem solving courts as stated by U.S. Department of Justice (2009):

- Effective management of domestic violence cases
- Specialized intake and court staffing
- Improved victim access, expedited hearings and assistance for victims by court staff
- Court processes to ensure victim's safety
- Increased court monitoring and enforcement of battering compliance with court orders
- Consideration of any children involved in the domestic violence
- Enhanced domestic violence training

Not all domestic violence courts are the same. Keilitz stated, "...the concept of a domestic violence court is not yet well developed or defined among the court community" (2001). There are many variations, some courts only allow misdemeanor level offenses, such as in Lexington County, South Carolina (Gover, Brank, & MacDonald, 2007), some have only

felony level cases, such as in Kings County, New York (Newmark, Rempel, Diffily & Kane, 2002), and in Stearns County they only allow repeat felony level offenders into their court.

Although there is no standard practice for the courts, they do share similar goals.

Labriola et al. found seven goals in common among 15 domestic violence courts: correct application of statutory requirements, effective management of domestic violence caseloads, assignment and training of dedicated judges and other staff, participation of the court in a coordinated community response, victim safety and services, offender accountability, and reduced recidivism (2010). Most of these goals are self-explanatory but the training of the judges is one of the most important because they are in the best position to have the strongest positive or negative impact. A well trained judge will understand all of the dynamics of domestic violence and this is a necessity. In the old court system, the judge either hears the civil law side, with divorce or custody cases and do not know about the current criminal case that is pending and vice versa (Karan, Keilitz, & Denaro, 1999). The domestic violence court deals with not only the criminal aspect but the civil as well. This is one of the key aspects because the same judge knows every piece of the case and can make informative choices. An example of this would be in regards to helping the victim leave the abuser. It is tough for the victim to leave because often times the abuser has control of the finances. Karan et al. states, “one of the services that many victim advocates view as crucial to increasing the chances of a victim with children successfully leaving an abusive partner is the establishment and enforcement of child support orders” (1999).

According to Labriola et al., there is a consensus among the research that domestic violence courts cause an increase use of batterer programs, drug and alcohol treatment programs and the offenders have special bail conditions including but not limited to drug testing, a more intense probationary period and special judiciary hearings to check on the status of the offender

(2010). With this increase in judicial oversight, the court may be more likely to catch violations of the conditions for the offenders release from jail or prison. Labriola et al. states, “judicial monitoring significantly increased the likelihood and severity of penalties for noncompliance with sentencing conditions” (2010). The goal of offender accountability is to reduce recidivism and increase the victim’s safety.

There have been mixed results with regards to recidivism. According to Labriola et al., they found 10 domestic violence court evaluation studies, three showed significant drop in re-arrests, five produced no significant difference with an increase or decrease of recidivism and two separate studies of the same court yielded mixed results (2010). Many courts rely upon the batterer treatment programs to treat the offenders. These programs have been shown to produce no or very modest results on reducing recidivism (Labriola et al., 2010). Of course the court has other ways of reducing recidivism by deterrent effects with judicial oversight and consequences for violating a condition of release. There have been no studies that have truly examined the impact that judicial monitoring has on recidivism and it is unknown whether strenuous judicial monitoring has any influence on recidivism (Labriola et al., 2010).

Domestic violence courts started coming about in the 1990’s and has been using coordinated community response which was pioneered by the Duluth model. This model believes that the patriarchal society is to blame for the offender’s behavior and not underlying situational or behavioral problems. The Duluth model was the first to use a community coordinated approach but it is not a domestic violence court. These courts are a type of problem solving courts, much like drug courts, and are employed to solve a particular problem that has plagued the criminal justice system. Domestic violence courts can be defined as having a set calendar and appointed judge(s) to the deal only with domestic violence cases. There are no

standard or common set of practices with these courts but they share many of the same goals: offender accountability, reducing recidivism, victim safety and several others. With having no common practices between the domestic violence courts, evaluation research has been mixed on recidivism. There is mixed reviews on whether there is a connection with increased conviction rates and the domestic violence courts but there is a general consensus on the increased use of batterer programs, substance treatment programs and special probation conditions. There is mixed reviews on whether the domestic violence courts reduce recidivism and several researchers conclude that the batterer treatment programs, which are the main tool in changing the offenders behavior, have little or no impact on recidivism rates.

Theory

Most of the criminal justice system is used to deter individuals from committing crime. Punishments, police officers walking the beat, and the threat to lose liberty are a constant reminder for people not to commit criminal acts. This idea to deter people from crime is not a new idea and was developed by Cesare Beccaria in 1764 and is called deterrence theory. He believed that the purpose of punishment was to deter the individual from recidivating and for the punishment to be successful, there were three things that needed to happen: promptness, severity and certainty of the punishment. Cesare Beccaria said (as cited in Moyer, 2001), “The more promptly and the more closely the punishment follows upon the commission of a crime, the more just and useful it will be....”

There are two different types of deterrence, general and specific. General deterrence is defined as to prevent crime in the general population (Stafford & Warr, 1993). An example would be executing people for the crime of homicide and this would show the public what happens when someone commits murder. Specific deterrence is defined as to prevent an

individual to commit further crime (Stafford & Warr, 1993). By tailoring the punishment to each individual and the closer in time the punishment is to the criminal act it will increase the effectiveness of holding the offender accountable and prevent further crime from happening. The belief of this court is that the swiftness and severity of the punishment that fits the criminal act or violation that was committed will decrease the chances of recidivism.

Chapter 3: METHODOLOGY

Conceptualization & Operationalization of the Research Problem

This is an evaluation research study on the Stearns County Domestic Violence Court. The court has been in operation since 2008 and it focuses on repeat felony offenders. It only allows 30-40 offenders in the court process at one time. The offenders have to reside within Stearns County itself to be allowed to be a part of this court. The goal of the court is a speedy, effective, consistent coordinated response for repeat felony level offenders to reduce recidivism and to ensure the safety of the victims and children (Kendall, 2013).

Research Population and Sampling

Data was obtained from the Stearns County Attorney's office on October 15th, 2014 on all offenders who have completed the domestic violence court proceedings up to that point since the courts inception. Completion of the domestic violence court will be defined as an offender who has been found guilty and has had a sentencing date.

Conceptualization and Operationalization

Stearns County Domestic Violence Court has many goals but there are only two main goals, holding the offender accountable for their actions and reducing recidivism. However, this research is only focusing on reducing recidivism. To do this, the court employs intensive supervision and swift punishment for their actions. There are two dependent variables, Recidivism or Not will be defined as when an offender commits a new offense and has court proceedings that are after or separate from their first set of proceedings, the Average Time Between X and Y Violation will be calculated by summing up all time differences between X and Y and then averaging it over the number of offenders who have committed Y amount of

violations. The reason that the Average Time Between X and Y Violations is the time between different violations is that the domestic violence court believes that swift punishment is the key in reducing recidivism. Therefore, it is vital to examine if they are succeeding in this.

The courts ultimate goal is to reduce recidivism. Recidivism will be defined as committing a new domestic violence crime as defined by Minnesota State Statute 609.2242 if there is a different sentencing dates for different crimes. There are multiple offenders who had committed crimes on different days but were sentenced on the same day. Therefore, it is essential to distinguish between crimes that were sentenced on different days.

Data Collection

The data from the domestic violence court was collected from the Stearns County Prosecutors office. The data is from the beginning of the court, 2008, through when this researcher received it, October of 2014. There were three datasets gathered for this analysis. The first had basic characteristic information, such as ethnicity, sex and age for both the offenders and the victim, but it also had data on the offenders crime(s); various dates, offense, first court appearance and sentence date; the DVC lethality level of the offenders; case number; and prison, supervision, jail and probation time. However, prison, supervision, jail and probation time will not be used in the analysis because the researcher does not know which sentences are consecutive or concurrent and the county attorney's office was unhelpful in this matter. The second dataset consisted of the same characteristic information but it focused on the violations of the offenders, who reported it and what was the sentencing for the violation. The final dataset was focused on the victims and what services they used. This dataset was also not used because of clear data entry errors and the objectivity of it was in question, see the limitations section in Chapter 5.

Race is defined by the Stearns County Attorney's office as one of several categories they identify with. This includes but not limited to the classes of White, Black, Asian and American Indian.

Sex is defined as either male or female. There were only male offenders and female victims. Therefore, the personal pronoun "he" will refer only to offenders and also "she" will only refer to victims in this study.

Age is a continuous variable and is defined as the age of the offender and victim at the time of the offense.

Offense date is the date that the criminalization took place.

First appearance is the date when the offender first appeared in front of a judge for their alleged offense.

Sentence date is after the time when the offender was found guilty of their actions and received his punishment for them.

Recidivism is defined as a person who has been convicted of two or more crimes and there are at least two different sentence dates for those convictions.

A violation is defined when an offender breaks a condition of release from incarceration that was set by the court. New domestic offenses are not considered a violation.

The time between a violation and it being reported to community corrections is a calculation between the date of it being reported to community corrections minus the date of the violation. The result is in days. The delay in a violation being reported to community corrections could have a few factors involved. One reason could be the victim does not report the violation or with holds the information and the violation is found out later through someone else, for example victims advocate coordinator. It could also be delayed through the supervision itself. It

takes time to check phone call records of the offender and it might not be done regularly. It could also be a lack of communication between the supervision and the community corrections.

Ultimately the responsibility of reporting falls upon the community corrections itself. They are the ones responsible for the protection of the victim and the punishment of the offenders.

Average number of violations is calculated by tallying the number of violations for the offender's first offense by recidivist category and then divides by the number of offenders in the same recidivist category.

Recidivism group is the offenders who have been convicted and sentenced for two or more crimes that have different sentence dates.

Non-recidivism group is the offenders who have been convicted of one or more crimes but only have one sentence date for all of the convictions.

The case number is the unique number given to every single charge brought upon the offenders.

First offense is defined as the offender's earliest criminal act decided by the case number that he was convicted of. If there was an earlier offense but he was found to be innocent or the charge was dismissed because of plea bargaining or lack of evidence then the next chronologically convicted criminal act was chosen as the first offense.

Time between first offense and first appearance date is calculated by subtracting the first appearance and offense date. The result is in days.

Time between first offense and sentence date is calculated by subtracting the first sentence date and offense date. The result is in days.

The DVC lethality assessment comes from Jacquelyn Campbell's danger assessment test. However, it is unclear whether or not Stearns County used the original 15 question (1986), the

new 20 question assessment (2009) or a mixture of both during the courts operational period. The assessment was given to the victims by a victim advocate coordinator. There are four possible outcomes, in order from weakest to strongest severity levels, variable, increased, severe and extreme severity.

The Average Time Between X and Y Violation is calculated by first finding the difference between the two dates of the violations and then averaging all possible offenders who had committed this amount of violations. This variable will have several subsets, such as the Average Time Between the 1st and 2nd Violation and the Average Time Between the 13th and 14th Violation, but each subset must have at least 30 offenders who have committed this amount of violations to be used in the analysis.

Data Analysis

Descriptive statistics will be used to describe the sample of offenders and victims. This is to get an overall view of the data. Along with the descriptive statistics, a difference between two means t-test will be used to see if there are differences between the recidivism and non-recidivism groups. This is to find out if there are any differences between the two groups that can be attributable to the DVC. Lastly, a correlation matrix will be calculated to see which variables would be correlated with the dependent variable to get a better estimation of which variables could be significant in a logistic regression.

A logistic regression will be used to examine which of the variables from the t-tests were actually important in regards to recidivism. The classification table that is outputted from SPSS will also be looked at. The cut value for all of the classification tables is .500. This means that there is a 50-50 chance for recidivating. However, according to several different studies, they found that recidivism could be as high as 62% (Puffett & Gavin, 2004) or as low as 41%

(Gondolf, 2000). The Violence Research Foundation also claims that the recidivism rate is between 30-40% (2015). Since the true recidivism rate for domestic violence is unknown, a 50-50 chance was chosen because it was in the middle of the two studies statistics. The foundation's statistic was not used because they did not have a resource to support their claim.

For the logistic regression, the following independent variables will be used: Age and Race for both the offender and victim, Jail Sentence First Conviction, DVC Level, Average Time Between Violation and Punishment, Average Time Between Sentence and Offense Date, Number of Felonies Originally Accused of, Number of Felonies Originally Convicted of, Number of Violations Pre- and Post-trial, the Number of Violations, and Time Between Offense Date and First Court Appearance. However, there are three sets of two variables that cannot be entered into the same model because of dependency issues: Average Time Between Sentence and Offense Date and Time Between Offense Date and First Court Appearance; the Number of Violations and the Number of Violations Pre- and Post-trial; and Number of Felonies Originally Accused of and Number of Felonies Originally Convicted of. From these dependency issues, eight models will be generated to examine the interaction of all the variables but only the two best models will be examined in this analysis. The two "best" models will be identified from the classification table in how well the model correctly predicted. The other 6 can be found in the Appendix.

Finally, an analysis of the time between consecutive violations will be conducted. First, basic descriptive statistics and t-tests will be used. Then a time series analysis will be used to fit a model, auto-regressive integrated moving averages (ARIMA) or linear regression, to the data and try and predict when the next violation will occur. For the analysis, not all of the offenders committed violations or even ten violations on different days and there are over 100 offenders.

For this research it is not practicable or even in the scope to examine each and every individual.

Therefore, the time between consecutive violations will be an average between all offenders. The goal of this part is to test whether the DVC's theory of quick punishment after the violation is reducing the likelihood to reoffend or not.

Chapter 4: DATA ANALYSIS

Descriptive Statistics, t-tests, Logistic Regression & Time Series Analysis

Descriptive Statistics

The samples were drawn from the years of 2008-October 2014. There were 191 individuals who had been brought charges against them. All of them were men. Of these people, there were 41 offenders, 21.5%, who recidivated at least once and 13, 6.81%, who were acquitted or dismissed of all charges against them. This leaves the sample population at 178. Table 1 shows the ethnic breakdown of the entire population and the recidivism and non-recidivism groups.

Table 1 Ethnicity by Recidivism

Ethnicity		Recidivated Y/N		Total
		N	Y	
American Indian	N	5	0	5
	% within column	3.64%	0%	2.81%
	% within row	100%	0%	100.00%
Asian	N	2	1	3
	% within column	1.46%	2.44%	1.69%
	% within row	66.67%	33.33%	100.00%
Black	N	50	17	67
	% within column	36.50%	41.46%	37.64%
	% within row	74.63%	25.38%	100.00%
Unknown	N	5	0	5
	% within column	3.65%	0%	2.81%
	% within row	100.00%	0%	100.00%
White	N	75	23	98
	% within column	54.74%	56.10%	55.06%
	% within row	76.77%	23.23%	100.00%
Total		137	41	178

From Table 1, it is easy to see that the population percentages for the recidivated and non-recidivated groups are not significantly different from each other and they correspond to the

sample population. There were no American Indians that recidivated. When looking at the proportions of people who recidivated within their ethnicity, almost the exact same proportion of Blacks and Whites recidivated. This plus the evidence of the two recidivated groups having similar proportions as the sample population looks like race is not a factor for recidivating.

Table 2 Age on the First Offense by Recidivist Group

	N	Mean	Variance	Median	Min	Max	Range
Recidivist	41	30.561	108.10	28	18	53	35
Non-Recidivist	137	32.343	67.67	31	19	54	35

Table 3 T-test of the Age Means Between the Recidivist Group

	Diff	SE	t-value	DF	P-value
Age of First Offense	1.782	1.769339	1.007156	176	0.3152

Table 2 shows the basic statistics for the age on the first offense between the recidivist groups. There are a few notable differences between the groups. First, the mean is about two years higher for the non-recidivists. The variance for the recidivist group is much higher but this could be from having a smaller population. When looking at Table 3, which shows the two tailed t-test between the two sample means, the difference in average age is not significantly different from the other group. This implies that the offender's age is not a factor for recidivism.

Table 4 Victim Age on First Offense by Recidivist Group

	N	Mean	Variance	Median	Min	Max	Range
Recidivists	41	28.317	78.22	26	18	53	35
Non-recidivists with Outliers	137	30.511	91.75	28	19	62	43
Non-recidivists without Outliers	136	30.279	85.032	28	19	59	40

Table 5 T-test for Difference between Means of Victim Age

	Diff	SE	t-value	DF	P-value
Hypothesis Testing t-test with Outliers	2.194	1.605483	1.366567	176	0.1735
Hypothesis Testing t-test without Outliers	1.962	1.591568	1.232747	175	0.2193

In looking at table 4, the victims of recidivating offenders were on average younger during the first offense than the victims of non-recidivating offenders. When testing for outliers in the dataset, there was one outlier in the non-recidivated group. It was found by using the Outlier Labeling Rule with the coefficient of 2.2 as suggested by Hoaglin, Iglewicz and Tukey (1986). However, the difference between two means t-tests for with and without outliers, in table 5, shows that that we cannot be 95% certain that there is a difference between the two means. Therefore, this implies that the victims age upon the first offense also does not have an affect on whether an offender recidivates or not.

Table 6 Time Between First Offense and First Appearance in Court by Recidivist Group

Recidivists by Group	N	Mean	Variance	Median	Min	Max	Range
Recidivists with Outliers	41	10.8	503.11	2	0	93	93
Recidivists without Outliers	35	2.97	8.21	2	0	16	16
Non-Recidivists with Outliers	137	17.68	2223.69	3	1	479	478
Non-Recidivists without Outliers	119	5.87	66.52	3	1	36	35

Table 7 T-test for Difference Between Means of Time Between First

Hypothesis Testing t-test	Diff	SE	t-value	DF	P-value
With Outliers	6.88	5.338756	1.28869	176	0.1992
Without Outliers	2.9	0.89076	3.255646	152	0.0014

Table 6 shows that the recidivists had, on average, less time to wait to be in front of a judge than offenders who did not recidivate. Remember the court believes in swift punishment following the act of a criminal offense, otherwise the offender will not associate the punishment to the felonious act. Therefore, it is shocking to find that on average the recidivists appeared in court approximately 7 days sooner than non-recidivating offenders. However, the first t-test in table 7 shows that there is no difference between the two means.

Again, the Outlier Labeling Rule was used with the same coefficient as before because when looking at the medians and ranges of the recidivists and non-recidivists groups with outliers in table 6, it shows strong evidence of outliers. The medians are very low but the maximum is over 45 times the median. After controlling for outliers, we find that there were 6 in the recidivist's group and 18 in the non-recidivist's group. Table 6 shows that the mean, variance and maximum have been drastically reduced for the recidivating groups without outliers. The mean for the non-recidivist's group is still higher than the recidivists by about 3 days. The most interesting statistic is in table 7. The t-test that controlled for outliers now shows that the mean

time between the first offense and first appearance date in court is significant. This suggests that the swiftness of the criminal justice system gets the offender to the court may have an affect on whether or not they recidivated. However, it suggests the slower it is to get the offenders in front of a judge the less likely they are to recidivate.

Table 8 Time Between First Offense and Sentence Date by Recidivist Group

Recidivist Groups	N	Mean	Variance	Median	Min	Max	Range
Recidivists with Outliers	41	124.15	4659.03	120	50	425	375
Recidivists without Outliers	40	116.63	2399.63	117.5	50	228	178
Non-Recidivists with Outliers	137	138.09	6495.366	117	40	587	547
Non-Recidivists without Outliers	133	128.25	3124.355	116	40	305	265

Table 9 T-test for Difference Between Means of Time Between First Offense and Sentence Date

Hypothesis Testing t-test	Diff	SE	t-value	DF	P-value
With Outliers	13.19	12.96746271	1.01716121	176	0.3105
Without Outliers	10.85	9.552694174	1.13580523	171	0.2576

Table 8 shows the time in days between the first offense and sentence date between offenders. Again, with no surprise this time, the non-recidivists take longer to be sentenced than recidivating offenders. Yet again, there were outliers found in this data category. The evidence comes from the median and maximum values but with the deciding factor coming from the Outliers Labeling Rule using the same coefficient. Yes, the means for the recidivist's groups without outliers are about 13 days apart but table 9 shows that there is no statistically significant difference between the two. This suggests that the time between the criminal act and the sentence date plays no role in whether or not the offenders will recidivate or not. Again, this goes against DVC's philosophy of swift punishment leads to less recidivism.

Table 10: Recidivist Domestic Violence Lethality Assessment

Recidivist Offender DVC test	N	%
No test	16	39.02%
Variable Danger	8	19.51%
Increased Danger	4	9.76%
Severe Danger	5	12.20%
Extreme Danger	8	19.51%
Total	41	100%

Table 11: Non-Recidivist Domestic Violence Lethality Assessment

Non-Recidivist Offender DVC test	N	%
No test	52	37.68%
Variable Danger	21	15.22%
Increased Danger	14	10.14%
Severe Danger	13	9.42%
Extreme Danger	38	27.54%
Total	138	100%

Tables 10 and 11 show the assessment results that describe how likely an offender are to inflict great bodily harm and or lethality upon a victim. The recidivist and non-recidivist groups are very similar in the breakdown on which category the offenders are put into.

This evaluation is not psychologically based that was given to the offender from a psychologist. The information used in the assessment was provided by the victim and the assessor was a victim advocate coordinator which was provided by the Stearns County Attorney's Office. However, there are a few problems with the assessment. Campbell, Webster and Glass, the authors of the revised 20 question assessment, state that they are unsure if the external validity of their study could apply to a rural area and to abused women (2009). They also state that women's assessment of the domestic violence is important but it should not be the only risk factor for predicting future violence (Campbell, Webster, & Glass, 2009). Regardless of the merits of the assessment, it was wildly underused by the Stearns County Attorney's Office.

The implementation of the assessment could account for why about 40% of the offenders do not have a lethality assessment on their first offense. Granted, some of the offenders who did not get assigned an evaluation were later given one; however, some people who received an evaluation for the first offense were not reevaluated at a later offense date. Also, when the assessment was given at a later date, there is a good possibility for the lethality evaluation to

change. However, this researcher still wonders why this assessment was not given out more frequently, especially when Campbell, Webster and Glass state that this assessment is, "...likely to capture more than 90% of potentially lethal IPV [intimate partner violence] cases by using the increased level of danger" (2009). Therefore, the county should be implementing this assessment much more often and pay closer attention to those offenders who receive an increased severity level or higher on this assessment.

Table 12 The Number of Accused Felonies by Recidivist Group

Recidivist Group	N	Mean	Variance	Median	Min	Max	Range
Recidivist 1st Charges	41	1.46	0.505	1	1	3	2
Recidivist 2nd Charges	41	1.39	0.344	1	1	3	2
Non-Recidivist with Outliers	137	1.62	1.208	1	1	7	6
Non-Recidivist without Outliers	132	1.48	0.664	1	1	4	3

Table 12 shows the number of felonies that were originally brought against the offenders and in the case of the recidivists, the number of felonies brought against them the second time going through the court. The first three rows of the table show all of the cases. The minimum and median numbers show that the data is skewed to the right. The ranges are very similar except for the non-recidivist group. From this it was found, yet again, that there were outliers. This means that all four cases are very similar. To show that there are no differences, a t-test was used again.

Table 13 T-test for Difference Between Means of the Number of Accused Felonies

Hypothesis Testing t-test	Diff	SE	t-value	DF	P-value
Between Groups With Original Charges and Outliers	0.16	0.14537741	1.10058364	176	0.2726
Between Groups With Original Charges and Without Outliers	0.02	0.13170944	0.15184941	171	0.8795
Within Recidivating Group	0.07	0.14390037	0.48644767	80	0.628

Table 13 shows all of the t-tests that were performed. Again, a two-tailed test was used because the presumption was that there are no differences between the averages. The first two rows show that there is no difference between the averages of the original charges with or without outliers. This means that recidivists are not charged with more crimes than non-recidivists. This also holds true for the t-test between the original charges and the charges that were brought against the recidivists the second time through the criminal justice system. There was no statistical significance which means that the recidivists did not commit more or less crime after being through the system once before. Therefore, it seems that the number of charges brought against an offender does not play a role in whether or not he will recidivate. Also, the evidence suggests that the court does not play a role in reducing or increasing the amount of crime for recidivating offenders.

Table 14 The Number of Convicted Felonies by Recidivist Group

Recidivist Group	N	Mean	Variance	Median	Min	Max	Range
Recidivist 1st Conviction	41	1.32	0.272	1	1	3	2
Recidivist 2nd Conviction	41	1.27	0.201	1	1	2	1
Non-Recidivist	137	1.36	0.469	1	1	4	3

Table 14 shows the number of convicted felonies for the first and second time through the domestic violence court and for the non-recidivist offenders. As we saw before with the charges, the median and minimum values show that the data is skewed to the right. The averages are very similar for all three rows but to make sure they are different, t-tests were used again.

Table 15 T-test for Difference Between Means of the Number of Originally Convicted Felonies

Hypothesis Testing t-test	Diff	SE	t-value	DF	P-value
Between Groups of 1st Conviction	0.04	0.10028711	0.39885486	176	0.6905
Within Recidivating Group	0.05	0.1074085	0.46551252	80	0.6428

The t-tests in table 15 show no differences between the average number of convictions for between recidivists groups and between the first and second convictions for the recidivists. Again, the two tailed t-test was used to show if there are differences between the means. This suggests that the number of convicted crimes does not affect whether or not the person will recidivate or whether or not a person who recidivates will be convicted of more or less crimes.

Table 16 The Number of Violations in Reference to the First Convictions by Recidivist Group

Recidivist Group	N	Mean	Variance	Median	Min	Max	Range
Recidivist with Outliers	41	26.707	1773.412	12	0	214	214
Recidivist without Outliers	37	14.405	118.359	11	0	50	50
Non-Recidivist with Outliers	137	17.131	3563.718	6	0	668	668
Non-Recidivist without Outliers	134	11.209	185.385	6	0	56	56

Table 16 shows the average number of violations for each recidivist group. The ranges and median values indicated that there might be outliers in the recidivist and non-recidivist groups and indeed there are. This was found out again by using the outlier labeling rule and 2.2 for the coefficient. When the outliers were taken out, the variance drastically reduced. The means between the groups with outliers has a difference of about 3 violations per person on average. This suggests that the recidivists commit more violations than the non-recidivists. However, a t-test is needed to confirm this suggestion.

Table 17 T-test for the Difference Between Means of the Number of Violations in Reference to the First Convictions

Hypothesis Testing t-test	Diff	SE	t-value	DF	P-value
With Outliers	9.576	8.3226493	1.15059516	176	0.2515
Without Outliers	3.196	2.14064524	1.49300778	169	0.1373

The t-tests for the difference between the means of the number of convictions for with and without outliers can be seen in Table 17. The results of the t-test show that there are no differences between recidivists and non-recidivists. This suggests that no matter how often the offender commits a violation of their condition of release, it does not play a role in whether or not the person will recidivate.

Table 18 The Number of Pre-Trial Violations in Reference to the First Convictions by Recidivist Group

Recidivist Group	N	Mean	Variance	Median	Min	Max	Range
Recidivist with Outliers	41	17.439	1755.102	5	0	214	214
Recidivist without Outliers	37	5.811	51.713	4	0	29	29
Non-Recidivist with Outliers	137	12.964	3361.55	3	0	668	668
Non-Recidivist without Outliers	126	4.944	48.405	2	0	30	30

Table 19 T-test for the Difference Between Means of the Number of Pre-Trial Violations in Reference to the First Convictions

Hypothesis Testing t-test	Diff	SE	t-value	DF	P-value
With Outliers	4.475	8.206352854	0.54530924	176	0.5862
Without Outliers	0.867	1.334846551	0.64951286	161	0.5169

Table 18 shows the number of pre-violations separated by the recidivist group. Again, outliers were found and the Outlier Labeling Rule was applied. The recidivists on average committed more violations than the non-recidivists. However, in looking at Table 19, there is no significant difference between the two averages. Therefore, it seems that the Number of Pre-Trial Violations would not be a good predictor whether someone recidivates or not.

Table 20 The Number of Post-Trial Violations in Reference to the First Convictions by Recidivist Group

Recidivist Group	N	Mean	Variance	Median	Min	Max	Range
Recidivist with Outliers	41	9.268	167.251	4	0	72	72
Recidivist without Outliers	40	7.7	68.113	4	0	30	30
Non-Recidivist with Outliers	137	4.168	62.626	0	0	36	36
Non-Recidivist without Outliers	121	1.669	10.79	0	0	14	14

Table 21 T-test for the Difference Between Means of the Number of Post-Trial Violations in Reference to the First Convictions

Hypothesis Testing t-test	Diff	SE	t-value	DF	P-value
With Outliers	5.1	2.129886563	2.39449372	176	0.0177
Without Outliers	6.031	1.338655502	4.50526666	159	0

Table 20 shows the number of post-trial violations for both recidivists and non-recidivists. Again, outliers were found in this dataset and they were taken out by applying the Outlier Labeling Rule. The average for the recidivists is 4.5 times higher than the non-recidivists. This is a rather large difference and Table 21 shows that this difference is significant. The difference could seem important for logistic regression. However, there is one question that comes up from these tables. Why is there such a large difference between post-trial violations and there was such a small difference for pre-trial? The most probable reason is that some of the non-recidivists are still incarcerated and cannot commit any post-trial violations. Nevertheless, it will be interesting to see what the logistic regression model says about this difference.

Table 22 The Time Between Violation was Reported to Community Corrections

Recidivist Group	N	Mean	Variance	Median	Min	Max	Range
Recidivist with Outliers	402	7.3308	194.357	1	0	78	78
Recidivist without Outliers	325	1.2185	4.406	1	0	12	12
Non-Recidivist with Outliers	935	4.9209	329.516	1	0	365	365
Non-Recidivist without Outliers	845	1.4899	3.864	1	0	9	9

Table 23 T-test for Difference Between Means for the Time it took for the Violation being Reported to Community Corrections

Hypothesis Testing t-test	Diff	SE	t-value	DF	P-value
With Outliers	2.4099	0.914274933	2.63585921	1335	0.0085
Without Outliers	0.2714	0.13464659	2.01564704	1168	0.0441

Table 22 shows the time in days between a violation and it being reported to community corrections. In looking at rows one and three of the table, there is, on average, an approximately 2.5 day difference for recidivists and non-recidivists. However, the large difference between the medians and the maximum values shows the possibility of these numbers being affected by outliers. Once the outlier labeling was applied, outliers were indeed found in the data. Rows two and four show the data without outliers. One interesting observation is that the average for the non-recidivists is now higher than the recidivists with range for the non-recidivists being smaller than that of recidivists.

However, the most interesting aspect comes from Table 23. This table shows the t-test for significance between the two means using the two tailed test. The first row shows the hypothesis test with outliers. The difference between the two is highly significant. What is curious is that the hypothesis test without outliers is also significant even though the average for the recidivist is now lower than the non-recidivist. From this information, it is hard to tell if the time between the

violation and it being reported to community corrections positively or negatively affects recidivism.

Table 24 The Time Between the Violation and it was Filed With the Court

Recidivist Group	N	Mean	Variance	Median	Min	Max	Range
Recidivist with Outliers	397	11.0076	288.785	4	0	132	132
Recidivist without Outliers	336	4.5476	25.15	3	0	27	27
Non-Recidivist with Outliers	923	7.8646	362.046	4	0	367	367
Non-Recidivist without Outliers	827	3.6759	8.607	3	0	14	14

Table 25 T-test for Difference Between Means of the Time Between the Violation and it was Filed with the Court

Hypothesis Testing t-test	Diff	SE	t-value	DF	P-value
With Outliers	3.143	1.058143338	2.97029702	1318	0.003
Without Outliers	0.8717	0.291990903	2.98536698	1161	0.0029

Table 24 shows the time between the violation and when it was filed with the court in days. Again, the first and third rows have a rather large difference between the means by approximately 3 days. Once again though, there were potential problems with outliers. The outlier labeling rule was used again and again it was found that there were outliers in the data. Rows two and four show the same information without outliers. Unlike in Table 22, where the non-recidivist's average became higher than the recidivists, the recidivist always has, on average, a longer time difference between the violation and when it was filed with the court than the non-recidivist. Without the outliers, the difference between the two shrank from about 3 days to 1 day.

Table 25 tested whether or not the time between the two dates were significantly different using a two tailed t-test again. Like in Table 21, Table 25 shows that both t-tests, with and

without outliers, were highly significant. These results show that the difference between the violation and court date might impact whether or not an offender will recidivate.

Table 26 The Time Between the Violation and the Punishment

Recidivist Group	N	Mean	Variance	Median	Min	Max	Range
Recidivist with Outliers	395	25.3266	1744.601	6	0	251	251
Recidivist without Outliers	371	16.4016	428.982	6	0	101	101
Non-Recidivist with Outliers	919	16.6072	1753.947	6	0	370	370
Non-Recidivist without Outliers	824	7.0024	43.179	5	0	31	31

Table 27 T-test for Difference Between the Means of the Time Between the Violation and Punishment

Hypothesis Testing t-test	Diff	SE	t-value	DF	P-value
With Outliers	8.7194	2.515004974	3.46695139	1312	0.0005
Without Outliers	9.3992	1.099403208	8.54936563	1193	0

Between Tables 22, 24 and 26, it is Table 26 that is the most significant to this research because it directly looks at the length of time between the violation and punishment. Again, rows one and three shows that there is about on average a 9 day difference between the two groups and that there is a great chance for outliers since the maximum values are far from the median values. Once the outlier labeling rule was applied and the outliers were taken out, the difference between the means did not decrease, as we have seen with every other comparison, it actually stayed approximately the same, 9 days. Table 27 shows the two tailed t-test for the difference between the means. Both hypothesis tests showed that the difference is highly significant at the 95% confidence level. This test strongly suggests that the time between the violation and punishment affects whether an offender will recidivate.

Table 28 The Number of People Who went to Jail

Recidivist Group	Y/N	N	%
Recidivist	Yes	32	78%
	No	9	22%
Non-Recidivist	Yes	73	53.30%
	No	64	46.70%

Table 29 The Number of People Who went to Prison

Recidivist Group	Y/N	N	%
Recidivist	Yes	9	22%
	No	32	78%
Non-Recidivist	Yes	63	46%
	No	74	54%

When looking at whether the person was sentenced to jail or prison affected recidivism, some interesting results occurred. Tables 28 and 29 shows the breakdown of how many people went either to jail or to prison as a result of their sentencing. Everyone went to either place; however, one person only received a local probation sentence. Therefore, the two tables are almost mirror images of each other. From Table 28, it is plain to see that the overwhelming majority of the recidivist were sent to jail for their punishment. However, the non-recidivists were approximately equally split between prison and jail sentences, with the tendency to lean towards jail sentences. It seems that going to jail increases the probability that an offender recidivates; however, it is not for certain.

Table 30 Z Test for Difference Between Two Population Proportions

Hypothesis test	Z-score	p-value
Jail Proportion	2.8283	0.00466
Prison Proportion	-2.7509	0.00596

The Z test was used to see if the population proportions between the two recidivists groups. Table 30 shows the outcome of this test. It was found that the proportions were significantly different from each other. Does this mean that going to jail increases the chances for

recidivating or is it more dependent on the length of stay? A logistic regression will be used to try and answer this question. Before analyzing a logistic regression, it is a must to look at a correlation between the independent and dependent variables.

Table 31 The Top 8 Frequencies of the Punishments Imposed For Violations

Type of Punishment	Frequency	Percent
Agent Verbal Reprimand,Court Verbal Reprimand	445	11.9
Court Verbal Reprimand	191	5.1
Defendant Requested Execution	106	2.8
Increased Bail	229	6.1
Jail,Reinstated Probation	311	8.3
New Charge	290	7.8
No Action	638	17.1
Revoke Phone Privileges	824	22.1

Frequencies were run for the type of punishments given to violations. There were 3,736 violations that were committed. From these violations, there were 85 different punishments given. A lot of these “punishments” were really just a combination of individual punishments. Two examples of this can be seen in Table 31. The first type of punishment was agent verbal reprimand and court verbal reprimand; the fifth type of punishment was jail and reinstated probation. Both of these “punishments” were really two individual punishments combined to make one. Since there was no way to classify all these punishments into individual groups, because of the problem of duplicity, this research will only look at violations that had triple digits for the frequency. Thus, only 8 types of punishment are shown in Table 31. The full frequency table can be found in the Appendix.

Table 31 shows eight different types of punishment, the largest of this being the revocation of phone privileges. No action would be the second largest but if the first

punishments, agent verbal reprimand, court verbal reprimand and just court verbal reprimand were combined, they would actually be the second largest. The percent column shows the percentages from the entire number of violations, not from what is in the table. It is interesting that two of the top three punishments are either a slap on the wrist or nothing at all. The others listed take some form of liberty away from the offender. Even one form of punishment, defendant requested execution, the defendant wants to be put in jail or prison.

Table 32 is the correlation matrix between the possible independent variables and the dependent variable, whether the person recidivated or not. At first glance, there are no variables that are highly correlated with recidivism. In fact there are only three variables that are over 20% correlated with the dependent variable: Average Time Between Violation and Punishment, .246 correlation and a p-value of .004; Number of Violations Post Trial, .226 correlation and a p-value of .002; and Jail Sentence on the First Conviction, .212 correlation and a p-value of .005. Those same three variables are the only ones that are also significant at the 95% confidence level. All of the other independent variables are all hovering near 0% correlation. These correlations show that most of the variables will most likely not be significant in the logistic regression.

Table 32 Correlations Between the Independent and
Dependent Variable

Independent Variables	Correlation and Significance	Recidivated or Not
Time Between Offense Date and First Court Appearance	Pearson Correlation	-.050
	Sig. (2-tailed)	.506
Average Time Between Sentence and Offense Date	Pearson Correlation	-.084
	Sig. (2-tailed)	.265
Average Time Between Violation and Punishment	Pearson Correlation	0.246
	Sig. (2-tailed)	.004
Number of Violations Pre Trial for First Conviction	Pearson Correlation	.035
	Sig. (2-tailed)	.647
Number of Violations Post Trial for First Conviction	Pearson Correlation	0.226
	Sig. (2-tailed)	.002
Jail Sentence First Conviction	Pearson Correlation	0.212
	Sig. (2-tailed)	.005
Number of Violations for First Conviction	Pearson Correlation	.072
	Sig. (2-tailed)	.340
Age on Offense Date	Pearson Correlation	-.086
	Sig. (2-tailed)	.251
Race	Pearson Correlation	.079
	Sig. (2-tailed)	.292
Number of Felonies Originally Accused of	Pearson Correlation	-.065
	Sig. (2-tailed)	.390
Number of Felonies Originally Convicted of	Pearson Correlation	-.031
	Sig. (2-tailed)	.680
DVC Level	Pearson Correlation	-.049
	Sig. (2-tailed)	.513
Victim age	Pearson Correlation	-.101
	Sig. (2-tailed)	.180
Victim race	Pearson Correlation	.096
	Sig. (2-tailed)	.203

Logistic Regression

Since the Time Between Offense Date and First Court Appearance variable and Average Time Between Sentence and Offense Date variable, Number of Felonies Originally Accused of variable and Number of Felonies Originally Convicted of variable, and Number of Violations Pre/Post Trial for First Conviction and Number of Violations for First Conviction variable are not independent from each other, there will be eight different logistic regression models to analyze all combinations of the variables. Also, of 178 cases that will be analyzed in the regression model 40 of them did not commit any violations. The Average Time Between Violation and Punishment was calculated and normally, SPSS would treat these 40 values as missing in its analysis. To be able to include these values, a dummy variable was created called MissingDV and in the Average Number of Violations variable, these 40 cases have a zero inputted. The MissingDV variable has a one if violations occurred and zero if they have not committed any. It is to be noted that 12 of these 40 cases that have not committed a violation were still incarcerated in prison at the time of this collection of data. Also, since there is a small amount of Asian, American Indian and Unknown offenders, these three categories have been combined to have three variables for Race in the logistic regression, White, Black and Other.

There will be either 10 or 11 independent variables for 178 cases. This gives an average of 17.8 or 16.18 cases per variable. A rule of thumb that many statisticians go by is that there needs to be at least 10 cases per variable and some even recommend at least 30 for logistic regression (Statistics Solutions, 2015). However, this rule of thumb has been challenged. According to Vittinghoff and McCulloch, they argue that the rule of ten cases per variable could be relaxed and show that it is even possible to have good research with logistic regression with

5-9 cases per variable (2006). Therefore, this research is within the guidelines for the number of cases per variable for logistic regression.

Models 2 and 8 were found to be the best models at predicting whether or not a person would recidivate. The former had the combination of variables from the three dependence categories: Time Between Offense Date and First Court Appearance, Number of Felonies Originally Accused of and Number of Violations for First Conviction; whereas, Model 8 contained Average Time Between Sentence and Offense Date, Number Originally Convicted of and Number of Violations for First Conviction. The only common variable between the two models is the Number of Violations for First Conviction. However, this does not mean much when looking at the output tables from the two models below.

Table 33 Output from the Binary Logistic Function in SPSS for Model 2

Variable	B	S.E.	df	Sig.
AgeonOffenseDate	-.006	.033	1	.858
Race	.315	.357	1	.378
Jail Sentence First Conviction	.695	.516	1	.177
Number of Felonies Originally Accused of	-.046	.243	1	.849
DVC Level	-.047	.128	1	.712
Time Between Offense Date and First Court Appearance	-.002	.007	1	.773
Average Time Between Violation and Punishment	.024	.010	1	.019
Victim Age	-.016	.032	1	.618
Victim Race	.403	.416	1	.333
Number of violations for First Conviction	.000	.003	1	.979
MissingDV	.708	.723	1	.328
Constant	-2.604	1.271	1	.040

Table 33 shows the output from model 2. After examining the correlation matrix, it is no surprise to find that the majority of the independent variables are not significant at the 95%

confidence interval. In fact, only one variable is significant, which is the Average Time Between Violation and Punishment. This is the same variable from the correlation matrix that was the most correlated with whether or not a person recidivates. It is interesting that as the average time increases between the violation and punishment, the more likely the person will recidivate and this variable plays a bigger role than the Time Between Offense Date and First Court Appearance, especially when both t-tests were highly significant. It is also a little surprising that Jail Sentence First Conviction was not significant, where this was the other one that was also correlated with the dependent variable.

Table 34 Output from the Binary Logistic Function in SPSS for Model 8

Variable	B	S.E.	df	Sig.
Age on Offense Date	-.003	.033	1	.918
Race	.306	.360	1	.394
Jail Sentence First Conviction	.761	.494	1	.123
DVC Level	-.033	.127	1	.798
Average Time Between Violation and Punishment	.024	.010	1	.018
Victim Age	-.017	.033	1	.614
VictimRace	.423	.419	1	.313
Average Time Between Sentence and Offense Date	-.001	.003	1	.800
Number Originally Convicted of	.059	.327	1	.857
Number of Violations for First Conviction	.000	.003	1	.955
MissingDV	.679	.711	1	.340
Constant	-2.808	1.376	1	.041

Table 34 shows the output from the logistic regression for Model 8. As was seen in Table 33, the majority of the variables were not significant. Again, the only one that was significant was the Average Time Between Violation and Punishment variable. There is not much difference between the two models. The biggest difference is that the Constant in Table 34 is more negative

and a bit more significant than the one in Table 33 but it is still insignificant. Otherwise, all of the coefficients are similar, as well as the significance values.

What is very interesting is which variables are not significant, Average Time Between Sentence and Offense Date and Offense Date and First Court Appearance. These two variables are the ones that the DVC argues upon; they claim that the closer the punishment follows the commission of the crime, the less likely a person would recidivate. However, the t-tests indicated the opposite to be true and now the logistic regression's output shows that when it comes to the punishment for their offense, it does not need to be fast and even maybe slower is better.

Table 35 Classification Table for Model 2

Observed			Predicted		
			Recidivated or Not		Percentage Correct
			No	Yes	
Step 1	Recidivated or Not	No	133	4	97.1
		Yes	34	7	17.1
	Overall Percentage				78.7

Table 35 shows the Classification Table for the logistic regression output for Model 2. This table evaluates how well the model can predict against the actual observed cases. In the two by two matrix, the table shows that the regression predicts well if the offenders did not recidivate. However, it predicts poorly for people who recidivated. This suggests that there is still some missing variable to explain recidivism.

Table 36 Classification Table for Model 8

Observed			Predicted		
			Recidivated or Not		Percentage Correct
			No	Yes	
Step 1	Recidivated or Not	No	133	4	97.1
		Yes	34	7	17.1
	Overall Percentage				78.7

It seems that there is no difference between the classification tables in Table 36 versus Table 35 nor should there be. There is only one variable that was significant in both models and that was the Average Time Between Violation and Punishment. This means that one model is not better than another in predicting who will recidivate.

The percentages of correct predictions are interesting and highly accurate, but are these numbers significant and are these models useful? To test this, according to Schwab, this number, the classification accuracy rate, should be 25% higher than the proportional by chance accuracy rate (2002). Since independent variables that have absolutely no relationship to the dependent variable can be expected to correctly predict some of the time, also known as by chance accuracy rate. This rate can be calculated by squaring and summing the proportion of cases for each group (Schwab, 2002). Then Schwab goes onto state that if the classification rate is 25% higher than the by chance accuracy rate the logistics model is useful (2002). Applying this formula to the classification tables above, the by chance accuracy rate is 64.58% and with a 25% increase it is 80.73%. Since the two classification tables both had a 78.7% classification accuracy rate, which is below 80.73%, it can be said that both models are not useful.

It is highly interesting that there were several variables were found to be significantly different, when separating them by people who recidivated or not, during the initial t –test stage; also, there were three variables that were significantly correlated with whether or not someone recidivated. However, from the logistic regression’s output, it is now known that only one

variable is significant and the most important, the Average Time Between Violation and Punishment. The longer this average time is for violations, the more likely an offender would recidivate. However, since the two most important variables for the DVC, Average Time Between Sentence and Offense Date and Offense Date and First Court Appearance, are insignificant, the founding on which the court is based, swift punishment, is irrelevant.

Time Series

At the beginning of this research, there were 178 possible offenders who may have committed a violation of their condition of release. From the nature of the variable, the Average Time Between X and Y Violation, the offender needed to commit at least two violations on separate days to be included in this part of the analysis. Some of these 178 offenders did not commit any or only one violation, which were 47 offenders. From each consecutive violation, more and more offenders dropped off. However, from the definition of the variable, the Average Time Between X and Y Violation, there needed to be at least 30 offenders who have committed Y number of violations. Thus, there are 13 variables in this analysis. Table 37 has the results of the descriptive statistics.

Table 37 The Average Time Between Consecutive Violations With Outliers

Time Between which Violations	N	Mean	Variance	Median	Min	Max	Range
Between 1st and 2nd	131	25.26	3741.486	6	1	558	557
Between 2nd and 3rd	115	19.03	1278.034	6	1	264	263
Between 3rd and 4th	103	23.06	2758.055	5	1	376	375
Between 4th and 5th	96	27.36	2360.592	10	1	407	406
Between 5th and 6th	85	27.49	2974.705	7	1	378	377
Between 6th and 7th	73	41.25	7600.022	13	1	599	598
Between 7th and 8th	59	37.47	2650.185	18	1	251	250
Between 8th and 9th	54	43.13	8531.096	6.5	1	434	433
Between 9th and 10th	49	25	1636.958	7	1	216	215
Between 10th and 11th	41	29.66	1581.53	10	1	161	160
Between 11th and 12th	37	26.65	1344.901	9	1	146	145
Between 12th and 13th	35	36.37	7940.299	11	1	518	517
Between 13th and 14th	31	27.81	2069.895	13	1	209	208

The averages in Table 37 show that they are fluctuating. At periods they are going up, from Between the 3rd and 4th to Between the 6th and 7th and between the high the increases there are dramatic decreases, from Between 8th and 9th to Between 9th and 10th. However, the variance along with the difference between the median and maximum value indicates once again of outliers.

Table 38 The Average Time Between Consecutive Violations Without Outliers

Time Between which Violations	N	Mean	Variance	Median	Min	Max	Range
Between 1st and 2nd	119	11.18	182.774	6	1	62	61
Between 2nd and 3rd	106	11.04	222.018	4	1	61	60
Between 3rd and 4th	94	9.96	150.321	4	1	52	51
Between 4th and 5th	93	21.25	638.493	9	1	106	105
Between 5th and 6th	79	15.56	442.711	7	1	79	78
Between 6th and 7th	67	20.33	637.072	10	1	112	111
Between 7th and 8th	56	28.61	1149.188	17.5	1	128	127
Between 8th and 9th	46	11.96	324.176	4	1	80	79
Between 9th and 10th	44	14	354.465	5.5	1	75	74
Between 10th and 11th	41	29.66	1581.53	10	1	161	160
Between 11th and 12th	35	20.29	649.21	8	1	95	94
Between 12th and 13th	33	19.06	627.559	7	1	103	102
Between 13th and 14th	29	18.14	596.98	10	1	102	101

After using, once again, the Outlier Labeling Rule with a constant of 2.2, Table 38 shows the results of the descriptive statistics after the removal of the outliers. The most dramatic example is the Between 8th and 9th variable from both tables. In Table 37, this variable had the highest average, 43.13, and now in Table 38, it has one of the lowest, 11.96. This shows the difference that outliers can make on a statistic. In the new table, there is not one average over 30; whereas, Table 37 had 4. There was only one variable, Between 10th and 11th that was not affected at all by outliers. Also, there was a lot more fluctuation in this table. The averages seem completely random. What is interesting is from the Between 10th and 11th to Between 13th and 14th variables, there is a decreasing trend. The time between is getting shorter which is the opposite of what should be happening. Next, t-tests were used to see if the differences between the consecutive variables were significant.

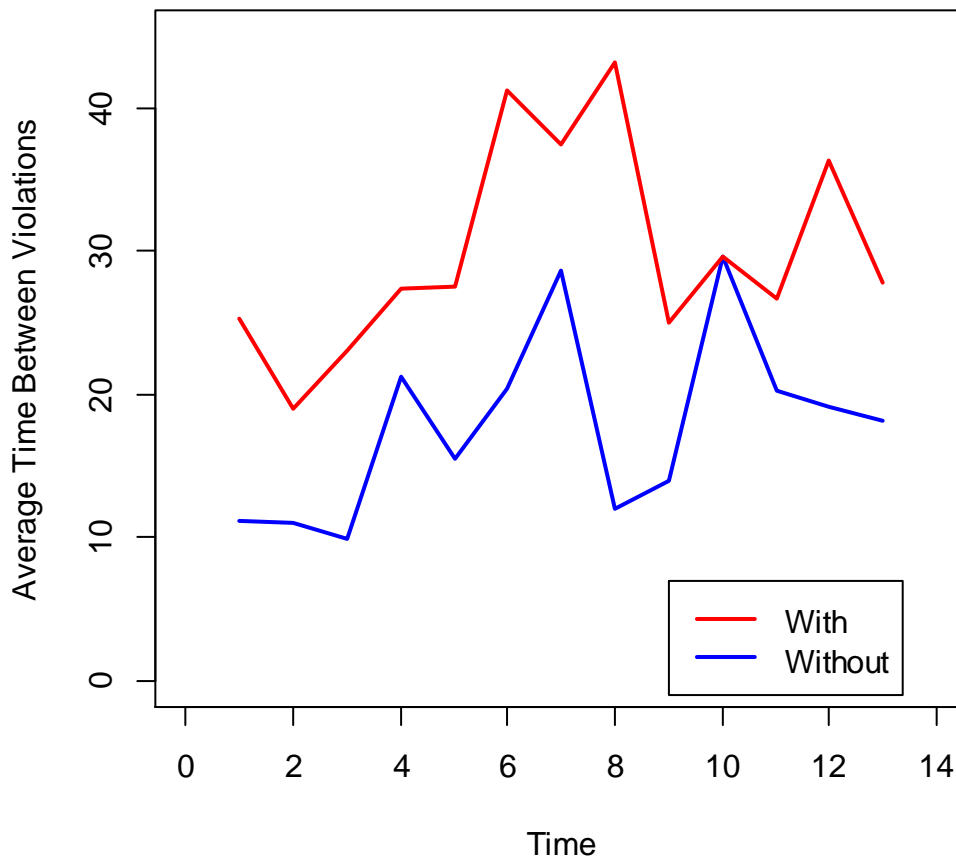
Table 39 T-test for Difference Between the Means of the Time Between Different Violations

T-test Between Different Violations	Diff	SE	t-value	DF	P-value
1st and 2nd, 2nd and 3rd	0.14	1.90536752	0.07347664	223	0.9415
2nd and 3rd, 3rd and 4th	1.08	1.92189204	0.56194624	198	0.5748
3rd and 4th, 4th and 5th	11.29	2.90941157	3.88050976	185	0.0001
4th and 5th, 5th and 6th	5.69	3.53121124	1.61134512	170	0.109
5th and 6th, 6th and 7th	4.77	3.88747656	1.22701704	144	0.2218
6th and 7th, 7th and 8th	8.28	5.47994084	1.51096522	121	0.1334
7th and 8th, 8th and 9th	16.65	5.25057317	3.17108237	100	0.002
8th and 9th, 9th and 10th	2.04	3.88629992	0.52492089	88	0.601
9th and 10th, 10th and 11th	15.66	6.82861078	2.29329222	83	0.0244
10th and 11th, 11th and 12th	9.37	7.55796001	1.23975252	74	0.219
11th and 12th, 12th and 13th	1.23	6.12909427	0.20068218	66	0.8416
12th and 13th, 13th and 14th	0.92	6.29304828	0.14619306	60	0.8876
13th and 14th, 1st and 2nd	6.96	4.70334277	1.47979859	146	0.1411

Table 39 shows the results of the t-tests from descriptive statistics in Table 38. T-tests were also conducted for Table 37 and the results can be found in the Appendix. Between the majority of these variables, there was no statistical significance between them. There were only 3 that were significant. When testing the difference between the first, Between 1st and 2nd, and the last, Between 13th and 14th, there was no statistical significance. This means that over a

period of 14 violations, the time between violations is not getting longer or shorter. There is no statistical difference between the two averages.

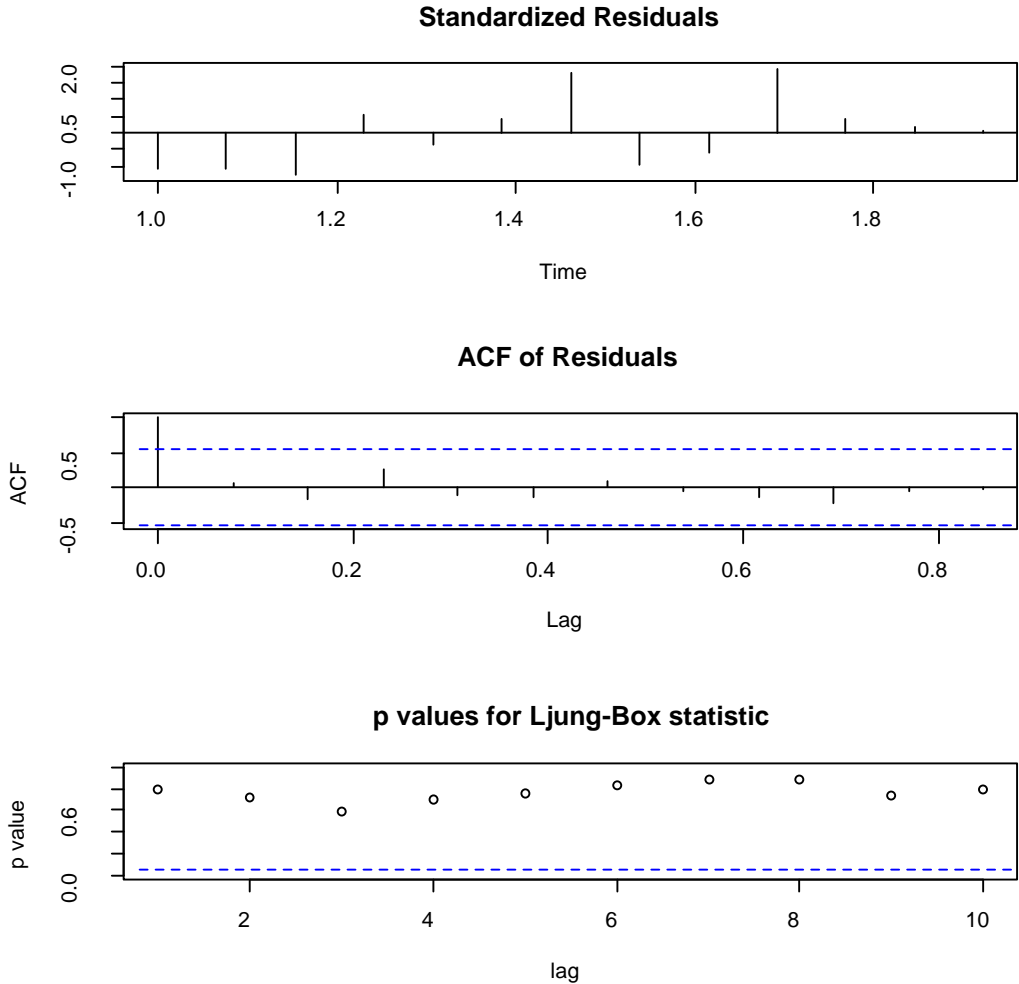
Graph 1 Average Time Between Consecutive Violations with and without Outliers



Graph 1 visualizes the averages of with and without outliers. It can be easily seen that the outliers had a major effect on the data. However, both graphs show a slight upward trend. From here on out, this research will only focus on the information that is without outliers. This is research is focused on the data without outliers because some of the biggest differences between violations occur between the last pre-trial violation and the first post-trial violation. This could be due to the fact that the offender was incarcerated for that period. In reality, the offender had no control and the true time between could only a few days.

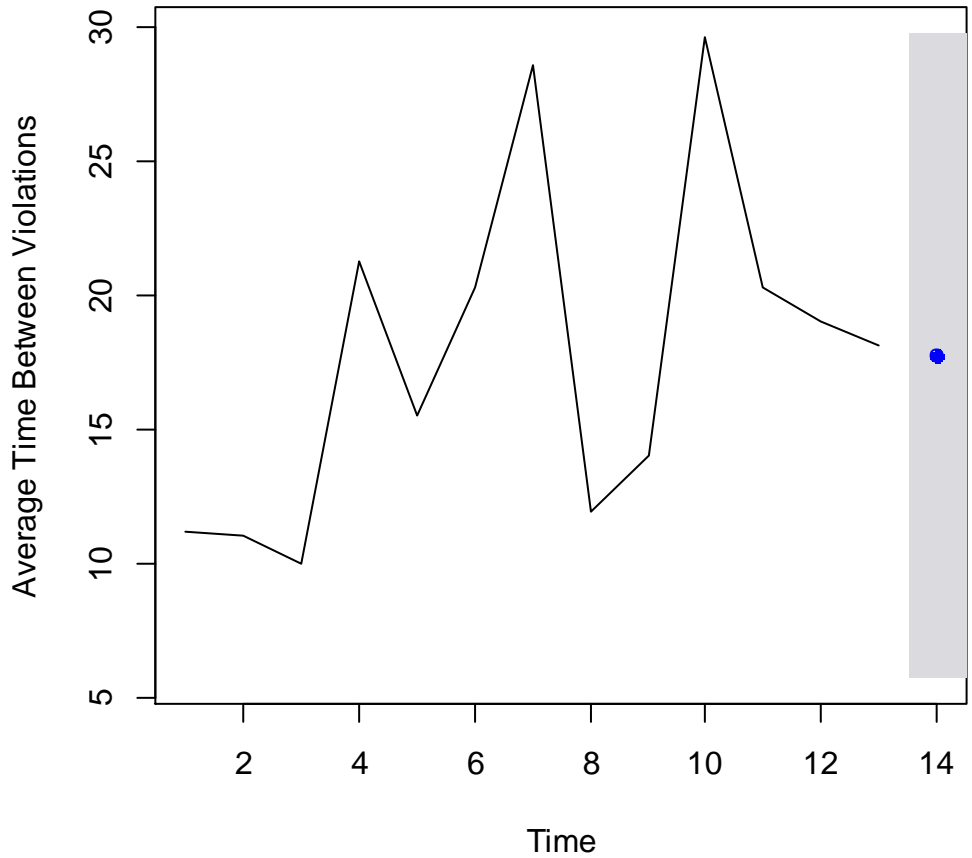
Using the `auto.arima()` function in R for the Average Time Between Violations without outliers fit the model $ARIMA(0,0,0)$ with a non-zero mean. The entire R code for this procedure can be found in the Appendix. This fitted model states that this time series is stationary. This is significant because, “a stationary series has no trend, its variations around its means have a constant amplitude, and...its short-term random time patterns always look the same in a statistical sense” (Nau, 2015). Therefore, if there is no trend in the data, then the Time Between Violations is not getting longer.

Graph 2 Diagnostics of the Model Arima(0,0,0) with non-zero mean



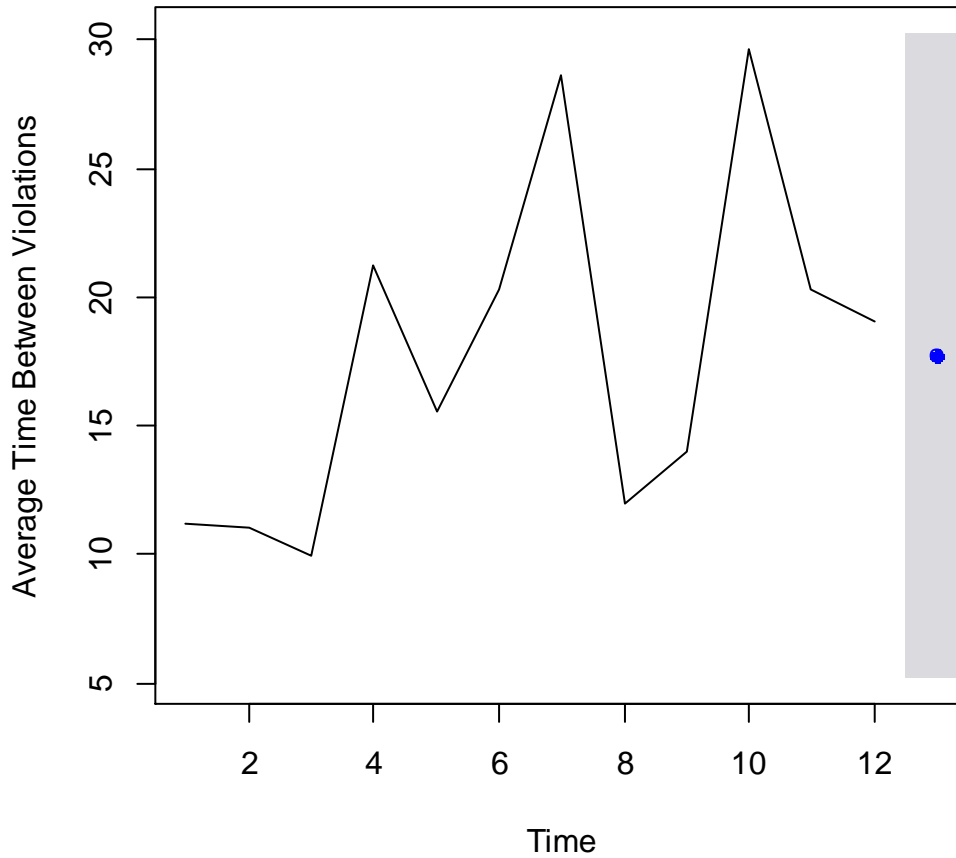
Graph 2 shows the results of the diagnostics from the model ARIMA(0,0,0). The graph for the ACF of Residuals is very good. None of the residuals crossed the blue dotted line, which would mean that a residual is significant. Since none of them are significant, this is the ideal situation (Penn State Eberly College of Science, 2015). Also, the Ljung-Box graph shows that none of the p-values are significant. This means that the model does not have a significant lack of fit. Therefore, these graphs give further evidence that the model ARIMA(0,0,0) is a good fit to the data and this allows predictions on when the next violation may occur.

**Graph 3 Forecasts from ARIMA(0,0,0)
with non-zero mean**



Graph 3 predicts when the next violation should be on average. The graph predicts that this should be in about 18 days. However, with such a limited amount of inputs into the time series equation, the ARIMA model cannot predict any further than one violation but it is possible to check the validity of the predictions.

**Graph 4 Forecasts from ARIMA(0,0,0)
with non-zero mean**



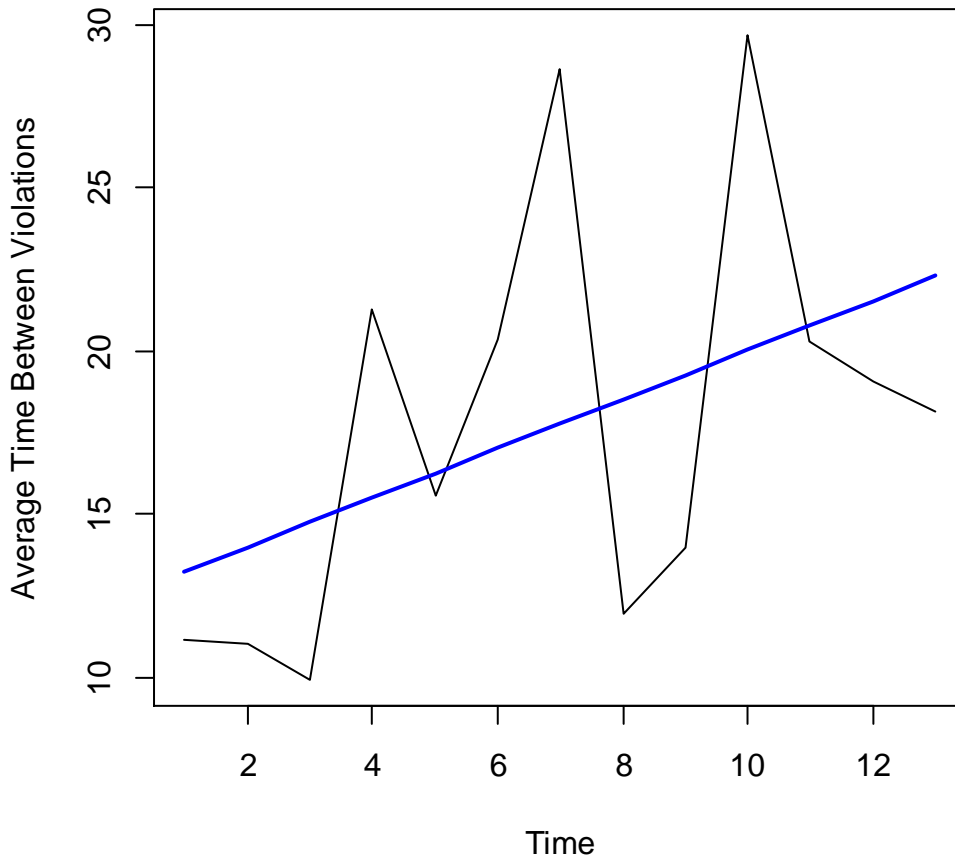
Graph 4 checks the validity of the ARIMA model. To do this the 13th data point was excluded and the model tried to predict this actual value. The prediction value was 17.74167 and the actual value was 18.14. This is very close and it shows how accurate this model predicts. The next model will be a linear regression.

Table 40 Linear Regression Output for Average Time Between Violations

Variable	Value	Std.Error	t-value	p-value
Intercept	12.506154	3.481879	3.591783	0.0042
Between which Violations	0.752308	0.438676	1.714953	0.1144

Table 40 shows the output of the coefficients for the independent variables from a linear regression. The dependent variable is the Average Time Between Violations and the only inputted variable was Between which Violations. The most noticeable aspect about this table is that the variable Between which Violation is not significant. The time between violations looks as if it is getting longer but from this output and the t-tests has shown that the time between violations is not significantly different between the first two violations and the last two.

Graph 5 Forecasts from Linear Regression Modelling



From Graph 5, it is able to see that a linear regression line does not fit this equation. The line is ever increasing but we have just learned that Time is not significant in this model. Looking at the right side of this graph, there is a large discrepancy between the predicted 13th observation and the actual. Again, the actual value of it is 18.14 and the predicted value from linear regression is 22.29. This is 4 days longer than the observed; whereas, the 13th prediction from ARIMA was only 10 hours shorter as the observed. Therefore, the ARIMA model is a better fit for the Average Time Between Violations.

Is the time between violations getting longer? It most likely is not. The linear regression showed that the trend line is indeed increasing, however, from the t-tests, there is no significant

difference between the first and last observation. So what is exactly going on with the violations? It is hard to say. There are not many observations and not all variables were controlled for. If it took some more than a year to commit another violation, is that really indicative of the program working or does it mean that the person got out of jail or prison and resumed their old ways? More than likely the latter is true. This researcher observed that the significant amount of these longer times between violations occurred when the last violation was pre-trial and the next was post-trial. Could that be because the punishment worked so well on the individual or was the offender incarcerated for this time frame? It is hard to say, but one thing is for certain, more research is needed.

Chapter 5: LIMITATIONS, CONCLUSIONS, & FURTHER RESEARCH

A Review of the Analysis & the Applicability of the Findings

Domestic violence is a very costly crime to the economy, criminal justice system and more importantly to the parties involved. This has led to a multitude of programs being implemented to reduce this crime rate, but with no avail. It is also a very special type of crime, where both parties are, in general, in a romantic or intimate relationship. With this type of crime and how much money is spent combating this problem with no results, the 7th District Court of Minnesota decided to implement a “Domestic Violence Court” to hold the offenders accountable and reduce recidivism.

Since the concept of a DVC is still fairly new, there is no standard concept of what it is. They hold similar beliefs but there are many variations on the ideas and implementations. Previous studies into this area have had mixed results. Stearns County DVC focused solely on repeat felony level offenders with a strong judicial oversight to curb recidivism. However, there has been no study that has examined the impact that judicial monitoring has on recidivism and it is unknown whether strenuous judicial monitoring has any influence on recidivism (Labriola et al., 2010). This study focused on whether or not this DVC was achieving its goal of reducing recidivism.

Limitations of this Study

This study had a wide scope when trying to evaluate the Stearns County DVC. However, from the beginning of this study there were some limitations to this. This study had limited access to crucial variables that could be important in evaluating this model. Variables such as, the length of incarceration for jail or prison, socioeconomic status of both the offender and victim, the domestic violence history of the offender or victim and the date of release from

prison or jail for the offender were either not given or not clear enough to use in this model. The length of incarceration was given to this researcher; however, the Stearns County Attorney's Office was not willing to give or tell which punishments had consecutive or concurrent sentences when this researcher contacted them about it. Since several offenders were convicted of multiple charges, this variable could be significant in evaluating this court.

The lack of socioeconomic status of both the offender and victim as a variable hurts this research. Not knowing whether they are employed or poor greatly limits this research. The majority of empirical research states, "...that domestic violence is disproportionately concentrated in poor populations..." and recent research suggests that "...nonfatal domestic violence rates increase with high male unemployment..." (Buzawa, Buzawa, & Stark, 2012). This could also explain why the average number of violations post-trial for recidivists is 4.5 times higher than non-recidivists. Offenders cannot get a job and the stress of not working and not having money could be making them violate their condition of release.

The history of the offender and victim could also be important information in developing a good model for whether a person recidivates or not. It is more than likely that if he commits a domestic violence crime once, the offender will probably do it again. Therefore, does the DVC work better for people who have a small domestic violence history or one who has a long one? This is an extremely important question to answer because if this court can reduce the amount of recidivists who have a long history of domestic violence, it would be a crowning achievement for the court. This variable is also important because there is more than one way to become a repeat felony level criminal in the state of Minnesota. Thus, this variable is a necessity in future research.

Knowing the date of release from prison or jail would have been of great help for this research. It would have made it possible to identify the offenders who are still incarcerated and not include them in the research. Only focusing on the offenders who have been released and examine the differences between the recidivists and non-recidivists would have made it possible to truly evaluate whether or not the DVC is achieving its goals. Just because out of 178 offenders, only 41 have recidivated, 23% of the sample population, which is below the estimated recidivism rate for domestic violence, does not mean that this is evidence to support the DVC. Lack of evidence to the contrary is not supporting evidence.

Another limitation is how well the DVC helps victims. The dataset about victims using the services was not used in this study. There were too many data issues to give an accurate analysis of the victims and the services they used. One such problem is data entry errors. On multiple occasions, a service type was labeled as either pre or post trial on a certain date and the next service type which was on the same date was labeled the opposite pre/post trial as the previous. How can two different service types on the same day be before and after the trial?

Another problem with the victim dataset is the voluntary nature of the services used. The Stearns County Attorney's Office stated that all of the service types were voluntary basis from the victim, meaning the victim had to initiate contact. However, this does not seem to be the case. There are service types called "Follow up/Check-in", "Victim Contact Home/Community Visit", "Victim Contact At Court" and other vague service types. Are all these types really victim initiated? It is probably not likely.

This data also does not take into account of domestic violence crimes these offenders may have committed outside of Stearns County. The county attorneys do not necessarily have

this information since the county or state the offense was committed would have jurisdiction in the offense. Therefore, this data is limited by the dark figure of domestic violence.

The last limitation of this study is its external validity. Since there is no standard practice for domestic violence courts and therefore a large variety with different laws and regulations, it is not possible to replicate the results for a different domestic violence court. Once they are standardized, it becomes possible to replicate the findings. Until that time however, there is a lack of external validity in this research.

Conclusion

The goal of this study was to evaluate the 7th Judicial District of Minnesota Domestic Violence Court. The goal of this court is to reduce recidivism through prompt punishment after an offense or violation. Even though there are limitations to this study, there are still several conclusions that can be drawn about the DVC, such as: which variables are and are not important for recidivism, whether or not the quickness of the punishment after an offense is an important factor and whether the court is reducing recidivism.

After examining multiple variables through t-tests and logistic regressions, it has become clear which ones are important or could be and which ones are not important for a person to recidivate. The characteristic variables, age and race, for the offenders and victims are not important at all. There is no difference in the t-tests or logistic regressions. There also seems to be no difference between a jail or a prison sentence, The Number of Felonies Originally Accused of, Number of Felonies Originally Convicted of, Time Between Offense Date and First Court Appearance, Average Time Between Sentence and Offense Date, and Number of Violations for First Conviction all did not matter for whether or not a person recidivated according to the logistic regression.

The variables that are on the fence would be the DVC Level and the number of violations post-trial. The DVC level is fairly close and the fact that there were a lot of no tests given makes it seem very probable that this variable could be significant. However, the Number of Violations Post-Trial is leaning the other way. The fact that there are offenders who are still incarcerated who have not had a chance to commit post-trial violations makes it seem likely that the difference in the averages of the offenders who recidivated and those who did not would shrink and not be significant anymore.

The two most important variables Time Between Offense Date and First Court Appearance and Average Time Between Sentence and Offense Date are the foundation of the DVC. Since the court argues that the quicker offenders appear in court after a commission of a crime the more he associates the punishment to the crime, this finding is significant because it contradicts the courts belief. When looking at the averages of these variables, the non-recidivists were slower to go to court and to get punished. However, the only variable that was significant in this research and is significant to the DVC is the Average Time Between Violation and Punishment. The longer the punishment comes after a violation for a condition of release the more likely a person would recidivate. What does this all exactly say for the DVC? It does not matter how long it takes from the time of an offense to punishment but it does matter how long it takes between violation and punishment. Thus, keeping a closer eye on the offenders before trial and after release from incarceration and giving them some sort of punishment for a violation is more important for the lowering the recidivism rate than the swiftness of the criminal justice system.

Is the DVC reducing recidivism through swift punishment? This is a tough question to answer. From the time series analysis, there was no significant difference in the time between the

1st and 2nd violation to the time between the 13th and 14th violation. This suggests that the offenders commit violations when they want it happens at pretty regular intervals. Also, there was no significance in the number of violations committed. All that mattered was how long it took for the criminal justice system to punish the offenders in some way shortly after a commission of a violation. Again, is the DVC reducing recidivism through swift punishment? The evidence suggests no but to be truly certain, there needs to be further research.

Further Research

Further research absolutely needs to be conducted to fully analyze this domestic violence court. The variables that were mentioned above in the limitations would be crucial for the next research step. There cannot be further research that is conducted without those variables. To be able to conduct further research, more cooperation from the Stearns County Attorney's Office is necessary. This author received very little cooperation and was not able to get the above variables or to get answers to data entry or clarifying questions with the victim's dataset.

The research model can and should be similar to this one but with adding more inputs and having more data points for the time series analysis. More data and more information never hurt in research. However, one interesting further research idea would be to do a survey or interview of the victims and offenders and how they perceive the domestic violence court. If this would be achieved, especially with the victims, that might be the strongest evidence in support of or against the DVC. The other type of research that should be conducted is a comparison study of the DVC and the traditional court system to show if recidivism rates are truly lower within the problem solving court. Millions of dollars are put into the DVC. This research does not fully show that the court is not effective and this is why further research is needed. Not only to save

the taxpayers money but, more importantly, to reduce the pain and suffering that comes with domestic violence.

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Appendix

Frequencies of the Punishments Imposed For Violations

Type of Punishment	Frequency	Percent
Unknown	9	.2
A&D	2	.1
A&D,Bail Reinstated	1	.0
A&D,Execute Sentence,Bail Reinstated	1	.0
A&D,Jail	17	.5
A&D,Jail,Bail Reinstated	1	.0
A&D,Jail,Reinstated Probation	5	.1
Agent Verbal Reprimand	14	.4
Agent Verbal Reprimand,A&D,No Action	1	.0
Agent Verbal Reprimand,Court Verbal Reprimand	445	11.9
Agent Verbal Reprimand,Court Verbal Reprimand,A&D,Bail Reinstated	1	.0
Agent Verbal Reprimand,Court Verbal Reprimand,A&D,Jail,Reinstated Probation	1	.0
Agent Verbal Reprimand,Court Verbal Reprimand,A&D,Jail,Reinstated Probation,Community Service Work Sanction	1	.0

Agent Verbal Reprimand,Court Verbal Reprimand,Increased Bail	1	.0
Agent Verbal Reprimand,Court Verbal Reprimand,Jail	2	.1
Agent Verbal Reprimand,Court Verbal Reprimand,New Charge	29	.8
Agent Verbal Reprimand,Court Verbal Reprimand,New Charge,Increased Bail	4	.1
Agent Verbal Reprimand,Court Verbal Reprimand,No Action	1	.0
Agent Verbal Reprimand,Court Verbal Reprimand,No Violation Found	1	.0
Agent Verbal Reprimand,Court Verbal Reprimand,Reinstated Probation,Community Service Work Sanction	1	.0
Agent Verbal Reprimand,Follow up UA,Court Verbal Reprimand	12	.3
Agent Verbal Reprimand,Jail	1	.0
Agent Verbal Reprimand,Warrant	1	.0
Bail Reinstated	3	.1
Bail Reinstated,No Action	1	.0
Body only Warrant	24	.6
Commit to DOC	27	.7
Community Service Work Sanction	3	.1
Court Verbal Reprimand	191	5.1
Court Verbal Reprimand,A&D	2	.1
Court Verbal Reprimand,Bail Reinstated	1	.0

Court Verbal Reprimand,Increased Bail	16	.4
Court Verbal Reprimand,New Charge	22	.6
Court Verbal Reprimand,No Action	8	.2
Court Verbal Reprimand,Warrant	6	.2
Defendant Requested Execution	106	2.8
Execute Sentence	63	1.7
Execute Sentence,Body only Warrant	2	.1
Execute Sentence,Defendant Requested Execution	1	.0
Follow up UA	11	.3
Follow up UA,Court Verbal Reprimand	1	.0
Follow up UA,Increased Bail,A&D	1	.0
Follow up UA,No Action	1	.0
Follow up UA,No Violation Found	1	.0
Follow up UA,Verbal Reprimand	1	.0
GPS	1	.0
Increased Bail	229	6.1
Increased Bail,A&D	9	.2
Increased Bail,A&D,Bail Reinstated	1	.0
Increased Bail,A&D,Jail	5	.1
Increased Bail,A&D,Jail,Community Service Work Sanction	1	.0
Increased Bail,Body only Warrant	3	.1
Increased Bail,Jail	2	.1
Increased Bail,Revoke Phone Privileges	5	.1
Jail	26	.7
Jail,Bail Reinstated	1	.0
Jail,Body only Warrant	9	.2
Jail,Body only Warrant,Reinstated Probation	7	.2
Jail,Reinstated Probation	311	8.3

Jail,Reinstated Probation,Stay of Imposition Revoked	9	.2
Jail,Reinstated Probation,Stay of Imposition Revoked,Updated Chemical Dependency Evaluation	13	.3
Jail,Reinstated Probation,Updated Chemical Dependency Evaluation	51	1.4
Jail,Updated Chemical Dependency Evaluation	1	.0
New Charge	290	7.8
New Charge,A&D,Bail Reinstated	3	.1
New Charge,A&D,Jail	8	.2
New Charge,Bail Reinstated	3	.1
New Charge,Increased Bail	86	2.3
New Charge,Increased Bail,A&D	3	.1
New Charge,Increased Bail,Bail Reinstated	1	.0
New Charge,Increased Bail,GPS	8	.2
New Charge,Increased Bail,Revoke Phone Privileges	16	.4
New Charge,Revoke Phone Privileges	35	.9
No Action	638	17.1
No Action,GPS	1	.0
No Action,No Violation Found	1	.0
No Violation Found	29	.8
Reinstated Probation	3	.1
Reinstated Probation,Community Service Work	1	.0
Revoke Phone Privileges	824	22.1
Updated Chemical Dependency Evaluation	1	.0
Verbal Reprimand	5	.1

Violation Dismissed	41	1.1
Violation Dismissed,Updated Chemical Dependency Evaluation	1	.0
Warrant	10	.3
Total	3736	100.0

Output from the Binary Logistic Function in SPSS for Model 1

Variable	B	S.E.	df	Sig.
Age on Offense Date	-.020	.036	1	.581
Race	.424	.384	1	.269
Jail Sentence First Conviction	.160	.587	1	.785
Number of Felonies Originally Accused of	-.234	.280	1	.403
DVC Level	-.202	.149	1	.176
Number of Violations Pre Trial	-.001	.003	1	.796
Number of Violations Post Trial	.019	.021	1	.357
Time Between Offense Date and First Court Appearance	-.008	.009	1	.402
Average Time Between Violation and Punishment	.024	.010	1	.021
Victim Age	.002	.035	1	.962
Victim Race	.338	.449	1	.452
Constant	-1.226	1.306	1	.348

Classification Table for Model 1

Observed			Predicted		
			Recidivated or Not		Percentage Correct
		No	Yes		
Step 1	Recidivated or Not	No	96	4	96.0
		Yes	31	7	18.4
	Overall Percentage				74.6

Output from Binary Logistic Function in SPSS for Model 3

Variable	B	S.E.	df	Sig.
Age on Offense Date	-.019	.036	1	.604
Race	.406	.384	1	.291
Jail Sentence First Conviction	.329	.567	1	.562
DVC Level	-.191	.150	1	.202
Time Between Offense Date and First Court Appearance	-.008	.009	1	.398
Average Time Between Violation and Punishment	.024	.010	1	.019
Victim Age	.002	.035	1	.951
Victim Race	.337	.451	1	.455
Number Originally Convicted of	-.100	.369	1	.786
Number of Violations Pre Trial	-.001	.003	1	.704
Number of Violations Post Trial	.019	.021	1	.378
Constant	-1.615	1.371	1	.239

Classification Table for Model 3

Observed			Predicted		
			Recidivated or Not		Percentage Correct
Recidivated or Not	No	Yes	No	Yes	
	Step 1	No		96	4
Yes			32	6	15.8
Overall Percentage					73.9

Output from the Binary Logistic Function in SPSS for Model 4

Variable	B	S.E.	df	Sig.
Age on Offense Date	-.016	.036	1	.653
Race	.466	.380	1	.220
Jail Sentence First Conviction	.535	.519	1	.302
DVC Level	-.209	.148	1	.159
Time Between Offense Date and First Court Appearance	-.009	.009	1	.352
Average Time Between Violation and Punishment	.026	.010	1	.012
Victim Age	.001	.035	1	.969
Victim Race	.259	.440	1	.556
Number Originally Convicted of	-.056	.362	1	.877
Number of Violations for First Conviction	-.001	.003	1	.821
Constant	-1.722	1.361	1	.206

Classification Table for Model 4

Observed			Predicted		
			Recidivated or Not		Percentage Correct
		No	Yes		
Step 1	Recidivated or Not	No	96	4	96.0
		Yes	31	7	18.4
	Overall Percentage				74.6

Output from the Binary Logistic Function in SPSS for Model 5

Variable	B	S.E.	df	Sig.
Age on Offense Date	-.016	.036	1	.660
Race	.426	.387	1	.271
Jail Sentence First Conviction	.130	.588	1	.825
DVC Level	-.170	.145	1	.241
Average Time Between Violation and Punishment	.023	.010	1	.026
Victim Age	.000	.035	1	.994
Victim Race	.352	.453	1	.438
Average Time Between Sentence and Offense Date	-.001	.003	1	.729
Number of Felonies Originally Accused of	-.246	.278	1	.375
Number of Violations Pre Trial	-.001	.003	1	.756
Number of Violations Post Trial	.021	.021	1	.310
Constant	-1.262	1.353	1	.351

Classification Table for Model 5

Observed			Predicted		
			Recidivated or Not		Percentage Correct
Recidivated or Not	No	Yes	No	Yes	
	Step 1	No		96	4
Yes			31	7	18.4
Overall Percentage					74.6

Output from the Binary Logistic Function in SPSS for Model 6

Variable	B	S.E.	df	Sig.
Age on Offense Date	-.012	.036	1	.730
Race	.497	.381	1	.193
Jail Sentence First Conviction	.356	.545	1	.513
DVC Level	-.188	.143	1	.188
Average Time Between Violation and Punishment	.024	.010	1	.016
Victim Age	-.002	.035	1	.953
Victim Race	.253	.439	1	.565
Average Time Between Sentence and Offense Date	-.001	.003	1	.763
Number of Felonies Originally Accused of	-.228	.275	1	.407
Number of Violations for First Conviction	.000	.003	1	.877
Constant	-1.352	1.343	1	.314

Classification Table for Model 6

Observed			Predicted		
			Recidivated or Not		Percentage Correct
		No	Yes		
Step 1	Recidivated or Not	No	96	4	96.0
		Yes	31	7	18.4
	Overall Percentage				74.6

Output from the Binary Logistic Function in SPSS for Model 7

Variable	B	S.E.	df	Sig.
Age on Offense Date	-.015	.036	1	.682
Race	.410	.388	1	.291
Jail Sentence First Conviction	.301	.568	1	.596
DVC Level	-.160	.146	1	.272
Average Time Between Violation and Punishment	.024	.010	1	.022
Victim Age	.000	.035	1	.997
Victim Race	.342	.454	1	.451
Average Time Between Sentence and Offense Date	-.001	.003	1	.774
Number Originally Convicted of	-.123	.364	1	.735
Number of Violations Pre Trial	-.001	.003	1	.664
Number of Violations Post Trial	.021	.021	1	.328
Constant	-1.654	1.416	1	.243

Classification Table for Model 7

Observed			Predicted		
			Recidivated or Not		Percentage Correct
Recidivated or Not	No	Yes	No	Yes	
	Step 1	No		97	3
Yes			32	6	15.8
Overall Percentage					74.6

T-test for Difference Between the Means of the Time Between Different Violations with Outliers

T-test Between Different Violations	Diff	SE	t-value	DF	P-value
1st and 2nd, 2nd and 3rd	6.23	6.29875392	0.98908452	244	0.3236
2nd and 3rd, 3rd and 4th	4.03	6.15553183	0.65469566	216	0.5134
3rd and 4th, 4th and 5th	4.3	7.16705888	0.59996717	197	0.5492
4th and 5th, 5th and 6th	0.13	7.71919875	0.01684113	179	0.9866
5th and 6th, 6th and 7th	13.76	11.7943385	1.16666145	156	0.2451
6th and 7th, 7th and 8th	3.78	12.207714	0.30964028	130	0.7573
7th and 8th, 8th and 9th	5.66	14.244355	0.39735039	111	0.6919
8th and 9th, 9th and 10th	18.13	13.8343979	1.31050156	101	0.193
9th and 10th, 10th and 11th	4.66	8.48417401	0.54925795	88	0.5842
10th and 11th, 11th and 12th	3.01	8.65578293	0.3477444	76	0.729
11th and 12th, 12th and 13th	9.72	16.2238824	0.59911677	70	0.551
12th and 13th, 13th and 14th	8.56	17.1358248	0.49953825	64	0.6191
13th and 14th, 1st and 2nd	2.55	9.76379887	0.26116884	160	0.7943