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Pretrial Release and Failure-To-Appear in McLean County, IL

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Actuarial risk assessment tools increasingly have been employed in jurisdictions across the U.S. to assist courts in the decision of whether someone charged with a crime should be detained or released prior to their trial. These tools should be continually monitored and researched by independent 3rd parties to ensure that these powerful tools are being administered properly and used in the most proficient way as to provide socially optimal results. McLean County, Illinois began using the Public Safety Assessment-Court™ (PSA-Court or simply PSA) risk assessment tool beginning in 2016. This study culls data from the McLean County Jail to test whether the PSA-Court has been successful with respect to Failure To Appear (FTA) in the 2 ½ years since its implementation.

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I. INTRODUCTION

At the end of 2016, the total incarcerated population in the U.S. was 2,162,400, according to a report by the Bureau of Justice Statistics (Kaeble & Cowhig 2018, 2). This is the lowest level that it has been in more than a decade and yet this is still a staggering number of people who are locked up. An estimated 740,700 of the incarcerated population were detained in local jails as of 2016, which is the latest year that this data is available (Kaeble & Cowhig 2018, 13). This is simply looking at one day. If we consider the number of estimated total number of annual admissions for local jails, the number rises to an astonishing 10,900,000. (Minton & Zeng, 2016, 3).

A large proportion of those held in local jails over the last decade are actually not yet even convicted of a crime. Of the 693,400 inmates confined in local jails at the end of 2015, 434,600 of them were unconvicted (Minton & Zeng, 2016). That means the majority of those inmates, (62.68%) in 2015, had not yet been found guilty. "Since 2005, more than 60% of all jail inmates were awaiting court action on a current charge" (Minton & Zeng, 2016). Furthermore, 32% of all the inmates in local jails were being held for non-felony offenses. The overcrowding of jails and the large costs associated with such a large incarcerated population in the U.S. has sparked debate about the need for reform of the jail system and how it can best be achieved (Abrams, 2013).

The criminal justice system in the United States has been experimenting with various pretrial risk assessment instruments ever since the Manhattan Bail Project used a model based on a point system developed by the Vera Institute in 1961 in New York City (Mamalian, 2011;

LowenKamp 2009; Yang, 2017; Christin, Rosenblat, & Boyd, 2015). Pretrial risk assessment instruments have become more popular in jurisdictions across the United States in the last few decades. Proponents argue that the instruments are more fair and objective and that the current bail system discriminates based on wealth.

These new risk assessment tools offer a possible way of remedying the overcrowded jails in the U.S. while being more just at the same time. Not enough studies have been conducted on the results of implementing these risk assessment tools. There is a lack of good research using sound data methods that examine the pretrial decision making process (Bechtel et all, 2017; Cadigan & Lowenkamp, 2011). Advancements in technology, especially the creation of large digital datasets of criminal justice statistics, allow us to complete objective data-based cost-benefit analysis of policy changes (Abrams, 2013; Christin, Rosenblat, & Boyd, 2015). After a policy change, there should be extensive research into the effectiveness of the change.

Much of the current research available is based on legal, criminological, sociological, and/or psychological theory without proper data backing it up (Bushway & Reuter, 2008; Reichert & Gatens, 2018; Abrams, 2013). There is a need for independent, transparent, and verifiable studies on the subject. How these tools are constructed and used should be transparent, accessible, and interpretable by the community that it serves (Eaglin, 2017). Hence, the importance of a continuing revalidation of the risk assessment instruments implemented in local jurisdiction based on local data (and not from a universal dataset). The instruments should be regularly tested to guarantee that the results truly are valid (Pretrial Justice Institute, 2009; Schnacke, 2014, 88).

I hope that this specific study will benefit McLean County and that the county's pretrial services division will continue to work with independent researchers to revalidate the use of the

Public Safety Assessment-Court™ risk assessment instrument for McLean County. I also hope that it can help members of the community in McLean County better understand how pretrial justice decisions are made within their jurisdiction. In this study, I will examine the likelihood that someone who has been released during the pretrial period will appear for their court date. Specifically, I am interested in examining whether the use of the Public Safety Assessment-Court™ in McLean County has resulted in improved odds that someone who is released will appear for their court date.

II. LITERATURE REVIEW

After a person is arrested, they are booked into jail and await their court hearing. Initially, a defendant is given a bond hearing. A judge decides whether or not a defendant can be released from jail during the period before their trial at the bond hearing. To ensure that a person returns for their court hearing, a judge may set a monetary bond that a defendant must pay before being released. The monetary bail system in the U.S. is a legacy from its long history of usage in England (Schnacke, 2014). "Otherwise called pretrial release, bail provides the legal means of allowing a defendant to remain free of state custody while awaiting trial, and to ensure to some degree his or her appearance in court at the commencement of trial" (Lim et al., 2005).

The idea is that a higher bail causes a higher opportunity cost and will act as a deterrent for these failures. The use of an actuarial risk assessment tool is a move away from the monetary bail system. It recommends only using high bail as a deterrent for those who are considered high risk. Using high bail for low risk defendants can be viewed as discriminatory towards the poor because only those who can afford bond are released. It could also be seen as going against the

8^{th} Amendment which states “Excessive bail shall not be required, nor excessive fines imposed,…”. Therefore, “setting bail with a purpose to detain an otherwise bailable defendant would be unconstitutional” (Schnacke, 2014, 59).

This is one of the largest criticisms of using a monetary bail system. It allows those with financial means to pay bail and walk free before their trial while punishing those who are not able to afford it. Rhodes and Matsuba found that the likelihood of posting bail increases with income, even when holding the bail amount constant which “raises questions about whether financial discrimination exists in federal pretrial release practices, the Bail Reform Act notwithstanding” (1984, 703).

Pretrial incarceration is when someone accused of a crime is held the entire time from their arrest until disposition, even though they are presumed innocent until proven otherwise. “The largest issue facing the federal pretrial services system is unnecessary pretrial detention.” (Cadigan & Lowenkamp, 2011). Being in jail is extremely disruptive to people’s everyday lives. A person could lose their job or housing as a result of only a couple of days in jail. The American Bar Association has commented in their Standards of Criminal Justice that “unnecessary detention imposes financial burdens on the community as well as on the defendant” (2007). Additionally, the ABA states that pretrial detention should not be used except if the defendant committed violent or dangerous crimes, poses a risk of failing to appear in court, or poses a risk to the community.

People who are incarcerated before their trial because they cannot afford bail are more likely to accept guilty pleas simply to get out of jail (Human Rights Watch, 2018). William Landes proved empirically that defendants held before their trials were more likely to accept plea bargains because of the higher opportunity costs of going to trial (Landes, 1974). Landes also noted that “defendants not released on bail are likely to have higher conviction probabilities in a trial and receive longer sentences if they settle than defendants released on bail” (1974; 2016). If we view making bail as a function of wealth, then the current bail system discriminates against the poor (Bushway & Reuter, 2008).

When pretrial detention is used as extensively as it has been, it takes away the liberty of thousands of defendants and produces massive expenses and logistical nightmares” (Lowenkamp & Wetzel, 2009). This is why many have advocated that pretrial release should be the norm except for when an individual poses a risk of not appearing to court or poses a risk to the general public. This seems to align with the U.S. Supreme Court’s opinion in the case of *United States vs. Salerno* where the court wrote, “In our society, liberty is the norm, and detention prior to trial or without trial is the carefully limited exception” (Schnacke,2014). In fact, the National Association of Pretrial Services Agencies recommends that:

> **In deciding pretrial release, a presumption in favor of pretrial release on a simple promise to appear (i.e., release on “personal recognizance”) should apply to all persons arrested and charged with a crime. When release on personal recognizance is deemed inappropriate, the judicial officer should assign the least restrictive condition(s) of release that will provide reasonable assurance that the defendant will appear for court proceedings and will protect the safety of the community, victims, and witnesses pending trial. (2004)**

It would seem that releasing more defendants before their trial would be more “fair” and less disruptive for these defendants. Another argument in favor of using pretrial release more extensively is that governments would save the massive amounts of money that it costs to house so many inmates. However, the savings in incarceration costs might not outweigh the increased court costs that would be a result of more defendants going to trial. Defendants are more likely to go to trial if they are released before their trial (Landes, 1974).

Another concern of using pretrial release more extensively is that these defendants might pose a risk to the general public. A pretrial services agency is tasked with evaluating how "risky" a person might be, and then offer the court an assessment. The three desired outcomes of pretrial justice policy is to: 1) maximize public safety, 2) maximize court appearance, and 3) maximize appropriate use of release, supervision, and detention by releasing as many defendants to avoid punishment before conviction (Clark, 2015; Yang 2017).

The assessment will be used by a judge to help determine whether the suspect should be released and on what conditions. According to the National Association of Pretrial Services Agencies, "The assessment and recommendations should be based on an explicit, objective, and consistent policy for evaluating risks and identifying appropriate release options" (NAPSA 2004). This is where pretrial risk assessment instruments come in to play. Risk assessment tools can help pretrial services agencies to predict defendant risk more effectively and thereby improve their recommendation to the court (Lowenkamp & Whetzel, 2009).

Many of the earlier pretrial assessment tools used predictors such as community ties, marriage status, residency, or whether the defendant owned a telephone or car (Mamalian, 2011; Siddiqi, 2002; Cadigan & Lowenkamp, 2011). "Overall, the most common risk factors found in pretrial risk assessment instruments include some combination of (1) current charge, (2) prior convictions, (3) prior incarcerations, (4) pending charges, (4) history of failure to appear, (5) community ties and residential stability, (6) substance abuse, (7) employment and education, and (8) age" (Bechtel et all, 2017). The problem is that some of these predictors can be strongly correlated with income, race, and other measures that shouldn't be considered. Using certain variables such as neighborhood, zip code, education, employment, etc. could end up being proxies for race (Christin, Rosenblat, & Boyd, 2015).

To avoid bias and discrimination, only objective factors should be used by the risk assessment instrument. Interview-dependent factors like employment, drug use, residency status, family situation, and mental health are viewed as biased and have been proven to be less effective at predicting risk than non-interview-based factors like prior convictions and prior failures to appear and thereby make them less effective for public safety (NLADA, 2017; Levin, 2007).

III. THE PSA- Court™ & ITS IMPLEMENTATION IN MCLEAN COUNTY, IL

The Public Safety Assessment is meant to be objective. The Public Safety Assessment-Court™ (PSA-C) was developed by Luminosity Inc. The Public Safety Assessment is "a tool that reliably predicts the risk a given defendant will reoffend, commit violent acts, or fail to come back to court with just nine readily available data points" (LJAF, 2013). It avoids using any factors that could be considered discriminatory; such as income, race, level of education, sex, or residency status (LJAF 2017). According to the Laura and John Arthur Foundation, the PSA only considers objective factors about a defendant, which include:

> **whether the current offense is violent; whether the person has a pending charge at the time of arrest; whether the person has a prior misdemeanor conviction; whether the person has a prior felony conviction; whether the person has a prior conviction for a violent crime; the person's age at the time of arrest; whether the person failed to appear at a pretrial hearing in the last two years; whether the person failed to appear at a pretrial hearing more than two years ago; and whether the person has previously been sentenced to incarceration. (2017).**

The Supreme Court of Illinois ordered a pilot program of the Public Safety Assessment-Court™ for Cook, Kane, McLean counties to be implemented by the Administrative Offices of Illinois Courts, or AOIC (Bonjean, 2016). A financial grant made by the Laura and John Arnold

Foundation supported the initiative. Most courts in Illinois use the Virginia Pretrial Risk Assessment Instrument or the Revised Virginia Risk Assessment (Reichert & Gatens, 2018).

For McLean County, it took nearly a year of preparation for the PSA to be implemented (McGuire & Rizvi, 2016). Since January 11, 2016, a PSA score is assigned to a defendant before every bond hearing in McLean County. The PSA rates a defendant's risk of reoffending, committing violent acts, or failing to appear back for court on a scale of 1 to 6; with 1 being the least risky and 6 being the riskiest. The ultimate decision of whether someone is released pre-trial is still made by the judges. Therefore, the PSA does not take away from judicial discretion, but instead offers judges an objective measurement of a defendant's riskiness that they may use along with their subjective evaluation of a particular case and defendant (LJAF, 2013).

Even though judges still have the final say on whether a defendant is released before trial or not, they are still likely to follow the predictions of the risk assessment tool according to (Christin, Rosenblat, & Boyd, 2015). According to Christin, Rosenblat, & Boyd, "A quantitative assessment provided by a software program generally seems more reliable, scientific, and legitimate than other sources of information, including one's feelings about an offender." (2015). That is why it is so critical that the data and predictions of the actuarial risk assessment tool are accurate.

Abrams and Rohlfs note that "the social cost of inefficiently low levels of bail is considerably higher than the social cost of inefficiently high levels". This essentially means that it would be better for society to err on the side of caution and have bail set too high rather than having it set too low. Schnacke, on the other hand, states that our values of equality freedom necessitate that we take on a certain amount to protect those values, and that "embracing risk requires us to err on the side of release when considering the right to bail" (2014; 7).

Critics of the PSA-Court, and pretrial risk assessment tools in general, have cited high profile cases such as the murder charges against Lamonte Mims in San Francisco. The PSA recommended that Mims be released with supervision on July 11, 2017 (Ho, 2017). Then Mims allegedly shot and killed Edward French only five days after his release. The non-profit that manages the PSA for the San Francisco sheriff's office had entered incorrect information about Mims which had resulted in him receiving a lower risk score (Westervelt, 2017). In a different case in New Jersey, three days after being released, Jules Black allegedly shot and killed Christian Rodgers (Gallo Jr., 2017). Neither of these defendants have been found guilty, but they have been charged with serious crimes. These cases illustrate both the importance of judicial discretion and of accurately administering the data which is used by the PSA. It also demonstrates how high the stakes are for accuracy in a decision about pretrial release.

Obviously these murder cases are tragic, but we must look at whether actuarial risk assessment tools make society safer as a whole. It is very likely that similar tragedies have occurred even before using these tools. So we cannot base the effectiveness of these tools solely on two cases. We need to look at a larger pool of data. According to Knox and Kelfer, "Although not everyone agrees that algorithms are an improvement, they appear to reduce the number of incarcerated individuals pretrial and increase the predictive accuracy of who should remain in jail and who should not." (2017). How have these tools performed within different jurisdictions? What kinds of studies have been conducted on their accuracy and effectiveness?

There are a number of well-conducted studies that evaluate actuarial risk assessment tools. "However, strong conclusions cannot be made as the quality of the pretrial research, overall, is weak at best" (Bechtel et all, 2017). According to survey results of different jurisdictions, 48% of pretrial programs have never validated their instruments (Mamalian, 2011).

More research must be conducted in order to constantly update these tools and ensure that they are used toward their best application (Schnacke, 2014, 88). Unfortunately there is no standard method of testing whether an actuarial risk assessment tool has been successful or not (Mamalian, 2011). However, I will try to use some of the best practices outlined in previous studies on the topic to create my model.

IV. THEORETICAL FRAMEWORK

The basic theoretical hypothesis is that after implementing the PSA, McLean County, IL should have experienced an increase in the number of pretrial releases and simultaneously see an equivalent amount or reduction of Failures To Appear in court.

The goal of the PSA is to keep high-risk defendants in jail, but release those who are low-risk. If it works, then there should be a reduction in the number of failures to appear and new criminal activity after the implementation of the PSA. In July 2013, all 120 counties in Kentucky began using the Public Safety Assessment-Court™ (LJAF, 2014). Six months after Kentucky's implementation of the PSA, more defendants were being released from jail during the pretrial and there was simultaneously an almost 15% reduction of the crime rate for those on pretrial release according to the Laura and John Arnold Foundation (2014). This initial evidence suggests that the PSA has been successful at recommending release for those who are low-risk and recommending pretrial detention for those who are high-risk of committing new crimes while on pretrial release. Furthermore, the tool proved to be objective in regards to both race and gender (LJAF, 2014). I would like to see whether McLean County has seen a similar reduction with regards to the number of defendants who fail to appear in court after the Public Safety Assessment-Court™ has been used for two and a half years.

One of the main goals of the PSA is to recommend detention for those who are high-risk of failing to appear to their court date. The hypothesis to be tested is whether less people failed to appear to their court date after the implementation of the PSAs in order to determine the effectiveness of PSAs. Toborg et al found that less restrictive release conditions that allowed for more pretrial releases did not cause an increase in rates of pretrial misconduct, and FTA rates were actually lower after introducing less restrictive release conditions (1984).

My main motivation is to discover whether the use of PSAs has accomplished its stated goals. I would like to measure the effects that PSAs have had (if any) on the amount of defendants who miss court appearances. Have more defendants been released before their trials? Has there been a reduction in the number or proportion of Failures To Appear. Measuring the effectiveness of the PSAs will help add to the literature on bail policy and provide the McLean County Criminal Justice Coordinated Council with valuable information that they can use when making policy decisions. My hypothesis is that after implementation of the PSAs, less people failed to appear to their trial dates. This is one way to determine the effectiveness of PSAs.

V. EMPIRICAL MODEL

I am interested in estimating the probability of whether someone fails to appear to a court hearing after they are released on bond. Because the dependent variable Failure To Appear (FTA) is binary, I will be using a logit model. This eliminates the problems faced by a linear probability model. Namely, a linear probability model might predict negative values or values that are larger than 1.

The predicted values for the logit model will be between 0 and 1, which is desirable for a model with probability. P(FTA = 1|X) is the probability that someone fails to appear to a court hearing, given certain defendant characteristics. P(FTA = 0|X) is the probability that someone does appear at their court hearing, given certain defendant characteristics.

$$P_i = E(FTA = 1|X_i) = \frac{1}{1+\exp[-(\beta 1+ \beta 2Xi]}$$

$$P_i = E(FTA = 0|X_i) = \frac{1}{1+\exp[(\beta 1+ \beta 2Xi]}$$

Taking the natural log of the ratio of these two equations gives us the logit model that I am trying to estimate.

$$L_i = \ln [P_i / (1 – P_i)] = \beta_1 + \beta_2 X_i$$

I will look at the goodness of fit of the model by calculating the percentage correctly predicted. The predicted values will be assigned $\hat{y} = 1$ if $\hat{y} \geq .48$ and $\hat{y} = 0$ if $\hat{y} < .48$. Then these results will be compared to the sample values to see the percentage predicted correctly. If this does not produce a high goodness of fit, the model can be adjusted so that $\hat{y} = 1$ is calculated at a different threshold value.

VI. DATA

The data I will use for this study is data from the Electronic Justice System or EJS by TRW (Dingle-Gold, 1998). The Stevenson at ISU has access to certain information from McLean County within EJS through its work with the McLean County Criminal Justice Coordinated Council. The dataset was created using convictions for misdemeanors and felonies for the years 2002 – June 2018. This means that all charges lesser than a misdemeanor are excluded (traffic violations, civil ordinance violations, etc). Also, only charges that resulted in a guilty disposition are included. This means that I am only looking at those who have been convicted. Also, only defendants who have been released during the pretrial period are included in the sample, because obviously a defendant will show up to court if they are detained in jail prior to their court appearance. They have no choice but to appear. This resulted in 14,707 observations for January 2002 – June 2018.

The independent variables of defendant characteristics that are available through the Stevenson Center's work with McLean County will be used in the model. They are listed in Table 1 below. The variable mental illness is based on whether defendants have self-reported having mental illness issues at the time of their booking into jail or if law enforcement officers have noted behavior typical of mental illness. The rest of the variables are explained sufficiently well in Table 1 below.

Table 1.

FTA	**(Dependent Variable) Dummy variable for failure to appear. 1 = failed to appear**
Bond_Amount	The dollar amount of bond required
Number_Counts	The number of counts charged in the defendant's case
Mental_Illness	Whether someone has been flagged as mentally ill by police, jail staff, or self-reported. 1 = Mental Illness
Age	Age at the time of booking
Post_PSA	Dummy variable where 1 = time period after Jan. 11, 2016
Violent	Dummy variable where 1 = current charge is violent
Drug	Dummy variable where 1 = current charge is a drug related charge
Priors	The number of prior misdemeanor or felony convictions
Probation	Dummy variable where 1 = Defendant is currently on probation
Class_X_Felony	Dummy variable where 1 = Current charge is a Class X felony
Class_1_Felony	Dummy variable where 1 = Current charge is a Class 1 felony
Class_2_Felony	Dummy variable where 1 = Current charge is a Class 2 felony
Class _3_Felony	Dummy variable where 1 = Current charge is a Class 3 felony
Class_4_Felony	Dummy variable where 1 = Current charge is a Class 4 felony
DUI	Dummy variable where 1 = Current charge is a DUI charge
Prior_FTA	The number of prior Failures To Appear in court
Prior_Drug	The number of prior drug charges
Prior_Violent	The number of prior violent charges
Black	Dummy variable where 1 = black
Hispanic	Dummy variable where 1 = hispanic
Asian	Dummy variable where 1 = asian
Male	Dummy variable where 1 = male

VII. RESULTS

I will run both a logit and probit model in order to estimate the effect of PSAs on the probability that someone will fail to appear in court. The results of the logit regression will be reported in both odds ratios and coefficients. The results of running a maximum likelihood estimation of the logit model with FTA as the binary dependent variable are reported in Table 2 below.

Column 1 shows the results in coefficient form. The odds ratios are reported in column 1. The coefficients listed in column 2 represent the partial effects at the average. All the variables are found to be significant except for variables Number_Counts, Drug and Priors. We would expect priors to be significant, but perhaps it is not significant because the vast majority (14,689) within the sample had no prior felony or misdemeanor charges. The most important result is that the coefficient on the dummy Post_PSA is negative and highly significant. The odds ratio is .78, which indicates that defendants are 78% less likely to miss their court dates after the PSA was implemented, when holding all other variables constant. This implies that in the period after PSAs were implemented less people missed their court dates.

This evidence supports the hypothesis that PSAs have decreased the amount of people failing to appear to their court dates. The probability of 78% seems high compared to other studies. For example, Levin found that "the odds of a defendant failing to appear for defendants in counties that utilize quantitative risk assessments are 0.40 times lower than the odds of a defendant failing to appear for defendants in counties that utilize qualitative risk assessments." (Levin, 2007). The .648 odds ratio on the Violent variable indicates that those with current violent charges are more likely to appear for their court dates. This is in line with Cadigan and Lowenkamp's findings "that violent defendants in fact perform better than most other defendants in terms of re-arrest, failure-to-appear, and technical violations leading to revocation of pretrial release." (2011).

The results, if we assume normality and estimate using the probit model, are reported in column 3. Most of the estimated coefficients have the same signs and significance levels as those from the logit model.

Table 2.

	(1)	(2)	(3)
VARIABLES	Logit Odds Ratio	Logit Coefficient	Probit
Bond_Amount	1.000***	-3.94e-06***	-2.25e-06***
	(1.31e-06)	(1.32e-06)	(7.20e-07)
Number_Counts	1.011	0.0113	0.00630
	(0.0148)	(0.0146)	(0.00847)
Mental_Illness	1.479***	0.391***	0.236***
	(0.0817)	(0.0552)	(0.0333)
Age	0.997*	-0.00333*	-0.00181*
	(0.00171)	(0.00172)	(0.00102)
Post_PSA	0.781***	-0.247***	-0.144***
	(0.0381)	(0.0488)	(0.0289)
Violent	0.648***	-0.433***	-0.249***
	(0.0821)	(0.127)	(0.0718)
Drug	1.061	0.0593	0.0349
	(0.125)	(0.117)	(0.0669)
Priors	0.934	-0.0686	-0.0468
	(0.113)	(0.121)	(0.0728)
Probation	1.701***	0.531***	0.329***
	(0.242)	(0.142)	(0.0879)
Class_X_Felony	0.193***	-1.646***	-0.910***
	(0.0641)	(0.332)	(0.169)
Class_1_Felony	0.287***	-1.249***	-0.724***
	(0.0659)	(0.230)	(0.125)
Class_2_Felony	0.417***	-0.875***	-0.511***
	(0.0530)	(0.127)	(0.0717)
Class_3_Felony	0.641***	-0.445***	-0.267***
	(0.0578)	(0.0903)	(0.0528)
Class_4_Felony	0.587***	-0.532***	-0.317***
	(0.0453)	(0.0772)	(0.0450)
DUI	0.755***	-0.281***	-0.174***
	(0.0506)	(0.0670)	(0.0396)
Prior_FTA	1.085***	0.0813***	0.0498***
	(0.00515)	(0.00474)	(0.00284)
Prior_Drug	0.672***	-0.398***	-0.216***
	(0.0842)	(0.125)	(0.0650)
Prior_Violent	0.815***	-0.205***	-0.113***
	(0.0600)	(0.0736)	(0.0385)
Black	1.701***	0.531***	0.320***
	(0.0678)	(0.0399)	(0.0240)
Hispanic	3.205***	1.165***	0.710***
	(0.247)	(0.0772)	(0.0472)
Asian	1.061	0.0596	0.0488
	(0.267)	(0.251)	(0.146)
Male	0.954	-0.0469	-0.0264
	(0.0438)	(0.0459)	(0.0277)
Constant	0.375***	-0.980***	-0.611***
	(0.0272)	(0.0724)	(0.0433)
Observations	14,714	14,707	14,707

seEform in parentheses

*** p<0.01, ** p<0.05, * p<0.1

When putting this dataset together, by far the greatest challenge (and there were many) was determining who was released pretrial. There was not a variable already constructed, so I had to create one (along with many of the other variables). I ran into hardships verifying who was and who was not released pretrial with such a large dataset. So after much trial and error, I created two separate datasets. The results in Table 1 are from the first dataset that I created with a variable that I called Pretrial.Release.Final and consisted of 14,689 different cases. This was based on information that I received indicating that pretrial release could be verified in two ways: 1) if a Case.Person.ID is present in the Case_People dataset, but not present in the Sentences dataset or 2) if the Case.Person.ID was present in both datasets, then the release date and sentence start date should be checked. However, this required switching from using Case.Person.ID to Booking.ID and checking on a case by case basis, which would have been highly impractical for the amount of cases in the dataset.

I was not convinced that my 1st dataset captured all the cases where someone was released before their trial. So I created a second dataset using a variable I created which I called Pretrial.Release.5. The second dataset that I created used the original 14,689 cases and added cases based on their Release_Type_Codes. This was my attempt at creating a dataset that include all cases where the defendant was released before their trial. This seemed like a reasonable workaround to going through hundreds of thousands of cases one by one to determine pretrial release.

This resulted in 59,531 cases under this expanded definition of pretrial release. This equals roughly 10% of the cases which seemed like a more reasonable estimate. The results of running the Logit and Probit regressions using this larger dataset is shown below in Table 3.

Table 3.

VARIABLES	(1) Logit Odds Ratio	(2) Logit Coefficient	(3) Probit
FTA			
Bond_Amount	1.000	-1.31e-07	-8.14e-08
	(1.99e-07)	(1.99e-07)	(1.12e-07)
Number_Counts	0.982***	-0.0179***	-0.0105***
	(0.00598)	(0.00609)	(0.00358)
Mental_Illness	1.678***	0.518***	0.312***
	(0.0466)	(0.0278)	(0.0169)
Age	0.996***	-0.00405***	-0.00234***
	(0.000867)	(0.000870)	(0.000524)
Post_PSA	0.479***	-0.737***	-0.434***
	(0.0145)	(0.0303)	(0.0176)
Violent	1.076	0.0736	0.0387
	(0.0571)	(0.0531)	(0.0318)
Drug	0.841***	-0.173***	-0.102***
	(0.0383)	(0.0455)	(0.0268)
Priors	0.891***	-0.116***	-0.0664***
	(0.00915)	(0.0103)	(0.00609)
Probation	1.520***	0.419***	0.244***
	(0.0305)	(0.0201)	(0.0120)
Class_X_Felony	0.524***	-0.647***	-0.378***
	(0.0577)	(0.110)	(0.0629)
Class_1_Felony	0.550***	-0.598***	-0.354***
	(0.0433)	(0.0787)	(0.0459)
Class_2_Felony	0.633***	-0.457***	-0.272***
	(0.0313)	(0.0494)	(0.0291)
Class_3_Felony	0.749***	-0.289***	-0.170***
	(0.0300)	(0.0400)	(0.0238)
Class_4_Felony	0.867***	-0.142***	-0.0855***
	(0.0296)	(0.0341)	(0.0204)
DUI	1.291***	0.256***	0.150***
	(0.0341)	(0.0264)	(0.0161)
Prior_FTA	1.173***	0.160***	0.0929***
	(0.00402)	(0.00343)	(0.00190)
Prior_Drug	0.715***	-0.335***	-0.184***
	(0.0397)	(0.0554)	(0.0303)
Prior_Violent	0.820***	-0.198***	-0.107***
	(0.0308)	(0.0375)	(0.0208)
Black	2.026***	0.706***	0.430***
	(0.0409)	(0.0202)	(0.0122)
Hispanic	1.811***	0.594***	0.364***
	(0.0750)	(0.0414)	(0.0253)
Asian	0.568***	-0.566***	-0.322***
	(0.0729)	(0.128)	(0.0722)
Male	1.040*	0.0396*	0.0217*
	(0.0224)	(0.0215)	(0.0130)
Constant	0.314***	-1.158***	-0.702***
	(0.0119)	(0.0380)	(0.0228)
Observations	59,531	59,531	59,531

The results are mostly similar to those of the smaller dataset. However, some of the distinct differences when using this larger dataset are that Number_Counts was found to be highly significant, Violent has changed signs to positive and is no longer significant, Drug is now highly significant, and Priors is now highly significant, Asian is now highly significant, and Male has changed signs to negative and is now significant.

I also checked the marginal effects after running the probit regression. The results are shown in Stata's output in Figure 1 below.

Figure 1.

```
. margins, dydx(*)

Average marginal effects                          Number of obs     =     59,531
Model VCE    : OIM

Expression   : Pr(FTA), predict()
dy/dx w.r.t. : Bond_Amount Number_Counts Mental_Illness Age Post_PSA Violent Drug Priors Probation Class_X_Felony Class_1_Felony
               Class_2_Felony Class_3_Felony Class_4_Felony DUI Prior_FTA Prior_Drug Prior_Violent Black Hispanic Asian Male
```

	dy/dx	Delta-method Std. Err.	z	P>|z|	[95% Conf.	Interval]
Bond_Amount	-2.82e-08	3.89e-08	-0.72	0.469	-1.04e-07	4.81e-08
Number_Counts	-.0036181	.0012379	-2.92	0.003	-.0060444	-.0011918
Mental_Illness	.1081019	.0057966	18.65	0.000	.0967408	.119463
Age	-.0008087	.0001814	-4.46	0.000	-.0011642	-.0004531
Post_PSA	-.1502748	.0059999	-25.05	0.000	-.1620344	-.1385152
Violent	.0134133	.0110018	1.22	0.223	-.0081498	.0349763
Drug	-.03537	.0092787	-3.81	0.000	-.0535559	-.017184
Priors	-.0229819	.0021024	-10.93	0.000	-.0271025	-.0188612
Probation	.0844857	.0041161	20.53	0.000	.0764183	.0925531
Class_X_Felony	-.1307564	.0217399	-6.01	0.000	-.1733658	-.088147
Class_1_Felony	-.1226208	.0158804	-7.72	0.000	-.1537458	-.0914957
Class_2_Felony	-.0941135	.0100544	-9.36	0.000	-.1138198	-.0744072
Class_3_Felony	-.0588835	.00823	-7.15	0.000	-.075014	-.0427531
Class_4_Felony	-.0295828	.0070545	-4.19	0.000	-.0434093	-.0157563
DUI	.0518696	.0055671	9.32	0.000	.0409582	.0627809
Prior_FTA	.0321602	.0006205	51.83	0.000	.0309441	.0333764
Prior_Drug	-.0636604	.0104809	-6.07	0.000	-.0842025	-.0431182
Prior_Violent	-.0371951	.007185	-5.18	0.000	-.0512774	-.0231127
Black	.148743	.0041066	36.22	0.000	.1406942	.1567917
Hispanic	.1259766	.0087267	14.44	0.000	.1088726	.1430806
Asian	-.111411	.0249974	-4.46	0.000	-.160405	-.0624171
Male	.0075235	.0045107	1.67	0.095	-.0013173	.0163643

One way to measure the effectiveness of this model is to examine the percent predicted correctly for the failure to appear variable FTA. After taking the predicted values and using the stipulation that $\widehat{\mathrm{FTA}} = 1$ if $\widehat{\mathrm{FTA}} \geq .48$, and $\widehat{\mathrm{FTA}} = 0$ if $\widehat{\mathrm{FTA}} < .48$, we can evaluate how often the model predicted correctly. The model predicted failure to appear correctly 68.2% of the time when using the first dataset. When using the expanded dataset, this bumps up but only by 1.1%. This is shown by the mean of the variable PredictedCorrect in Figure 1 below. The variable was constructed as: PredictedCorrect = 1

if $\widehat{FTA} \geq .48$ and FTA = 1

if $\widehat{FTA} < .48$ and $FTA = 0$

Figure 2. (Output from STATA showing the Predicted Correct variable when using the larger Pretrial.Release.5 dataset)

Variable	Obs	Mean	Std. Dev.	Min	Max
PredictedC~t	59,553	.6820143	.4656978	0	1

Figure 3. (Output from STATA showing the Predicted Correct variable using the smaller Pretrial.Release.Final Dataset)

Variable	Obs	Mean	Std. Dev.	Min	Max
PredictedC~t	14,729	.6931903	.4611854	0	1

This seems like decent accuracy around 70%. Especially considering that, "The National Institute of Corrections reports that the new recidivism predictors generally have a 73 percent accuracy rate, which is a significant improvement over a 55 percent accuracy rate when largely using judicial discretion alone" (Knox & Kelfer, 2017). This is close to Cadigan, Johnson, and Lowenkamp's results of a validation for Failure To Appear/New Criminal Activity of about .69 (2012). But that still leaves much to be desired, if 30% of the time the model is inaccurate.

VIII. SHORTCOMINGS

I realize that there are several shortcomings in this study. Firstly, there is some uncertainty on how to verify if the pretrial release is measured correctly. This is something that can continue to be honed and perfected. I think that this original study was a good initial step into constructing an accurate binary variable of pretrial release which can be used as a filter.

Another shortcoming of this model is that it only predicts correctly 68 - 69% of the time. Apparently, this is pretty close to the average for similar studies, but improvement is needed. Also the dataset could be expanded to charges that do not result in a conviction, because it is still possible that someone fails to appear to court even if the trial does not eventually result in a conviction. Although this model was limited, it proved to be a good initial study of the probability that a person fails to appear to court given certain defendant characteristics.

IX. RECOMMENDATIONS

McLean County already monitors its pretrial services better than most jurisdictions. According to Clark & Henry, "45 percent of pretrial programs (N = 178) report that they do not calculate FTA rates." (2003). Around 75% of the programs that do calculate FTA do so only for those under pretrial supervision (Clark & Henry, 2003).

The Stevenson Center of Illinois State University should continue its partnership with the McLean County Criminial Justice Coordinating Council and continue to study and monitor the results of using the PSA. I think that the Stevenson Center should continue close collaboration with McLean County's Pretrial Services Unit in order to verify results and revalidate the usage of an actuarial risk assessment tool. This study focused only on the PSA's effect on Failures To Appear, but its effect on New Criminal Activity by those released before their trial should also be examined.

X. CONCLUSION

This initial study of the first 2 ½ years of using the PSA indicated positive results showing that defendants are less likely to miss their court dates by as much as 78% (when all other variables remain constant). Levin found that counties using quantitative risk assessments had 40% lowers odds of a defendant Failing To Appear (2007). So my results of close of 78%, seem higher than expected. Of course, these initial results should be tested and verified to ensure accuracy. The reduction in the probability of Failure To Appear after implementation of the PSA in McLean County suggest that the PSA has been successful in this regard. The results indicate that the PSA should continue to be administered in McLean County and continue to be monitored.

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XII. APPENDIX

I have included summary descriptive statistics in the Appendix for the sake of transparency. It will also allow for me to work with other researchers and data experts to further study the PSA in McLean County and create more accurate results in the future.

These are the graphics for the smaller dataset. The smaller dataset is created by using the filter of (Select If Pretrial.Release.Final = 1). The smaller dataset makes up 14,729 unique Case.Person.IDs. There are 10,602 unique Person.IDs and 4,127 duplicates (repeat offenders). The following tables are outputs from SPSS.

Statistics

Indicator of each last matching case as Primary

N	Valid	14729
	Missing	0

Indicator of each last matching case as Primary

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Duplicate Case	4127	28.0	28.0	28.0
	Primary Case	10602	72.0	72.0	100.0
	Total	14729	100.0	100.0	

Showing the Mean, Standard Error of Mean, Median, Std. Deviation, Variance, Skewness, Kurtosis.

Report

	Original. Bond.Amount	Bond.Amount	Number. Counts	Charge Severity	Mental. Illness.2_max	Age	Pretrial. Release.5	Pretrial. Release.Final	Post.PSA	Violent	Drug	FTA
N	11857	14716	14729	14729	14729	14729	14729	14729	14729	14729	14729	14727
Mean	6612.27	11782.31	2.0118	7.1695	.1318	30.7966	1.0000	1.0000	.2042	.0487	.0595	.3100
Std. Error of Mean	689.167	1102.289	.01555	.01152	.00279	.09330	.00000	.00000	.00332	.00177	.00195	.00381
Median	1000.00	1500.00	1.0000	8.0000	.0000	27.0000	1.0000	1.0000	.0000	.0000	.0000	.0000
Std. Deviation	75043.341	133718.194	1.88756	1.39864	.33834	11.32312	.00000	.00000	.40310	.21520	.23665	.46250
Variance	5631503004	1.788E+10	3.563	1.956	.114	128.213	.000	.000	.162	.046	.056	.214
Skewness	53.595	47.117	5.353	-1.787	2.177	1.052	.	.	1.468	4.195	3.723	.822
Kurtosis	3395.240	2814.658	57.264	2.601	2.738	.651	.	.	.155	15.599	11.863	-1.325

Report

	Priors	Probation	Class.M. Felony	Class.X. Felony	Class.1. Felony	Class.2. Felony	Class.3. Felony	Class.4. Felony	DUI	Misdemeanor	Prior.FTA	Prior.Drug	Prior.Violent
N	14729	14729	14729	14729	14729	14729	14729	14729	14729	14729	14727	14729	14729
Mean	.0066	.0153	.0005	.0143	.0155	.0386	.0636	.1051	.1082	.6542	2.5086	.0299	.0502
Std. Error of Mean	.00125	.00101	.00018	.00098	.00102	.00159	.00201	.00253	.00256	.00392	.03250	.00216	.00369
Median	.0000	.0000	.0000	.0000	.0000	.0000	.0000	.0000	.0000	1.0000	1.0000	.0000	.0000
Std. Deviation	.15202	.12292	.02180	.11883	.12372	.19256	.24408	.30669	.31067	.47566	3.94408	.26224	.44754
Variance	.023	.015	.000	.014	.015	.037	.060	.094	.097	.226	15.556	.069	.200
Skewness	29.115	7.887	45.843	8.175	7.832	4.793	3.576	2.576	2.522	-.648	2.512	13.107	12.622
Kurtosis	966.316	60.209	2099.857	64.843	59.355	20.979	10.791	4.634	4.364	-1.580	8.374	242.145	196.046

The following tables show descriptive statistics for the different variables used in this study.

Charge Severity

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Criminal Felony Class M	7	.0	.0	.0
	Criminal Felony Class X	211	1.4	1.4	1.5
	Criminal Felony Class 1	229	1.6	1.6	3.0
	Criminal Felony Class 2	568	3.9	3.9	6.9
	Criminal Felony Class 3	937	6.4	6.4	13.3
	Criminal Felony Class 4	1548	10.5	10.5	23.8
	DUI	1594	10.8	10.8	34.6
	Criminal Misdemeanor	9635	65.4	65.4	100.0
	Total	14729	100.0	100.0	

Race.Race.Code

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	A	88	.6	.6	.6
	B	5657	38.4	38.4	39.0
	H	832	5.6	5.6	44.7
	I	14	.1	.1	44.7
	U	45	.3	.3	45.1
	W	8093	54.9	54.9	100.0
	Total	14729	100.0	100.0	

Sex.Sex.Code

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	F	3095	21.0	21.0	21.0
	M	11634	79.0	79.0	100.0
	Total	14729	100.0	100.0	

Mental.Illness.2_max

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	.00	12787	86.8	86.8	86.8
	1.00	1942	13.2	13.2	100.0
	Total	14729	100.0	100.0	

Age

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	17.00	148	1.0	1.0	1.0
	18.00	588	4.0	4.0	5.0
	19.00	953	6.5	6.5	11.5
	20.00	1034	7.0	7.0	18.5
	21.00	940	6.4	6.4	24.9
	22.00	781	5.3	5.3	30.2
	23.00	676	4.6	4.6	34.8
	24.00	672	4.6	4.6	39.3
	25.00	599	4.1	4.1	43.4
	26.00	529	3.6	3.6	47.0
	27.00	519	3.5	3.5	50.5
	28.00	397	2.7	2.7	53.2
	29.00	427	2.9	2.9	56.1
	30.00	401	2.7	2.7	58.8
	31.00	381	2.6	2.6	61.4
	32.00	336	2.3	2.3	63.7
	33.00	350	2.4	2.4	66.1
	34.00	347	2.4	2.4	68.4

	35.00	297	2.0	2.0	70.4
	36.00	300	2.0	2.0	72.5
	37.00	291	2.0	2.0	74.5
	38.00	275	1.9	1.9	76.3
	39.00	263	1.8	1.8	78.1
	40.00	248	1.7	1.7	79.8
	41.00	248	1.7	1.7	81.5
	42.00	240	1.6	1.6	83.1
	43.00	230	1.6	1.6	84.7
	44.00	208	1.4	1.4	86.1
	45.00	217	1.5	1.5	87.5
	46.00	172	1.2	1.2	88.7
	47.00	227	1.5	1.5	90.3
	48.00	166	1.1	1.1	91.4
	49.00	140	1.0	1.0	92.3
	50.00	135	.9	.9	93.3
	51.00	120	.8	.8	94.1
	52.00	118	.8	.8	94.9
	53.00	83	.6	.6	95.4
	54.00	86	.6	.6	96.0
	55.00	66	.4	.4	96.5
	56.00	58	.4	.4	96.9
	57.00	56	.4	.4	97.2
	58.00	67	.5	.5	97.7
	59.00	61	.4	.4	98.1
	60.00	23	.2	.2	98.3
	61.00	35	.2	.2	98.5
	62.00	39	.3	.3	98.8
	63.00	32	.2	.2	99.0
	64.00	24	.2	.2	99.1
	65.00	28	.2	.2	99.3
	66.00	10	.1	.1	99.4
	67.00	8	.1	.1	99.5
	68.00	15	.1	.1	99.6
	69.00	11	.1	.1	99.6
	70.00	16	.1	.1	99.7
	71.00	7	.0	.0	99.8
	72.00	5	.0	.0	99.8

	73.00	5	.0	.0	99.9
	74.00	3	.0	.0	99.9
	75.00	2	.0	.0	99.9
	76.00	2	.0	.0	99.9
	77.00	2	.0	.0	99.9
	78.00	3	.0	.0	99.9
	79.00	4	.0	.0	100.0
	82.00	1	.0	.0	100.0
	85.00	1	.0	.0	100.0
	86.00	1	.0	.0	100.0
	88.00	2	.0	.0	100.0
	Total	14729	100.0	100.0	

Pretrial.Release.5

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	1.00	14729	100.0	100.0	100.0

Pretrial.Release.Final

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	1.00	14729	100.0	100.0	100.0

Post.PSA

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	.00	11722	79.6	79.6	79.6
	1.00	3007	20.4	20.4	100.0
	Total	14729	100.0	100.0	

Violent

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	.00	14012	95.1	95.1	95.1
	1.00	717	4.9	4.9	100.0
	Total	14729	100.0	100.0	

Drug

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	.00	13852	94.0	94.0	94.0
	1.00	877	6.0	6.0	100.0
	Total	14729	100.0	100.0	

FTA

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	.00	10162	69.0	69.0	69.0
	1.00	4565	31.0	31.0	100.0
	Total	14727	100.0	100.0	
Missing	System	2	.0		
Total		14729	100.0		

Priors

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	.00	14689	99.7	99.7	99.7
	1.00	17	.1	.1	99.8
	2.00	7	.0	.0	99.9
	3.00	7	.0	.0	99.9
	4.00	3	.0	.0	100.0
	5.00	4	.0	.0	100.0
	6.00	1	.0	.0	100.0
	7.00	1	.0	.0	100.0
	Total	14729	100.0	100.0	

Probation

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	.00	14503	98.5	98.5	98.5
	1.00	226	1.5	1.5	100.0
	Total	14729	100.0	100.0	

Class.M.Felony

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	.00	14722	100.0	100.0	100.0
	1.00	7	.0	.0	100.0
	Total	14729	100.0	100.0	

Class.X.Felony

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	.00	14518	98.6	98.6	98.6
	1.00	211	1.4	1.4	100.0
	Total	14729	100.0	100.0	

Class.1.Felony

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	.00	14500	98.4	98.4	98.4
	1.00	229	1.6	1.6	100.0
	Total	14729	100.0	100.0	

Class.2.Felony

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	.00	14161	96.1	96.1	96.1
	1.00	568	3.9	3.9	100.0
	Total	14729	100.0	100.0	

Class.3.Felony

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	.00	13792	93.6	93.6	93.6
	1.00	937	6.4	6.4	100.0
	Total	14729	100.0	100.0	

Class.4.Felony

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	.00	13181	89.5	89.5	89.5
	1.00	1548	10.5	10.5	100.0
	Total	14729	100.0	100.0	

DUI

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	.00	13135	89.2	89.2	89.2
	1.00	1594	10.8	10.8	100.0
	Total	14729	100.0	100.0	

Misdemeanor

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	.00	5094	34.6	34.6	34.6
	1.00	9635	65.4	65.4	100.0
	Total	14729	100.0	100.0	

Prior.FTA

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	.00	6612	44.9	44.9	44.9
	1.00	2163	14.7	14.7	59.6
	2.00	1323	9.0	9.0	68.6
	3.00	979	6.6	6.6	75.2
	4.00	742	5.0	5.0	80.3
	5.00	589	4.0	4.0	84.3
	6.00	456	3.1	3.1	87.3
	7.00	383	2.6	2.6	90.0
	8.00	288	2.0	2.0	91.9
	9.00	230	1.6	1.6	93.5
	10.00	170	1.2	1.2	94.6
	11.00	175	1.2	1.2	95.8
	12.00	93	.6	.6	96.4
	13.00	114	.8	.8	97.2
	14.00	87	.6	.6	97.8
	15.00	65	.4	.4	98.2
	16.00	35	.2	.2	98.5
	17.00	60	.4	.4	98.9
	18.00	37	.3	.3	99.1
	19.00	28	.2	.2	99.3
	20.00	27	.2	.2	99.5
	21.00	22	.1	.1	99.7
	22.00	7	.0	.0	99.7
	23.00	3	.0	.0	99.7
	24.00	12	.1	.1	99.8
	25.00	6	.0	.0	99.9
	26.00	5	.0	.0	99.9
	27.00	3	.0	.0	99.9
	30.00	5	.0	.0	99.9
	33.00	2	.0	.0	100.0
	34.00	2	.0	.0	100.0
	35.00	2	.0	.0	100.0
	36.00	2	.0	.0	100.0
	Total	14727	100.0	100.0	
Missing	System	2	.0		

Total	14729	100.0		

Prior.Drug

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	.00	14461	98.2	98.2	98.2
	1.00	162	1.1	1.1	99.3
	2.00	66	.4	.4	99.7
	3.00	28	.2	.2	99.9
	4.00	6	.0	.0	100.0
	5.00	3	.0	.0	100.0
	7.00	1	.0	.0	100.0
	8.00	2	.0	.0	100.0
	Total	14729	100.0	100.0	

Prior.Violent

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	.00	14433	98.0	98.0	98.0
	1.00	127	.9	.9	98.9
	2.00	63	.4	.4	99.3
	3.00	39	.3	.3	99.5
	4.00	27	.2	.2	99.7
	5.00	17	.1	.1	99.8
	6.00	7	.0	.0	99.9
	7.00	6	.0	.0	99.9
	8.00	2	.0	.0	99.9
	9.00	5	.0	.0	100.0
	10.00	2	.0	.0	100.0
	11.00	1	.0	.0	100.0
	Total	14729	100.0	100.0	

The following tables show descriptive statistics for the larger dataset that was created using the variable Pretrial.Release.5. Of the 59,553 unique Case.Person.IDs, there are 34,426 unique Person.IDs and 25,127 duplicate Person.IDs (returning inmates).

Frequencies

Statistics

Indicator of each last matching case as Primary

N	Valid	59553
	Missing	0

Indicator of each last matching case as Primary

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Duplicate Case	25127	42.2	42.2	42.2
	Primary Case	34426	57.8	57.8	100.0
	Total	59553	100.0	100.0	

Shows the Mean, Median, Standard Deviation, Variance, skewness, & kurtosis.

Report

	Original. Bond.Amount	Bond.Amount	Number. Counts	Charge Severity	Mental. Illness.2_max	Age	Pretrial. Release.5	Pretrial. Release.Final	Post.PSA	Violent	Drug	FTA
N	47697	59534	59553	59553	59553	59553	59553	59553	59553	59553	59553	59551
Mean	5770.93	7531.00	2.3671	7.0042	.1220	29.3000	1.0000	.2473	.1250	.0436	.0790	.3617
Std. Error of Mean	290.042	289.368	.00800	.00577	.00134	.04433	.00000	.00177	.00136	.00084	.00111	.00197
Median	1500.00	1500.00	2.0000	8.0000	.0000	25.0000	1.0000	.0000	.0000	.0000	.0000	.0000
Std. Deviation	63344.055	70604.619	1.95187	1.40821	.32724	10.81914	.00000	.43146	.33072	.20411	.26972	.48049
Variance	4012469327	4985012256	3.810	1.983	.107	117.054	.000	.186	.109	.042	.073	.231
Skewness	106.506	80.829	3.577	-1.484	2.311	1.208	.	1.171	2.268	4.473	3.122	.576
Kurtosis	14705.080	9009.780	26.038	1.561	3.339	.955	.	-.628	3.143	18.005	7.747	-1.669

Report

	Priors	Probation	Class.M. Felony	Class.X. Felony	Class.1. Felony	Class.2. Felony	Class.3. Felony	Class.4. Felony	DUI	Misdemeanor	Prior.FTA	Prior.Drug	Prior.Violent
N	59553	59553	59553	59553	59553	59553	59553	59553	59553	59553	59550	59553	59553
Mean	.3420	.6075	.0002	.0110	.0195	.0478	.0731	.1186	.1831	.5467	1.8828	.0241	.0290
Std. Error of Mean	.00404	.00200	.00006	.00043	.00057	.00087	.00107	.00132	.00158	.00204	.01341	.00093	.00128
Median	.0000	1.0000	.0000	.0000	.0000	.0000	.0000	.0000	.0000	1.0000	.0000	.0000	.0000
Std. Deviation	.98560	.48832	.01477	.10445	.13814	.21336	.26032	.32330	.38674	.49782	3.27143	.22803	.31208
Variance	.971	.238	.000	.011	.019	.046	.068	.105	.150	.248	10.702	.052	.097
Skewness	4.027	-.440	67.663	9.363	6.957	4.239	3.280	2.360	1.639	-.188	2.923	13.728	16.571
Kurtosis	20.263	-1.806	4576.385	85.662	46.407	15.969	8.757	3.568	.686	-1.965	11.768	254.323	368.175

The following graphics are the FREQUENCIES for the variables in the larger dataset of 59,553 unique Case.Person.IDs. These results are outputs from SPSS.

Charge Severity

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Criminal Felony Class M	13	.0	.0	.0
	Criminal Felony Class X	657	1.1	1.1	1.1
	Criminal Felony Class 1	1159	1.9	1.9	3.1
	Criminal Felony Class 2	2847	4.8	4.8	7.9
	Criminal Felony Class 3	4354	7.3	7.3	15.2
	Criminal Felony Class 4	7062	11.9	11.9	27.0
	DUI	10903	18.3	18.3	45.3
	Criminal Misdemeanor	32558	54.7	54.7	100.0
	Total	59553	100.0	100.0	

Race.Race.Code

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	A	424	.7	.7	.7
	B	18581	31.2	31.2	31.9
	H	2809	4.7	4.7	36.6
	I	51	.1	.1	36.7
	U	211	.4	.4	37.1
	W	37477	62.9	62.9	100.0
	Total	59553	100.0	100.0	

Sex.Sex.Code

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	F	13917	23.4	23.4	23.4
	M	45635	76.6	76.6	100.0
	U	1	.0	.0	100.0
	Total	59553	100.0	100.0	

Mental.Illness.2_max

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	.00	52290	87.8	87.8	87.8
	1.00	7263	12.2	12.2	100.0
	Total	59553	100.0	100.0	

Age

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	17.00	717	1.2	1.2	1.2
	18.00	2960	5.0	5.0	6.2
	19.00	4661	7.8	7.8	14.0
	20.00	4716	7.9	7.9	21.9
	21.00	4369	7.3	7.3	29.3
	22.00	3911	6.6	6.6	35.8
	23.00	3335	5.6	5.6	41.4
	24.00	2853	4.8	4.8	46.2
	25.00	2465	4.1	4.1	50.4
	26.00	2162	3.6	3.6	54.0
	27.00	1889	3.2	3.2	57.2
	28.00	1671	2.8	2.8	60.0
	29.00	1575	2.6	2.6	62.6
	30.00	1535	2.6	2.6	65.2
	31.00	1364	2.3	2.3	67.5

	32.00	1245	2.1	2.1	69.6
	33.00	1205	2.0	2.0	71.6
	34.00	1128	1.9	1.9	73.5
	35.00	1066	1.8	1.8	75.3
	36.00	1053	1.8	1.8	77.0
	37.00	981	1.6	1.6	78.7
	38.00	879	1.5	1.5	80.2
	39.00	883	1.5	1.5	81.6
	40.00	893	1.5	1.5	83.1
	41.00	832	1.4	1.4	84.5
	42.00	758	1.3	1.3	85.8
	43.00	794	1.3	1.3	87.1
	44.00	761	1.3	1.3	88.4
	45.00	746	1.3	1.3	89.7
	46.00	621	1.0	1.0	90.7
	47.00	690	1.2	1.2	91.9
	48.00	585	1.0	1.0	92.9
	49.00	492	.8	.8	93.7
	50.00	473	.8	.8	94.5
	51.00	429	.7	.7	95.2
	52.00	377	.6	.6	95.8
	53.00	325	.5	.5	96.4
	54.00	305	.5	.5	96.9
	55.00	255	.4	.4	97.3
	56.00	215	.4	.4	97.7
	57.00	191	.3	.3	98.0
	58.00	191	.3	.3	98.3
	59.00	179	.3	.3	98.6
	60.00	106	.2	.2	98.8
	61.00	105	.2	.2	99.0
	62.00	103	.2	.2	99.2
	63.00	88	.1	.1	99.3
	64.00	67	.1	.1	99.4
	65.00	73	.1	.1	99.5
	66.00	44	.1	.1	99.6
	67.00	36	.1	.1	99.7
	68.00	37	.1	.1	99.7
	69.00	26	.0	.0	99.8

		Frequency	Percent	Valid Percent	Cumulative Percent
	70.00	31	.1	.1	99.8
	71.00	17	.0	.0	99.9
	72.00	19	.0	.0	99.9
	73.00	12	.0	.0	99.9
	74.00	9	.0	.0	99.9
	75.00	7	.0	.0	99.9
	76.00	9	.0	.0	100.0
	77.00	5	.0	.0	100.0
	78.00	7	.0	.0	100.0
	79.00	8	.0	.0	100.0
	80.00	1	.0	.0	100.0
	81.00	1	.0	.0	100.0
	82.00	1	.0	.0	100.0
	83.00	2	.0	.0	100.0
	85.00	1	.0	.0	100.0
	86.00	1	.0	.0	100.0
	88.00	2	.0	.0	100.0
	Total	59553	100.0	100.0	

Pretrial.Release.5

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	1.00	59553	100.0	100.0	100.0

Pretrial.Release.Final

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	.00	44824	75.3	75.3	75.3
	1.00	14729	24.7	24.7	100.0
	Total	59553	100.0	100.0	

Post.PSA

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	.00	52109	87.5	87.5	87.5
	1.00	7444	12.5	12.5	100.0
	Total	59553	100.0	100.0	

Violent

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	.00	56959	95.6	95.6	95.6
	1.00	2594	4.4	4.4	100.0
	Total	59553	100.0	100.0	

Drug

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	.00	54849	92.1	92.1	92.1
	1.00	4704	7.9	7.9	100.0
	Total	59553	100.0	100.0	

FTA

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	.00	38013	63.8	63.8	63.8
	1.00	21538	36.2	36.2	100.0
	Total	59551	100.0	100.0	
Missing	System	2	.0		
Total		59553	100.0		

Priors

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	.00	49840	83.7	83.7	83.7
	1.00	4711	7.9	7.9	91.6
	2.00	2326	3.9	3.9	95.5
	3.00	1234	2.1	2.1	97.6
	4.00	685	1.2	1.2	98.7
	5.00	348	.6	.6	99.3
	6.00	211	.4	.4	99.7
	7.00	96	.2	.2	99.8
	8.00	64	.1	.1	99.9
	9.00	21	.0	.0	100.0
	10.00	8	.0	.0	100.0
	11.00	7	.0	.0	100.0
	12.00	2	.0	.0	100.0
	Total	59553	100.0	100.0	

Probation

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	.00	23376	39.3	39.3	39.3
	1.00	36177	60.7	60.7	100.0
	Total	59553	100.0	100.0	

Class.M.Felony

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	.00	59540	100.0	100.0	100.0
	1.00	13	.0	.0	100.0
	Total	59553	100.0	100.0	

Class.X.Felony

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	.00	58896	98.9	98.9	98.9
	1.00	657	1.1	1.1	100.0
	Total	59553	100.0	100.0	

Class.1.Felony

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	.00	58394	98.1	98.1	98.1
	1.00	1159	1.9	1.9	100.0
	Total	59553	100.0	100.0	

Class.2.Felony

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	.00	56706	95.2	95.2	95.2
	1.00	2847	4.8	4.8	100.0
	Total	59553	100.0	100.0	

Class.3.Felony

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	.00	55199	92.7	92.7	92.7
	1.00	4354	7.3	7.3	100.0
	Total	59553	100.0	100.0	

Class.4.Felony

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	.00	52491	88.1	88.1	88.1
	1.00	7062	11.9	11.9	100.0
	Total	59553	100.0	100.0	

DUI

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	.00	48650	81.7	81.7	81.7
	1.00	10903	18.3	18.3	100.0
	Total	59553	100.0	100.0	

Misdemeanor

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	.00	26995	45.3	45.3	45.3
	1.00	32558	54.7	54.7	100.0
	Total	59553	100.0	100.0	

Prior.FTA

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	.00	30318	50.9	50.9	50.9
	1.00	9521	16.0	16.0	66.9
	2.00	5294	8.9	8.9	75.8
	3.00	3516	5.9	5.9	81.7
	4.00	2551	4.3	4.3	86.0
	5.00	1903	3.2	3.2	89.2
	6.00	1433	2.4	2.4	91.6
	7.00	1160	1.9	1.9	93.5
	8.00	828	1.4	1.4	94.9
	9.00	638	1.1	1.1	96.0
	10.00	481	.8	.8	96.8
	11.00	416	.7	.7	97.5
	12.00	287	.5	.5	98.0
	13.00	273	.5	.5	98.4
	14.00	201	.3	.3	98.8
	15.00	158	.3	.3	99.0
	16.00	107	.2	.2	99.2
	17.00	126	.2	.2	99.4

		Frequency	Percent	Valid Percent	Cumulative Percent
	18.00	76	.1	.1	99.6
	19.00	54	.1	.1	99.6
	20.00	57	.1	.1	99.7
	21.00	42	.1	.1	99.8
	22.00	24	.0	.0	99.9
	23.00	15	.0	.0	99.9
	24.00	17	.0	.0	99.9
	25.00	15	.0	.0	99.9
	26.00	10	.0	.0	100.0
	27.00	6	.0	.0	100.0
	28.00	1	.0	.0	100.0
	29.00	1	.0	.0	100.0
	30.00	5	.0	.0	100.0
	31.00	2	.0	.0	100.0
	32.00	3	.0	.0	100.0
	33.00	3	.0	.0	100.0
	34.00	2	.0	.0	100.0
	35.00	2	.0	.0	100.0
	36.00	3	.0	.0	100.0
	40.00	1	.0	.0	100.0
	Total	59550	100.0	100.0	
Missing	System	3	.0		
Total		59553	100.0		

Prior.Drug

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	.00	58631	98.5	98.5	98.5
	1.00	613	1.0	1.0	99.5
	2.00	185	.3	.3	99.8
	3.00	81	.1	.1	99.9
	4.00	23	.0	.0	100.0
	5.00	11	.0	.0	100.0
	6.00	5	.0	.0	100.0
	7.00	2	.0	.0	100.0
	8.00	2	.0	.0	100.0
	Total	59553	100.0	100.0	

Prior.Violent

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	.00	58720	98.6	98.6	98.6
	1.00	433	.7	.7	99.3
	2.00	185	.3	.3	99.6
	3.00	96	.2	.2	99.8
	4.00	55	.1	.1	99.9
	5.00	26	.0	.0	99.9
	6.00	14	.0	.0	100.0
	7.00	10	.0	.0	100.0
	8.00	3	.0	.0	100.0
	9.00	6	.0	.0	100.0
	10.00	2	.0	.0	100.0
	11.00	2	.0	.0	100.0
	13.00	1	.0	.0	100.0
	Total	59553	100.0	100.0	