

RECIDIVISM IN MONTGOMERY COUNTY, MARYLAND

Pre-Release and Reentry Services Division

Montgomery County Department of Correction and Rehabilitation

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Contents

Executive Summary.....	2
The Pre-Release Center.....	2
Performance Indicators in Reentry Programs.....	6
Why Policymakers Care About Recidivism.....	11
Recidivism Predictors.....	14
Benchmarking Recidivism	20
Building A Definition of Recidivism	23
Recidivism Research in Montgomery County	31
Data Analysis: Methodology	32
Data Analysis: Recidivism by Sub-Group.....	34
Data Analysis: Further Recidivism Analysis.....	42
Conclusions	44
Appendix A: Original and Created Variables.....	52
Appendix B: Descriptive Statistics.....	61
Appendix C: T-Tests.....	66
Appendix D: Correlation Coefficients.....	92
Appendix E: Regressions	94
Appendix F: Methodology for Adding Future Months to Analysis	95

Executive Summary

This capstone project examines recidivism as a correctional systems metric in Montgomery County, Maryland. The first component serves as a resource and springboard for CountyStat's investigation into a recidivism measure. It explores the magnitude, causes and patterns of recidivism, generally defined as the return of an ex-offender to the criminal justice system. It explains the methodological and theoretical problems in regarding recidivism as an evaluative measure of program performance and comparing recidivism rates across jurisdictions. After identifying great diversity amongst jurisdictions in the various elements of a recidivism definition - measure type, time period, triggering act, and informing databases – this paper concludes that PRC should maintain its current definition of recidivism. The second component of this paper consists of a quantitative analysis of a sample of Montgomery County Pre-Release Center releases in 2010 and 2012. The highest rates appeared among males, young adults, those without college education, higher LSIR, African-Americans, and Drug Court offenders. Applying regression analysis reveals that the apparent differences by race and gender to be attributable to correlation with the true predictors of recidivism: age and LSIR risk. Interventions and resources should be targeted to these populations.

The Pre-Release Center

Pre-Release and Reentry Services (PRRS), a division of Montgomery County's Department of Correction and Rehabilitation, facilitates the transition between incarceration and release. Eligible offenders may serve the final portion of their sentence at PRRS' residential facility: the Pre-Release Center (PRC). PRC offers controlled access to the community, holistic

programming, and case management in order to improve residents' reintegration into the community upon exiting the criminal justice system. In the long-term, it seeks to improve public safety in Montgomery County (PRRS, 2014). Over 17,000 individuals completed PRC since its establishment in the late 1960s (RicciGreene Associates & Alternative Solutions Associates, Inc., 2014). The Center is nationally known, and often referenced as a model of pre-release services.

The County's support for PRC reflects the larger political culture of a government committed to social services. In an interview, the Special Assistant to the County Executive (and former director of the County's Department of Health and Human Services) described the jurisdiction's self-identification as a "compassionate county" as a culture enabled by its affluence and political progressivity (C. Short, personal communication, March 26, 2014). The population of over one million (U.S. Census Bureau, 2014) and economic prosperity¹, sustained during the recent recession, allow for a sufficient tax base to support extensive social service programs.

PRC limits eligibility to three categories: (1) local offenders with an original sentence of at most 18 months and release date of at most 12 months (2) offenders in the Federal Bureau of Prisons (FBI) being released in MoCo's vicinity within 6 months, and (3) members of Circuit Court's Adult Drug Court program (RicciGreene Associates & Alternative Solutions Associates, Inc., 2014). Major pending legal matters (such as detainers or warrants), prior escape convictions, or public safety concerns, render applicants ineligible. Otherwise, criminal history doesn't disqualify candidates. By accepting high-risk participants convicted of sexual and violent crimes, PRC differs from most halfway houses (S. LoBuglio, personal communication, April 11, 2014). PRC either rejected or found ineligible only 5% of screened applicants (10p12). Given the

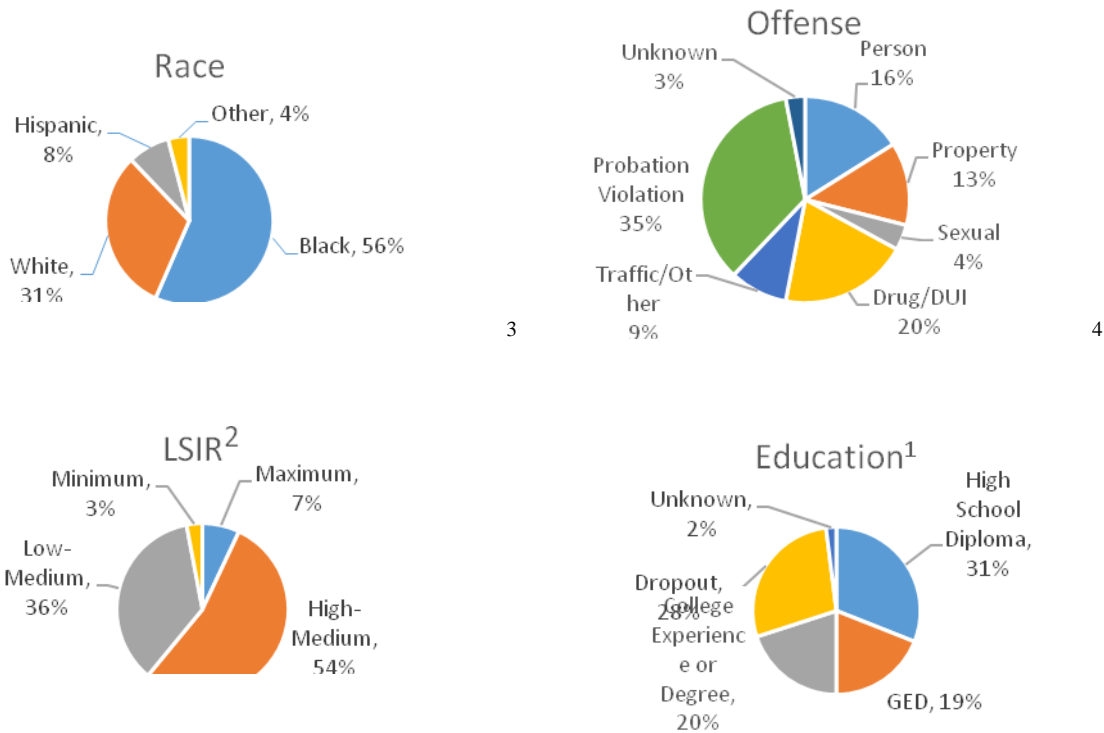
¹ The median family income, \$94,800, exceeds that of Maryland by over \$23,000 (U.S. Census Bureau, n.d.a).

overall decline in the correctional population in the County, PRC has developed new relationships with other criminal justice programs to ensure that its resources are utilized. For example, six years ago, PRRS began partnering with the Adult Drug Court (Riccigreene Associates & Alternative Solutions Associates, Inc., 2014). Furthermore, in 2007, PRC received support to revise county law to modify minimum and maximum remaining sentence policies governing PRC eligibility (Riccigreene Associates & Alternative Solutions Associates, Inc., 2014).

Built in 1978, PRC contains 4 residential units. The average daily population of 152 individuals (Montgomery County Department of Correction and Rehabilitation, n.d) is near capacity level but projected to remain fairly stable over the next two decades in the Master Facilities Confinement Study (MFCS). A February 2014 snapshot located 4% of the DOCR population in PRC and 1% in PRRS-supervised home confinement. A ten-minute walk takes residents to the White Flint metro station and other public transportation.

PRC's population is demographically representative of the jail population, suggesting that minimal observable "creaming" occurs (S. LoBuglio, personal communication, April 11, 2014). As an important caveat, the extent to which the voluntary nature of the program leads to differentiation between PRC and other DOCR residents in non-tangible characteristics is unknown. Because PRC requires more structured programs than the traditional jail, and employment, residents presumably possess different attitudes on average than peers electing against participation.

The facility is overwhelmingly male, with females comprising 8% of the admitted population in 2013 (PRRS, 2014). For both sexes, the average age is 33 (PRRS, 2014). The most common PRC offense was violation of parole in the MFCS (2014). At 18% of the county population, Hispanic/Latinos are under-represented in PRC (U.S. Census Bureau). African Americans are over-represented, comprising 17% of the county but 56% of PRC². 61% of residents in 2013 left PRC with employment. The charts below provide further population statistics:



PRC requires employment within 28 days of entry, a facet of its emphatic work-first philosophy.

Work Release Coordinators help residents with applications and stress long-term career

² Over the last few decades, Montgomery transformed from mostly upper-middle class whites to a “minority-majority” district).

³ Pre-Release and Reentry Services, 2014

⁴ Riccigreene Associates & Alternative Solutions Associates, Inc., 2014

planning. Additionally, PRS provides mental health services, GED classes, Alcoholics Anonymous, anger management, conflict resolution, and other programs (RicciGreene Associates & Alternative Solutions Associates, Inc., 2014). Other government agencies and community groups facilitate supplemental services such as mediation and mentoring. These programs, along with regular Community Advisory meetings, exemplify the county-wide practice of inter-agency collaboration and engagement of stakeholders, regarded as vital to addressing complex social problems (C. Short, personal communication, March 26, 2014).

Indeed, the Master Facilities Confinement Study highlighted the “growing complexity” of MoCo’s correctional population (2014). Trends include the increasing frequency of offenders with substance abuse disorders, mental health needs, and limited English skills. On a more positive note, crime in Montgomery County continues to decrease following national and state trends. According to the Department of Police, reported crime dropped 9% between 2012 and 2013 (Montgomery County Department of Police, 2014). Other than forcible rapes, commercial robbery and commercial burglary, crime dropped in every offense category. Crimes with at least a 20% reduction included murder, arson, vandalism, and juvenile offenses.

Performance Indicators in Reentry Programs

While exact definitions of the term differ, recidivism is the return of an offender to the criminal justice system. Return can be defined as a re-incarceration, but also can denote re-arrest, re-conviction, or a violation of probation (as discussed at length in “Building A Definition of Recidivism”). Policymakers liken recidivism to a revolving door, wherein an individual will

cycle repeatedly in and out of a criminal justice system. Recidivism is a popular performance measure of programs targeting the incarcerated, yet no consensus exists on measurement of the concept. Before delving into the technical variations of recidivism definitions, it is important to understand its role amongst other performance measures.

Recidivism in isolation produces a dangerously limited view of a correctional system.

Conceptually, third-parties can't evaluate the effectiveness of reentry programs by recidivism rates because they are inextricably shaped by factors external to the program (a challenge covered in-depth in “Benchmarking Recidivism”). Given that most studies do not incorporate a control group, the statistic reflects the functioning of the larger correctional system rather than the success of the particular program. Similarly, recidivism rates offer limited practical information to practitioners concerned with data-driven program improvement. Lastly, as a unidimensional statistic, recidivism mischaracterizes a program because it ignores successes in other domains.

For these reasons, shorter-term performance indicators must exist to fill in the “black box” between a correctional facility’s programming and subsequent recidivism rates. Such indicators reveal the functioning of the program and offer evaluation opportunities. Exemplifying this process, The Center for What Works created a template organizing 25 proposed performance indicators for reentry programs by their stage between the program and recidivism. In general, performance indicators vary by domain measured, time period, and data source. The State of Maryland’s Task Force on Prisoner Reentry, following the Council of State Governments’ Re-Entry Policy Council, recommends the following typology: activities, outputs, short-term

outcomes, long-term outcomes, and impacts (Fieselmann, 2011). It further divides outputs and outcome into domains identified as crucial to community reintegration: substance abuse; mental health; housing; employment; education; family, relationships and pro-social responsibility; and financial responsibility.

Activities indicators track the real-world implementation of the program. While relatively easy to measure, they tend to offer more logistical information than performance evaluation. A basic measure is participation in a particular program. PRC reports the number of residents enrolled in substance abuse, mental health, and Montgomery College. Additionally, it produces monthly averages for programs such as relapse-prevention and Welcome Home (PRRS, 2012). However, there is no way for an analyst to identify the number or hours of activities attended on a per-resident basis. Case managers' files describe assigned treatments and actual attendance, but these qualitative notes can't be easily extracted for quantitative analysis (S. Murphy, personal communication, April 2, 2014). Higher attendance in a particular treatment isn't a goal, as it doesn't necessarily indicate if treatments correspond to participants' criminogenic needs. Ideally, PRC could report the percentage receiving treatment for each assessed LSIR domain, such as substance abuse and mental health.

Other activities measures assess behavior for which program staff can be considered responsible. All three of PRRS' CountyStat metrics fall into the category of outputs: (1) the number of escapes from PRC; (2) the number of apprehensions; and, (3) the percentage of PRRS inmates participating in "Self growth and development programs" (DOCR, n.d). Since FY 2008, the earliest year for which data is readily available, PRRS scored 100% in Headline Measure 10

(DOCR, 2011), indicating that the measure is meaningless (DOCR, 2011). These measures disregard the mission of PRC: to improve post-release transitions into society and reduce recidivism.

Output measures track if the activities produced the desired effect, and are often assessed as a snapshot of an individual's status upon release. Did a resident attending resume workshops obtain a job? Did a resident enrolled in Montgomery College earn a GED? Other proposed outputs include: feeling prepared to avoid reoffending (Roman, Kane, Turner, & Frazier, 2006), possessing a thirty-day supply of necessary medicine, holding a bank account, finding a mental health provider, etc. The Bureau of Justice Administration (BJA) asks about another type of output: the number completing treatment (S. Murphy, personal communication, April 2, 2014). This figure is problematic for facilities like PRC serving residents with short stays, especially regarding deep-rooted issues like substance abuse. Rather, PRC's Deputy Chief of Program and Services states that their "goal is to initiate treatment services they will continue post-release" and to enable them to continue progressing on their own (*ibid*).

PRC tracks the following outputs regarding releases: the percentage holding employment, the percentage with housing, and the percentage successfully completing PRC (PRRS, 2014). Moreover, PRC calculates the annual gross income earned by residents, gross taxes paid, family support paid, and fines/restitution paid. It reports this data to the public through Quarterly Chief Reports (*ibid*). Providing this information as a per-resident basis would better reveal yearly trends by accounting for changing population size.

Outcomes assess the situation of the ex-offender after a designated time following release. Performance indicator typologies can disaggregate outcomes by length of time (Maryland Task Force on Prisoner Reentry, 2011). For example, “does an ex-offender has stable housing at 30 days?” functions as a short-term outcome, and the same question functions as a long-term outcome if assessed at 1 year. Alternatively, distinguishing them by conceptual order is possible. In this case, whether an individual possesses insurance functions as a short-term outcome and the health of that individual is a long-term outcome. In practice, conflating the two practices may not be distinguishable, as the assessment should be done at a particular time after release for consistency. Other conditions of interest are the sector (private versus public) in which the individual is employed, wages as comparable to pre-incarceration, strength of relationships with family, and receipt of food stamps? Other government agencies or community-based organizations potentially hold answers. For example, 2009 report for Montgomery County recommends linking criminal justice data to the jurisdiction’s unemployment insurance database as a means of studying the ex-offender’s financial status. Barriers to such measures tend to be technological and legal. Surveys of individuals would likely require an unfeasible amount of administrative time to establish initial communication and to obtain a reasonable response rate. PRC doesn’t track individuals after release, so it has no information on outcomes.

Impacts refer to the ultimate goals of the program for the individual and society. For reentry programs, they consist of reduced recidivism and improved public welfare (Fieselmann, 2011). Recidivism is the most common proxy for public safety in reentry studies (146p12) and the most frequent dependent variable for prison-based education (Davis, Bozick, Steele, Saunders, &

Miles, 2013). PRC began computing 1 and 3-year recidivism rates in July of 2013. (“Recidivism in Montgomery County” details the methodology”).

While activities, outputs, and outcomes can be worthwhile in their own right, practitioners generally regard their achievement as valuable inasmuch as they contribute to achieving the desired impact. Establishing performance indicators from treatment to short-term effects to long-term effects can expose blockage points inhibiting recidivism reduction. As an hypothetical illustration, comprehensive performance measurement would reveal if low attendance (an activity) is inhibiting effectiveness of a soft-skills program, if residents attend but still struggle to obtain employment (an output), if employment issues reduce child support payments (short-term outcome), if their relationships with their families consequently suffer (long-term outcome) and if they are prone to higher recidivism (impact). Evaluators of the national Serious and Violent Offender Initiative put this approach into practice. After finding “modest” improvements in intermediate outcomes yet no recidivism effects, the report concludes, “If the underlying model that links services to improved intermediate outcomes that in turn improve recidivism is correct, the level of improvement in these intermediate outcomes may have been insufficient to result in observable reductions in recidivism” (Lattimore and Visher, 2009).

Why Policymakers Care About Recidivism

Reducing recidivism is a frequently cited policy goal and topic of extensive research. Interest in tracking recidivism stems from the expanding conception of the role of corrections in the late 1990s (Fieselmann, 2011). Instead of just supervision of inmates, policymakers began to see

corrections as mechanisms to promote public safety and social welfare. In this sense, recidivism indicates the failure of incarceration to accomplish key goals of deterrence and rehabilitation.

Beyond social responsibility, the magnitude and cost of recidivism at every level of government earns the attention of policymakers. The Bureau of Justice Statistics (BJS) examined prisoners released in 2005 from 30 states and found that 68% had been rearrested within 3 years (Cooper, Durose & Synder, 2014). This percentage exactly corresponds to the recidivism of the preceding BJS study of 1994 releases from 15 states (Langan & Levin, 2002). Further indicating the stability of the national recidivism rate, Pew's Center on the States published a landmark study finding average recidivism for the 33 states with data for prisoners released in 1999 and 2004 dropped only 2 percentage points. However, this statistic conceals notable transformations in recidivism at the state-level. Recidivism increased by at least 10% in nine states and decreased by at least 10% in six states (The Pew Center on the States). On the local level, 9 million people accounted for an estimated 12 million jail bookings between July 2004 and June 2005 (La Vigne, Davies, Lachman, & Neusteter, 2013). In a typical case study, one out of every five releases each year from the Philadelphia Prison System (PPS) between 1996 and 2003, had already been through PPS at least once that same year (Roman et al., 2006). The half of the population that had experienced multiple incarcerations contributed to over three-quarters of total releases.

Reducing recidivism appeals to governments as a means to reduce crime and ensuing expenditures. Local governments are no exception, as they account for one-third of incarcerated Americans (Glazer & Herberman, 2013). Counties spend \$23.3 billion annually on correctional facilities (Istrate & Nowakowski, 2013). The rise in jail inmates in the last decade further

increased pressure on budgets (Glazer & Herberman, 2013). By reducing recidivism, jurisdictions produce savings in police agencies, courts and corrections facilities. In fact, budget distress stemming from the Recession of 2008 helped fuel government interest reentry programming, an obscure topic in the decade prior (Katel, 2009). According to Attorney General Eric Holder, “Even a modest reduction in recidivism rates would prevent thousands of crimes and save hundreds of millions of taxpayer dollars” nationwide (*ibid*). Local and state governments cite cost savings from reducing recidivism as one justification for reentry and other programming. Travis County, Texas, conducted a cost-benefit analysis of its Mental Health Public Defender Office, calculating the cost savings from reduced jail beds, legal representation and bookings (Jefferies & Calkins, 2012). Other analyses forecast meaningful cost savings from incremental drops in re-offending rates due to the high per-capita cost of incarceration (Katel, 2009). For example, Pennsylvania calculated a \$45 million savings would accrue from reducing recidivism by 10% (Palazzolo, 2013). More dramatically, the Rand Corporation determined that a correctional educational program would reach cost-effectiveness if it reduced the three-year re-incarceration rate by two to three percentage points (Davis et al., 2013). New York City’s Center for Employment Opportunities (CEO) decreased recidivism in clients by five percentage points, with financial benefits outweighing costs by more than two to one (Redcross, Millenky, Rudd & Levshin, 2012).

Even the process of measuring recidivism can be valuable to corrections and reentry programs. By highlighting sub-populations at risk, disaggregated recidivism analyses assist agencies in targeting interventions to produce the highest benefit. For example, Hampden identifies chronic offenders, defined as those with at least two re-incarcerations within the first year of release,

through its recidivism analysis (Lyman & Lupo, 2014). A facility finding residents with original offense A to recidivate at a higher rate than offense B might consider investing in programs addressing motivations for offense A. However, facilities should be cautious in such decisions, as characteristics may be simply correlated with the factors truly causative of recidivism. Additionally, analyses of the timing of recidivism can assist pre-release programs in scheduling delivery of after-care resources. Evaluators of New York City's CEO found the program to be effective in reducing recidivism for participants within three months of release from prison, but not for those participating more than three months afterwards (Redcross et al., 2012).

While improving public safety and knowledge of correctional population flows are relevant concerns for all levels of governments, Montgomery County is a rarity among localities in its measurement accomplishments. Since 2013, the Pre-Release Center began reporting 1 and 3-year recidivism rates. Following a CountyStat MoCo's performance monitoring body) meeting with DOCR in early 2014, CountyStat designated the development of a recidivism measure and a benchmark methodology as formal follow-up tasks (94). While agency documents from 2008, 2009 and 2010 describe such measures as in-progress, PRC's new recidivism collection marks the actualization of these years of sustained interest to CountyStat. Furthermore, the Office of Management and Budget expressed support for measuring recidivism, in keeping with the county's transition to a performance-based budget (K. Miller, personal communication, April 3, 2014).

Recidivism Predictors

Since contextual factors and heterogeneous populations make absolute recidivism rates of little comparative value to Montgomery County, the literature review conducted for this project focuses on recidivism variation by sub-groups. The jurisdictions discussed in this section also informed the subsequent discussion of the different definitions of recidivism and the selection of sub-groups for the MoCo data analysis. The chart below summarizes the primary studies referenced in this paper. They were selected for convenience, variation, and/or analysis of a particular sub-group. Therefore, they should not be interpreted as nationally representative. The analysis references other jurisdictions and studies, but focuses on the following studies:

Study Referenced As	BJS	Montgomery	Hampden	Baltimore
Population	Prison, 30 states	Jail, Montgomery County (MD)	Jail, Hampden County (MA)	Prison, Maryland
Released	2005	2003-2004	2010 & 2012	2002 & 2003

(Note: In the following discussion, recidivism rates are 3 year figures if not specified. In order to correspond with Montgomery County’s recidivism definition, the re-conviction definition is used when possible.)

Gender: Recidivism is highest among males. An important factor in the recidivism differential between men and women is the differences in the offenses for which they were incarcerated. Compared to men, more drug and property crimes lead to women being incarcerated (Spjeldnes & Goodkind, 2009). The percentage of women sent to jail for violent crime is slowly increasing, but this is more due to stricter sentencing policies for women (especially prosecution of domestic

violence) and for the relatively lighter categories of crime in which their offenses tend to fall, than to heightened frequency of criminal activity (Spjeldnes & Goodkind, 2009). BJS found men 18% more likely to be re-arrested than women (Cooper, Durose & Synder, 2014). Montgomery found men to be 40% more likely to be reconvicted (Uchida, LoBuglio, Flower, Piehl & Still, 2009), nearly equivalent to Hampden's differential of 37% (Lyman & Lupo, 2014). Baltimore found men to be 52% more likely to be rearrested within six months. Gender was statistically significant in predicting re-arrest, with an odds ratio of 1.89, meaning men were almost twice as likely to be re-arrested as females holding other factors constant (Visher et al., 2004).

Age: Recidivism is higher for the young. BJS used five age categories and found a reduction in recidivism rates for each subsequent age group, with one exception (Cooper, Durose & Synder, 2014). The oldest group (40 and older) had 26% greater likelihood of recidivism than the youngest adult age group (24 and younger) (Cooper, Durose & Synder, 2014). Montgomery divided the population into two groups: over and under age 30. It found higher recidivism in the younger group, but didn't report the recidivism rates of either group (Uchida et al., 2009). Baltimore used exact age and found the average recidivator to be 2 years younger than a non-recidivator (Visher, LaVigne & Travis, 2004). In multivariate analysis, a statistically significant odds ratio of .96 means that younger age is associated with higher likelihood of re-arrest (Visher et al., 2004). Age at first arrest is a common LSIR element and noted in several studies.

Race/Ethnicity: Generally, whites recidivate at a lower rate. BJS found blacks 12% more likely to recidivate than whites and Hispanics/Latinos to be 7% more likely than whites (Cooper, Durose & Synder, 2014). Montgomery found non-whites recidivate at a higher rate than whites,

but doesn't report the recidivism rates by race (Uchida et al., 2009). One researcher notes the interaction between race and a criminal history, describing a "double dose of employment discrimination" for black ex-offenders (Bloom, 2006). Baltimore attributes a finding of no recidivism differentiation by race to be due to the dominance of blacks in the sample (Visher et al., 2004).

Criminal History: Predictably, offenders with longer criminal history have a higher recidivism rate. BJS found individuals with at least 10 prior arrests recidivated at a 20% higher rate than those with 5 to 9 arrests, and 59% higher rate than those with 0 to 4 arrests (Cooper, Durose & Synder, 2014). Montgomery's multivariate analysis found the number of prior arrests to predict higher recidivism, a strongly statistically significant conclusion (Uchida et al., 2009). In Baltimore's multivariate regression, the number of prior arrests is the third of three statistically significant recidivism predictors, with an odds ratio of 1.07 (Visher et al., 2004).

Type of Initial Offense: BJS property offenders to recidivate at the higher rates compared to violent, drug-related, or public order offenses. Individuals serving property crimes recidivated at the highest rates, exceeding violent offenders, the category with the lowest rate by 21% (Cooper, Durose & Synder, 2014). Likewise in Montgomery, property offenders recidivated at the highest rates for males (Uchida et al., 2009).

Mental Health/Substance Abuse: Baltimore recidivators were two and a half times as likely to engage in post-release substance use (drug and alcohol) as non-recidivators (Visher et al., 2004). Researchers found the higher rates of substance abuse - before and after prison - in recidivators,

to be statistically significant. Supporting this finding, an Urban Institute study of Texas and Ohio prisoners found statistically significant variation in recidivism by self-reported substance abusers, with males 67% more likely to recidivate than their peers, and females almost three times as likely. Meanwhile, the same study found no differences in 1-year re-incarceration for those with and without mental illness despite higher self-reported crime (Mallik-Kane & Visser, 2008). On the other hand, other literature identifies correlations between mental health and recidivism. PRC recognizes the high criminogenic risk of its population with mental health issues. In a federal grant application, PRC cited anecdotal evidence that nearly all mentally ill DOCR offenders with “serious and persistent” co-occurring behavioral health disorders recidivate (n.d.).

Housing: Recidivism studies rarely explore homelessness. A study of individuals exiting New York State prisons between 1995 and 1998 found a higher rate of recidivism among those released without stable housing (Metraux & Culhane, 2004). Furthermore, ex-offenders with a prior stay in a homeless shelter produced 31% higher rates of recidivism. Beyond homelessness, a spatial perspective of recidivism considers the locations receiving ex-offenders. Individuals returning to their pre-incarceration communities situate themselves in the same contexts that potentially fueled their original crime (LoBulgio, 2007). Furthermore, these destinations tend to lack the services and characteristics ex-offenders need to progress. “People leaving prison disproportionately return to at-risk communities; that is, communities characterized by high rates of unemployment, crime, drug use, and poverty...places where resources are already strained by social problems and their social ties to these resources have been weakened by time

incarcerated.” (Draine & Wolff, 2009). PRC’s RAS observed that employed offenders often can't afford to leave their old neighborhoods, inducing them to return to negative lifestyles.

Employment: Multiple studies find that post-incarceration employment and higher earnings predict less recidivism (Brazzell, Crayton, Mukamal, Solomon, & Lindahl, 2009). Theoretically, employment increases an offender’s sense of security, improves relationships with family, and hinders a return to his negative, pre-incarceration lifestyle. In an interview, PRC’s Reentry Assessment Specialist (RAS) emphasized the relationship between financial stability and recidivism, based on his case management experience (T. Alexander, March 27, 2014). Other personal challenges related to recidivism, notably maintaining consistency with medication and stable housing, require financial security. In principle, steady employment reduces financial motivation for crimes (Bloom, 2006). One review of the relevant literature describes the rarity of experimental evaluations of work-placed reentry programs, an ideal methodology to pinpoint the causal influence of employment on re-offending. Fewer still attempts to isolate the benefits of employment assistance from other interventions (Duran, Plotkin, Potter, & Rosen, 2013,). Nonetheless, some work release programs have been proven to reduce recidivism (*ibid*).

However, parsing the relationship of employment and recidivism presents difficulties for researchers. Establishing the order of causality is a challenge; the personal characteristics inclining ex-offenders to hold a job likely overlap with those deterring employment. Moreover, researchers posit a vicious cycle; incarceration disrupts employment and earnings, in turn, prompting recidivism (Bloom, 2006). Time spent incarcerated can erode connections to contacts who might assist with job search afterwards (Solomon, Osborne, LoBuglio, Mellow, &

Mukamal, 2008). Moreover, many policies bar ex-offenders from holding certain licenses and professions and render them ineligible for financial aid (Spjeldnes & Goodkind, 2009). Potential employers can automatically reject applicants with a criminal record, fearing a relapse, such as employee theft (Solomon et al., 2008). Alternatively, the offense can act as a “market signal” that the ex-offender possess personality traits incompatible with the workforce, such as laziness or quickness to anger.

Benchmarking Recidivism

There is no consensus regarding absolute standards for recidivism rates. Unlike student test scores, experts haven’t established “acceptable” or “excellent” thresholds. Third parties monitoring recidivism tend to hold an ipsative assessment rather than a criterion-referenced assessment, meaning they focus on the changes compared to the starting point rather than their proximity to a pre-established goal. A literature review yielded no efforts to define acceptable recidivism nor any jurisdictions striving towards an absolute rate, such as “5% recidivism by 2015”. Instead, policymakers scrutinize the direction and magnitude of change compared to prior years. For example, Pennsylvania Department of Correction will award a bonus to halfway house contractors if the state recidivism rate drops by 1% or more (Palazzolo, 2013). A federal grant asks states to submit plans to halve their recidivism rates (Bureau of Justice Assistance (BJA), 2013).

CountyStat utilizes two types of benchmarks: internal and external. Internal benchmarks (such as agency website views and fire response time) mark a particular department’s progress towards a

specified objective, while external benchmarks track “quality-of-life” indicators (such as home ownership and commute time) influenced by multiple departments and non-governmental factors (CountyStat, 2014). Internal benchmarks compare data to prior years, while external benchmarks compare Montgomery County to jurisdictions in the region and peer jurisdictions across the nation. Should recidivism be internally or externally benchmarked?

There are limited opportunities to externally benchmark Montgomery County’s recidivism. A policymaker seeking to compare the county to another jurisdiction might first look toward states. In fact, the bulk of recidivism research, especially the large-scale studies, utilize state-level data. A 2012 review by the Council of State Governments identified at least 34 states who published annual recidivism statistics. However, two key differences between jails and state prisons inhibit recidivism comparisons: population and sentence duration. State prisons hold offenders who, on average, are committed for much more serious crimes. The average stay in a state prison is 2.5 years, while over four out of every five people entering jail each year will exit within a month (Solomon et al., 2008). If states aren’t a fair benchmark, what about other local jurisdictions? The primary challenge is finding data, as “very few” measure recidivism (La Vigne et al., 2013). Jails, especially small ones, focus their resources towards control and safety rather than research. Moreover, the short stays of most residents and diverse legal status upon exit add logistical difficulties in recidivism calculation (Solomon et al., 2008).

Beyond these technical concerns, the great extent to which factors outside the DOCR’s control shape recidivism suggests that external benchmarks aren’t appropriate. Returning to the language of performance measurement, the characteristics of a jurisdiction – penal code, school quality,

economic opportunity, etc. – influence short and long-term outcomes and thus recidivism rates. Actors and policies in the criminal justice system further impede the validity of inter-jurisdiction comparisons by influencing the composition of the incarcerated population and their likelihood of re-offending. Jurisdictions with higher police-to-population ratios or more energetic police will produce more arrests for the same number of crimes committed. Speedier courts with shorter time between a charge and sentence, result in higher recidivism for a given time period after release. Jurisdictions with judges sentencing a higher share of offenders to parole or probation (Lyman and Lobuglio, 2007), more aggressive compliance officers (i.e. in administering more frequent drug tests) (The Pew Center on the States, 2011), or longer parole periods (LoBuglio, 2007), will generate more ex-offenders charged with a technical violation and higher recidivism. For these reasons, some recidivism studies warn readers against uninformed inter-jurisdictional comparisons (The Pew Center on the States, 2011). In one apt analogy, judging the performance of a corrections department by recidivism is equivalently misleading as attributing the difference in Baltimore and Salt Lake City crimes to superior police in the latter (Fieselmann, 2011).

In conclusion, the lack of comparable data prevents recidivism from being externally benchmarked, while the major role of non-DOCR factors limits internally benchmarked data to a trend indicator but not a performance measure. The recidivism rate is more meaningful as an indicator of the combined efforts of government agencies (education, social service, workforce development, correctional facilities) than of PRC alone. Montgomery County should concentrate on changes in its recidivism rate, and between sub-groups, rather than engage in comparisons to other jurisdictions. Moreover, an awareness of shifts in the county-wide characteristics discussed

above will promote a deeper comprehension of MoCo recidivism rates. The 2014 budget of Prince George's County, Maryland, exemplifies such an understanding. A note that shifts in police strategy to greater arrests of repeat offenders contributed to a rising recidivism rate follows the rate itself (County Office of Management and Budget, 2013).

Building A Definition of Recidivism

This section outlines the major components of a recidivism definition. While the recidivism rate has “long been considered the leading statistical indicator of return on correctional investment” (The Pew Center on the States, 2011), a literature review reveals numerous variations of recidivism definitions used by governments and researchers. In selecting a recidivism measure, policymakers weigh data desires against limited databases, and staff with little time for data collection. More often than not, jurisdictions report data for multiple definitions of recidivism, due to the lack of consensus on a definition and the greater ability to identify more trends with more information (141). No indication of convergence exists, nor is there a visible federal push to standardize the heterogeneity of recidivism measures. The Bureau of Justice Assistance (BJA) Adult Recidivism Reduction Planning grants allows each state applicant to use any definition meeting requirements of specifying a population, offering a baseline, and remaining feasible for future data collection (BJA, 2013). On the same note, the Transition from Jail to Community Initiative (a partnership of the National Institute of Corrections and Urban Institute) encouraged sites to create recidivism definitions sensitive to local priorities (Willison, Jannetta, Dodd, Neusteter, Warwick, Greer, & Matthews, 2012).

Binary Measure Versus Count Measure: As presented thus far, recidivism is a binary measurement: either an ex-offender did or did not recidivate within a given time period. The recidivism rate is the ratio of the number of individuals recidivating at least once to the total number of individuals in the population. Several sites participating in the Transition from Jail to Community Initiative (TJC) fault such a measure for failing to capture if a program reduced, but did not eliminate, the recidivism of an offender (Willison et al., 2012). This critique is especially applicable to the chronic users that disproportionately draw jail resources and are the target population of many anti-recidivism programs. An alternative is supplementing the binary measure with a count measure. The Social Impact Bond for Peterborough Prison defines success as a 7.5% drop in reconviction events, a departure from the traditional outcome of recidivism rate (Social Finance Limited, 2011). Another count measure is the number of days before an individual’s first re-offense (Uchida et al., 2009).

Time Period: The duration of time during which recidivism is tracked begins upon release from the correctional facility, not release from community supervision. The literature review produced periods ranging from 6 months to 10⁵ years. A meta-analysis of prison-based education and an Urban Institute publication focused on local government (La Vigne et al., 2013) found both one and three years to be popular for jail recidivism. Pew describes 3 years as “typical” (2011) and Maryland’s Department of Legislative Services calls them “the most common” (Department of Public Safety and Correctional Services, 2014).

Jurisdiction	Maximum Time Period Reported
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⁵ RAND Corporation referenced but didn’t cite this 10-year study (Davis et al., 2013).

5 years	BJS
3 years	Council of State Governments publication; Pew; Maryland Department of Public Safety and Correctional Services; Hampden; Maryland Department of Juvenile Services; Virginia Department of Corrections; Center of Employment Opportunity evaluation;
6 month	Baltimore

Of course, the time period is an artificial deadline of data collection; nothing differentiates an individual who recidivates a day before or a day after. However, the length is important for data comparisons and trend analysis. Unresolved cases will drive recidivism downward for shorter time selections. Consider an ex-offender who commits a crime in month 11 and is convicted in month 13. He would be counted as a recidivist under a 3-year measure but not under a 1 year measure. In fact, Hampden found open cases for 14% of 2012 releases at the one year mark (Lyman & Lupo, 2014). The delay between arrest and sentencing justifies a 3-year period for many jurisdictions (Fieselmann, 2011). On the other hand, shorter time periods mean less time collecting data, an especial boon if the process isn't automated. In Montgomery County, doubling the data collection period doubles the hours of work. Jurisdictions using 3-year time frequently report recidivism rates at 1 and/or 2 years as well. Producing rates for multiple time periods provides a richer dataset and allows for survival rate analysis. The shorter time periods inform elected official concerned with changes in recidivism under their short-terms, and more broadly, for stakeholders interested in faster feedback on new programs or populations. Finally, the time period chosen may influence the types of recidivism identified. One study found that

minor crimes account for a greater share of 1-year recidivism, whereas serious crimes are more dispersed over the 3 year measure (Uchida et al., 2009).

Criminal Event. Studies vary regarding the contact point with the criminal justice system defined as recidivism. Note that the criminal act chosen in the definition is not necessarily the cut-off for the time period. In other words, a jurisdiction using three-year re-conviction could count as recidivists those who are re-arrested within three years of release, provided those arrests eventually led to a re-conviction.

- *Arrest*: An arrest is the legal deprivation of an individual's liberty. It may lead to a charge, the formal allegation that "a defendant has committed an offense, including a citation or indictment" (Maryland Courts, 2014). The relationship of police policy to arrests makes this measure especially difficult to compare across jurisdictions (Uchida et al., 2009). Moreover, an arrest-based recidivism measure counts those eventually proven innocent, which results in over-capturing recidivism. On the other hand, prosecutors sometimes drop minor charges or those lacking sufficient evidence (La Vigne et al., 2013), so in that sense arrests recognize recidivism that other measures omit. Additionally re-arrest excludes parole violators who are incarcerated without a preceding arrest.
- *Adjudication*: An adjudication occurs when an arrest results in a referral to the courts for possible sanctioning (Cooper, Durose & Synder, 2014). BJS's adjudications definition generates roughly three-quarters of the recidivism rate of arrests (*ibid*).
- *Conviction*: A conviction is "the determination of guilt based on a plea, a jury verdict, or a finding of a judge" (Maryland Courts, 2014). This measure somewhat adjusts for more

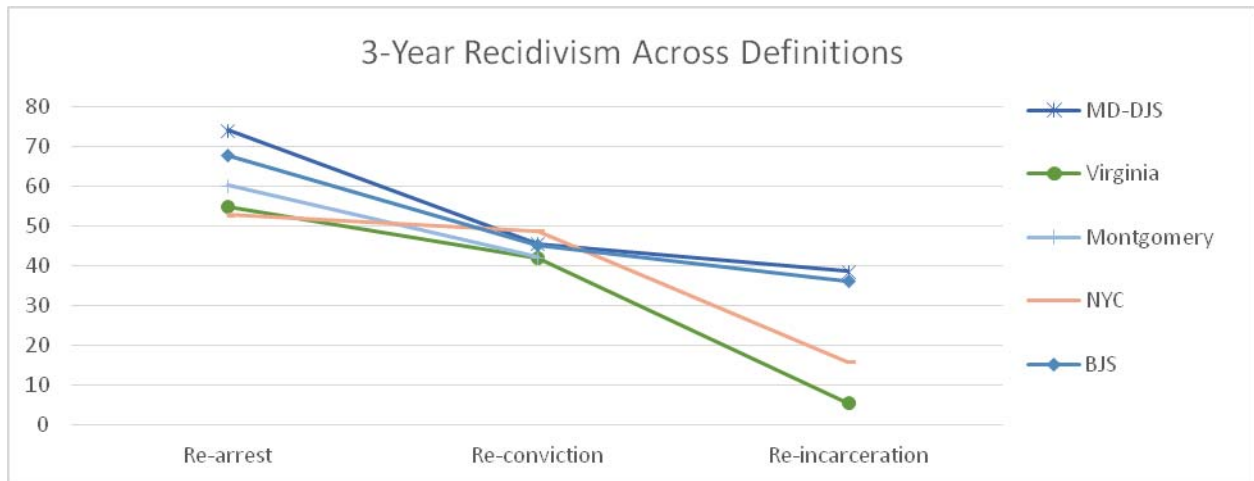
aggressive police, but not judicial policy. It includes individuals found guilty and given a sentence other than incarceration. However, re-convictions ignore ex-offenders arrested on parole then incarcerated without a conviction (Visher et al., 2004). The literature can use “reconviction” to refer only to those stemming from a prosecution of a new offense, or more broadly to include technical violations (La Vigne et al., 2013). Peterborough chose re-convictions as a recidivism measure, considering it a reasonable approximation of government expenditures (Cave, Williams, Jolliffe, & Hedderman, 2012).

- *Arraignment*: An arraignment is the “procedure in which the accused is brought before the court to plead to the criminal charge” (Maryland Courts, 2014). A study of Hampden County’s reentry program used the arraignment definition and included parole and probation violations resulting in incarceration (LoBuglio, 2007).
- *Incarceration*: Incarceration is the physical return to jail or prison (Langan and Levin, 2002). This measure captures individuals who reoffended on parole and who were sent to prison without prosecution, a population omitted by the re-conviction measure. However, it excludes offenders found guilty but sentenced to a fine or other punishment besides incarceration (Langan & Levin, 2002). A meta-analysis of prison-based education identified re-conviction as the most common recidivism definition (Davis et al., 2013). Pew defines recidivism as re-incarceration, as does Douglas County, Kansas, (Willison et al., 2012) and two recent publications by the Council of State Governments. Denver, Colorado, uses re-incarceration but limits recidivism to medium- and high-risk offenders resentenced for a new offense (Willison et al., 2012). The Transition from Jail to Community Initiative selected returns to jail as a Core Performance Measures. Montgomery chose to track reconvictions

rather than re-incarcerations because the later requires searching additional databases for each release (S. Murphy, personal communication, April 2, 2014).

- Lastly, studies sometimes supplement bureaucratic data with self-reported crime (Mallik-Kane & Visser, 2008). This is feasible with a representative sample rather than an entire population.

The graph below illustrates the variance in 3-year recidivism rates for the three common recidivism definitions. As included jurisdictions aren't representative of all jurisdictions tracking recidivism, (and differ in other recidivism definition elements), the graph is intended to suggest the influence of the definition on the final rate rather than generalizable patterns.



The selection of a criminal event for the recidivism definition interacts with the time period to influence the difference the final recidivism figure. Generally, the earlier the event falls in the criminal justice system, the higher the recidivism rate. At 3 years, BJS recidivism is 50% if defined by adjudication, 45% if defined by conviction and 22% if defined by imprisonment. Interestingly, the differences between definitions vary widely between jurisdictions. Hampden's

3-year re-conviction rate is about 70% of its re-conviction rate, while that of the CEO evaluation was 30%. One reason for the drop is definitional; not every arrest will result in a conviction and not every convicted criminal will serve time in prison. But a secondary driver of these statistics is the time lag of the criminal justice system. The later in the system selected as a recidivism definition, the more bureaucratic processing time and court delays are at play. Therefore, a jurisdiction choosing a measure later in the system might consider using a longer time period of analysis. PRRS' recidivism researcher raised this point in light of her experience while employed by the courts.

A brief analysis of the BJS cohort released 1994 suggests that the choice of measure sometimes influences the magnitude of differences between sub-groups. For the five sub-group classifications examined by this author – female/male, black/white, Hispanic/non-Hispanic, age 18 to 24 versus 45 and over, violent crime/property crime, the percent differences between the sub-groups grew – by between .5 percentage points to 9 percentage points - when moving from re-arrest to re-conviction as a definition (author's analysis). This information wasn't available to be analyzed for the 2005 cohort.

Inclusion of Technical Violations: A technical violation of a parole or probation condition can be failure to report to a probation officer or a positive drug test. Some recidivism analyses exclude technical violations from their recidivism definition. Alternatively, analyses compare technical violations and new offenses in order to disaggregate recidivism, as did Pew (2011). This distillation can reveal the influence of community supervision policies on recidivism rates, which can otherwise be interpreted as changes in crimes committed by ex-offenders. For example,

Michigan saw recidivism drop 18% between 1999 and 2004, driven by a large reduction in incarceration of technical violations, but that number hides the 21% rise in re-incarceration for new offenses (The Pew Center on the States, 2011). As another example, Hampden re-incarcerate parolees at higher rates than non-parolees in total, but since parolees re-offend at lower rates, technical violations drive the difference (Lyman & Lupo, 2014). Segregating technical violations and new offenses is a way to “tell the story” of recidivism.

Database: Unsurprisingly, increasing the scope of crime data sources, raises the rate of recidivism. Studies frequently exclude offenses outside the system of analysis. For example, some states do not account for a released individual who re-offends in a neighboring state, while counties often limit searches to databases within their jurisdiction and state (18p12). Maryland ignores crimes managed by federal, out-of-state, or Maryland county judicial systems (Fieselmann, 2011). BJS found that 14% of 5-year recidivators were re-arrested at least once in states other than that of their original prison, suggesting the importance of expanding recidivism research outside the jurisdiction in question (Cooper, Durose & Synder, 2014). For local governments, the effect on recidivism rates from ignoring other jurisdictions may relate to its location. Counties near their state’s border conceivably “lose” more recidivism as a result of ignoring neighboring states than counties in the middle of a large state. Pragmatic and political motivations discourage jurisdictions from expanding their recidivism searches to more available criminal databases. If databases aren’t automated or combinable, it can be highly tedious and time-consuming to incorporate them (Uchida et al., 2009), especially if each individual must be searched individually. Furthermore, the certainty that each additional database will increase recidivism is a political disincentive (*ibid*). The Montgomery study exposes the dramatic jump in

recidivism from expanding databases. Federal and local databases revealed 40% more convictions than reliance on state records alone.

Population: Within a given jail, the population spans many complicated and dynamic legal statuses (Lyman and Lobuglio 2007). Most are detained and awaiting trial, and other statuses include sentenced awaiting transfer to a state prison, undocumented immigrant with a pending deportation, serving a short sentence, in protective custody, or a juvenile with their own rules (Solomon et al., 2008). Identifying which inmates are subject to the recidivism calculation upon exit can be logistically tricky. Limiting recidivism to Pre-Release Center participants avoids this problem, but it would need to be addressed if the analysis expands to include MCCF releases. Another decision is whether to account for releases that cannot recidivate due to deportation, death, or re-incarceration. Omitting this adjustment will bias the recidivism rate downwards (Lyman and Lobuglio, 2007).

This exploration of the many dimensions of a recidivism measure relates to the earlier discussion of benchmarking. A jurisdiction selecting a recidivism definition will begin by considering its logistical feasibility and value to stakeholders. If it wishes to compare itself to a specific peer, it might need to sacrifice its ideal definition for one that aligns with the peer's methodology. Equally important to consider in selecting a benchmark jurisdiction is establishing a common definition of recidivism. Failure to account for differing methodologies leads to invalid inter-jurisdictional comparisons.

Recidivism Research in Montgomery County

My data analysis builds off a 2009 study of recidivism that exhaustively examined the criminal histories of 2,182 local sentenced MoCo offenders who exited DOCR from the beginning of July 2003 and the end of 2004 (Uchida et al., 2009). It utilized 9 data sources across local, state and national levels. The analysis disaggregated recidivism by crime type, gender and seriousness of offense. Supplementing regression analysis, it conducted hazards regression and survival curves, varying with 9 dependent variables, 3 arrest-related definitions of recidivism and 6 conviction-related ones. As a precursor to the current monthly recidivism research, the 2009 study informed PRC's selection of conviction as a recidivism definition. The amount of recidivism exposed by supplementing the Maryland State Record of Arrest and Prosecution with federal and other state criminal databases led PRC to include those databases in future research. The study concluded with recommendations to improve further research: developing a cohesive system combining all the criminal justice data sources and allowing linkages between government databases. While it calculated recidivism for all incarcerated offenders, this analysis is limited to PRRS participants.

The 2009 study paved the way for PRC to begin regular recidivism research in 2013. Since July 2013, PRRS's researcher has conducted monthly investigations of re-convictions and average days until first conviction, reporting results publically in the Quarterly Chief's Report. Every month, she produces 1-year recidivism rates for PRC residents released in the same month exactly one year prior, and 3-year recidivism rates for residents released exactly three years prior.

Data Analysis: Methodology

This paper conducts in-depth analysis of PRC's existing recidivism databases. A detailed description of its methodology and sources, informed through interviews with the database creator, precedes the data analysis.

PRC's researcher begins with a list of all PRC residents released for a given month. The population includes residents completing home confinement. To limit research to those released into the community, residents revoked (sent back to MCCF due to an attempted escape) or administered and removed (sent back to MCCF, likely for behavioral problems) are excluded. These exceptions reduce the population by roughly 20%⁶. In order to identify the recidivism of participants released exactly 12 months prior and 36 months prior, she searches two databases. The Maryland Judiciary Case Search website provides traffic and criminal case records from the Maryland District Court and criminal case records from the Maryland Circuit Court (65). Secondly, the Federal Bureau of Investigations METERS database includes local, state and national crimes. Next, the status, category, and outcome of a charge determine if it counts as recidivism. Pending cases and probation before judgment are excluded, as are non-incarcerable traffic offenses and civil charges. If a charge is *nolle prosequi* (decision against prosecution), results dismissed, or results in a non-guilty verdict, it doesn't count as recidivism (70).

The database obtained for this paper's analysis consists of only the following variables: release date, criminal system of origin, Maryland State Identification Number, FBI Identification Number, date of birth, gender, offense served at PRC, inside worker status, release location, race, LSIR, educational attainment, and employment status. The first six characteristics exist for every

⁶ The researcher provided 15% as an initial estimate. Random examination of three months led to a higher estimate: 24% of the original April 2012 data were excluded; 20% of April 2013; and 20% of January 2013.

month, but the last seven were omitted for July 2010 and July 2012. Appendix A outlines these variables, and other created variables. This information must be located on the performance system (PRRS' internal client management system) for each individual release, making the process time-consuming. Occasional typos and inconsistent data entry result from the manual nature of the database creation and multiple employees entering the original information.

Descriptive statistics, bivariate analysis, correlational matrices, and regression modeling informed the data analysis. First, descriptive statistics reveal the raw differences in recidivism between sub-groups. Next, bivariate analyses (t-tests) assess the significance of these differences, given the size of the sample and possibility of chance variation. Correlational matrices describe the relationships between independent variables. Lastly, and most importantly, regression models reveal the role of each independent variable in predicting recidivism when the other variables are held constant. 1-year recidivism incorporates all 13 months of data, while 3-year recidivism is limited to a 6 month sub-set (excluding 2012 and 2013). Therefore, 1 and 3-year recidivism rates describe different populations and aren't perfectly comparable. In the results below, "recidivism" without a specified time period refers to trends consistent across 1 and 3-year definitions.

Data Analysis: Recidivism by Sub-Group

Summary

After 1 year, 52 of the 403 releases recidivated, or **13%**. This rate doubles to **28%** for 3-year recidivism, 59 out of the 209 person sample. Recidivators produced an average of 1.6

convictions within their first year of release and 2.1 by the end of their third year. Recidivism was higher in **males, young adults, those without college education, higher LSIR, African-Americans, and Drug Court offenders**. Re-offending spikes in the first six months after release and the last half of the third year. While crimes comprise most recidivism, traffic accounts for one-fifth of three-year offenses.

Recidivism By Release Date

Rates fluctuate wildly by release month. They range between 0% and 23% for one-year recidivism and 20% to 40% for three-year recidivism. The sizable variation by month indicates the importance of a long-term perspective on recidivism rates. By year of release, 2012's rate of 9% is nearly half of 2010's 17% rate. (Unlike 2011 and 2013, multiple months of data exist for these years.) This difference achieves statistical significance⁷ under bivariate analysis. However, a detailed examination of the characteristics of the populations in question must accompany even tentative conclusions about changes in annual recidivism.

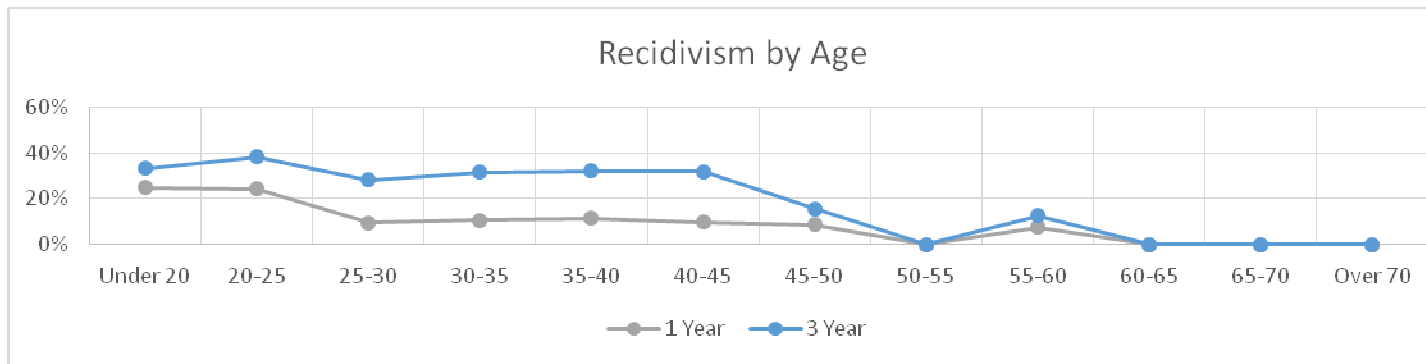
Age:

Confirming a common finding in the literature review, age is a strong predictor of recidivism in the PRC sample. The age of the ex-offender is the second most highly correlated variable with recidivism (tying with education for 1-year recidivism). A quarter of teenagers and ages 20 to 25 recidivate by 1 year. Rates then drop and stabilize to about one in every ten residents their mid-40s. Only one release over age 50 recidivated, whether using the 1 or 3 year measure. Comparing the young (under age 25) to ages 25 to 45, the stark 1-year recidivism differences somewhat diminish under 3-year recidivism, in which the young are 23% more likely to recidivate.

⁷ This analysis uses the p-value of .1 as a significance threshold.

However, the 3-year difference between the two age groups fails to achieve statistical significance under bivariate analysis. A logit regression (see Appendix E) demonstrates that holding gender, LSIR, criminal justice system of origin, and race constant, exact age is a statistically significant predictor of recidivism. A one year increase in age results in a 0.038 reduction in the log odds of recidivism. Putting these statistics into practice, the average⁸ 25-year-old's 1-year recidivism rate is 32% higher than that of the average 35-year old.

Specifically, a male, local, 35-year-old offender with average LSIR will recidivate at the rate of 12%, while a 25-year-old offender with these characteristics will recidivate at the rate of 16%, 39% higher. Meanwhile, a 45-year-old with these characteristics will recidivate at a rate of 8%, 41% higher. Note that the drop in recidivism is greater between age 25 to 35 than age 35 to 45, despite the difference being ten years in each case.



Education

GED holders recidivate at the highest rates, reaching almost half by 3 years. Holding a GED is correlated with recidivism to the same degree as age; each variable explains almost one-fifth of

⁸ "Average" means that each characteristic in the regression is set at the average of the population. As nobody is "65% black" or "8% female", the average offender doesn't exist. To enrich interpretation, the analysis also provides the recidivism rates of an individual with particular characteristics.

whether an ex-offender recidivates. Bivariate tests confirms the GED recidivism rate to be significantly significant in comparison to those without high school diplomas, as well as to high school graduates, for both 1 and 3-year recidivism. Contrary to expectations, high school graduates recidivate at equivalent rates to those without high school diplomas after 1 year. The former are actually 29% more likely to recidivate by three years than the latter, but this difference doesn't achieve statistical significance under a bivariate regression. Nobody with college experience recidivates by 1 year, and only one recidivates by 3 years. The regression does not account for educational attainment, due to complications in analysis. Accounting for education in a future regression analysis would uncover the degree to which its correlation with age (for the categories of no high school diploma and college experience, as indicated by their correlational coefficients) explains its correlation with recidivism.

Employment

1-year recidivism is identical between those employed and unemployed at release. The employment requirement at PRC explains this finding. PRC revokes residents who don't find employment (generally those with other unsuitable behaviors) after a given time. Additionally, being an inside worker isn't a statistically significant predictor, according to a bivariate test. This is likely due to the many possible reasons for a resident working for PRC, rather than an external employer. Explanations range from disabilities to a PRC stay whose short duration obstructs employment (J. Henriquez, personal communication, March 13, 2014).

Gender: Recidivism sharply and significantly diverges by gender, with the male rate dwarfing that of females by a factor of five after 1 year and seven after 3 years. Due to the small size of

the female population, over-sampling females would be recommended for future gender analysis. (Exactly one female recidivated in the 1 and 3 year dataset.) However, bivariate tests confirmed that gender differences are statistically significant for both 1 and 3-year recidivism.

	Recidivism Rate	
	1 Year	3 Year
Male	14%	31%
Female	3%	5%

LSIR

The Level of Service Inventory-Revised (LSIR) is a 54-item questionnaire administered to inmates in order to assess likelihood of re-offending. Topics cover ten domains with proven correlation to recidivism, including peers, education, and employment. Most importantly, LSIR accounts for previous criminal history, a predictor that the literature review found to be strongly predicative of future re-offending. The responses generate a composite numerical score which is classified into four categories. LSIR informs case managers' development of reentry plans, but doesn't influence PRC eligibility or programming (134).

This analysis found LSIR to be the variable most highly correlated with 1 and 3-year recidivism. Higher LSIR means higher recidivism. No one-year recidivism occurred among residents evaluated at minimum risk. The recidivism rate steadily increases with LSIR score, reaching two-thirds of maximum offenders after 3 years. Bivariate tests of both 1 and 3-year recidivism found the differences between each of the four categories to be statistically significant for all but

the lowest two. In the regression analysis, LSIR achieves high statistical significance for 1 and 3-year recidivism. Holding the other variables (age, gender, criminal justice system of origin, and race) constant, a one-unit increase in the LSIR score increases the likelihood of 1-year recidivism by log odds of .104. An average offender with an LSIR of 25 (the first score falling in the high-medium category) is 3.3 times as likely to recidivate as an average offender with an LSIR of 13 (the first score falling in the low-medium category). An average offender with an LSIR score of 37 (the first score falling in the maximum category) is 2.9 times as likely to recidivate as an average offender with an LSIR of 25. These ratios also hold true for a male, local offender of average age (34).

Finding LSIR to be a statistically significant predictor is important for the Pre-Release Center, as a data-based indication that LSIR is performing its intended purpose. Although LSIR is a rigorously validated tool used nationally, it has not yet been tested for predictability for the PRC population. This analysis supports its value for PRC case managers in developing individualized plans for their residents.

LSIR Category	Recidivism Rate	
	1 Year	3 Year
Minimum (0-12)	0%	15%
Low-Medium (13-24)	7%	18%
High-Medium (25-36)	16%	35%
Maximum (37-40)	36%	67%

Race

At 16%, blacks experience much higher 1-year recidivism than Hispanics at 10%, Whites at 9%, and Other at 17%. Blacks also hold the highest 3-year recidivism rate of 34%, exceeding Hispanic at 30%, Other at 25%, and White at 24%. However, bivariate analysis demonstrates the only statistically significant inter-race difference lies between blacks and whites for 1-year recidivism, perhaps due to the low sample size of Hispanic and Other offenders. In the regression modeling, neither Black nor Hispanic achieved statistical significance, with White as the base case. However, Other race category is statistically significant for 1-year regression, with a log odds of 1.475. This means that an average Other offender is 3.7 times as likely to recidivate as an average White offender. For the specific case of a male, local offender of average age (34) and LSIR (25), an Other racial identification makes the recidivism rate 3.6 times as likely to recidivate as a White individual with those same characteristics. While these calculations are mathematically valid, they present little value to PRC because individuals identifying as other are a tiny minority of the population – only 4% of this paper's sample.

System

The criminal justice system of origin produces strikingly different recidivism rates. A little over one-fourth of Drug Court offenders recidivated by 1 year, twice the rate of local offenders and five times the rate of federal offenders. This ranking remains for three-year recidivism, but the percent differences between the sub-groups diminish. Considering that federal offenses tend to be more serious crimes than those adjudicated by local, their low rates are unanticipated. Further analysis suggests two explanations. First, the average federal offender is 39 years old, compared to the average age of 32 and 33 for Drug Court and local offenders respectively. As evidenced in

the raw statistics and regression analysis, older individuals are less likely to re-offend. Secondly, education acts as a confounding factor. One-third of federal offenders received some college education, triple the rate of local offenders and quadruple the rate of Drug Court offenders. Bivariate analysis of each category to the other two categories affirms that the differences are all statistically significant, for both 1 and 3-year recidivism. However, using local as a base case, neither Drug Court nor federal status achieves statistical significance for 1-year recidivism. On the other hand, Drug Court offenders barely attain statistical significance in the 3-year recidivism analysis. Holding age, gender, LSIR and race constant, being a Drug Court offender increases the log odds of recidivating by 1.04. The average Drug Court offender’s probability of recidivating is nearly twice that of the average local offender. Specifically, a male Drug Court offender with average age and LSIR is 83% more likely to recidivate than a local offender with the same characteristics.

	Recidivism Rate	
System	1 Year	3 Year
Drug Court	27%	56%
Federal	5%	14%
Local	14%	30%

Release Location

As the dataset contains only four releases labeled as homeless or ‘needs housing’, and two classified as released to sober housing, their sample sizes are too small for recidivism analysis. Geographical analysis of release location doesn’t yield any meaningful results for states or cities.

Of the 6 external states to which PRC released individuals, only DC and Virginia received more than one release. The difference between their recidivism rates and that of Maryland doesn't reach statistical significance under bivariate testing. The three percentage point difference in recidivism rates for Maryland and total out-of-state releases isn't significant either. PRC releases residents to 72 unique cities. One-fifth of those with a specified city of release go to Silver Spring; one-seventh to Gaithersburg; and one-tenth to Rockville. No large and statistically significant differences appear in comparing recidivism rates by release city.

Data Analysis: Further Recidivism Analysis

This section explores recidivism trends beyond sub-group differentiation.

Recidivism Over Time

Analyzing the cumulative recidivism rates reveals that almost one-quarter of those who will eventually recidivate by 3 years re-offend during the first 6 months, and the same share in the second 12 months. About 8% do so in each of the next 6 month time periods. However, one-third of releases become recidivators in the last 6 months of the 3-year analysis.

Recidivist Event Type

Almost three quarters of 1-year recidivators were convicted for crimes only, while 15% limited themselves to traffic offenses. (As a reminder, PRC decided against classifying non-incarcerable traffic crimes as recidivist offenses). By 3 years, the percentage of just traffic rises slightly, while just crime falls slightly. From another perspective, traffic violations prompted at least one

conviction for 27% of 1-year recidivators and 31% of 3-year recidivators. On the other hand, crimes causes at least one conviction for 85% of 1-year recidivators and 80% of 3-year recidivators. The similarity of the share of traffic and criminal convictions in 1 and 3-year measures contradicts the hypothesis mentioned earlier, that the time period chosen might alter the perception of the type of crime. Further disaggregating by age and education reveals interesting 1-year recidivism trends (examined in lieu of 3-year because of larger sample sizes). Of 3-year recidivators, 8% of under 25-year olds have committed only traffic offenses, a rate that more than doubles for 25 to 45 year olds. 85% of under 25 year olds have committed only crimes, compared to 68% for 25 to 45 year olds. The percentage of those convicted for only crimes is highest for high school graduates, and lowest for those with college experience, while the reverse is true for only traffic convictions.

Type of Recidivism of Individual		
	1 Year	3 Year
Recidivism: Just Criminal	73%	69%
Recidivism: Just Traffic	15%	20%
Recidivism: Mix	12%	10%

Other Observations

- Differences between sub-groups tend to increase with time. For ten population divisions examined (release month, age group, education, employment, gender, inside worker, LSIR category, system, race and release city), the percentage point difference between the

minimum and maximum is larger for 3-year recidivism than 1-year recidivism. This pattern follows that of the BJS study discussed previously.

- The dataset indicates VOP caused at least one conviction for 3 (6%) of one-year recidivators and 6 (14%) of three-year recidivators. However, 16% of convictions for the 1 and three-year recidivism samples lacked VOP information.

Conclusions

First of all, the review of existing recidivism definitions reveals the vast heterogeneity regarding the time period, criminal event, and population. There is no consensus among jurisdictions and researchers on a definition of recidivism. PRC should maintain its current 1 and 3-year re-conviction definition, in order to compare future data against the current baseline. The 3 year time period allows greater recognition of cases progressing slowly through the criminal justice system, while re-convictions are a more valid definition of crime than arrests in omitting those arrested but not found guilty. Moreover, PRC's incorporation of local, state and federal criminal justice databases improves the validity of its recidivism rate, a worthwhile achievement despite reducing generalizability to jurisdictions with more limited databases.

Second, the recidivism rate is not an appropriate performance indicator of a correctional facility, due to the large and non-quantifiable influence of contextual factors. The role of politics, demographics and criminal justice policy on recidivism rates makes inter-jurisdictional comparisons of recidivism rates difficult. Therefore, PRC's recidivism rate is meaningful as an

indicator of the combined efforts of government agencies (education, social service, workforce development, correctional facilities), not as an indication of the facility's performance. For these reasons, I recommend against benchmarking PRC's recidivism rates to another jurisdiction. Instead, PRC should focus on changes in its recidivism rate over time and the differences between sub-groups. A baseline recidivism rate of MCCF would be a highly valuable comparison group to the Pre-Release Center, despite the intangible differences in population. Another helpful aid to future recidivism research would be tracking the number of hours in which residents participated in particular programs at PRC. This would allow researchers to investigate the connection between program participation, recidivism magnitude and recidivism type. Lastly, the complexity of categorizing initial and recidivist offenses prevented this researcher from examining specialist recidivism, an important research question.

For the PRC, the most helpful takeaway from the data analysis component is the progression beyond merely identifying sub-groups with the highest recidivism rates. The regression analysis demonstrates that racial and gender differences fall away once criminal history and age are taken into account. The quantitative work indicates the need to dedicate programmatic funding and attention towards residents under age 25, and those with high LSIR. These two categories of offenders should be prioritized as recipients of PRC resources, and development of additional programs for their criminogenic needs. Lastly, this study supports PRC's use of LSIR as a predictive tool of re-offending. As LSIR has not been validated for the PRC population, this study should give case managers greater confidence in the use of LSIR for their clients.

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APPENDICES

Appendix A: Original and Created Variables

Neither the list of variables nor the value/notes are exhaustive depictions of the variables created in the Stata Do-Files. They offer a helpful starting point to the key variables and some of their characteristics.

	Stata storage type	Values/Note
(DOB) BirthDate	int	1940 thru 1994
Age	float	18 to 70
AgeSq	float	324 to 4904
AgeCen	float	-16 to 36
AgeGroup_12Cat	float	1 "Under 20" 2 "20-25" 3 "25-30" 4 "30-35" 5 "35-40" 6 "40-45" 7 "45-50" 8 "50-55" 9 "55-60" 10 "60-65" 11 "65-70" 12 "Over 70"
AgeGroup_3Cat	float	1: <25 2: 25-45 3: >=45
Age_MiddleToYoung	float	. : >=45 0: <25 1: 25-45
Age_OldToYoung	float	. : 25-45 0: <25 1 : >=4
AgeCurrent	float	19 to 73
Education	str	many categories

Education2	str	fixes extra spaces, spelling and capitalization inconsistency in Highest Level of Education
Education_8Cat	float	.=Unknown,missing, N/A 1= No High School 2 = High School, No Degree 3 = GED 4 = High School, Degree 5 = College, No Degree 6 = College, Associate's Degree (AS,AA) 7 = College, Bachelor's Degree (BA/BS) 8 = Advanced Degree

Education_4Cat	float	.=Unknown,missing, N/A 1= No High School Diploma 2 = GED 3 = High School, Degree 4 = At Least Some College
Employed (EmployedWhenReleased)	str	uncleaned
Employed2	str	no yes n/a
Employed3	long	1 = N/A 2= No 3= Yes
EmployedIndicator	float	. = missing or N/A 0 = No 1=Yes
Gender	str	male female
Gender2	long	0=male 1=female
Gender_Male	float	0 = female 1 = male
InsideWorker	str	no yes n/a

InsideWorker2	long	. = missing or N/A 0 = No 1=Yes
LSIRScore	str	ex. High-Medium(30)
LSIR2	str	cleaned
LSIRCategory	str	N/A min: -12 low-medium: 13-24 high medium: 25-36 max: 37-40
LSIRCategory2	long	. = missing or N/A 1= min 2=low-medium 3=high medium 4=max
LSIRNum	str	#
LSIRNum2	byte	8 to 42
LSIRSq	LSIRSq	#
OffenseServedatPRC	str	many, messy
Offense_VOP	float	0 = no 1= yes (VOP in original offense)
(Type) System	str	uncleaned
System2	long	Local Federal Drug State
System3	long	Local Federal Drug State

System_Drug	byte	0: No 1: Yes
OffenseType_Fed	byte	0: No 1: Yes
OffenseType_Local	byte	0: No 1: Yes
OffenseType_State	byte	0: No 1: Yes
Race	str	white other black Asian Hispanic
Race 2	str	white other/Asian black Hispanic
Race 3	long	1=black 2=Hispanic 3=Other 4=White
Race_Black	byte	0: No 1: Yes
Race_Hispanic	byte	0: No 1: Yes
Race_Other	byte	0: No 1: Yes
Race_White	byte	0: No 1: Yes
Race_NotWhite	byte	0: No 1: Yes
Release Date	int	<i>ex. 18nov2012</i>
ReleaseMonth	str	<i>ex. 2010-09</i>
ReleaseLocation	str	<i>city, state, zip code</i> <i>city</i> <i>state</i>
ReleaseYear	int	####
ReleaseYear_2010	byte	0: not 2010 1: 2010
ReleaseYear_2011	byte	0: not 2011 1: 2011

ReleaseYear_2012	byte	0: not 2012 1: 2012
ReleaseYear_2013	byte	0: not 2013 1: 2013
ReleaseLocation_Type	float	0=Housing 1=Unknown /NA 2= Homeless/ Needs Housing 3=Sober/Okinawa Sober
ReleaseZip	str	<i>5 digits</i>
ReleaseZip2	long	<i>5 digits</i>
ReleaseCity	str	city name
ReleaseCity2	long	city name
ReleaseCity2Freq	float	frequency of city as release location
ReleaseState	str	
ReleaseState2	long	
ReleaseStateMD	float	. = unknown or not- state 0=state, not MD 1=MD
LSIR Score	str	ex. High- Medium(30)
LSIR2	str	modified
LSIRCategory	str	min: -12 low-medium: 13-24 high medium: 25-36 max: 37-40
LSIRCategory2	long	1= min 2=low-medium 3=high medium 4=max
LSIRNum	str	#

LSIRNum2	byte	#
LSIRSq	float	#
Charge[X]Conviction	str	missing yes no
Charge[X]Conviction2	float	0 = no 1 = yes
Charge[X]VOPViolation	str	mi = no Charge, charge missing VOP info no = not VOP yes = VOP
Charge[X]VOPViolation2	float	mi = no Charge, charge missing VOP info 0 = not VOP 1 = VOP
TotVOPRecidivism	float	0 - 7 no mi allowed
Charge[X]TimefromReleasetoChar	int	#
(Charge[X]CaseType) (Charge[X]Type)	str	uncleaned
Charge[X]Type2	str	1=serious traffic/traffic 2=criminal
Charge[X]DateIssued	int	
Charge[X]DateofConviction	int	
Charge[X]CaseNum	str	alphanumeric

Charge[X]Charge	str	disorderly conduct dri while lic revoked etc
(Charge[X]Plea/Disposition) Charge[X]PleaDisposition	str	guilty/guilty guilty/PBJ guilty not guilty/guilty
Charge[X]Sentence	str	uncleaned
Charge[X]TimeToRecidivism1	float	#
Charge[X]TimeToRecidivism2	float	#
Charge[X]TimeToRecidivism3	float	#
Charge[X]TimeToRecidivism4	float	#
Charge[X]TimeToRecidivism5	float	#
Charge[X]TimeToRecidivism6	float	#
Charge[X]TimeToRecidivism7	float	#
Recidivism_1Yr	float	0 = No 1 = Yes
Recidivism_3Yr	float	0 = No 1 = Yes
Recidivism_Count_[X]Yr	float	# cumulative
Recidivism_CountVOP_[X]Yr	float	#VOP
Recidivism_CountTraffic_[X]Yr	float	# traffic recidivist events

Recidivism_CountCriminal_[X]Yr	float	# traffic criminal events
Recidivism_Type_[x]Yr	float	0: no Recidivism 1: ecidivism: Just Traffic 2: Recidivism: Mix 3: Recidivism: Just Criminal
Recidivism_AtLeastOneTraffic_[X]Yr	float	. = non-recidivator 0 = No 1 = Yes
Recidivism_AtLeastOneCrim_[X]Yr	float	. = non-recidivator 0 = No 1 = Yes

Appendix B: Descriptive Statistics

Note: The first two columns in the tables below refer to the complete data-set, as thus are not reflective of the limited 3-year recidivism rates.

Recidivism by Release Year				
	Population		Recidivism Rate	
	Number	Percent	1 Year	3 Year
2010	186	46%	17%	28%
2011	23	6%	0%	26%
2012	162	40%	9%	.
2013	32	8%	16%	.
Total	403	100%	13%	28%

Recidivism by Release Month				
	Population		Recidivism Rate	
	Number	Percent	1 Year	3 Year
2010 Jul	37	9%	14%	24%
2010-Aug	43	11%	23%	40%
2010-Sep	34	8%	15%	26%
2010-Oct	40	10%	13%	20%
2010-Nov	32	8%	22%	31%
2011-Jan	23	6%	0%	26%
2012-Jul	24	6%	13%	.
2012-Aug	25	6%	4%	.
2012-Sep	21	5%	19%	.
2012-Oct	31	8%	3%	.
2012-Nov	24	6%	17%	.
2012-Dec	37	9%	5%	.
2013-Jan	32	8%	16%	.

Recidivism by Age Group				
	Population		Recidivism Rate	
	Number	Percent	1 Year	3 Year
Under 20	16	4%	25%	33%
20-25	90	22%	24%	38%
25-30	74	18%	9%	28%
30-35	57	14%	11%	31%
35-40	44	11%	11%	32%
40-45	41	10%	10%	32%

45-50	34	8%	9%	16%
50-55	24	6%	0%	0%
55-60	13	3%	8%	13%
60-65	3	1%	0%	0%
65-70	4	1%	0%	0%
Over 70	3	1%	0%	0%

Recidivism by Age Group				
	Population		Recidivism Rate	
	Number	Percent	1 Year	3 Year
Under 25	106	26%	25%	38%
25-45	216	54%	10%	31%
45 and Over	81	20%	5%	10%

Recidivism by Education				
	Population		Recidivism Rate	
	Number	Percent	1 Year	3 Year
Unknown	66	16%	12%	24%
No High School	11	3%	18%	36%
High School, No Degree	81	20%	12%	18%
GED	49	12%	29%	48%
High School, Degree	140	35%	13%	30%
College, No Degree	35	9%	0%	0%
College, Associate's	2	1%	0%	.
College, Bachelor's	13	3%	0%	14%
Advanced Degree	3	1%	0%	0%

Recidivism by Education				
	Population		Recidivism Rate	
	Number	Percent	1 Year	3 Year
No High School Degree	92.00	27.54	13%	23%
GED	49.00	14.67	29%	48%
High School Degree	140.00	41.92	13%	30%
Least Some College	53.00	15.87	0%	5%

Recidivism by Employment At Release				
	Population		Recidivism Rate	
	Number	Percent	1 Year	3 Year
No	77	19%	13%	26%
Yes	255	63%	13%	31%

Recidivism by Gender				
	Population		Recidivism Rate	
	Number	Percent	1 Year	3 Year
Male	363	90%	14%	31%
Female	39	10%	3%	5%

Recidivism by Inside Worker				
	Population		Recidivism Rate	
	Number	Percent	1 Year	3 Year
No	308	76%	13%	30%
Yes	24	6%	17%	13%

Recidivism by LSIR				
	Population		Recidivism Rate	
	Number	Percent	1 Year	3 Year
Minimum	19	5%	0%	15%
Low-Medium	132	33%	7%	18%
High-Medium	168	42%	16%	35%
Maximum	22	5%	36%	67%

Recidivism by Race				
	Population		Recidivism Rate	
	Number	Percent	1 Year	3 Year
Black	180	45%	16%	34%
Hispanic	30	7%	10%	30%
White	114	28%	9%	24%
Other	18	4%	17%	25%

Recidivism by Top Release Cities				
	Population		Recidivism Rate	
	Number	Percent	1 Year	3 Year
Gaithersburg	44	15%	16%	37%
Germantown	20	7%	5%	14%
Rockville	27	9%	19%	33%

Silver Spring	57	19%	16%	28%
Remaining Cities (Under 10 Releases)	134	45%	12%	29%
Washington	18	6%	17%	20%

Recidivism by Release State				
	Population		Recidivism Rate	
	Number		1 Year	3 Year
DC	18	6%	17%	20%
KS	1	0%	0%	100%
MD	263	88%	13%	30%
NY	1	0%	100%	100%
OH	1	0%	0%	.
SC	1	0%	0%	.
VA	15	5%	13%	17%

Recidivism by System				
	Population		Recidivism Rate	
	Number	Percent	1 Year	3 Year
Drug Court	30	7%	27%	56%
Federal	86	21%	5%	14%
Local	285	71%	14%	30%
State	1	0%	0%	0%

Type of Recidivism of Individual		
	1 Year	3 Year
Recidivism: Just Criminal	73%	69%
Recidivism: Just Traffic	15%	20%
Recidivism: Mix	12%	10%

Type of Recidivism By Age					
	Total Recidivators	At Least One Criminal Conviction	At Least One Traffic Conviction	Only Criminal Convictions	Only Traffic Convictions
Under 25	26	57%	36%	85%	8%
25 to 45	22	43%	64%	68%	18%

Recidivism Over Time						
Months After Release	0-6	6-12	12-18	18-24	24-30	30-36

Cumulative Recidivism	6%	13%	15%	18%	20%	0.28
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Appendix C: T-Tests

1 Year Recidivism T-Test:Age_MiddleToYoung

Two-sample t test with equal variances

Group	Obs	Mean	Std. Err.	Std. Dev.	[95% Conf. Interval]	
Under 25	106	.245283	.0419886	.4322989	.1620274	.3285386
25-45	216	.1018519	.0206271	.303156	.0611945	.1425092
combined	322	.1490683	.0198787	.3567101	.1099594	.1881773
diff		.1434312	.0416027		.0615818	.2252805

diff = mean(Under 25) - mean(25-45) t = 3.4476
 Ho: diff = 0 degrees of freedom = 320

Ha: diff < 0 Ha: diff != 0 Ha: diff > 0
 Pr(T < t) = 0.9997 Pr(|T| > |t|) = 0.0006 Pr(T > t) = 0.0003

3 Year Recidivism T-Test:Age_MiddleToYoung

Two-sample t test with equal variances

Group	Obs	Mean	Std. Err.	Std. Dev.	[95% Conf. Interval]	
Under 25	53	.3773585	.0672194	.4893644	.242473	.512244
25-45	114	.3070175	.0433914	.4632932	.2210514	.3929837
combined	167	.3293413	.0364771	.4713875	.2573225	.4013601
diff		.0703409	.0784154		-.0844861	.225168

diff = mean(Under 25) - mean(25-45) t = 0.8970
 Ho: diff = 0 degrees of freedom = 165

Ha: diff < 0 Ha: diff != 0 Ha: diff > 0
 Pr(T < t) = 0.8145 Pr(|T| > |t|) = 0.3710 Pr(T > t) = 0.1855

1 Year Recidivism T-Test:Age_OldToMiddle

Two-sample t test with equal variances

Group	Obs	Mean	Std. Err.	Std. Dev.	[95% Conf. Interval]	
25-45	216	.1018519	.0206271	.303156	.0611945	.1425092

45 and O	81	.0493827	.024224	.2180157	.0011755	.09759
-----+						
combined	297	.0875421	.0164274	.2831048	.0552128	.1198714
-----+						
diff		.0524691	.0368215		-.019997	.1249352

diff = mean(25-45) - mean(45 and O)				t = 1.4250		
Ho: diff = 0				degrees of freedom = 295		

Ha: diff < 0 Ha: diff != 0 Ha: diff > 0
 Pr(T < t) = 0.9224 Pr(|T| > |t|) = 0.1552 Pr(T > t) = 0.0776
 3 Year Recidivism T-Test:Age_OldToMiddle

Two-sample t test with equal variances

Group	Obs	Mean	Std. Err.	Std. Dev.	[95% Conf. Interval]	
-----+						
25-45	114	.3070175	.0433914	.4632932	.2210514	.3929837
45 and O	42	.0952381	.0458438	.2971018	.0026547	.1878215
-----+						
combined	156	.25	.0347804	.4344073	.1812952	.3187048
-----+						
diff		.2117794	.0767927		.0600763	.3634826

diff = mean(25-45) - mean(45 and O)				t = 2.7578		
Ho: diff = 0				degrees of freedom = 154		

Ha: diff < 0 Ha: diff != 0 Ha: diff > 0
 Pr(T < t) = 0.9967 Pr(|T| > |t|) = 0.0065 Pr(T > t) = 0.0033
 1 Year Recidivism T-Test:Age_OldToYoung

Two-sample t test with equal variances

Group	Obs	Mean	Std. Err.	Std. Dev.	[95% Conf. Interval]	
-----+						
Under 25	106	.245283	.0419886	.4322989	.1620274	.3285386
45 and O	81	.0493827	.024224	.2180157	.0011755	.09759
-----+						
combined	187	.1604278	.0269099	.3679876	.1073399	.2135157
-----+						
diff		.1959003	.0525146		.0922958	.2995048

diff = mean(Under 25) - mean(45 and O)				t = 3.7304		
Ho: diff = 0				degrees of freedom = 185		

Ha: diff < 0 Ha: diff != 0 Ha: diff > 0

Pr(T < t) = 0.9999 Pr(|T| > |t|) = 0.0003 Pr(T > t) = 0.0001
 3 Year Recidivism T-Test:Age_OldToYoung

Two-sample t test with equal variances

Group	Obs	Mean	Std. Err.	Std. Dev.	[95% Conf. Interval]	
Under 25	53	.3773585	.0672194	.4893644	.242473	.512244
45 and O	42	.0952381	.0458438	.2971018	.0026547	.1878215
combined	95	.2526316	.0448175	.4368266	.1636455	.3416177
diff		.2821204	.0858798	.1115801	.4526607	

diff = mean(Under 25) - mean(45 and O) t = 3.2851
 Ho: diff = 0 degrees of freedom = 93

Ha: diff < 0 Ha: diff != 0 Ha: diff > 0
 Pr(T < t) = 0.9993 Pr(|T| > |t|) = 0.0014 Pr(T > t) = 0.0007
 1 Year Recidivism T-Test:Education_HSExpforTtest1

Two-sample t test with equal variances

Group	Obs	Mean	Std. Err.	Std. Dev.	[95% Conf. Interval]	
NoHSD	92	.1304348	.0353043	.3386266	.0603072	.2005624
HSD	140	.1285714	.028391	.3359269	.0724374	.1847055
combined	232	.1293103	.0220771	.3362686	.0858121	.1728086
diff		.0018634	.0452286	-.0872519	.0909786	

diff = mean(NoHSD) - mean(HSD) t = 0.0412
 Ho: diff = 0 degrees of freedom = 230

Ha: diff < 0 Ha: diff != 0 Ha: diff > 0
 Pr(T < t) = 0.5164 Pr(|T| > |t|) = 0.9672 Pr(T > t) = 0.4836
 3 Year Recidivism T-Test:Education_HSExpforTtest1

Two-sample t test with equal variances

Group	Obs	Mean	Std. Err.	Std. Dev.	[95% Conf. Interval]	
NoHSD	39	.2307692	.0683479	.4268328	.092406	.3691324
HSD	74	.2972973	.0534958	.4601885	.1906803	.4039143

combined | 113 .2743363 .04216 .4481667 .1908017 .3578709

-----+-----
diff | -.0665281 .0888555 -.2426011 .109545
-----+-----

diff = mean(NoHSD) - mean(HSD) t = -0.7487
Ho: diff = 0 degrees of freedom = 111

Ha: diff < 0 Ha: diff != 0 Ha: diff > 0
Pr(T < t) = 0.2278 Pr(|T| > |t|) = 0.4556 Pr(T > t) = 0.7722
1 Year Recidivism T-Test:Education_HSExpforTtest2

Two-sample t test with equal variances

-----+-----
Group | Obs Mean Std. Err. Std. Dev. [95% Conf. Interval]
-----+-----
NoHSD | 92 .1304348 .0353043 .3386266 .0603072 .2005624
GED | 49 .2857143 .0652051 .4564355 .1546107 .4168179
-----+-----
combined | 141 .1843972 .0327757 .3891903 .1195978 .2491966
-----+-----
diff | -.1552795 .0678102 -.2893524 -.0212066
-----+-----

diff = mean(NoHSD) - mean(GED) t = -2.2899
Ho: diff = 0 degrees of freedom = 139

Ha: diff < 0 Ha: diff != 0 Ha: diff > 0
Pr(T < t) = 0.0118 Pr(|T| > |t|) = 0.0235 Pr(T > t) = 0.9882
3 Year Recidivism T-Test:Education_HSExpforTtest2

Two-sample t test with equal variances

-----+-----
Group | Obs Mean Std. Err. Std. Dev. [95% Conf. Interval]
-----+-----
NoHSD | 39 .2307692 .0683479 .4268328 .092406 .3691324
GED | 33 .4848485 .0883478 .5075192 .30489 .664807
-----+-----
combined | 72 .3472222 .0565011 .4794281 .2345621 .4598823
-----+-----
diff | -.2540793 .1100921 -.4736511 -.0345074
-----+-----

diff = mean(NoHSD) - mean(GED) t = -2.3079
Ho: diff = 0 degrees of freedom = 70

Ha: diff < 0 Ha: diff != 0 Ha: diff > 0
Pr(T < t) = 0.0120 Pr(|T| > |t|) = 0.0240 Pr(T > t) = 0.9880
1 Year Recidivism T-Test:Education_HSExpforTtest3

diff | .0004584 .0437936 -.0856915 .0866082

diff = mean(No) - mean(Yes) t = 0.0105
Ho: diff = 0 degrees of freedom = 330

Ha: diff < 0 Ha: diff != 0 Ha: diff > 0
Pr(T < t) = 0.5042 Pr(|T| > |t|) = 0.9917 Pr(T > t) = 0.4958
3 Year Recidivism T-Test:EmployedIndicator

Two-sample t test with equal variances

Group | Obs Mean Std. Err. Std. Dev. [95% Conf. Interval]
-----+-----
No | 31 .2580645 .0798889 .4448027 .0949096 .4212195
Yes | 131 .3053435 .0403931 .4623207 .2254305 .3852565
-----+-----
combined | 162 .2962963 .035987 .4580391 .225229 .3673636
-----+-----
diff | -.047279 .091693 -.2283636 .1338056

diff = mean(No) - mean(Yes) t = -0.5156
Ho: diff = 0 degrees of freedom = 160

Ha: diff < 0 Ha: diff != 0 Ha: diff > 0
Pr(T < t) = 0.3034 Pr(|T| > |t|) = 0.6068 Pr(T > t) = 0.6966
1 Year Recidivism T-Test:Gender2

Two-sample t test with equal variances

Group | Obs Mean Std. Err. Std. Dev. [95% Conf. Interval]
-----+-----
Male | 363 .1404959 .0182642 .3479804 .1045785 .1764132
Female | 39 .025641 .025641 .1601282 -.0262665 .0775486
-----+-----
combined | 402 .1293532 .0167586 .3360087 .0964076 .1622989
-----+-----
diff | .1148548 .0564002 .0039771 .2257326

diff = mean(Male) - mean(Female) t = 2.0364
Ho: diff = 0 degrees of freedom = 400

Ha: diff < 0 Ha: diff != 0 Ha: diff > 0
Pr(T < t) = 0.9788 Pr(|T| > |t|) = 0.0424 Pr(T > t) = 0.0212
3 Year Recidivism T-Test:Gender2

Two-sample t test with equal variances

diff = mean(No) - mean(Yes) t = 1.0757
 Ho: diff = 0 degrees of freedom = 161

Ha: diff < 0 Ha: diff != 0 Ha: diff > 0
 Pr(T < t) = 0.8582 Pr(|T| > |t|) = 0.2837 Pr(T > t) = 0.1418
 1 Year Recidivism T-Test:LSIRIndicator1v2

Two-sample t test with equal variances

Group	Obs	Mean	Std. Err.	Std. Dev.	[95% Conf. Interval]	
0	19	0	0	0	0	0
1	132	.0681818	.0220224	.2530179	.0246163	.1117473
combined	151	.0596026	.0193305	.237537	.0214074	.0977979
diff		-.0681818	.0582128		-.1832111	.0468474

diff = mean(0) - mean(1) t = -1.1713
 Ho: diff = 0 degrees of freedom = 149

Ha: diff < 0 Ha: diff != 0 Ha: diff > 0
 Pr(T < t) = 0.1217 Pr(|T| > |t|) = 0.2434 Pr(T > t) = 0.8783
 3 Year Recidivism T-Test:LSIRIndicator1v2

Two-sample t test with equal variances

Group	Obs	Mean	Std. Err.	Std. Dev.	[95% Conf. Interval]	
0	13	.1538462	.1041543	.3755338	-.0730867	.380779
1	67	.1791045	.0471982	.3863337	.0848703	.2733387
combined	80	.175	.0427496	.3823644	.089909	.260091
diff		-.0252583	.1165867		-.2573646	.2068479

diff = mean(0) - mean(1) t = -0.2166
 Ho: diff = 0 degrees of freedom = 78

Ha: diff < 0 Ha: diff != 0 Ha: diff > 0
 Pr(T < t) = 0.4145 Pr(|T| > |t|) = 0.8290 Pr(T > t) = 0.5855
 1 Year Recidivism T-Test:LSIRIndicator2v3

Two-sample t test with equal variances

Group	Obs	Mean	Std. Err.	Std. Dev.	[95% Conf. Interval]	
-------	-----	------	-----------	-----------	----------------------	--

Ha: diff < 0 Ha: diff != 0 Ha: diff > 0
 Pr(T < t) = 0.0104 Pr(|T| > |t|) = 0.0209 Pr(T > t) = 0.9896
 3 Year Recidivism T-Test:LSIRIndicator3v4

Two-sample t test with equal variances

Group	Obs	Mean	Std. Err.	Std. Dev.	[95% Conf. Interval]	
0	79	.3544304	.0541614	.4813969	.2466034	.4622574
1	12	.6666667	.1421338	.492366	.3538323	.9795011
combined	91	.3956044	.051543	.4916892	.2932052	.4980036
diff		-.3122363	.149573		-.6094347	-.0150379
diff = mean(0) - mean(1)				t = -2.0875		
Ho: diff = 0				degrees of freedom = 89		

Ha: diff < 0 Ha: diff != 0 Ha: diff > 0
 Pr(T < t) = 0.0198 Pr(|T| > |t|) = 0.0397 Pr(T > t) = 0.9802
 1 Year Recidivism T-Test:Race_BlackToHisp

Two-sample t test with equal variances

Group	Obs	Mean	Std. Err.	Std. Dev.	[95% Conf. Interval]	
Hispanic	30	.1	.0557086	.3051286	-.0139369	.2139369
Black	180	.1555556	.0270895	.3634445	.1020996	.2090115
combined	210	.147619	.0245366	.3555696	.099248	.1959901
diff		-.0555556	.070182		-.1939147	.0828036
diff = mean(Hispanic) - mean(Black)				t = -0.7916		
Ho: diff = 0				degrees of freedom = 208		

Ha: diff < 0 Ha: diff != 0 Ha: diff > 0
 Pr(T < t) = 0.2147 Pr(|T| > |t|) = 0.4295 Pr(T > t) = 0.7853
 3 Year Recidivism T-Test:Race_BlackToHisp

Two-sample t test with equal variances

Group	Obs	Mean	Std. Err.	Std. Dev.	[95% Conf. Interval]	
Hispanic	10	.3	.1527525	.4830459	-.0455502	.6455502

Black	82	.3414634	.0526889	.4771187	.2366289	.4462979
-----+-----						
combined	92	.3369565	.0495493	.4752599	.238533	.4353801
-----+-----						
diff		-.0414634	.1600131		-.3593574	.2764306
-----+-----						
diff = mean(Hispanic) - mean(Black)					t =	-0.2591
Ho: diff = 0					degrees of freedom =	90

Ha: diff < 0 Ha: diff != 0 Ha: diff > 0
Pr(T < t) = 0.3981 Pr(|T| > |t|) = 0.7961 Pr(T > t) = 0.6019
1 Year Recidivism T-Test:Race_BlackToWhite

Two-sample t test with equal variances

Group	Obs	Mean	Std. Err.	Std. Dev.	[95% Conf. Interval]	
-----+-----						
White	114	.0877193	.0266117	.2841352	.0349967	.1404419
Black	180	.1555556	.0270895	.3634445	.1020996	.2090115
-----+-----						
combined	294	.1292517	.0195989	.3360503	.0906793	.1678241
-----+-----						
diff		-.0678363	.0400972		-.1467523	.0110798
-----+-----						
diff = mean(White) - mean(Black)					t =	-1.6918
Ho: diff = 0					degrees of freedom =	292

Ha: diff < 0 Ha: diff != 0 Ha: diff > 0
Pr(T < t) = 0.0459 Pr(|T| > |t|) = 0.0918 Pr(T > t) = 0.9541
3 Year Recidivism T-Test:Race_BlackToWhite

Two-sample t test with equal variances

Group	Obs	Mean	Std. Err.	Std. Dev.	[95% Conf. Interval]	
-----+-----						
White	68	.2352941	.0518221	.4273363	.1318567	.3387315
Black	82	.3414634	.0526889	.4771187	.2366289	.4462979
-----+-----						
combined	150	.2933333	.0372988	.4568152	.2196304	.3670363
-----+-----						
diff		-.1061693	.0746691		-.2537246	.041386
-----+-----						
diff = mean(White) - mean(Black)					t =	-1.4219
Ho: diff = 0					degrees of freedom =	148

Ha: diff < 0 Ha: diff != 0 Ha: diff > 0

Pr(T < t) = 0.0786 Pr(|T| > |t|) = 0.1572 Pr(T > t) = 0.9214
 1 Year Recidivism T-Test:Race_HispToWhite

Two-sample t test with equal variances

Group	Obs	Mean	Std. Err.	Std. Dev.	[95% Conf. Interval]
White	114	.0877193	.0266117	.2841352	.0349967 .1404419
Hispanic	30	.1	.0557086	.3051286	-.0139369 .2139369
combined	144	.0902778	.023965	.2875796	.0429064 .1376491
diff		-.0122807	.0592085		-.1293248 .1047634

diff = mean(White) - mean(Hispanic) t = -0.2074
 Ho: diff = 0 degrees of freedom = 142

Ha: diff < 0 Ha: diff != 0 Ha: diff > 0
 Pr(T < t) = 0.4180 Pr(|T| > |t|) = 0.8360 Pr(T > t) = 0.5820
 3 Year Recidivism T-Test:Race_HispToWhite

Two-sample t test with equal variances

Group	Obs	Mean	Std. Err.	Std. Dev.	[95% Conf. Interval]
White	68	.2352941	.0518221	.4273363	.1318567 .3387315
Hispanic	10	.3	.1527525	.4830459	-.0455502 .6455502
combined	78	.2435897	.0489173	.4320263	.1461829 .3409966
diff		-.0647059	.1470921		-.3576652 .2282534

diff = mean(White) - mean(Hispanic) t = -0.4399
 Ho: diff = 0 degrees of freedom = 76

Ha: diff < 0 Ha: diff != 0 Ha: diff > 0
 Pr(T < t) = 0.3306 Pr(|T| > |t|) = 0.6613 Pr(T > t) = 0.6694
 1 Year Recidivism T-Test:Race_OtherToWhite

Two-sample t test with equal variances

Group	Obs	Mean	Std. Err.	Std. Dev.	[95% Conf. Interval]
White	114	.0877193	.0266117	.2841352	.0349967 .1404419
Other	18	.1666667	.0903877	.3834825	-.0240347 .357368

combined | 132 .0984848 .0260337 .2991042 .046984 .1499857

-----+-----
diff | -.0789474 .0758372 -.2289821 .0710874

-----+-----
diff = mean(White) - mean(Other) t = -1.0410
Ho: diff = 0 degrees of freedom = 130

Ha: diff < 0 Ha: diff != 0 Ha: diff > 0
Pr(T < t) = 0.1499 Pr(|T| > |t|) = 0.2998 Pr(T > t) = 0.8501
3 Year Recidivism T-Test:Race_OtherToWhite

Two-sample t test with equal variances

-----+-----
Group | Obs Mean Std. Err. Std. Dev. [95% Conf. Interval]
-----+-----
White | 68 .2352941 .0518221 .4273363 .1318567 .3387315
Other | 12 .25 .1305582 .452267 -.0373568 .5373568

-----+-----
combined | 80 .2375 .0478782 .428236 .1422007 .3327993

-----+-----
diff | -.0147059 .1349324 -.2833357 .2539239

-----+-----
diff = mean(White) - mean(Other) t = -0.1090
Ho: diff = 0 degrees of freedom = 78

Ha: diff < 0 Ha: diff != 0 Ha: diff > 0
Pr(T < t) = 0.4567 Pr(|T| > |t|) = 0.9135 Pr(T > t) = 0.5433
1 Year Recidivism T-Test:Race_OtherToBlack

Two-sample t test with equal variances

-----+-----
Group | Obs Mean Std. Err. Std. Dev. [95% Conf. Interval]
-----+-----
Black | 180 .1555556 .0270895 .3634445 .1020996 .2090115
Other | 18 .1666667 .0903877 .3834825 -.0240347 .357368

-----+-----
combined | 198 .1565657 .0258905 .3643119 .1055075 .2076238

-----+-----
diff | -.0111111 .0902863 -.1891684 .1669462

-----+-----
diff = mean(Black) - mean(Other) t = -0.1231
Ho: diff = 0 degrees of freedom = 196

Ha: diff < 0 Ha: diff != 0 Ha: diff > 0
Pr(T < t) = 0.4511 Pr(|T| > |t|) = 0.9022 Pr(T > t) = 0.5489
3 Year Recidivism T-Test:Race_OtherToBlack

diff = mean(MD) - mean(DC) t = -0.4018
 Ho: diff = 0 degrees of freedom = 279

Ha: diff < 0 Ha: diff != 0 Ha: diff > 0
 Pr(T < t) = 0.3441 Pr(|T| > |t|) = 0.6881 Pr(T > t) = 0.6559
 3 Year Recidivism T-Test:ReleaseState_DCnotMD

Two-sample t test with equal variances

Group	Obs	Mean	Std. Err.	Std. Dev.	[95% Conf. Interval]	
MD	118	.2966102	.0422278	.458711	.2129803	.3802401
DC	5	.2	.2	.4472136	-.355289	.755289
combined	123	.2926829	.0411932	.456855	.2111368	.374229
diff		.0966102	.2092715		-.3176979	.5109183

diff = mean(MD) - mean(DC) t = 0.4616
 Ho: diff = 0 degrees of freedom = 121

Ha: diff < 0 Ha: diff != 0 Ha: diff > 0
 Pr(T < t) = 0.6774 Pr(|T| > |t|) = 0.6452 Pr(T > t) = 0.3226
 1 Year Recidivism T-Test:ReleaseState_VAnotMD

Two-sample t test with equal variances

Group	Obs	Mean	Std. Err.	Std. Dev.	[95% Conf. Interval]	
MD	263	.1330798	.0209843	.3403086	.0917605	.1743992
VA	15	.1333333	.0908514	.3518658	-.0615234	.3281901
combined	278	.1330935	.0204091	.3402884	.0929168	.1732702
diff		-.0002535	.0904964		-.1784044	.1778974

diff = mean(MD) - mean(VA) t = -0.0028
 Ho: diff = 0 degrees of freedom = 276

Ha: diff < 0 Ha: diff != 0 Ha: diff > 0
 Pr(T < t) = 0.4989 Pr(|T| > |t|) = 0.9978 Pr(T > t) = 0.5011
 3 Year Recidivism T-Test:ReleaseState_VAnotMD

Two-sample t test with equal variances

Group	Obs	Mean	Std. Err.	Std. Dev.	[95% Conf. Interval]	
-------	-----	------	-----------	-----------	----------------------	--

Ha: diff < 0 Ha: diff != 0 Ha: diff > 0
Pr(T < t) = 0.2719 Pr(|T| > |t|) = 0.5438 Pr(T > t) = 0.7281
1 Year Recidivism T-Test:GTnotSS

Two-sample t test with equal variances

```
-----
Group |  Obs   Mean  Std. Err.  Std. Dev.  [95% Conf. Interval]
-----+-----
0 |   57  .1578947  .0487274  .3678836  .0602821  .2555074
1 |   20   .05    .05    .2236068  -.0546512  .1546512
-----+-----
combined |  77  .1298701  .0385603  .3383649  .0530707  .2066695
-----+-----
diff |           .1078947  .0876415           -.0666962  .2824856
-----+-----
diff = mean(0) - mean(1)                       t = 1.2311
Ho: diff = 0                                   degrees of freedom = 75
```

Ha: diff < 0 Ha: diff != 0 Ha: diff > 0
Pr(T < t) = 0.8889 Pr(|T| > |t|) = 0.2221 Pr(T > t) = 0.1111
3 Year Recidivism T-Test:GTnotSS

Two-sample t test with equal variances

```
-----
Group |  Obs   Mean  Std. Err.  Std. Dev.  [95% Conf. Interval]
-----+-----
0 |   25   .28  .0916515  .4582576  .0908406  .4691594
1 |    7  .1428571  .1428571  .3779645  -.2067017  .492416
-----+-----
combined |  32   .25  .0777714  .4399413  .0913842  .4086158
-----+-----
diff |           .1371429  .1895903           -.2500522  .5243379
-----+-----
diff = mean(0) - mean(1)                       t = 0.7234
Ho: diff = 0                                   degrees of freedom = 30
```

Ha: diff < 0 Ha: diff != 0 Ha: diff > 0
Pr(T < t) = 0.7625 Pr(|T| > |t|) = 0.4751 Pr(T > t) = 0.2375
1 Year Recidivism T-Test:System_FedToLocal

Two-sample t test with equal variances

```
-----
Group |  Obs   Mean  Std. Err.  Std. Dev.  [95% Conf. Interval]
-----+-----
Local |  285  .1403509  .0206115  .3479617  .0997802  .1809215
```


Pr(T < t) = 0.0337 Pr(|T| > |t|) = 0.0674 Pr(T > t) = 0.9663
 3 Year Recidivism T-Test: System_DrugToLocal

Two-sample t test with equal variances

Group	Obs	Mean	Std. Err.	Std. Dev.	[95% Conf. Interval]	
Local	139	.3021583	.0390891	.4608542	.2248672	.3794494
Drug	18	.5555556	.1205169	.51131	.3012871	.809824
combined	157	.3312102	.037682	.4721546	.2567773	.405643
diff		-.2533973	.1168965		-.4843132	-.0224814

diff = mean(Local) - mean(Drug) t = -2.1677
 Ho: diff = 0 degrees of freedom = 155

Ha: diff < 0 Ha: diff != 0 Ha: diff > 0
 Pr(T < t) = 0.0159 Pr(|T| > |t|) = 0.0317 Pr(T > t) = 0.9841
 1 Year Recidivism T-Test: System_FedToDrug

Two-sample t test with equal variances

Group	Obs	Mean	Std. Err.	Std. Dev.	[95% Conf. Interval]	
Drug	30	.2666667	.0821176	.4497764	.0987174	.434616
Fed	86	.0465116	.0228417	.2118255	.0010961	.0919271
combined	116	.1034483	.0283988	.3058647	.0471957	.1597009
diff		.220155	.06179		.0977495	.3425606

diff = mean(Drug) - mean(Fed) t = 3.5630
 Ho: diff = 0 degrees of freedom = 114

Ha: diff < 0 Ha: diff != 0 Ha: diff > 0
 Pr(T < t) = 0.9997 Pr(|T| > |t|) = 0.0005 Pr(T > t) = 0.0003
 3 Year Recidivism T-Test: System_FedToDrug

Two-sample t test with equal variances

Group	Obs	Mean	Std. Err.	Std. Dev.	[95% Conf. Interval]	
Drug	18	.5555556	.1205169	.51131	.3012871	.809824
Fed	50	.14	.0495696	.3505098	.0403862	.2396138

combined | 68 .25 .0529009 .4362322 .1444093 .3555907

-----+-----
diff | .4155556 .1094509 .1970298 .6340813
-----+-----

diff = mean(Drug) - mean(Fed) t = 3.7967
Ho: diff = 0 degrees of freedom = 66

Ha: diff < 0 Ha: diff != 0 Ha: diff > 0
Pr(T < t) = 0.9998 Pr(|T| > |t|) = 0.0003 Pr(T > t) = 0.0002

. ttest Recidivism_1Yr, by (ReleaseYear_2012v2010)

Two-sample t test with equal variances

-----+-----
Group | Obs Mean Std. Err. Std. Dev. [95% Conf. Interval]
-----+-----
2010 | 186 .172043 .0277483 .3784365 .1172992 .2267868
2012 | 162 .0925926 .0228442 .2907595 .0474796 .1377055
-----+-----
combined | 348 .1350575 .018348 .3422771 .0989702 .1711447
-----+-----
diff | .0794504 .0365882 .0074872 .1514137
-----+-----

diff = mean(2010) - mean(2012) t = 2.1715
Ho: diff = 0 degrees of freedom = 346

Ha: diff < 0 Ha: diff != 0 Ha: diff > 0
Pr(T < t) = 0.9847 Pr(|T| > |t|) = 0.0306 Pr(T > t) = 0.0153

Appendix D: Correlation Coefficients.

One-year Recidivism

	Recidivism: 1 Year	Age	Education: No High School Diploma	Education: GED	Education: High School, Degree	Education: At Least Some College	Employed	Gender	Inside Worker	LSIR	Race: Black	Race: Hispanic	Race: Other	System: Federal	System: Drug
Recidivism: 1 Year	1.00														
Age	-17%	1.00													
Education: No High School Diploma	-0.01	-0.18	1.00												
Education: GED	0.17	-0.04	-0.27	1.00											
Education: High School, Degree	0.02	-0.01	-0.52	-0.35	1.00										
Education: At Least Some College	-0.17	0.27	-0.28	-0.18	-0.35	1.00									
Employed	0.01	-0.07	-0.01	0.08	0.02	-0.09	1.00								
Gender	-0.08	0.00	-0.01	-0.05	-0.02	0.09	0.00	1.00							
InsideWorker	0.04	0.00	0.03	-0.08	0.07	-0.05	-0.47	0.02	1.00						
LSIR	0.24	-0.22	0.31	0.18	-0.19	-0.30	0.05	0.06	-0.02	1.00					
Race: Black	0.07	-0.15	0.09	0.05	-0.01	-0.14	-0.09	0.01	0.10	0.14	1.00				
Race: Hispanic	-0.02	-0.06	0.03	-0.04	0.05	-0.07	0.01	-0.05	0.00	-0.14	-0.34	1.00			
Race: Other	0.06	-0.06	0.08	-0.05	-0.01	-0.05	0.04	-0.06	0.00	-0.10	-0.23	-0.07	1.00		
System: Federal	-0.12	0.25	-0.04	0.02	-0.16	0.25	0.00	-0.04	-0.14	-0.18	0.10	-0.12	0.02	1.00	
System: Drug	0.15	-0.08	-0.04	0.21	-0.05	-0.09	0.04	-0.08	-0.03	0.25	-0.10	-0.09	-0.06	-0.14	1.00

Three-year Recidivism

	Recidivism: 3 Year	Age	Education: No High School Diploma	Education: GED	Education: High School, Degree	Education: At Least Some College	Employed	Gender	InsideWorker	LSIR	Race: Black	Race: Hispanic	Race: Other	System: Federal	System: Drug
Recidivism: 3 Year	1.00														
Age	-0.26	1.00													
Education: No High School Diploma	-0.04	-0.21	1.00												
Education: GED	0.22	0.00	-0.32	1.00											
Education: High School, Degree	0.01	-0.07	-0.49	-0.44	1.00										
Education: At Least Some College	-0.24	0.38	-0.22	-0.19	-0.30	1.00									
Employed	0.09	-0.13	0.00	0.10	0.01	-0.14	1.00								
Gender	-0.12	0.02	-0.16	-0.07	0.09	0.18	0.05	1.00							
InsideWorker	-0.13	0.07	0.06	-0.01	0.00	-0.07	-0.33	-0.06	1.00						
LSIR	0.36	-0.25	0.22	0.27	-0.22	-0.32	0.16	-0.05	-0.04	1.00					
Race: Black	0.10	-0.11	0.10	0.08	-0.02	-0.19	0.03	-0.07	0.06	0.14	1.00				
Race: Hispanic	-0.03	-0.11	-0.08	-0.06	0.12	0.01	0.04	0.05	-0.05	-0.17	-0.24	1.00			
Race: Other	0.02	-0.18	0.26	-0.07	-0.10	-0.10	0.05	-0.08	0.10	-0.11	-0.26	-0.07	1.00		
System: Federal	-0.21	0.32	0.01	0.01	-0.22	0.30	-0.07	0.01	-0.10	-0.25	0.23	-0.13	-0.06	1.00	
System: Drug	0.23	-0.05	-0.08	0.13	-0.01	-0.04	0.02	-0.09	-0.07	0.28	-0.16	-0.09	-0.09	-0.17	1.00

Appendix E: Regressions

One-year Recidivism

Logistic regression

Number of obs = 341
 LR chi2(8) = 39.38
 Prob > chi2 = 0.0000
 Pseudo R2 = 0.1501

Log likelihood = -111.44113

Recidivism_1Yr	Coefficient	Std. Err.	z	P>z	[95% Conf. Interval]	
Age	-0.0381354	0.0189129	-2.02	0.044	-0.0752041	-0.0010667
Gender	-1.522081	1.046447	-1.45	0.146	-3.57308	0.5289172
LSIR	0.1035948	0.0282595	3.67	0	0.0482072	0.1589824
Drug Court	0.7005991	0.5289864	1.32	0.185	-0.3361952	1.737393
Federal	-0.5974953	0.5825391	-1.03	0.305	-1.739251	0.5442604
Black	0.6525801	0.4364426	1.5	0.135	-0.2028317	1.507992
Hispanic	0.2830359	0.7508433	0.38	0.706	-1.18859	1.754662
Other Race	1.474726	0.8025698	1.84	0.066	-0.0982816	3.047734
Constant	-3.962628	1.086859	-3.65	0	-6.092832	-1.832423

Three-year Recidivism

Logistic regression

Number of obs = 171
 LR chi2(8) = 34.77
 Prob > chi2 = 0.0000
 Pseudo R2 = 0.1682

Log likelihood = -85.949969

	Recidivism_1Yr	Coefficient	Std. Err.	z	P>z	[95% Conf. Interval]	
Age	-0.0365328	0.0204224	-1.79	0.074	-0.0765599	0.0034943	0.003494
Gender	-1.655654	1.089707	-1.52	0.129	-3.791441	0.4801315	0.480132
LSIR	0.089063	0.0299596	2.97	0.003	0.0303434	0.1477827	0.147783
Drug Court	1.040991	0.6306208	1.65	0.099	-0.1950032	2.276985	2.276985
Federal	-0.3615462	0.5569054	-0.65	0.516	-1.453061	0.7299684	0.729968
Black	0.4496594	0.4524963	0.99	0.320	-0.4372172	1.336536	1.336536
Hispanic	0.5510136	0.8542834	0.65	0.519	-1.123351	2.225378	2.225378
Other Race	0.4186349	0.833271	0.5	0.615	-1.214546	2.051816	2.051816
Constant	-2.265379	1.14091	-1.99	0.047	-4.501522	-0.0292354	-0.02924

Appendix F: Methodology for Adding Future Months to Analysis

Follow these same steps for each new month of recidivism information:

1. Add the worksheet for the new month to my modified Excel workbook.

2. Change worksheet names to the year followed by the two-digit month without a space between. For example, “July 2010” becomes “2010-06”. This naming convention makes sorting by release month easier.
3. Insert a new row C to be identical to row B (original variable names) with the following exceptions: Rename each variable that is attached to a specific charge X as “ChargeX[Variable]”. For example, “Conviction” for Charge 2 should be renamed “Charge2Conviction”. Remove the spaces between words for “Charge X Time From Release to Char”. Rename “Release Location (City, State, Zip Code)” “ReleaseLocation”.
4. Modify data entries causing import problems. Highlight the following changes in red. These changes were already made:

Variable	Changed this	To this	Month
Charge 1Case #	9/6/2013	blank	2012-10
Charge 1Date of Conviction	0D00296590	blank	2012-10
charge 1 date issued	N/A	blank	2010-09
Charge 1Time from Release to Charge	N/A	blank	2010-09
Charge 2Time from Release to Charge	N/A	blank	2010-09
charge 2 date issued	N/A	blank	2010-08 2010-09 2010-10
charge 2 date issued	Plea 10/1/2013	10/1/2013	2012-11
Charge 2 Time from Release to Charge	N/A	blank	2010-08 2010-09 2010-10 2010-11
Charge 2 Time from Release to Charge	<u>_</u>	blank	2010-11
Charge2DateofConviction	N/A	blank	2010-09 2010-11
Charge 3Date Issued	N/A	blank	2010-08
Charge 3Time from Release to Charge	N/A	blank	2010-08 2010-09
Charge 4 Time from Release to Charge	N/A	blank	2010-08 2010-10 2010-09
Charge 4 Date Issued	N/A	blank	2010-10 2010-09

5. In the DataCombination Do-File, replace all references to “C:\Users\Sarah BS\Dropbox_Project Course\Data\” with the pathway to the folder in which you saved the Excel workbook.
6. Add the new month of data by using the following code. The underlined portions should be modified for the month in question.

```
import excel "C:\Users\Sarah BS\Dropbox\_Project course\data\OriginalData_recd3.13.xls",
sheet("2010-09") cellrange(A3:CF37) firstrow
gen ReleaseMonth="2010-09"
  foreach var of varlist _all {
    capture assert missing(`var')
    if !_rc {
      drop `var'
    }
  }
```

7. Run the DataCombination file
8. Run the DataAnalysis Do-Files.