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VERA INSTITUTE OF JUSTICE
377 BROADWAY
NEW YORK, N.Y. 10013
TELEPHONE (212) 334-1300 • FAX (212) 941-9407

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TO: Jail Population Management Project Advisory Committee, and Staff of the Planning Unit, Office of the Deputy Mayor for Public Safety

FROM: Laura Winterfield, Project Director

SUBJECT: Models for Predicting Incarceration — Felony Cases

INTRODUCTION

This memorandum asks (and attempts to answer) the question: What predicts incarceration in cases arraigned on felony charges? It describes the construction and content of models that predict both pretrial detention and custodial sentences in these cases.

This is the third in a series of analytic memoranda prepared for the Office of the Deputy Mayor for Public Safety under the Jail Population Management Project. The first memorandum — the *Jail Use Analysis* — displays and discusses the pattern of demand for the city's jail capacity, by various categories of inmates in the custody of the Department of Correction (DOC). The second memorandum — the Eligible Pool Analysis — provides estimates of the numbers admitted to DOC custody who are eligible for the city's various existing alternative programs.[1] The fourth memorandum — the Ineligible Pool Analysis — presents information about those admitted to DOC who are *not* eligible for any existing alternative program, and will discuss some implications for the city's alternative program investment strategy.

STATEMENT OF THE PROBLEM

The Office of the Deputy Mayor is charged with monitoring the jail displacement effects of currently funded alternative programs, as well as attempting to displace additional jail use by encouraging revision of those programs or funding new programs designed to serve as alternatives to pretrial detention, custodial sentences, or both.

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[1] Throughout this series of memoranda, the categories of alternative programs have been defined as follows:

ATD: Programs designed principally as alternatives to pretrial detention only.

ATI: Programs designed principally to serve as alternative penal measure in cases that would otherwise draw jail or prison time at disposition.

ATD/I: Programs that intervene when an individual is in pretrial detention, offering an alternative to continued detention *and* an alternative penal measure at disposition.

These definitions have also been used to categorize DOC inmates, by the type of jail days they use. "ATD-only" users of jail capacity are those admitted to DOC at or after arraignment, but who are released before disposition and sentence. "ATI-only" inmates are those who are at liberty when sentenced, but are admitted to begin serving a local or state term. "ATD/I" inmates are those in DOC custody pretrial, who remain in custody through disposition, and stay in custody to begin serving a custodial sentence.

Alternative programs can achieve displacement effects either by targeting intake *only* on those who are in custody at the time of program intervention, or, if defendants at liberty are targeted, by using program screening criteria to target intake on the jail-bound offenders among them. The magnitude of displacement effects depends on the degree to which a program effectively targets, within a jailbound group, those who would (absent program intake) be relatively heavier users of jail capacity. This memorandum deals with prediction of displacement *per se*, not with the magnitude of displacements achieved.[2]

While the task of developing the criteria that target a program's intake on jailbound defendants and offenders is generally thought to be a program responsibility, it remains the city's function to oversee that process, and it is clearly in the city's interest to assist programs to develop screening criteria that achieve whatever displacement effects are desired. To this end, general predictors of incarceration of the kind developed in this memorandum provide a context within which city can review existing programs' screening criteria and processes. For example, the models developed in this memorandum permit city policy-makers to examine the degree of overlap between a program's screening criteria and the factors that predict jail use. (This is particularly important where programs screen and take into their caseloads defendants who are *not* in DOC custody at the time of program intervention — for them, displacement effects will be achieved only to the extent that the individuals taken into the program would otherwise have been admitted to DOC custody at some later point.) If there is no overlap between a program's screening criteria and the factors predicting jail use, further inquiry is clearly warranted: It may be that the program is targeting a sub-population defined by variables more specific or sensitive than those available for use as general predictors in this research project; or it may be that the program is simply not effectively targeting jail-bound defendants and offenders. In any event, the models for predicting incarceration that are discussed in this memorandum provide city officials and program operators a framework for informed discussion of program screening criteria and processes.

There is a second use to which these models for predicting incarceration can be put: The relevant set of predictors can be applied to a specific programs' actual intake, to estimate what proportion would have been jailbound if the program had not intervened. Ideally, this type of analysis would be carried out as part of the periodic monitoring of program performance undertaken by the Deputy Mayor's staff; some ideas of how this might be done are presented at the conclusion of this memorandum.[3]

SOURCES OF DATA AND STRUCTURE OF ANALYSIS

Data Sources Used. The unit of analysis is a defendant-arrest. The Jail Population Management Consultant contract specified that a random sample of 1985 New York City summary arrests (N=10,000) be used for generating models to predict incarceration. This data set was developed by the New York City Criminal Justice Agency (CJA), which interviews virtually all defendants between arrest and Criminal Court arraignment. The

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[2] "Length-of-stay" for pretrial detainees is discussed at greater length in the concluding section of this memorandum.

[3] Models of the kind developed here are also useful in the process by which individual programs can refine and further specify their screening criteria in order to screen *out* potential candidates for intake who would not be likely to use jail or prison resources. This topic is also discussed at greater length in the concluding section of this memorandum.

data include CJA's interview information for each defendant and a summary of information about the dockets and any indictments stemming from the arrest. Before beginning the analysis, Vera requested detailed criminal history information for each defendant-arrest from the state's Division of Criminal Justice Services (DCJS), and the database was supplemented with the prior record information DCJS provided.[4]

Defining Outcome Measures for the Analysis. The Request for Proposals which led to this Jail Population Management Project called for the identification of factors predicting both pretrial detention and custodial sentences, but did not specify how those outcomes should be defined operationally.[5] To conduct the prediction analyses, three separate outcomes needed operational definition: *pretrial detention, non-mandatory custodial sentence,* and *mandatory custodial sentence.*

The operational definition of *pretrial detention* used in this analysis was generated with an eye on the relevant data available for felony cases, in the database that was specified for the research.[6] The database recorded detention status at Criminal Court arraignment, at the final hearing in Criminal Court, at Supreme Court arraignment, and at Supreme Court disposition. ("At" is "at the conclusion of". Operationally, it means "immediately after".)

The first decision to be made concerned whether the composite dependent measure of pretrial detention should attempt to capture detention status in both the Criminal and the Supreme Court phases of case processing, across the entire pretrial period. This possibility was rejected for several reasons: First, the bulk of detention time, for those arraigned in Supreme Court, occurs after Supreme Court arraignment.[7] Second, a more inclusive variable would have contained unnecessarily redundant information (detention status at one point is frequently the same as at the next point), and would be much more difficult to score.[8] Third, increasing the number of variables initially included in the dependent measure would have increased the necessity of dropping

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[4] DCJS returned information on approximately 80 percent of the defendants in the random sample. For the remaining 20 percent, DCJS could not return criminal record information either because the sample case had been sealed and there were no priors, or because the sample case had been sealed and all prior arrests had ended with acquittal, dismissal or another disposition that required sealing of those records.

[5] How this might be done was, of course, constrained by the information available in the source data for the model-building research, as specified in the RFP and described above.

[6] For the reasons discussed on page 5 below, prediction models were developed only for cases commenced by felony arrest that got at least as far as Supreme Court indictment.

[7] From the *Jail Use Analysis* memorandum, it can be seen that Supreme Court defendants who enter DOC before disposition and who remain in custody after sentence (and who are, therefore, the targets for ATD/I programs), and who spend time in pretrial detention during both the Criminal Court and the Supreme Court phases of case-processing, spend only 7 to 12 days in detention during the Criminal Court phase, but spend from 65 days to 126 days in pretrial detention after Supreme Court arraignment. (The amount of pretrial detention time ranges as stated, depending on the ultimate disposition of the case.)

[8] To be useful in building predictive models, variables must either be interval (with finite intervals between values, like "number of days"), or be amendable to ranking in some kind of hierarchy from best to worst. While ranking probably could have been done with the more inclusive pretrial detention variable, the number of possible categories would have produced an outcome variable extremely difficult to model.

cases — if a case were missing information on any of the underlying variables (court-processing points) included in the composite dependent measure, it could not be included in the analysis. Finally, most alternative programs for which prediction of incarceration in felony cases is relevant intervene for intake *after* Supreme Court indictment; for them, prediction of pretrial detention during the Criminal Court phase of case processing is of no consequence. Thus, it was decided that the operational definition of pretrial detention would be focused on detention status during the Supreme Court phase of case processing.[9]

The next decision, in giving operational definition to pretrial detention, concerned whether to model detention status at each point of Supreme Court case processing. After all, an offender could be in detention immediately after Supreme Court arraignment but be released subsequently and be at liberty at the time of disposition and sentence (or vice versa) — and such an offender would not really meet a commonsensical definition of "in pretrial." Therefore, a composite variable was constructed: "Always In" (in detention both immediately after Supreme Court arraignment and at Supreme Court disposition), which was scored as "1", and "Not Always In" (a category that included offenders who were out of detention at both stages, as well as those who were in detention immediately after one hearing but out at the other), which was scored as "0".

The *custodial sentence* variable was given operational definition by considering the thought process of the alternative program staffs, when they try to target appropriate felony-charged defendants for alternative sentences. The programs must strive for two separate distinctions:

- First, they try to avoid wasting time on individuals who, upon conviction, will be bound for mandatory terms in state prison — either because they carry a predicate felony conviction or because they will be subject to a mandatory sentencing law (*i.e.*, the program should be trying to predict non-mandatory incarceration, and trying to avoid targeting cases for which no alternative sentence is feasible).
- Second, after eliminating the mandatory prison cases, they try to avoid intake of cases bound for non-custodial disposition (*i.e.*, the programs should be trying to predict non-mandatory incarceration, distinguishing the jail- and prison-bound cases from those likely to end with probation, fine, discharge or dismissal).

Thus, three sentence categories were specified:

1. non-custodial dispositions (which included probation, conditional and unconditional discharges, fines, adjournments in contemplation of dismissal, dismissals, and acquittals);
2. mandatory prison; and
2. non-mandatory incarceration (defined as local jail sentences or split sentences, and sentences to state prison imposed on non-predicate felons convicted of felonies not carrying mandatory state time).

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[9] As will be seen below, data about Criminal Court bail setting *were* included in the analysis, as independent variables.

To construct the models, these three sentence categories were then used as outcome variables in two separate model-building analyses: The first model, built from the cases in the sample that in fact ended with custodial sentences, distinguishes mandatory prison time (scored as "1") from non-mandatory incarceration (scored as "0"). After the cases that actually ended with mandatory prison sentences were eliminated from the sample, the second model was built to distinguish non-mandatory incarceration (scored as "1") from non-custodial disposition (scored as "0"). These two analyses produce variables which help distinguish those who are appropriate targets for ATI felony programs from those who are not.

In summary, three separate prediction models were developed:

- **Always In** versus **Not Always In** pretrial detention
- **Mandatory Prison** versus **Non-mandatory Incarceration.**
- **Non-mandatory Incarceration** versus **Non-custodial Disposition**

Specifying the Population. Because models for predicting incarceration in misdemeanor cases, prepared for staff of the Center for Alternative Sentences and Employment Services, are already available to the city,[10] this project focused on felony cases, defined as cases arraigned on felony charges that proceeded at least as far as Supreme Court indictment.

One additional specification was made: Because severity of the arraignment charge is typically used as a screening criteria by alternative programs, and because it is undoubtedly related both to pretrial detention and to type of sentence, the models for cases arraigned on A and B felony charges were developed separately from the models for those arraigned on C, D, or E felonies. (The distribution of cases, by borough and arraignment charge category, is presented in Appendix A, Table A-1.) Because most of the city's ATD, ATI and ATD/I programs will not accept offenders facing A and B felony charges, only the models for the C, D, and E felony arraignment charges are discussed in this memorandum.[11]

Case processing and outcomes do often differ by borough, and it was hoped that borough-specific prediction models could be developed. However, when the research sample's distribution on the dependent measures was examined (*see*, Appendix A, Tables A-2 through A-4), it was found that there were simply not enough cases in several of the boroughs to permit such an analysis. Therefore, cases from all boroughs were analyzed together, and "borough" was treated as an independent variable. This permits the models to indicate whether, in addition to the general predictors, "borough" is important in predicting outcomes. In models where "borough" does appear to matter, borough-specific models (built from data sets large enough for the task) should be created to help indicate what those differences really are.[12]

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[10] A summary of the findings from the misdemeanor analysis is presented in Appendix E.

[11] Appendix D contains the model information for the three models developed on those with A or B felony charges at arraignment.

[12] These analyses would require data drawn specifically to ensure large enough numbers from all the boroughs of concern.

Analytic Approach to Prediction. There are two stages in development of a prediction model: the first is finding the model with the best overall "fit"; the second is determining how individual cases will be scored (using the model's predictive variables) and, after scoring them, assessing the model's adequacy. Once such a model has been developed, and its predictive adequacy has been assessed, the predictive variables can be examined and compared to the screening criteria used by the alternative programs.

The general approach to development of the models (and the variables to be included in them) is, first, to examine each potential predictor (*e.g.*, prior record, charge, age) for its relationship, as an independent variable, to the outcome measure of interest (*i.e.*, "Always In" or "Not Always In" pretrial detention, and "Mandatory Incarceration", "Non-mandatory Incarceration", or "Non-custodial Disposition"). The general categories of variables available for testing in this way included (a) characteristics of the individuals (*e.g.*, demographics, CJA release information and employment/residence information, and DCJS information on prior arrests, convictions, sentences, and revocations), and (b) characteristics of the cases (*e.g.*, charge, bail amount and detention status immediately after arraignment and at disposition in both Criminal Court and Supreme Court). A complete list of variables initially considered is found in Appendix B.

For each model, the variables found individually to be highly related to the outcome measure for which prediction was desired were selected for further testing (the significance level used in this analysis was .05 or less); all bivariate combinations of these variables were then examined for redundancy. This was a search for high intercorrelations between variables, and the value used in this analysis, as a measure of redundancy, was a correlation of .4 or above. Decisions were then made about which variable to keep in the model, when several variables were highly correlated with each other: The rule used, when redundancy was found, was to retain the variable for which the fewest cases were missing data, and not to include in the model-building analysis the other, redundant variables. This helped avoid skewing the sample because of non-random distributions of missing data. For example, because OCA seals cases disposed by dismissal, potentially useful Supreme Court variables were missing in many of the sample cases that ended with non-custodial dispositions. (*E.g.*, Supreme Court arraignment charge would be missing from the data, if the case had been dismissed and sealed by OCA.) That is why Criminal Court arraignment charge was chosen for the model, even though it is the Supreme Court outcome that is being predicted. Appendix C sets forth the hierarchy developed for selecting groups of predictor variables, from among variables with high intercorrelations.

The independent variables identified as having potential value in a model were then tested for their predictive capability, using a statistical technique designed for model-building. In this case, the technique used was logistic regression (LOGIT), which is the technique of choice for dichotomous dependent measures.[13] The variables are entered into the model and either retained or rejected, depending on how they perform

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[13] Mathematically, this model has the following form: With Y denoting the dependent variable for the nth observation, the vector of the independent variables for the nth observation is Xn1, Xn2,...Xnp. Then, XnB = Xn1*B1 + Xn2*B2 + ... + Xnp*Bp where B = (B1...Bp) denotes the vector of regression parameters. The model assumes the probability that Yn = 1 is 1/(1+ exp(- ALPHA - XnB)), where ALPHA is the intercept parameter." *See*, Douglas C. McDonald, *Punishment Without Walls* (New Brunswick: Rutgers University Press, 1986), p. 220.

on the chosen decision specification.[14] Then the model's overall fit is assessed, as determined by both the significance of the chi square statistic, and the pseudo R^2.[15] Finally, the "content" of the model is specified, by the specific variables found to be predictive, as is the individual importance of those variables; the latter is determined by examining the individual weights (standardized estimates).

The next step in building a model is to determine what the "cutpoint" should be. The cutpoint is a value which determines how cases will be classified — cases with scores on the prediction equation higher than that value will be categorized as predicted to be "yes" on the outcome measure (e.g., "Always In" pretrial detention, or "Non-mandatory Incarceration"), while cases with scores lower will be predicted as "no."[16]

Once the cutpoint is chosen (with an eye on the total number of correct predictions achieved at that value), there are various ways to express a sense of the accuracy of the model. The total proportion of correct predictions is an obvious test of accuracy, but the proportion of false positives is also important — making operational use of a model that has a high rate of falsely predicting incarceration will impose burdens on defendants and offenders who otherwise would bear less, and will deploy resources on cases that will not as a result be displaced from jail. While the false positive rate typically can be reduced by choosing a different cutpoint, the proportion of true positives correctly predicted by the model will decline if that is done, as will the overall proportion predicted correctly. The false negative rate is also a concern: Operational use of a model that has a high false negative rate will lead programs not to target defendants and offenders whose use of jail capacity could in fact be displaced.

Thus, a model's "false positive" and "false negative" rates help assess the degree to which the model is correct overall, and whether it errs towards overestimating incarceration as the outcome. Another accuracy measure is a score denoting the model's efficiency, as a proportionate improvement over chance: This is called the "Relative Improvement Over Chance (RIOC)" score (Loerber and Dishion, 1983). RIOC provides an estimation of a model's percent correct, as a function of the range of possible predictive efficiency. This range is determined by the selection ratio and the base rate, which determines the maximum number of correct predictions possible, and the number that would be expected by chance alone. RIOC, therefore, assesses how an instrument performs relative to its expected performance and its best possible performance; this is expressed in percentage terms. RIOC is scored from "0", indicating no relative improvement, to "1," indicating total improvement. The higher the RIOC score, the more efficient the model.

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[14] For this analysis, a forward stepwise technique was used. The variable with the most explanatory power is chosen first. Then, the remaining variables are examined, with the next most significant being entered. This process is repeated until there are no further variables significantly related to the dependent measure, at the .05 level of significance or less.

[15] Pseudo R^2 uses the chi square statistic but controls for sample size. This is important, because chi square is notoriously sample-size dependent, with significance occurring more easily in larger samples. Pseudo R^2 ranges from "0" to "1," increasing as the quality of model fit improves.

[16] Changing the cutpoint has an effect on the "selection ratio" — the proportion of cases predicted to be either "yes" or "no." Predicted values on cases are evaluated in terms of the actual scores on the dependent measure (the base rate). Depending on the relationship between the actual scores and the predicted scores, models with different cutpoints will have differing rates of overall correct predictions, as well as different rates of false positives (those predicted to be "yes" that are actually "no") and false negatives (those predicted to be "no" that are actually "yes"). Typically, the cutpoint closest to the actual distribution of the base rate will produce the highest proportion of correct predictions.

After prediction models are developed and assessed, through the steps described above, they are conventionally validated on a new sample. This procedure provides an estimate of the amount of shrinkage (as measured on the indices described above) that may occur when a model is applied to a new sample, rather than to the sample used to generate it. This helps determine the degree to which the apparent accuracy of a model is sample-dependent: If there is little shrinkage, the model is stable across different samples, and can be used with more confidence than a model for which there is a great deal of shrinkage.

There are typically two ways of creating a validation sample: either by drawing an entirely new sample, or by splitting an original "construction sample" in two, building the model on one half and validating it on the other. For the analysis reported in this memorandum, as time and resources would not permit creation of a separate validation sample, it was originally intended that the split sample approach be used. But, as noted above, the construction sample was dangerously small for some of the originally intended analyses (particularly, the borough-specific models); it was apparent early on that a split sample approach to validation would further endanger the prospects for borough-specific modeling, and the model was not split. As it turned out, the sample was too small for the borough-specific analyses to be done. Once the boroughs were combined, a validation sample could, in fact, have been created by using the split sample approach, but time and resources do not now permit starting the process all over again. It would in any event make more sense to use the split sample approach in a re-modelling exercise on a new and more recent sample — one large enough to support the construction of borough-specific models.

RESULTS OF THE MODELS

Predicting "Always In" Pretrial Detention. Seven variables, out of the eleven initially included, were found significantly related to pretrial detention. The most important of these were: the number of prior felony convictions and the number of prior misdemeanor convictions (both of which were positively related to pretrial detention). The number of prior misdemeanor convictions proved to be more important than number of prior felonies (although the latter was the second most important predictor among the seven). The impact of these prior record variables on the dependent measure was generally twice as strong as that of the other variables.[17] Both the CJA release recommendation and the borough variable ("Manhattan" or "not Manhattan") are the least powerful variables, among the seven found to have significance.

Table 1 presents the model for predicting pretrial detention. Table 2 presents the members of the sample, by the independent variables in the model: In Table 2, the column to the left shows the characteristics of those predicted "Always In" pretrial detention; the column to the right shows the others.

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[17] Despite the primacy of prior record in the model, the more serious the arraignment charge, the more likely an individual is to be held in pretrial detention, and non-whites are more likely to be held in pretrial detention than whites. It should be added that, in research of this type, it is not possible to determine the extent to which the predictive weight of being "white" or "not white" indicates race bias in any part of the system — these variables are available for coding and analysis, but are highly correlated with socio-economic variables that are not available for coding, and it certainly is likely that it is these invisible characteristics (themselves associated with race in New York City) that produce the observed patterns in the model.

Table 1
Prediction Model for C, D, & E Felonies
Dependent Measure: "**Always In**" versus "**Not Always In**" Pretrial Detention

DISTRIBUTION OF CASES USED IN MODELING

Total Cases with Known Outcomes:	645	
Number Cases Deleted:	92	
"**Always In**" Pretrial Detention:	248	(44.8%)
"**Not Always In**" Pretrial Detention:	305	(55.2%)
Total Cases Used in Modeling:	553	(100.0%)

COEFFICIENTS	**Unstandardized Estimates**	**Standardized Estimates**
Intercept	.46	–
Predictors:		
Number prior felony convictions	.84***	.41
Number prior misdemeanor convictions	.28***	.61
Criminal Court arraignment charge severity	.62***	.24
Ethnicity = white	-1.47***	-.30
Verified employment status	.32**	.20
Lack of favorable CJA ROR recommendation	.29**	.17
Borough = Manhattan	.61**	.16

Overall Model X^2: 201.66***
DF: 7
Pseudo R^2: .19

* $p \leq .05$
** $p \leq .01$
*** $p \leq .001$

MODEL ADEQUACY

Cutpoint: .35

Percent Predicted "**Always In**" Pretrial: 59%
Percent Predicted "**Not Always In**" Pretrial: 41%

Total Correct:	75%
True Positives:	88%
True Negatives:	65%
False Positives:	33%
False Negatives:	14%
RIOC:	.70

As can be seen in Table 1, a model with a significant chi square was produced: The pseudo R^2 is .19. In social science research a value of .19, while not suggesting an enormously powerful fit, is considered a good fit. The model fares quite well in terms of accuracy, as well, predicting correctly at an overall rate of 75 percent. It does substantially better than the coin-toss method when used to predict those likely to be in pretrial detention — the model is correct 88 percent as compared with the 50 percent that would be gained from tossing a coin. Similarly, when used to predict those actually not in pretrial detention, the model does better than would be expected by chance (65 percent versus 50 percent). The RIOC shows a substantial improvement over chance, as well (close to three fourths, or .70). However, the model errs towards predicting "Always In" pretrial detention (59 percent, as opposed to the actual base rate of 45 percent), and this produces an undesirable false positive rate of 33 percent (misclassifying as "Always In" 33 percent of those who would not actually be "Always In").

In Table 2, sample cases that the model predicts as "Always In" pretrial detention can be compared with those that the model predicts as "Not Always In"; the table is set up to permit comparison of the two groups as they are defined by the independent variables used as predictors in the model. The expected picture emerges. Those who are predicted to be "Always In" pretrial detention are the ones who have prior felony or misdemeanor convictions, are arraigned on C felony charges, are non-white, have no verified employment, and are not recommended for ROR after the CJA interview — particularly those arrested and arraigned in Manhattan.[18] Conversely, those predicted to be "Not Always In" pretrial detention are more likely to have no prior convictions, to be arraigned on a D or E felony (rather than a C felony), to be white, to have a verified job, and to have received a favorable CJA release recommendation.

Table 2

Characteristics (Independent Variables) of C, D & E Felony Defendants:
Comparing Those the Model Predicts as "**Always In**" Versus Those It Predicts as "**Not Always In**"

Independent Variables	Cases Predicted to Be "Always In" Pretrial (N = 325)	Cases Predicted to Be "Not Always In" Pretrial (N = 228)
Number Prior Felony Convictions	mean = .90	mean = .15
Number Prior Misdemeanor Convictions	mean = 3.0	mean = .32
Arraigned on a C Felony	48%	25%
Ethnicity is White	5%	34%
No Verified Employment	79%	41%
Favorable CJA Release Recommendation	35%	67%
Borough is Manhattan	44%	22%

Predicting <u>Mandatory Prison</u>. As shown in Table 3, below, a significant chi square was found, along with a high pseudo R^2, for the model predicting mandatory prison terms in sample cases (after the cases that ended with non-custodial dispositions were eliminated). This indicates an excellent overall "fit" for the model, in which only two independent variables were important, out of the seven initially entered: (1) the number of prior felony convictions, and (2) whether the Criminal Court arraignment charge

[18] It should be remembered that these variables are not absolutes: rather, they represent trends, as can be seen by the frequency distributions. Thus, for example, while only 5 percent of those predicted to be "Always In" pretrial detention will be white, not all of those predicted to be out of pretrial detention will be white: rather, 34 percent will be white. The difference between 5 percent and 34 percent is dramatic, and permits the variable to achieve statistical significance, but does not imply that *all* of those not in pretrial detention will be white.

carried a mandatory sentence by statute.[19] When the weights of these variables are examined, it is obvious (and not surprising) that prior record is by far the more powerful variable, having a standardized estimate four times greater than that found for Criminal Court arraignment charges carrying statutorily mandated prison terms. (Of course, if the prior record variable did not have such great predictive power, or if the model were constructed without regard to it, a Criminal Court arraignment charge carrying statutorily mandated prison time would have emerged as a more powerful predictive variable.)

Table 3

Prediction Model for C, D, & E Felonies

Dependent Measure: **Mandatory Prison** versus **Non-mandatory Incarceration**

DISTRIBUTION OF CASES USED IN MODELING		
Total Cases with Known Outcomes:	451	
Number Cases Deleted:	75	
Mandatory Prison:	191	(50.6%)
Non-mandatory Incarceration:	186	(49.4%)
Total Cases Used in Modeling:	377	(100.0%)

COEFFICIENTS	Unstandardized Estimates	Standardized Estimates
Intercept	-.89	--
Predictors:		
Number prior felony convictions	2.89***	1.61
Criminal Court Arraignment Charge is Mandatory	1.60**	.43

Overall Model X^2: 217.26***
DF: 2
Pseudo R^2: .74

** $p \leq .01$
*** $p \leq .001$

MODEL ADEQUACY

Cutpoint: .50

Percent Predicted **Mandatory Prison:** 54%
Percent Predicted **Non-mandatory Incarceration:** 46%

Total Correct:	83%
True Positives:	86%
True Negatives:	80%
False Positives:	18%
False Negatives:	15%
RIOC:	.71

[19] At first blush, it might appear that including as independent variables "number of prior felony convictions" and "arraignment charge carries a mandatory sentence" is inappropriate because they seem to define the dependent variable (Mandatory Prison Sentence). But because not all defendants with prior felony convictions received mandatory sentences, and because not all arraigned on charges carrying statutory mandatory sentences got mandatory sentences, and because the correlations of both these variables with the dependent variable was less than .6, it was appropriate to include them in the modeling.

This model for predicting mandatory prison terms is easily the most accurate of the three models developed for this project, predicting accurately at the highest overall rate, having the highest proportion of true positives and true negatives, and a very low rate of false positives (18%). The RIOC is .71, a substantial improvement over chance.[20]

In Table 4, below, the characteristics of those whom the model predicts will receive mandatory prison terms can be compared with the characteristics of those it predicts will receive non-mandatory jail and prison terms. For the most part, the expected is found: All of those predicted to receive a non-mandatory prison term have no prior felony conviction (mean = 0), while the mean number of prior felony convictions for those receiving mandatory prison sentences is 1.5. There seems to be no operational utility to the model's identification of arraignment charge as an independent variable with predictive power. As Table 3 shows, the weight given by the model to this variable is quite low (because of the enormous power of the other independent variable). In any event, Table 4 shows that essentially the same proportions of the two groups were arraigned on charges carrying statutorily mandated prison terms.

Table 4

Characteristics (Independent Variables) of C, D & E Felony Defendants in the Sample:
Those Predicted to Get **Mandatory Prison** versus
Those Predicted to Get **Non-mandatory Incarceration**

Independent Variables	**Cases Predicted to Get Mandatory Prison (N = 204)**	**Cases Predicted to Get Non-mandatory Incarceration (N = 173)**
Number Prior Felony Convictions	mean = 1.5	mean = 0
Arraigned on Charge a With Mandatory Sentence	36%	43%

Predicting <u>Non-mandatory Incarceration</u> (Versus Non-custodial Dispositions). From the city's policy perspective, the data presented in Tables 5 and 6 present the findings of central importance. Table 5 shows that a model with a good overall "fit" was produced for the prediction of non-mandatory incarceration, as indicated by the significant chi square and pseudo R^2; this model included five of the ten variables initially considered. While prior felony convictions appears as a weighty variable, its operational importance is negligible — it is predictive only because those with prior felony convictions who are not *convicted* do not get incarcerated (if convicted, they face mandatory prison sentences as predicate felons, and mandatory sentences were removed from the sample in order to build this third model). The most weighty variable — and the most important operationally — is detention status immediately after Criminal Court arraignment. This variable has twice the impact on the dependent measure as any of the remaining predictors, which all seem to be of about equal importance.[21]

[20] Traditionally, the **severity** of charge is the independent variable used in predictive modelling of this kind. Here, because the existence of a statutory mandated prison sentence is logically more powerful than severity (measured conventionally by the felony class of the charge), this variable was chosen. It is, of course, redundant with charge severity. This model produces essentially identical results when "Severity of Arraignment Charge" is substituted for "Arraignment Charge Carries a Mandatory Prison Sentence".

[21] All the variables are positively related to the dependent measure (non-custodial disposition), except borough and number of prior felony convictions, for each of which the relationship is . . . *(cont'd)*

Table 5

Prediction Model for C, D, & E Felonies

Dependent Measure: **Non-mandatory Incarceration** versus **Non-custodial Disposition**

DISTRIBUTION OF CASES USED IN MODELING

Total Cases with Known Outcomes:	641	
Number Cases Deleted:	226	
Non-mandatory Incarceration:	185	(44.6%)
Non-custodial Dispositions:	230	(55.4%)
Total Cases Used in Modeling:	415	(100.0%)

COEFFICIENTS	**Unstandardized Estimates**	**Standardized Estimates**
Intercept	-1.1358***	--
Predictors:		
Number prior felony convictions	-.88***	-.32
Number prior misdemeanor convictions	.16**	.20
Detention immediately after Criminal Court arraignment	1.34***	.34
Number of open cases	.24*	.16
Borough is Richmond	-.87**	-.19

Overall Model X^2: 84.88***

DF: 5

Pseudo R^2: .17

* $p \leq .05$

** $p \leq .01$

*** $p \leq .001$

MODEL ADEQUACY

Cutpoint: .40

Percent Predicted **Non-mandatory Incarceration:**	52%
Percent Predicted **Non-custodial Disposition:**	48%

Total Correct:	67%
True Positives:	79%
True Negatives:	56%
False Positives:	39%
False Negatives:	27%
RIOC:	.40

This model is not as accurate as either of the preceding ones, although the predictions are still better than what would be achieved by chance. The model's overall rate of correct predictions is 67 percent: it correctly predicts those actually receiving non-mandatory custodial sentences (rather than a non-custodial dispositions) 79 percent of

(footnote continued)

negative. Thus, not having been arrested in Richmond County is predictive of non-mandatory incarceration, and the higher the number of prior felony convictions, the greater the likelihood of a non-custodial disposition. This last, apparently counter-intuitive point is discussed in the text above.

the time — nearly a 30 percent improvement over a coin toss. The model's RIOC (which indicates a 40 percent improvement over chance), is not as strong as the RIOC for the pretrial detention prediction model, but is nevertheless almost half again better than chance. This model over-predicts non-mandatory incarceration (versus non-custodial dispositions) — it predicts non-mandatory incarceration for 39 percent of those who actually receive non-custodial dispositions.

Examination of the distribution of the variables, found in Table 6, makes general intuitive sense, with one surprise. Prior felony convictions has an effect opposite of what might be expected: More of those with no prior felony convictions are found in the group receiving non-mandatory custodial sentences than in the group getting non-custodial dispositions. On reflection, this too makes sense because having a prior felony conviction precludes an offender from receiving a non-mandatory custodial sentence (and his mandatory sentence removes him from the sample from which the model in Table 5 was built), but it does not bar dismissal of the case — a non-custodial disposition.

The other variables show the expected trends: most of those receiving non-mandatory terms of incarceration have prior misdemeanor convictions, are in detention immediately after Criminal Court arraignment, are not white, are not likely to have their cases arrested and arraigned in Richmond County, and are likely to have open cases. Viewed from another perspective, those whose cases are predicted to end with non-custodial dispositions are more likely to be out of detention immediately following Criminal Court arraignment, to have no prior misdemeanor convictions, to have been arrested and arraigned in Richmond County, and to have no other outstanding criminal cases.

Table 6

Characteristics (Independent Variables) of C, D & E Felony Defendants in Sample:
Those Predicted to Get **Non-mandatory Incarceration** Compared with
Those Predicted to Get **Non-custodial Dispositions**

Independent Variables	Cases Predicted to Be Non-mandatory Incarceration (N = 216)	Cases Predicted to Be Non-custodial Dispositions (N = 199)
Number Prior Felony Convictions	mean = .15	mean = .49
Number Prior Misdemeanor Conviction	mean = 1.9	mean = .56
Number Open Cases	mean = 1.1	mean = .51
Not Detained After Criminal Court Arraignment	3%	63%
Borough is Richmond	4%	39%

Summary of the Prediction Models. All three analyses produced models with good overall "fit". The three models produced also had relatively good rates of prediction, and were certainly better than chance. However, the first and last of the models (the model for predicting pretrial detention, and the model for predicting non-mandatory incarceration versus non-custodial disposition), while substantially better than chance at correctly predicting incarceration, overclassified offenders approximately one-third of the time.

POTENTIAL USES FOR THESE MODELS

These models were built in order to help the city assess the screening and targeting criteria of ATD, ATI, and ATD/I programs, and in particular to assess the extent to which the criteria used in current programs are appropriate — given the city's objective of using these programs to displace some of the demand for its jail capacity. The remainder of this memorandum is given over to discussion of several of the uses and several of the limitations of the models developed above. In general, it is assumed that the models would be used to help displace from jail some of the days defendants would otherwise spend in pretrial detention ("ATD" displacement), and to help displace some of the jail days otherwise used by offenders sentenced to non-mandatory incarceration ("ATI" displacement).

ATD Displacement. The pretrial detention model is not likely to prove very useful to the city. The reasons for this can be seen from an examination of current ATD program intervention strategies.

First, several of the ATD programs (specifically, BEX and Bronx Bailbond Supervision) intervene only in the cases of defendants who are in detention at the time of intervention. Similarly, the bail memoranda prepared by ACAAP and by CCJA are prepared exclusively for defendants who are in pretrial detention. In assessing the appropriateness of the screening criteria used by programs such as these, detention status exists by definition and need not be predicted: The central challenge is to find predictors of the **length** of the pretrial detention (*i.e.*, distinguishing those who will consume jail capacity for longer periods from those likely to be released or sentenced quickly). This is, in fact, the central challenge in assessing the screening and targeting criteria for any program model in which the intervention is exclusively for defendants who are in pretrial detention at the time of screening, and in which the primary objective is to displace as much ATD time as possible — although many such programs appropriately have the secondary objective of avoiding a custodial sentence after a successful ATD intervention. The 1985 data set specified for this project, however, was not structured in a way that readily permits analysis of the length-of-stay in detention.

When using court databases to determine length-of-stay in detention (the 1985 data set is a court-based set), the actual DOC admission and release dates are not typically available. Nevertheless, when such a database contains data about the detention status at each court event (*e.g.*, whether the defendant was in detention at the conclusion of the hearing), as does the database routinely maintained by CJA, proxy measures of actual time in detention can be created. For those not released at arraignment, this can be done by searching for the first court date where an "out" detention status follows the "in after arraignment" status; for a rough measure of the length of stay at DOC, the time between the two hearings can be divided in half.[22] Unfortunately, in

[22] For defendants admitted to DOC pretrial, who are released at some point before disposition or sentence but who are also re-admitted at least once more during the pretrial period of case-processing, a cumulative measure of total time in detention can be created by following the same logic. This group, however, may represent a different type of offender, conceptually, than the "long-stayers" who are targets for alternative program intervention. This is because defendants who cycle in and out of detention are most likely to be the defendants for whom warrants have been ordered, and a pattern of warrants is typically seen as disqualifying a defendant for alternative program interventions.

the 1985 data set used for this research project, detention status was available at only two points during the Supreme Court phase of court processing — at the initial Supreme Court arraignment, and at disposition. Because it takes so long, on average, to dispose of felony cases in the Supreme Court, using a defendant's detention status at just these two dates would (when the whole period is divided in half) create an artificially long length-of-stay for some unknown (but large) number of defendants who were released at some post-arraignment point and remained at liberty through disposition. The appropriate database for analysis of this type would either be one based on all court appearances or one containing the actual DOC admission and DOC release dates.

The potential utility of analyses of the kind suggested is nicely illustrated by the ATD displacement research carried out as part of the planning for Bronx Bailbond Supervision Project. That project aimed to displace the jail use of long-staying ATD candidates, by posting bond for and maintaining intensive community supervision over defendants predicted to remain in pretrial detention for significant periods; the project also hoped that successful pretrial community supervision of long-stayers would encourage the court to avoid custodial sentences in project cases. Therefore, a database was developed that isolated characteristics of Bronx detainees who stay in pretrial detention the longest and who would be probation-eligible if convicted. That research produced screening criteria that identify a target group of Bronx detainees facing specified charges who, if held eight days or more on bails up to $7,500, average 99 days in pretrial detention overall. At disposition, 89% of these long-stayers are probation-eligible (by both conviction charge and prior record), 71% are still in detention at disposition, and 72% receive a custodial sentence. Screening criteria having this degree of specificity, derived from analyses of this kind, help alternative programs target their intake efforts on pools of individuals whose intake has a high probability of displacing demand for jail (and prison) resources.

To estimate the likely ATD displacement effects of a program like BEX (and any other early-intervention program that attempts to achieve ATD displacement by facilitating or expediting bail-making) the appropriate analytic framework is quite different. The first step is to determine whether program operations appear to increase the rate of early release from custody. Then, using BEX as an example, the task is to estimate the mean length of stay in pretrial detention for those with bails under $2,500 at first arraignment who most closely resemble the defendants whose release was expedited by BEX program effort. Analysis of this kind, while far from simple, would permit assessment of the ATD displacement effects of such programs.

Analytically, yet another set of questions is appropriate for assessing the ATD displacement effects of programs that screen for intake from among defendants who are at liberty rather than in pretrial detention at the time of program intervention. Such programs are focused primarily on achieving ATI displacement effects rather than ATD displacement effects (that is, they may intervene during the pretrial period *because* doing so is viewed as strategically useful in securing a non-custodial sentence in a case otherwise likely to draw jail or prison time). Because the defendants targeted by such programs are not in pretrial detention at the point of intervention, the pretrial detention prediction model developed in this research project is not really relevant. Much more useful is the model developed for predicting non-mandatory incarceration and distinguishing cases in that category from those likely to end with a non-custodial disposition.

ATI Displacement. The models for predicting non-mandatory incarceration should be more immediately useful to the Office of the Deputy Mayor for Public Safety.

It is clear from these models that having prior felony convictions does, in fact, predict mandatory incarceration in felony arrest cases that reach Supreme Court arraignment. Most of the programs intervening for the purpose of offering an ATI in Supreme Court already use this factor to exclude candidates from further screening efforts.[23] The more difficult problem is to refine program screening criteria to target intake on defendants and offenders who have a high probability of drawing non-mandatory jail or prison terms rather than non-custodial dispositions. The general objective is to find criteria that avoid excessive intake from groups whose chances of dismissal or non-custodial sentence are high. Again, the independent variables identified in the model-building process described above are, by and large, commonsensical, and are at least reflected in screening criteria already used by some ATD/I and ATI projects.

For example, felony defendants who remain in pretrial detention after Criminal Court arraignment are more likely to get jail or prison sentences when their cases are disposed in Supreme Court than are those who are released at Criminal Court arraignment, and some programs focus their intake efforts primarily or exclusively on detainees.[24] Operationally, being in detention immediately after Supreme Court arraignment (rather than after Criminal Court arraignment) is likely to be more useful as a program eligibility criterion, both because most felony ATI programs do not pick up cases for screening until that point and because their screening staff would not face the missing data problem that led to the use of the Criminal Court data in the prediction model.[25]

It should be noted that the importance of detention status in the felony prediction models underscores a central finding of the *Jail Use Analysis*: it was found there, from analyzing the pattern of demand for jail capacity, that programs targeting those who come into detention before disposition and who stay post-sentence (the ATD/I programs) isolate the individuals who make the greatest use of jail resources. Similarly, the prediction model-building research shows that those who remain in detention pretrial are the most likely to get the prison and jail sentences that ATI programs aim to displace.

Another predictor of custodial sentences is a history of prior misdemeanor convictions. Thus, while ATI programs appropriately steer clear of most Supreme Court defendants burdened by multiple prior felony convictions, their jail displacement objectives would be well-served by screening *out* candidates who have no prior

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[23] The two defense-based advocacy programs, ACAAP and CCJA, do not automatically exclude from further screening felony defendants with prior felony convictions, because reducing the length of state prison terms is one of these programs' principal objectives.

[24] Detention status immediately after Criminal Court arraignment has predictive power in felony cases disposed in the Supreme Court because 81% of those who are in pretrial detention immediately after Criminal Court arraignment are still in detention when their cases are "disposed" in the Criminal Court (*i.e.*, transferred to Supreme Court), and 70% are still in detention when arraigned in Supreme Court.

[25] Detention status immediately after Supreme Court arraignment was not used in the prediction model because it is heavily redundant with detention status immediately after Criminal Court arraignment and because Supreme Court processing data were missing in the cases sealed by OCA: Thus, the decisional rule for discarding redundant variables led to the use of the Criminal Court data. (*See*, discussion at page 6, above.)

misdemeanor convictions. Currently, of the programs categorized by the Deputy Mayor's Office as ATI programs (ISP, TASC, CSSP, and CEP), only one (CSSP) has an eligibility criteria that restrict intake to candidates who have accumulated a minimum number of prior misdemeanor convictions.[26] ISP's eligibility criteria do not address prior convictions at all, and both TASC and CEP have only upper bounds on the number of priors that are acceptable. (TASC screens out those with more than 3 priors, and CEP screens out those with more than 4 prior convictions). It may be appropriate to suggest that the screening criteria used by these programs, whether or not they include an upper limit on prior misdemeanor convictions, require a minimum number of prior misdemeanor convictions for eligibility. Of course, the city cannot be certain about the extent that jail displacement objectives really require such amendments to screening criteria, without a separate research inquiry that applies the prediction model to a large sample of those actually taken into those programs (to see what percentage would be predicted to draw custodial sentences).

A major challenge faces the Office of the Deputy Mayor for Public Safety, in assessing the likely ATI displacement effects of programs that screen for intake from among defendants who are at liberty — who are not in pretrial detention at time of program intervention. The prediction models suggest that ATI intake should be targeted on those in pretrial detention. So does the *Jail Use Analysis*. Nevertheless, it is of course possible that the screening staff of these projects have special expertise and knowledge, permitting them to do much better than the prediction models at identifying the relatively few defendants at liberty pretrial who are in fact likely to get custodial sentences. A potentially useful step would be to use the prediction equation developed in this research, for distinguishing cases ending with non-custodial dispositions from those drawing non-mandatory incarceration, as a scoring device: the task would be to score all those defendants found initially eligible by such a program, on each of the variables found to be predictive of custodial sentences. The final scores would predict custodial sentences for some number of these defendants, despite their being at liberty rather than in pretrial detention: the likelihood of custodial sentence in these cases would depend on how they score on the number of prior convictions, the number of open cases, the borough of arraignment, and ethnicity, as well as on detention status after Criminal Court arraignment. This would provide at least a sense of the degree of ATI displacement likely to be achieved by ATI programs that target intake on those defendants who are not in detention at the time of program intervention.

Ongoing Monitoring of Programs. The prediction models should be useful to the Office of the Deputy Mayor for Public Safety as tools for monitoring program performance against jail displacement goals. There are really two separate tasks under this heading, presenting two different levels of difficulty in securing the data necessary for implementation.

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26 Historically, this is the result of CSSP basing its screening criteria on the predictive model-building research conducted by Douglas McDonald and reported by him in *Punishment Without Walls* (New Brunswick: Rutgers University Press, 1986). That work gave clear direction to CSSP program planners that defendants with *no* prior convictions were very unlikely to draw custodial terms in the Criminal Court, and that there was, for each borough, a logical cutpoint in the number of priors (below which the probability of a custodial sentence was too low to warrant further screening of defendants for intake, if displacement effects desired by CSSP's planners were to be achieved).

First, the data currently collected by the various programs should be examined, to see whether the data collected are of the right kind (and are collected reliably enough) to permit periodic assessment of the proportion of those taken into a program who are drawn from pretrial detention. That information emerges as important in its own right, in any determination of the jail displacement efficacy of a program's eligibility criteria and screening processes.

Second, programs might be asked to add to their routine data collection tasks information about the factors the model-building research found would help predict incarceration. If the programs are already capturing data about prior convictions for those it screens, the additional variables it would be necessary to collect are: number of open cases, ethnicity, and detention status immediately after Criminal Court arraignment (and, in cases transferred to the Supreme Court, immediately after Criminal Court disposition or Supreme Court arraignment). For ATD programs, the additional variables are: verified employment, CJA release recommendation, and arraignment charge. Much of this information is collected by programs already: if the practice were standardized across programs, the Deputy Mayor's Office would have a relatively simple way of estimating current levels of displacement, and the likely displacement effects of various patterns of investment in program expansion.

Whatever uses are found for these models, it is appropriate to conclude with a reminder that no prediction model is perfect. Certainly, these are not. They should be used to develop estimates where estimates are needed, to guide the evolution of eligibility criteria and screening processes when greater displacement of jail use is desired, and to frame policy discussion and decisions about the city's alternative program investment strategy.

Using the Prediction Models to Refine Program Eligibility Criteria. With additional analytic work, the variables found to predict incarceration can be transformed into specific screening criteria that help avoid excessive intake of candidates whose chances of drawing custodial sentences are relatively low. First, for predictive variables that are continuous (*e.g.*, number of prior felony convictions, number of prior misdemeanor convictions) a specific criterion must be stated and then tested to determine what proportion of the pool of candidates eligible under that version of the screening criteria would be predicted to draw custodial sentences. For example, setting an eligibility criterion at two or more prior convictions might add nothing to the power of the screening criteria to target jailbound candidates, while setting the criterion at three or more priors would; and setting the criterion at four or more priors might do little to further increase the percentage of eligible candidates who would be displaced from jail, while so substantially reducing the pool of candidates as to be counter-productive. This is a trial-and-error process, in which the search is for a set of criteria that reduce the percentage in the eligible pool who do not draw custodial sentences, while maintaining the largest pool size compatible with that objective. Fortunately, most of the variables in these models are dichotomous (*e.g.*, detention status immediately after Criminal Court arraignment is either yes or no), so the iterative model-testing process is not endless. This was the work done, when the misdemeanor prediction models developed by Douglas

McDonald for CSSP were transformed into screening criteria that specified the combination of factors (and their values) that would be required for eligibility in each borough where that project operated.[27]

UPDATING THESE MODELS

To the extent the products of this prediction model-building research suggest a need to validate, refine and update them, it becomes important to acknowledge the peculiar difficulties presented to such research by the current condition of the databases available to the city. The many obstacles encountered in implementing this research design, previously detailed to the Office of the Deputy Mayor for Public Safety, powerfully illustrate the inefficiency of developing one-shot databases for addressing specific program investment or program design issues. This is particularly so, given the desirability of innovation in the design of even the existing alternative programs, and the likelihood of changes over time in the composition of the DOC population and the dispositional process. If the kinds of policy questions addressed by this research are of continuing priority importance to the city, it may be time for the city to turn its attention to the design, construction, and maintenance of a policy-relevant database that draws constantly on the various sources of data required for analyses of these questions. Such a database need not be "on-line" (though it could and should have automated batch access to the various on-line systems that track defendant, court, and detention events). But it should maintain the general classes of variables that will always be useful in analyses of the kind performed in this research, and of the kind that permit proper design of new ATD, ATI and ATD/I programs.

[27] Thus, for Brooklyn CSSP, a defendant is not considered sufficiently jailbound to be screened for intake unless he or she meets two of the following three criteria: six or more prior arrests, a conviction within 18 months of the arrest date for the current case, or a jail or prison sentence served on the most recent prior conviction. *See*, Douglas C. McDonald, *Punishment Without Walls* (New Brunswick: Rutgers University Press, 1986).

PREDICTING INCARCERATION

Appendix A

Table A-1

Distribution of Sample Cases,
by Borough and Arraignment Charge Severity

	Borough									
	Brooklyn		Manhattan		Queens		Richmond		Bronx	
Arraignment Charge	N	%	N	%	N	%	N	%	N	%
A & B Felonies	177	46.2	198	42.1	112	40.4	120	38.0	152	53.0
C, D, & E Felonies	206	53.8	272	57.9	165	59.6	196	62.0	135	47.0
Total	383	100.0	470	100.0	277	100.0	316	100.0	287	100.0

Table A-2

Distribution of Pretrial Detention Outcomes in Sample Cases, by Borough and and Charge

	Borough									
	Brooklyn		Manhattan		Queens		Richmond		Bronx	
	N	%	N	%	N	%	N	%	N	%
For A & B Felonies										
Always In	70	57.9	77	53.1	49	56.3	54	60.0	37	40.2
Not Always In	53	43.1	68	46.9	38	43.7	36	40.0	55	59.8
Total	123	100.0	145	100.0	87	100.0	90	100.0	92	100.0
For C, D, & E Felonies										
Always In	73	57.5	99	45.2	67	60.4	74	67.3	42	53.9
Not Always In	54	42.5	120	54.8	44	39.6	36	32.7	36	46.1
Total	127	100.0	219	100.0	111	100.0	110	100.0	78	100.0

Table A-3

Distribution of Non-Custodial Disposition and Non-Mandatory Incarceration, by Borough and Charge

	Borough									
	Brooklyn		Manhattan		Queens		Richmond		Bronx	
	N	%	N	%	N	%	N	%	N	%
For A & B Felonies										
Non-Custodial	53	69.7	57	64.0	24	48.0	46	60.5	47	66.2
Non-Mandatory Incarceration	23	30.3	32	36.0	26	52.0	30	39.5	24	33.8
Total	76	100.0	89	100.0	50	100.0	76	100.0	71	100.0
For C, D, & E Felonies										
Non-Custodial	92	62.2	82	47.7	71	62.8	114	78.1	59	67.8
Non-Mandatory Incarceration	47	33.8	90	52.3	42	37.2	32	21.9	28	32.2
Total	139	100.0	172	100.0	113	100.0	146	100.0	87	100.0

Table A-4

Distribution of Non-Mandatory Incarceration and Mandatory Prison, by Borough and Charge

	Borough									
	Brooklyn		Manhattan		Queens		Richmond		Bronx	
	N	%	N	%	N	%	N	%	N	%
For A & B Felonies										
Non-Mandatory Incarceration	23	23.5	32	29.9	26	40.0	30	40.5	24	30.4
Mandatory Incarceration	75	75.5	75	70.1	39	60.0	44	59.5	55	69.6
Total	98	100.0	107	100.0	65	100.0	74	100.0	79	100.0
For C, D, & E Felonies										
Non-Mandatory Incarceration	47	50.5	90	53.9	42	60.0	32	48.5	28	50.9
Mandatory Incarceration	46	49.5	77	46.1	28	40.0	34	51.5	27	49.1
Total	93	100.0	167	100.0	70	100.0	66	100.0	55	100.0

PREDICTING INCARCERATION

Appendix B

APPENDIX B

LIST OF PREDICTOR VARIABLES

OFFENDER VARIABLES

-gender;
-ethnicity;
-CJA release recommendation (stamp);
-verified New York City address and verification on one or more responses to "lives with," "how long at current address," or "employment/schooling/training";
-verified length of time at current adress;
-verified employment.

CASE VARIABLES

-days between arraignment on this case and most recent disposition date;
-number of open cases at arraignment;
-arraignment charge, in Criminal and Supreme Court (severity level and type);
-conviction charge, in Criminal and Supreme Court (severity level and type);
-arraignment bail amount, in Criminal and Supreme Court;
-arraignment release status, in Criminal and Supreme Court;
-disposition bail amount, in Criminal and Supreme Court;
-disposition release status, in Criminal and Supreme Court;
-sentence.

CRIMINAL HISTORY VARIABLES: COUNTS

-number of arrests;
-number of misdemeanor arrests;
-number of felony arrests;
-number of violent felony arrests;
-number of convictions;
-number of misdemeanor convictions;
-number of felony convictions;
-number of violent felony convictions;
-number of sentences to probation;
-number of jail sentences;
-number of prison sentences;
-number of probation revocations;
-number of parole revocations.

RECENCY OF PRIOR RECORD: COUNTS

The same information in the criminal history counts was also calculated to determine the number that occurred within the last two years.

ADDITIONAL PRIOR RECORD VARIABLES COMPUTED

-age at first arrest;
-length of arrest record;
-number of arrests per year at risk.

PREDICTING INCARCERATION

Appendix C

APPENDIX C

PREDICTOR VARIABLE SELECTION HIERARCHY

The approach followed overall was first to examine all potential predictor variables to determine which ones were highly related to the specific outcome measures. Once these were isolated, the individual predictors were examined together so that redundant variables, measuring similar concepts, could be eliminated. The hierarchy, or order of selection mirrors the discussion below.

The selection process began with the prior record variables. When examining of these, the conviction variables (rather than the counts of sentences) were seen as the logical starting point, because of the temporal sequencing of criminal justice outcomes (i.e., before a sentence can occur, there must be a conviction).

Then, when choosing between convictions and arrests, convictions were seen as more important to retain than arrests, for several reasons. The first one concerns reliability. Arrests without convictions are supposed to be sealed and not appear on the criminal arrest record (RAP sheet). However, whether the appropriate authorities complete the paperwork is variable, making arrest counts unstable. Secondly, it is best to mirror real world operations, and program screeners will be using RAP sheets, where arrests may be sealed and thus unavailable.

Another choice needed to be made between total counts of all convictions (inclusive of both felonies and misdemeanors), and individual counts of each. Because offenders convicted of either mostly felony offenses or misdemeanor offenses are often qualitatively different types of offenders, the individual counts of felony and misdemeanor convictions were used.

Once the specific conviction variables were decided upon, the prior sentence and revocation variables were examined for additional factors not redundant with those already chosen. Then the recency prior record counts were reviewed for inclusion.

The severity and type of the present offense variables available as predictors were then reviewed for high intercorrelations. The relationship between type and severity was not strong, allowing for both to be included as potential predictors in the models.

Data were available for both type and severity for four points in the case process: Criminal Court arraignment and disposition, and the same two in Supreme Court. Because there were high intercorrelations among those four points, the Criminal Court arraignment charge type and severity was used. The rationale for this concerns, again, the screening process. Many programs screen prior to final disposition, and thus the Criminal Court arraignment charge is the most stable at the point that the screening process typically occurs.

At that point, the bail and release status variables were reviewed for redundancy, both within and across the categories.[1] Bail was found to be a different concept (with a relatively low correlation) from release status, and thus both were kept. Again, both bail and release status were available for the same four points in the criminal process; those for Criminal Court arraignment were kept because of the desire to mirror the screening process.

Finally, the CJA interview information was reviewed. Here, when a decision had to be made, it was seen as most appropriate to keep individual components of items rather than composites, in order to isolate what the individual scores imply. Specifically, in the CJA dataset the variable "VNYCR" is composed of both a verified New York City address and verification of either length of time at current address, or verified school or employment. If the response for VNYCR is "No, not verified," it is unclear which factor was not verified. Because each factor could disclose something qualitatively different from the other, the individual items, rather than the composite, were retained where appropriate.

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[1] Release status was eligible for inclusion only in the models for predicting sentencing outcomes. The release status variables were components of the outcome measure in the pretrial detention models, and thus could not be included as predictor variables as well.

PREDICTING INCARCERATION

Appendix D

Table D-1

Predictive Model for A & B Felonies
Dependent Measure: Always in Pretrial Detention Versus
Not Always in Pretrial Detention

DISTRIBUTION OF CASES
USED IN MODELING

Total Cases with Known Outcomes:	537
Number Cases Deleted:	110
Always in Pretrial Detention:	252 (59.0%)
Not Always in Pretrial Detention:	175 (41.0%)
Total Cases Used in Modeling:	427 (100.0%)

COEFFICIENTS	Unstandardized Estimates	Standardized Estimates
Intercept	.04	-
Predictors:		
Number prior felony convictions	.95***	.41
Crim. Court arrgn. charge type	-.48***	-.43
CJA ROR recommendation	.34**	.19

Overall Model X^2: 91.73***
DF: 3
Pseudo R^2: .18

* $p \leq .05$
** $p \leq .01$
*** $p \leq .001$

MODEL ADEQUACY

Cutpoint: .55
Percent Predicted Not Always in Pretrial: 72%
Percent Predicted Always in Pretrial: 28%

Total Correct:	71%
True Positives:	50%
True Negatives:	86%
False Positives:	28%
False Negatives:	29%
RIOC:	.52

Table D-2

Characteristics on the Independent Variables for A & B Felonies
Dependent Measure: Not Always in Pretrial Detention Versus
Always in Pretrial Detention

Independent Variables	Cases Predicted to Be Not Always in Pretrial (N = 304)	Cases Predicted to Be Always in Pretrial (N = 123)
Number Prior Felony Convictions	mean = .23	mean = 1.1
Arraigned in Criminal Court on Crime Against Person	2%	24%
CJA ROR Recommendation = Yes	57%	42%

Table D-3

Predictive Model for A & B Felonies
Dependent Measure: Non-Custodial Disposition
Versus Non-Mandatory Incarceration

DISTRIBUTION OF CASES
USED IN MODELING

Total Cases with Known Outcomes:	362
Number Cases Deleted:	125
Non-Custodial Disposition:	123 (51.9%)
Non-Mandatory Incarceration:	114 (48.1%)
Total Cases Used in Modeling:	237 (100%)

COEFFICIENTS	Unstandardized Estimates	Standardized Estimates
Intercept	-2.61**	-
Predictors:		
Number prior felony convictions	-.84*	-.22
Crim. Court arrgn. charge severity	.69*	.19
Crim. Court arrgn. charge type	.28**	.25
Number open cases	.26*	.16

Overall Model X^2: 23.86***
DF: 4
Pseudo R^2: .09

* $p \leq .05$
** $p \leq .01$
*** $p \leq .001$

MODEL ADEQUACY

Cutpoint: .50
Percent Predicted Non-Custodial Disposition: 45%
Percent Predicted Non-Mandatory Incarceration: 55%

Total Correct:	65%
True Positives:	71%
True Negatives:	59%
False Positives:	38%
False Negatives:	31%
RIOC:	.35

Table D-4

Characteristics on the Independent Variables for A & B Felonies
Dependent Measure: Non-Custodial Disposition
Versus Non-Mandatory Incarceration

Independent Variables	Cases Predicted to Be Non-Custodial Disposition (N = 106)	Cases Predicted to Be Non-Mandatory Incarceration (N = 131)
Number Prior Felony Convictions	mean = .33	mean = .01
Arraigned in Criminal Court on A Felony	12%	1%
Arraigned in Criminal Court for Crime Against Person	13%	2%
Number Open Cases	mean = .74	mean = 1.02

Table D-5

Predictive Model for A & B Felonies
Dependent Measure: Non-Mandatory Incarceration Versus Mandatory Prison

DISTRIBUTION OF CASES
USED IN MODELING

Total Cases with Known Outcomes:	423
Number Cases Deleted:	25
Non-Mandatory Incarceration:	129 (32.4%)
Mandatory Prison:	269 (67.6%)
Total Cases Used in Modeling:	398 (100%)

COEFFICIENTS	Unstandardized Estimates	Standardized Estimates
Intercept	.96	-
Predictors:		
Borough is Brooklyn	1.4**	.33
Number prior felony convictions	3.54***	1.59
Crim. Court arrgn. charge type	-.69***	-.64
Crim. Court arrgn. detention status	.94*	.18
Ethnicity = White	-1.47**	-.24

Overall Model X^2: 206.00***
DF: 5
Pseudo R^2: .69

* $p \leq .05$
** $p \leq .01$
*** $p \leq .001$

MODEL ADEQUACY

Cutpoint: .60
Percent Predicted Non-Mandatory Incarceration: 29%
Percent Predicted Mandatory Prison: 71%

Total Correct:	85%
True Positives:	91%
True Negatives:	73%
False Positives:	13%
False Negatives:	21%
RIOC:	.69

Table D-6

Characteristics on the Independent Variables for A & B Felonies
Dependent Measure: Non-Mandatory Incarceration Versus Mandatory Prison

Independent Variables	Cases Predicted to Be Non-Mandatory Incarceration (N = 117)	Cases Predicted to Be Mandatory Prison (N = 281)
Borough is Brooklyn	76%	78%
Number Prior Felony Convictions	mean = 0	mean = .79
Arraigned in Criminal Court for Crime Against Person	6%	21%
Out after Criminal Court Arraignment	28%	8%
Ethnicity = Non-White	77%	95%

PREDICTING INCARCERATION

Appendix E

APPENDIX E

SUMMARY OF THE COMMUNITY SERVICE SENTENCING PROJECT MODELS FOR PREDICTING INCARCERATION IN MISDEMEANOR CASES

INTRODUCTION

In 1989, the Vera Institute of Justice undertook a replication of the prediction analysis done by Doug McDonald[1], to determine the predictors of a jail sentence among those who were eligible for Community Service Sentencing but who had not received that sentence, and to apply that prediction model to offenders who had received the alternative sentence (to determine the proportion of program participants who would be predicted to get jail sentences had the program not intervened). The prediction work was completed and submitted to CASES in early 1990.

SAMPLE SPECIFICATION

The samples were randomly drawn, separately for each of the four boroughs in which CSSP operates (Staten Island was not included). Cases were sampled from the pool of cases considered "paper-eligible" by CSSP screeners at an early point in case-processing, but rejected as CSSP candidates at some later point. (This method was adopted in order to isolate a set of offenders who did not receive the CSSP sanction who were roughly comparable to those who did.) The sampling percentages were: for Brooklyn, 12 percent of the reject pool; for Manhattan, 12 percent; for the Bronx, 14 percent; and for Queens, 100 percent.[2]

VARIABLE SPECIFICATION

There were two general types of variables included in this analysis -- (1) offender and court case variables, and (2) variables describing prior record. A complete list follows:

Offender and Case Variables

- marital status;
- gender;
- ethnicity;
- detention status at sentencing;
- days between arraignment on this case and most recent disposition date;
- number of open cases at arraignment;
- arraignment charge (severity level and type);
- conviction charge (severity level and type);
- arraignment bail amount;
- whether the charge was reduced from arraignment to conviction;
- sentence to jail.

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1 *See*, Douglas C. McDonald, *Punishment Without Walls* (New Brunswick: Rutgers University Press, 1986).

2 A sample of cases was also drawn from the pool of offenders who *did* receive a community service sentence in CSSP. Those sampling proportions were 35% of the participants in Queens, 50% in both Brooklyn and Manhattan, and 66% in the Bronx.

<u>Criminal History Variables (prior information)</u>

Overall:
- number of arrests*;
- number of misdemeanor arrests*;
- number of felony arrests*;
- number of violent felony arrests*;
- number of convictions*;
- number of misdemeanor convictions*;
- number of felony convictions*;
- number of violent felony convictions*;
- number of probation sentences;
- number of jail sentences;
- number of prison sentences;

*The starred criminal history variables, in addition to being calculated for each defendant's entire criminal history, were calculated for the two year period preceding the sample case.

- age at first arrest;
- length of arrest record;
- number of arrests per year at risk;
- number of convictions per year at risk;
- probability of probation on a past arrests;
- probability of jail sentence on past arrests;
- probability of prison sentence on past arrests;
- probability of probation on past convictions;
- probability of jail sentence on past convictions;
- probability of prison sentence on past convictions.

RESULTS OF THE PREDICTIVE MODELS

While it was possible to build adequate predictive models for all of the boroughs[3], there were problems with the results in two -- Brooklyn and Queens. The variables specified for the final models in each borough, and the overall accuracy of each model, is given below.[4]

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[3] With adequacy meaning a significant chi square statistic.

[4] For the CSSP modeling analysis, the cutpoint with the highest score was picked, combining the percentage total correct predictions, and the lowest false positive rate. This cutpoint then produced a proportion of correct positives and negatives, and false positives and negatives.

Manhattan (N = 105)

For Manhattan, there were four variables found to be important in predicting custodial sentence:

- in pretrial detention at time of sentencing;
- age of first adult arrest;
- total convictions of any type;
- bail at arraignment (ROR = 0).

Using a cutpoint of .45, these variables produced a model with a total correct prediction rate of 80 percent; there were 94 percent true positives, 52 percent true negatives, and the false positive and false negative rates were each 19 percent. Because it demonstrated such a high degree of accuracy, the Manhattan model was seen as valid.

Bronx (N = 82)

For the Bronx model there were three variables included in the final prediction model. They are:

- in pretrial detention at time of sentencing;
- number of prior felony and misdemeanor convictions;
- age of first adult arrest.

With a cutpoint of .65, the overall total correct prediction rate was 73%, with 89% true negatives and 60% true positives. The false negative rate was 35%, while the false positive rate was 13%. This model was also seen as valid.

Queens (N = 28)

The model produced for Queens isolated two variables as predictive:

- days since last conviction;
- number of prior jail sentences.

The cutpoint used was .70, which produced a models with 71% rate of total correct predictions. However, because the number of cases used in the modeling was so small, these results are not seen as valid. A further analysis of Queens should be done.

Brooklyn (N = 81)

The model finally developed for Brooklyn specified two predictive variables:

- in pretrial detention at time of sentencing;
- imprisoned on the most recent conviction.

However, while the overall predictive model was statistically significant, the model was not sufficiently accurate. Using a .50 cutpoint, while the overall total correct prediction rate was 69% percent, the false positive rate was 44%. This model can be seen to err towards "in" predictions and, while accurately predicting the true "ins" 77 percent of the time, it predicts as "ins" those who are really "outs" in close to half of the cases that will not result in custodial sentences (making the model minimally better than a coin toss). Thus, it is suggested that this modeling exercise be repeated on a new sample; until that occurs, these predictors should be used with caution.