DISTRICT OF COLUMBIA
COURT SERVICES AND OFFENDER SUPERVISION AGENCY &
PRETRIAL SERVICES AGENCY
RESEARCH REVIEW COMMITTEE

RECOMMENDATION STATEMENT FOR AGENCY RESEARCH

DATE: March 8, 2010

I. RESEARCH PROPOSAL SUMMARY

Principal Researcher: Spurgeon Kennedy, Director, Office of Research, Analysis and Development, District of Columbia Pretrial Services Agency

Title: Risk Assessment and Validation for Pretrial Defendants

Institution: Pretrial Services Agency through a contract with The Urban Institute (UI) (Contract number: PSA-90-PMD1).

Description:

PSA selected UI to develop and validate a practical risk assessment instrument to better identify and control factors associated with failure to appear in court and re-arrest while on pretrial supervision. The project has several components, including: (1) development of a set of cohorts for data analysis from PRISM; (2) identification of potential risk factors through bivariate and multivariate analyses; (3) comparison of methods to model the pretrial risk; (4) an analysis of the potential suppression of risk through PSA's supervision protocols; and (5) final validation of the risk prediction models after accounting for the suppression effect.

This request applies only to PSA.

Type of Data and Analysis:

UI will develop of a set of cohorts for data analysis from PRISM and examine data elements for a relationship to pretrial misconduct, using bivariate and multivariate analyses. There are several methods linear regression models and, if needed, clustering models, classification tree models, and automatic interaction detector analysis. Vendors also may employ a risk modeling method that recently has been implemented by CSOSA for use with an offender population. Regression-based modeling techniques will be applied to assign weights to identified predictors of risk.

UI will study the supervision suppression through the most appropriate methodology to the circumstances at hand. This will be informed from review of the PRISM data and meetings with RAD staff.

Following detection and quantifying of the suppression effect, UI will construct an instrument that predicts latent risk. The instrument will be tested on a validation sample similar to the population used to create the instrument.

Subjects:

UI will create data files that include all defendants-papered cases processed by PSA from 01/2008 to 06/2009 (18 months). Both intake and exit cohorts will be examined as there are advantages and disadvantages in either approach. At midpoint of this project, UI will seek to accrue additional cases progressively to enrich the sample. The final prediction models will be fine-tuned on the most recent and richest data available as of the third quarter of 2010.

II. RECOMMENDATION

The RRC recommendation for this study:

■ **Support** ☐ Support with Conditions ☐ Do Not Support

I **ACCEPT** the RRC recommendation	I **DO NOT ACCEPT** the RRC recommendation
Susan Shaffer	
Susan W. Shaffer, Director, D.C. Pretrial Services Agency	
Comments:	

D.C. PRETRIAL SERVICES AGENCY
OFFICE OF RESEARCH, ANALYSIS AND DEVELOPMENT

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Research Review Committee (RRC) Submission
Request for Agency Research

Tuesday, January 12, 2010

Name, Agency and Agency component:

Spurgeon Kennedy, Director
Office of Research, Analysis and Development (RAD)
District of Columbia Pretrial Services Agency (PSA)

Contracted Vendors:
KiDeuk Kim, Co-Principal Investigator, Urban Institute
Avi Bhati, Ph.D., Co-Principal Investigator, Maxarth LLC.
Megan Denver, Project Coordinator, Urban Institute

Title of the study:

Risk Assessment and Validation for Pretrial Defendants

Purpose of the project:

This project supports the goals identified under PSA Statement of Work PSA-90-PMD1. PSA has selected the Urban Institute (UI) to develop and validate a practical risk assessment instrument to better identify and control factors associated with failure to appear in court and re-arrest while on pretrial supervision. The project will have several components, as outlined in the Statement of Work, including: (1) development of a set of cohorts for data analysis from PSA's Pretrial Real-time Information System Manager (PRISM); (2) identification of potential risk factors through bivariate and multivariate analyses; (3) comparison of methods to model the pretrial risk; (4) an analysis of the potential suppression of risk through PSA's supervision protocols; and (5) final validation of the risk prediction models after accounting for the suppression effect.

Location of the project:

RAD staff will collect and validate project data at PSA's 633 Indiana Avenue offices. Vendor staff will conduct research activities from the companies' 2100 M Street NW. Washington, DC 20037 (UI) and 509 Cedar Spring Street Gaithersburg, MD 20877 (Maxarth LLC) addresses. When necessary, vendor staff will collect data at 633 Indiana Avenue, under RAD staff supervision.

Methods to be employed:

The vendors will examine data elements from PRISM for a relationship to pretrial misconduct, using bivariate and multivariate analyses. Of particular interest will be the extent to which multiple risk factors compete or interact with each other in predicting pretrial misconduct. Once risk factors are identified, vendors will consider each in the framework of statistical prediction, using as methods. There are several methods linear regression models and, if needed, clustering models, classification tree models, and automatic interaction detector analysis. Vendors also may employ a risk modeling method that recently has been implemented by Court Services and Offender Supervision for use with an offender population. Regression-based modeling techniques will be applied to assign weights to identified predictors of risk. Vendors also will test the value of the econometrics approach of converting certain predictors—such as defendant age—into categories and assigning the mean failure rate within each category as the relative weight to that category. This would assign more risky age categories a higher score than less risky categories, rather than a generic "age" risk score. This new variable captures the relative ranking of the various age categories of age.

Vendors will study the supervision suppression through the most appropriate methodology to the circumstances at hand. This will be informed from review of the PRISM data and meetings with RAD staff.

Following detection and quantifying of the suppression effect, vendors will construct an instrument that predicts latent risk. The instrument will be tested on a validation sample similar to the population used to create the instrument.

Anticipated results:

As described in PSA-90-PMD1, this project will help PSA meet its objectives of ensuring that its risk assessment includes factors empirically related and appropriately weighted to pretrial failure, and yield results or products thereof that can assist PSA with two fundamental decision-making processes: (1) whether or not to make a pretrial release recommendation and (2) what level of supervision intensity to assign to pretrial defendants. Specifically, decision-making tools (e.g. supervision matrix) or guidelines will be formulated for field operations, based on our validated prediction models.

Further, PSA hopes to test a potentially innovative method to account for the mediating effect of supervision on risk: one that may be used by other pretrial programs nationally.

Duration of the study:

October 1, 2009 to September 30, 2011.

Sample size required and/or time frame for sample collection:

The data set will be similar in variables and composition to the set approved for use by Abt Associates for its study of defendant and system effects on pretrial misconduct. The proposed data will include all defendants and papered United States criminal cases processed by PSA from January 2008 to June 2009. As with the Abt data set, the final evaluation file will not include any personal or case identifiers that can be recognized or used outside of PRISM.

PSA and the vendors do not anticipate the need for any data besides the historical information in PRISM, therefore there are no known confidentiality concerns regarding developing the data or submitting it to the vendors for use.

Agency resources needed to support the study and description of the support needs:

PSA staff support and resources are needed for data extraction from PRISM, including technical support as to how to understand the structure and contents of PRISM, and background on current PSA field operations, supervision assignments, and use of the current risk assessment instrument. Staff collaboration also is needed to organize focus groups, interviews, meetings, and/or training with PSA staff, and to document features of supervision programs. As noted in PSA-90-PMD1, PSA has agreed to provide this assistance through RAD.

Deliverables:

The vendors will produce two reports. The first will detail efforts to identify risk factors and specify risk models. It will include risk factors found predictive in the analysis and their relationship to pretrial failure. The final report will describe analytic procedures and findings and include the vendors' recommendations on implementing the risk assessment instrument.

		2009	2010				2011		
Task		Qtr 4	Qtr 1	Qtr 2	Qtr 3	Qtr 4	Qtr 1	Qtr 2	Qtr 3
1	Background Review								
2	Research Design and Plans	•							
3	Data Acquisition and Processing								
4	Development of Risk Models								
5	Risk Suppression Analysis								
6	Model Estimation and Validation								
7	Implementation of Risk Models								
8	Dissemination and Management							•	•

- Deliverables

Appendix: Detailed Statement of Research

a. Review of Prior Research

Risk assessment instruments are evidence-based methods that are used for a variety of criminal justice populations (juveniles, domestic violence offenders, etc). In general, objective risk assessment instruments are considered a strategic method of reducing recidivism among probationers and parolees (Pew Center on the States, 2008). Although there has been less research on risk assessments for pretrial defendants when compared to persons already convicted of a crime, the pretrial research community has developed standards and guidelines for implementing objective assessments in recent years (American Bar Association, 2007; Lotze, Clark, Henry, & Juszkiewicz, 1999; Mahoney et al., 2001; NAPSA, 2004).

While pretrial instruments have many similar considerations as general risk assessment instruments, there are certain considerations that are specific to the goals of pretrial services. Specifically, pretrial defendants have the presumption of innocence, more legal protections, and different intended outcomes compared to convicted offenders (VanNostrand, 2007). Therefore, pretrial assessment instruments should – depending on state statues – predict potential danger to the community and/or whether defendants will return to court. Researchers have also suggested that pretrial risk assessment should include only relevant risk factors, and treat all defendants fairly instead of producing different results based on race, ethnicity, gender, or financial status (Lotze et al., 1999; VanNostrand 2003; VanNostrand 2007).

A recurring issue with objective and standardized instruments is the removal of criminal justice practitioners as decision makers in the risk assessment process. There are often differing goals and information available to statisticians, policy makers, and practitioners. Gottfredson and Gottfredson (1979: 7) made two points about the clinical versus statistical debate: (1) some statistical methods are more reliable and valid than clinical judgments, and (2) the two methods can be effective when used together, "possibly mutually supportive."

A related issue concerns staff disagreements with the objective decisions when there are errors or exceptional cases. Although a meta-analysis of over 100 studies conducted by Grove, Zald, Lebow, Snitz, and Nelson (2000) found actuarial methods to be more accurate than clinical judgments,[1] researchers have acknowledged the margins of error in predicting recidivism (Ashford & LeCroy, 1990; M. R. Gottfredson & Gottfredson, 1984; S. D. Gottfredson, 1987; S. D. Gottfredson & Moriarty, 2006; Klein & Caggiano, 1986; Wiebush, Baird, Krisberg, & Onek, 1995). Therefore, although not desirable in large quantities, occasional staff overrides to instrument assessments are inevitable, and more generally, the involvement of criminal justice practitioners is important (Andrews, Bonta, & Hoge, 1990).

[1] Objective instruments outperformed clinical judgments by about 10% on average and in 33%-47% of studies; they were less predictive than clinical techniques in only 6%-16% of studies.

Another issue to consider for any type of risk assessment instrument is how valid the instrument is for the population. The literature consistently emphasizes that validating a risk assessment instrument on a local population is critical when jurisdictions adopt an instrument (Gottfredson & Moriarty, 2006; Wright, Clear, & Dickerson, 1984), even if the instrument is intended to be multi-jurisdictional (e.g., the Virginia Pretrial Risk Assessment Instrument). Miller and Lin (2007) found that using a generic instrument for their New York City juvenile sample – even when the instrument was validated using local data – was less reliable than clinical judgments because important (and jurisdiction specific) elements were not included. Yet only about a quarter of the pretrial services agencies that use objective risk assessment instruments reported validating the instrument on their local jurisdiction's data (Clark and Henry, 2003). However, there has been an increased emphasis on validating pretrial risk assessment instruments in recent years, most notably in Ohio (Latessa et al., 2009), Virginia (VanNostrand, 2003; VanNostrand & Rose, 2009), New York City (Peterson, 2006; Siddiqi, 1999; 2000; 2002) and the District of Columbia (Winterfield, Coggeshall, & Harrell, 2003)[2].

b. Research Method

1) Identification of risk factors

There are several risk assessment tools that have recently been developed for pretrial agencies (Cooprider, 2009; Brennan and Dieterich, 2009; Siddiqi, 2004; VanNostrand, 2009; VanNostrand and Keebler, 2009). Although such tools predicting the likelihood of pretrial failure vary on the measurement of risk factors, there are a few domains commonly identified to be significant in predicting the risk of pretrial failure outcomes (see Table 1), which is also coherent with a larger body of research on criminal behavior and recidivism (Goldkamp, Gottfredson, and Weiland, 1990; Smith et al., 1989; Smith and Polsenberg, 1992; Visher and Linster, 1990).

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[2] Earlier notable contributions to pretrial risk assessment include the Vera Institute's Manhattan Bail Project (Ares, Rankin, & Sturz, 1963) and an evaluation of the District of Columbia's transition to include safety and appearance as having separate risk factors in their pretrial risk assessment instrument (Toborg, Yezer, Tseng, & Carpenter, 1984).

Table 1. Domains of Risk Factors

Domains	Measurement
Current charge types	Offense type Charge seriousness (felony or misdemeanor) Pending charges Outstanding warrants
Prior criminal history	History of rule violations and pretrial misconduct Type and frequency of prior arrest(s) Type and frequency of prior conviction(s) Length and frequency of prior incarceration(s) Age at first arrest
Criminogenic needs	History of drug use/treatment and mental illness
Community ties	Employment Support from family, friend, and religious groups
Residential stability	Length at current residence Frequency of moving in recent past

Those domains shown in Table 1 are also consistent with finding from the Abt study (2009:28-29), which identified the following factors to be predictive of FTA and re-arrest for any crime:

- Demographics (race, gender, and age)
- Education
- Employment
- Residential stability (had lived at their current address for less time)
- Prior criminal history
- Commitment offense types and conditions
- Criminogenic needs (required mental health or substance abuse treatment)

Drawing upon those prior studies, this project will identify risk factors predicting pretrial misconduct. As noted in PSA-90-PMD1, the current instrument utilizes risk factors commonly promoted in the literature, yet has still encountered problems with accuracy and may be missing other relevant factors that previous research has not addressed. Therefore, data elements available in PRISM will be closely examined in relation to pretrial misconduct. First, a bivariate relationship between risk factors and outcome variables will be examined. We will study the effect of risk factors on pretrial misconduct one by one. This exercise will provide basic information upon which risk models are constructed and also inform multivariate analysis which follows next. Second, two or more risk factors will be simultaneously examined in relation to pretrial misconduct. Of particular interest is to examine the extent to which multiple risk factors compete or interact with each other in predicting pretrial misconduct.

2) Risk modeling

Once risk factors are identified, we will consider each and all of those risk factors in the framework of statistical prediction. There are several methods that can be used for this procedure, including linear regression models, clustering models, classification tree models, and automatic interaction detector analysis (Gottfredson and Gottfredson, 1979; Steadman et al., 2000; Winterfield et al., 2003). We will first focus on one of the most conventional approaches in actuarial risk assessment, linear regression models. This study also proposes another risk modeling method that has recently been implemented for offenders in District of Columbia. This new approach is potentially promising and deserves further elaboration below.

Approach to combining information: Regression-based modeling

Linear regression models are perhaps the most widely used approach in actuarial prediction. For several reasons, there is a proclivity not only in risk prediction but also in behavioral science in general for simple, single linear orderings (see DeSoto, 1961). This study will first attempt to model predictive risk factors in a multivariate regression framework. In its general form, the model can be described as:

$$\hat{y} = a + b_1 X_1 + b_2 X_2 + \ldots + b_i X_i + \ldots + b_n X_n,$$

where $\hat{y}$ is the predicted outcome of pretrial misconduct (e.g. re-arrest), a is an intercept (constant), X_i is a risk factor (e.g. the number of prior felony arrests), and b_i is its weight.

Although regression equations estimated for each outcome measure may change from one model to the next, our effort will focus on identifying the optimal combination of risk factors that would best predict outcome measures with the least amount of error. Also important is the extent to which findings from the regression models are intuitive and practically replicable because esoteric or complex models would have little utility. Along with model fit indices, model parsimony and interpretability will therefore be considered as model selection criteria.

Approach to combining predictions

Besides regression based modeling, other approaches may be applied to assign weights to predictors of risk. A recent strand in the econometrics literature has investigated the relative value of combining information or combining forecasts. Following this strand, Bhati and Coggeshall (2009) developed a new approach to assign weights to predictors in a risk assessment model. A brief description of the approach is provided here. Consider a predictor measured on a continuous scale—e.g., age—that is related to risk of FTA. We can convert age into age categories and assign the mean FTA rate within each category as the relative weight to that category. In the sample, this will mean more risky age categories will have a higher score than less risky categories. This new variable captures the relative ranking of the various categories of age. Next, consider another variable on a nominal scale—e.g., current charge—that is also associated with risk of FTA. The same strategy of assigning group specific FTA rates to each of the categories will result in a new measure providing the relative ranking of the various charges in terms of their riskiness of FTA. These two variables form bivariate predictions of the risk of FTA given the attributes (age or charge). How do we combine these in a reasonable manner?

Bhati and Coggeshall (2009) use a simple principal component analysis to convert these bivariate predictions into composite predictions. Hence, following the literature on combining predictions rather than information, Bhati and Coggeshall (2009) combine bivariate predictions into a number of components. Attributes that make similar predictions are grouped together. If there are K predictions included in the analysis, then K composite principal components are created from them. Finally, the components themselves are collapsed into a single score—the final risk score—by weighting them with their internal coherence. The final risk score is also normalized to a restricted range—typically 0 to 100.

This strategy has several appealing properties. First, the attributes are allowed to have a non-linear relationship with the risk score. This typically produces better predictions. Second, the weighting of the attributes ensures that less relevant predictors are downweighted and good predictors are upweighted automatically. This is done while combining the bivariate predictions. Consequently, the strategy yields a parameter – much like a regression parameter – that captures the importance of the predictor (among all the included predictors). Finally, one of the key advantages of this strategy is that, if constructed correctly, the scores are guaranteed to be normalized to the 0 – 100 range in all future samples. This normalization is not guaranteed when regression based strategies are used to convert attributes (like age and current charge) into a risk score.

In past applications, this strategy has proven to be very robust to the low base rate issue—typically serious arrests among pre-trial population are low. For example, the strategy as used in Bhati and Coggeshall (2009) to develop scores for risk of serious violent re-arrest among post-adjudication samples had base rates as low as 3-4%.

3) Suppression analysis

Risk suppression can be defined as the lowering of the risk of FTA or re-arrest that can be expected in the data because the data were generated while the criminal justice agency was deploying its resources to mitigate risk. Such a mitigating effect of supervision, as discussed in PSA-90-PMD1, is another methodological consideration that deserves careful attention. Unlike other prediction problems – where the agent whose risk is being predicted is the sole determinant of the risk – the criminal justice system is never turned off. Therefore, the observed FTA and re-arrests are recorded despite the best efforts of the pre-trial agency to detect and mitigate it. To the extent that risk is suppressed, its detection and quantification becomes crucial. Using suppressed risk measures (FTA and re-arrest) to construct and validate an instrument would yield an instrument that misses true (or latent) risk. There exist several techniques that can be utilized for detecting and quantifying the suppression effect inherent in pretrial data. These include standard multivariate regression analysis, regression discontinuity designs, analysis of natural experiments, propensity score matching from different periods, inverse probability weighted analysis, and secondary analysis of published sources. Each of these approaches is better suited for specific situations. Our initial analysis of the jurisdictions and their mechanism will guide us in our choice of the appropriate approaches for detecting and quantifying suppression effects.

Multivariate regression analysis is a standard approach to analyzing the effects of a set of predictors on some outcome of interest net of other predictors (Green 2000). Such analysis has the potential of quantifying the effects of suppression mechanisms net or salient factor that predict risk. Its weakness, however, lies in the assumption that the model predicting risk is completely defined and important sources of risk are not ignored. Multivariate regressions are most appropriate when the suppression mechanism is informal and less well understood.

Regression Discontinuity designs are applicable when the jurisdiction employs a formal grid based system for classifying and supervising individuals differentially (Berk and deLeeuw, 1999; Imbens and Lemieux, 2007). In this approach, the ability to identify points of discontinuity around which individuals who may be considered almost identical are treated differently provides the opportunity to detect and quantify suppression effects.

Natural experiments exist when an agency or jurisdiction has just adopted a new pretrial practice or scheme and data is available for the period prior to, and since, the adoption of this practice. If the process of adopting the new practice is fairly discrete, then one is able to exploit the fact that individuals before and after the policy shift should be comparable in their proclivity for misconduct so that any difference in the risk that is observed must be because of the suppression of risk by the new policy. This analysis can be augmented by propensity score matching (Rosenbaum and Rubin, 1983) or inverse probability weighting (Wooldridge, 2007) to ensure that any differences in the risk is not due to systematic difference in sample characteristics.

Finally, when cases are randomly assigned by a judge or supervision officer, then use can be made of this randomization for identifying and estimating the effects of differential treatment by utilizing instrumental variable methods.

Clearly, each approach has its pros and cons. We propose to study the suppression mechanism by utilizing the most appropriate methodology to the circumstances at hand. This will be informed by a set of meetings between PSA personnel and the research team to better understand the suppression mechanism, its sources, and the operationalization of several features such as randomization.

Adjustment to risk scores

Once we detect and quantify the suppression effect in the data, the next task is to construct an instrument that predicts latent risk. Below, we provide the basic mechanics of doing so. Consider that for each individual in the sample we are able to detect and quantify a suppression effect (denoted s_i). Let the suppression effect be a number between 0 and 1 (where 0 indicates full suppression and 1 indicates no suppression). Then we can write the basic *suppressed* model as:

$$y_i \approx s_i r_i \qquad \forall i \tag{1}$$

where r_i is the latent risk we'd like to estimate and y_i is the observed (suppressed outcome, e.g., FTA). One may now proceed by modeling the risk using any modeling strategy as described in the previous sub-section. For example, suppose we were to just create categories of individuals and compute the mean risk scores among the categories and create the risk score as a simple additive sum of all score. In this case, we'd compute the risk score within the *j*th category (r_j) by first creating dummy variables d_{ij} that are set to 1 if the individual belongs to the *j*th category (e.g., someone with prior history of FTA) and 0 if the individual does not belong to this category (e.g., no prior record of FTA). Now we can use this variable to transform (1) into an equality as:

$$\sum_i d_{ij} y_i = \sum_i d_{ij} s_i r_j \qquad \forall j \tag{2}$$

or

$$\frac{\sum_i d_{ij} y_i}{\sum_i d_{ij} s_i} = r_j \qquad \forall j \tag{3}$$

Note that the (3) provides the unsuppressed risk for the *j*th category because if risk is being suppressed for individual who belong in that category, then s_i will be less than 1 for some or all the individuals in that category. If s_i were 1 for everyone (i.e., if there were no suppression) than (3) would yield the mean failure rate within the category as the risk level. However, with $\sum_i d_{ij} s_i < \sum_i d_{ij}$ we are guaranteed that r_j will be higher than the mean failure rate within the category. And the extent of suppression will be reflected in the amount by which the final risk score will be scaled up. This will result in the construction of latent (unsuppressed) risk scores.

4) Model validation

After prediction models are constructed, it would be necessary to evaluate the performance of such models. We are primarily interested in testing the predictive validity of risk models. The "split-sample" or "hold-out" method is one of the most conventional approaches to estimating how well the prediction models perform on data yet to be seen. This procedure involves partitioning data into two subsets, one for developing (training) a model and the other for testing (validating) the model.

Following the split-sample approach, we will first partition data into two random subsets. Model adequacy will be evaluated based on model fit indices and diagnostic test statistics such as Receiver Operating Characteristic (ROC) curve. In its simplest form, it is a parametric plot of the hit rate (the probability of correctly predicting an outcome of interest) versus the false alarm rate, as a decision threshold is varied across the full range of a continuous forecast quantity (see Hanley and McNeil, 1982). In addition to the random-subsets partitioning, we will also develop temporal subsets by splitting data by time (e.g. arrest date). The earlier half will be used as a training sample and the latter half as a validation sample. This method would most closely resemble the reality of deploying a new risk assessment instrument for field operations such that the models we develop are applied to future data yet to be seen.

Based on results of those analyses, we might also consider cross-validation and bootstrapping for model validation (Efron and Tibshirani, 1997). As an elaborate version of the split-sample method, cross-validation allows one to divide data into k subsets of approximately equal size. Iterative training and validating a prediction model has shown a markedly superior performance over the split-sample method especially for datasets with a challenge (e.g. a small sample size or skewed distribution).

c. Significance of anticipated results

As described in PSA-90-PMD1, consistent with the Agency's mission to control pretrial misconduct, the results of this study will help PSA review and, if needed, revise its risk assessment. Specifically, these activities will help verify that: 1) the factors in PSA's risk assessment instrument (RAI) are predictive of future failure to appear and risk to community safety, 2) Agency release recommendations are the most effective—but least intrusive—for the pretrial defendant population, and 3) PSA has the capacity to validate and improve its RAI internally.

Reducing FTA and pretrial re-arrest are legitimate criminal justice system objectives. As such, numerous studies have demonstrated the utility of a prediction tool in identifying high-risk offenders (see Farrington and Tarling, 1985; Greenwood and Abrahamse, 1982 for general discussion and see Cooprider, 2009; Brennan and Dieterich, 2009; Siddiqi, 2004; VanNostrand, 2009 for pretrial models). The fact that prediction accompanies prediction errors, however, has raised concerns and suspicion about the implementation of risk models.

Further, it has recently been suggested that the current approaches to testing the predictive accuracy in risk models is mostly flawed by design (Bushway and Smith, 2007). That is, if you predict risk accurately (risk assessment) and respond to it adequately (supervision conditions), you cannot validate the prediction because the predicted outcome would not, and should not, occur as predicted. Therefore, ironically, most validation studies are not valid.

Our proposed research centers on that challenge. The research design and methods proposed in this document allow an examination of whether or not, and how much, criminal justice inputs would suppress the risk of pretrial misconduct. Not only does our approach employ advanced techniques to develop risk models but our approach also offers an innovative method to account for the mediating effect of supervision on risk. In other words, we can answer what the risk of pretrial misconduct would have been if supervision had not been applied. By examining latent (or true) risk, not suppressed risk, our risk models will be validated with much rigor.

d. Benefits of research and/or participation to PSA

PSA outlined several expected benefits to this research in its Statement of Work for PSA-90-PMD1. The Agency's internal review of its risk assessment uncovered several shortcomings, including frequent staff overrides of recommendations, RAI weighting of failure to appear factors apparently not correlated to actual missed court appearances, and some RAI factors not associated strongly to pretrial misconduct. There also is little difference in the current RAI in failure to appear rates among the Low/Medium and High Risk/No Recommendation categories, confirming the lack of correlation between risk scores and missed scheduled court appearances. Finally, PSA and its partner agencies are interested in the potential benefits of separate assessments to help identify and reduce the risk of rearrest on violent felony offenses and within certain high risk populations such as defendants charged with domestic violence offenses and those initially detained pretrial but later released to PSA supervision.

Lessons learned from this project will be integral to the day-to-day operations of PSA. More specifically, policy recommendations for how to improve current practices for risk assessment and supervision of pretrial defendants will be delivered to PSA before the end of project period. We will also make efforts to ensure that knowledge we learn from this project will be transferred to PSA staff in form of meetings, training, data presentations, and/or written reports.

e. Specific resources required from the Agency

In order for this project to achieve aimed goals, PSA staff support will be required for two major tasks. First, data files required for this project will be primarily extracted from PRISM. We will request of PSA staff to offer technical support with understanding and extracting data from PRISM or other administrative records maintained by PSA. PSA has agreed through its Statement of Work to offer this support through its Office of Research, Analysis and Development.

Second, this project involves understanding current practices in PSA's field operations, with particular reference to supervision assignments and use of the current risk assessment instrument. Such efforts are important to develop suppression analysis and a practical decision-making tool. We expect to collaborate with PSA Office of Research, Analysis, and Development in communicating with and learning from field staff – which may include, but is not limited to, the following tasks:

- Conducting focus groups, interviews, and/or meetings
- Developing training for PSA field staff
- Documenting current practices of PSA field operations

f. Description of all possible risks, discomforts, and benefits to individual subjects

We analyze administrative records of pretrial defendants for this project based entirely on retrospective data. There is no direct involvement of those defendants in the study. Further, under no circumstances will communication or interpersonal contact between the project staff and study subjects be required for this study. There is no basis to suspect discomforts or benefits to individual subjects whose administrative records are to be analyzed for this study.

PSA will also sanitize data before handing them over to the Urban Institute for use. All individual identifiers will be removed from data files. There is minimal or no risk that can be anticipated for study subjects in this project.

g. Description of steps taken to minimize any potential risks or discomforts

This project relies on retrospective data that have already been collected as part of PSA routine operations. Under no circumstances will we have the ability or intention to identify study subjects whose administrative records are to be analyzed for this study. Their participation in this project is unconscious and non-experiential. There is no basis to suspect discomforts to study subjects in this project, and hence no specific procedures deemed required.

h. Description of physical and/or administrative procedures to be followed to (1) ensure the security of any individually identifiable data that are being collected for the project; and (2) destroy research records or remove individual identifiers from those records when research has been completed:

There will be no individually identifiable information needed or developed for this project. All data files will be completely sanitized by PSA staff before release to project staff. Therefore, no specific procedures will be required to ensure the security of individual identity or destroy such information. For the duration of project period, we will adhere to general protocols, as guided by the Urban Institute Policy and Procedures, which prescribe ethical responsibilities in the performance of research involving human subjects.

i. **Description of any anticipated effects of the research project on Agency programs and operations**

This project anticipates interacting with PSA field staff to understand current practices. During the course of such activities, we anticipate possibilities to increase staff awareness and compliance with use of a risk and needs assessment instrument. For example, through focus groups or training, we may assist PSA field staff to better understand how actuarial risk assessment can outperform clinical judgment or how risk assessment tools can be utilized for pretrial release decision-making.