The Construction and Validation of the Federal Post Conviction Risk Assessment (PCRA)

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THE UNITED STATES PROBATION system was created in 1925 by the Federal Probation Act. This Act gave the U.S. Courts the power to appoint federal probation officers and the authority to sentence defendants to probation instead of a prison term. One of the primary functions of federal probation is to supervise convicted offenders who are sentenced to a term of probation or a term of supervised release following a period of imprisonment, and offenders released early from prison on parole or mandatory release by the U.S. Parole Commission or military authorities.

The federal probation and pretrial services system is organized into 94 districts within 11 regional circuits and operates under a decentralized management structure. As a result of being decentralized, each district operates with a great deal of autonomy; however, despite this autonomy, the system maintains cohesion through the Administrative Office of the U.S. Courts (AO). The AO serves as the administrative headquarters for this decentralized system and develops national policies that help districts in their efforts to protect the community and reduce recidivism.

During the past two decades, advancements in social science research, the need to use resources more efficiently and effectively, and increased expectations to reduce recidivism have sparked a major philosophical shift in the field of probation. Although probation officers are still required to monitor offender behavior and report noncompliance to the court, the general focus has shifted to reducing future criminal behavior (Alexander & VanBenschoten, 2008). Arguably, the best chance for reducing recidivism occurs when officers not only have a reliable way of distinguishing high-risk offenders from low-risk offenders but also can intervene in the criminogenic (crime supporting) needs of high-risk offenders (Andrews et al., 1990; Lowenkamp & Latessa, 2004; Bonta & Andrews, 2007; Campbell, French & Gendreau, 2007). For federal probation, this has meant looking for more effective ways to manage offenders by predicting their potential to reoffend and/or their potential dangerousness to the community (Walklate, 1999).

This article explains the process the AO used to develop a risk assessment instrument for use with its post-conviction supervision population. We provide a brief overview of the principles of effective classification and a summary of the evolution of risk assessments and then explain why the AO chose to create its own risk assessment instrument rather than use an existing instrument. However, the primary purpose of the article is twofold: (1) To present the methodology and results produced in the development of the Post Conviction Risk Assessment (PCRA) tool, and (2) to discuss limitations of the PCRA as well as future developments.

Principles of Effective Risk Classification

In general terms, the principles of effective risk classification refer to the prediction or identification of offenders most likely to violate the law or conditions of supervision during a period of criminal justice supervision, the identification of factors that can be influenced to change the likelihood of recidivism, and the acknowledgement of factors that might influence the benefits of a particular service (Van Voorhis & Brown, 1996). Risk of recidivism, criminogenic need, and general responsivity are three of the primary principles of effective classification (Andrews et al. 1990). The fourth principle, professional discretion, targets the professional's ability to look beyond the application of the first three principles when circumstances indicate a need to do so (Gottfredson, 1987).

The principles of effective risk classification suggest that agencies should use actuarial assessment tools to identify dynamic risk factors, especially in high-risk offenders, while also identifying potential barriers to treatment (Bonta & Andrews, 2007; Latessa et al., 2010). Actuarial risk assessments rest on

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three factors: (1) certain individual characteristics and behaviors are statistically predictive of future involvement in criminal behavior; (2) the more risk factors an offender has, the greater the likelihood of future criminal behavior; and (3) when properly validated and administered, actuarial risk predictions are more accurate than clinical predictions (Meehl, 1954; Sawyer, 1966; Gottfredson, 1987; Andrews and Bonta, 1994). Andrews and Bonta (1998) argue that it is the combined assessment of risk and need that improves the ability to predict who is likely to offend and outlines what interventions should take place to reduce risk and subsequently recidivism.

Brief History of Risk Assessment Tools

Purpose of a Risk Assessment Tool

The assessment of offenders has long been acknowledged as a necessary component for criminal justice practitioners who are responsible for assessing and managing offenders. In the field of probation, the primary purpose for using a risk assessment tool is to help keep communities safe from offenders who are most likely to reoffend. Although security was the primary reason for the development of risk assessment instruments, the ability to classify offenders at the appropriate risk level is also beneficial. Consequently, risk assessment tools help probation officers identify which offenders need intensive interventions and what needs should be targeted by the interventions.

Evolution of Risk Assessment Instruments

The evolution of risk assessment is described as following a generational path that started with the most basic form of assessment and has progressed to a more complex form of risk assessment (Bonta & Wormith, 2007). Each generation utilized the best available methods to predict the risk of recidivism and then applied the results of the assessment to supervision strategies. This tradition continues today, with researchers continually refining their understanding of criminal behavior and the associated enhancements to risk/needs prediction tools (VanBenschoten, 2008).

First generation

For most of the 20th century, professional judgment or intuition was the most common method used to predict criminal behavior. This form of assessment involved an unstructured interview with the offender and a review of official documentation (Bonta, 1996; Van Voorhis & Brown, 1996; Andrews & Bonta, 2006; Connolly, 2003). Guided by their own professional training and experience, probation officers and clinical professionals made judgments about who required enhanced supervision or correctional programming (Bonta & Andrews, 2007). One of the inherent weaknesses of such an unstructured process is the lack of a quantitative way to determine how decisions are reached, which leads to a lack of consistency and agreement resulting in low inter-rater reliability (O'Rourke, 2008). In other words, the same interview conducted by different interviewers could net dramatically different results; therefore, the conclusions and recommendations regarding the offender could vary depending on the interviewer (Wardlaw & Millier, 1978; Monahan, 1981; Van Voorhis & Brown, 1996).

Second generation

Although second-generation risk tools have been available since the late 1920s, it was not until the 1970s that the assessment of risk began to depend more upon actuarial, evidence-based science and less on professional judgment and intuition. Second generation risk assessments are often referred to as actuarial methods (O'Rourke, 2008). Actuarial risk assessments consider individual items (e.g., history of substance abuse) that have been demonstrated to increase the risk of reoffending and assign these items quantitative scores (Bonta & Andrews, 2007). Burgess (1928) established the first of these models. In the Burgess method, each variable in the model can be scored as a "point," and the prediction is based on the aggregate number of points assigned to an offender (Connolly, 2003). For example, the presence of a risk factor may receive a score of one and its absence a score of zero. The scores on the items can then be summed—the higher the score, the higher the risk that the offender will reoffend (Bonta & Andrews, 2007). This technique gives equal weight to all predictors, even though there may be unequal effects. There is little research, if any, indicating that more complex (i.e., weighted) scoring methods produce better prediction than simple (i.e., unweighted) methods (Gottfredson 1987).

Third generation

Recognizing the limitations of second-generation risk assessment, research began to develop in the late 1970s and early 1980s on assessment instruments that included dynamic risk factors (Bonta & Wormith, 2007). The third generation of assessment is commonly referred to as risk-need assessments (Andrews & Bonta, 1995; Bonta & Andrews, 2007). These instruments combined the static predictor variables of the second-generation instruments with dynamic criminogenic need items (e.g., present employment, criminal friends, and family relationships) that were sensitive to changes in an offender's circumstances (Connolly, 2003; Bonta & Andrews, 2007). Third-generation risk assessment tools exceed statistical risk prediction by adding the element of need identification. As previous instruments assisted in decision-making regarding supervision conditions, third-generation assessments help identify areas that require intervention to mitigate recidivism risk while under supervision (Van Voorhis & Brown, 1996).

Fourth generation

The last few years has seen the introduction of fourth-generation risk assessment instruments. These new risk assessment instruments go beyond the third-generation risk-need assessments. Not only do fourth-generation instruments include risk-need assessments, they also assess a broader range of risk factors along with responsivity factors important to treatment for integration into the case management plan (Bonta & Andrews, 2007; Bonta & Wormith, 2007). Some examples of responsivity factors include reading and cognitive abilities, race, gender, motivation to change, as well as external factors such as treatment setting and counselor characteristics (Andrews et al., 1990; Bonta & Wormith, 2007). One other aspect of fourth-generation risk assessments is the attempt to explicitly link identified needs with supervision and treatment services (Bonta & Wormith, 2007).

Post Conviction Risk Assessment Tool

Actuarial risk assessments are not new to the federal probation system; in fact, they have been part of the supervision process since the early 1980s. To better assist probation officers in identifying high-risk offenders and intervening in their criminogenic needs, the AO chose to develop a risk assessment instrument tailored specifically to its population of offenders. The Post Conviction Risk Assessment (PCRA) is an actuarial risk and needs assessment tool developed from data collected on federal offenders who started a term of supervision between October 1, 2005 and August 13, 2009. This tool is designed to target treatment interventions prioritized by risk, need, and responsivity.

How the PCRA Came into Existence

In the *Strategic Assessment of the Federal Probation and Pretrial Services System* (hereafter cited as IBM, 2004), the authors identified shortcomings with the AO's use of the Risk Prediction Index (RPI).[1] One of the concerns expressed by the authors was the RPI's static nature, which causes a disconnection between the risk score and case management (IBM, 2004). Put another way, if an offender's risk to recidivate changes during the course of supervision, the RPI does not reflect this change; therefore, officers are not able to consistently and effectively interpret those changes and provide the proper supervision response.

To address the RPI's shortcomings, the Strategic Assessment recommended that the AO research other data-driven supervision tools (IBM, 2004). The desire to meet this recommendation, coupled with emerging criminal justice literature about more advanced risk assessment tools, influenced the AO to develop its own Research to Results (R2R) effort. During the R2R effort, 16 of the 94 federal probation districts were awarded funding to implement evidence-based practices[2] into their districts. Of those 16 districts, five districts chose to use a commercially available risk and needs tool to conduct risk assessments. In addition, AO staff members met with developers of three commonly used off-the-shelf risk/needs tools (LS/CMI, COMPAS, RMS)[3] to better understand the advantages and disadvantages of each tool.

Since the federal criminal justice system represents a distinctive population and since specific trailer assessments for special needs populations (such as sex offenders) are also required, it became obvious that more flexibility would be needed. At the conclusion of the experimentation and information gathering stage, the AO assembled a panel of experts to examine the options of purchasing a commercially available tool or building a new tool. After much discussion, the consensus of the group was to build a new tool with data specific to federal probation.

Construction and Validation of the PCRA

Methods

Data used to construct and validate the PCRA came from federal presentence reports (PSR), existing risk assessments, criminal history record checks, and PACTS.[4] Criminal history records or rap sheets were used to identify any new arrest after the start of supervision. The five R2R districts that were using a commercially available risk assessment tool were asked by the AO to provide data to assist in the development of the PCRA.[5] Each district provided a list of offenders who had received an assessment using an off-the-shelf risk prediction instrument and who also had a completed PSR. In total, the five districts submitted a list of 4,746 offenders, from which 479 cases were randomly selected.[6] Districts were then asked to provide rap sheets on the randomly selected cases. PACTS was the main source of data for scored elements on the PCRA; it included data on roughly 100,000 offenders.

Data Elements

There are two sets of items included on the PCRA: scored and not scored. The first set of items are rated and scored and thus contribute to an offender's risk score. Rated and scored items used to develop the PCRA were based on prior research in the area of predicting criminal behavior (for example Gendreau, Little, & Goggin, 1996; Simourd & Andrews, 1994; Hubbard & Pratt, 2002; Andrews & Bonta, 2006) that were also available in PACTS. Based on a review of extant research, data elements related to criminal history, peer associations, family, employment, substance abuse, and attitudes were selected from PACTS. As a result of bivariate analyses, some interval and ratio variables (e.g., age, prior arrests, education, and drug and alcohol problems) were collapsed into ordinal measures. Multivariate models and completeness of data were used to identify the most predictive and practical data elements to be included on the instrument. Variables included on the PCRA had a significance level of .10 or below (see Table 1).

The second set of data elements are rated but not scored and do not contribute to an offender's risk score. These items were identified as potentially predictive in a smaller sample of offenders from five of the R2R districts. With the exception of peer relationships, which came from the COMPAS and RMS, data elements came from the PSR. A total of 104 elements were collected from the PSR; however, four of those elements were personal identifiers (i.e., first name, last name, middle initial, and PACTS number). Additional rated but not scored items were added based on probation officers' input on what data they need to supervise a case (see Appendix 1). A total of 29 factors were identified as potential predictors and included on the assessment. These potential predictors were included as "test items" and future analysis will determine whether these items will become rated and scored PCRA items.[7]

Sample

In order to construct and validate the PCRA, the researchers devised three sample groups. A construction group was created for the construction of the instrument, and two validation groups[8] were created for the validation of the instrument. These groups were created using an existing analysis file from PACTS data that contained 185,297 offenders on probation or

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[1] The RPI uses 8 largely static questions to determine the risk that an offender will recidivate during his or her term of supervision; the results are intended to assist officers in creating the offender's initial supervision case plan.

[2] Districts were required to submit a proposal, which included a budget, outlining an area of evidence-based practices (EBP) they wanted to implement. The areas of EBP available were risk assessment, cognitive behavioral interventions, motivational interviewing, and other. The "other" category was open and districts that chose this option tended to use it for drug courts and workforce development.

[3] LSI (Level of Service Inventory), COMPAS (Correctional Offender Management Profiling for Alternative Sanctions), RMS (Risk Management Services).

[4] PACTS (Probation/Pretrial Services Automated Case Tracking System) is an electronic case management tool used by probation and pretrial services officers in all 94 federal districts to track federal defendants and offenders. At the end of each month, districts submit case data into a national repository that is accessible to the Administrative Office of the U.S. Courts (AO), Office of Probation and Pretrial Services.

[5] One district was not an R2R district but had been using a commercially available risk assessment tool (RMS) longer than the other four R2R districts.

[6] Districts were initially informed that 100 cases from each district would be randomly selected, but one district only permitted 10 percent of their cases to be selected, which limited their sample to 64 cases.

[7] Due to ongoing data collection, the test items have yet to be analyzed. Decisions to include or omit test items will be determined by statistical significance and by how a test item impacts the predictive accuracy of the PCRA.

[8] Two validation samples were developed in order to test the robustness of the instrument.

TABLE 1.
Multivariate Model Predicting Arrest During Initial Case Plan Period (Split Sample Construction Only)

Variable	B	SE	Wald	df	Sig	Exp(B)
Community Supervision Violation	.343	.052	43.551	1	.000	1.410
Varied Offending Pattern	.226	.049	21.416	1	.000	1.253
Institutional Adjustment	.227	.103	4.848	1	.028	1.255
Violent Offending	.320	.079	16.312	1	.000	1.378
Unemployed	.368	.045	66.248	1	.000	1.445
Poor Work Outlook	.322	.061	27.495	1	.000	1.380
Alcohol Problems	.479	.102	22.079	1	.000	1.615
Lacks Social Support	.267	.048	30.673	1	.000	1.306
Family Problems	.191	.051	14.278	1	.000	1.210
Single	.097	.054	3.175	1	.075	1.102
Not Motivated to Change	.383	.050	59.803	1	.000	1.467
Drug Problems	.710	.062	132.195	1	.000	2.033
Arrest History	.149	.021	50.543	1	.000	1.160
Age	.383	.033	136.614	1	.000	1.467
Educational Attainment	.234	.045	27.195	1	.000	1.264
Mental Health Problems	.068	.049	1.920	1	.166	1.070
Gambling Addiction	-.395	.283	1.945	1	.163	.674
Criminal Associates	-.080	.050	2.529	1	.112	.923
Weapon Concerns	-.086	.064	1.789	1	.181	.917
Financial Problems	-.070	.078	.806	1	.369	.932
Life Skills Deficiencies	-.019	.060	.103	1	.748	.981
Female	-.215	.058	13.586	1	.000	.807
Race			3.106	4	.540	
Asian	.613	.490	1.568	1	.211	1.846
Black	.638	.467	1.866	1	.172	1.892
Native American/Eskimo	.668	.475	1.977	1	.160	1.951
White	.683	.466	2.145	1	.143	1.980
Constant	-4.540	.472	92.691	1	.000	.011

Model $\Pi^2(26) = 1503.78$, $p < .000$; -2LL = 15868.80; Nagelkerke $R^2 = .119$

supervised release.[9] The construction group was created from data obtained from the initial case plan.[10] Using a near 50/50 split, data from the first case plan was divided into two sample groups; one became the construction sample and the other became the first validation group. One validation group (Validation) was taken from the initial case plan the offender receives during his or her term of supervision and the second validation group was taken from subsequent case plans (hence the name Subsequent Case Plan). Both the construction (N=51,428) and validation (N=51,643) groups comprised offenders who started a term of supervised release or probation on or after October 1, 2005. The subsequent case plan group comprised 193,586 case plan periods.

Analysis

A fairly straightforward and traditional approach was used in the development of the PCRA. Multivariate logistic regression

[9] Data from the analysis file was assembled from PACTS and matched with data from the Federal Bureau of Prisons (BOP), the U.S. Sentencing Commission (USSC), and the Census Bureau. Arrest data came from ATLAS (Access to Law Enforcement System) and from the FBI's Computerized Criminal History (CCH) database. Arrest data are current through August 13, 2009. Offenders in the analysis file began active post-conviction supervision between October 1, 2004 and August 13, 2009 (see Baber, 2010). Of the 185,297 offenders in the analysis file, only 103,071 had criminal histories and other relevant items used to construct the PCRA.

[10] As outlined in the *Guide to Judiciary Policy*, Volume 8, Part E, Supervision of Federal Offenders, case plans are to be submitted within 30–60 days of the start of the offender's supervision term. This plan is formally evaluated and modified during the sixth month of supervision and updated annually for the duration of the supervision term.

models[11] were used to determine which items were superfluous. As a result, the total number of items included in the multivariate model was reduced to ensure that statistical significance and direction of the relationship were maintained. Once the multivariate model was finalized, bivariate cross tabulations were used to assign appropriate weights. This method was chosen due to its transparency and, to date, there is little research indicating the superiority of complex weighting structures over dichotomous coding risk factors (see Gottfredson & Gottfredson, 1979; Silver, Smith, and Banks, 2000; Gottfredson & Snyder, 2005; Harcourt, 2007).[12] The bivariate cross tabulations are presented in Appendices 2–4.

Once the final scoring algorithm was determined, a score was calculated with a cutoff score developed by visual inspection of the data. Although the data cutoffs were fairly evident in the data, alternate cutoffs were tested with confirmation of best fit as determined through the use of chi-square statistics. A final set of analyses was conducted to determine how changes or stability in risk category from the beginning to the end of supervision was correlated with change in the probability of a new arrest.

Findings

Table 1 displays the results of a multivariate model predicting arrest during the initial case plan period using a split sample from the construction sample. As Table 1 shows, many of the variables included in the multivariate model were statistically significant at the .001 level. Odds ratios in the model also appear to be consistent with existing research that support well-accepted beliefs that alcohol and drug problems, unemployment, poor attitude (not motivated to change), criminal history, and lack of social support increase an offender's chances of getting re-arrested. Females appear to have a decreasing effect on the likelihood of re-arrest, which is also consistent with much of the existing research on gender and crime (Gendreau et al., 1996).

From the multivariate analysis, variables were selected for inclusion on the risk assessment instrument (see Appendix 5). To gain a better understanding of the bivariate relationships between the significant predictors in the multivariate model, we conducted a series of cross tabulations. Those results are reported in Appendices 2–4. In general, the bivariate cross-tabulations allowed us to assign 1 or 2 points to each of the factors. Although this approach may seem counter to prevailing wisdom on the development of weights for risk assessment, there is evidence that suggests that this approach produces an instrument that still outperforms clinical approaches to prediction (Dawes, 1979) and is more robust across time and sample variations (Gottfredson and Snyder, 2005; and McEwan, Mullen, & MacKenzie, 2009).

Table 2 presents the descriptive statistics on the risk assessment score, which can theoretically range from 0 to 19. There are 15 scored items. The scoring for each of the 15 items is displayed in detail in Appendix 5. Table 2 presents the number of cases in each sample, minimum and maximum values, mean, and standard deviation of the linear risk score. There are no significant differences in the length of the prediction period or average risk score for the construction sample and first validation sample (6.46 and 6.43, respectively). However, there are differences in the mean risk score between the subsequent case plan sample and construction sample and subsequent case plan sample and first validation sample. The difference in prediction periods is a matter of policy, as the first case plan period is approximately 6 months while the third case plan is completed 12 months after the second case plan or 18 months after the beginning of supervision. The lower mean risk score might simply be a function of lower-risk offenders surviving supervision to the third and subsequent case plan periods. At any rate, there could be some debate that the difference in risk scores is not practically significant, and this argument might be valid since all three mean scores fall into the low-risk category.

Table 3 presents the distribution of risk categories by the type of sample used. In all three samples, low and low-moderate risk offenders accounted for at least 85 percent of the cases, whereas high-risk offenders accounted for only 1 percent. There was no statistically significant difference between the construction sample and the validation sample at an alpha level of .01. However, there was a significant difference between the second validation sample (subsequent case plan) and the construction sample as well as between the second validation and the first validation sample. This is likely due to higher-risk offenders having a greater likelihood of revocation and thereby

TABLE 2.
Descriptive Statistics

Sample Group	N	Minimum	Maximum	Mean	Std. Deviation
Construction	51,428	0	16	6.4634	2.83052
Validation	51,643	0	16	6.4272	2.80699
Subsequent Case Plan	193,586	0	17	6.0320	2.73192

TABLE 3.
Distribution Across Risk Categories

	Sample					
	Construction		Validation		Subsequent Case Plan	
Risk Category	N	%	N	%	N	%
Low	19,080	37%	19,175	37%	83,037	43%
Low-Moderate	24,751	48%	25,175	49%	90,003	47%
Moderate	7,019	14%	6,748	13%	19,244	10%
High	578	1%	545	1%	1,302	1%

[11] When the outcome variable is composed of only two values (e.g., arrest or no arrest), which is typical for risk classification in probation, logistic regression is usually the best approach to use. The main advantage of logistic regression is that few statistical assumptions are required for its use. In addition, it generates probability values that are constrained between zero and one. Logistic regression calculates the probability of an event occurring or not occurring (e.g., getting arrested or not getting arrested) and presents the results in the form of an odds ratio (Exp(B)). For the purposes of this article, the odds ratio is the number by which you multiply the odds of getting re-arrested for each one-unit increase in the independent variable (i.e., a variable in the equation). An odds ratio greater than 1 indicates that the odds of getting re-arrested increase when the independent variable increases; an odds ratio less than 1 indicates that the odds of getting re-arrested decrease when the independent variable increases (Menard, 2002).

[12] While the iterative classification processes seem to rate higher on some measures of utility, they also tend to have higher degrees of predictive shrinkage (see Silver et al., 2000).

failing to survive to the second and subsequent case plan periods. This finding, like that of the linear risk score, might be more an issue of sample size rather than holding practical significance. The change in the percentage of low-risk cases seems to be what drives the overall significant chi-square test.

The next set of analyses focused on assessing the PCRA's predictive ability. AUC-ROC (Area of the Curve-Receiver Operating Characteristics)[13] was chosen as the measure to assess prediction in large part because it is not impacted by base rates. Another convenient property of the AUC-ROC over a correlation coefficient is that AUC-ROC is a singular measure and does not have differing calculations depending on level of measurement of the variables being evaluated (Rice & Harris, 2005). Table 4 displays the AUC-ROC between risk scores and re-arrests. A fourth sample (long-term follow-up) that includes initial case plan data on all offenders placed on supervision between September 30, 2005 and September 30, 2006 is introduced in Table 4. The data therefore allow for a follow-up period between three and four years. As Table 4 shows, the AUC for each of the four sample groups is close to or exceeds the AUC-ROC value associated with large effect sizes (Rice & Harris, 2005). The AUC for the second validation sample rose to .73, while the AUC for the long-term follow-up sample rose even higher to .78. Based on these results, the PCRA appears to have very good predictive validity in terms of accurately classifying offenders' risk level.

To put the AUC values into practical terms,[14] we calculated the failure[15] rates by each category of risk for each sample. These results are presented in Table 5. With the exception of the long-term follow-up sample, the failure rates were relatively unchanged for a risk category across samples. For example, low-moderate risk offenders failed at a rate of 13 percent in both the construction and initial validation samples, and at 12 percent in the subsequent case plan sample. However, in the long-term follow-up sample, the low-moderate risk group's failure rate increased significantly to 42 percent. Overall, the failure rate for the long-term follow-up group was 44 percent, but the failure rate was significantly higher for high-risk offenders in this same group. Moderate-risk offenders failed at a rate of 71 percent and high-risk offenders had an 83 percent failure rate. The uniform increase in failure rates across categories of risk and across the various samples continues to support the validity of the PCRA.

Survival analysis was conducted for each risk category and the survival curves associated with those analyses are displayed in Figure 1. All possible data points, regardless of follow-up time, were used in the analysis.[16] The follow-up period ranged from 0 to 60 months. Survival rates for each risk category are displayed at 6 months, 12 months, 36 months, and 60 months. As Figure 1 shows, high-risk offenders have a very steep decrease in survival, as only 69 percent survived the first 6 months of supervision. As time passes, survival rates continue to drop rapidly for high-risk offenders, as only 46 percent survived at 12 months and only 17 percent at 36 months. After 60 months of supervision, a mere 6 percent of the high-risk offenders remain. In contrast to high-risk offenders, low-risk offenders have a significantly different experience on supervision. For example, while the survival rate for high-risk offenders was only 17 percent at 36 months, 90 percent of the low-risk offenders survived at this time period. Moreover, the survival rate for low-risk offenders decreased only 5 percentage points through 60 months to 85 percent.

Low-moderate risk offenders have a survival curve that is almost precisely between the survival curves of the low- and moderate-risk cases. Interestingly, the survival curve for the moderate-risk offenders seems to follow a form that is closer to the high-risk offenders than to the lower-risk offenders. Note that the survival rates continue to grow throughout the follow-up period for each group, and each

TABLE 4.
*AUC-ROC Between Risk Score and Re-arrest**

Sample	AUC	Lower 95% CI	Upper 95% CI	Significance
Construction	.709	.699	.719	.000
Validation	.712	.702	.721	.000
Subsequent Case Plan	.734	.729	.739	.000
Long-term Follow Up	.783	.778	.789	.000

* Analyses based on TSR versus probation supervision were estimated. AUC-ROC values for the probation sub-sample were .65 (construction), .64 (validation), .72 (subsequent case plan), and .76 (long-term follow-up). While AUC-ROC values for the construction and validation samples were somewhat smaller than those generated for the overall sample, the AUC-ROC values for the subsequent case plan and long-term follow-up probation sub-samples were very similar to those generated for the overall sample.

TABLE 5.
Cross-tabulation between Risk Categories and Re-arrest

	Sample			
Risk Category	Construction	Validation	Subsequent Case Plan	Long-term Follow-Up*
Low	5%	5%	4%	11%
Low-Moderate	13%	13%	12%	42%
Moderate	27%	28%	27%	71%
High	39%	42%	41%	83%
χ^2	1354.76	1444.74	6761.77	4997.40

*Outcome measure is arrest for new criminal behavior only.

13 The AUC measures the probability that a score drawn at random from one sample or population (e.g., offenders with a re-arrest) is higher than that drawn at random from a second sample or population (e.g., offenders with no re-arrest). The AUC can range from .0 to 1.0 with .5 representing the value associated with chance prediction. Values equal to or greater than .70 are considered good.

14 Rice and Harris indicate that the AUC holds the same meaning as the common language effect size indicator. That is, the probability that the PCRA score for a randomly selected recidivist is higher than the PCRA score for a randomly selected non-recidivist. For example, using the long-term follow-up data (AUC = .78), if you randomly select a recidivist and a non-recidivist, the recidivist's PCRA score should be higher than the non-recidivist's score 78 percent of the time.

15 Failure is defined as any new arrest during a term of supervision.

16 STATA adjusts for cases that were lost during follow-up when calculating survival tables.

curve (with the exception of low-risk offenders) shows little sign of leveling off.

One of the major benefits of third- and fourth-generation risk assessment is the ability to measure change in risk over time. While many of the risk factors on the PCRA would be considered stable, some would also be considered acute (for a full discussion see Serin, Lloyd, & Hanby, 2010; Serin, Mailloux, & Wilson, 2010). Therefore, analyses were conducted that compared actual failure rates based on changes in initial and subsequent PCRA assessments. Table 6 outlines changes in failure rates based on first and last case plan assessment categories. The failure rates are based on the risk category for the last case plan period of the offender's supervision term; therefore, to be included in this table, the offender had to have at least two case plan periods that allowed for the scoring of the PCRA. According to the results presented in Table 6, not surprisingly, offenders in the higher risk categories (moderate and high) failed at a higher rate than offenders in the lower risk categories (low and low-moderate). However, offenders whose risk rating increased while under supervision appear to fail at a higher rate than offenders who maintained their initial rating through to their last assessment. For example, low-moderate risk offenders whose risk category increased to moderate had a failure rate of 41 percent, whereas low-moderate risk offenders who remained low-moderate risk or were reassessed as low risk had a failure rate between 16 and 18 percent. Similarly, moderate-risk offenders who continued to be moderate risk had a 38 percent failure rate, while those who were reassessed as low-moderate had an 18 percent failure rate and moderate-risk offenders reassessed as high risk had a 61 percent failure rate.

FIGURE 1.
Survival Analysis for the Four Risk Categories

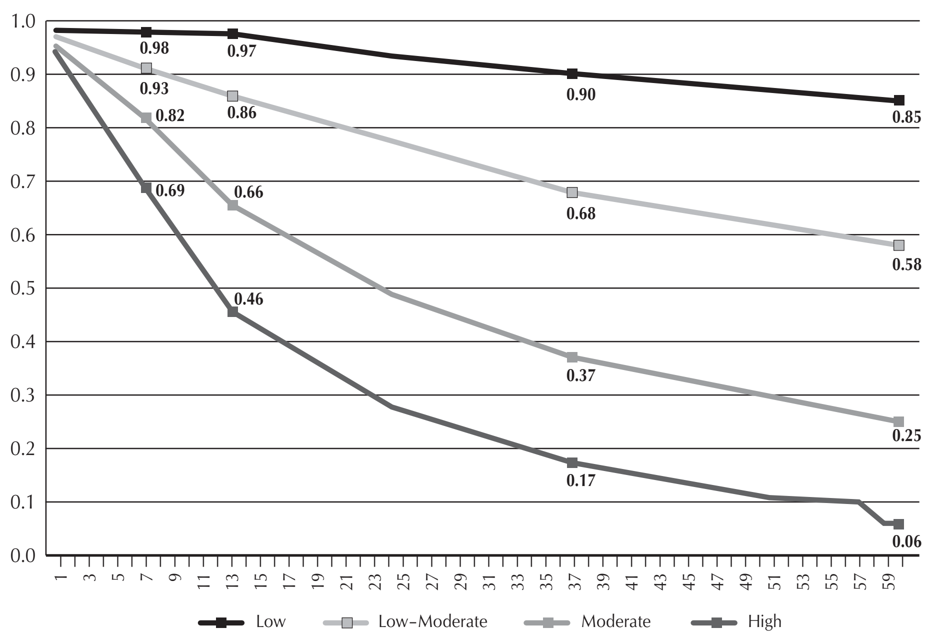

TABLE 6.
Changes in Failure Rates Based on First and Last Case Plan Assessment Categories

	Last Case Plan Assessment Category			
Initial Case Plan Assessment Category	**Low**	**Low-Moderate**	**Moderate**	**High**
Low (n = 13,589)	4%	18%	–	–
Low-Moderate (n = 15,660)	5%	16%	41%	–
Moderate (n = 3,581)	–	18%	38%	61%
High (n = 233)	–	–	37%	53%
χ^2	237.65	396.23	162.85	10.54

Discussion

As previously stated, the purpose of this article is twofold: (1) To present the methodology and results produced in the development of the PCRA and (2) to discuss limitations of the PCRA as well as future developments. This article has provided details on the methods, measures, and sample used in the development of the PCRA. A fairly traditional model was followed in the development of the PCRA. Our efforts were supported by a relatively large dataset and fairly complete data. The sample was fairly representative of the population served and allowed for a construction and two validation samples. The overall results have demonstrated that the PCRA provides adequate predictive validity both in the short term (6–12 months) as well as in longer follow-up periods (up to 48 months).

Multivariate analysis (see Table 1) of proposed predictors revealed that 15 factors were significantly related to the outcome of interest (new arrest). Seven additional factors tested were determined to be unrelated to a prediction of new arrest once the effects of the other factors were controlled. One additional measure, being female, was found to be significantly related to a new arrest. Subsequent models, not reported here, indicated that the addition of gender to the models yielded no increase in the predictive validity of the model. In addition, non-significant differences were noted in the AUCs between males and females for each sample (i.e., construction, validation, subsequent case plan, and long-term follow-up). Therefore, we concluded that the instrument performs equally well for males and females, even though the failure rates for males might be slightly higher than for females with similar risk scores.

The creation of the risk score and categories allowed for the identification of four risk categories: low, low-moderate, moderate, and high. Approximately 80 percent of each sample was made up of low and low-moderate risk offenders. Much smaller percentages were identified in each sample as moderate and high risk (approximately 12 percent and 1 percent, respectively). Due to the distribution of risk categories being heavily skewed toward lower risk, the validity of the instrument may be brought into question. However, it should be noted that a current validated risk prediction instrument used in the federal system (RPI) yields a similarly skewed distribution. Analysis of failure rates by risk score and category using the PCRA yielded AUC-ROC values over the traditionally accepted value of

.70 and an AUC value for the long-term follow-up over .78. All of the AUC-ROC values were close to or exceeding the value associated with large effect sizes. Practically speaking, the instrument provided categorizations that are associated with the group failure rates that are differentiated and meaningful for meeting the risk principle (see Tables 4 and 5).

The final analysis conducted in this study related to the dynamic nature of the PCRA. Recall from Table 6 that changes in actual failure rates were associated with changes in risk category from the initial assessment to the last assessment. This finding is rather important, as it provides the opportunity to track meaningful changes in risk that occur throughout the supervision process. Moreover, Table 6 confirmed that the PCRA identifies and measures dynamic risk factors that, apparently, when changed through supervision, services, or some other unmeasured process (natural desistance), lead to commensurate reductions in actual failure rates. The dynamic nature of the PCRA adds to its usefulness in developing case plans throughout the life of the supervision term.

Limitations and Future Research

Although this study was fairly comprehensive in scope and the dataset used was large and representative of the population served, there are a number of limitations and areas for future research that deserve mention. First, while the dataset was large and comprehensive, we have not investigated how scoring algorithms might be adjusted for each district. As with any measure, there is a distribution of AUC values when that test is calculated for each district. Data from 17 districts generated AUC values below .70; however, only three districts had 95 percent confidence intervals that failed to cross the .70 threshold. While this finding may have been due to small samples in some districts, subsequent analysis should focus on bringing AUC values between risk scores and re-arrests up to larger values.

A second limitation is that the data used in this research came from an administrative dataset. While it proved useful for our initial task of creating and validating a risk assessment instrument, it will be important to conduct similar validation analyses once we have an ample sample of offenders that were actually assessed using the assessment protocol.

The third limitation involves the nature of the outcome measure being predicted. In this research we focused exclusively on the likelihood of a re-arrest and not the severity of the offense. We found it important to assess and determine the likelihoods of re-arrest as a first step in the assessment process. Because we do recognize that there is more than one dimension to an assessment in the criminal justice system, future analysis will focus on predicting the dangerousness of an offender.

Fourth, while the PCRA is apparently dynamic, with changes in risk associated with changes in actual failure rates, it may not be sensitive enough for use on a monthly or shorter schedule. Due to the high value associated with a dynamic risk assessment, it will be necessary to make the PCRA more sensitive to change, or supplement it with a more sensitive trailer assessment that increases its utility as a guide to service allocation.

Finally, because rated but not scored items outnumber scored items on the assessment, future analysis will review the impact of rated but not scored items. For example, the PCRA currently has only one scored item in the area of cognitions. As a result of current testing on 80 self-report items that relate to criminal thinking styles, the number of scored items in the area of cognitions will likely increase. Continued analyses on rated but not scored items will also increase the understanding of the impact of self-reported attitudes, as well as guide adjustments to algorithms based on district, gender, and race differences, if relevant.

Policy Implications

Notwithstanding the limitations discussed above, there are two major policy implications that stem from this research. First, the federal probation system now has a dynamic fourth-generation risk assessment for use on offenders under its jurisdiction. The instrument can be used to identify higher-risk offenders for enhanced services (see Andrews et al., 1990) and can also be used to identify targets for change to be addressed by external service providers. The second major policy implication is the apparent necessity for ongoing reassessment. Data analyzed in this study indicate that changes in levels of risk are associated with changes in actual failure rates. Therefore officers need to monitor risk in a standardized way to ensure that supervision and services are having intended impacts. If intended impacts are not being achieved, then officers will be able to modify supervision services to reduce the risk of recidivism.

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APPENDIX

APPENDIX 1.

Rated Test Items

Domain	Factor	Rating
Criminal History	Arrested Under Age 18	Yes/No
Employment	Number Of Jobs in Past 12 Months	None/One/More than One
Employment	Employed Less than 50% of the Last 24 Months	Yes/No
Substance Abuse	Disruption at Work, Home, School	Yes/No
Substance Abuse	Use When Physically Hazardous	Yes/No
Substance Abuse	Legal Problems Related to Use	Yes/No
Substance Abuse	Continued Use Despite Social/Interpersonal Problems	Yes/No
Social Networks	Lives with Spouse and/or Children	Yes/No
Social Networks	Lack of Family Support	Yes/No
Social Networks	Companions	Good Support and Influence/Occasional Association with Negative Peers/More Than Occasional Association with Negative Peers/No Friends
Attitudes	Antisocial Attitudes	Yes/No
Attitudes	General Criminal Thinking (PICTS)	Scale Scores
Other	No or Unstable Home	One Address in Past 12 Months/More Than One Address in Past 12 Months or No Permanent Address
Other	Risk Influence at Home	No Criminal Risks Present/Criminal Risks at Home
Other	Financial Stressors	Adequate Income to Manage Debts/No Plan in Place to Meet Financial Debts, Expenses Exceed Income
Other	Pro Social Recreation	Engages in Prosocial Activities/Has No Interests, Does Not Engage in Them, or Recreation Presents Criminal Risk
Responsivity	Low Intelligence	Check Box
Responsivity	Physical Handicap	Check Box
Responsivity	Reading and Writing Limitations	Check Box
Responsivity	Mental Health Issues	Check Box
Responsivity	No Desire to Change/Participate in Programs	Check Box
Responsivity	Homeless	Check Box
Responsivity	Transportation	Check Box
Responsivity	Child Care	Check Box
Responsivity	Language	Check Box
Responsivity	Ethnic or Cultural	Check Box
Responsivity	History of Abuse or Neglect	Check Box
Responsivity	Interpersonal Anxiety	Check Box
Responsivity	Social Security Card, Driver's License, ID	Check Box

APPENDIX 2.

Cross Tabulations between Risk Factors and Re-arrest for Construction Sample

Domain	Variable	Arrest Rate	χ2	P
Criminal History	Prior Arrests 0 = No prior arrests 1 = 1-2 prior arrests 2 = 3-6 prior arrests 3 = 7 or more prior arrests	 9% 12% 13% 20%	618.33	.000
Criminal History	Community Supervision Violations 0 = No prior CS violations 1 = 1 or more CS violations	 11% 20%	423.49	.000
Criminal History	Varied Offending Pattern 0 = 1 type of offending 1 = 2 or more types of offending	 14% 20%	209.81	.000
Criminal History	Institutional Adjustment 0 = No adjustment problems 1 = Adjustment problems	 12% 22%	98.57	.000
Criminal History	Violent Offense 0 = No history or current violence 1 = History or current violence	 15% 19%	50.405	.000
Criminal History	Age 0 = 41+ 1 = 26-40 2 = 25 or younger	 11% 16% 23%	638.77	.000
Education & Employment	Highest Grade 0 = High school degree or more 1 = GED or less than HS degree	 11% 18%	467.44	.000
Education & Employment	Unemployed 0 = Currently employed 1 = Currently unemployed	 11% 18%	318.08	.000
Education & Employment	Good Work History 0 = Stable work history 1 = Unstable work history	 8% 15%	352.17	.000
Substance Abuse	Alcohol Problems 0 = No current problems 1 = Current problems	 12% 28%	264.62	.000
Substance Abuse	Drug Problems 0 = No problems 1 = Current problems	 12% 29%	836.48	.000
Social Networks	Family Problems 0 = No problems 1 = Current problems	 12% 18%	213.77	.000
Social Networks	Married 0 = Married 1 = Single	 10% 16%	187.69	.000
Social Networks	Social Support 0 = Social support present 1 = No social support	 9% 15%	361.23	.000
Attitudes	Motivated to Change 0 = Offender motivated to change 1 = Offender resistant to supervision	 8% 16%	473.99	.000

Note: Number of cases ranges from 31, 773 to 48,470 depending on risk factor.

APPENDIX 3.
Cross Tabulations between Risk Factors and Re-arrest for Validation Sample

Domain	Variable	Arrest Rate	χ2	P
Criminal History	Prior Arrests 0 = No prior arrests 1 = 1-2 prior arrests 2 = 3-6 prior arrests 3 = 7 or more prior arrests	 9% 11% 14% 20%	612.91	.000
Criminal History	Community Supervision Violations 0 = No prior CS violations 1 = 1 or more CS violations	 11% 19%	369.56	.000
Criminal History	Varied Offending Pattern 0 = 1 type of offending 1 = 2 or more types of offending	 14% 20%	196.50	.000
Criminal History	Institutional Adjustment 0 = No adjustment problems 1 = Adjustment problems	 12% 21%	87.241	.000
Criminal History	Violent Offense 0 = No history or current violence 1 = History or current violence	 15% 19%	59.047	.000
Criminal History	Age 0 = 41+ 1 = 26-40 2 = 25 or younger	 11% 16% 22%	499.76	.000
Education & Employment	Highest Grade 0 = High school degree or more 1 = GED or less than HS degree	 11% 18%	502.72	.000
Education & Employment	Unemployed 0 = Currently employed 1 = Currently unemployed	 11% 18%	379.277	.000
Education & Employment	Good Work History 0 = Stable work history 1 = Unstable work history	 8% 15%	371.27	.000
Substance Abuse	Alcohol Problems 0 = No current problems 1 = Current problems	 12% 29%	283.03	.000
Substance Abuse	Drug Problems 0 = No problems 1 = Current problems	 12% 28%	701.78	.000
Social Networks	Family Problems 0 = No problems 1 = Current problems	 12% 18%	197.87	.000
Social Networks	Married 0 = Married 1 = Single	 11% 16%	164.99	.000
Social Networks	Social Support 0 = Social support present 1 = No social support	 9% 15%	398.44	.000
Attitudes	Motivated to Change 0 = Offender motivated to change 1 = Offender resistant to supervision	 8% 16%	507.97	.000

Note: Number of cases ranges from 31, 607 to 48,434 depending on risk factor.

APPENDIX 4.

Cross Tabulations between Risk Factors and Re-arrest for Subsequent Case Plan Periods

Domain	Variable	Arrest Rate	$\chi 2$	P
Criminal History	Prior Arrests 0 = No prior arrests 1 = 1-2 prior arrests 2 = 3-6 prior arrests 3 = 7 or more prior arrests	 6% 8% 11% 17%	3567.58	.000
Criminal History	Community Supervision Violations 0 = No prior CS violations 1 = 1 or more CS violations	 10% 19%	2946.37	.000
Criminal History	Varied Offending Pattern 0 = 1 type of offending 1 = 2 or more types of offending	 11% 18%	1679.04	.000
Criminal History	Institutional Adjustment 0 = No adjustment problems 1 = Adjustment problems	 11% 21%	631.19	.000
Criminal History	Violent Offense 0 = No history or current violence 1 = History or current violence	 11% 16%	304.23	.000
Criminal History	Age 0 = 41+ 1 = 26-40 2 = 25 or younger	 8% 13% 19%	3183.72	.000
Education & Employment	Highest Grade 0 = High school degree or more 1 = GED or less than HS degree	 8% 15%	2509.84	.000
Education & Employment	Unemployed 0 = currently employed 1 = currently unemployed	 9% 15%	1235.60	.000
Education & Employment	Good Work History 0 = Stable work history 1 = Unstable work history	 6% 12%	2083.60	.000
Substance Abuse	Alcohol Problems 0 = No current problems 1 = Current problems	 11% 24%	1344.46	.000
Substance Abuse	Drug Problems 0 = No problems 1 = Current problems	 9% 27%	5720.49	.000
Social Networks	Family Problems 0 = No problems 1 = Current problems	 9% 15%	1254.19	.000
Social Networks	Married 0 = Married 1 = Single	 8% 13%	1096.37	.000
Social Networks	Social Support 0 = Social support present 1 = No social support	 9% 12%	744.26	.000
Attitudes	Motivated to Change 0 = Offender motivated to change 1 = Offender resistant to supervision	 7% 13%	2039.84	.000

Note: Number of cases ranges from 152,241 to 236,866 depending on risk factor.

APPENDIX 5.
Scored PCRA Data Items

VARIABLE NAME	VARIABLE DESCRIPTION	SCORED ITEM
Date of Birth	Record offender's data of birth in MM/DD/YY format.	Captured in 1.7
# Adult Conv	Record the total number of adult convictions.	Captured in 1.2
# Other Arrests	Record the total number of other arrests.	Captured in 1.2
# Violent Arrests	Record the total number of prior arrests for violent crimes.	Captured in 1.3
# DV	Record the number of arrests for domestic violence.	Captured in 1.3
HXSONC	History of sex offending offenses without contact.	Captured in 1.3
HXSOC	History of sex offending with contact. Code Y for yes, N for no, and U for unknown.	Captured in 1.3
HXSOSR	History of sex offending statutory rape. Code Y for yes, N for no, and U for unknown.	Captured in 1.3
HXSOO	History of other sex offending. Code Y for yes, N for no, and U for unknown.	Captured in 1.3
Varied	How many different types of offenses has the offender engaged in (property, drug, sex, violent, order, other)?	Captured in 1.4
Inst Adj1 .	Record the number of times an offender was written up during prior terms of incarceration.	Captured in 1.6
Inst Adj2	Record the number of times the offender was officially punished for institutional infractions.	Captured in 1.6
CS Vio	During how many previous periods of supervision did the offender a) commit a new crime or b) have violations that were reported to the court or paroling authority?	Captured in 1.5
High Grade	Record the highest grade the offender completed. If received a GED, code the highest grade completed in school. GED does not equal 12.	Captured in 2.1
Employed PSR	Was the offender employed at the time of the pre-sentence report? Code Y for yes, N for no, and U for unknown.	Captured in 2.2
Employed Arrest	Was the offender employed at the time of the arrest? Code Y for yes, N for no, and U for unknown.	Captured in 2.2
Alc Current	Does the offender have a current alcohol problem? Code Y for yes, N for no, and U for unknown.	Captured in 3.5
Drug Current	Does the offender have a current drug problem? Code Y for yes, N for no, and U for unknown.	Captured in 3.6