Age, Risk Assessment, and Sanctioning:

Overestimating the Old, Underestimating the Young

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Note: The views expressed in this article are those of the authors alone and do not reflect the official position of the Administrative Office of the U.S. Courts.
Abstract

While many extoll the potential contribution of risk assessment to reducing the human and fiscal costs of mass incarceration without increasing crime, others adamantly oppose the incorporation of risk assessment in sanctioning. The principal concern is that any benefits in terms of reduced rates of incarceration achieved through the use of risk assessment will be offset by costs to social justice—which are claimed to be inherent in any risk assessment process that relies on variables for which offenders bear no responsibility, such as race, gender, and age. Previous research has addressed the variables of race and gender. Here, based on a sample of 7,350 federal offenders, we empirically test the predictive fairness of an instrument—the Post Conviction Risk Assessment (PCRA)—that includes the variable of age. We found that the strength of association between PCRA scores and future arrests was similar across Younger (i.e., 25 years and younger), Middle (i.e., 26-40 years), and Older (i.e., 41 years and older) age groups (AUC values .70 or higher). Nevertheless, rates of arrest within each PCRA risk category were consistently lower for Older than for Younger offenders. Despite its inclusion of age as a risk factor, PCRA scores overestimated rates of recidivism for Older offenders and underestimated rates of recidivism for Younger offenders.

Key words: risk assessment, age, test bias, disparities, sentencing
The past dozen years have seen a sea-change in the relationship between an offender’s age and the criminal sanction he or she receives (Skeem, Scott, & Mulvey, 2014). In Roper v. Simmons (2005), the United States Supreme Court abolished the death penalty for offenders who were under the age of 18 when their crimes were committed. In Graham v. Florida (2010), the Court abolished mandatory sentences of life without parole for juveniles convicted of nonhomicide offenses, a holding that was extended to juveniles convicted of homicide in Miller v. Alabama (2012), and made retroactive in Montgomery v Louisiana (2016).

Less dramatic but perhaps equally significant for criminal sanctioning have been recent developments at the other end of the offender age distribution. Reducing the criminal sanctions imposed on older offenders is seen by many as an important step in reversing the “historically unprecedented and internationally unique” (Travis, Western, & Redburn, 2014, p. 2) level of incarceration that currently characterizes the United States. Approximately one percent of the adult American population—2.3 million people—now reside in jails or prisons (Sabol, West, & Cooper, 2009), a rate of incarceration seven times higher than that of democracies in Western Europe (International Centre for Prison Studies, 2013).

To be sure, the reasons offered to justify reductions in criminal sanctioning are starkly different in the cases of younger and older offenders. Juveniles, the Supreme Court held in Roper, have “diminished culpability” when they commit crime. This is so for three reasons: juveniles are characterized by “a lack of maturity and an underdeveloped sense of responsibility;” juveniles are “more vulnerable or susceptible [than adults] to negative influences and outside pressures, including peer pressure;” and “the character of a juvenile is not as well formed as that of an adult” (Roper v. Simmons, 2005). “Diminished culpability” or
blameworthiness is not the justification offered for reductions in the criminal sanctioning of aging offenders, however. Rather, fiscal concerns underlie proposals to take advanced age into account in sanctioning decisions. The costs associated with “mass incarceration” have simply become fiscally unsustainable (Travis, Western, & Redburn, 2014). Reducing the sanctioning of older—and therefore lower risk (see below)—offenders is seen as a way to reduce these costs without jeopardizing historically low crime rates (Zimring, 2012). Aging offenders (variously defined) now make up 19 percent of the federal prison population (Office of the Inspector General, U. S. Department of Justice, 2015) and 10 percent of the state prison population (Carson & Sabol, 2016), and incarcerating them is disproportionately expensive:

Aging inmates on average cost 8 percent more per inmate to incarcerate than inmates age 49 and younger. [W]e found that this cost differential is driven by increased medical needs, including the cost of medication, for aging inmates. [Bureau of Prisons’] institutions with the highest percentages of aging inmates in their population spent five times more per inmate on medical care ($10,114) than institutions with the lowest percentage of aging inmates ($1,916). [Bureau of Prisons’] institutions with the highest percentages of aging inmates also spent 14 times more per inmate on medication ($684) than institutions with the lowest percentage ($49) (Office of the Inspector General, U. S. Department of Justice, 2015, pp 1-2).

While many across the political spectrum (Arnold & Arnold, 2015) extoll the potential contribution of risk assessment to reducing the fiscal costs of mass incarceration without increasing crime, others are equally adamant in opposition to incorporating risk assessment in sanctioning. The principal concern is that any benefits in terms of reduced rates of incarceration achieved through the use of risk assessment will be offset by costs to social justice claimed to be
inherent in the risk assessment enterprise. Based on a sample of over 34,000 offenders, Skeem and Lowenkamp (2016) have examined this claim with respect to the variable of race and one well-known risk assessment instrument—the federal Post Conviction Risk Assessment [PCRA] (Johnson, Lowenkamp, VanBenschoten & Robinson, 2011). There were two relevant findings. First, the PCRA was free of predictive bias—the instrument predicted re-arrest for both African American and white offenders strongly, and with similar form (i.e., a given PCRA score corresponded to a similar probability of recidivism, across races). Second, on average, African American offenders obtained modestly higher PCRA scores than white offenders (mostly because of higher scores on the criminal history scale). Although these differences do not reflect test bias, some uses of the PCRA could have disparate impact on African American offenders.

Skeem, Monahan, and Lowenkamp (2016) examined similar questions with respect to the variable of gender and the PCRA. Their results also supported two observations. First, ignoring the effects of gender on recidivism can translate to discrimination against women. The PCRA—like many other risk assessment instruments and all sentencing guidelines—omits gender. The PCRA strongly predicts recidivism for both women and men. Nevertheless, the instrument overestimates women’s likelihood of recidivism: at a given PCRA score, the odds of a violent arrest are more than twice as high for men than women (OR=2.27). Second, men obtained slightly higher average scores on the PCRA than women—entirely as a function of men’s greater criminal history. Given that criminal history is emphasized in most sentencing guidelines, it is not clear that use of the PCRA would increase any disparate impact on men.

In the current study, we use a comparable sample of federal offenders to examine questions regarding the same instrument (the PCRA) as Skeem and Lowenkamp (2016) and Skeem, Monahan, and Lowenkamp (2016), but with a focus on the role played by the variable of
age rather than of race or gender in risk assessment. Unlike race and gender, age is included in the PCRA: Young age contributes up to two of the PCRA’s 18 total possible points. First, however, we situate age and crime in empirical and in legal contexts (Bushway & Piehl, 2007).

**Empirical Context: Older Age as a Promotive Factor**

That older people commit crime, particularly violent crime, at lower rates than younger people is a staple in criminology and has been known for as long as official records have been kept. An early review (Sampson & Lauritsen, 1994, p. 18) concluded that “age is one of the major individual-level of correlates of violent offending. In general, arrests for violent crime peak around age 18 and decline gradually thereafter. More than two-thirds of those arrested for violent crimes are age 30 or younger.” More recent reviews reach similar conclusions (Sweeten, Piquero & Steinberg, 2013; Ulmer & Steffensmeier, 2014).

Elsewhere (Monahan & Skeem, 2016, p. 498), we have described “risk factors” in the context of criminal sanctioning as variables which “predict the unwelcome outcome of reoffending,” and distinguished “risk factors” from “promotive factors,” which “predict the welcome outcome of desistance from offending.” Consistent with this distinction, older age is properly described as a promotive factor in sanctioning decisions. That is, studies of the recidivism rates of both state and federal offenders show a robust effect of an offender’s age on the likelihood that he or she will desist from offending.

Durose, Snyder, and Cooper (2014, Table 14) studied the recidivism rates of offenders released from prisons in thirty U. S. states. Eighty-four percent of state prisoners aged 24 and younger at release were re-arrested for non-traffic offenses within five years, compared with 69 percent of state prisoners aged 40 and older at release. While federal
prisoners are less likely to be re-arrested than state prisoners, a similar pattern of declining re-arrest rates with advancing age is apparent: the 8-year re-arrest rate of federal prisoners younger than 21 at release was 68 percent, compared with 16 percent of federal prisoners older than 60 (Hunt & Dumville, 2016). Another recent study of federal prisoners reported that no inmate released at age 70 or older (n=10) was re-arrested within three years (Office of the Inspector General, U. S. Department of Justice, 2015).

Meta-analytic reviews indicate that—like other demographic variables (e.g., race, gender)—age is a weak, but robust predictor of general recidivism across studies (e.g., sample-weighted average $r = .11$; Gendreau et al., 1996). Given its utility in predicting recidivism, age is explicitly included as an item on risk assessment instruments built to inform sanctioning decisions in several states (e.g., California, Pennsylvania, and Virginia; see Monahan & Skeem 2014), and, as mentioned, age is included as an item on the PCRA.

**Legal Context for Considering Age at Sanctioning**

Michael Tonry is one of the most outspoken critics of the use of risk assessment to inform decisions regarding criminal sanctioning. Yet even Tonry would take an offender’s age into account in setting a sentence:

Ascribed characteristics for which individuals bear no responsibility, such as race, ethnicity, gender, and age, should not be included among parole and sentencing criteria (except, for different multiple reasons, for consideration of youth and advanced age as mitigating factors) (Tonry, 2014, p. 169, emphasis added).

Formal legal policies that reflect the stark lack of scholarly or political consensus on the use of some demographic variables (e.g., gender) in the risk assessment process are notably more
tolerant concerning the use of age as a factor in sentencing adult offenders. The federal Sentencing Guidelines state that “Age may be a reason to depart downward [from the sentence recommended elsewhere in the Guidelines] in a case in which the defendant is elderly and infirm and where a form of punishment such as home confinement might be equally efficient as and less costly than incarceration” (U. S. Sentencing Commission, 2015; §5H1.1). The highly influential Model Penal Code (American Law Institute, 2012) takes no position in favor of or opposed to the use of advanced age as a promotive factor in sentencing.

Lay opinion appears highly favorable to the use of age in criminal sanctioning. In a recent survey of American adults, Scurich and Monahan (2016) found that more than three-quarters of the respondents were open to the possibility of using advanced age as a promotive factor in sentencing, and less than one-quarter were unalterably opposed.

**Bringing Psychological Science to the Controversy**

The PCRA includes an offender’s current age as an explicit promotive factor. The relevant PCRA item is scored as follows: 0 = 41 years and older; 1 = 26 to 40 years; and 2 = 25 years and younger. Whether the PCRA is subject to age bias is an empirical question. Ample guidance on test fairness is available from similar efforts undertaken in more mature fields (e.g., cognitive tests used to inform high-stakes education and employment decisions, see Reynolds 2000; Sackett, Borneman & Connelly, 2008). The criteria that indicate when a test is biased have been distilled in the *Standards for Educational and Psychological Testing* (American Educational Research Association, American Psychological Association, and National Council on Measurement in Education, 2014), which we refer to as the “Standards.”
Given that the raison d'etre for risk assessment instruments is to predict recidivism, the paramount indicator of test bias is *predictive bias* (also known as “differential prediction;” Standard 3.7). On utilitarian grounds alone, any instrument used to inform sentencing must be shown to predict recidivism with similar accuracy across groups. If the instrument is unbiased, a given score will have the same meaning regardless of group membership (e.g., an average risk score of X will relate to an average recidivism rate of Y for all relevant age groups). This is commonly tested by examining whether groups systematically deviate from a common regression line that relates test scores to the criterion (i.e., whether the groups share intercepts and slopes; Cleary, 1968; see also Sackett & Bobko, 2010).

Given a pool of instruments that are free of predictive bias, some instruments will yield greater mean score differences between groups than others (e.g., young people, on average, will obtain higher risk scores than older people). These instruments are not necessarily biased: “subgroup mean differences do not in and of themselves indicate lack of fairness” (Standard 3.6, p. 65). The notion that mean differences are indicative of test bias is unequivocally rejected in the professional literature because group differences in scores may reflect *true* differences in recidivism risk, based on group variation “in experience, in opportunity, or in interest in a particular domain” (Sacket et al., 2008, p. 222). Age is associated with differences in biology and in socialization (e.g., Petras, Nieuwbeerta, & Piquero, 2010; Mata, Josef, & Hertwig, 2016) that can relate to risk-taking and criminal behavior. Age differences in such circumstances can manifest as valid group differences in risk scores.

Even if mean score age differences do not reflect test bias, using instruments that yield such differences to inform sentencing may create *disparate impact* (in legal terms; see Griggs *v. Duke Power*, 1971) or inequitable social consequences (in moral terms; see Reynolds & Suzuki
An instrument can perfectly measure risk, and yet the *use* of the instrument could still be seen as unfair.

In our view, risk assessment instruments used to inform sanctioning (i.e., decisions about imprisonment, release, community supervision, and risk reduction services) must be empirically examined for both predictive bias and disparate impact. That is, risk assessment must be both empirically valid and perceived as morally fair across groups. This study is among the first to examine such issues with respect to age.

**Present Study**

In this study, which was approved by the Administrative Office of US Courts, Probation and Pretrial Services Office, we use a large sample of federal offenders with an average age of 35 (SD= 11.70) to empirically examine the relationships among current age, risk assessment, and recidivism. In the federal system, risk assessment is not used to inform sentencing decisions. Instead, the Federal Post Conviction Risk Assessment or “PCRA” (Johnson et al., 2011) is used to inform decisions designed to reduce risk—i.e., to identify *whom* to provide with relatively intensive services (i.e., higher-risk offenders) and *what* to target in those services (i.e., variable risk factors). When federal probationers are found to violate conditions of probation—including treatment conditions—judges may “revoke a term of supervised release, and require the defendant to serve in prison all or part of the term of supervised release…without credit for time previously served on postrelease supervision” (17 USC §3583(e)(3). Given that a probationer’s PCRA score is used to decide whether he or she is subject to extra demands that can be enforced with imprisonment, both predictive bias and disparate impact with regard to age are legitimate and important concerns.
The PCRA was developed by the Administrative Office of the US Courts (Probation and Pretrial Services Office), and is administered post-conviction, upon intake to a term of supervised release or probation. Given that the PCRA is well-validated and includes major risk factors tapped by many other risk assessment instruments, these federal data are well-suited for addressing two aims with broader implications:

1. To what extent is the instrument—and the risk factors it includes—free of predictive bias?
   We hypothesize that the PCRA will be free of predictive bias or—at most—will modestly overestimate recidivism for older offenders. This hypothesis is based on our past finding that the PCRA overestimates recidivism for women (Skeem et al., in press). Although the PCRA includes age (unlike gender) as a risk factor, age is not weighted heavily in scoring.

2. To what extent is age correlated with scores on the instrument, such that different age groups manifest mean score differences relevant to disparate impact? On one hand, older offenders will obtain lower scores on the PCRA’s blunt “age” item than their younger counterparts. On the other hand, older offenders will have had more time to accrue a varied criminal history than their younger counterparts (e.g., a 52-year old has had 32 more years to accrue criminal history than a 20-year old). Only one PCRA item references a “varied offending pattern,” but criminal history is heavily weighted in total PCRA scores. On balance, we hypothesize that—if they exist—mean score differences will be small and will favor younger offenders, since they have had less time to accrue a substantial criminal history.

**METHOD**

**Participants and Matching**

Participants were 7,350 offenders drawn from a larger dataset on over 150,000 offenders assessed between August 2010 and November 2013 (see Walters & Lowenkamp, 2016). Because
even trivially small differences can become statistically significant in samples as large as ours 
(Lin, Lucas & Shmueli, 2013), we use an alpha level of .001 to signal statistical significance and 
focus on effect sizes in interpreting results.

Offender eligibility criteria were: (a) assessed with the PCRA at least 12 months prior to 
the collection of follow-up arrest data (to permit tests of predictive bias: \( n \) lost = 83,894), (b) no 
missing data on PCRA items (to permit analyses at the risk factor level; \( n \) lost = 1,007), and (c) 
race coded as either “Black” or non-Hispanic “White” (to permit relevant racial comparisons; \( n 
\) lost = 17,238). Application of these criteria yielded an eligible pool of 48,475 offenders whose 
characteristics are shown in Table 1. There were no significant differences between the eligible 
sample and the population from which it was drawn in age, sex, conviction offense, and PCRA 
total scores.

Within the eligible sample of 48,475 offenders, age was associated with other 
demographic risk factors that could confound the results. Specifically, young people were 
relatively likely to be Black \( (d=0.44) \) and male \( (d= 0.13) \). To isolate the effect of age on risk and 
recidivism—without creating non-representative groups—we adopted a conservative age-group 
matching approach. Specifically, we created three age groups, based on the PCRA age item 
(Younger=25 years and younger; Middle=age 26-40 years; Older=41 years and older). The 
smallest group was the Younger \( (n=2,450) \). So, using ccmatch in STATA (Cook, 2015), we 
randomly matched each offender in the Younger group on race (Black/White) and sex 
(Female/Male) to an offender in the Older group and then to an offender in the Middle group. 
That generated 2450 cases in each group for a total of 7,350 cases. This process yielded a race-
matched sample of 7,350 offenders. As shown in Table 1, the matched and unmatched samples 
were similar in race, but the matched sample had modestly higher PCRA scores and was
younger, less likely to be male and less likely to have a drug offense than the unmatched sample. The prototypic offender in the matched sample was male, age 35, and convicted of a drug offense.

[Insert Table 1]

All offenders were followed for a minimum of one year, but the follow up period (i.e., time at risk for re-offending) was variable beyond that point. Age was not significantly associated with the length of the follow-up period ($r = .01, ns$) (see Flores, Holsinger, Lowenkamp, & Cohen, 2016).

**Measures of Risk**

The history, development, and predictive utility of the Post Conviction Risk Assessment are detailed elsewhere (see Johnson, Lowenkamp, VanBenschoten, & Robinson, 2011; Lowenkamp et al., 2013; Lowenkamp, Holsinger, & Cohen, 2015). The PCRA is an actuarial instrument that explicitly includes variable risk factors and was constructed and validated on large, independent samples of federal offenders. Items that most strongly predicted recidivism in the construction sample contribute most strongly to total scores (Johnson et al., 2011). Fifteen items are scored and weighted (all items are weighted 1 except for the number of misdemeanor and felony arrests (where 0 = none, 1 = one or two, 2 = three through seven, and 3 = eight or more) and age in years at intake to supervision (where 0 = 41 and older, 1 = 26 to 40, and 2 = 25 or younger). Each of the fifteen items is nested under one of five domains—criminal history, employment, social networks, substance abuse, and attitudes. With the exception of criminal history, the PCRA domain scores are changeable over time. The items are summed to yield a
total PCRA risk score from 0 to 18. Total PCRA scores place an offender into a risk category: low (0-5), low/moderate (6-9), moderate (10-12), or high (13-18).

The PCRA has been shown to be reliable and valid. Specifically, officers must complete a training and certification process to administer the PCRA. The certification process has been shown to yield high rates of inter-rater agreement in scoring (Lowenkamp et al., 2013). The accuracy of the PCRA in predicting recidivism rivals that of other well-validated instruments (see Monahan & Skeem, 2014). For example, based on a sample of over 100,000 offenders, Lowenkamp et al. (2015) found that the PCRA moderately-to-strongly predicted both re-arrest for any crime and re-arrest for a violent crime, over up to a two-year period (AUCs=.70-.77). Finally, scores on the PCRA have been shown to change over time. Overall, 18% of the offenders have a change in risk classification from the initial assessment to the first reassessment. Higher percentages (~ 40%) of moderate and high-risk offenders are categorized in risk classes that differ from the initial assessment. These changes in classification are associated with changes in the probability of recidivism (Cohen, Lowenkamp, & VanBenschoten, 2016).

The PCRA was administered by officers when an offender entered supervision or when reassessing an offender. In the present study, the results of the earliest assessment were selected for analyses as this provided the longest follow up time period. In addition to the total PCRA score, the sub-scores from the five PCRA domains were also calculated and analyzed.

**Arrest Criteria**

Data from the National Crime Information Center (NCIC) and Access to Law Enforcement System were used to collect information on arrests. A standard criminal history check was retrieved on each participant that yielded their entire criminal history. The date and types of arrests that occurred after the date of PCRA administration were coded from these data.
The result was two dichotomous measures that we used in analyses of predictive fairness: arrest for any offense (excluding technical violations of standard conditions of supervision), and arrest for any violent offense. Violence was defined using the NCIC definitions (i.e., homicide and related offenses, kidnapping, rape and sexual assault, robbery, assault).

Our analyses separate “violent arrest” because it is the most unbiased criterion available and “[c]onfidence in the criterion measure is a prerequisite for an analysis of predictive bias” (Society for Industrial and Organizational Psychology, 2003). Differential selection theory (i.e., the theory that disparities in arrest reflect bias in policing and decisions about arrest) applies less to crimes of violence than crimes that involve greater police discretion (e.g., drug use, “public order” crimes; see Piquero & Brame, 2008). In our view, official records of arrest are a valid criterion. For example, changes in variable risk factors on the PCRA change the likelihood of future re-arrest (Cohen, Lowenkamp & VanBenschoten, 2015), suggesting that arrest statistics track risk-relevant behavior.

In the present sample, the base rate for any arrest and for violent arrest was 30.10% and 8.41%, respectively. Young age was modestly but significantly associated with any arrest ($\phi = -0.19; p < 0.001$) and with violent arrest ($\phi = -0.10; p < 0.001$).

Analyses

We calculated descriptive statistics, effect sizes, and measures of predictive validity. To test the PCRA’s predictive fairness, we followed the standard practice of comparing the relative fit of specific nested regression models. Analyses are meant to represent the predictive fairness of PCRA scores in the federal population as a whole, across its 94 districts. To address concerns that the data may cluster by district, we used robust standard errors in the regression models to adjust for any heteroscedasticity. Specifically, the variance-covariance estimator with clustering
by district was used to address the potential correlation between error terms within districts (STATA vce[cluster]; Guiterrez & Drukker, 2007; Rogers, 1993).

We retained the PCRA age item in the analyses reported below. We do so because age is included in PCRA scores in practice, and it is important to test for predictive bias as the test exists. However, we also completed a series of analyses to test the age-predictive fairness of PCRA Total scores, excluding the age item. As shown later (see “supplemental analyses”), the pattern of results was largely similar.

**RESULTS**

**Testing Predictive Fairness**

Our first aim was to test the extent to which the PCRA, and the risk factors it includes, are free of predictive bias by age. We hypothesized that the PCRA would be free of predictive bias or—at most—would modestly overestimate recidivism for older offenders. As shown below, results are largely consistent with this hypothesis: The PCRA predicts recidivism quite well across age groups, but predicted probabilities of recidivism associated with PCRA scores—which are based on all age groups—underestimate arrest rates for the Younger age group and overestimate arrest rates for the Older age group.

**Degree of prediction as a function of age.** We began our analyses by examining whether the degree of relationship between PCRA scores and arrest varied as a function of age (see Arnold, 1982). Table 2 presents arrest rates for offenders classified in each PCRA risk classification (low to high) by age group. Results indicate that rates for any arrest and for violent arrest increase monotonically as risk classifications increase across age groups.

[Insert Table 2]
Table 2 also presents DIF-R and AUC values for the overall sample and by age group. The Dispersion Index for Risk (DIFR; see Silver, Smith & Banks, 2000) roughly indicates the extent to which PCRA risk classifications create reasonably sized groups of offenders with arrest rates that are as different as possible. DIFR ranges from 0 to infinity, increasing as the classification model disperses cases into subgroups whose baserates of re-arrest are distant from the total sample baserate and whose subgroup sample sizes are large in proportion to the total sample size. As shown in Table 2, DIFR values consistently indicate that the PCRA classifications perform quite well, in terms of base rate dispersion—but DIF-R differences across age groups cannot be statistically compared.

Unlike the DIFR (which focuses on PCRA risk classifications), the Area Under the ROC Curve (AUC) focuses on PCRA Total Scores. The AUC is widely used to assess the accuracy of risk assessment tools, partly because its values are not heavily influenced by differences in base rates of offending (unlike correlations; see Babchishin & Helmus, 2016). Use of the AUC in the present study is critical, given that age is inversely associated with arrest (see above), and that AUC differences can be statistically compared. Minimum AUCs of .56, .64, and .71 correspond to “small,” “medium,” and “large” effects, respectively (see Rice & Harris, 1995).

As shown in Table 2, all AUC values were .70 or higher, indicating generally strong predictive utility across age groups. Although AUCs were consistently in the lower range of “large” for the Older group and consistently at the high range of “Medium” for the Younger group, these differences are not statistically significant at our criterion of $p < .001$.

**Form of prediction as a function of age.** Given these findings about the strength of the relationship between the PCRA and recidivism across age groups, we next examined whether the form of the relationship between PCRA scores and arrest varies by age (see Arnold, 1982).
Ideally, an average PCRA score of X will relate to an average arrest rate of Y, regardless of an offender’s age.

To test whether the form of the relationship between the PCRA and arrest was similar across age (measured continuously), we estimated a series of bivariate logistic regression models (four models for any arrest; four models for violent arrest). These models were compared to test for “subgroup differences in regression slopes or intercepts, [which] signal predictive bias” (Society for Industrial and Organizational Psychology, 2003; see also Aguinis, Culpepper & Pierce, 2010). In Models One and Two, only age and only the PCRA total score, respectively, were used to predict any arrest. Model Three included both age and the PCRA, and Model Four included age, the PCRA, and the interaction between age and PCRA.

[Insert Table 3]

The results are summarized in Table 3—and convey two main findings. First, the slope of the relationship between PCRA scores and arrest is similar across age. Specifically, comparison of Models Three and Four for indicate that age does not significantly moderate the utility of the PCRA in predicting any arrest, $\Delta \chi^2 (1) = 3.9$, ns or violent arrest, $\Delta \chi^2 (1) = 3.6$, ns. Second, the intercept of the relationship between PCRA scores and arrest increases with decreasing age. That is, comparison of Models Two and Three indicate that age adds small, but significant incremental utility to the PCRA in predicting both any arrest ($\Delta \chi^2 [1] =137.30, p<.001$) and violent arrest ($\Delta \chi^2 [1] = 29.70, p < .001$). The odds ratios from Model 3 indicate that, after taking PCRA total scores into account, every one-year decrease in age is associated with a 3% and 2% increase in the odds of any arrest and violent arrest, respectively.

Notably, these results obtained with PCRA Total scores were similar to those obtained when we ran parallel analyses at the PCRA domain level. For example, across all five PCRA
domains, there were no significant interactions between domain scores and age in predicting arrest (indicating no slope bias); and age added significant incremental utility in predicting arrest to all five domain scores (indicating intercept bias; Model 3 odds ratios for age fell in the narrow range of 1.03 to 1.05 across domains; details available from authors). In short, there is little variation in predictive fairness across specific domains or risk factors.

To concretize age differences in the form of the relation between the PCRA total scores and arrest, we computed Model Three with age coded categorically (i.e., 25 years and younger, 26-40 years, 41 years and older). Results were similar to those obtained with age coded continuously. They indicate that, after controlling for PCRA total scores, the odds of any arrest for the Younger group are 1.42 and 2.07 times higher than the odds of any arrest for the Middle- and Older group, respectively; and the odds of violent arrest for the Younger group are 1.37 and 1.63 times higher than the odds of violent arrest for the Middle- and Older-group. Differences between the Younger and Older group for any arrest are meaningful.

These results are available in visual form in Figure 1. Here, we calculated predicted probabilities of any arrest and for violent arrest based on Model Three. We grouped the predicted probabilities together for each PCRA score and plotted the average for each score. As shown in Figure 1, the slope of the relationship between the PCRA and arrest does not differ by age group (although the distance between lines representing different ages may appear to increase with PCRA scores, the distance is actually constant or even decreasing, relative to the base rates of the outcome criterion). At the same time, the intercept of the relationship between the PCRA and arrest increases with decreasing age, which translates to underestimation- and overestimation- of recidivism for the Younger and Older groups, respectively.

[Insert Figure 1]
As noted earlier, compared to the larger unmatched sample (N=48,475), the matched sample of focus (N=7,350) had modestly higher PCRA scores and was younger, less likely to be male and less likely to have a drug offense. To explore test fairness for factors that include both age and its risk-relevant correlates, we completed the four regression models with the eligible unmatched sample. We obtained a similar pattern of results as with the matched sample. For example, age added incremental utility to the PCRA in predicting arrest, but did not significantly moderate the PCRA’s utility in predicting any arrest.

**Summary.** Overall, results are consistent with our general expectation of predictive fairness by age. Although the degree of association between the PCRA and future arrests was similar across age groups, there were some age differences in the form of this association. Age does not moderate the relationship between PCRA scores and re-arrest (i.e., slopes are similar), but PCRA scores may under- and overestimate rates of recidivism for the Younger and Older offenders, respectively (i.e., intercepts increase with decreasing age).

**Assessing Age-Related Score Differences Relevant to Disparate Impact**

Our second aim was to assess the extent to which age correlated with scores on the PCRA, such that different age groups manifest mean score differences relevant to disparate impact. We hypothesized that, if they exist, mean score differences will be small and might favor Younger offenders, who have had less time to accrue a varied criminal history than Older offenders. Results are partially consistent with our tentative hypothesis, at best: After omitting age from the PCRA, there were essentially no mean score differences by age (see Table 4).

Even when age is left in the PCRA as an item, mean score differences are small and favor Older offenders. Specifically, average PCRA total scores for the Younger, Middle, and Older age groups were 7.63, 7.24 and 6.00 respectively—raw differences of two or fewer points on an 18-
point scale that translate into $d$ values of 0.11 (Younger/Middle CI=0.06-0.17), 0.37
(Middle/Older CI=0.32-0.43) and 0.49 (Younger/Older CI=0.43-0.54). According to
conventional classifications, minimum $d$ values of .2, .5, and .8 define small, medium, and large
effects, respectively (Cohen, 1988). Our $d$ values correspond to 95% overlap (Younger/Middle),
85% overlap (Younger/Older) and 81% overlap (Middle/Older) between age groups in PCRA
scores (see Cohen, 1988). Score differences are small, but possibly meaningful (especially the
Younger/Older difference).

[Insert Table 4]

Table 4 provides mean scores and standard deviations for PCRA total scores and risk
domains, by age group. The last columns indicate the proportion of the difference in the PCRA
total means that is attributable to a given risk domain. This estimate reflects the fact that some
domains contribute more points to PCRA total scores than others. As shown in those columns,
the criminal history domain accounted for the majority of the differences between the Younger-
and Older- groups’ PCRA scores; whereas the employment/education domain accounted for
about half of the difference between the Younger- and Middle groups.

Table 5 provides raw effect sizes for each domain—i.e., the correlation between age and
PCRA domain scores. By convention, minimum $r$ values of .10, .30, and .50 define small,
medium, and large effects, respectively (Cohen, 1988). Age had a small effect on criminal
history ($r = -.19$) and social networks ($r = -.13$); but associations with the remaining domains were
trivial.

[Insert Table 5]

Supplemental Analyses: What if the PCRA excluded Age as an Item?
**Predictive fairness.** For the reasons noted above, the central results focus on PCRA scores that include its age item (which contributes up to 2 of 18 possible points on the scale). To determine how predictive fairness might differ if the age item were excluded from PCRA total scores, we ran the four regression models described above, using age-excluded PCRA scores. The results were largely similar to those with age-included PCRA scores. First, the slope of the relationship between modified PCRA scores and arrest is similar across age. Specifically, comparison of Models Three and Four indicate that age does not significantly moderate the utility of the modified PCRA in predicting any arrest, $\Delta \chi^2 (1) = 4.48$, ns or violent arrest, $\Delta \chi^2 (1) = 1.98$, ns. Second, the intercept of the relationship between modified PCRA scores and arrest is higher for older offenders. That is, comparison of Models Two and Three indicate that age adds significant incremental utility to the modified PCRA in predicting both any arrest ($\Delta \chi^2 [1] = 322.30, p < .001$) and violent arrest ($\Delta \chi^2 [1] = 86.62, p < .001$). Odds ratios from Model 3 indicate that—after taking modified PCRA total scores into account—every one-year decrease in age is associated with a 5% and 4% increase in the odds of any arrest and violent arrest, respectively.

To yield more interpretable estimates, we computed Model Three with age-excluded PCRA total scores and age coded categorically. Results indicate that, after controlling for modified PCRA total scores, the odds of any arrest for the Younger group are 1.79 and 3.22 times higher than the odds of any arrest for the Middle- and Older group, respectively. The odds of violent arrest for the Younger group are 1.72 and 2.52 times higher than the odds of violent arrest for the Middle- and Older- group, respectively, after taking modified PCRA scores into account. Combined with results reported earlier, these findings indicate that excluding age as a risk factor in the PCRA significantly increases the instrument’s intercept bias (exacerbating
underestimation of recidivism for the Younger offenders and overestimation of recidivism for the Older offenders).

**Age-related score differences.** It is possible that this increase in predictive bias is accompanied by a decrease in age-related score differences relevant to disparate impact. To assess whether this is the case, we provide results for PCRA Total- and Criminal History- scores that *exclude* age as an item in Tables 4 and 5.

As shown in Table 4, most of the age difference in PCRA-Total and Criminal History scores is accounted for by the PCRA’s inclusion of age. For example, the difference between the Younger-and Older groups in PCRA Total scores decreases from 1.62 to -0.14 when age is removed; and Criminal History decreases from 0.96 to -0.79. As shown in Table 5, the small inverse association between age and PCRA Total scores and Criminal History scores becomes trivial, when age is removed from the PCRA. By definition, inclusion of age in PCRA scores contributes to mean score differences by age. But the point to emphasize is that the PCRA’s inclusion of age as a risk factor both decreases predictive bias and increases age-related mean score differences.

**Putting Predictive Fairness and Mean Score Differences Together**

Returning to the full PCRA (including its age item), Figure 2 provides a visual summary of the study’s main findings. The bar chart displays arrest rates for any offense by PCRA classification (low to high) and by age group. The line graph in the figure displays the percentage of offenders within each PCRA classification (e.g., “low”) that is in the Older group.

First, the line graph indicates that the percentage of offenders who are Older increases modestly, as PCRA risk classifications increase (e.g., 41% of low-risk offenders are in the Older
group, whereas roughly 20% of high-risk offenders are Older. This indicates that Older offenders tend to obtain lower PCRA scores than Younger offenders.

Second, the bar chart indicates that rates of arrest increase steeply and systematically by PCRA risk classification for all age groups (indicating slope fairness). However, it also shows that rates of arrest within each PCRA risk classification are consistently lower for Older than Younger offenders (indicating intercept bias). For example, 30% of all offenders classified as low/moderate risk by the PCRA were re-arrested (Table 2). As shown in Figure 2 and Table 2, within offenders classified as low/moderate risk, 37% of the Younger subgroup, 29% of the Middle subgroup, and 24% of the Older subgroup are re-arrested. So the general base rate of recidivism for the low/moderate group underestimates recidivism for the younger offenders and overestimates recidivism for the older offenders.

[Insert Figure 2]

**DISCUSSION**

While an increasing number of scholars and policy makers endorse the potential of risk assessment to reduce the fiscal burden of mass incarceration without prompting an increase in the crime rate, many others are convinced that any fiscal benefits accruing to the use of risk assessment in criminal sanctioning will be offset by the moral costs inherent in a risk assessment enterprise that bases sanctioning decisions in part on risk factors for which an offender bears no responsibility, or on variables that correlate so highly with these risk factors as to be considered “proxies” for them (Monahan & Skeem, 2016). Race, gender, and age are the three risk factors that have attracted the most intense criticism in this regard.
Regarding race, Skeem and Lowenkamp (2016) have examined one well-known risk assessment instrument—the federal Post Conviction Risk Assessment [PCRA]—and found it to be free of predictive bias (i.e., the PCRA predicted re-arrest for both African American and white offenders strongly and with similar form). However, African American offenders obtained modestly higher mean PCRA scores than white offenders (primarily due to higher scores on the criminal history scale). Although not a reflection of test bias, this finding suggests that some uses of the PCRA could have a legally disparate impact on African American offenders.

Regarding gender, Skeem, Monahan, and Lowenkamp (2016) found that ignoring the effects of gender on recidivism—which the PCRA and most other risk assessment instruments do ignore—can translate into discrimination in the sanctioning of offenders who are women. The PCRA strongly predicts recidivism for both women and men, but the instrument greatly overestimates women’s likelihood of recidivism.

In this study, we used a comparable sample of federal offenders to examine questions regarding the same instrument (the PCRA) as Skeem and Lowenkamp (2016) and Skeem, Monahan, and Lowenkamp (2016), with a focus on the role played by age as a risk factor for recidivism. Unlike race and gender, age is included in the PCRA: Young age contributes up to two of the PCRA’s 18 total possible points. Our first study aim was to test the extent to which the PCRA and the risk factors it includes are free of predictive bias by age. Based on our past finding that the PCRA overestimates recidivism for women (Skeem et al., 2016), we hypothesized that the PCRA would modestly overestimate recidivism for Older offenders. Our results are consistent with this hypothesis: although the degree of association between the PCRA and future arrests was similar across age groups, there were age differences in the form of this association. Age does not moderate the relationship between PCRA scores and re-arrest (i.e.,
slopes are similar), but PCRA scores overestimate rates of recidivism for Older offenders (i.e., intercepts increase with decreasing age). In addition (and not hypothesized by us), we found that since intercepts increase with decreasing age, PCRA scores underestimate rates of recidivism by Younger offenders.

Our second study aim was to determine the extent to which age is correlated with PCRA scores such that different age groups manifest mean score differences relevant to disparate impact. On one hand, Older offenders will obtain lower scores on the PCRA’s blunt “age” item than their Younger counterparts. On the other hand, Older offenders will have had more time to accrue criminal history than their Younger counterparts, and criminal history is heavily weighted in total PCRA scores. We tentatively hypothesized that mean score differences, if they exist, will be small and will accrue to the benefit of Younger offenders. Our results are partially consistent with this hypothesis, at best: although there were small mean score differences, they favored Older offenders, who had lower scores than their Younger counterparts. Rates of arrest within each PCRA risk classification are consistently lower for Older than for Younger offenders (indicating intercept bias). For example, 30% of all offenders classified as low/moderate risk by the PCRA were re-arrested. However, within this group of low/moderate risk offenders, 37% of the Younger subgroup, 29% of the Middle subgroup, and 24% of the Older subgroup are re-arrested. Using the “general” base rate of recidivism for the low/moderate group underestimates recidivism for Younger offenders in that group and overestimates recidivism for Older offenders in that group.

There are several ways that the inclusion of age on the PCRA might be improved to address this under- and overestimation issue. For example, the number of categories on the age variable could be expanded from three (i.e., 25 or younger; 26-40; 41 or older) to some larger
number, to better capture very high risk Younger offenders and very low risk Older ones. In addition to (or instead of) expanding the number of age categories, the weighting of offenders’ scores on the age variable could be modified (from “0” for 41 or older; “1” for 26 to 40, and “2” for 25 or younger) to assign greater relative weight to younger offenders. A simpler alternative for avoiding both overestimating Older offenders’ likelihood of recidivism and underestimating Younger offenders’ likelihood of recidivism would be to explicitly interpret PCRA scores in an age-specific manner. That is, continuing with the above example, one could explicitly acknowledge that Older offenders who score between 6 and 9 on the PCRA do not present the same “low/moderate” risk of recidivism presented by Younger offenders who score within the same range on the instrument. Instead, “low/moderate” Older offenders have a 24 percent chance of recidivism while “low/moderate” Younger offenders have a 37 percent chance of recidivism.

Our findings here—while limited to one risk assessment instrument (the PCRA) used in one criminal sanctioning system (the federal system)—are thoroughly consistent with the vast literature in developmental criminology that, compared with middle age (here, 26 to 40 years old), younger age is a risk factor for recidivism and older age is a promotive factor for desistance from offending. Expanding the number of age categories on a risk assessment instrument, or increasing the weight given to the age variable, or interpreting categorical risk estimates in an age-specific fashion, all might enhance the predictive validity of offender risk assessment. In addition, such actions could go far in attenuating the overestimation of risk among older offenders, thereby decreasing the costs associated with housing resource-intensive prisoners (Tonry, 2014). However, the same steps that diminish the overestimation of risk among older offenders will also diminish the underestimation of risk among younger offenders, thus increasing the risk-based sanctions imposed on them. Youth, it seems, both “diminishe[s]
culpability” for past crime (Roper v. Simmons, 2005) and enhances risk for future crime. How to parse the orthogonal concerns of backward-looking culpability and of forward-looking risk when sanctioning young offenders has become a fundamental dilemma of the 21st-century justice system (Monahan & Skeem, 2016).
References


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http://dx.doi.org/10.1037/pas0000210

Table 1. Characteristics of the Eligible and Age-Matched Sample

<table>
<thead>
<tr>
<th></th>
<th>Eligible Unmatched Sample (n = 48,475)</th>
<th>Age Matched Sample (n = 7,350)</th>
</tr>
</thead>
<tbody>
<tr>
<td>White</td>
<td>48.62</td>
<td>50.00</td>
</tr>
<tr>
<td>Male*</td>
<td>85.24</td>
<td>77.96</td>
</tr>
<tr>
<td>Age*</td>
<td>39.99 (11.12)</td>
<td>35.34 (11.69)</td>
</tr>
<tr>
<td>PCRA Total*</td>
<td>6.74 (3.45)</td>
<td>6.96 (3.41)</td>
</tr>
<tr>
<td>Offense*</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Drugs</td>
<td>46.49</td>
<td>39.17</td>
</tr>
<tr>
<td>Other</td>
<td>8.03</td>
<td>12.76</td>
</tr>
<tr>
<td>Firearm</td>
<td>15.58</td>
<td>17.99</td>
</tr>
<tr>
<td>Sex Offense</td>
<td>3.09</td>
<td>1.47</td>
</tr>
<tr>
<td>Violent</td>
<td>4.78</td>
<td>6.30</td>
</tr>
<tr>
<td>White Collar</td>
<td>17.02</td>
<td>16.11</td>
</tr>
<tr>
<td>Property</td>
<td>5.01</td>
<td>6.21</td>
</tr>
</tbody>
</table>

Note: PCRA = Post Conviction Risk Assessment

*p < .001
Table 2. Predictive Utility of PCRA by Age Group

<table>
<thead>
<tr>
<th>Feature</th>
<th>Any Arrest</th>
<th>Violent Arrest</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Ages in Years</td>
<td>Ages in Years</td>
</tr>
<tr>
<td></td>
<td>All</td>
<td>≤ 25</td>
</tr>
<tr>
<td>% Arrested by PCRA Classification</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Low</td>
<td>14</td>
<td>22</td>
</tr>
<tr>
<td>Low/Moderate</td>
<td>30</td>
<td>37</td>
</tr>
<tr>
<td>Moderate</td>
<td>52</td>
<td>58</td>
</tr>
<tr>
<td>High</td>
<td>68</td>
<td>72</td>
</tr>
<tr>
<td>DIF-R, PCRA Categories</td>
<td>0.82</td>
<td>0.71</td>
</tr>
<tr>
<td>AUC, PCRA Total</td>
<td>0.73</td>
<td>0.70</td>
</tr>
<tr>
<td>Upper 99.9% CI</td>
<td>0.75</td>
<td>0.74</td>
</tr>
<tr>
<td>Lower 99.9% CI</td>
<td>0.71</td>
<td>0.68</td>
</tr>
</tbody>
</table>

Note: PCRA=Post Conviction Risk Assessment

¹Any Arrest Z = -2.86, ns; Violent Arrest Z = -1.92, ns
Table 3. Logistic Regression Models Testing Predictive Fairness of PCRA Total Scores by Age

<table>
<thead>
<tr>
<th></th>
<th>Model 1</th>
<th>99.9% CI</th>
<th>Model 2</th>
<th>99.9% CI</th>
<th>Model 3</th>
<th>99.9% CI</th>
<th>Model 4</th>
<th>99.9% CI</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>ANY ARREST</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Age in Years</td>
<td>1.04*</td>
<td>1.03/1.05</td>
<td>--</td>
<td>--</td>
<td>1.03*</td>
<td>1.02/1.03</td>
<td>1.04*</td>
<td>1.03/1.06</td>
</tr>
<tr>
<td>PCRA</td>
<td>--</td>
<td>--</td>
<td>1.30*</td>
<td>1.26/1.34</td>
<td>1.29*</td>
<td>1.25/1.32</td>
<td>1.39*</td>
<td>1.29/1.50</td>
</tr>
<tr>
<td>PCRA x Age</td>
<td>--</td>
<td>--</td>
<td>--</td>
<td>--</td>
<td>--</td>
<td>--</td>
<td>1.00</td>
<td>0.99/1.00</td>
</tr>
<tr>
<td>(Constant)</td>
<td>0.07*</td>
<td>0.05/0.11</td>
<td>0.06*</td>
<td>0.05/0.08</td>
<td>0.02*</td>
<td>0.01/0.03</td>
<td>0.01*</td>
<td>0.01/0.02</td>
</tr>
<tr>
<td>Model X²</td>
<td>267.56</td>
<td></td>
<td>899.39</td>
<td></td>
<td>1016.5</td>
<td></td>
<td>1009.2</td>
<td></td>
</tr>
<tr>
<td>Model R²</td>
<td>0.03</td>
<td></td>
<td>0.12</td>
<td></td>
<td>0.13</td>
<td></td>
<td>0.13</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>Model 1</th>
<th>99.9% CI</th>
<th>Model 2</th>
<th>99.9% CI</th>
<th>Model 3</th>
<th>99.9% CI</th>
<th>Model 4</th>
<th>99.9% CI</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>VIOLENT ARREST</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Age in Years</td>
<td>1.04*</td>
<td>1.03/1.04</td>
<td>--</td>
<td>--</td>
<td>1.02*</td>
<td>1.02/1.03</td>
<td>1.05*</td>
<td>1.03/1.07</td>
</tr>
<tr>
<td>PCRA</td>
<td>--</td>
<td>--</td>
<td>1.29*</td>
<td>1.26/1.33</td>
<td>1.29*</td>
<td>1.25/1.31</td>
<td>1.45*</td>
<td>1.31/1.61</td>
</tr>
<tr>
<td>PCRA x Age</td>
<td>--</td>
<td>--</td>
<td>--</td>
<td>--</td>
<td>--</td>
<td>--</td>
<td>1.00</td>
<td>0.99/1.00</td>
</tr>
<tr>
<td>(Constant)</td>
<td>0.02*</td>
<td>0.01/0.03</td>
<td>0.01*</td>
<td>0.01/0.01</td>
<td>0.004*</td>
<td>0.003/0.006</td>
<td>0.001*</td>
<td>0.001/0.004</td>
</tr>
<tr>
<td>Model X²</td>
<td>109.22</td>
<td></td>
<td>393.21</td>
<td></td>
<td>423.11</td>
<td></td>
<td>387.91</td>
<td></td>
</tr>
<tr>
<td>Model R²</td>
<td>0.02</td>
<td></td>
<td>0.1</td>
<td></td>
<td>0.1</td>
<td></td>
<td>0.11</td>
<td></td>
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</tbody>
</table>

*Note:* Values for predictors are odds ratios. N=7,350

* p < .001
Table 4. PCRA Total and Domain Scores by Age Group

<table>
<thead>
<tr>
<th>Variable</th>
<th>Group Scores</th>
<th>Group Differences</th>
<th>% of Group Difference Attributable to Each Domain</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Younger M SD</td>
<td>Middle M SD</td>
<td>Older M SD</td>
</tr>
<tr>
<td>PCRA Total</td>
<td>7.63 3.32</td>
<td>7.25 3.33</td>
<td>6.00 3.36</td>
</tr>
<tr>
<td>Criminal History</td>
<td>4.65 2.09</td>
<td>4.70 2.16</td>
<td>3.69 2.32</td>
</tr>
<tr>
<td>Employment/Education</td>
<td>1.20 1.07</td>
<td>1.01 0.98</td>
<td>0.96 0.95</td>
</tr>
<tr>
<td>Drugs/Alcohol</td>
<td>0.33 0.57</td>
<td>0.26 0.54</td>
<td>0.21 0.49</td>
</tr>
<tr>
<td>Social Networks</td>
<td>1.28 0.74</td>
<td>1.16 0.81</td>
<td>1.04 0.80</td>
</tr>
<tr>
<td>Attitudes</td>
<td>0.17 0.37</td>
<td>0.12 0.33</td>
<td>0.10 0.30</td>
</tr>
<tr>
<td>PCRA Total, w/o age</td>
<td>5.78 3.31</td>
<td>6.24 3.32</td>
<td>5.92 3.33</td>
</tr>
<tr>
<td>Criminal History, w/o</td>
<td>2.81 2.08</td>
<td>3.69 2.15</td>
<td>3.61 2.29</td>
</tr>
<tr>
<td>PCRA Total, w/o age</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Table 5. Association of Age with PCRA Scores

<table>
<thead>
<tr>
<th>Variable</th>
<th>Correlation</th>
</tr>
</thead>
<tbody>
<tr>
<td>PCRA Total</td>
<td>-0.21</td>
</tr>
<tr>
<td>Criminal History</td>
<td>-0.19</td>
</tr>
<tr>
<td>Employment</td>
<td>-0.09</td>
</tr>
<tr>
<td>Drug</td>
<td>-0.09</td>
</tr>
<tr>
<td>Social Networks</td>
<td>-0.13</td>
</tr>
<tr>
<td>Cognitions</td>
<td>-0.09</td>
</tr>
<tr>
<td>PCRA Total, excluding age item</td>
<td>0.12</td>
</tr>
<tr>
<td>Criminal History, excluding age</td>
<td>-0.00</td>
</tr>
</tbody>
</table>
Figure 1. Predicted Probability of Arrest by PCRA score and Age Group

Panel A. Any arrest

Panel B. Violent arrest
Figure 2. Rate of Arrest and Percent in Oldest Age Group by PCRA Score

Panel A. Any arrest

Panel B. Violent arrest