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The John F. Finn Institute
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Risk Assessment for Offender-Focused Enforcement

Smart Policing Initiative

Robert E. Worden
Kenan M. Worden
Madison A. Bryant
Sarah J. McLean

September, 2021

421 New Karner Road
Suite 12
Albany, NY 12205
518.456.6323

Robert E. Worden, Ph.D., Director • Sarah J. McLean, Ph.D., Associate Director

The John F. Finn Institute for Public Safety, Inc., is an independent, not-for-profit and non-partisan corporation, whose work is dedicated to the development of criminal justice strategies, programs, and practices that are effective, lawful, and procedurally fair, through the application of social science findings and methods. The Institute conducts social research on matters of public safety and security – crime, public disorder, and the management of criminal justice agencies and partnerships – in collaboration with municipal, county, state, and federal criminal justice agencies, and for their direct benefit. The findings of the Institute's research are also disseminated through other media to criminal justice professionals, academicians, elected public officials, and other interested parties, so that those findings may contribute to a broader body of knowledge about criminal justice and to the practical application of those findings in other settings.

The Finn Institute was established in 2007, building on a set of collaborative projects and relationships with criminal justice agencies dating to 1998. The first of those projects, for which we partnered with the Albany Police Department (APD), was initiated by John Finn, who was at that time the sergeant who commanded the APD's Juvenile Unit. Later promoted to lieutenant and assigned to the department's Administrative Services Bureau, he spearheaded efforts to implement problem-oriented policing, and to develop an institutional capability for analysis that would support problem-solving. The APD's capacity for applying social science methods and results thereupon expanded exponentially, based on Lt. Finn's appreciation for the value of research, his keen aptitude for analysis, and his vision of policing, which entailed the formulation of proactive, data-driven, and – as needed – unconventional strategies to address problems of public safety. Lt. Finn was fatally shot in the line of duty in 2003. The Institute that bears his name honors his life and career by fostering the more effective use of research and analysis within criminal justice agencies, just as Lt. Finn did in the APD.

We gratefully acknowledge the cooperation of the Syracuse Police Department and Onondaga Crime Analysis Center, and their continued willingness to subject their operations to the scrutiny of researchers. We also thank Kelly J. Becker, formerly a Senior Research Analyst at the Finn Institute, for her assistance with the construction of the data files.

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Introduction

The Chronic Offender Recognition and Enforcement (CORE) strategy is one of several strategies that Syracuse and Onondaga County have adopted to address gun violence in the City of Syracuse. Following the lead of other cities in fashioning initiatives to address chronic violent offenders, CORE was designed as a proactive approach to identifying and concentrating enforcement efforts on the most violent and active offenders.[1] Offenders are assessed for their risk of gun violence and those at the highest assessed risk are placed on the CORE list. The CORE strategy was launched in 2008 and, in 2017, revised to build on a model of offender-focused policing model and to incorporate components of other best practices. We refer to the current strategy as CORE 2.0.

In general, offenders' risk can be assessed using either actuarial or clinical approaches. Actuarial procedures assign weights to a number of research-based risk factors; the weighted combination of risk factors represents a risk score. Clinical procedures rely on assessments made by clinicians and may be either unstructured or based on "structured professional judgment" that directs their attention to specific risk factors; in either case, the assessments turn on clinicians' judgments about how to interpret and weigh both quantitative and qualitative information to form an estimate of the future risk of violence. In many instances, actuarial tools tend to be more accurate than purely clinical judgements.

The procedure for assessing risk and forming the CORE list is a hybrid, including actuarial and clinical elements. It has remained in many respects the same for the past decade, and it begins with the computation of CORE scores for known gang and group members. The CORE score is based on a weighted sum of risk factors, such as arrests for gun offenses in the previous three years. The CORE scoring algorithm is, then, a prediction of risk: CORE offenders are identified as individuals who are, relative to others, very likely to be involved in gun violence in the future. CORE scores form the partial basis for placement of offenders on the CORE list, but placement turns also on the judgments of analysts in the Central New York Crime Analysis Center (OCAC) about the details of the risk factors, including law enforcement intelligence about the offenders.

CORE scoring and the judgments that are made in forming the CORE list have not been evaluated for their predictive accuracy, and it is conceivable that the scoring algorithm and/or the process of forming the CORE list leave room for improvement. The more accurately that the procedures assess and predict risk, the more successfully the CORE 2.0 strategy will focus its efforts on the highest-risk offenders. Hence we have analyzed the predictive accuracy of CORE scores and the CORE list, including an

[1] See Tim Bynum and Scott H. Decker, *Chronic Violent Offenders Lists: Case Study 4*, Project Safe Neighborhoods: Strategic Interventions (Washington: United States Department of Justice, 2006).

examination of how the risk factors that comprise CORE scores are combined to form the list.

We have also conducted analysis of a wider set of risk factors to form alternative risk models, and we have applied the models to the prediction of not only gun offending but also gun victimization. Insofar as an alternative model performs better than the current CORE algorithm, we can consider how additional risk factors that contribute to accurate prediction can be incorporated into the selection of offenders for the CORE list.

Analytic Approach

Our central question concerns whether the predictions of individual offenders' involvement in gun violence based on CORE scores could be made more accurately if additional factors were incorporated into the risk assessment process. First, we assess the process and predictive accuracy of CORE list formation. We analyze – and retrospectively "predict" – involvement in gun violence in 2017 based on CORE scores and the CORE list of January, 2017. Then we extend the range of risk factors considered and evaluate alternative risk assessment models or procedures, similarly "predicting" involvement in gun violence in 2017 based on identifiable factors in the three previous years, 2014 through 2016. These analyses thereby simulate a risk assessment performed in early-2017, based on each of several different risk assessment procedures, and shows how successfully those procedures would have predicted gun offending and gun victimization in 2017. In this way, we can estimate the predictive accuracy of CORE scores and alternative methods; we can also assess the contributions to prediction made by each of a number of discrete factors.

Outcomes

We considered three outcomes as indicators of gun offending: arrests for a fatal or nonfatal shooting, arrests for criminal possession of a weapon (CPW) and particularly a firearm, and arrests for other gun offenses.[2] Most of the analysis summarized here concentrates on the combined outcome of any of these gun-related arrests. We also analyzed violent victimization as an outcome. All data on outcomes were drawn from the Syracuse Police Department's record management system.

[2] We considered treating as an outcome involvement in a shooting as a victim. We found that the factors associated with shooting victimization appear to be different from those associated with the perpetration of gun violence, and so for this analysis we set aside as an outcome involvement in a shooting incident as a victim.

Analytic Methods

We rely primarily on logistic regression analysis to estimate the contributions of individual risk factors to the prediction of involvement in gun violence.[3] The predictive accuracy of a risk prediction model as a whole can be evaluated using a receiver operating characteristic (ROC) curve. ROC curves are produced by plotting the rate of true positive predictions ("sensitivity") against the rate of false positive predictions ("specificity"). Prediction is of course more successful when the rate of true positives is high and false positives low. See Figure 1 for a generic illustration. In this instance, a true positive is an offender predicted to engage in gun offending who does in fact engage in gun crime; a false positive, correspondingly, is an offender predicted to engage in gun offending who does not engage in gun crime. At any level of predictive accuracy represented by a ROC curve, increases in the number of true positives – people correctly predicted to engage in gun offending – come at the cost of additional false positives – people erroneously predicted to engage in gun offending, as one moves to the right on the curve. A higher level of predictive accuracy – more true positives without additional false positives – is represented by a curve that more closely follows the left-hand axis and top border of a graph – in Figure 1, the "excellent" curve. Predictive accuracy is measured by the *area under the curve* (AUC). An AUC of 1 indicates a perfect prediction, while an AUC of 0.5 indicates prediction that is no better than chance.[4] In Figure 1, a larger area can be readily seen under the "excellent" curve than that under the "good" curve. The accuracy of different risk prediction models can be directly compared in terms of their AUCs.

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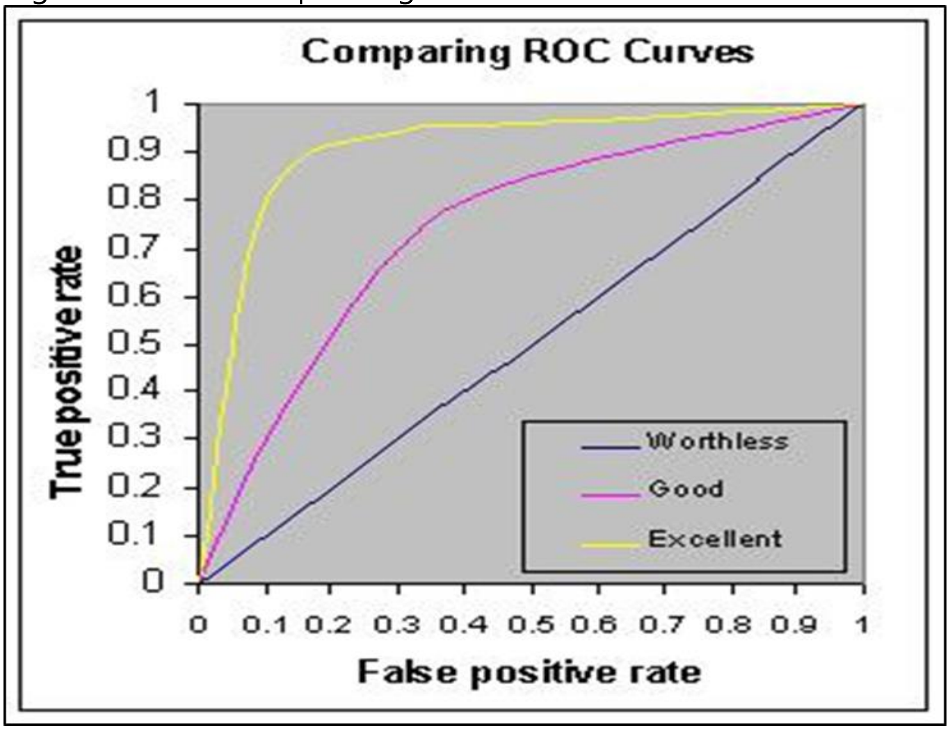
[3] The regression coefficients each reflect the independent effect of a factor in the risk model on the outcome, controlling for the influences of other factors, allowing us to assess the predictive value of each risk factor For example, since gang membership is correlated with arrests for criminal possession of a weapon, the association of either factor with gun offending in 2017 will reflect the effect that it shares with the other factor in addition to its independent effect. Regression analysis removes the shared effects.

[4] Logistic regression is only one of several analytic methods that can be applied for this purpose, and to allow for the possibility that another method might be more successful with the same set of risk factors, we also applied artificial neural network (ANN) analysis. An artificial neural network (ANN) is a deep learning system inspired by the biological neural networks that constitute the brain of an animal. The structure of an ANN consists of layers: an input layer, a number of hidden layers, and an output layer. Each of the layers is made of a collection of nodes, or "neurons," which are connected to other nodes in preceding and successive layers, similar to the neurons in the brain of an animal. These connections between nodes are weighted such that when a node receives a signal from a preceding node, it can determine the significance of the signal's contribution to obtaining a correct answer. Modifying the weights of the connections between nodes is where "learning" takes place in a neural network. This modification occurs after each instance of data is passed through the neural network and is achieved by the ANN through a comparison of the true answer of an instance and a node's determination. A higher weight will be assigned to a node that more greatly contributes to obtaining the correct answer than a node that often produces incorrect signals.

Figure 1. Receiver Operating Curves



Source: http://gim.unmc.edu/dxtests/roc3.htm

CORE

We begin our analysis with the CORE list and CORE scoring, which forms a baseline against which we can assess other risk assessment models. We examine outcomes for CORE offenders and others for whom CORE scores were computed by OCAC. We also analyze the formation of the CORE list in terms of its components. We include in our analysis of CORE scores the 364 people for whom CORE scores were computed by OCAC and equaled or exceeded a total of 2. For this purpose we use the same data compiled and used by OCAC to form the CORE list.

The formation of the CORE list begins with CORE scores for identified members of gangs and violent groups. CORE scores are based on several factors:

- The number of arrests for gun offenses in connection with shots fired incidents;
- The number of other arrests for criminal possession of a weapon (CPW) involving a firearm;
- The number of arrests for Part I violent offenses involving a firearm;
- The number of arrests for other Part I violent offenses;
- Whether or not the individual is the subject of gun intelligence;
- Whether or not the individual is the subject of felony-level drug intelligence;
- Whether or not the individual is the under correctional supervision.

Treating gun and drug intelligence and correctional supervision as binary characteristics, respectively, these factors are summed to form the CORE score.

CORE List Formation

Placement on the CORE list is not a simple function of the CORE score. Offenders who are incarcerated and expected to remain incarcerated for at least three months are removed from consideration for the CORE list, regardless of their CORE scores. Offenders who have not had police contact in the previous six months are treated as inactive, notwithstanding their CORE score. Among the remaining offenders, the numerical scores are blended with detailed intelligence to arrive at a final list. Thus the placement of offenders on the CORE list is based on a process that is partly actuarial and partly clinical.

We statistically analyzed placement on the January 2017 CORE list in terms of the CORE score components. We formed a statistical model of the analysts' judgments in identifying the offenders to be placed on the CORE list from among the much larger number for whom scores are at least 2, and who were not removed from consideration due to their incarcerated status. For each component of the CORE score, we estimate an odds ratio that represents the increase in the odds of placement on the CORE list attributable to that component; see Table 1. An offender with a "gun crime" arrest, for example, is two and one-half times more likely to be placed on the CORE list as a result, other things being equal. An offender on whom there is gun intelligence is twelve and one-half times more likely to be designated a CORE offender.

Table 1. CORE Score Components and Likelihood of CORE List Placement

CORE Component	**Odds Ratio**
Gun crime arrest	2.49
CPW arrest	3.54
Violent gun crime arrest	5.77
Other violent offense arrest	6.88
Gun Intelligence	12.46
Drug Intelligence	5.34
Supervision	1.51

It seems clear from these results that while the CORE score is a simple sum of its components, some components of the score have a greater influence than others on the judgments about who among the offenders qualifies as a CORE offender at the time. As a result, one of the two offenders with CORE scores of 5 was omitted from the CORE list, along with 13 offenders with CORE scores of 4. Twelve offenders with CORE scores of only 2 were nevertheless designated as CORE offenders. See Table 2. Our point is not that the judgments made in forming the CORE list are erroneous or misguided, but rather that the numerical CORE scores do not determine CORE list placement. As we indicated above, the formation of the CORE list is a hybrid risk assessment procedure, including both actuarial and clinical elements.

Table 2. CORE Scores and
CORE List Placement

CORE Score	Offenders on CORE List
CORE = 5 (N=2)	1
CORE = 4 (N=24)	11
CORE = 3 (N=68)	24
CORE = 2 (N=270)	12

CORE Outcomes

CORE scores are associated with the likelihood that offenders would be arrested for a gun offense: the proportion engaged in gun offending rises almost monotonically with the CORE scores, from 6.3 percent with a score of 2 to 50 percent with a score of 5, and 12 to 13 percent with scores of 3 or 4. See Table 3.

Though the different components of the CORE scoring algorithm are weighted equally in computing the CORE score, they are not equally related to the outcome. For example, among the offenders who had been arrested for a "gun crime" – i.e., for a shooting or shots-fired incident – in 2014-2016, 5.9 percent engaged in gun offending in 2017. (See Table 3.) However, 13.3 percent of the offenders with a CPW arrest in the

Table 3. 2017 Gun Offending by CORE Scores,
CORE Score Components, and CORE List

CORE Scores	Percent with 2017 Gun Offense	CORE Components	Percent with 2017 Gun Offense
CORE score > 1 (N=364)	8.2	Gun crime arrest	5.9
CORE = 2 (N=270)	6.3	Supervision	7.9
CORE = 3 (N=68)	13.2	Violent gun crime arrest	8.4
CORE = 4 (N=24)	12.5	Drug Intelligence	8.7
CORE = 5 (N=2)	50.0	Gun Intelligence	9.7
CORE List	**Percent with 2017 Gun Offense**	CPW arrest	13.3
CORE list (N=48)	16.7	Other violent offense arrest	20.0

base period engaged in gun offending in 2017, and 20 percent of those arrested for a non-gun violent offense in the base period registered a gun offense in 2017.

Table 3 also shows that among the 48 offenders placed on the CORE list in January of 2017, 16.7 percent (8) were arrested for a gun crime in 2017.[5] As we'll see below, CORE offenders were, then, nearly 10 times more likely to be arrested for a gun offense than the population of recent arrestees. They were also more than twice as likely to be arrested for a gun offense than the remaining 348 unincarcerated offenders whose CORE score was at least 2, 22 (7 percent) of whom were arrested for a gun crime in 2017.

The percentages shown in Table 3 represent simple bivariate associations between CORE components and gun offending, which could overstate the independent effects of any one factor on outcomes. In a multivariate context, such that the predictive power of each factor is estimated independently of the other factors, it is clear that some factors are more predictive than others; see Table 4. Arrests for gun crimes other than CPW, other things being equal, have little predictive power. Arrests for other violent offenses and for CPW have substantial predictive value: with each arrest for CPW, the offender is nearly 3 times more likely to engage in gun crime in 2017, and the odds of later gun offending is nearly 6 times greater with each arrest for other violent offenses. Gun intelligence is also independently associated with higher risk. Supervision status and drug intelligence also contributes to prediction.

Table 4. Estimated Effects of CORE Score Components on Gun Offending

CORE Component	**Odds Ratio**
Other violent offense arrest	5.85
Gun Intelligence	4.42
CPW arrest	2.93
Supervision	2.72
Drug Intelligence	2.16
Violent gun crime arrest	1.42
Gun crime arrest	0.67
AUC = 0.667	

This actuarial prediction of future gun offending weights the components somewhat differently than the hybrid procedure by which we infer the CORE list has been formed. Table 5 lists the CORE components two ways: in order of their odds ratios in predicting gun offending in the next year – the actuarial prediction of future gun offending – and in order of their odds ratios is predicting CORE list placement. Gun intelligence is weighed much more heavily in CORE placements than the statistical

[5] The CORE list then included 49 offenders, but we are missing information on one of those.

results suggest that it should, as have violent gun crime arrests. Supervision status may have received too little weight in CORE list formation, according to these results. If we think of the odds ratios as weights, the CORE scores would have greater predictive accuracy if they were formed by weighting the individual components according to the statistical analysis of gun offending. Weighted accordingly, these factors together predict gun violence better than the CORE scores, with 67 percent of the area under the curve, versus only 56 percent for the CORE scores.

Table 5. Relative Importance of CORE Score Components.

Actuarial prediction of future gun offending	**Odds Ratio**	**Hybrid assessment for CORE list placement**	**Odds Ratio**
Other violent offense arrest	5.85	Gun Intelligence	12.46
Gun Intelligence	4.42	Other violent offense arrest	6.88
CPW arrest	2.93	Violent gun crime arrest	5.77
Supervision	2.72	Drug Intelligence	5.34
Drug Intelligence	2.16	CPW arrest	3.54
Violent gun crime arrest	1.42	Gun crime arrest	2.49
Gun crime arrest	0.67	Supervision	1.51

The formation of the CORE list is presently a hybrid risk assessment model consisting of an actuarial – statistical – component and a clinical component of human judgment. This is as it should be. It is possible that the actuarial component could be improved, however, such that the judgments would be based on and informed by a stronger numerical foundation. One aspect of CORE scoring and CORE list formation that may admit of improvement is in the middle region of numerical risk, where it may be possible to tap available information to better differentiate among offenders at high – but not the highest – risk.

Alternative Risk Models

Alternative risk models can be formed using a wider array of risk factors than those currently used in computing CORE scores. For these analyses we include 47,986 people on whom information is available and who also appear to have a likelihood of involvement in violence that is not negligible:

- People arrested, 2014-2017;
- People stopped, 2014-2017;
- Gang members/affiliates as of November 2016;
- Victims of non-domestic violent offenses, 2014-2017;
- People involved as victims or shooters in 2017 shootings (even if not included above).

Let us characterize this population as at-risk persons. In 2017, among the 47,986 at-risk persons included in our analysis, 774 (or 1.6 percent) engaged in a gun offense; they were a perpetrator in shooting incident (36); they were arrested for CPW (728); and/or they were arrested for some other gun offense (295).

As potential predictors (for 2014-2016 unless otherwise specified) we consider:

- Counts of arrest, by selected offense categories (e.g., weapon possession, robbery, drug possession);
- Involvement in shootings as victim or shooter;
- Gang membership, by individual gang (as of November, 2016);
- Affiliation with (as opposed to membership in) any gang (as of November, 2016);
- Counts of vehicle stops by police;
- Counts of pedestrian stops by police;
- Counts of selected (non-domestic) victimizations;
- Counts of offenses of selected types in which person is an identified suspect; and
- Age (as of 12/31/2016).

The potential utility of many if not all of these factors for assessing the risk of gun violence is probably intuitive. However, for guidance we have also drawn on the demonstrably successful risk assessment tool developed by the Albany Police Department for its Violent Offender Identification Directive (VOID). We previously evaluated the predictive accuracy of the VOID tool and found that it performs quite well.[6]

Gun Offending

We first analyze the simple associations between each of a number of the identified risk factors and the outcome of primary interest, an arrest for a gun offense in 2017. We caution that the associations revealed in this fashion may overstate the risk attributable to any one factor, whose influence on offenders' behavior could be confounded with that of other factors. Estimates of the independent effects of these factors are generated by the multivariate analysis presented below.

Gang members are clearly at substantially higher risk: they are more than four times as likely to be arrested for a gun offense as non- members. Gang associates are also at elevated risk. Some gangs' members appear to be at higher risk than others'. Members of 1500 and O-Block are the most likely to engage in gun violence, and several other gangs' members are at a level of risk higher than the gang average. See Table 6.

[6] Andrew P. Wheeler, Robert E. Worden, and Jasmine R. Silver, "The Accuracy of the Violent Offender Identification Directive Tool to Predict Future Gun Violence," *Criminal Justice and Behavior* 46 (2019): 770-788.

Table 6. Gun Offending and Gang Affiliation.

Gang Membership	**Percent with 2017 Gun Offense**
Not gang members	1.5
Gang members	6.3
Gang associates	2.6
1500	12.4
O-Block	12.5
Uptown	8.5
Pioneer Homes	4.4
LAMA	5.9
Furman Fast Cash	7.4
Bricktown	8.6
Brighton Brigade	7.0

At-risk persons, and particularly those with multiple arrests in the preceding three years or with particular charges, are at elevated risk. The risk of gun offending rises with the count of arrests beyond the first. Risk is also higher, as we might expect, among those with prior arrests for weapons or violent offenses. But even arrests for some non-violent offenses, such as larceny and disorderly conduct, are associated with elevated risk. See Tables 7 and 8.

Table 7. Percentages of 2014-2016 At-Risk Persons with a Gun Offense in 2017, by Type of Charge.

Count	Any charge	CPW	Reckless endangerment	Menacing	Assault	Robbery	Larceny	Disorderly conduct
0	1.3	1.47	1.59	1.53	1.53	1.56	1.52	1.58
1	1.51	4.38	4.76	5.59	3.72	5.59	2.07	2.92
2	3.14	6.74	*	6.38	2.48	5.08	3.23	5.66
3	3.37	4.55		*	14.29	8.33	3.54	*
4	4.23	*			*	*	1.64	*
5	5.48	*					6.78	
6	6.19						0	
7	6.9						0	*
8+	4.76						0	

* Fewer than 10 cases

Table 8. Percentages of 2014-2016 Suspects with a Gun Offense in 2017, by Type of Offense.

Count	Pedestrian stops	Vehicle stops	Aggravated assault	Simple assault	Menacing	Reckless endangerment
0	1.53	1.74	1.58	1.58	1.6	1.61
1	3.24	0.81	4.72	5.31	8.45	11.11
2	3.9	2.62	9.09	*		
3	12.31	2.64		*		
4	0	4.44	*			
5	*	5.71				
6	*	6.25				
7	*	0				
8+	*	9.76				

* Fewer than 10 cases

Violent victimization is also associated with violent offending, as Table 9 shows. The likelihood of gun offending in 2017 is greater for people who in 2014-2016 were victims of aggravated assaults, menacing, and reckless endangerment.

Table 9. Percentages of 2014-2016 Victims with a Gun Offense in 2017, by Type of Offense.

Count	Aggravated assault	Simple assault	Menacing	Reckless endangerment
0	1.58	1.62	1.6	1.61
1	3.48	1.31	4.8	8.0
2	9.26	*		
3	0			

* Fewer than 10 cases

From these risk factors we formed and estimated five predictive models:

- Model I includes counts of arrests, overall and for individual types of offenses;
- Model II includes gang membership and gang association;
- Model III includes membership in individual gangs, rather than representing gang membership overall as a risk factor;
- Model IV includes status as a suspect, in individual types of violent offenses and in pedestrian and vehicle stops, respectively;
- Model V includes counts of selected types of violent victimization.

The results are shown in Table 10.[7] The table includes for each such factor and each outcome an odds ratio, interpretable as the increase in the odds of later gun violence

[7] In an analysis that included all of these factors, the logistic regression analysis generally outperformed the ANN analysis by a small margin, and both performed substantially better than chance (i.e., AUC > 0.50). Thus we concentrate on logistic regression models.

associated with the factor. Statistical significance levels are also shown as a rough guide to the reliability of the estimates.

A number of factors appear to contribute to the prediction of later gun violence, though none of the five models, by itself, predicts very well. The areas under the curve vary from 0.521 to 0.619. Model III, which allows for the estimated effects of membership in different gangs to vary, predicts no better overall than Model II. Though not all gangs are equally violence-prone, these results suggest that for the purpose of predicting gun violence, it will suffice to take account of gang membership generally and set aside the identity of individual gangs. Suspicion of violent offending appears to have some predictive value even when it falls short of probable cause for arrest. And violent victimization may be a proxy for involvement in a street life that raises the risk of violent offending.

From the factors shown in Table 10 we drew a subset that appear to have some predictive value, forming a single model. We estimated the predictive accuracy of that model first for all of the 47,986 people on whom we assembled data and then for only the offenders for whom CORE scores were analyzed. This model performs better than any of Models I through V, with an area under the curve of 0.66 for all of the offenders; see Table 11. Gang membership and arrests on various types of charges are featured prominently, based on the odds ratios, but so too are victimizations and offenses of which people were only suspected and not arrested. People suspected of reckless endangerment were 7 times more likely to engage in a gun crime in 2017, and victims of non-firearm aggravated assaults were nearly twice as likely.

Any of these three outcomes is, overall, rare, even among the people – including gang members and others with police contact in 2014-2017 – analyzed here, making risk assessment seem akin to finding the proverbial needle in a haystack. The estimated probabilities of any one individual experiencing these outcomes direct attention to people who were at demonstrable risk. For a tiny fraction – 99, or about 21 in 10,000 – the estimated probability of at least one such outcome was 0.10 or greater. Of those, 13 actually committed a gun offense in 2017.

Among these 99 high-risk people, we find 48 who had CORE scores of 2 or greater, and 13 were among the 49 offenders on the CORE list in January, 2017. We also find 83 gang members and associates, along with 16 people with no known gang affiliation. Gang-affiliated people are at substantially higher risk of involvement in gun violence, as the logistic regression results indicate. The gang database included 1,303 gang members and associates in November of 2016, 72 (5.5 percent) of whom committed a gun offense in 2017. Thirteen of the 83 had an estimated probability of a gun offense of at least 0.10, taking account of all of the factors in the risk model. Among the remaining gang members and associates, the mean predicted probability was 0.03.

Table 10. Alternative Risk Models: Estimated Effects of Risk Factors on Gun Offending.

	I		II		III		IV		V	
Risk factor	**Odds ratio**	**Sig level**	**Odds ratio**	**Sig level**	**Odds ratio**	**Sig level**	**Odds ratio**	**Sig level**	**Odds ratio**	**Sig level**
Arrests with charge of weapon possession	1.52	0.00								
Arrests with charge of robbery	1.50	0.01								
Arrests with charge of menacing	1.39	0.06								
Total arrests, 2014-2016	1.16	0.00								
Arrests with charge of UPM	1.09	0.53								
Arrests with charge of disorderly conduct	1.09	0.61								
Arrests with charge of criminal mischief	1.08	0.46								
Arrests with charge of assault	1.07	0.64								
Arrests with charge of CPCS	1.05	0.56								
Arrests with charge of loitering	1.01	0.89								
Arrests with charge of reckless endangerment	1.00	0.99								
Arrests with charge of larceny	0.97	0.64								
Arrests with charge of burglary	0.83	0.31								
Arrests for shooting incidents	0.55	0.35								
Arrests with charge of marijuana sale	0.52	0.48								
Arrests with charge of CSCS	0.21	0.12								
Arrests with charge of violating order of protection	0.00	0.96								

	I		II		III		IV		V	
Risk factor	**Odds ratio**	**Sig level**	**Odds ratio**	**Sig level**	**Odds ratio**	**Sig level**	**Odds ratio**	**Sig level**	**Odds ratio**	**Sig level**
Identified gang member			4.38	0.00						
Identified gang associate			1.77	0.14	1.90	0.09				
Member of O-Block					11.32	0.00				
Member of 1500					9.62	0.00				
Member of Highland Street					7.29	0.00				
Member of Furman Fast Cash					6.43	0.01				
Member of Uptown					6.40	0.00				
Member of Bricktown					6.31	0.00				
Member of Brighton Brigade					5.52	0.00				
Member of Lick City					5.48	0.08				
Member of Bootcamp					4.80	0.00				
Member of LAMA					4.48	0.00				
Member of Pioneer Homes					3.77	0.04				
Member of 110					2.24	0.06				
Suspect in reckless endangerment							6.39	0.02		
Suspect in menacing							3.95	0.00		
Suspect in simple assault (non-firearm)							2.45	0.00		
Suspect in aggravated assault (non-firearm)							2.24	0.00		
Pedestrian stops							1.42	0.00		
Vehicle stops							1.07	0.08		
Victim in reckless endangerment									4.73	0.04
Victim in menacing									2.85	0.01
Victim in aggravated assault (non-firearm)									2.09	0.00
Victim in simple assault									0.72	0.46
Area Under the Curve (AUC)	0.619		0.577		0.579		0.565		0.521	

Table 11. Integrated Risk Model: Estimated Effects of Risk Factors on Gun Offending.

	All		CORE	
Risk factor	**Odds ratio**	**Sig level**	**Odds ratio**	**Sig level**
Arrests with charge of marijuana sale	2.01	0.18	0.00	0.99
Arrests with charge of weapon possession	1.23	0.25	0.56	0.15
Arrests with charge of robbery	1.71	0.00	1.45	0.31
Arrests with charge of menacing	1.05	0.86	0.94	0.94
Arrests for shooting incidents	0.24	0.17	0.29	0.37
Arrests with charge of UPM	1.07	0.67	0.73	0.37
Total arrests, 2014-2016	1.13	0.00	1.08	0.16
Identified gang member/associate	4.11	0.00	1.38	0.59
Suspect in reckless endangerment	7.08	0.02	-	-
Suspect in menacing	0.56	0.58	5.17	0.21
Suspect in simple assault (non-firearm)	1.66	0.16	1.60	0.62
Suspect in aggravated assault (non-firearm)	0.91	0.80	2.34	0.30
Pedestrian stops	1.14	0.14	1.36	0.10
Victim in menacing	2.17	0.23	-	-
Victim in aggravated assault (non-firearm)	1.82	0.01	1.57	0.47
Age	0.94	0.00	0.88	0.01
Area Under the Curve (AUC)	0.659		0.717	

The estimated predictive values of these indicators among all of the at-risk individuals do not all hold equally well among the offenders on whom CORE list formation concentrates, however. In this high-risk subpopulation, the predictors that stand out are (1) suspect status in menacing, aggravated assault, and simple assault, (2) robbery arrests, (3) aggravated assault victimization, and (4) age. Only robbery arrests are included among the components of CORE scores.

Many of the 2017 gun offenders (702) are found among the 46,683 people who were not identified gang members or associates, and they include 6 whose estimated probability of gun offending was at least 0.05. Some research suggests that predictive accuracy can be improved by taking account of the social connections among at-risk persons. Such connections have proven useful in predicting the risk of gunshot victimization.[8] In this instance, we might hypothesize that individuals who associate with gun offenders may be at elevated risk of engaging in gun violence.

[8] See, e.g.: Andrew V. Papachristos, Anthony A. Braga, and David M. Hureau, "Social Networks and the Risk of Gunshot Injury," *Journal of Urban Health* 89 (2012): 992-1003; Andrew V. Papachristos and Christopher Wildeman, "Network Exposure and Homicide Victimization in an African-American Community," *American Journal of Public Health* 104 (2014): 143–150; and Andrew V. Papachristos, Christopher Wildeman, and

Thus we added to the risk models an indicator, for each at-risk person, of his/her first-degree connection to a gun offender in 2014-2016. The indicator is based on co-offending, i.e., having been arrested for the same offense (other than a gun offense). Such an indicator reliably, but conservatively, identifies social connections. An individual who participated in a crime with another person who was a gun offender is documentably linked to the offender. This indicator surely understates the prevalence of such connections, however; some connections between gun offenders and others are not captured by this indicator.

We found that the social connection indicator has considerable predictive value, but that nevertheless it does not substantially improve the predictive accuracy of the models. Added to Models I through V above, the odds ratios associated with the indicator range from 1.95 to 3.52 and are all statistically significant with a p-value of no more than 0.002. Even so, the AUCs of the models change very little. The social connections identified through co-offending are largely redundant information in predicting gun offending.

Violent Victimization

As Lauritsen and Laub observe, "research … has consistently found that one of the strongest correlates of victimization is involvement in deviant or criminal behavior and, alternatively, that victimization is one of the strongest correlates of offending."[9] The oft-noted overlap between victims and offenders can be seen in Syracuse. Of 127 persons who were victims of gun violence in 2017, and who represented about one-quarter of one percent of the at-risk persons in our analysis, 16 were also gun offenders in 2017, representing two percent of gun offenders. Offenders were disproportionately represented among victims.

Some research shows that predictors of criminal behavior also predict victimization.[10] We might, then, expect to find a great deal of congruence between the risk factors for gun offending and risk factors for violent victimization. Other research, however, demonstrates that the overlap between victims and offenders is partial – that some people exhibit a tendency toward either victimization or offending.[11]

Elizabeth Roberto, "Tragic, but Not Random: The Social Contagion of Nonfatal Gunshot Injuries," *Social Science & Medicine* 125 (2015): 139-150.

[9] Janet L. Lauritsen, and John H. Laub, "Understanding the Link Between Victimization and Offending: New Reflections on an Old Idea," *Crime Prevention Studies* 22 (2007): 55-75, p. 56.

[10] See, e.g., Janet L. Lauritsen, John H. Laub, and Robert J. Sampson, "Conventional and Delinquent Activities: Implications for the Prevention of Violent Victimization among Adolescents," *Violence and Victims* 7 (1992): 91–108.

[11] See Christopher J. Schreck, Eric A. Stewart, and D. Wayne Osgood, "A Reappraisal of the Overlap of Violent Offenders and Victims," *Criminology* 46 (2008): 871-905.

Table 12. Estimated Effects of Risk Factors on Violent Victimization.

	I		II		III		IV		V	
Risk factor	**Odds ratio**	**Sig level**	**Odds ratio**	**Sig level**	**Odds ratio**	**Sig level**	**Odds ratio**	**Sig level**	**Odds ratio**	**Sig level**
Arrests with charge of weapon possession	2.43	0.00								
Arrests with charge of robbery	0.67	0.50								
Arrests with charge of menacing	0.71	0.42								
Total arrests, 2014-2016	1.04	0.38								
Arrests with charge of UPM	1.93	0.00								
Arrests with charge of disorderly conduct	1.54	0.16								
Arrests with charge of criminal mischief	1.50	0.05								
Arrests with charge of assault	0.71	0.24								
Arrests with charge of CPCS	1.16	0.43								
Arrests with charge of reckless endangerment	1.12	0.85								
Arrests with charge of larceny	1.01	0.97								
Arrests with charge of burglary	0.57	0.30								
Arrests for shooting incidents	0.00	0.97								
Arrests with charge of marijuana sale	6.81	0.00								
Arrests with charge of CSCS	1.85	0.38								

Note: Some variables were omitted from statistical modeling due to complete or quasi-complete separation. This occurs when the outcome variable in a logistic regression model separates a predictor variable, or a set of predictor variables, to a certain degree. For example, when a predictor X1 always predicts the absence of an event when it is less than a certain value *a*, and the presence of an event when it is greater than or equal to *a*, the maximum likelihood estimate for X1 will not exist.

	I		II		III		IV		V	
Risk factor	**Odds ratio**	**Sig level**	**Odds ratio**	**Sig level**	**Odds ratio**	**Sig level**	**Odds ratio**	**Sig level**	**Odds ratio**	**Sig level**
Identified gang member			13.39	0.00						
Identified gang associate			13.54	0.00	14.48	0.00				
Member of 1500					45.56	0.00				
Member of Highland Street					29.48	0.00				
Member of Furman Fast Cash					28.37	0.00				
Member of Bricktown					26.67	0.00				
Member of Brighton Brigade					13.31	0.00				
Member of Bootcamp					11.65	0.00				
Member of LAMA					8.90	0.01				
Member of Pioneer Homes					16.89	0.00				
Member of 110					10.73	0.00				
Member of Crips					214.78	0.00				
Suspect in reckless endangerment							0.00	0.99		
Suspect in menacing							0.00	0.98		
Suspect in simple assault (non-firearm)							2.99	0.02		
Suspect in aggravated assault (non-firearm)							1.51	0.45		
Pedestrian stops							1.50	0.00		
Vehicle stops							1.38	0.00		
Victim in reckless endangerment									0.00	0.99
Victim in menacing									0.00	0.97
Victim in aggravated assault (non-firearm)									2.94	0.00
Victim in simple assault									0.88	0.89
Area Under the Curve (AUC)	0.639		0.621		0.624		0.627		0.522	

We estimated the effects of the same set of risk factors examined above, as predictors of gun offending, on violent victimization. We began, as above, with five predictive models, the estimated parameters of which are shown in Table 12, above. We derived from these findings a single integrated model, the estimated parameters of which are shown in Table 13.

Table 13. Integrated Risk Model: Estimated Effects of Risk Factors on Violent Victimization.

	All		**CORE**	
Risk factor	**Odds ratio**	**Sig level**	**Odds ratio**	**Sig level**
Arrests with charge of marijuana sale	8.83	0.00	-	-
Arrests with charge of weapon possession	2.06	0.00	0.91	0.83
Arrests with charge of robbery	0.47	0.18	0.68	0.54
Arrests with charge of menacing	0.90	0.79	0.26	0.31
Arrests for shooting incidents	-	-	0.35	0.47
Arrests with charge of UPM	1.63	0.02	1.56	0.19
Total arrests, 2014-2016	0.99	0.76	0.94	0.44
Identified gang member/associate	7.66	0.00	0.81	0.75
Suspect in menacing	-	-	11.21	0.14
Suspect in simple assault (non-firearm)	1.99	0.19	0.88	0.93
Suspect in aggravated assault (non-firearm)	0.76	0.64	4.24	0.11
Pedestrian stops	1.20	0.19	1.58	0.04
Victim in aggravated assault (non-firearm)	2.32	0.00	3.11	0.08
Age	0.94	0.00	0.87	0.03
Area Under the Curve (AUC)	0.802		0.838	

As previous research would lead us to expect, we find among the risk factors for violent victimization some that are also risk factors for gun offending, and one that predicts victimization but not offending. Gang affiliation is a risk factor for both offending and victimization among the at-risk persons analyzed here, and so is age, prior arrests for weapon possession or marijuana sale, and a prior (non-firearm) aggravated assault victimization. Arrests for unlawful possession of marijuana predict victimization but not offending. Two predictors of offending – prior arrests for robbery, and the total count of arrests – do not predict victimization.

Conclusions

The analysis reported here represents an evaluation the predictive accuracy of CORE scores and the hybrid – actuarial and clinical – risk assessment that underlies placement of offenders on the CORE list. The prediction of gun violence, which is (fortunately) infrequent, is quite challenging. The bases on which selection for the CORE list rests perform well, and given that the CORE 2.0 lists are limited to 30 to 35 offenders, they are unlikely to include anyone who is low-risk.

It may be possible to refine the process at the margin to enhance its effectiveness in focusing enforcement on the highest risk offenders. The criteria that guide CORE list placement are applied in an implicitly weighted fashion, and the weights could be explicitly established and rooted in actuarial predictions. Additional indicators that have demonstrable predictive value, and which can be derived from information that is contained in the record management system, could be incorporated into the assessments. It bears repeating, however, that the improvements would be only at the margin.