Predicting and Preventing Shootings among At-Risk Youth

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The beating death of Chicago Public Schools (CPS) student Derrion Albert, captured on video and viewed millions of times on YouTube, caused a national furor. The death of Albert was not an isolated incident. In a typical year, more than 250 CPS students are shot; approximately 30 of these shootings are fatal. To deal with this problem, CPS CEO Ron Huberman launched the \$60 million Violence Prevention Initiative in September of 2009, a program that has received national attention as an innovative attempt to reduce violence and increase educational success of students most at risk for violence. One important component of this Initiative involved CPS contracting with Youth Advocate Programs, Inc. (YAP) to pair troubled students with advocates, who in Huberman's words "act as part mentor, part truant officer and part role model to the youths."1

Because of the highly targeted and resource intensive nature of the advocacy program (\$15,000 per student per year), correctly identifying the youths most at risk for violence is critical. The authors of this paper worked with CPS to build a predictive model of violent victimization, which became one of the inputs determining which students would be included in the program. In this paper, we report on the construction of that predictive model, as well as preliminary findings regarding the YAP mentoring intervention.

I. A Predictive Model of Getting Shot

At the request of CPS leadership, we, as well as the Boston Consulting Group, were asked to build

¹ As quoted in http://www.chicagobreakingnews. com/2010/05/cps-presents-progress-report-on-preventingyouth-violence.html. models to predict which Chicago high school students were most at risk of being shot. We based these predictions on retrospective data covering shootings between September 2007 and October 2009. Working with CPS, we were able to assemble a wide range of covariates. These included fixed student characteristics such as race and gender, a large number of behavioral variables (e.g., school misconduct, past shootings, test scores, progress toward graduation), and a handful of school-level controls, such as the type of school (military, charter, alternative, etc.) and each school's per capita shooting rate from the previous two years. All of these variables reflect information that was known prior to the fall of 2009.

The key results from estimating a linear probability model are presented in Table 1.2 The mean probability that a given student will be the victim of violence in our two-year sample period is 0.0027. The first column on the table reports means and standard deviations for the covariates in the overall sample. Column 2 shows estimation results for the full sample. Only the coefficients of greatest interest are reported in the table; the full set of covariates is described in the table notes. and complete results are available in the online Appendix (http://www.aeaweb.org/articles.php? doi=10.1257/aer.101.3.288). Controlling for other factors, being male is the single most important predictor-virtually all students shot are male. Despite the fact that blacks have much higher raw victimization rates than other groups (black males have a mean victimization rate of 0.0080 compared to 0.0027 for Hispanics and 0.0004 for all others), the coefficient on black is small and statistically insignificant in the regression, as is the Hispanic coefficient. This implies that the differences in risk across race are largely being captured by other covariates. A number of behavioral factors predict violent victimization: serious misconduct at school, suspensions, and incarceration history. The strongest predictor is

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² Logit estimation yields similar patterns, but for ease of interpreting the coefficients, we focus on the linear probability model.

		Regression coefficients			
	Mean	Full sample	African American males	Hispanic males	
Male	0.488	0.003	_	_	
	(0.500)	(0.000)			
African American	0.510	0.001		_	
	(0.500)	(0.001)			
Hispanic	0.363	0.000		_	
	(0.481)	(0.001)			
School per capita shooting history	0.002	0.152	0.119	0.265	
	(0.005)	(0.040)	(0.092)	(0.117)	
Times shot previously	0.002	0.008	0.011	-0.012	
	(0.048)	(0.003)	(0.007)	(0.008)	
Serious misconducts per day	0.000	0.347	0.799	-0.327	
	(0.002)	(0.093)	(0.231)	(0.231)	
Overage	0.100	0.002	0.006	0.002	
	(0.300)	(0.001)	(0.002)	(0.001)	
Free lunch status	0.813	0.000	0.000	0.000	
	(0.390)	(0.001)	(0.002)	(0.002)	
ISAT math score \times 100	1.731	0.000	(0.001)	(0.001)	
	(1.249)	(0.001)	(0.004)	(0.003)	
ISAT reading score \times 100	1.611	(0.004)	(0.008)	(0.004)	
c	(1.162)	(0.001)	(0.004)	(0.003)	
Percent of days suspended	0.009	0.030	0.000	0.140	
	(0.030)	(0.007)	(0.018)	(0.020)	
Percent of days absent	0.141	0.012	0.024	0.016	
	(0.161)	(0.001)	(0.003)	(0.003)	
Juvenile jail	0.015	0.024	0.025	0.014	
	(0.120)	(0.001)	(0.003)	(0.004)	
Adult detention center	0.003	0.007	0.009	-0.006	
	(0.059)	(0.003)	(0.006)	(0.007)	

TABLE 1—COEFFICIENTS FOR THE VIOLENCE PREDICTION MODEL

Notes: The means in the first column are calculated for the full sample of CPS students, as are the coefficients in the second column. Columns 3 and 4 show coefficients for OLS run only on the African American male and Hispanic male subsets, respectively. Variables not shown include: school type, transfer status, credits behind, ESL status, and disability status.

having spent time in a juvenile detention center, which raises the likelihood of being shot by 2.5 percentage points—a tenfold increase over the mean probability. Other factors correlated with victimization are being overage (implying that the student previously failed a grade), low test scores, suspensions, absences, and an indicator for whether the student had spent time in an adult detention center. The school-related variable with the greatest explanatory power is per capita shooting rate. A one-standard-deviation change in this variable increases the likelihood of being shot by 0.00075, or about one-fourth of the average victimization rate. Because black and Hispanic males were heavily overrepresented among the students at high risk, columns 3 and 4 of the table present estimates on these two subsamples of the data. Serious misconduct, absences, juvenile detention, and being overage have particularly detrimental effects on black males; suspensions and absences are strong predictors for Hispanics.

In terms of prediction, the model performed reasonably well out of sample. During the 2009– 2010 school year, the 250 students predicted to be most at risk were victimized at a rate of 2.0 percent, compared with an overall rate of 0.15 percent and a rate of 0.32 percent for black and Hispanic males. The 1,000 students predicted to be most at risk had a victimization rate of 1.4 percent. The next 4,000 students had a victimization rate of 0.83 percent. Students ranked between 5,000 and 10,000 were shot at a rate of 0.44 percent. Therefore, the model was able to identify a high-risk group that had victimization rates more than ten times higher than the population as a whole and six times higher than the typical black or Hispanic male. Though modest, we believe that this improvement in predictive accuracy is useful to policymakers and program administrators as a way to screen for who is most likely to benefit from a program. (See Amanda Agan, Levitt, and List (2010) for examples using economic experiments to screen.)

II. A Preliminary Evaluation of the YAP Mentoring Program

YAP was founded in 1975 to provide mentorship and support services to at-risk youth. YAP employs a community-based model which recruits and trains community members to serve as mentors for at-risk youth and their families. YAP has contracts with dozens of major cities and metropolitan areas and currently works with over 8,000 families per year. We are unaware of any previous evaluations of YAP involving a plausible control group. For a more detailed discussion of YAP, see Jeff Fleischer et al. (2006).

The YAP mentoring program in Chicago began enrolling youths in December 2009. In advance of that, two different criteria were used to determine which students would be referred to the program. The 53 students who were judged to be most at risk for violent victimization based on a predictive model similar to the one described above were referred. Independently, high school principals were asked to provide names of students they felt were most at risk and would benefit from the program. Fifty students were initially referred to YAP through this latter channel. An additional 129 students were referred to YAP in early February 2010, some based on regression models and some on principal nominations.3 Of the 232 students referred to YAP in the sample period, 203 were black males, 20 were Hispanic males, and 1 was a white male. Additionally there were 7 black females and 1 Hispanic female.

Ultimately, about two-thirds of those referred to YAP enrolled in the program. The remainder of the students either declined to participate or could not be found by YAP. Our analysis focuses on the group referred to YAP for treatment, rather than the subset of the group actually treated, because of concerns about selection effects across those referred students who do or do not elect to participate.⁴ When we limit our analysis either to (i) just those students who participate in YAP, or (ii) those students who most intensively utilize the YAP resources, the substance of our conclusions are unchanged.

The CPS elected not to randomize who was referred to YAP. Thus, any evaluation of the program requires construction of a control group. The most natural control group for students referred based on the predictive model is the set of students with predictions that were just below the threshold for YAP referral and who were not referred to YAP via the principals' list. Somewhat arbitrarily, we chose the number of students below the threshold to include as controls to be equal to the number above the threshold. To construct a control group for the principals' list, we use a propensity score approach. Using a similar set of covariates as in Table 1, we predict the likelihood that a student will be assigned to the principals' list. For each student on the list, we assign the closest match who is not referred to YAP as a control.5

Table 2 presents a comparison of means for the treatment and control groups. We divide the sample into three periods corresponding to school semesters: spring 2009, fall 2009, and spring 2010. Because the YAP interventions did not begin until December 2009, both spring and fall 2009 represent preperiods that allow us to evaluate the degree of balance between treatments and controls before treatment

³ Students continued to be referred to YAP after the February wave, but in this preliminary analysis we restrict attention to those referred no later than February to ensure that sufficient time has passed to give the intervention a chance of working.

⁴ Students who elected to participate in YAP had both better attendance and lower dropout rates before and after the YAP program, suggesting that there was some important selection on who opted into treatment. Full results for the treated sample are available on request from the authors.

⁵ When finding a match for a particular student referred to YAP, we exclude that student from the regression so that his own characteristics will not influence the coefficients.

	Pretreatment				Posttreatment	
	Spring 2009		Fall 2009		Spring 2010	
	Treatment	Control	Treatment	Control	Treatment	Control
Victim of a shooting	2.59%	3.45%	2.27%	0.76%	0.86%	0.86%
Dropping out this period	6.0%	6.9%	4.5%	13.6%	12.9%	13.4%
Minor misconduct	1.99	1.17**	1.22	0.60**	0.81	0.52
Serious misconduct	0.71	0.52**	0.30	0.13**	0.28	0.16**
Courses completed	6.74	6.61	6.45	6.50	6.59	6.63
Courses failed	4.68	4.37	3.61	3.70	3.70	3.65
GPA	0.59	0.73	0.87	0.87	0.80	0.81
Days absent	76.34	79.92	29.23	29.91	25.72	24.72
Days present	68.42	70.01	33.81	31.38	29.61	28.16
Percent days suspended	8.3%	6.5%**	5.2%	3.1%**	4.4%	2.7%**

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A

Notes: The fall 2009 treatment and control groups do not include the students from the second wave of referrals who were referred from the principals' list, which was generated during that semester and therefore is not pretreatment. Attendance figures for the treatment and control groups in the second semester 2008–2009 column are for the whole 2008–2009 year, not just the second semester.

**Significant at the 5 percent level.

commenced. We separate spring and fall 2009 because the predictive model was based exclusively on information from spring 2009. Thus, fall 2009 represents an out-of-sample preperiod, which took place after model selection was complete.⁶ These two preperiod comparisons are displayed in columns 1 through 4. Spring 2010 outcomes, which reflect the treatment period, are shown in columns 5 and 6. Space constraints do not allow us to present regression analysis of the estimated treatment effects (available on request from the authors), but regression estimates tell a story consistent with the raw data and demonstrate that, with the exception of the shooting victim outcome, we have power to detect reasonable improvements in the variables considered.

Focusing first on the spring of 2009 in columns 1 and 2, those students referred to YAP (denoted "treatment") have slightly worse outcomes than the controls on most of the outcome variables considered, although only for serious misconducts, minor misconducts, and percent days suspended are the differences across the two groups statistically significant (1.99 for the treatment group versus 1.17 for the controls). The grade point averages (GPAs) in both groups are shockingly low (0.59 and 0.73, respectively, on a four-point scale), with students in both groups failing roughly two-thirds of their classes. The fact that the students in the treatment group look slightly worse on average is due to the fact that the various worst kids in the system were the ones assigned to YAP; the differences between the most at-risk children and the next group of kids is not that large, however, as evidenced by the similarities between the two groups.

Columns 3 and 4 show data for the fall of 2009—a period after the predictive model's estimates were generated but before YAP interventions began to show a more mixed pattern across the two groups. The students who will be referred to YAP have statistically significantly more minor and serious misconducts, and spend more time suspended from school. On the other hand, the control students are more likely to drop out of school that semester (although the difference is not statistically significant). For a number of the variables—courses completed or failed, GPA, absences—the means across the groups are quite similar.

The final two columns of Table 2 report the outcomes after the YAP intervention takes place. There is little evidence of an ameliorative impact of YAP. The students referred to YAP continue

⁶ Unlike the predictive model, the principal's list was constructed in fall 2009 and thus is potentially influenced by fall 2009 student outcomes. Thus, we exclude the principals' list and the matched controls for that list when displaying data for fall 2009.

to exhibit elevated levels of minor and serious misconduct, with statistically significant differences across the groups, as was the case in the fall of 2009. The YAP students continue to be suspended at a slightly higher rate. In contrast to fall 2009, the YAP students also have slightly more absences, more failed courses, and lower GPAs than the treatment group. The only variable where YAP students improve is in shooting victimizations, where the rates now match the treatment group; on that variable, however, there is almost no power to test the intervention. For the two groups to be statistically different on shootings would require a gap of 1.6 percent. The scale of intervention undertaken was far too small to possibly generate meaningful findings

III. Conclusion

on the outcome of greatest interest.7

It is not often that academic economists studying crime get the opportunity to go beyond analyzing what has happened in the past, and instead get to be involved in generating models that are implemented as public policy. The project described in this paper represents one of these rare chances. The results of the intervention, however, provide further evidence of just how difficult it is for social programs to change human behavior. Despite a large and intensive effort, there is little evidence of improved educational outcomes and insufficient power to evaluate the impact on shootings. These findings are consistent with the mixed results obtained in prisoner rehabilitation programs (Robert Martinson 1974; Mark W. Lipsey and Francis T. Cullen 2007), as well as most training programs (Robert J. LaLonde 2003).

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⁷ Although unavailable to us, it would be of great interest to evaluate other criminal justice outcomes such as arrests.