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Supplementary Information for

When policing predicts crime: The criminogenic effects of police stops on adolescent Black and Latino boys

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Other supplementary materials for this manuscript include the following:

Not applicable.

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Supplementary Information Text

Study Goals

The goal of the present study was to examine the effects of police contact on non-White boys' development. We partnered with a large city in the southern United States to collect data from public high schools. Our partnering city selected the six public high schools that it and the local police department deemed were in high-intensity policing neighborhoods. Boys were surveyed during ninth and tenth grades, because the design of the study was to examine boys' transition into high school.

Univariate and Bivariate Analyses

Means and standard deviations for each variable employed in this study are depicted in Table 1 and bivariate correlations among the study variables across each wave are presented in Table S1. As depicted in Table 1, average levels for each variable in the study were low. Descriptively, we found that 40% of the boys in our sample (N = 259) said they were stopped by police at least once over the course of the study. Of the 259 boys in the sample who experienced any stops, 25.5% (N = 66) were stopped once while 74.5% (N = 193) were stopped more than once. Additionally, 71 boys were stopped at Wave 1, 126 were stopped at Wave 2, 122 at Wave 3, and 139 at Wave 4. In Figure S1, we present a histogram of the count of police stops each boy experienced across the four waves of data. In the present study, the average age of first stop was 15 (M = 15.00; SD = .79); boys were more likely to be stopped for the first time during Waves 1 (n = 71) and 2 (n = 70) than during Waves 3 (n = 12) and 4 (n = 33). Consistent with existing research (1), these descriptive analyses suggest that boys who are stopped once are likely to be stopped repeatedly. Because boys dropped out of the study and boys opted into the study at later waves, these rates are an underestimation of how many boys experienced this volume of pedestrian stops.

Rates of police stops were lowest at Wave 1, when 15.2% of participants reported having been stopped by police during the previous six months. The percentage of boys reporting any police stops peaked at Wave 2 (when 28.5% of the participants said they had been stopped), then declined through Wave 3 (25.9%) and Wave 4 (21.2%).

Too few boys completed responses with regard to how they rated the quality of their contact with law enforcement while being stopped to include this measure in the analyses (1 = *poorly*, 4 = *neutral*, 7 = *pretty well*). Among boys who did report on these measures, boys on average reported below the midpoint across each wave ($M_{\text{Wave 1}}$ = 3.99, $SD_{\text{Wave 1}}$ = 1.66; $M_{\text{Wave 2}}$ = 3.34, $SD_{\text{Wave 2}}$ = 1.56; $M_{\text{Wave 3}}$ = 3.48, $SD_{\text{Wave 3}}$ = 1.75; $M_{\text{Wave 4}}$ = 3.35, $SD_{\text{Wave 4}}$ = 1.66). In other words, boys in our study on average self-reported that they were treated slightly worse than neutrally by police.

Over the course of the two-year study, 52.6% of the boys in our sample (n = 339) reported involvement in any kind of delinquent behavior. This prevalence is lower than the general 70% of respondents that, according to previous research, typically self-report engaging in delinquent behavior at this age (2). Consistent with our predictions, boys' delinquent behavior tracked the temporal pattern of police stops: the percentage of boys reporting any delinquent behavior was lowest at Wave 1 (when 9.6% of the sample said they had engaged in a delinquent act during the previous six months), peaked at Wave 2 (when 26.2% said so), then declined through Wave 3 (25.2%) and Wave 4 (20.8%). Boys who said they had been involved in any delinquency reported, on average, 2 types of delinquent behavior.

Model Construction

We performed a series of step-wise multi-level models in a sequential fashion to build our final model. First, we began at the univariate level and estimated separate autoregressive models for each key construct (i.e., police stops, psychological distress, and delinquent behavior). The autoregressive model is a group-based approach in that coefficients estimate change in boys' rank ordered position in a distribution of scores. The model represents a variable at time *t* as being predicted by its immediately preceding value at time $t – 1$ plus random error. Results from these analyses are presented in Table S2, which presents autoregressive models, their coefficients (including standard errors), and their fit indices. For each autoregressive model, we tested whether constraining parameter estimates to be equal across time and adding covariates yielded significant decrement in model fit. We found that neither these constraints nor covariates caused significant decrement to model fit. Analyses and results are depicted in Table S2. Thus, we retained each model at the univariate level with constraints and covariates.
As a result, these models separately communicate that (1) boys who reported being stopped by police were likely to report being stopped again in subsequent waves, (2) boys who reported on psychological distress were likely to report distress again in subsequent waves, and (3) boys who reported engaging in delinquent behavior were likely to report engaging in delinquent behavior in subsequent waves, over and above the effects of our covariates.

In a step-wise multi-level model, we tested whether constraints in all cross-lagged paths among the three constructs (i.e., police stops, psychological distress, and delinquent behavior) to be equivalent across time yielded significant decrement in model fit relative to a model with these paths set to be freely estimated. From this analysis, we found that constraining these paths to be equivalent across time did not yield significant decrement in model fit $\Delta\chi^2(27) = 28.28$, $p = ns$. Thus, we retained the model with these final estimates as reported in the main text of the manuscript.

Sensitivity Analyses

The only statistically significant racial differences found in this study were as follows: compared to Latinos, multiracial boys reported more frequent delinquent behavior at Waves 2 and 4; compared to multiracial boys, Black boys reported greater depression at Wave 1; compared to multiracial boys, Latino boys reported greater anxiety at Wave 3. No other statistically significant between-group racial differences emerged. None of these group differences affected the relationships we found among police stops, delinquency, and psychological distress.

To determine whether our findings were consistent across racial groups, we compared a model in which the parameter estimates were freely estimated across race and another model in which these parameters were constrained across racial groups. We used Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC), which are indices that help determine which model is the most parsimonious. We would retain the model with smaller AIC and BIC values over a model with greater AIC and BIC values. A model in which parameter estimates were freely estimated across groups provided an AIC value of 22130.45 and a BIC value of 24267.43, whereas a model with constrained estimates across groups provided an AIC value of 22121.49 and a BIC value of 24205.05. We therefore retained the model with constrained estimates, which indicated that race did not moderate our final model. That is, we found that police stops increased delinquency to the same degree for Latino and Black boys. The fit indices indicated the model fit the data well, χ^2 (62) = 190.58, p < .001, RMSEA = .06 90% CI [.05, .07], CFI = .89, SRMR = .05.

We estimated a longitudinal interaction model to test whether boys who reported little or no involvement in delinquency at the prior wave were just as likely to have been stopped by police six months later as boys who had reported higher levels of delinquent behavior at the previous wave. In this model, we examined the inter-relationships between stops and delinquency over the four waves, with covariates. In this model, we estimated an interaction term by taking the product of centered terms for police stops and delinquency within each wave and we regressed police stops six months later onto each interaction term. Simultaneously, we also regressed delinquent behavior six months later onto each interaction term at the previous wave; this was to test whether police stops at one wave buffered or magnified past engagement in delinquent behavior on subsequent engagement in delinquent behavior six months later. The interaction term did not predict delinquent behavior six months later (b = .08, SE = .05, p = *ns*) or police stops six months later (b = .04, SE = .15, p = *ns*). In other words, boys who reported little or no involvement in delinquent behavior at the prior wave were just as likely to have been stopped by police six months later as boys who had reported higher levels of delinquent behavior at the previous wave. Additionally, we found that police contact at the previous wave did not deter or magnify boys' prior engagement in delinquent behavior on subsequent delinquent behavior six months later. This model produced acceptable fit indices, χ^2 (97) = 159.19, p < .001, RMSEA .03, 90% CI [.02, .04], CFI .95, SRMR .05.

To explore whether the relationship between police-initiated contact and later delinquent behavior varied with adolescents' age at first contact, we tested another longitudinal interaction model. In this model, we examined the inter-relationships between stops and delinquency over the four waves, with controls. This model included (centered) interaction terms for stops and adolescents' age, and we regressed delinquency (from six months later) onto each interaction term. This model produced acceptable fit indices, χ^2 (143) = 176.02, p < .05, RMSEA .02, 90% CI [.01, .03], CFI .93, SRMR .05. We found a significant main effect of stops on delinquency six months later (b = .09, SE = .03, p < .001), no significant main effect of age on delinquency six months later (b = -.01, SE = .01, p = *ns*), and a significant interaction of stops and age on delinquency six months later (b = -.06, SE =.02, p < .05). We performed a simple slope analysis to plot and interpret the interaction. The interaction suggested that the relationship between police stops and delinquent behavior six months later was stronger for younger adolescents who were stopped for the first time than for older adolescents who were stopped for the first time.

We performed a set of sensitivity analyses to test for potential regression artifacts associated with having variables with the limited variation in our delinquency measure. In these analyses, we transformed the dependent variable (delinquent behavior) by summing the number of *types* of delinquent acts across for each respondent. This type of transformation is a common practice to induce variation in a measure (3) and is commonly known as "versatility" of delinquency among criminologists (4, 5). This transformation resulted in more variability in self-reported delinquency (new range = 0 – 15) following the transformation (M_{Wave1} = .41, SD_{Wave1} = 15.36; M_{Wave2} = 2.13, SD_{Wave2} = 15.36; M_{Wave3} = 1.71, SD_{Wave3} = 12.98; M_{Wave4} = 2.14, SD_{Wave4} = 18.39) compared to before the transformation (M_{Wave1} = 1.15, SD_{Wave1} = .28; M_{Wave2} = 1.18, SD_{Wave2} = .36; M_{Wave3} = 1.14, SD_{Wave3} = .32; M_{Wave4} = 1.18, SD_{Wave4} = .39). Results from these sensitivity analyses produced acceptable fit indices, χ^2 (292) = 517.34, p < .001, RMSEA = .04 90% CI [.03, .04], CFI = .95, SRMR = .05, and were consistent with the original analyses in the manuscript, such that experiencing pedestrian stops predicted more types of delinquent behavior, and psychological distress mediated this relationship. To ease interpretation of the results, we retained the average of frequency of delinquent behavior over the sum of types of delinquent behaviors.

We performed another set of analyses to determine whether our analyses were robust if we excluded cross-lagged paths between 1- and 1.5- year intervals. Table S3 presents results from this traditional autoregressive and cross-lagged path analysis. Consistent with our results, we found that more frequent police stops predicted greater psychological distress six months later (but not vice-versa), which in turn predicted greater engagement with delinquent behavior six months later (but not vice-versa), and more frequent police stops still predicted greater engagement in delinquent behavior six months later (but not vice-versa). This model produced acceptable fit indices, χ^2 (359) = 582.53, p < .001, RMSEA .03, 90% CI [.03, .04], CFI .95 SRMR .04, as presented in Table S3.

There is evidence in the literature to suggest that peer influence may exacerbate the effect of policing on adolescents' criminal behavior and attitudes toward criminal behavior (6). We did not include a direct measure of peer influence regarding delinquent behavior in our survey. However, during Wave 1, adolescents reported on whether a friend, during the past six months, "was hassled by police" and whether a friend "was arrested by police." This measure of self-knowledge regarding peer contact with the police is central to many studies (6–9). When we added these to our final models, self-knowledge of peer contact with police was associated with greater police contact up to six and 18 months later. However, the key inter-relationships among police contact, distress, and delinquent behavior were consistent with those presented in the manuscript. These peer-related variables during Wave 1 were associated with contemporaneous delinquent behaviors, but they were not associated with delinquent behaviors longitudinally. This sensitivity analysis produced acceptable fit indices, χ^2 (397) = 725.59, p < .001, RMSEA = .03 90% CI [.02, .03], CFI = .94, SRMR = .04.

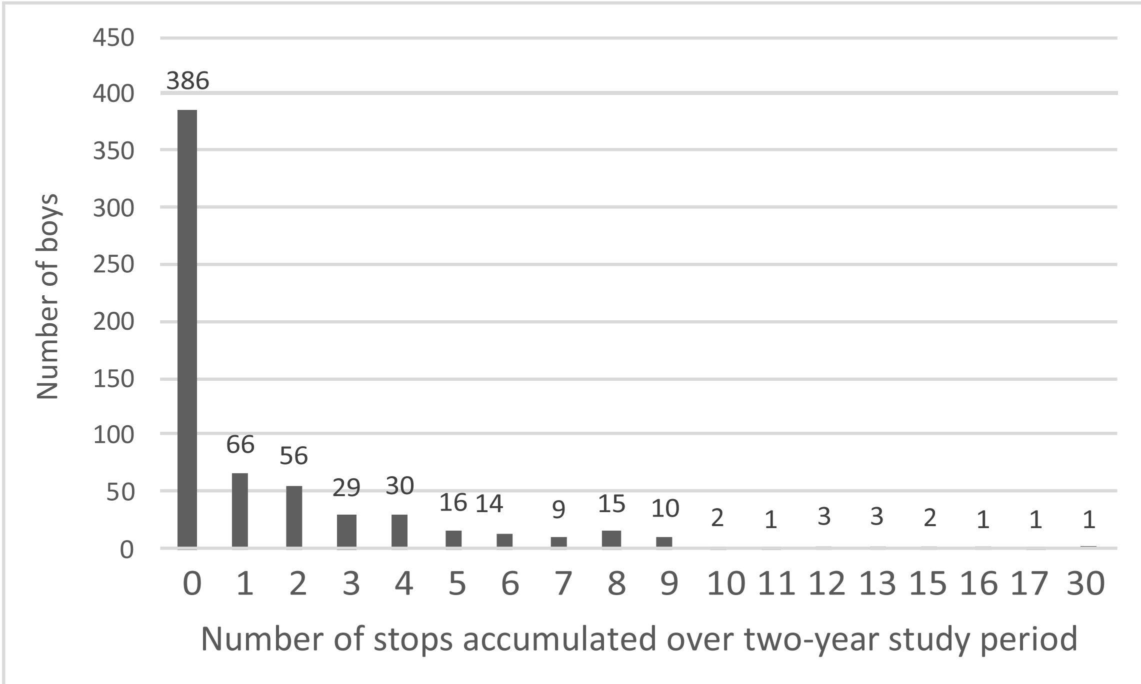

Fig. S1. Histogram of cumulative pedestrian stops across the four waves of data.

Table S1. Bivariate correlations among study variables at each wave.

	1	2	3	4	5
Wave 1					
1. Police Stops	1				
2. Depression	.14**	1			
3. Anxiety	.11*	.72**	1		
4. Stress	.13**	.75**	.82**	1	
5. Delinquency	.45**	.24**	.22**	.26**	1
Wave 2					
1. Police Stops	1				
2. Depression	.06	1			
3. Anxiety	.09	.81**	1		
4. Stress	.05	.87**	.84**	1	
5. Delinquency	.30**	.29**	.39**	.28**	1
Wave 3					
1. Police Stops	1				
2. Depression	.15**	1			
3. Anxiety	.17**	.81**	1		
4. Stress	.10*	.84**	.81**	1	
5. Delinquency	.34**	.39**	.44**	.36**	1
Wave 4					
1. Police Stops	1				
2. Depression	.17**	1			
3. Anxiety	.20**	.85**	1		
4. Stress	.16**	.86**	.85**	1	
5. Delinquency	.23**	.40**	.47**	.40**	1

Note: * $p < .05$, ** $p < .01$, *** $p < .001$.

Table S2. Unstandardized parameter estimates and standard errors for separate autoregressive path analyses for boys' self-reported police stops, psychological distress, and delinquency. These estimates are results from step-wise multi-level analyses with added complexity in a sequential fashion.

	Wave 1 -> Wave 2	Wave 2 -> Wave 3	Wave 3 -> Wave 4	$\Delta\chi^2$	Δdf	*p*-value
Police Stops						
No constraints	.70 (.11)***	.62 (.08)***	.51 (.11)***	-	-	-
Constraints added	.61 (.06)***	.61 (.06)***	.61 (.06)***	1.58	2	*ns*
Covariates added	.43 (.07)***	.43 (.07)***	.43 (.07)***	64.49	57	*ns*
Final model fit:	χ^2 (62) = 76.68, p = ns, RMSEA .02 90% CI [.00, .03] CFI .94 SRMR .04					
Psychological Distress						
No constraints	.37 (.07)***	.49 (.08)***	.52 (.06)***	-	-	-
Constraints added	.46 (.05)***	.46 (.05)***	.46 (.05)***	2.87	2	*ns*
Covariates added	.31 (.04)***	.31 (.04)***	.31 (.04)***	213.56	193	*ns*
Final model fit:	χ^2 (252) = 406.46, p < .001, RMSEA .03 90% CI [.03, .04] CFI .96 SRMR .04					
Delinquency						
No constraints	.61 (.10)***	.42 (.11)***	.42 (.12)***	-	-	-
Constraints added	.46 (.08)***	.46 (.08)***	.46 (.08)***	2.62	2	*ns*
Covariates added	.36 (.06)***	.36 (.06)***	.36 (.06)***	62.89	57	*ns*
Final model fit:	χ^2 (62) = 85.37, p < .05, RMSEA .02 90% CI [.01, .04] CFI .89 SRMR .04					

Note: * $p < .05$, ** $p < .01$, *** $p < .001$.

Table S3. Unstandardized parameter estimates and standard errors from a traditional autoregressive and cross-lagged path analysis.

	Wave 1 to Wave 2	Wave 2 to Wave 3	Wave 3 to Wave 4
Stability Coefficients			
Police Stops	.42 (.07)***	.42 (.07)***	.42 (.07)***
Distress	.32 (.05)***	.32 (.05)***	.32 (.05)***
Delinquency	.30 (.06)***	.30 (.06)***	.30 (.06)***
Cross-lagged Effects			
Police stops and distress			
Police Stops → Distress	.06 (.03)*	.06 (.03)*	.06 (.03)*
Distress → Police Stops	.03 (.05)	.03 (.05)	.03 (.05)
Distress and delinquency			
Distress → Delinquency	.06 (.03)*	.06 (.03)*	.06 (.03)*
Delinquency → Distress	.01 (.07)	.01 (.07)	.01 (.07)
Police stops and delinquency			
Police Stops → Delinquency	.09 (.03)***	.09 (.03)***	.09 (.03)***
Delinquency → Police Stops	.11 (.09)	.11 (.09)	.11 (.09)

Model fit: χ^2 (359) = 582.53, $p < .001$, RMSEA .03, 90% CI [.03, .04], CFI .95 SRMR .04.

Note: * $p < .05$, ** $p < .01$, *** $p < .001$.

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