## Appendix

### I. Description of the Chicago Area Study Data

The Chicago Area Study (CAS) was an online survey administered by the research firm Gfk for the Institute for Government and Public Affairs at the University of Illinois between August 15 and September 16 in 2014. The CAS includes 1,794 total respondents, with 500 respondents from around the state of Illinois and 1,274 sampled from the Chicago metropolitan area. Treating Chicago as a case study, we exclude the representative state sample of 500 from the analysis. The Chicago metropolitan area sample includes eligible voters in Cook County and the five collar counties (i.e., DuPage, Kane, Lake, McHenry and Will counties). Median time to completion was 28 minutes. The survey included a probability KnowledgePanel from Knowledge Networks, with an incidence rate of 93 percent (n=946). This was combined with a non-probability opt-in web panel, with an incidence rate of four percent (n=848). Additional information regarding KnowledgePanel sampling and data collection procedures are available at http://www.knowledgenetworks.com/ganp/reviewer-info.html.

Table A1 displays descriptive statistics for variables from the CAS included in our analysis, including the mean, standard deviation and the minimum and maximum values. Table A2 displays the correlations between all variables. Coding of key variables in the analysis is described in the article. However, our choice to code nonvoting political participation as a straightforward index of activities requires elaboration here. The variable ranges from 0-7. It includes participation in a wide variety of activities (e.g., volunteering, donating to a political cause, signing petitions, etc.). As underlying conditions may increase individual participation in certain types of political activities relative to other types of political activities, we examined different iterations of the nonvoting political participation index, collapsing and/or excluding items to produce subsets of participation indices. Scale variations produced comparable relationships between key independent and dependent variables. We elected to include all nonvoting activities in a single index.

**Table A1. Summary Statistics—Chicago Area Study, Metro Chicago Subsample**

| Variable | Mean | Standard Deviation | Min | Max |
|---|---|---|---|---|
| Registered | 0.883189 | 0.321318 | 0 | 1 |
| Voted | 0.787504 | 0.409231 | 0 | 1 |
| Nonvoting | 1.511869 | 1.177441 | 0 | 7 |
| Detained (i.e. Questioned) | 0.112174 | 0.315702 | 0 | 1 |
| Correctional Control (i.e. Prison) | 0.048731 | 0.215388 | 0 | 1 |
| CSO Connection | 0.42428 | 0.494424 | 0 | 1 |
| Black | 0.15546 | 0.362482 | 0 | 1 |
| Latino | 0.224152 | 0.417183 | 0 | 1 |
| Other Race | 0.094974 | 0.293291 | 0 | 1 |
| Political Interest | 2.644216 | 1.108069 | 1 | 4 |
| Efficacy | 2.856627 | 0.799743 | 1 | 4 |
| Education | 3.022498 | 0.993784 | 1 | 4 |
| Female | 0.508456 | 0.500121 | 0 | 1 |
| Age: 18-34 | 0.303693 | 0.460029 | 0 | 1 |
| Age: 65+ | 0.15857 | 0.365416 | 0 | 1 |
| Democrat | 0.415249 | 0.492955 | 0 | 1 |
| Independent | 0.369161 | 0.482764 | 0 | 1 |
| Income | 3.096861 | 1.733759 | 1 | 6 |
| Married | 0.489279 | 0.500078 | 0 | 1 |
| Unemployed | 0.143731 | 0.350952 | 0 | 1 |

**Table A2. Correlation Matrix—Chicago Area Study, Metro Chicago Subsample**

| | Registered | Vote | Nonvoting | Detained | Correctional Control | Personal Connection to CSO | Black | Latino | Other | Political Interest | Efficacy | Education | Female | Age:18-34 | Age: 65+ | Democrat | Independent | Income | Married | Unemployed |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Registered | 1 | | | | | | | | | | | | | | | | | | | |
| Vote | .69 | 1 | | | | | | | | | | | | | | | | | | |
| Nonvoting | .06 | .07 | 1 | | | | | | | | | | | | | | | | | |
| Detained | .05 | -.02 | .11 | 1 | | | | | | | | | | | | | | | | |
| Correctional Control | -.09 | -.08 | .05 | .17 | 1 | | | | | | | | | | | | | | | |
| Personal Connection to CSO | .14 | .20 | .23 | .04 | .01 | 1 | | | | | | | | | | | | | | |
| Black | .07 | .08 | -.04 | .09 | .09 | .05 | 1 | | | | | | | | | | | | | |
| Latino | -.12 | -.14 | .03 | .09 | -.04 | -.10 | -.21 | 1 | | | | | | | | | | | | |
| Other | -.14 | -.17 | .01 | -.07 | .11 | -.13 | -.13 | -.17 | 1 | | | | | | | | | | | |
| Political Interest | .07 | .14 | .24 | .02 | .05 | .16 | -.01 | -.15 | .03 | 1 | | | | | | | | | | |
| Efficacy | .13 | .19 | .19 | .02 | .13 | .12 | .01 | -.14 | .04 | .46 | 1 | | | | | | | | | |
| Education | .04 | .10 | .08 | .04 | -.19 | .24 | -.12 | -.11 | -.06 | .09 | .07 | 1 | | | | | | | | |
| Female | -.02 | -.01 | -.03 | -.09 | .01 | -.02 | .10 | -.04 | -.05 | -.15 | -.26 | -.07 | 1 | | | | | | | |
| Age: 18-34 | -.18 | -.24 | .10 | .09 | .20 | -.07 | -.03 | .28 | .17 | -.17 | -.13 | -.07 | .13 | 1 | | | | | | |
| Age: 65+ | .12 | .16 | -.02 | -.07 | -.10 | .06 | .02 | -.21 | -.11 | .22 | .13 | .00 | -.01 | -.28 | 1 | | | | | |
| Democrat | .10 | .15 | -.05 | -.04 | .00 | -.01 | .31 | .10 | -.14 | -.02 | -.03 | -.06 | .12 | -.07 | .00 | 1 | | | | |
| Independent | -.16 | -.22 | .02 | .06 | -.04 | -.02 | -.17 | .00 | .18 | .00 | -.08 | .12 | -.06 | .16 | -.01 | -.63 | 1 | | | |
| Income | .13 | .19 | .05 | -.06 | -.04 | .24 | -.17 | -.16 | -.07 | .09 | .15 | .40 | -.03 | -.19 | -.06 | -.05 | -.05 | 1 | | |
| Married | .06 | .12 | .04 | -.02 | -.05 | .16 | -.16 | -.11 | -.05 | .06 | .11 | .15 | -.06 | -.30 | .00 | -.06 | -.09 | .52 | 1 | |
| Unemployed | -.06 | -.15 | .06 | .13 | .02 | -.10 | .03 | .10 | .07 | -.12 | -.17 | -.15 | .17 | .24 | -.15 | -.04 | .12 | -.20 | -.07 | 1 |

### a. Criminal Justice Contact: CAS Demographics

Table A3 compares the demographic composition of the subsample of individuals in the CAS who have been under correctional control and/or detained by the police for questioning to known statistics for the general population of custodial citizens. It is difficult to find accurate and current demographic characteristics of the custodial population of the Chicago metropolitan area, inclusive of those who have served time in prison, have been on probation/parole, or have otherwise been detained by the police at some point in time in Chicago and the surrounding suburbs. We reviewed demographic information for the Illinois prison and parole populations in 2014, provided by the Illinois Department of Corrections. We also reviewed a summary of the demographic composition of Cook County jail admissions in 2011, provided by the Cook County Sherriff's Office.

We lack data on the demographics of stops (i.e., pedestrian or driver) or arrests that do not lead to admissions, charges, or convictions; individuals who spend time in jail in any of the other five counties under study; those who spent time in federal prison in Illinois; or those who may have been sentenced to probation without prison or jail. As Table A3 demonstrates, custodial citizens in the CAS are more female, less Black, more Latino, older and more likely to be married than the cohort of individuals admitted to the Cook County jail in 2011 and the Illinois state prison population in 2010. That the CAS subsample is older, more likely to be married, and disproportionately white likely skews the findings in our favor.

**Table A3. Comparison of survey sample of those with criminal justice contact to known population statistics**

| | Cook county jail admissions 2011[a] | Prison & Parole Population, Illinois 2014[b] | Chicago Area Study 2014 |
|---|---|---|---|
| % Male | 87 | 93 | 59 |
| % Black | 67 | 59 | 25 |
| % White | 14 | 29 | 42 |
| % Latino | 20 | 12 | 28 |
| Avg. Age | 33 | 37 | 44 |
| % Married | 14 | 15 | 50 |

[a] *Cook county jail admissions data come from a report by the Cook County Sherriff's Reentry Council, found here:* *https://ecommons.luc.edu/cgi/viewcontent.cgi?article=1000&context=criminaljustice_facpubs*
[b] *Data on the state prison population come from Illinois Department of Corrections, available fromhttps://www2.illinois.gov/idoc/reportsandstatistics/Documents/FY2014 Annual Report.pdf; Data only available for prison population.*

## II. Description of the Aggregate Data

The aggregate dataset allowed us to evaluate the relationship between CSO density, the density of felony convictions and four measures of political participation: voter turnout in 2014, voter turnout in 2015, 311 calls per 1,000 people in the population in 2014, and the mean rate of attendance at police beat meetings between 2013-2015. It also includes a battery of relevant community-level covariates from the 2014 American Communities Survey (five-year estimates) of the U.S. Census Bureau. The aggregate-level data allow a broader exploration of the association among unwanted criminal justice contact, CSOs, and political participation. It permits a validity test of the results from the CAS-based, individual-level analysis. Nonetheless, we recognize the limitations of drawing inferences about individual behavior from aggregate data and that aggregation reduces statistical power and opportunities for interactions between variables.

There are three spatial units for analysis in the context of our Chicago study: police beat, voter precinct, and census tract. Voter turnout is measured at the precinct level. The set of demographic controls in the fully specified models are measured at the census tract level. Attendance at police beat meetings is measured at the police beat level. In Chicago, police beats (N=270) are the largest of the three spatial units. Census tracts (N=802) are the next largest of the three spatial units in the city. Voter precincts (N=2,582) are the smallest spatial units in the city. Using simple area weighting, we evaluate the data at the level of police beats. Aggregating data upward generates more precise estimates than disaggregating them into smaller units. We used ArcMap to re-estimate the data at the level of police beat.

We obtained geospatial data for the remaining variables—felony convictions, 311 calls, and the presence of civils society organizations (CSOs) in the city of Chicago. For instance, the underlying data for 311 calls included the call and the address from which it originated. Using ArcMap, we geocoded each variable, located each observation within its respective police beat, and obtained a count for each variable in each police beat. We then calculated the rate of 311 calls, felony convictions, and CSOs per 1,000 people by police beat. The body of the article describes our data on 311 calls and CSO densities. Our measure of felony convictions at the community level requires elaboration here, as does our explanation for why we exclude other aggregate measures of criminal justice contact.

Data on felony convictions in Chicago are available from the Chicago Justice Project (CJP). It acquired the data from the Office of the Chief Judge of the Circuit Court of Cook County (CCCC), to support an open data initiative with the Civic Works Project of the Smart Chicago Collaborative, funded by the Knight Foundation and the Chicago Community Trust, with coding provided by the Supreme Chi-Town Coding Crew of FreeGeek Chicago. CJP received the data after threatening the Clerk of the CCCC with litigation. The data include records of criminal convictions and sentences by the Criminal Division of the CCCC between 2005 and 2009. It includes 173,204 individuals charged with felonies by the State's Attorney.

The original dataset we obtained from CJP included a small set of misdemeanor convictions. Neither CJP nor we could determine whether the misdemeanors were true misdemeanors or felonies converted to misdemeanors during adjudication. We do know, based on annual caseload reports from the Clerk of the CCCC, that the number of misdemeanors in the original data set represented a tiny fraction of the universe of misdemeanor cases adjudicated between 2005 and 2009. Therefore, we excluded the misdemeanor records. The data also do not include the race of defendants, initial charge(s) against defendants, or prior convictions of defendants, which may have influenced CCCC rulings on cases. Furthermore, "Class 4" or low-level felonies suitable for 1 to 3 years of imprisonment and maximum fines of $25,000 (e.g., possession of 30-500 grams of marijuana, aggravated assault, stalking, first-time weapons offenses, and second-time domestic battery) comprise most convictions in the dataset.

We know felony conviction rates do not reflect all the dimensions of criminal justice contact at the level of communities. For instance, conviction rates reveal nothing about detentions by police of civilians for questioning during traffic and pedestrian stops or arrests of civilians without charges or convictions. We hoped to include investigatory stop data in our analysis, mirroring to some degree extant analyses of the influences of "stop-and-frisk," over-policing, and aggressive policing on political behavior and attitudes in other cities.[1] Although investigatory stop data is available from the Chicago Police Department, it is only available for determining police stops of civilians since 2016. Our outcome variables predate 2016.

The crime rate could be a crude measure of criminal justice contact, as well as a confounder affecting nonvoting political participation such as calls to the 311-nonemergency system or attendance at police-community meetings. Crime rate data are available and we explored using them in our final models. Crime rates and felony conviction rates in Chicago, however, are highly correlated (.76, p<.001). Including crime rates in the models causes felony conviction rates to lose statistical significance. Substituting crime rates for felony conviction rates reveals substantively similar relationships between crime rate and 311 calls, attendance at police beat meeting, and voting. The crime rate, however, is a noisier measure of criminal justice contact than the felony conviction rate at the aggregate-level. Consequently, we only included felony conviction rate as one of our two key independent variables, alongside CSO density.

Table A4 displays the descriptive statistics for each variable included in the aggregate analysis. Table A5 includes the correlations between the variables.

**Table A4. Summary Statistics for Chicago Communities (i.e., Police Beats)**

| Variable | Mean | Standard Deviation | Min | Max |
|---|---|---|---|---|
| Turnout 2014 | 0.4721974 | 0.0791275 | 0.2818991 | 0.6682504 |
| Turnout 2015 | 0.3845028 | 0.0709097 | 0.2548666 | 0.5840403 |
| CAPS Meeting Attendance, per 1k | 3.627306 | 3.08605 | .5505524 | 36.16111 |
| 311 Calls, per 1k | 87.54144 | 38.24694 | 1.875586 | 220.9799 |
| log(convictions per 1k) | 1.467256 | 1.278755 | -4.60517 | 3.485244 |
| log(CSOs per 1k) | 0.3048258 | 0.856416 | -3.154606 | 5.022093 |
| % Owner Occupied Housing | 0.8426338 | 0.0712818 | 0.6362199 | 0.9483946 |
| % 18-34 | 0.3017615 | 0.0981003 | 0.1556468 | 0.6416742 |
| % 65+ | 0.1065698 | 0.0400492 | 0.0260632 | 0.2271568 |
| % Black | 0.4430794 | 0.3906857 | 0.0047804 | 0.9861732 |
| % Latino | 0.2293612 | 0.252215 | 0.0022183 | 0.9223155 |
| % BA+ | 0.3077995 | 0.2397754 | 0.0347437 | 0.8606575 |
| % Poverty | 0.2470364 | 0.1122547 | 0.0559867 | 0.5659656 |
| % Unemployed | 0.3636436 | 0.0990407 | 0.1192998 | 0.5765404 |

| Table A5: Correlation Matrix—Chicago Communities (Police Beats) | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Turnoutv2014 | Turnout 2015 | CAPS Meeting Attendance, per 1k | 311 Calls, per 1k | log(convict) | log(CSOs per 1k) | % Owner-Occupied Housing | % 18-35 | % 65+ | % Black | % Latino | % BA+ | % Poverty | % Unemployed |
| Turnout 2014 | 1 | | | | | | | | | | | | | |
| Turnout 2015 | .61 | 1 | | | | | | | | | | | | |
| CAPS Meeting Attendance, per 1k | .07 | .04 | 1 | | | | | | | | | | | |
| 311 Calls, Per 1k | -.19 | .16 | .13 | 1 | | | | | | | | | | |
| log(Convict) | -.31 | -.53 | .24 | .17 | 1 | | | | | | | | | |
| log(CSOs per 1k) | .52 | .05 | .05 | -.18 | -.24 | 1 | | | | | | | | |
| % Owner-Occupied Housing | .28 | .67 | -.09 | .17 | -.52 | -.11 | 1 | | | | | | | |
| % 18-35 | .11 | .03 | -.18 | -.34 | -.59 | .36 | .23 | 1 | | | | | | |
| % 65+ | .46 | .37 | .09 | .17 | .13 | .19 | .01 | -.57 | 1 | | | | | |
| % Black | .07 | -.52 | .17 | -.04 | .70 | .13 | -.67 | -.50 | .35 | 1 | | | | |
| % Latino | -.65 | .09 | -.09 | .32 | -.06 | -.60 | .28 | -.02 | -.40 | -.57 | 1 | | | |
| % BA+ | .57 | .42 | -.18 | -.31 | -.73 | .50 | .47 | .78 | -.16 | -.53 | -.28 | 1 | | |
| % Poverty | -.39 | -.72 | .17 | -.18 | .72 | -.13 | -.81 | -.36 | -.06 | .73 | -.16 | -.66 | 1 | |
| % Unemployed | -.28 | -.46 | .17 | .08 | .69 | -.13 | -.66 | -.66 | .35 | .77 | -.15 | -.80 | .77 | 1 |

## III. Analysis of the Chicago Area Study

### a. Nonvoting Political Participation Battery

Table A6 and A7 display the full models evaluating the relationship between a CAS respondent having been under correctional control, having been detained by the police, and connections to CSOs and each item in the nonvoting political participation battery. CSO connections are positively correlated with all activities but one, namely having written an op-ed or called into a radio show. Having been under correctional control is positively associated with volunteering and having donated to a political or social cause. Having been detained by the police is positively correlated with signing petitions and writing letters to public officials. Since there is no apparent pattern in the types activities underlying the positive relationships observed in the main analysis, we elected to use a conventional nonvoting political participation index.

**Table A6. Effects of Involuntary Criminal Justice Contact on Nonvoting Political Activities**

| | Petition | Share | Protest | Letter |
|---|---|---|---|---|
| Correctional Control | 0.012 (0.347) | -0.624 (0.499) | 0.263 (0.561) | 0.636 (0.394) |
| Detained by Police | 0.604** (0.198) | 0.380 (0.240) | 0.457 (0.308) | 0.694** (0.233) |
| CSO Connection | 0.732*** (0.135) | 0.533** (0.177) | 1.832*** (0.292) | 0.898*** (0.177) |
| Black | 0.041 (0.201) | -0.084 (0.273) | -0.766 (0.418) | -0.250 (0.262) |
| Latino | 0.196 (0.184) | 0.164 (0.236) | 0.580 (0.310) | 0.221 (0.238) |
| Other Race | -0.483 (0.279) | 0.129 (0.320) | 0.584 (0.431) | -0.270 (0.369) |
| Political Interest | 0.330*** (0.070) | 0.468*** (0.095) | 0.808*** (0.153) | 0.396*** (0.094) |
| Political Efficacy | 0.174 (0.101) | 0.281* (0.134) | 0.429* (0.193) | 0.554*** (0.138) |
| Education | 0.241** (0.084) | 0.283* (0.112) | 0.187 (0.161) | 0.253* (0.110) |
| Female | 0.154 (0.135) | 0.313 (0.176) | -0.812** (0.252) | 0.144 (0.171) |
| Age: 18-34 | 0.385* (0.169) | 1.026*** (0.212) | 0.244 (0.292) | 0.130 (0.221) |
| Age: 65+ | -0.084 (0.184) | -0.155 (0.246) | -1.047** (0.373) | 0.254 (0.220) |
| Democrat | 0.069 (0.184) | -0.250 (0.232) | 0.569 (0.337) | -0.008 (0.220) |
| Independent | 0.085 (0.184) | -0.303 (0.231) | 0.089 (0.343) | -0.510* (0.230) |
| Income | -0.050 (0.048) | -0.071 (0.062) | 0.032 (0.086) | 0.091 (0.061) |
| Married | -0.077 (0.153) | 0.255 (0.201) | -0.492 (0.281) | -0.067 (0.197) |
| Unemployed | 0.172 (0.206) | 0.114 (0.264) | 0.765* (0.364) | 0.286 (0.278) |
| Constant | -3.384*** (0.426) | -5.284*** (0.587) | -7.977*** (0.917) | -6.110*** (0.599) |
| Observations | 1,229 | 1,229 | 1,229 | 1,229 |
| Log Likelihood | -689.689 | -458.62 | -248.345 | -461.939 |
| Akaike Inf. Crit. | 1,415.38 | 953.239 | 532.691 | 959.877 |

*Activities are modeled using logistic regression; *p<.05; **p<.01; ***p<.001.*

**Table A7. Effects of Involuntary Criminal Justice Contact on Nonvoting Political Activities**

| | Donate | Volunteer | Opinion |
|---|---|---|---|
| Correctional Control | 1.408** (0.437) | 1.276* (0.542) | -0.609 (0.330) |
| Detained by Police | -0.524 (0.337) | 0.246 (0.352) | 0.016 (0.196) |
| CSO Connection | 0.980*** (0.237) | 2.193*** (0.378) | -0.675*** (0.129) |
| Black | -0.005 (0.363) | 0.202 (0.400) | -0.214 (0.191) |
| Latino | 0.801** (0.286) | 0.925* (0.367) | -0.320 (0.175) |
| Other Race | -0.350 (0.490) | 0.217 (0.609) | -0.040 (0.250) |
| Political Interest | 0.556*** (0.128) | 0.404* (0.161) | -0.077 (0.065) |
| Political Efficacy | 0.430* (0.176) | 0.628** (0.222) | -0.240* (0.096) |
| Education | 0.191 (0.141) | 0.595** (0.193) | -0.161* (0.079) |
| Female | -0.033 (0.223) | -0.366 (0.274) | -0.192 (0.129) |
| Age: 18-34 | 0.872*** (0.264) | -0.252 (0.353) | -0.305 (0.161) |
| Age: 65+ | -0.086 (0.315) | -0.142 (0.358) | -0.179 (0.175) |
| Democrat | -0.776** (0.293) | -0.393 (0.334) | 0.212 (0.172) |
| Independent | -0.517 (0.284) | -1.098** (0.365) | 0.316 (0.173) |
| Income | -0.013 (0.079) | -0.155 (0.101) | -0.047 (0.046) |
| Married | -0.105 (0.257) | -0.199 (0.319) | 0.361* (0.147) |
| Unemployed | 0.609 (0.323) | 0.977* (0.400) | -0.089 (0.198) |
| Constant | -6.342*** (0.777) | -8.508*** (1.062) | 2.310*** (0.394) |
| Observations | 1,229 | 1,229 | 1,229 |
| Log Likelihood | -315.47 | -194.852 | -750.976 |
| Akaike Inf. Crit. | 666.94 | 425.704 | 1,537.95 |

*Activities are modeled using logistic regression; *p<.05; **p<.01; ***p<.001.*

## b. Fully specified models, re: the moderating effect of CSO connections on participation among those with and without criminal justice contact

**Table A8. The Interactive Effects of Contact and CSO Connections on Political Participation**

| | Registered to Vote | Voted in 2012 | Nonvoting Political Participation |
|---|---|---|---|
| Correctional Control | -0.160 (0.662) | -1.565** (0.574) | -0.213 (0.196) |
| CSO Connection | 0.601* (0.243) | 0.551* (0.273) | 0.255*** (0.054) |
| Detained by Police | 0.533 (0.419) | 0.519 (0.471) | 0.131 (0.112) |
| Correctional Control*CSO | 0.356 (1.483) | 2.518 (1.389) | 0.519* (0.249) |
| Detained*CSO | 1.027 (1.025) | -0.911 (0.676) | 0.109 (0.139) |
| Black | 0.277 (0.397) | 0.390 (0.383) | -0.087 (0.075) |
| Latino | -0.588* (0.266) | -0.168 (0.308) | 0.100 (0.066) |
| Other Race | -0.552 (0.342) | -0.610 (0.397) | -0.069 (0.098) |
| Political Interest | 0.052 (0.108) | 0.307** (0.117) | 0.165*** (0.026) |
| Political Efficacy | 0.471** (0.152) | 0.271 (0.162) | 0.107** (0.037) |
| Education | -0.002 (0.130) | 0.235 (0.139) | 0.077* (0.031) |
| Female | 0.082 (0.224) | 0.082 (0.241) | -0.014 (0.049) |
| Age: 18-34 | -0.518* (0.250) | -0.168 (0.274) | 0.148* (0.061) |
| Age: 65+ | 1.282* (0.505) | 0.846* (0.424) | -0.062 (0.067) |
| Democrat | 0.328 (0.333) | 0.530 (0.341) | 0.001 (0.066) |
| Independent | -0.556 (0.303) | -0.424 (0.309) | -0.041 (0.066) |
| Income | 0.162* (0.079) | 0.265** (0.089) | -0.017 (0.018) |
| Married | -0.344 (0.250) | 0.119 (0.276) | 0.035 (0.056) |
| Unemployed | -0.199 (0.276) | -0.628* (0.288) | 0.133 (0.074) |
| Constant | 0.527 (0.610) | -0.997 (0.681) | -0.759*** (0.153) |
| Observations | 1,229 | 1,140 | 1,229 |
| Log Likelihood | -335.809 | -290.046 | -1,696.76 |
| Akaike Inf. Crit. | 711.619 | 620.092 | 3,433.52 |

*[a]Registered to vote and voted in 2012 are modeled using logistic regression. [b]We evaluate non-voting participation using a Poisson regression model. *p<.05; **p<.01; ***p<.001.*

## c. Robustness Checks

The CAS under-sampled individuals with involuntary criminal justice contact, raising questions about the distribution of those with criminal justice contact and CSO connections in relationship to political participation. Specifically, low N-values in cells with CSO connections and without them among those who report criminal justice contact and those who do not may be insufficient to generate reliable estimates from multivariate interaction models, referred to as a lack of common support. To assess common support, we follow recommended tests,[2] which begin with an assessment of bivariate relationships among key variables of interest (Figure A1).

The top panel of Figure A1 displays the relationship among those who have been under correctional control. The bottom plot displays the relationship among those who have been detained by the police. The plots suggest there is an issue of common support among those who have been under correctional control. There are very few individuals within the context of the overall CAS sample who report having been under correctional control. Even so, those who have had correctional control are relatively distributed evenly across levels of the moderator (i.e., CSO connections, coded 0/1). Therefore, we proceeded with additional robustness checks to evaluate the validity and stability of the models.

We evaluate the stability of the findings by subjecting them to a variety of specifications and model choices (Tables A9-A11). We model the data using Poisson (Table A9), Ordinary Least Squares (Table A10), and quasi-Poisson (Table A11). We treat the data as an unbounded count, modeled using Poisson. However, since the nonvoting political participation index ranges from 0-7, OLS might be suitable. Alternatively, count data often are overdispersed. Therefore, a model that relaxes the Poisson assumption that the variance is equal to the mean is preferred. A negative binomial regression model is the most common alternative. Table A9 includes results from a test for overdispersion. It reveals an absence of overdispersion. In fact, the data are slightly underdispersed. Accordingly, negative binomial regression models of the data fail to converge, and reverts to a Poisson distribution. We might still be concerned that Poisson is not the best fit and wish to subject the data to an alternative model that accounts for both overdispersion and underdispersion. Accordingly, we model the data using quasi-Poisson.

Substantively speaking, the findings discussed in the main body of the article hold, even when modeled using quasi-Poisson.

For each model choice, we first evaluate the key independent variables of interest. We do this to assess whether the statistical findings produced by fully specified models are a result of saturation or near saturation. We then add a set of variables most commonly associated with political participation, including race, education, income, age and gender. The final model further includes political efficacy and interest, party identification, marital status and employment status. In sum, the substantive findings presented in the article hold across nine model specifications, improving confidence in the internal validity of the data and analysis.

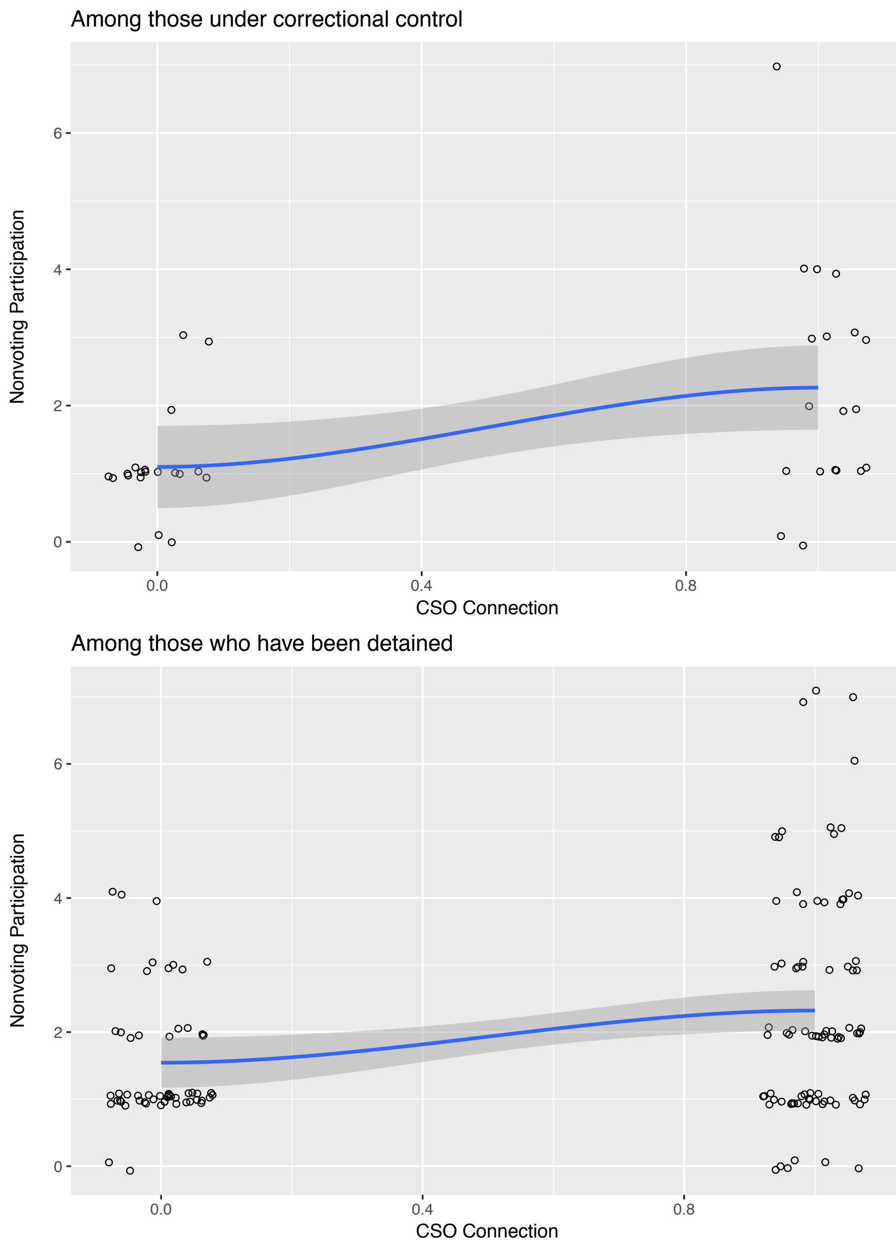


Figure A1: The bivariate relationship between CSO connections and non-voting participation.

**Table A9. The Interactive Effects of Contact and CSO Connections on Political Participation (Poisson)**

| | Model 1 | Model 2 | Model 3 |
|---|---|---|---|
| Correctional Control | -0.199 (0.193) | -0.170 (0.194) | -0.213 (0.196) |
| CSO Connection | 0.366*** (0.050) | 0.332*** (0.052) | 0.255*** (0.054) |
| Detained by Police | 0.218** (0.109) | 0.155 (0.110) | 0.131 (0.112) |
| Correctional Control *CSO | 0.430* (0.244) | 0.529** (0.246) | 0.519** (0.249) |
| Detained*CSO | 0.071 (0.136) | 0.123 (0.137) | 0.109 (0.139) |
| Black | | -0.068 (0.069) | -0.087 (0.075) |
| Latino | | 0.088 (0.063) | 0.100 (0.066) |
| Other Race | | -0.044 (0.095) | -0.069 (0.098) |
| Education | | 0.089*** (0.030) | 0.077** (0.031) |
| Female | | -0.084* (0.047) | -0.014 (0.049) |
| Age: 18-34 | | 0.077 (0.057) | 0.148** (0.061) |
| Age: 65+ | | 0.036 (0.065) | -0.062 (0.067) |
| Income | | -0.013 (0.015) | -0.017 (0.018) |
| Political Interest | | | 0.165*** (0.026) |
| Political Efficacy | | | 0.107*** (0.037) |
| Democrat | | | 0.001 (0.066) |
| Independent | | | -0.041 (0.066) |
| Married | | | 0.035 (0.056) |
| Unemployed | | | 0.133* (0.074) |
| Constant | 0.184*** (0.036) | -0.029 (0.108) | -0.759*** (0.153) |
| Observations | 1,294 | 1,294 | 1,229 |
| Log Likelihood | -1,834.09 | -1,822.70 | -1,696.76 |
| Akaike Inf. Crit. | 3,680.19 | 3,673.40 | 3,433.52 |
| Test for overdispersion | .779 | .765 | .660 |

**p<.1; **p<.05; ***p<.01. Tests for overdispersion were carried out using the R package "AER," following the methods developed by Cameron and Trivedi (1990).*[3]

**Table A10. The Interactive Effects of Contact and CSO Connections on Political Participation (Ordinary Least Squares Regression)**

| | Model 1 | Model 2 | Model 3 |
|---|---|---|---|
| Correctional Control | -0.244 (0.235) | -0.203 (0.235) | -0.256 (0.235) |
| CSO Connection | 0.529*** (0.069) | 0.481*** (0.071) | 0.364*** (0.072) |
| Detained by Police | 0.287* (0.148) | 0.196 (0.149) | 0.180 (0.147) |
| Correctional Control*CSO | 0.753** (0.355) | 0.890** (0.355) | 0.833** (0.350) |
| Detained*CSO | 0.305 (0.204) | 0.379* (0.204) | 0.357* (0.201) |
| Black | | -0.100 (0.093) | -0.120 (0.099) |
| Latino | | 0.130 (0.089) | 0.149 (0.091) |
| Other Race | | -0.070 (0.126) | -0.119 (0.128) |
| Education | | 0.124*** (0.040) | 0.105*** (0.040) |
| Female | | -0.125* (0.065) | -0.014 (0.067) |
| Age: 18-34 | | 0.115 (0.080) | 0.222*** (0.084) |
| Age: 65+ | | 0.056 (0.090) | -0.085 (0.091) |
| Income | | -0.020 (0.021) | -0.024 (0.024) |
| Political Interest | | | 0.236*** (0.033) |
| Political Efficacy | | | 0.156*** (0.049) |
| Democrat | | | 0.001 (0.090) |
| Independent | | | -0.046 (0.090) |
| Married | | | 0.062 (0.076) |
| Unemployed | | | 0.191* (0.102) |
| Constant | 1.203*** (0.045) | 0.920*** (0.143) | -0.112 (0.197) |
| Observations | 1,294 | 1,294 | 1,229 |
| Adjusted R2 | 0.081 | 0.093 | 0.152 |

**p<.05; **p<.01; ***p<.001.*

**Table A11. The Interactive Effects of Contact and CSO Connections on Political Participation (Quasi-Poisson)**

| | Model 1 | Model 2 | Model 3 |
|---|---|---|---|
| Correctional Control | -0.199 (0.173) | -0.170 (0.171) | -0.213 (0.161) |
| CSO Connection | 0.366*** (0.044) | 0.332*** (0.046) | 0.255*** (0.044) |
| Detained by Police | 0.218** (0.097) | 0.155 (0.097) | 0.131 (0.092) |
| Correctional Control*CSO | 0.430* (0.218) | 0.529** (0.216) | 0.519** (0.204) |
| Detained*CSO | 0.071 (0.122) | 0.123 (0.120) | 0.109 (0.114) |
| Black | | -0.068 (0.061) | -0.087 (0.062) |
| Latino | | 0.088 (0.055) | 0.100* (0.054) |
| Other Race | | -0.044 (0.083) | -0.069 (0.081) |
| Education | | 0.089*** (0.026) | 0.077** (0.025) |
| Female | | -0.084* (0.041) | -0.014 (0.040) |
| Age: 18-34 | | 0.077 (0.050) | 0.148** (0.050) |
| Age: 65+ | | 0.036 (0.057) | -0.062 (0.055) |
| Income | | -0.013 (0.013) | -0.017 (0.014) |
| Political Interest | | | 0.165*** (0.021) |
| Political Efficacy | | | 0.107*** (0.031) |
| Democrat | | | 0.001 (0.054) |
| Independent | | | -0.041 (0.054) |
| Married | | | 0.035 (0.046) |
| Unemployed | | | 0.133* (0.061) |
| Constant | 0.184*** (0.032) | -0.029 (0.095) | -0.759*** (0.125) |
| Observations | 1,294 | 1,294 | 1,229 |
| Estimated Scale Parameter | .799 | .772 | .673 |

## IV. Analysis of the Supplemental Aggregate Data

### a. Fully specified models: The moderating effect of CSO density on participation among high conviction police beats

**Table A12. Interactive Effect of Conviction Rates and CSO Densities on Voting and Nonvoting Political Participation**

| | 2014 Voter Turnout | 2015 Voter Turnout | CAPS Meeting Attendance | 311 Calls |
|---|---|---|---|---|
| log(Convictions) | -0.005 | -0.006 | 0.567 | 10.046*** |
| | (0.004) | (0.004) | (0.378) | (2.940) |
| log(CSOs) | 0.004 | -0.003 | 0.847** | 9.568** |
| | (0.004) | (0.004) | (0.326) | (3.250) |
| Convictions*CSOs | -0.001 | -0.002 | -0.048 | 1.117 |
| | (0.002) | (0.002) | (0.145) | (1.275) |
| % 18-34 | -0.351*** | -0.305*** | -0.057 | 15.511 |
| | (0.063) | (0.063) | (4.941) | (49.095) |
| % 65+ | 0.301** | 0.606*** | -0.959 | 19.140 |
| | (0.108) | (0.109) | (8.471) | (84.462) |
| % Black | 0.082*** | -0.030 | -3.335* | 25.466 |
| | (0.018) | (0.019) | (1.447) | (14.378) |
| % Latino | -0.056* | 0.052* | -5.081* | 56.397** |
| | (0.025) | (0.025) | (1.974) | (19.713) |
| % College Graduate | 0.288*** | 0.178*** | -7.513* | -79.811* |
| | (0.040) | (0.040) | (3.254) | (30.961) |
| % Poor | -0.018 | -0.077 | 6.048 | -304.029*** |
| | (0.056) | (0.056) | (4.364) | (43.537) |
| % Unemployed | -0.024 | 0.080 | -5.856 | -4.058 |
| | (0.065) | (0.066) | (5.139) | (50.898) |
| % Owner Occupied | 0.235*** | 0.236*** | 9.700 | -39.875 |
| | (0.064) | (0.064) | (5.002) | (49.903) |
| Constant | 0.256*** | 0.160* | 0.065 | 173.482** |
| | (0.069) | (0.070) | (5.488) | (54.236) |
| Observations | 270 | 270 | 268 | 270 |
| Adjusted R2 | 0.773 | 0.713 | 0.076 | 0.4 |

[a]All dependent variables are continuous, and modeled using Ordinary Least Squares regression. *p<.05; **p<.01; ***p<.001.

**b. Robustness check**

From the aggregate analysis, we concluded that the density of CSOs in a given police beat increases demands made of local government via 311 calls and participation in police beat meetings. We concluded that the positive impact of CSOs held among both low and high conviction communities. We found that even after interacting CSO density and conviction rate, the positive impact of both variables persisted regarding 311 calls. The possibility remains, however, that communities with high conviction rates contact government officials more because of the community-level needs or deficits related to conviction rates. To address the possibility, we employed a matching causal inference strategy.[4] We interpret the results presented in the article to mean that CSO density increases nonvoting political behaviors in both high and low conviction communities, and that these trends are not due simply to higher levels of need in high conviction communities. To establish this empirically, we needed to compare the impact of CSO density among similarly situated communities that differ only on conviction rate (treatment = high conviction rate; control = low conviction rate).

High conviction communities are different from low conviction communities on multiple dimensions (e.g., poverty and race) that might influence variation in requests of police and the government.[5] We, therefore, matched communities on a set of demographic attributes, including poverty, unemployment, home ownership, race, age, and educational attainment. We classified high conviction police beats as those falling one standard deviation above the mean level of convictions per capita. Overall, we generated a total of 88 police beats for evaluation, with 44 high conviction beats and 44 low conviction beats, matched on mean demographics. A comparison of mean levels of each variable for matched police beats demonstrates that treatment and control groups are far more balanced post-match than pre-match. For example, the mean percentage of individuals with incomes below the federal poverty line in high conviction police beats pre-match was 38, compared to a mean of 22 percent in low conviction police beats. The match yielded a mean of 34 percent of individuals with poverty level or lesser incomes in low conviction beats. Tables A13 and A14 demonstrate the improvement in balance between high and low conviction police beats resulting from processing the data via matching.

**Table A13: Summary of Balance for All Data (Pre-match)**

| | Means Treated | Means Control | SD Control | Mean Diff | eQQ Med | eQQ Mean | eQQ Max |
|---|---|---|---|---|---|---|---|
| distance | 0.614 | 0.0752 | 0.161 | 0.5388 | 0.5607 | 0.5322 | 0.8421 |
| % Poverty | 0.3787 | 0.2214 | 0.1012 | 0.1573 | 0.1547 | 0.1581 | 0.2085 |
| % Unemployed | 0.4737 | 0.3422 | 0.0923 | 0.1315 | 0.127 | 0.1333 | 0.2613 |
| % Homeowner | 0.7586 | 0.859 | 0.0611 | -0.1005 | 0.1044 | 0.0986 | 0.1254 |
| % Black | 0.8777 | 0.3585 | 0.3683 | 0.5192 | 0.6925 | 0.5192 | 0.817 |
| % Latino | 0.0896 | 0.2566 | 0.2629 | -0.167 | 0.1062 | 0.1695 | 0.517 |
| % < 18 | 0.2561 | 0.3106 | 0.1044 | -0.0545 | 0.0262 | 0.0668 | 0.3136 |
| % 65+ | 0.1036 | 0.1071 | 0.0425 | -0.0035 | 0.0141 | 0.0164 | 0.062 |
| % College Educated | 0.1035 | 0.3476 | 0.242 | -0.244 | 0.1795 | 0.2447 | 0.6446 |

**Table A14: Summary of Balance for Matched Data (Post-match)**

| | Means Treated | Means Control | SD Control | Mean Diff | eQQ Med | eQQ Mean | eQQ Max |
|---|---|---|---|---|---|---|---|
| distance | 0.614 | 0.3463 | 0.1989 | 0.2676 | 0.3028 | 0.2677 | 0.4408 |
| % Poverty | 0.3787 | 0.3355 | 0.0971 | 0.0432 | 0.0428 | 0.0474 | 0.0946 |
| % Unemployed | 0.4737 | 0.4498 | 0.0486 | 0.0239 | 0.0261 | 0.0261 | 0.0501 |
| % Homeowner | 0.7586 | 0.7919 | 0.0669 | -0.0333 | 0.0338 | 0.0333 | 0.0577 |
| % Black | 0.8777 | 0.8208 | 0.235 | 0.0569 | 0.0119 | 0.0677 | 0.3699 |
| % Latino | 0.0896 | 0.1322 | 0.2099 | -0.0426 | 0.0116 | 0.0538 | 0.3528 |
| % < 18 | 0.2561 | 0.2503 | 0.0428 | 0.0058 | 0.0137 | 0.0172 | 0.0683 |
| % 65+ | 0.1036 | 0.1131 | 0.0406 | -0.0095 | 0.0102 | 0.0149 | 0.0513 |
| % College Educated | 0.1035 | 0.1353 | 0.0547 | -0.0318 | 0.0263 | 0.0318 | 0.0694 |

To evaluate the relative roles of conviction rate and CSO density on voting and nonvoting behavior, we first compared means on each of our dependent variables in the treatment and control groups. If need or other deficits drive nonvoting political behavior, then the mean level of attendance at police beat meetings and requests for non-emergency assistance should be higher and statistically different in high conviction communities than in low conviction communities. This should be particularly true of attendance at police beat meetings, where requests for 311 calls may be from rates of disorder associated with poverty but not necessarily and probably least attributable to crime rates.

Table A15 provides results from comparison of means tests. Voter turnout in high conviction rate communities is statistically lower than voter turnout in low conviction rate communities; attendance at police beat meetings is higher in high conviction rate communities than in low conviction rate communities; and there is no difference between the two classes of communities when it comes to requests for non-emergency assistance. The results fit general observations of collective efficacy found by other aggregate-level studies of Chicago.[6] Nevertheless, our results suggest attendance at police beat meetings is perhaps due to higher levels of need to address issues related to policing, and not necessarily CSO density. Also, the findings suggest that, to the extent that CSO density improves nonvoting participation when measured as requests for non-emergency assistance, nonvoting political participation is not solely a result of need.

To evaluate the role of CSO density on political participation, we use the new sample from the match, interacting CSO density with the treatment, namely high/low conviction rate (Table A16 and Figure A2). The results generally corroborate conclusions we drew from an analysis of the full sample before the matching. To be clear, greater CSO density is associated with greater attendance at police beat meetings and requests for non-emergency assistance among low conviction communities that are comparable in other ways to their high conviction counterparts. Conviction rates by themselves do not appear to impact nonvoting behavior nor does CSO density operate differently for low conviction communities or high conviction communities. In sum, the overriding factor that seems most important to nonvoting participation is CSO density.

**Table A15: Difference in Means Test between High Conviction and Low Conviction Police Beats, Post-Match**

| | Difference in Means | P-Value | Lower Bound | Upper Bound |
|---|---|---|---|---|
| 2014 Voter Turnout | -0.023 | 0.042 | -0.045 | -0.001 |
| 2015 Voter Turnout | -0.042 | 0.000 | -0.060 | -0.024 |
| Police Beat Meetings | 0.720 | 0.021 | 0.113 | 1.328 |
| 311 Calls | -3.302 | 0.627 | -16.937 | 10.333 |

**Table A16. Matched Analysis: Interactive Effect of Conviction Rates and CSO Densities on Voting and Nonvoting Participation**

| | 2014 Voter Turnout | 2015 Voter Turnout | Meeting Attendance | 311 Calls |
|---|---|---|---|---|
| Log(Convictions per 1000 Pop) | -0.022* | -0.042*** | 0.610 | -1.432 |
| | (0.010) | (0.010) | (0.495) | (7.991) |
| Log(CSO per 1000 Pop) | 0.070*** | 0.003 | 0.880* | 17.965** |
| | (0.007) | (0.008) | (0.380) | (6.087) |
| Convict*CSOs | -0.055*** | -0.002 | -0.386 | -18.233 |
| | (0.016) | (0.017) | (0.813) | (13.096) |
| Observations | 88 | 88 | 88 | 88 |
| Adjusted R2 | 0.518 | 0.192 | 0.061 | 0.064 |

[a]*All dependent variables are continuous, and modeled using Ordinary Least Squares regression. *p<.05; **p<.01; ***p<.001.*

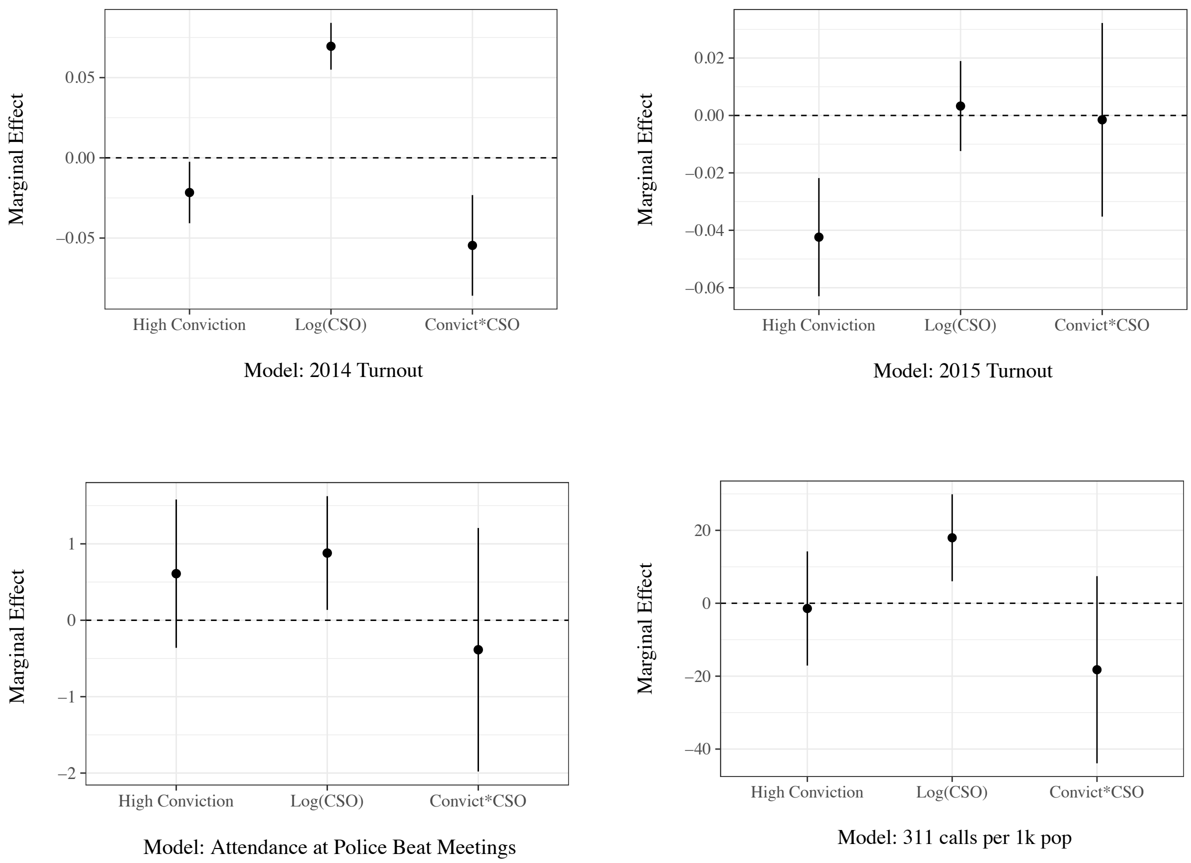


**Figure A2**: The marginal effect of conviction rate, CSOs per 1000 in the population, and their interaction on voting, attendance at police beat meetings and requests for non-emergency assistance, among matched police beats. Coefficient estimates reflect models presented in Table A16.

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**Notes**

[1] E.g., Lerman and Weaver 2014b; Kang and Dawes 2017; Laniyonu 2018.
[2] E.g., Hainmueller, Mummolo, and Xu 2016.
[3] Cameron and Trivedi 1990.
[4] Ho, Imai, King, and Stuart 2007.
[5] Nevertheless, a key finding from one of the largest studies of the effects of race and poverty on collective efficacy and neighborhood effects in Chicago, generally, concludes that “disadvantaged neighborhoods residents typically have fewer opportunities and effective models for involvement in anticrime efforts, but when they do, residents are at least as likely to be involved as residents of better-endowed neighborhoods.” Sampson 2012; also see Gonzalez, Collingwood, and El-Khatib 2017.
[6] Sampson 2012.