Pre-Analysis Plan for the: 'Randomized Impact Evaluation of the Community Auxiliary Police, Bougainville, Papua New Guinea'*

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This document summarizes key features of the Randomized Impact Evaluation of the Community Auxiliary Police in Papua New Guinea and outlines the pre-analysis plan (PAP). Randomization was implemented by the project partners, New Zealand Police (NZ Pol) and Bougainville Police Service (BPS), under observation by the research team in December 2015 and January 2016. This document predates endline data collection, and is therefore blind to outcomes. Any contingency not accounted for in this PAP will be dealt with according to the Standard Operating Procedures for Don Green's lab at Columbia. The study has ethical approval from the Columbia University IRB, protocol AAAQ2155. It has the written approval and support of the Autonomous Bougainville Government Ministry for Justice and Correctional Services, the Bougainville Police Service, and the New Zealand Police Service. All research activities were conducted on a 3-year research visa accorded by the PNG National Research Institute after review of the proposed study.

1 Motivation

In developing countries, the state is often unable to deliver the protections of the law to all its citizens. When the state's reach is limited, the few interactions citizens have with police are often marked by corruption, absenteeism, or abuse, contributing to dissatisfaction and distrust. These citizens sometimes instead rely on informal security providers, such as chiefs, families, or mobs, whose punitive and remedial procedures may be biased toward certain social groups at the expense of other groups. For example, men may receive systematically more beneficial outcomes from the informal justice system than women.

This study seeks to measure the effectiveness of a novel project implemented in Papua New Guinea by the New Zealand and Bougainville Police Services that seeks to overcome the challenges of policing in weak state environments, called the Community Auxiliary Police (CAP). The CAP project transfers the state's constitutional police powers to carefully selected community members in villages located in remote parts of the country, and trains those officers in investigative techniques and legal norms, particularly surrounding gender-based violence. CAP officers are unarmed but do have powers of arrest, detention and investigation in the communities that they come from.

By anchoring the powers of the state's policing apparatus directly in the community while retaining a degree of community accountability through oversight by the Council of Elders, a local government body, the CAP project is thought to deliver effective and accountable policing to areas the state could not formerly reach. The CAP has roughly ten times more women officers proportionally when compared to the central police, and performs the immediate tasks of frontline policing when there are problems in communities that it might take the central police more than a day to reach. Preparatory fieldwork suggests that communities that do not presently have CAP officers have expressed demand for the project, but budget constraints prevent its roll out to the entirety of the Bougainville territory. In focus groups with citizens, police officers in the central and CAP services, and other policy stakeholders, the project is thought to have brought much-needed legal protections to vulnerable members of remote communities, in particular women, and to have brought the formal and informal justice sectors into closer alignment. A survey with over 70 existing members of the CAP revealed that they believe their presence reduces crime rates in the communities in which they work.

Nevertheless, empowering local actors to use the coercive powers of the state specially reserved for the police may create adverse power inequalities, even if the CAP are not armed. It is also unclear to what extent those hired into the CAP act as agents of a distinct set of state-based norms–say, around gender violence–, as opposed to simply upholding the pre-existing set of norms while wearing a uniform.

In partnership with the Bougainville and New Zealand Police, researchers are conducting the first randomized evaluation to study the impact of the Community Auxiliary Police program on crime, norms and citizens' relationship to the state.

1.1 Background

During a resource conflict in the 1990s commonly referred to as the "Bougainville Crisis", young male combatants took control of certain areas of the autonomous region of Bougainville, Papua New Guinea. At the time, police from the mainland were at the forefront of efforts to quell the rebellion, and engaged in extremely violent repression that is thought to have deeply undermined trust in the police and in the state more broadly.

Moreover, the armed uprising of the younger generation is thought to have undermined the informal policing power of traditional village authorities, such as the chiefs. As a result, members of some communities lack access to policing of any type, either informal or state-provided. In areas that do have informal policing, norms about justice and sentencing can often diverge strongly from those contained in the state law and Human Rights charters. For example, mobs frequently kill those accused of sorcery, while perpetrators of sexual assault against women often simply compensate their victims' families with material goods, only to subsequently reoffend.

To deliver legal protection to citizens in remote areas in Bougainville, the Community Auxiliary Police (CAP) program transfers policing powers to individuals who are well-respected and accountable to their communities. The New Zealand Police helps recruit, train, and manage the CAP. There are presently 320 CAP officers located throughout Bougainville's roughly 8,000 villages.

While only around 2 percent of all central police officers are women, approximately 20 percent of CAP officers are women, due to a deliberate drive to recruit women into the service. In a context where tradition typically prohibits men from gathering thorough evidence from female victims of assault, having female police officers may improve reporting of gender-related crimes and victims' satisfaction with policing outcomes.

2 Intervention Description

Within the communities in which they live, CAP officers are authorized by the Police Act of 1988 to use the full powers of the police for offenses whose punishment comprises a prison term of no more than 12 months, and the power of detention and referral to the central police for all other offenses. They are uniformed officers and in practice work in their communities as full time police, conducting arrests, dispelling tension, investigating crimes and mediating conflicts. Importantly, they are not armed. Thus, their capacity for physical coercion relies in large part on support from the community and on their own physical strength. Thus, while CAP officers clearly have greater *de jure* coercive power than their fellow community members, they are relatively equal in terms of their *de facto* capacity for violent coercion.

CAP officers may operate as a vector for the introduction of new norms into their communities. The New Zealand Police provides in-depth monthly trainings on human rights, including how to investigate and prosecute sexual offense cases. CAP officers are paid a small allowance of around 30 USD a month, although payments are very irregular and many CAP officers are thought to subsist mainly through community support.

To be eligible for recruitment, a candidate for the CAP must not be a chief and must be nominated by a local-level government called the Council of Elders, an elected body representing the paramount chiefs of several villages. The COE also has seats reserved for women, the youth and the church, and plays a supervisory role over the CAP project at the local level.

3 Randomization

The study randomizes the areas in which the CAP program is implemented. Treatment villages have a uniformed CAP officer work and live there as full time agents of the state police. Villages in the comparison group will maintain the status quo, which often means very poor access to state policing, or none at all.

3.1 Treatment Conditions

For subjects living in housholds in villages that are part of the study ("households"), there are two treatment conditions: having a candidate to the CAP recruited in one's village (treatment); and not having a candidate to the CAP recruited in one's village (control). The study also analyzes outcomes among those who applied and were hired or almost hired as CAP officers ("candidates"), thus the two treatment conditions for those subjects are: being hired as a CAP officer (treatment), and not being hired as a CAP officer (control).

In December 2015 and January 2016, the Bougainville Police Service and the New Zealand police service expanded the serving CAP force in the North and Central regions, respectively by recruiting 35 new members into the force. They received over 400 applicants for the position, which they narrowed down to a shortlist of around 55 through an intensive interview and literacy testing process. Candidates cannot apply directly, but must be nominated by the council of paramount chiefs in their COE. Each COE receives an alotted share of the new recruits - usually 1-2. Around 10 applicants to the positions were given positions in a non-random fashion, either because they were from the South (where not enough candidates applied to make randomization feasible), or because they were from a COE in which a village was thought in dire need of a CAP officer.

For the remaining 45 candidates on the shortlist, among whom the police were indifferent, 17 were hired at random through a COE-level lottery. Although the Columbia Univerity research team advised on the randomization procedure, it was designed and implemented entirely by the police.

The procedure worked as follows: in each COE, the applicant was given a number from 1 through to the number of applicants from that COE, and the numbers were placed into a hat. Then, as many numbers as recruits allotted to that COE were drawn at random from the hat, without replacement. The draw was only done once, and the name of the candidate to which the number corresponded was recorded. These candidates were subsequently recruited into the CAP.

Households are thus assigned to treatment through a clustered assignment at the village level, within COE blocks. Note that this implies differential probabilities of assignment to treatment, a feature of the study that is accounted for through the use of inverse probability weighted estimators.

The outcome of the assignment process is displayed in tables 1 and 2. The first column displays the outcome of the random assignment. The second displays the gender of the candidate, the third the unique ID for that candidate, the fourth the unique ID for that candidate's village, and the fifth the block in which the random draw took place. The final columns show the probability that a candidate was recruited for a given candidate given the COE they were recruited in, and the probability that a given village cluster had a candidate recruited in it, given the fact that two or more candidates sometimes come from the same village. These probabilities can be used to construct inverse probability weights for estimation of the treatment effects.

Assignment	Gender	Cand. ID	Village ID	COE (Block)	Candidate Pr(Treated)	Village Pr(Treated)
Not recruited	M	1	1	Hagogohe	0.50	0.50
Recruited	M	2	2	Hagogohe	0.50	0.50
Not recruited	F	3	1	Haku	0.33	0.33
Recruited	F	4	2	Haku	0.33	0.33
Not recruited	M	5	3	Haku	0.33	0.33
Recruited	M	6	1	Halia	0.50	0.50
Not recruited	F	7	2	Halia	0.50	0.50
Not recruited	M	8	1	Peit	0.20	0.80
Not recruited	F	9	1	Peit	0.20	0.80
Recruited	F	10	1	Peit	0.20	0.80
Not recruited	M	11	1	Peit	0.20	0.80
Not recruited	F	12	2	Peit	0.20	0.20
Not recruited	F	13	1	Tsitalato	0.50	0.50
Recruited	M	14	2	Tsitalato	0.50	0.50
Not recruited	M	15	1	Suir	0.25	0.25
Not recruited	M	16	2	Suir	0.25	0.50
Recruited	M	17	3	Suir	0.25	0.50
Not recruited	M	18	4	Suir	0.25	0.25
Recruited	F	19	1	Tinputz	0.33	0.33
Not recruited	F	20	2	Tinputz	0.33	0.67
Not recruited	M	21	2	Tinputz	0.33	0.67
Recruited	M	22	1	Carterets	0.50	0.50
Recruited	F	23	2	Carterets	0.50	0.50
Not recruited	F	24	3	Carterets	0.50	0.50
Not recruited	M	25	4	Carterets	0.50	0.50
Not recruited	F	26	1	Kunua	0.40	0.40
Recruited	F	27	2	Kunua	0.40	0.40
Not recruited	F	28	3	Kunua	0.40	0.70
Not recruited	F	29	3	Kunua	0.40	0.70
Recruited	F	30	4	Kunua	0.40	0.40
Not recruited	M	31	1	Selau	0.33	0.33
Recruited	M	32	2	Selau	0.33	0.33
Not recruited	F	33	3	Selau	0.33	0.33

Table 1: Random assignment in the North region.

Assignment	Gender	Cand. ID	Village ID	COE (Block)	Candidate Pr(Treated)	Village Pr(Treated)
Recruited	M	34	1	Terra	0.50	0.50
Not recruited	F	35	2	Terra	0.50	0.50
Not recruited	M	36	1	Rau	0.33	0.33
Not recruited	M	37	2	Rau	0.33	0.33
Recruited	M	38	3	Rau	0.33	0.33
Not recruited	F	39	1	Eivo and Torau	0.50	0.50
Recruited	F	40	2	Eivo and Torau	0.50	0.50
Not recruited	M	41	1	North Nasioi	0.33	0.33
Not recruited	F	42	2	North Nasioi	0.33	0.33
Recruited	F	43	3	North Nasioi	0.33	0.33
Recruited	F	44	1	Bolave	0.50	0.50
Not recruited	M	45	2	Bolave	0.50	0.50

Table 2: Random assignment in the Central region.

The 45 candidates who applied live in 39 different villages. The assignment process was blocked on the COE level, and resulted in 17 candidates recruited at random, and 28 randomly not recruited.

4 Sampling and Measurement

The data used in this study comes from four main sources: household surveys enumerated in the villages in which the experiment took place; interviews with the candidates who were and were not hired as CAP in the recruitment lottery; expectations about treatment effects and attitudes on justice elicited from CAP members who were already working prior to randomization; and crime data on non-experimental villages collected independently by different researchers in the month preceding this data collection effort. I describe the sampling procedure and survey measures used for each below.

4.1 Household Data

Data on households will be collected from September to December 2016, using a team of pidgin-speaking enumerators who will travel to the 39 villages included in the evaluation.

Interviews will be conducted with either a male or a female head of household in each household. Recruitment takes place in two phases. First, an enumerator meets with the village assembly chairperson in each village in order to gather the names of all households and the number of adult (18-65) members in each household. Second, 25 households are chosen at random to have men surveyed in them, and 25 are chosen to have women surveyed in them, allowing for overlap if there are fewer than 50 households in the village, but preventing it if there are more. The male or female head of household is interviewed in each household, depending on which gender was randomly assigned to be interviewed there. Subjects that cannot be reached for whatever reason will be replaced at random from within the household. Households that cannot be reached will be replaced on the day of data collection by proceeding along the randomly-ordered list of households.

Respondents will be gender-matched with enumerators. They will be asked to recall specific property crimes or assaults that they or members of their household have experienced over the past year (covering pre- and post-randomization). They will also be asked a range of subjective questions about their feelings of safety, their attitudes and perceptions of their community's norms on gender violence, their trust in the state, their views on formal and informal policing, and their perceptions of procedural justice.

4.2 Data on Candidates

Data on candidates will be collected in parallel to the data on households, from September to December 2016. The sample is already defined as the candidates who took part in the recruitment lottery, and so no specific sampling procedure is required. Candidates will simply be contacted using the contact details kept on record by the Police.

The survey will measure attitudinal and behavioral outcomes. To avoid priming candidates, no questions will be asked about their current employment, and enumerators will be blind as to whether the respondent was or was not hired. Attitudinal outcomes include questions about perceptions of power over others, entitlement, norms about justice and gender, and beliefs about procedural justice. Behavioral games will be used to measure honesty / corruption. Specifically, candidates will play three variations of the same dice-rolling game. In each, they role the dice 13 times, reporting on each roll the number that they rolled. They receive a token for each even roll, and win the game if they win the most tokens. In the first game, only the respondent observes the roll values, and is playing against the enumerator for a small prize. Thus, it is possible for the respondent to cheat by deviating from the known distribution of rolls, and "steal" the prize from the enumerator. In the second game, if the respondent loses, the prize goes to a randomly selected community member, and he or she is thus "stealing" from the community by cheating. In the third, the respondent again plays against the community, but now the enumerator also rolls the dice. If the enumerator rolls a 6, he or she reveals the true number rolled by the respondent, after they have declared it. This third scenario allows for some monitoring of "theft" by community members.

4.3 Data on Expectations

Data on expectations about treatment effects will also be used as informative prior information in Bayesian estimation procedures. In the summer of 2015, a survey experiment was carried out among 87 existing members of the CAP, in order both to understand how they perceived norms related to justice and gender, but also in order to elicit expectations about the likely treatment effects of this study. All answers were coded by a research assistant hired for the task. As an example, figure 1 shows the distribution of beliefs about effect sizes in answer to the following question:

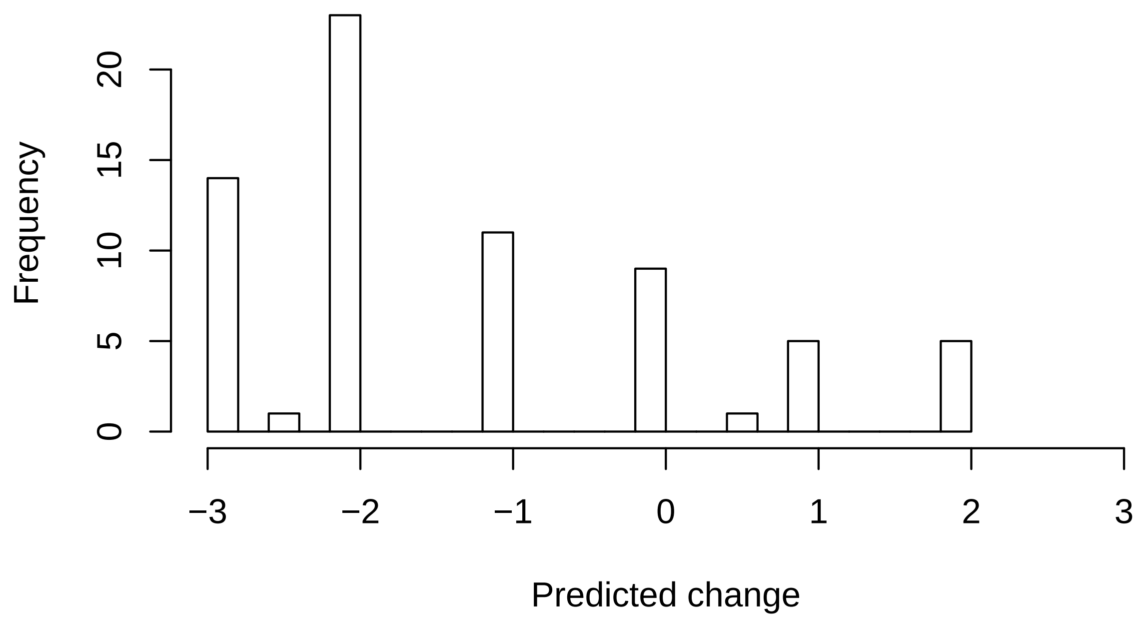

Figure 1: Expectations of serving CAP about effects of treatment on the rate of theft in the community.

Next year, research will be conducted to understand if and how the CAP system changes life in the village. We are interested in what you think we will find. Imagine a village like yours, except there are no CAP officers present there. Think about the sorts of problems a village faces when there are no CAP. Now imagine that a CAP officer is recruited in the village. After the CAP has been in the village for 6 months, how would the situation in that village have changed? It may be that things don't change at all, or that only some things change.

If about 4 incidences of theft occurred per week before the CAP was there, how many incidences of theft would take place per week after the CAP had been there for 6 months?

4.4 Non-Experimental Crime Data

In the month preceding the beginning of data collection efforts, one of Bougainville's first region-wide crime victimization surveys will be conducted by the New Zealand Police, independently of this project. The data will be useful for developing empirical priors in Bayesian models. For example, determining what are appropriate plausible ranges for specifications of the prior on cluster-level variance can be estimated without double-use of the experimental data by using the non-experimental estimates of the cluster-level variance. Note that non-parametric, non-Bayesian inference is pre-specified below in section 6, in addition to Bayesian models with informative and uninformative prior specifications.

5 Outcomes, Estimands and Hypotheses

This section specifies the potential outcomes of the impact evaluation and uses them to define the key estimands of interest that the estimation strategy will aim to recover. In addition, it specifies in pseudo-code how outcomes will be constructed and coded. Finally, it associates each estimand with a hypothesis, which is useful for frequentist inference strategies in which one-tailed tests will be conducted. Finally, the section distinguishes between the 'main results' of the study, and the ancillary outcomes that are intended to elucidate mechanisms.

5.1 Potential Outcomes and Estimands

For household and candidate outcomes, I am interested in conditional and unconditional sample average treatment effects (SATE). The potential outcomes and estimands are defined at different levels depending on the family of outcomes considered. In the following formalization, I index the different levels of the study as follows:

- Incidents are units of analysis indexed $g \in \{1...G\}$,
- Households are units of analysis indexed $h \in \{1...H\}$,
- Candidates are units of analysis indexed $i \in \{1...I\}$,
- Villages are clusters indexed $j \in \{1...J\}$, and

- COEs are blocks indexed $k \in \{1...K\}$.

I also define a non-nested temporal level to indicate whether a g incident took place pre- or post-randomization using indicator $T \in \{0, 1\}$, where incidents that occur post-randomization take 1 and 0 otherwise.

For individuals from households, the random assignment mechanism Z varies at level j since it is cluster assigned within COE blocks. For individual candidates to the CAP, the random assignment mechanism varies at i, since individuals are assigned within COE blocks.

Household outcomes of interest can be grouped into seven families varying at different levels:

1. victimization incidents (g);
2. reporting incidents (g);
3. perceptions of security (h);
4. perceptions of formal and informal procedural justice (h);
5. gender norms and attitudes (h).
6. trust in the state (h); and,
7. knowledge of the state (h);

Candidate outcomes of interest can be grouped into five families

1. honesty (i);
2. perceptions of self-efficacy, entitlement, power and respect (i);
3. beliefs about justice (i);
4. attitudes and legal knowledge (i); and,
5. alignment with community norms (i).

Each table below describes a different estimand. The first row contains the name of the outcome in pseudo-code. Note that two estimands can be defined with respect to the same outcome, for example among different sub-populations. The second row gives a generic name for the estimand, depending on how it is defined. For example, average differences between individual treatment and control potential outcomes taken at the level of the sample are defined as sample average treatment effects (SATEs), whereas slightly more complicated quantities of interest include conditional SATEs, or differences in SATEs. The third row describes symbolically how the estimand could be defined in math, using the generic Y and Z to denote outcome and treatment, respectively. The fourth row states the direction of the hypothesis and whether it will be investigated using a two- or one-tailed test. The fourth row briefly explains the reasoning behind the direction of the hypothesis. The fifth row explains in pseudo-code and English how the outcome is constructed, for example if it is an additive index or recoded ordinal variable. The sixth row describes the raw variables used to build the outcome. And the final row indicates whether the estimand can be considered a 'main result' of the study.

5.2 Household Outcomes

5.2.1 Victimization incidents

Outcome Name:	`n_incidents`
Estimand Name:	Sample Average Difference in Differences
Estimand:	$\mathrm{E}[(Y_g(Z=1,T=1)-Y_g(Z=1,T=0))-(Y_g(Z=0,T=1)-Y_g(Z=0,T=0))]$
Hypothesis direction:	one-tailed (-)
Hypothesis explanation:	Having a CAP hired in the village should reduce the number of post-treatment incidents of crime that happen there.
Construction of outcome:	Assuming that reporting of pre-treatment incidents is not affected by treatment, this outcome is generated by subtracting the sum of all pre-treatment crime incidents from the sum of all post-treatment crime incidents within subjects. The estimand is the average difference of these within-subject differences across treatment and control.
Variables used:	`prop_incident_n`, `prop_inc_pre_yesno_1...5`, `assault_n`, `assault_pre_yesno_1...5`.
Main result:	Yes

Table 3: Potential outcomes, estimands, hypotheses and pseudo-code for the Sample Average Difference in Differences on `n_incidents`.

Outcome Name:	`n_incidents`
Estimand Name:	SATE
Estimand:	$\mathrm{E}[(Y_g(Z=1)-Y_g(Z=0)\mid T=1]$
Hypothesis direction:	one-tailed (-)
Hypothesis explanation:	Having a CAP hired in the village should reduce the number of post-treatment incidents of crime that happen there.
Construction of outcome:	This estimand does not assume that reporting of pre-treatment incidents is unaffected by treatment. The outcome is generated by taking the sum of all post-treatment crime incidents within subjects.
Variables used:	`prop_incident_n`, `prop_inc_pre_yesno_1...5`, `assault_n`, `assault_pre_yesno_1...5`.
Main result:	Yes

Table 4: Potential outcomes, estimands, hypotheses and pseudo-code for the SATE on `n_incidents`.

Outcome Name:	`assault_incidents`
Estimand Name:	Sample Average Difference in Differences
Estimand:	$E[(Y_g(Z=1,T=1) - Y_g(Z=1,T=0)) - (Y_g(Z=0,T=1) - Y_g(Z=0,T=0))]$
Hypothesis direction:	one-tailed (-)
Hypothesis explanation:	Having a CAP hired in the village should reduce the number of post-treatment incidents of assault that happen there.
Construction of outcome:	Assuming that reporting of pre-treatment incidents is not affected by treatment, this outcome is generated by subtracting the sum of all pre-treatment assault incidents from the sum of all post-treatment assault incidents within subjects. The estimand is the average difference of these within-subject differences across treatment and control.
Variables used:	`assault_n`, `assault_pre_yesno_1...5`.
Main result:	No

Table 5: Potential outcomes, estimands, hypotheses and pseudo-code for the Sample Average Difference in Differences on `assault_incidents`.

Outcome Name:	`assault_incidents`
Estimand Name:	SATE
Estimand:	$E[(Y_g(Z=1) - Y_g(Z=0) \mid T=1]$
Hypothesis direction:	one-tailed (-)
Hypothesis explanation:	Having a CAP hired in the village should reduce the number of post-treatment incidents of assault that happen there.
Construction of outcome:	This estimand does not assume that reporting of pre-treatment incidents is unaffected by treatment. The outcome is generated by taking the sum of all post-treatment assault incidents within subjects.
Variables used:	`assault_n`, `assault_pre_yesno_1...5`.
Main result:	No

Table 6: Potential outcomes, estimands, hypotheses and pseudo-code for the SATE on `assault_incidents`.

Outcome Name:	`prop_incidents`
Estimand Name:	Sample Average Difference in Differences
Estimand:	$E[(Y_g(Z=1,T=1) - Y_g(Z=1,T=0)) - (Y_g(Z=0,T=1) - Y_g(Z=0,T=0))]$
Hypothesis direction:	one-tailed (-)
Hypothesis explanation:	Having a CAP hired in the village should reduce the number of post-treatment incidents of property theft and damage that happen there.
Construction of outcome:	Assuming that reporting of pre-treatment incidents is not affected by treatment, this outcome is generated by subtracting the sum of all pre-treatment property theft and damage incidents from the sum of all post-treatment property theft and damage incidents within subjects. The estimand is the average difference of these within-subject differences across treatment and control.
Variables used:	`prop_incident_n`, `prop_inc_pre_yesno_1...5`.
Main result:	No

Table 7: Potential outcomes, estimands, hypotheses and pseudo-code for the Sample Average Difference in Differences on `prop_incidents`.

Outcome Name:	`prop_incidents`
Estimand Name:	SATE
Estimand:	$E[(Y_g(Z=1) - Y_g(Z=0) \mid T=1]$
Hypothesis direction:	one-tailed (-)
Hypothesis explanation:	Having a CAP hired in the village should reduce the number of post-treatment incidents of property theft and damage that happen there.
Construction of outcome:	This estimand does not assume that reporting of pre-treatment incidents is unaffected by treatment. The outcome is generated by taking the sum of all post-treatment property theft and damage incidents within subjects.
Variables used:	`prop_incident_n`, `prop_inc_pre_yesno_1...5`.
Main result:	No

Table 8: Potential outcomes, estimands, hypotheses and pseudo-code for the SATE on `prop_incidents`.

Outcome Name:	`vaw_incidents`
Estimand Name:	Conditional Sample Average Difference in Differences
Estimand:	$E[(Y_g(Z=1,T=1) - Y_g(Z=1,T=0)) - (Y_g(Z=0,T=1) - Y_g(Z=0,T=0)) \mid \text{victim} = \text{female}]$
Hypothesis direction:	one-tailed (-)
Hypothesis explanation:	Having a CAP hired in the village should reduce the number of post-treatment incidents of assault against women or girls that happen there.
Construction of outcome:	Assuming that reporting of pre-treatment incidents is not affected by treatment, this outcome is generated by subtracting the sum of all pre-treatment incidents of assault against women or girls from the sum of all post-treatment incidents of assault against women or girls within subjects. The estimand is the average difference of these within-subject differences across treatment and control.
Variables used:	`assault_n`, `assault_pre_yesno_1...5`, `assault_victim_gender_1...5`.
Main result:	Yes

Table 9: Potential outcomes, estimands, hypotheses and pseudo-code for the Conditional Sample Average Difference in Differences on `vaw_incidents`.

Outcome Name:	`vaw_incidents`
Estimand Name:	Conditional Sample Average Treatment Effect
Estimand:	$E[Y_g(Z=1,T=1) - (Y_g(Z=0,T=1) \mid \text{victim} = \text{female}]$
Hypothesis direction:	one-tailed (-)
Hypothesis explanation:	Having a CAP hired in the village should reduce the number of post-treatment incidents of assault against women or girls that happen there.
Construction of outcome:	This estimand does not assume that reporting of pre-treatment incidents is unaffected by treatment. The outcome is generated by taking the sum of all post-treatment incidents of assault against women or girls within subjects.
Variables used:	`assault_n`, `assault_pre_yesno_1...5`, `assault_victim_gender_1...5`.
Main result:	Yes

Table 10: Potential outcomes, estimands, hypotheses and pseudo-code for the Conditional Sample Average Treatment Effect on `vaw_incidents`.

Outcome Name:	`sexual_assaults`
Estimand Name:	Conditional Sample Average Difference in Differences
Estimand:	$\mathrm{E}[(Y_g(Z=1,T=1) - Y_g(Z=1,T=0)) - (Y_g(Z=0,T=1) - Y_g(Z=0,T=0)) \mid \text{assault kind} = \text{sexual assault}]$
Hypothesis direction:	one-tailed (-)
Hypothesis explanation:	Having a CAP hired in the village should reduce the number of post-treatment incidents of sexual assault.
Construction of outcome:	Assuming that reporting of pre-treatment incidents is not affected by treatment, this outcome is generated by subtracting the sum of all pre-treatment incidents of sexual assault from the sum of all post-treatment incidents of sexual assault within subjects. The estimand is the average difference of these within-subject differences across treatment and control.
Variables used:	`assault_n`, `assault_pre_yesno_1...5`, `assault_kind_1...5`.
Main result:	No

Table 11: Potential outcomes, estimands, hypotheses and pseudo-code for the Conditional Sample Average Difference in Differences on `sexual_assaults`.

Outcome Name:	`sexual_assaults`
Estimand Name:	Conditional Sample Average Treatment Effect
Estimand:	$\mathrm{E}[Y_g(Z=1,T=1) - (Y_g(Z=0,T=1) \mid \text{assault kind} = \text{sexual assault}]$
Hypothesis direction:	one-tailed (-)
Hypothesis explanation:	Having a CAP hired in the village should reduce the number of post-treatment incidents of assault against women or girls that happen there.
Construction of outcome:	This estimand does not assume that reporting of pre-treatment incidents is unaffected by treatment. The outcome is generated by taking the sum of all post-treatment incidents of sexual assault within subjects.
Variables used:	`assault_n`, `assault_pre_yesno_1...5`, `assault_victim_gender_1...5`.
Main result:	No

Table 12: Potential outcomes, estimands, hypotheses and pseudo-code for the Conditional Sample Average Treatment Effect on `sexual_assaults`.

Outcome Name:	`land_dispute_freq`
Estimand Name:	SATE
Estimand:	$\text{E}[(Y_h(Z=1) - Y_h(Z=0)]$
Hypothesis direction:	one-tailed (-)
Hypothesis explanation:	Having a CAP hired in the village should reduce the frequency of violent land disputes that respondents report observing in the village.
Construction of outcome:	Ordinal variable: 1 = Never; 2 = Once a month or less; 3 = A few times a month; 4 = A few times a week; 5 = Everyday / almost everyday.
Variables used:	`land_dispute_freq`.
Main result:	No

Table 13: Potential outcomes, estimands, hypotheses and pseudo-code for the SATE on `land_dispute_freq`.

Outcome Name:	`drunk_freq`
Estimand Name:	SATE
Estimand:	$\text{E}[(Y_h(Z=1) - Y_h(Z=0)]$
Hypothesis direction:	one-tailed (-)
Hypothesis explanation:	Having a CAP hired in the village should reduce the frequency of drunk and disorderly behavior that respondents report observing in the village.
Construction of outcome:	Ordinal variable: 1 = Never; 2 = Once a month or less; 3 = A few times a month; 4 = A few times a week; 5 = Everyday / almost everyday.
Variables used:	`drunk_freq`.
Main result:	No

Table 14: Potential outcomes, estimands, hypotheses and pseudo-code for the SATE on `drunk_freq`.

Outcome Name:	`n_reported_incidents`
Estimand Name:	Sample Average Difference in Differences
Estimand:	$E[(Y_g(Z = 1, T = 1) - Y_g(Z = 1, T = 0)) - (Y_g(Z = 0, T = 1) - Y_g(Z = 0, T = 0))]$
Hypothesis direction:	one-tailed (-)
Hypothesis explanation:	Having a CAP hired in the village should reduce the number of post-treatment incidents of crime that respondents report happening to other people in the village.
Construction of outcome:	Assuming that reporting of pre-treatment incidents is not affected by treatment, this outcome is generated by subtracting the sum of all pre-treatment crime incidents that happened to others in the village from the sum of all post-treatment crime incidents that happened to others in the village within subjects. The estimand is the average difference of these within-subject differences across treatment and control.
Variables used:	`assault_report_n`, `assault_report_n_pre`, `sex_assault_report_n`, `sex_assault_report_n_pre`, `prop_report_n`, `prop_report_n_pre`.
Main result:	Yes

Table 15: Potential outcomes, estimands, hypotheses and pseudo-code for the Sample Average Difference in Differences on `n_reported_incidents`.

Outcome Name:	`n_reported_incidents`
Estimand Name:	SATE
Estimand:	$E[(Y_g(Z = 1) - Y_g(Z = 0) \mid T = 1]$
Hypothesis direction:	one-tailed (-)
Hypothesis explanation:	Having a CAP hired in the village should reduce the number of post-treatment incidents of crime that respondents report happening to other people in the village.
Construction of outcome:	This estimand does not assume that reporting of pre-treatment incidents is unaffected by treatment. The outcome is generated by taking the sum of all post-treatment crime incidents within subjects.
Variables used:	`assault_report_n`, `assault_report_n_pre`, `sex_assault_report_n`, `sex_assault_report_n_pre`, `prop_report_n`, `prop_report_n_pre`.
Main result:	Yes

Table 16: Potential outcomes, estimands, hypotheses and pseudo-code for the SATE on `n_reported_incidents`.

Outcome Name:	`n_reported_assault_incidents`
Estimand Name:	Sample Average Difference in Differences
Estimand:	$E[(Y_g(Z=1,T=1) - Y_g(Z=1,T=0)) - (Y_g(Z=0,T=1) - Y_g(Z=0,T=0))]$
Hypothesis direction:	one-tailed (-)
Hypothesis explanation:	Having a CAP hired in the village should reduce the number of post-treatment incidents of assault that respondents report happening to other people in the village.
Construction of outcome:	Assuming that reporting of pre-treatment incidents is not affected by treatment, this outcome is generated by subtracting the sum of all pre-treatment assault incidents that happened to others in the village from the sum of all post-treatment assault incidents that happened to others in the village, within subjects. The estimand is the average difference of these within-subject differences across treatment and control.
Variables used:	`assault_report_n`, `assault_report_n_pre`.
Main result:	No

Table 17: Potential outcomes, estimands, hypotheses and pseudo-code for the Sample Average Difference in Differences on `n_reported_assault_incidents`.

Outcome Name:	`n_reported_assault_incidents`
Estimand Name:	SATE
Estimand:	$E[(Y_g(Z=1) - Y_g(Z=0) \mid T=1]$
Hypothesis direction:	one-tailed (-)
Hypothesis explanation:	Having a CAP hired in the village should reduce the number of post-treatment incidents of assault that respondents report happening to other people in the village.
Construction of outcome:	This estimand does not assume that reporting of pre-treatment incidents is unaffected by treatment. The outcome is generated by taking the sum of all post-treatment assault incidents within subjects.
Variables used:	`assault_report_n`, `assault_report_n_pre`.
Main result:	No

Table 18: Potential outcomes, estimands, hypotheses and pseudo-code for the SATE on `n_reported_assault_incidents`.

Outcome Name:	`n_reported_sex_assault_incidents`
Estimand Name:	Sample Average Difference in Differences
Estimand:	$\text{E}[(Y_g(Z=1,T=1) - Y_g(Z=1,T=0)) - (Y_g(Z=0,T=1) - Y_g(Z=0,T=0))]$
Hypothesis direction:	one-tailed (-)
Hypothesis explanation:	Having a CAP hired in the village should reduce the number of post-treatment incidents of sexual assault that respondents report happening to other people in the village.
Construction of outcome:	Assuming that reporting of pre-treatment incidents is not affected by treatment, this outcome is generated by subtracting the sum of all pre-treatment sexual assault incidents that happened to others in the village from the sum of all post-treatment sexual assault incidents that happened to others in the village, within subjects. The estimand is the average difference of these within-subject differences across treatment and control.
Variables used:	`sex_assault_report_n`, `sex_assault_report_n_pre`.
Main result:	No

Table 19: Potential outcomes, estimands, hypotheses and pseudo-code for the Sample Average Difference in Differences on `n_reported_sex_assault_incidents`.

Outcome Name:	`n_reported_sex_assault_incidents`
Estimand Name:	SATE
Estimand:	$\text{E}[(Y_g(Z=1) - Y_g(Z=0) \mid T=1]$
Hypothesis direction:	one-tailed (-)
Hypothesis explanation:	Having a CAP hired in the village should reduce the number of post-treatment incidents of sexual assault that respondents report happening to other people in the village.
Construction of outcome:	This estimand does not assume that reporting of pre-treatment incidents is unaffected by treatment. The outcome is generated by taking the sum of all post-treatment sexual assault incidents within subjects.
Variables used:	`sex_assault_report_n`, `sex_assault_report_n_pre`.
Main result:	No

Table 20: Potential outcomes, estimands, hypotheses and pseudo-code for the SATE on `n_reported_sex_assault_incidents`.

Outcome Name:	`n_reported_prop_incidents`
Estimand Name:	Sample Average Difference in Differences
Estimand:	$E[(Y_g(Z=1,T=1) - Y_g(Z=1,T=0)) - (Y_g(Z=0,T=1) - Y_g(Z=0,T=0))]$
Hypothesis direction:	one-tailed (-)
Hypothesis explanation:	Having a CAP hired in the village should reduce the number of post-treatment incidents of property theft or damage that respondents report happening to other people in the village.
Construction of outcome:	Assuming that reporting of pre-treatment incidents is not affected by treatment, this outcome is generated by subtracting the sum of all pre-treatment property theft or damage incidents that happened to others in the village from the sum of all post-treatment property theft or damage incidents that happened to others in the village, within subjects. The estimand is the average difference of these within-subject differences across treatment and control.
Variables used:	`prop_report_n`, `prop_report_n_pre`.
Main result:	No

Table 21: Potential outcomes, estimands, hypotheses and pseudo-code for the Sample Average Difference in Differences on `n_reported_prop_incidents`.

Outcome Name:	`n_reported_prop_incidents`
Estimand Name:	SATE
Estimand:	$E[(Y_g(Z=1) - Y_g(Z=0) \mid T=1]$
Hypothesis direction:	one-tailed (-)
Hypothesis explanation:	Having a CAP hired in the village should reduce the number of post-treatment incidents of property theft or damage that respondents report happening to other people in the village.
Construction of outcome:	This estimand does not assume that reporting of pre-treatment incidents is unaffected by treatment. The outcome is generated by taking the sum of all post-treatment property theft or damage incidents within subjects.
Variables used:	`prop_report_n`, `prop_report_n_pre`.
Main result:	No

Table 22: Potential outcomes, estimands, hypotheses and pseudo-code for the SATE on `n_reported_prop_incidents`.

5.2.2 Reporting incidents

Outcome Name:	`report_to_police`
Estimand Name:	Conditional SATE
Estimand:	$\text{E}[(Y_g(Z=1) - Y_g(Z=0) \mid g : \text{incident}_g = \text{ crime of passion or } T_g = 0]$
Hypothesis direction:	one-tailed (+)
Hypothesis explanation:	Having a CAP hired in the village should increase the proportion of crimes that are reported to the police.
Construction of outcome:	Outcome takes 1 if incident reported to police (CAP or BPS), and 0 if not reported or reported to a different actor. The estimand is conditional on the incident either being characterized as a crime of passion, or on it occuring prior to the randomization. If it can be assumed that the recall of such incidents or their incidence rate are unaffected by treatment, then the effect can be identified without the risk of post-treatment bias.
Variables used:	`prop_inc_pre_yesno_1...5`, `prop_inc_did_report_1..5`, `prop_inc_when_report_1..5`, `prop_inc_report_to_1...5`, `assault_pre_yesno_1...5`, `assault_premed_1...5`, `assault_did_report_1...5`, `assault_when_report_1...5`, `assault_report_to_1...5`.
Main result:	Yes

Table 23: Potential outcomes, estimands, hypotheses and pseudo-code for the Conditional SATE on `report_to_police`.

Outcome Name:	`report_to_police`
Estimand Name:	Conditional sample average difference in differences
Estimand:	$\text{E}[(Y_g(Z=1) - Y_g(Z=0) \mid g: \text{ incident}_g = \text{ crime of passion } \text{ or } T_g = 0 \text{ and gender}_h = \text{ woman}] - \text{E}[(Y_g(Z=1) - Y_g(Z=0) \mid g: \text{incident}_g = \text{ crime of passion } \text{ or } T_g = 0 \text{ and } \text{ gender}_h = \text{man}]$
Hypothesis direction:	one-tailed (+)
Hypothesis explanation:	Having a CAP hired in the village should increase the proportion of crimes that are reported to the police more so for women than for men.
Construction of outcome:	Outcome takes 1 if incident reported to police (CAP or BPS), and 0 if not reported or reported to a different actor. The estimand is conditional on the incident either being characterized as a crime of passion, or on it occuring prior to the randomization. If it can be assumed that the recall of such incidents or their incidence rate are unaffected by treatment, then the effect can be identified without the risk of post-treatment bias.
Variables used:	`sex`, `prop_inc_pre_yesno_1...5`, `prop_inc_did_report_1..5`, `prop_inc_when_report_1..5`, `prop_inc_report_to_1...5`, `assault_pre_yesno_1...5`, `assault_premed_1...5`, `assault_did_report_1...5`, `assault_when_report_1...5`, `assault_report_to_1...5`.
Main result:	Yes

Table 24: Potential outcomes, estimands, hypotheses and pseudo-code for the Conditional sample average difference in differences on `report_to_police`.

Outcome Name:	`outcome_beneficial`
Estimand Name:	Conditional SATE
Estimand:	$\mathrm{E}[(Y_g(Z=1) - Y_g(Z=0) \mid g : \text{incident}_g = \text{crime of passion or } T_g = 0]$
Hypothesis direction:	no effect
Hypothesis explanation:	Having a CAP hired in the village should neither increase nor decrease the proportion of incidents that the respondent perceives as having an outcome that benefited them. Rather it should change their perception of the fairness of those incidents.
Construction of outcome:	Outcome takes 1 if incident had an outcome perceived to benefit the respondent, and 0 if outcome perceived to not have benefited the respondent. The estimand is conditional on the incident either being characterized as a crime of passion, or on it occuring prior to the randomization. If it can be assumed that the recall of such incidents or their incidence rate are unaffected by treatment, then the effect can be identified without the risk of post-treatment bias.
Variables used:	`prop_inc_pre_yesno_1...5`, `prop_inc_when_report_1..5`, `prop_inc_outcome_beneficial_1...5`, `assault_pre_yesno_1...5`, `assault_premed_1...5`, `assault_when_report_1...5`, `assault_outcome_beneficial_1...5`.
Main result:	No

Table 25: Potential outcomes, estimands, hypotheses and pseudo-code for the Conditional SATE on `outcome_beneficial`.

Outcome Name:	`outcome_fair`
Estimand Name:	Conditional SATE
Estimand:	$\mathrm{E}[(Y_g(Z=1) - Y_g(Z=0) \mid g : \text{incident}_g = \text{crime of passion or } T_g = 0]$
Hypothesis direction:	one-tailed (+)
Hypothesis explanation:	Having a CAP hired in the village should increase proportion of incidents that the respondent perceives as having an outcome that was fair. However those incidents need not have had outcomes that necessarily benefited the respondent more on average.
Construction of outcome:	Outcome takes 1 if incident had an outcome perceived to be fair by the respondent, and 0 if outcome perceived not to be fair by the respondent. The estimand is conditional on the incident either being characterized as a crime of passion, or on it occuring prior to the randomization. If it can be assumed that the recall of such incidents or their incidence rate are unaffected by treatment, then the effect can be identified without the risk of post-treatment bias.
Variables used:	`prop_inc_pre_yesno_1...5`, `prop_inc_when_report_1..5`, `prop_inc_outcome_fair_1...5`, `assault_pre_yesno_1...5`, `assault_premed_1...5`, `assault_when_report_1...5`, `assault_outcome_fair_1...5`.
Main result:	No

Table 26: Potential outcomes, estimands, hypotheses and pseudo-code for the Conditional SATE on `outcome_fair`.

5.2.3 Perceptions of security

Outcome Name:	`safe_index`
Estimand Name:	SATE
Estimand:	$\text{E}[Y_h(Z=1) - Y_h(Z=0)]$
Hypothesis direction:	one-tailed (-)
Hypothesis explanation:	Being hired into the CAP will increase the number of everyday situations in which the respondent feels safe.
Construction of outcome:	Additive index normalized to 1: 0 = no place or time in which respondent feels safe; 1 = respondent feels safe in all listed places at all listed times.
Variables used:	`safe_water_day`, `safe_water_night`, `safe_toilet_day`, `safe_toilet_night`, `safe_home_day`, `safe_home_night`, `safe_path_day`, `safe_path_night`, `safe_meeting_day`, `safe_meeting_night`.
Main result:	Yes

Table 27: Potential outcomes, estimands, hypotheses and pseudo-code for the SATE on `safe_index`.

Outcome Name:	`attack_risk`
Estimand Name:	SATE
Estimand:	$\text{E}[Y_i(Z=1) - Y_i(Z=0)]$
Hypothesis direction:	one-tailed (-)
Hypothesis explanation:	Having a CAP hired in the respondent's village will decrease their perceived probability of being attacked.
Construction of outcome:	Index from branched questions. 0 = very unlikely, 1 = just unlikely, 2 = just possible, 3 = very likely
Variables used:	`attack_risk`, `attack_risk_yes`, `attack_risk_no`.
Main result:	No

Table 28: Potential outcomes, estimands, hypotheses and pseudo-code for the SATE on `attack_risk`.

Outcome Name:	`theft_risk`
Estimand Name:	SATE
Estimand:	$\text{E}[Y_i(Z=1) - Y_i(Z=0)]$
Hypothesis direction:	one-tailed (-)
Hypothesis explanation:	Having a CAP hired in the respondent's village will decrease their perceived probability of being robbed.
Construction of outcome:	Index from branched questions. 0 = very unlikely, 1 = just unlikely, 2 = just possible, 3 = very likely
Variables used:	`theft_risk`, `theft_risk_yes`, `theft_risk_no`.
Main result:	No

Table 29: Potential outcomes, estimands, hypotheses and pseudo-code for the SATE on `theft_risk`.

5.2.4 Perceptions of formal and informal procedural justice

Outcome Name:	`police_proc_justice_index`
Estimand Name:	SATE
Estimand:	$\mathrm{E}[Y_i(Z=1) - Y_i(Z=0)]$
Hypothesis direction:	one-tailed (+)
Hypothesis explanation:	Having a CAP hired in the village should improve the respondent's perception of the police in terms of procedural justice (an increase on the procedural justice index).
Construction of outcome:	Index of procedural justice constructed in same manner as described in Rosenbaum et al. (2015), with slight adjustments to question wording in order to adapt to local context. Index has quality of treatment and quality of decision-making dimensions.
Variables used:	`treat_polite_first/second_forum`, `seem_concerned_first/second_forum`, `take_seriously_first/second_forum`, `listen_first/second_forum`, `treat_same_first/second_forum`, `competent_first/second_forum`, `explain_first/second_forum`.
Main result:	Yes

Table 30: Potential outcomes, estimands, hypotheses and pseudo-code for the SATE on `police_proc_justice_index`.

Outcome Name:	`chief_proc_justice_index`
Estimand Name:	SATE
Estimand:	$\mathrm{E}[Y_i(Z=1) - Y_i(Z=0)]$
Hypothesis direction:	two-tailed (+/-)
Hypothesis explanation:	Having a CAP hired in the village may improve or worsen the respondent's perception of the chiefs in terms of procedural justice (an increase on the procedural justice index). This depends on whether the CAP works to undermine or improve chief-based policing.
Construction of outcome:	Index of procedural justice constructed in same manner as described in Rosenbaum et al. (2015), with slight adjustments to question wording in order to adapt to local context. Index has quality of treatment and quality of decision-making dimensions.
Variables used:	`treat_polite_first/second_forum`, `seem_concerned_first/second_forum`, `take_seriously_first/second_forum`, `listen_first/second_forum`, `treat_same_first/second_forum`, `competent_first/second_forum`, `explain_first/second_forum`.
Main result:	Yes

Table 31: Potential outcomes, estimands, hypotheses and pseudo-code for the SATE on `chief_proc_justice_index`.

Outcome Name:	`police_rank`
Estimand Name:	SATE
Estimand:	$\mathrm{E}[Y_i(Z=1) - Y_i(Z=0)]$
Hypothesis direction:	one-tailed (+)
Hypothesis explanation:	Having a CAP hired in the village will increase the respondent's belief in the likelihood that the police responds to problems in the community, relative to other potential responder
Construction of outcome:	Branched rank: 1 = police (CAP or BPS) most likely; 2 = police second most likely; 3 = police third most likely; 4 = police least likely.
Variables used:	`stop_crime_rank_1`, `stop_crime_rank_2`, `stop_crime_rank_3`, `stop_crime_rank_4`.
Main result:	No

Table 32: Potential outcomes, estimands, hypotheses and pseudo-code for the SATE on `police_rank`.

Outcome Name:	`police_more`
Estimand Name:	SATE
Estimand:	$\mathrm{E}[Y_i(Z=1) - Y_i(Z=0)]$
Hypothesis direction:	one-tailed (+)
Hypothesis explanation:	Having a CAP hired in the village will increase the respondent's view that the police is more likely than the chief to respond to community problems.
Construction of outcome:	Additive index, subtracting rank of chief from rank of police. Max value is 3 (chief ranked last, police first), minimum value is -3 (chief ranked first, police ranked last).
Variables used:	`stop_crime_rank_1`, `stop_crime_rank_2`, `stop_crime_rank_3`, `stop_crime_rank_4`.
Main result:	No

Table 33: Potential outcomes, estimands, hypotheses and pseudo-code for the SATE on `police_more`.

Outcome Name:	`police_son_caught`
Estimand Name:	SATE
Estimand:	$\mathrm{E}[Y_i(Z=1) - Y_i(Z=0)]$
Hypothesis direction:	two-tailed (+/-)
Hypothesis explanation:	Having a CAP hired in the village might increase or decrease the respondent's anticipated discrepancy in punishment for a son of the local police. On the one hand, if the CAP make the informal institutions look corrupt by comparison, the respondent might anticipate even less harsh punishments for the son of the local police. On the other hand, if the CAP work with the chief to make punishment fairer, the respondent may expect equal or even harsher punishments for the son of the local police
Construction of outcome:	Branched ordinal: 1 = A lot less harshly; 2 = Slightly less harshly; 3 = Neither more nor less harshly; 4 = A little more harshly.
Variables used:	`police_son_caught_yesno`, `police_son_caught_yes`, `police_son_caught_no`.
Main result:	No

Table 34: Potential outcomes, estimands, hypotheses and pseudo-code for the SATE on `police_son_caught`.

Outcome Name:	`chief_son_caught`
Estimand Name:	SATE
Estimand:	$\mathrm{E}[Y_i(Z=1) - Y_i(Z=0)]$
Hypothesis direction:	two-tailed (+/-)
Hypothesis explanation:	Having a CAP hired in the village might increase or decrease the respondent's anticipated discrepancy in punishment for a son of the chief. On the one hand, if the CAP make the informal institutions look corrupt by comparison, the respondent might anticipate even less harsh punishments for the son of the chief. On the other hand, if the CAP work with the chief to make punishment fairer, the respondent may expect equal or even harsher punishments for the son of the chief.
Construction of outcome:	Branched ordinal: 1 = A lot less harshly; 2 = Slightly less harshly; 3 = Neither more nor less harshly; 4 = A little more harshly.
Variables used:	`chief_son_caught_yesno`, `chief_son_caught_yes`, `chief_son_caught_no`.
Main result:	No

Table 35: Potential outcomes, estimands, hypotheses and pseudo-code for the SATE on `chief_son_caught`.

Outcome Name:	`gender_bias_adultery_formal`
Estimand Name:	SATE
Estimand:	$E[Y_i(\text{complainant} = \text{woman}) - Y_i(\text{complainant} = \text{man}) \mid \text{forum} = \text{formal}]$
Hypothesis direction:	one-tailed (+)
Hypothesis explanation:	When the respondent is presented with a female vs. a male accused of adultery, they will expect the formal district court to mete out a harsher punishment.
Construction of outcome:	Ordinal: 5 = The accused would be sent to jail; 4 = The accused would be beaten; 2 = The accused would have to pay a fine; 3 = The accused would be let go due to a lack of evidence; 1 = The defendant would be punished for wasting everyone's time. The gender of the complainant is randomly assigned at the respondent level. This estimand does not rely on the main random assignment (of CAP officers to villages).
Variables used:	`man_woman_adultery_random`, `man_woman_adultery_wanbel`.
Main result:	No

Table 36: Potential outcomes, estimands, hypotheses and pseudo-code for the SATE on `gender_bias_adultery_formal`.

Outcome Name:	`gender_bias_theft_formal`
Estimand Name:	SATE
Estimand:	$E[Y_i(\text{complainant} = \text{woman}) - Y_i(\text{complainant} = \text{man}) \mid \text{forum} = \text{formal}]$
Hypothesis direction:	one-tailed (+)
Hypothesis explanation:	When the respondent is presented with a female vs. a male accused of theft, they will expect the formal district court to mete out a harsher punishment.
Construction of outcome:	Ordinal: 5 = The accused would be sent to jail; 4 = The accused would be beaten; 2 = The accused would have to pay a fine; 3 = The accused would be let go due to a lack of evidence; 1 = The defendant would be punished for wasting everyone's time. The gender of the complainant is randomly assigned at the respondent level. This estimand does not rely on the main random assignment (of CAP officers to villages).
Variables used:	`man_woman_theft_random`, `man_woman_theft_district`.
Main result:	No

Table 37: Potential outcomes, estimands, hypotheses and pseudo-code for the SATE on `gender_bias_theft_formal`.

Outcome Name:	`gender_bias_theft_informal`
Estimand Name:	SATE
Estimand:	$\mathrm{E}[Y_i(\text{complainant} = \text{woman}) - Y_i(\text{complainant} = \text{man}) \mid \text{forum} = \text{informal}]$
Hypothesis direction:	one-tailed (+)
Hypothesis explanation:	When the respondent is presented with a female vs. a male accused of theft, they will expect the wanbel court to mete out a harsher punishment.
Construction of outcome:	Ordinal: 5 = The accused would be sent to jail; 4 = The accused would be beaten; 2 = The accused would have to pay a fine; 3 = The accused would be let go due to a lack of evidence; 1 = The defendant would be punished for wasting everyone's time. The gender of the complainant is randomly assigned at the respondent level. This estimand does not rely on the main random assignment (of CAP officers to villages).
Variables used:	`man_woman_theft_random`, `man_woman_theft_wanbel`.
Main result:	No

Table 38: Potential outcomes, estimands, hypotheses and pseudo-code for the SATE on `gender_bias_theft_informal`.

Outcome Name:	`mob_violence_index`
Estimand Name:	SATE
Estimand:	$\mathrm{E}[Y_i(Z = 1) - Y_i(Z = 0)]$
Hypothesis direction:	one-tailed (-)
Hypothesis explanation:	Having a CAP hired in the village should decrease the belief that mob violence should be used to punish criminals.
Construction of outcome:	Ordinal, constructed by summing two mob violence questions. 0 = no case in which mob violence is justified; 1 = One instance in which mob violence is seen as justified; 2 = two cases in which mob violence seen as justified.
Variables used:	`mob_violence_majority`, `mob_violence_minority`.
Main result:	No

Table 39: Potential outcomes, estimands, hypotheses and pseudo-code for the SATE on `mob_violence_index`.

Outcome Name:	police_ask_bribe
Estimand Name:	SATE
Estimand:	$\mathrm{E}[Y_i(Z=1) - Y_i(Z=0)]$
Hypothesis direction:	one-tailed (-)
Hypothesis explanation:	Having a CAP hired in the village will decrease the respondent's perceived likelihood of the police demanding a bribe in order to come to the village to investigate serious incidents.
Construction of outcome:	Ordinal: 1 = Very unlikely; 2 = Somewhat unlikely; 3 = Somewhat likely; 4 = Very likely.
Variables used:	police_ask_bribe.
Main result:	No

Table 40: Potential outcomes, estimands, hypotheses and pseudo-code for the SATE on police_ask_bribe.

Outcome Name:	police_come_to_village
Estimand Name:	SATE
Estimand:	$\mathrm{E}[Y_i(Z=1) - Y_i(Z=0)]$
Hypothesis direction:	one-tailed (+)
Hypothesis explanation:	Having a CAP hired in the village will increase the respondent's perceived likelihood of the police coming to the village to investigate serious incidents.
Construction of outcome:	Ordinal: 1 = Very unlikely; 2 = Somewhat unlikely; 3 = Somewhat likely; 4 = Very likely.
Variables used:	police_come_to_village.
Main result:	No

Table 41: Potential outcomes, estimands, hypotheses and pseudo-code for the SATE on police_come_to_village.

Outcome Name:	police_interact
Estimand Name:	SATE
Estimand:	$\mathrm{E}[Y_h(Z=1) - Y_h(Z=0)]$
Hypothesis direction:	one-tailed (+)
Hypothesis explanation:	Having a CAP hired in the village will increase the frequency with which the respondent interacts with the police.
Construction of outcome:	Ordinal: 1 = Twice a week or more; 2 = Once a week; 3 = 1 - 3 times a month; 4 = Once every 2-3 months; 5 = 1 - 4 times in the year; 6 = Never.
Variables used:	police_interact.
Main result:	No

Table 42: Potential outcomes, estimands, hypotheses and pseudo-code for the SATE on police_interact.

Outcome Name:	police_legitimacy
Estimand Name:	SATE
Estimand:	$\mathrm{E}[Y_i(Z=1) - Y_i(Z=0)]$
Hypothesis direction:	one-tailed (+)
Hypothesis explanation:	Having a CAP hired in the village will increase the likelihood that a respondent believes the police should step in and arrest people in the village if they commit crimes.
Construction of outcome:	Binary: 0 = It is better for the community to handle its own problems if someone in the village commits a serious crime; 1 = If someone commits a serious crime, the police should come into the village and arrest that person.
Variables used:	police_legitimacy.
Main result:	Yes

Table 43: Potential outcomes, estimands, hypotheses and pseudo-code for the SATE on police_legitimacy.

Outcome Name:	police_trust
Estimand Name:	SATE
Estimand:	$\mathrm{E}[Y_h(Z=1) - Y_h(Z=0)]$
Hypothesis direction:	one-tailed (+)
Hypothesis explanation:	Having a CAP hired in the respondent's village will increase the belief that the police (in general) cares about their wellbeing.
Construction of outcome:	Ordinal: 0 = do not care at all; 1 = do not care much; 2 = care somewhat; 3 = care a lot.
Variables used:	police_care_yes_no, police_care_yes, police_care_no.
Main result:	No

Table 44: Potential outcomes, estimands, hypotheses and pseudo-code for the SATE on police_trust.

Outcome Name:	`right_punishment_rape`
Estimand Name:	SATE
Estimand:	$\mathrm{E}[Y_i(Z=1) - Y_i(Z=0)]$
Hypothesis direction:	two-tailed (+/-)
Hypothesis explanation:	Having a CAP hired in the village might increase or decrease the severity with which the respondent thinks a rapist should be punished, depending on whether the baseline is less than 4 (increase) or more than 4 (decrease).
Construction of outcome:	Ordinal: 1 = The accused should not be punished; 2 = The accused should apologize to the family of the woman; 3 = The accused should give the family of the woman some compensation, such as a pig; 4 = The accused should be sent to prison for a few months; 5 = The accused should be sent to prison for some years; 6 = The accused should be beaten harshly; 7 = The accused should be killed.
Variables used:	`right_punishment_rape`.
Main result:	Yes

Table 45: Potential outcomes, estimands, hypotheses and pseudo-code for the SATE on `right_punishment_rape`.

Outcome Name:	`right_punishment_witchcraft`
Estimand Name:	SATE
Estimand:	$\mathrm{E}[Y_i(Z=1) - Y_i(Z=0)]$
Hypothesis direction:	one-tailed (-)
Hypothesis explanation:	Having a CAP hired in the village should decrease the severity with which the respondent thinks an accused witch should be punished.
Construction of outcome:	Ordinal: 1 = The accused should not be punished; 2 = The accused should apologize to the family of the woman; 3 = The accused should give the family of the woman some compensation, such as a pig; 4 = The accused should be sent to prison for a few months; 5 = The accused should be sent to prison for some years; 6 = The accused should be beaten harshly; 7 = The accused should be killed.
Variables used:	`right_punishment_witchcraft`.
Main result:	Yes

Table 46: Potential outcomes, estimands, hypotheses and pseudo-code for the SATE on `right_punishment_witchcraft`.

Outcome Name:	`police_vs_chief`
Estimand Name:	SATE
Estimand:	$\mathrm{E}[Y_i(Z=1) - Y_i(Z=0)]$
Hypothesis direction:	one-tailed (+)
Hypothesis explanation:	Being hired into the CAP will increase the respondent's view that the police should step in and handle situations differently to how the chief might.
Construction of outcome:	Ordinal: 1 = The police should never be able to tell the chief how to resolve issues in the community. The chief always knows what's best; 2 = Sometimes the chief should let the police step in and handle issues, even if not everyone agrees; 3 = The police most often knows the best way to handle a situation, and the chief should always defer to their authority.
Variables used:	`police_vs_chief`.
Main result:	No

Table 47: Potential outcomes, estimands, hypotheses and pseudo-code for the SATE on `police_vs_chief`.

5.2.5 Gender norms and attitudes

Outcome Name:	`vaw_intolerance`
Estimand Name:	SATE
Estimand:	$\mathrm{E}[Y_h(Z=1) - Y_h(Z=0)]$
Hypothesis direction:	one-tailed (-)
Hypothesis explanation:	Having a CAP hired in the respondent's village will decrease the number of cases of domestic violence that the respondent views as acceptable.
Construction of outcome:	Additive index normalized to 1: 0 = no action by wife justifies domestic violence of husband; 1 = all cases of domestic violence by husband justified.
Variables used:	`disobeys`, `disobeys_yes`, `disobeys_no`, `gossip`, `unfaithful`, `neglects`, `no_housework`, `no_sex`.
Main result:	Yes

Table 48: Potential outcomes, estimands, hypotheses and pseudo-code for the SATE on `vaw_intolerance`.

Outcome Name:	`vaw_intolerance_comm`
Estimand Name:	SATE
Estimand:	$\mathrm{E}[Y_h(Z=1) - Y_h(Z=0)]$
Hypothesis direction:	one-tailed (-)
Hypothesis explanation:	Having a CAP hired in the respondent's village will decrease the number of cases of domestic violence that the respondent thinks the community views as acceptable.
Construction of outcome:	Additive index normalized to 1: 0 = no action by wife justifies domestic violence of husband; 1 = all cases of domestic violence by husband justified.
Variables used:	`vaw_intolerance_comm`, `gossip_community`, `neglects_community`, `unfaithful_community`.
Main result:	Yes

Table 49: Potential outcomes, estimands, hypotheses and pseudo-code for the SATE on `vaw_intolerance_comm`.

5.2.6 Trust in the state

Outcome Name:	trust_state
Estimand Name:	SATE
Estimand:	$E[Y_h(Z = 1) - Y_h(Z = 0)]$
Hypothesis direction:	one-tailed (+)
Hypothesis explanation:	Having a CAP hired in the respondent's village will increase the likelihood that the respondent trusts the government to make the right decisions for the people in his or her village.
Construction of outcome:	Binary: 0 = does not trust; 1 = does trust.
Variables used:	trust_state.
Main result:	Yes

Table 50: Potential outcomes, estimands, hypotheses and pseudo-code for the SATE on trust_state.

Outcome Name:	government_cares
Estimand Name:	SATE
Estimand:	$E[Y_h(Z = 1) - Y_h(Z = 0)]$
Hypothesis direction:	one-tailed (+)
Hypothesis explanation:	Having a CAP hired in the respondent's village will increase the likelihood that the respondent thinks the government cares about people in his or her village.
Construction of outcome:	Binary: 0 = do not care; 1 = do care.
Variables used:	government_cares.
Main result:	Yes

Table 51: Potential outcomes, estimands, hypotheses and pseudo-code for the SATE on government_cares.

Outcome Name:	chief_political_legitimacy
Estimand Name:	SATE
Estimand:	$E[Y_h(Z = 1) - Y_h(Z = 0)]$
Hypothesis direction:	one-tailed (+)
Hypothesis explanation:	Having a CAP hired in the respondent's village will increase the likelihood that the respondent thinks they should vote independently of the chief.
Construction of outcome:	Binary: 0 = vote as chief says; 1 = vote independently.
Variables used:	chief_political_legitimacy.
Main result:	No

Table 52: Potential outcomes, estimands, hypotheses and pseudo-code for the SATE on chief_political_legitimacy.

5.2.7 Knowledge of the state

Outcome Name:	slap_illegal
Estimand Name:	SATE
Estimand:	$\mathrm{E}[Y_h(Z=1) - Y_h(Z=0)]$
Hypothesis direction:	one-tailed (+)
Hypothesis explanation:	Having a CAP hired in the village will increase the respondent's confidence in the knowledge that a man is breaking the law if he slaps his wife.
Construction of outcome:	Ordinal: 1 = he is definitely not breaking the law; 2 = he is probably not breaking the law; 3 = he is probably breaking the law; 4 = he is definitely breaking the law.
Variables used:	slap_illegal, slap_illegal_yes, slap_illegal_no.
Main result:	No

Table 53: Potential outcomes, estimands, hypotheses and pseudo-code for the SATE on slap_illegal.

Outcome Name:	know_president
Estimand Name:	SATE
Estimand:	$\mathrm{E}[Y_h(Z=1) - Y_h(Z=0)]$
Hypothesis direction:	one-tailed (+)
Hypothesis explanation:	Having a CAP hired in the village will increase the respondent's knowledge of the State's leadership.
Construction of outcome:	Binary: 1 = Correctly names president; 0 = Does not know / incorrectly names president.
Variables used:	know_president.
Main result:	No

Table 54: Potential outcomes, estimands, hypotheses and pseudo-code for the SATE on know_president.

5.3 Candidate Outcomes

5.3.1 Honesty

Outcome Name:	`evens_game_1`
Estimand Name:	Conditional SATE
Estimand:	$\mathrm{E}[Y_i(Z=1) - Y_i(Z=0) \mid \text{game} = 1]$
Hypothesis direction:	two-tailed (+/-)
Hypothesis explanation:	Game 1 is played against the enumerator: cheating involves stealing the prize from the enumerator. Respondent is never at risk of having true roll revealed. If being hired as a police officer increases corruption, the number of evens will increase. If it increases honesty, the number will decrease.
Construction of outcome:	Proportion of number of evens rolled in game 1.
Variables used:	`g1r1`, ..., `g1r21`.
Main result:	Yes

Table 55: Potential outcomes, estimands, hypotheses and pseudo-code for the Conditional SATE on `evens_game_1`.

Outcome Name:	`evens_game_2`
Estimand Name:	Conditional SATE
Estimand:	$E[Y_i(Z=1) - Y_i(Z=0) \mid \text{game} = 2]$
Hypothesis direction:	two-tailed (+/-)
Hypothesis explanation:	Game 2 is played against a community member: cheating involves stealing the prize from a community member. Respondent is never at risk of having true roll revealed. If being hired as a police officer increases corruption, the number of evens will increase. If it increases honesty, the number will decrease.
Construction of outcome:	Proportion of number of evens rolled in game 2.
Variables used:	`g2r1`, ..., `g2r21`.
Main result:	Yes

Table 56: Potential outcomes, estimands, hypotheses and pseudo-code for the Conditional SATE on `evens_game_2`.

Outcome Name:	`evens_game_3`
Estimand Name:	Conditional SATE
Estimand:	$E[Y_i(Z=1) - Y_i(Z=0) \mid \text{game} = 3]$
Hypothesis direction:	two-tailed (+/-)
Hypothesis explanation:	Game 3 is played against a community member: cheating involves stealing the prize from a community member. Respondent is at risk of having true roll revealed if enumerator rolls a 6. If being hired as a police officer increases corruption, the number of evens will increase. If it increases honesty, the number will decrease.
Construction of outcome:	Proportion of number of evens rolled in game 3.
Variables used:	`g3r1`, ..., `g3r21`.
Main result:	Yes

Table 57: Potential outcomes, estimands, hypotheses and pseudo-code for the Conditional SATE on `evens_game_3`.

Outcome Name:	`strategic_overall_control`
Estimand Name:	Sub-group quantity
Estimand:	$Pr[n(1) = Y_{i1}, ..., n(6) = Y_{i6} \mid Z = 0, Pr(n(1)), ..., Pr(n(6))]$
Hypothesis direction:	NA
Hypothesis explanation:	The probability of observing the joint distribution of roll outcomes across all games in the control group, given the known probabilities of each roll outcome. Intended as a measure of strategic play. Using the known probabilities of the rolls, we can compute for each respondent the probability of the observed proportion of rolls of each number, given the known distribution of rolls and the number of rolls. The null of no strategy will be rejected at $\alpha = .1$.
Construction of outcome:	Probability: min = 0, max = 1.
Variables used:	`g1r1`, ..., `g4r21`.
Main result:	No

Table 58: Potential outcomes, estimands, hypotheses and pseudo-code for the Sub-group quantity on `strategic_overall_control`.

Outcome Name:	`strategic_overall_treatment`
Estimand Name:	Sub-group quantity
Estimand:	$Pr[n(1) = Y_{i1}, ..., n(6) = Y_{i6} \mid Z = 1, Pr(n(1)), ..., Pr(n(6))]$
Hypothesis direction:	NA
Hypothesis explanation:	The probability of observing the joint distribution of roll outcomes across all games in the treatment group, given the known probabilities of each roll outcome. Intended as a measure of strategic play. Using the known probabilities of the rolls, we can compute for each respondent the probability of the observed proportion of rolls of each number, given the known distribution of rolls and the number of rolls. The null of no strategy will be rejected at $\alpha = .1$.
Construction of outcome:	Probability: min = 0, max = 1.
Variables used:	`g1r1`, ..., `g4r21`.
Main result:	No

Table 59: Potential outcomes, estimands, hypotheses and pseudo-code for the Sub-group quantity on `strategic_overall_treatment`.

Outcome Name:	`community_sociotropy`
Estimand Name:	Difference in conditional SATEs
Estimand:	$E[Y_i(Z = 1) - Y_i(Z = 0) \mid \text{game} = 2] - E[Y_i(Z = 1) - Y_i(Z = 0) \mid \text{game} = 1]$
Hypothesis direction:	one-tailed (-)
Hypothesis explanation:	If being hired as a CAP officer makes the candidate's preferences intrinsically more sociotropic towards community members, then they will play fewer evens when playing against a member as opposed to the enumerator.
Construction of outcome:	Difference in proportions of evens rolled in game 2 vs. game 1.
Variables used:	`g1r1`, ..., `g2r21`.
Main result:	Yes

Table 60: Potential outcomes, estimands, hypotheses and pseudo-code for the Difference in conditional SATEs on `community_sociotropy`.

Outcome Name:	`community_accountability`
Estimand Name:	Difference in conditional SATEs
Estimand:	$E[Y_i(Z=1) - Y_i(Z=0) \mid \text{game} = 3] - E[Y_i(Z=1) - Y_i(Z=0) \mid \text{game} = 2]$
Hypothesis direction:	one-tailed (-)
Hypothesis explanation:	If being hired as a CAP officer makes the candidate feel accountable towards community members, then they will play fewer evens when playing against a member as opposed to the enumerator.
Construction of outcome:	Difference in proportions of evens rolled in game 3 vs. game 2.
Variables used:	`g2r1`, ..., `g3r21`.
Main result:	Yes

Table 61: Potential outcomes, estimands, hypotheses and pseudo-code for the Difference in conditional SATEs on `community_accountability`.

5.3.2 Perceptions of self-efficacy, entitlement, power and respect

Outcome Name:	`calm_men`
Estimand Name:	SATE
Estimand:	$\mathrm{E}[Y_i(Z=1) - Y_i(Z=0)]$
Hypothesis direction:	one-tailed (+)
Hypothesis explanation:	Being hired into the CAP will increase the respondent's belief in their power to confront unruly young men.
Construction of outcome:	Index from branched questions. 0 = would not stop if threatened, 1 = would stop only if threatened, 2 = would stop if convinced, 3 = would stop immediately.
Variables used:	`stop_drunks`, `stop_drunks_yes`, `stop_drunks_no`.
Main result:	No

Table 62: Potential outcomes, estimands, hypotheses and pseudo-code for the SATE on `calm_men`.

Outcome Name:	`happy_right`
Estimand Name:	SATE
Estimand:	$\mathrm{E}[Y_i(Z=1) - Y_i(Z=0)]$
Hypothesis direction:	two-tailed (+/-)
Hypothesis explanation:	Being hired into the CAP might increase the extent to which respondents think they have a right to be happy at the expense of others, if the increase in power increases their sense of entitlement. However, the new role may promote a sense of community responsibility that increases willingness for self-sacrifice, decreasing the view that they have a right to be happy at the expense of others.
Construction of outcome:	Branched ordinal: 1 = strongly disagree (that I have the right to be happy at the expense of someone else); 2 = disagree somewhat; 3 = agree somewhat; 4 = agree strongly.
Variables used:	`happy_right`, `happy_right_yes`, `happy_right_no`.
Main result:	No

Table 63: Potential outcomes, estimands, hypotheses and pseudo-code for the SATE on `happy_right`.

Outcome Name:	`impunity`
Estimand Name:	SATE
Estimand:	$\mathrm{E}[Y_i(Z = 1) - Y_i(Z = 0)]$
Hypothesis direction:	two-tailed (+/-)
Hypothesis explanation:	Being hired into the CAP could increase the respondent's belief in their impunity if it makes them think they are more powerful. Alternatively, it may make them feel more accountable to community - i.e. held to higher standards, and so decrease perceived impunity to punishment.
Construction of outcome:	Ordinal: 1 = similar thief killed; 2 = similar thief bashed; 3 = similar thief made to pay; 4 = similar thief not punished.
Variables used:	`you_steal`.
Main result:	No

Table 64: Potential outcomes, estimands, hypotheses and pseudo-code for the SATE on `impunity`.

Outcome Name:	`more_recognition`
Estimand Name:	SATE
Estimand:	$\mathrm{E}[Y_i(Z = 1) - Y_i(Z = 0)]$
Hypothesis direction:	two-tailed (+/-)
Hypothesis explanation:	Being hired into the CAP might increase the extent to which respondents think they do not get enough recognition, since their increased power increases their sense of entitlement. Being hired might also be understood as an honor that recompenses their efforts, and will thus decrease the perception of not getting enough recognition..
Construction of outcome:	Branched ordinal: 1 = strongly disagree (that my work does not receive adequate recognition); 2 = disagree somewhat; 3 = agree somewhat; 4 = agree strongly.
Variables used:	`more_recognition`, `more_recognition_yes`, `more_recognition_no`.
Main result:	No

Table 65: Potential outcomes, estimands, hypotheses and pseudo-code for the SATE on `more_recognition`.

Outcome Name:	`opinion_of_others`
Estimand Name:	SATE
Estimand:	$\mathrm{E}[Y_i(Z=1) - Y_i(Z=0)]$
Hypothesis direction:	two-tailed (+/-)
Hypothesis explanation:	Being hired into the CAP may increase the extent to which they care about the opinions of others, since they feel they are now in a position of responsibility. Alternatively, it may decrease their regard for the feelings of others if they feel that their newfound power puts them above the judgment of the community.
Construction of outcome:	Branched ordinal: 1 = not very important at all; 2 = not very important; 3 = somewhat important; 4 = very important.
Variables used:	`opinion_of_others_yesno`, `opinion_of_others_yes`, `opinion_of_others_no`.
Main result:	No

Table 66: Potential outcomes, estimands, hypotheses and pseudo-code for the SATE on `opinion_of_others`.

Outcome Name:	`prop_support`
Estimand Name:	SATE
Estimand:	$\mathrm{E}[Y_i(Z=1) - Y_i(Z=0)]$
Hypothesis direction:	one-tailed (+)
Hypothesis explanation:	Being hired into the CAP will increase the respondent's belief that the community would support them in a dispute with a relative of the chief.
Construction of outcome:	Branched ordinal: 1 = $\leq 1/4$ of community would support; 2 = $1/4 < 1/2$ community would support; 3 = 1
Variables used:	`whose_side`, `whose_side_yes`, `whose_side_no`.
Main result:	No

Table 67: Potential outcomes, estimands, hypotheses and pseudo-code for the SATE on `prop_support`.

Outcome Name:	`relative_impunity`
Estimand Name:	SATE
Estimand:	$\text{E}[Y_i(Z=1) - Y_i(Z=0)]$
Hypothesis direction:	two-tailed (+/-)
Hypothesis explanation:	Being hired into the CAP could increase the respondent's belief in their impunity if it makes them think they are more powerful *than the average community member*. Alternatively, it may make them feel more accountable to community - i.e. held to higher standards, and so decrease perceived impunity to punishment *relative to the average community member*.
Construction of outcome:	Ratio of ordinals normalized to 1: the punishment someone like resp. (with the same job, same amount of respect) would receive if they were caught stealing divided by typical punishment someone would receive for theft divided by the punishment . Values greater than 1 indicate that the resp. sees self as relatively more immune to punishment.
Variables used:	`you_steal`, `someone_else_steal`.
Main result:	No

Table 68: Potential outcomes, estimands, hypotheses and pseudo-code for the SATE on `relative_impunity`.

Outcome Name:	`respect`
Estimand Name:	SATE
Estimand:	$\text{E}[Y_i(Z=1) - Y_i(Z=0)]$
Hypothesis direction:	one-tailed (+)
Hypothesis explanation:	Being hired into the CAP will increase the extent to which respondents see themselves as respected by the community.
Construction of outcome:	Ordinal: 1 = My community is not very respectful of me; 2 = I am respected about as much as most people in my community; and, 3 = Very highly, I am one of the most respected people in my community.
Variables used:	`respect`.
Main result:	No

Table 69: Potential outcomes, estimands, hypotheses and pseudo-code for the SATE on `respect`.

Outcome Name:	respect_improve
Estimand Name:	SATE
Estimand:	$\mathrm{E}[Y_i(Z=1) - Y_i(Z=0)]$
Hypothesis direction:	one-tailed (+)
Hypothesis explanation:	Being hired into the CAP will increase the extent to which respondents see themselves as being more respected by the community between now and christmas.
Construction of outcome:	Ordinal: 1 = People respect me a lot less; 2 = People respect me a little less; 3 = People respect me about the same; 4 = People respect me a little more; 5 = People respect me a lot more.
Variables used:	respect_improve.
Main result:	No

Table 70: Potential outcomes, estimands, hypotheses and pseudo-code for the SATE on respect_improve.

5.3.3 Beliefs about justice

Outcome Name:	police_more
Estimand Name:	SATE
Estimand:	$\mathrm{E}[Y_i(Z=1) - Y_i(Z=0)]$
Hypothesis direction:	one-tailed (+)
Hypothesis explanation:	Being hired into the CAP will increase the respondent's view that the police is more likely than the chief to respond to community problems.
Construction of outcome:	Additive index, subtracting rank of chief from rank of police. Max value is 3 (chief ranked last, police first), minimum value is -3 (chief ranked first, police ranked last).
Variables used:	stop_crime_rank_1, stop_crime_rank_2, stop_crime_rank_3, stop_crime_rank_4.
Main result:	No

Table 71: Potential outcomes, estimands, hypotheses and pseudo-code for the SATE on police_more.

Outcome Name:	police_vs_chief
Estimand Name:	SATE
Estimand:	$\mathrm{E}[Y_i(Z=1) - Y_i(Z=0)]$
Hypothesis direction:	one-tailed (+)
Hypothesis explanation:	Being hired into the CAP will increase the respondent's view that the police should step in and handle situations differently to how the chief might.
Construction of outcome:	Ordinal: 1 = The police should never be able to tell the chief how to resolve issues in the community. The chief always knows whatâĂŹs best; 2 = Sometimes the chief should let the police step in and handle issues, even if not everyone agrees; 3 = The police most often knows the best way to handle a situation, and the chief should always defer to their authority.
Variables used:	police_vs_chief.
Main result:	No

Table 72: Potential outcomes, estimands, hypotheses and pseudo-code for the SATE on police_vs_chief.

Outcome Name:	`cand_or_chief_man`
Estimand Name:	SATE
Estimand:	$\mathrm{E}[Y_i(Z=1) - Y_i(Z=0)]$
Hypothesis direction:	one-tailed $(+)$
Hypothesis explanation:	Being hired into the CAP will increase the respondent's perceived likelihood of a man reporting problems to him or her over the chief.
Construction of outcome:	Binary: $0 =$ They are more likely to go to the chief for help; $1 =$ They are more likely to come to me for help.
Variables used:	`cand_or_chief_man`.
Main result:	No

Table 73: Potential outcomes, estimands, hypotheses and pseudo-code for the SATE on `cand_or_chief_man`.

Outcome Name:	`cand_or_chief_man_v_woman`
Estimand Name:	SATE
Estimand:	$\mathrm{E}[Y_i(Z=1) - Y_i(Z=0)]$
Hypothesis direction:	one-tailed $(+)$
Hypothesis explanation:	Being hired into the CAP will increase the respondent's perceived likelihood that a woman is more likely than man to report to him or her over the chief.
Construction of outcome:	Ordinal, obtained by subtracting `cand_or_chief_man` from `cand_or_chief_woman`: -1 $=$ a man more likely than a woman to report to the candidate over the chief; $0 =$ man and woman equally likely to report to candidate over chief; $1 =$ woman more likely than man to report to candidate over chief.
Variables used:	`cand_or_chief_man`, `cand_or_chief_woman`.
Main result:	No

Table 74: Potential outcomes, estimands, hypotheses and pseudo-code for the SATE on `cand_or_chief_man_v_woman`.

Outcome Name:	`cand_or_chief_woman`
Estimand Name:	SATE
Estimand:	$\text{E}[Y_i(Z=1) - Y_i(Z=0)]$
Hypothesis direction:	one-tailed (+)
Hypothesis explanation:	Being hired into the CAP will increase the respondent's perceived likelihood of a woman reporting problems to him or her over the chief.
Construction of outcome:	Binary: 0 = They are more likely to go to the chief for help; 1 = They are more likely to come to me for help.
Variables used:	`cand_or_chief_woman`.
Main result:	No

Table 75: Potential outcomes, estimands, hypotheses and pseudo-code for the SATE on `cand_or_chief_woman`.

Outcome Name:	`police_rank`
Estimand Name:	SATE
Estimand:	$\text{E}[Y_i(Z=1) - Y_i(Z=0)]$
Hypothesis direction:	one-tailed (+)
Hypothesis explanation:	Being hired into the CAP will increase the respondent's belief in the likelihood that the police responds to problems in the community, relative to other potential responder
Construction of outcome:	Branched rank: 1 = police (CAP or BPS) most likely; 2 = police second most likely; 3 = police third most likely; 4 = police least likely.
Variables used:	`stop_crime_rank_1`, `stop_crime_rank_2`, `stop_crime_rank_3`, `stop_crime_rank_4`.
Main result:	No

Table 76: Potential outcomes, estimands, hypotheses and pseudo-code for the SATE on `police_rank`.

5.3.4 Gender attitudes and legal knowledge

Outcome Name:	`vaw_intolerance`
Estimand Name:	SATE
Estimand:	$\mathrm{E}[Y_i(Z=1) - Y_i(Z=0)]$
Hypothesis direction:	one-tailed (-)
Hypothesis explanation:	Being hired into the CAP will decrease the number of cases of domestic violence that the respondent views as acceptable.
Construction of outcome:	Additive index normalized to 1: 0 = no action by wife justifies domestic violence of husband; 1 = all cases of domestic violence by husband justified.
Variables used:	`disobeys`, `disobeys_yes`, `disobeys_no`, `gossip`, `unfaithful`, `neglects`, `no_housework`, `no_sex`.
Main result:	Yes

Table 77: Potential outcomes, estimands, hypotheses and pseudo-code for the SATE on `vaw_intolerance`.

Outcome Name:	`slap_illegal`
Estimand Name:	SATE
Estimand:	$\mathrm{E}[Y_i(Z=1) - Y_i(Z=0)]$
Hypothesis direction:	one-tailed (+)
Hypothesis explanation:	Being hired into the CAP will increase the respondent's confidence in the knowledge that a man is breaking the law if he slaps his wife.
Construction of outcome:	Ordinal: 1 = he is definitely not breaking the law; 2 = he is probably not breaking the law; 3 = he is probably breaking the law; 4 = he is definitely breaking the law.
Variables used:	`slap_illegal`, `slap_illegal_yes`, `slap_illegal_no`.
Main result:	No

Table 78: Potential outcomes, estimands, hypotheses and pseudo-code for the SATE on `slap_illegal`.

5.3.5 Alignment with community norms

Outcome Name:	`vaw_intolerance_comm_align`
Estimand Name:	Difference in conditional SATEs
Estimand:	$\mathrm{E}[Y_i(Z=1) - \mathrm{E}[Y_h(Z=1)] \mid j=x] - \mathrm{E}[Y_i(Z=0) - \mathrm{E}[Y_h(Z=0)] \mid j=x]$
Hypothesis direction:	two-tailed (+/-)
Hypothesis explanation:	Being hired as a CAP officer could make the difference in intoleranc of violence against women greater and more positive, if the officer becomes more intolerant of VAW than the community becomes. It may also make the difference smaller, if the community is brought into line with the already-progressive views of the candidate through the elevation of the latter into a moral authority. Interpretation will depend on analysis of the baseline levels of outcomes among the control.
Construction of outcome:	Difference in additive violence intolerance index for candidate vs. average of that index for community.
Variables used:	`vaw_intolerance`.
Main result:	No

Table 79: Potential outcomes, estimands, hypotheses and pseudo-code for the Difference in conditional SATEs on `vaw_intolerance_comm_align`.

Outcome Name:	`police_rank_comm_align`
Estimand Name:	Difference in conditional SATEs
Estimand:	$\mathrm{E}[Y_{ij}(Z=1) - \mathrm{E}[Y_{hj}(Z=1)] \mid j=x] - \mathrm{E}[Y_{ij}(Z=0) - \mathrm{E}[Y_{hj}(Z=0)] \mid j=x]$
Hypothesis direction:	two-tailed (+/-)
Hypothesis explanation:	Being hired as a CAP officer could make the difference in community views about the role of the police larger and more positive, if the officer views his or her role as more important than the community. It may also make the difference larger and more negative, if CAP officers do not change their view but the community does. Interpretation will depend on analysis of the baseline levels of outcomes among the control.
Construction of outcome:	Difference in importance candidate attaches to police minus average of importance that his or her community attaches to the police.
Variables used:	`police_rank`.
Main result:	No

Table 80: Potential outcomes, estimands, hypotheses and pseudo-code for the Difference in conditional SATEs on `police_rank_comm_align`.

Outcome Name:	`policing_comm_align_index`
Estimand Name:	Difference in conditional SATEs
Estimand:	$E[Y_i(Z=1) - E[Y_h(Z=1)] \mid j=x] - E[Y_i(Z=0) - E[Y_h(Z=0)] \mid j=x]$
Hypothesis direction:	two-tailed (+/-)
Hypothesis explanation:	Being hired as a CAP officer could make the difference in community views about the role of the police larger and more positive, if the officer views his or her role as more important than the community. It may also make the difference larger and more negative, if CAP officers do not change their view but the community does. Interpretation will depend on analysis of the baseline levels of outcomes among the control.
Construction of outcome:	Difference in additive index for candidate vs. average of that index for community. Index is constructed here by summing components that are each given a maximum value of 1 and a minimum value of 0, and then normalizing the sum to 1, so that 1 indicates a value of complete replacement of the chief's legitimacy by the police, and 0 complete dominance of the chief over police. The first component takes 1 if the police are ranked more likely than the chief to respond to community problems. The second component takes 0 if the respondent thinks the police should never be able to tell the chief how to resolve issues in the community, .5 if they think sometimes the chief should let the police step in and handle issues, even if not everyone agrees, and 1 if they think the police most often knows the best way to handle a situation, and the chief should always defer to their authority. The third component takes 1 if the respondent thinks the police should play a larger role in the community, 0 if not. The fourth component normalizes `police_rank` to 1. The fifth and sixth components are just `cand_or_chief_man` and `cand_or_chief_woman` coded as above.
Variables used:	`police_more`, `police_vs_chief`, `police_bigger_role`, `cand_or_chief_man`, `cand_or_chief_woman`.
Main result:	No

Table 81: Potential outcomes, estimands, hypotheses and pseudo-code for the Difference in conditional SATEs on `policing_comm_align_index`.

6 Estimation Strategy

This PAP specifies both randomization inference strategies – using null-hypothesis testing – and Bayesian inference strategies – using prior and posterior probability distributions – in order to estimate the above-defined estimands. Many of the specifications are the same in the two approaches, however the characterization of uncertainty is different.

6.1 Assumptions for Identification of Estimands that Pose Risks of Post-Treatment Bias

In addition to the classic assumptions of the exclusion restriction holding and non-interference (Stable Treatment Unit Value Assumption), the identification of some of the causal estimands relies on additional assumptions whose violation could lead to post-treatment bias. Both Randomizationa Inference (RI) and Bayesian Inference (BI) rely on these assumptions. I describe both the assumptions and a method for interrogating them in this section.

Assumption 1: No effect of treatment on recall of pre-treatment incidents. Note that many estimands rely on a difference-in-differences between incidents recalled from the pre-treatment period and incidents recalled from the post-treatment period.

In all likelihood there will be a certain degree of measurement error in recall due to the difficulties inherent in recalling events from the past. However, this is only problematic if that error is systematic in nature between treatment and control as pertains to the recall of pre-treatment incidents. If the error in the recall of pre-treatment incidents is not systematically different in treatment and control, then this data can be used to increase precision of estimates by accounting for differing baseline incidence rates. The null hypothesis of zero systematic difference can be tested using randomization inference under the sharp null of no effect of treatment on pre-treatment incidence rates. Moreover, pre-treatment incidents can be used to identify the effects of the treatment on reporting behavior if recall is unaffected by treatment. Whereas analyzing reporting of post-treatment incidents is prone to treatment bias if the treatment also affects the incidence rate of post-treatment incidents, the incidence rate of pre-treatment incidents is by definition unaffected by treatment. Thus, any effects on reporting behavior can be identified by analyzing incidents that occured prior to treatment but were reported post treatment.

If the null of no effect is rejected then only post-treatment recall data will be used. Since failure to reject this null does not constitute proof in favor of the null, in addition to reporting the results under the assumption of no effect on pre-treatment recall, I will construct a confidence interval for the joint significance of constant effects on both the pre- and post-treatment incident reports using the method described in Bowers, Fredrickson, and Panagopoulos (2013) and Aronow (2016). In this method, the sum of squared residuals is used as a test statistic to evaluate a range of additive effects models under hypothesized models of effects, using the random assignment mechanism as the sole stochastic component.

Assumption 2: No effect of treatment on incidence of crimes of passion. Another assumption that allows for the identification of post-treatment reporting behavior is that crimes of passion are not affected by the treatment because they are not susceptible to deterrence mechanisms. This assumption can be formally interrogated using the same tests as described above: a test for the sharp null of no effect on pre-meditated crime incidents, on one hand, and the construction of a confidence interval using inverted hypothesis tests, on the other.

6.2 Specifications

All specifications using RI and BI will take account of the blocked design through the inclusion of block dummies and inverse-probability weighting.

One point of difference in the RI and BI esitmation procedures resides in the manner in which intra-cluster correlation is accounted for in variance estimates. Estimates of the variance in randomization inference will be computed using cluster-robust standard errors, whereas specifications used in bayesian models will account for clustering through the inclusion of a random effect.

All estimands will be estimated with and without covariates. Covariates include an index for assets owned by households, gender, age, relationship to the chief, enumerator-reported relative wellbeing, and road distance to the nearest town with a central police station (Arawa, Wakunai or Buka).

Thus, for all estimates of SATEs among households, the full model within which others are nested can be written:

$$Y_h = \alpha_j + \tau z_h + \mathbf{X}_h^\top \boldsymbol{\gamma} + \epsilon_h, \tag{1}$$

where α_j is a cluster-specific random effect that is only estimated in Bayesian models, τ is the effect of the treatment, and $\boldsymbol{\gamma}$ is a vector of covariate coefficients and block dummies.

For difference-in-differences estimands, the pre-treatment baseline value is simply added to equation 1 on the right-hand side. For heterogeneous effects among subgroups, an interaction with z_h is included.

Specifications for candidate models are almost identical but exclude the random effect.

6.3 Randomization Inference

For the non-Bayesian estimates, inferences will be made on the basis of p-values computed through randomization inference using well-powered test statistics. The specific testing procedure to be used is outlined in Rosenbaum (2002); Bowers, Fredrickson, and Panagopoulos (2013); Greevy et al. (2004) and Aronow (2016).

The procedure involves inverted hypothesis tests over a K-length vector $\boldsymbol{\theta}$ of hypothesized effects. I firstly obtain the predicted values $\hat{\mathbf{y}}$ from a restricted version of equation 1 that excludes the term τz_h, so that the residuals are equal to sample variance and the treatment effect, $\mathbf{r} = \mathbf{y} - \hat{\mathbf{y}} = \tau\mathbf{z} + \boldsymbol{\epsilon}$. I then construct the 'uniformity trial' under some θ_k using $\mathbf{r}_{0k} = \mathbf{r} - \theta_k\mathbf{z}$. Thus, if the true effect is constant and additive, there is some $\theta^* = \tau$ whereby $\mathbf{r}_0^* = \boldsymbol{\epsilon}$. Any two random draws from $\mathbf{r}_0^*$ will thus be random draws from the same distribution, $\boldsymbol{\epsilon}$.

We can formally test the hypothesis that $\theta_k = \theta^*$ using the Kolmogorov-Smirnov (KS) or Sum of Squared Residuals (SSR) test-statistics, which provides a non-parametric measure for the equality of two distributions and for goodness of fit of the hypothesized effects model, respectively.

I then compute a p-value corresponding to each element of $\boldsymbol{\theta}$,

$$\phi_k = \Pr(\mathcal{SSR}(\mathbf{r}_{0k}, \mathbf{Z}) > \mathcal{SSR}(\mathbf{r}_{0k}, \mathbf{z})), \tag{2}$$

where $\mathcal{SSR}()$ is the test statistic, and $\mathbf{Z}$ is the matrix of all permutations of the treatment assignment. If a hypothesized effect creates a much larger observed difference in the treatment and control distributions than we would expect under the uniformity trial, we reject θ_k with some level of confidence. This test has the attractive feature of showing the range of effects that could plausibly have generated the data, given sample variance and the assignment mechanism. The confidence interval consists of all effects for which we fail to reject the null. By ensuring that 0 is in θ_k, this method contains a test of the null of no average treatment effect, the specific p-value of which will be reported.

6.4 Bayesian Inference

Bayesian models will be employed in order to make use of data on expert expectations and on non-experimental units to increase the precision of estimates. Expert expectations (see section 4.3) will be used to form informative priors over the treatment effect term, τ. Similarly, informative empirical priors on the variance term of the random effect, α, will be derived from an independent survey conducted one month prior to data collection in 15 non-experimental villages throughout Bougainville. In both cases, priors will be modeled hierarchically using the micro-data from both expert opinions and non-experimental villages, so as to incorporate uncertainty about the hyperparameters of the priors. For example, suppose that the mean of the expectations on some estimand is 5 and the standard deviation around that mean is 2. Rather than expressing the informative prior over τ as $\tau \sim \mathcal{N}(5, 2)$, for example, the raw data will be used to model hierarchical empirical priors, i.e. $\tau \sim \mathcal{N}(\mu_\tau, \sigma_\tau)$, $\mu_\tau \sim \mathcal{N}(x_i, v_i)$, $\sigma_\tau \sim \text{Cauchy}(0, 5)$. Here, rather than simply take the mean of the expectations, information about the location and scale of the i'th expert guess (x_i and v_i, respectively), is incorporated into the model, so that expert uncertainty is propagated in the model. The approach to modeling priors is thus akin to the supra-bayesian consensus prior approach advocated by Albert et al. (2012); Roback and Givens (2001) and French (1983). The advantage of this method of empirically-based informative priors is that the researcher only provides very weakly informative hyper-priors (such as hyper-priors on the variance term σ_τ) that are easily overwhelmed by the data, and thus reduces sensitivity of posterior inferences to researcher-provided information. Nevertheless, all Bayesian specifications will report sensitivity analyses to show how the posterior inference changes when no informative prior information at all is given, and when empirical prior information is provided but researcher hyper-priors are very diffuse.

7 Strategies for Imperfect Implementation

This section describes strategies to be pursued in case of issues arising with the data collection. As stated above, any contingency not accounted for in this plan will be dealt with according to the Standard Operating Procedures for Don Green's lab at Columbia.

7.1 Non-Compliance

Non-compliance is not anticipated but could arise at the cluster-level. If the no-defiers assumption is plausible, any cluster-level non-compliance will be dealt with using instrumental variables estimators. Since intent-to-treat effects are not of primary interest in this study, all specifications reporting the "main results" will seek to recover the proportion of the treatment effect explained by actually receiving treatment as a result of the assignment. Blocks that contain non-compliers will not be discarded. For non-Bayesian specifications, P-values will be calculated parametrically using 2SLS and as outlined in Imbens and Rosenbaum (2005). Inference in Bayesian specifications will be performed using the method outlined in Frangakis, Rubin, and Zhou (2002).

7.2 Item-Level Missingness

Any covariate information that is missing at the item-level will be imputed using multivariate imputation by chained equations as implemented in the `MICE` package for `R`, with only the covariates as predictors (no treatment indicator or outcome). When an item is missing from one outcome for a respondent who has otherwise answered, two approaches will be taken. First, the item will be imputed using MICE and all of the outcomes from that same family of outcomes, but excluding any covariates or treatment indicator information. The results of this exercise are the results that will be reported. Second, the effect will be estimated among all outcomes that are observed. These results will be made available in an appendix.

7.3 Attrition

If cluster-level attrition occurs, it will be dealt with in two ways, depending on the nature of the attrition. If surveying in a village is made impossible by factors that cannot plausibly be related to the treatment assignment, such as bad weather, pre-treatment social problems, or a permission refusal at the block level, then the experiment will simply be analyzed through the exclusion of the block containing the attritting cluster, since this approach is not prone to the problem of differential attrition. If the attritting cluster would have always attritted regardless of treatment status, then we need not worry about the problem of "hidden attritters" that just so happened to be assigned to a condition that prevented attrition.

However, if the cluster cannot be surveyed for reasons apparently related to the treatment, such as outrage over not having a CAP hired in the village, then the trimming bounds approach specified in the Green lab SOP will be employed.

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