Pre-Analysis Plan for "Candidate Entry into Local Government"

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Overview

This pre-analysis plan (PAP) governs the analysis of data collected under the research initiative entitled "Candidate Entry into Local Government." The initiative explores the governance challenge of how to get high human capital, high integrity, representative citizens to put themselves forward for consideration as political candidates. It evaluates an intervention that was designed to tackle this challenge in collaboration with partners in government and civil society, which was implemented in the lead up to the June 24th, 2023, Local Council Elections in Sierra Leone. The intervention: i) identified, screened, and encouraged high quality potential candidates to enter politics; and ii) shared information about these aspirants with political parties. Field teams identified potential candidates via a combination of structured community nominations and screening on technocratic merit. The initiative was randomly assigned across two levels: first, across 150 of 300 rural local government wards (the most local administrative unit); and second, with varied saturation across the 92 host constituencies (the second higher administrative unit) that contain these wards to account for potential spillover effects. Key outcomes of interest concern the number and quality of people in the pool of aspirants, selected candidates, and elected officials. At the time of writing this PAP, the intervention has been implemented, data collection for key outcomes is ongoing (detailed below), and data analysis has not yet begun.

Intervention

The intervention evaluated was dubbed the "Local Champions Initiative," which operated across rural district councils in Sierra Leone. The intervention generated curated lists of high-quality potential aspirants (i.e., those who aspire to be political candidates) to share with party leaders with encouragement to include them in the pool of individuals under their consideration. This eases the information and logistical constraints on identifying potential candidates while placing no direct obligation on parties. It proceeded in the following stages:

- ***Community nominations:*** A key aspect of representation is the support of local voters. Field teams elicited the names of popular individuals via private household visits. Enumerators first explained the skills and competencies that are needed to be an effective Local Councillor and then asked respondents to list up to 5 individuals from their ward that they thought would make good candidates. Respondents were then asked to think of up to 5 additional names of female potential candidates in particular. Teams implemented these private elicitations in around 80 households from up to three of the largest communities in each ward.[1]

- ***Technocratic quality screening****:* The research team selected the most popular individuals (top 10 by total nominations across households) generated by the community elicitations and screened these individuals privately using a comprehensive set of questions designed to gauge the nominees' skills and preparation for local public office. The screening instrument includes questions that have been empirically verified in related work to positively correlate with the public spending performance of Members of Parliament, the quality of local infrastructure grant proposals drafted by community members, and anonymous peer reviews conducted among currently serving members of Local Council. This multi-faceted quality screening narrows the list of potential candidates to those of the highest quality and capability. Nominees were informed about the details of the Local Champions Initiative and given the option to participate (or not). If interested, nominees chose which party (or parties) they were interested in having their profile shared with.

- ***Information provision:*** The two-track process above generated lists of high quality, representative potential candidates to share with political parties for their consideration as they screened aspirants and awarded party symbols. The research team compiled short profiles of the top two community nominees per ward who scored the highest on the technical screening, met eligibility requirements, and were interested in putting themselves forward for consideration as candidates. These profiles were then shared with party officials from the relevant party in a given ward. The profiles present information under free disposal, with no obligation on parties to select any of the nominees.

Within the research sample (more details below), some wards received the full treatment, which comprises the nominations and screening procedures, followed by information provision to parties. Other wards received partial treatment, which is the nominations and screening only, with no information provision to parties. All remaining wards form a pure control group, where similar data was collected but no interventions were implemented.

The Political Parties Regulation Commission (PPRC), the government agency with the authority to regulate the conduct of political parties with respect to their members and the broader electorate, invited all registered parties to join the initiative and associated research. Party leaders decided whether or not to opt into the initiative. Both major parties, the All People's Congress (APC) and the Sierra Leone People's Party (SLPP) opted into the initiative and were assigned equal numbers of treatment and control wards.

[1] More specifically, teams visited the headquarter community of each of the 3 largest chiefdom sections per ward. In wards that contain fewer than 3 sections, teams visited fewer communities but conducted more surveys per community visited, as these tend to be in larger town locations.

Institutional Context

The Government of Sierra Leone unexpectedly changed the electoral system shortly before the 2023 election. This policy change occurred after our initial random assignment was completed and fieldwork had begun, requiring us to make some changes to the design midstream. It is thus useful to describe how the electoral system was originally structured and the key policy changes that were enacted, before delving into the research design and subsequent adjustments.

When we initially designed this experiment, elections for district councils were organized as first-past-the-post, single member jurisdictions at the ward level (the most local administrative unit). This is how district council elections have been run since the end of the civil war (in 2002) and reintroduction of decentralization in 2004. The Local Champions Initiative operated in 14 of the 15 district councils nationwide.[2] The initial random assignment was done across wards inside these councils, treating them as races that were fully independent of one another.

Shortly before the 2023 election, the government changed the electoral system to district-block, proportional representation (PR). Each party was asked to compile a list of candidates that was twice as long as the number of Council seats (where number of seats is equivalent to number of wards) in a given district. There were no clear guidelines about how this change would affect geographic representation: e.g., while parties could simply nominate two candidates per ward for the list, which would align closely with the old system, there was no requirement to do so. Parties were free, for example, to abandon the use of wards as the basic unit of representation, moving instead to a higher electoral administrative unit, like the Parliamentary constituency, or perhaps to an alternative unit, like the traditional chieftaincies. This raises the question of whether the ward-level processes would remain independent of one another, and thus whether the intervention studied could introduce partial interference across units (e.g. the intervention might increase geographic representation of treated wards at the potential expense of control wards). We thus adjusted our random assignment midstream in anticipation of potential interference (explained further below).

In addition, there was little guidance issued about how parties should rank candidates within their district-level lists: e.g., should they rank 1 candidate per ward to cover all wards, and then start again with the second candidate per ward, or cluster all candidates from a particular ward at the top of the list? And, at the same time, the government stipulated a women's empowerment quota, calling for 1 of every 3 candidates to be female. It was not clear how this gender-based allocation relates to the underlying ward structure, either.

Research Design

[2] The study sample excludes the 7 urban city councils as well as the Western Area Rural District Council, which is adjacent to the capital and relatively more urban than the rural district councils in the sample.

Sample

In order to study the Local Champions Initiative, we first selected an experimental sample of wards within the 14 councils. We focused the sample on wards whose boundaries did not cut across chiefdom boundaries (chiefdoms are traditional authority divisions that are more salient to citizens than ward boundaries) and excluded wards where the intervention had been piloted. This generated a study sample of 250 wards, located in 92 distinct Parliamentary constituencies (the next higher unit of formal state administration).

Since the Local Champions Initiative was done in collaboration with the two major political parties in Sierra Leone, each unit in our sample was available for both parties. Thus, the random assignment of treatments was done on a full sample of 500 party-wards and 184 party-constituencies. Nonetheless, as there are clear regional patterns of support for each major party, which map directly to which party community nominees tend to be willing to have their profile shared with, we delineate a stronghold sample (250 wards, 92 constituencies) that assigns wards to the party that historically dominates politics in that locality (defined at the district level). We will also analyze impacts in weakhold areas, as it is possible that the intervention will be particularly impactful where parties are less popular and must work harder to find high quality, interested candidates.

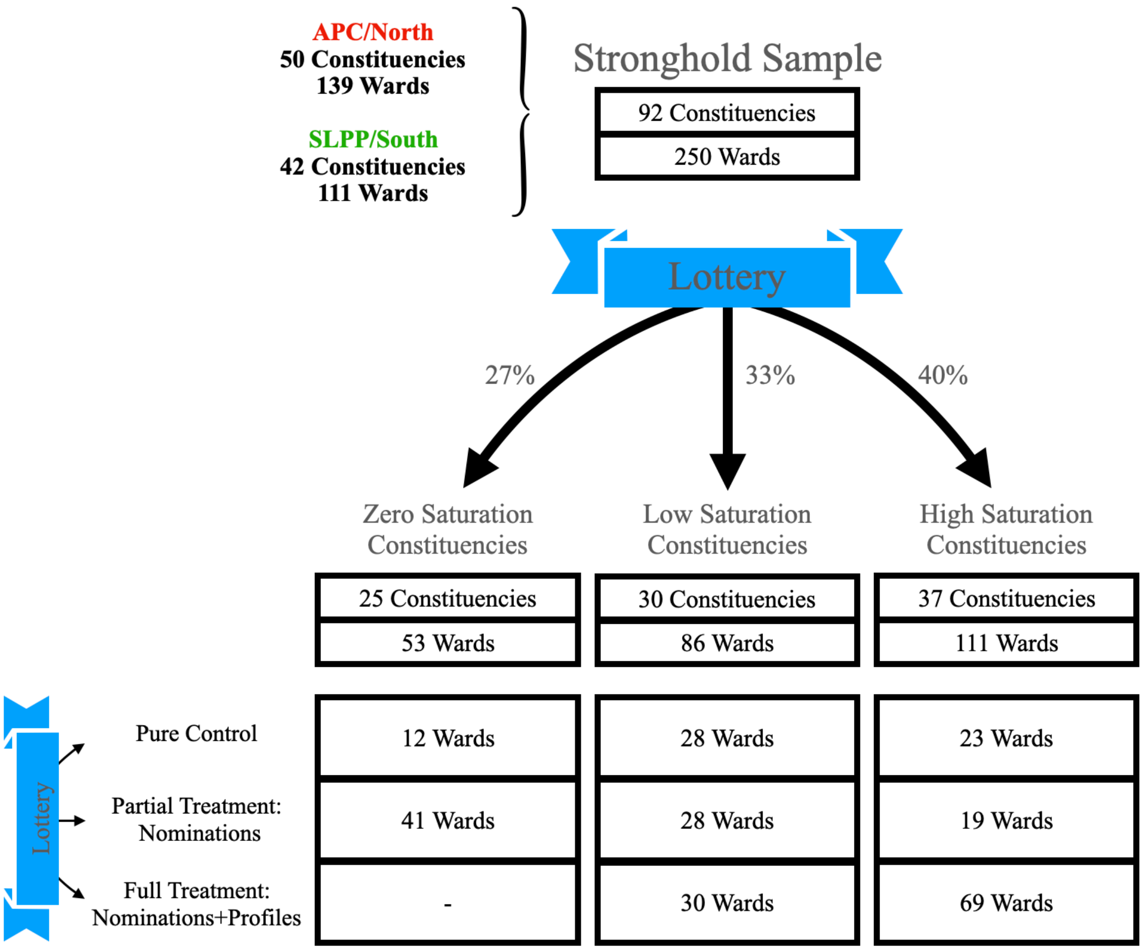
Treatment Assignment

At a high level, there were two rounds of treatment assignment. The first, at the ward-level, randomly allocated the nominations plus screening process (treatment) versus status quo (control group). This was completed under the preexisting electoral system. The second, at the constituency-level, randomly assigned the profile information sharing component among the treated units, which created three groups (full treatment, partial treatment, and pure control). This was completed after the switch to PR, and in response, uses a saturation design to measure potential local spillovers across wards within a given district-level candidate list. Figure 1 displays the assignments for the stronghold sample.

More specifically, the first randomization assigned approximately two thirds of the 250 sample wards to the nominations/screening procedure and the remaining third to a pure control group, stratified by district and partisan competitiveness (as measured by 2018 electoral returns). Field teams completed the nominations and screening procedures, but did not share any information with parties, before the policy switch to district-block PR.

Once the policy switch was announced, we refocused assignment of the profile information sharing component upwards, to the constituency level, to be able to estimate potential spillover effects across wards (following Baird et al 2018). As both parties indicated that they intended to compile candidate lists that were broadly representative of the full geographic breadth of the district, the constituency seemed like a reasonable level of clustering to contain local spillovers.[3] This second stage of randomization grouped wards into their 92 distinct host constituencies and assigned constituencies to three levels of treatment saturation, stratified by district: (a) zero saturation constituencies (no information sharing in any wards), (b) low saturation constituencies (treat ⅓ of wards with information sharing), and (c) high saturation constituencies (treat ⅔ of wards).

Figure 1 – Experimental Design



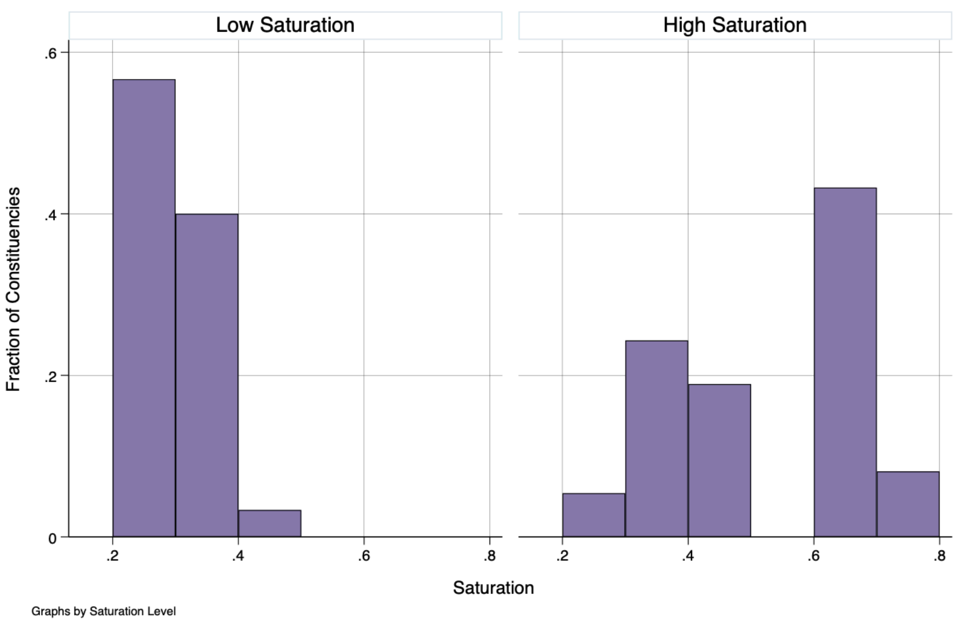
Notes: This Figure displays the random assignments undergirding the research design. Brackets at the top of the figure delineate the stronghold sample, which assigns wards and constituencies to the locally dominant party based on 2018 electoral data measured at the district level. The lottery on the left-hand side indicates ward-level random assignments, which first allocated wards to pure control versus the nominations and screening treatment, and second allocated treated wards to profile information sharing versus no sharing. The lottery at the top of the figure allocates constituencies to three levels of saturation for the information-sharing component. The grid in the middle displays the number of wards in each of the resulting assignment cells.

[3] Nationwide, there are on average 3.4 wards per constituency. There are 2.7 wards per constituency in our sample as we drop wards that cross chiefdom boundaries.

Note that the constituency-level assignment was blind to the results of the nomination process, so was not conditional on the field team finding any minimum number of high-quality nominees who were willing to participate. Expecting that some wards would have an insufficient number of willing nominees, we assigned more constituencies to the high saturation arm than in the low saturation arm, and more into the low saturation arm than to pure controls. This resulted in a division of 27% of constituencies in pure control, 33% in low saturation, and 40% in high saturation.

Figure 2 displays the distribution of *effective* saturation levels, after accounting for how many wards in a given constituency were available for the information treatment (e.g., if a constituency contains only a single ward where nominations were held, high levels of effective saturation are not possible).[4] Table 1 shows that the constituency-level randomization achieved balance on measures of population, population density, electoral outcomes in the 2018 elections, and number of wards per constituency.

Figure 2: Effective Saturation Levels Across Constituencies



Notes: This Figure plots the distribution of effective saturation levels of full treatment wards across constituencies. The X-axis shows the share of wards located within a given constituency that were assigned to full treatment, i.e., assigned to both the nomination and screening process in the first round of ward-level randomization and then assigned to the information-sharing treatment in the second round of ward-level randomization. The group of zero saturation constituencies are omitted from the figure as they contain no full treatment wards (saturation share = 0.0).

[4] Another restriction on high saturation is that effective saturation is measure for all wards within a constituency even those that cross chiefdom boundaries and are thus out of the research sample.

Once the constituency-level saturation was assigned, we randomly assigned the required number of nomination wards within each party-constituency to the information sharing condition, or full treatment. Given the effective saturation levels shown above, we end up with 40% of the party-wards in our sample being fully treated. As Figure 1 shows, for the stronghold sample this is 99 fully treated wards, 88 partially treated wards (only nominations), and 63 pure control wards. Table 2 shows that the assignments to partial and full treatment are reasonably balanced across population, population density, and 2018 electoral outcomes at the ward-level.

Table 1: Constituency-level Measures of Balance Across Saturation Assignment

	(1)	(2)	(3)	(4)	(5)
VARIABLES	Population	Avg. PopDensity	Turnout	Win Margin	Num. Wards
Low Saturation	-1,261	-123.8	-968.0	-0.0140	-0.0267
	(1,417)	(102.6)	(768.9)	(0.0324)	(0.104)
High Saturation	-2,314*	-168.5*	-509.7	-0.00277	-0.0662
	(1,379)	(99.89)	(748.5)	(0.0315)	(0.101)
Constant	54,371***	368.6***	16,754***	0.630***	3.568***
	(1,049)	(75.98)	(569.3)	(0.0240)	(0.0768)
Observations	184	184	184	184	184
District FE	YES	YES	YES	YES	YES
Ftest pvalue	0.246	0.235	0.453	0.892	0.797

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Notes: This Table tests for balance on observable characteristics across constituencies assigned to the three levels of full treatment saturation. Assignments for the two major political parties were conducted independently, which are pooled in this analysis, yielding a sample of 184 party-constituency observations. Avg. PopDensity is the average population density of the wards in a given constituency and population data comes from the 2015 census. Turnout and Win margin are based on the presidential race of 2018.

Data Sources

We are in process of collecting data from two types of sources: (i) surveys that we designed to capture characteristics of potential candidates related to quality, representation and demographics; and (ii) administrative records from the political parties and the Electoral Commission for Sierra Leone (ECSL).

Individual Survey Data

We designed a comprehensive survey instrument to collect information on politicians and potential candidates. We use this instrument to collect information from three groups of respondents: i) sitting incumbent Local Councillors (LC); ii) community nominees (CN) identified by the ward-level elicitation process; and iii) individuals outside the Local Champions initiative who filed a candidate application with the parties, whom we refer to as status quo (SQ) aspirants. Data collection for LC and CN is complete, data collection for SQ is ongoing.

Table 2: Ward-level Measures of Balance Across Treatment Assignment

	(1)	(2)	(3)	(4)
VARIABLES	Population	PopDensity	Turnout	Win Margin
Partial Treatment	529.9*	-105.6	-45.87	-0.0124
	(272.3)	(101.1)	(124.3)	(0.0136)
Full Treatment	254.1	-109.0	-135.3	-0.00472
	(242.5)	(89.98)	(119.7)	(0.0131)
Constant	14,752***	293.5***	4,649***	0.624***
	(193.5)	(71.79)	(74.52)	(0.00814)
Observations	500	500	650	650
Const FE	YES	YES	YES	YES
Ftest pvalue	0.143	0.458	0.518	0.655

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: This Table tests for balance on observable characteristics across wards assigned to treatment arms. Assignments for the two major political parties were conducted independently, which are pooled in this analysis, yielding a sample of 500 party-ward observations. Population data comes from the 2015 census. Turnout and Win margin are based on the presidential race of 2018.

The survey aims to capture observable indicators of politician quality. As quality is an amorphous and multi-dimensional object, we selected measures that we have empirically validated in related work to positively correlate with observable outputs of performance. Specifically, we pulled measures from three separate validation exercises.

We first used data from Casey, Meriggi and Kamara (2021) to select measures of Parliamentary candidates that positively predict the subsequent public spending of elected MPs, as verified by field audits. Second, we select measures from a screening instrument used in Casey, Glennerster, Miguel and Voors (2022) to identify high skill members of rural communities in Sierra Leone. These individuals were involved in drafting a proposal for local infrastructure that was submitted to a district-level grants competition. We choose measures that positively correlate with the quality of the submitted proposals and the likelihood that their proposal was selected as a winning grant. Third, during the piloting activity for this current research program, we surveyed all sitting Local Councillors. We collected both self-reported performance measures (like amount of development spending in their wards and number of visits with their constituents) and anonymous peer ratings of competence in office and lack of corruption. We select measures that positively predict either type of outcome.

We compile these verified measures into a screening instrument. We use this instrument to i) rank community nominees on their technical merits as part the treatment intervention; and ii) to compare the merits of individuals in different pools (e.g. how do the nominees compare to SQ aspirants, how do they compare to incumbent Councillors?). In order to avoid overfitting our prediction of quality, particularly with variables that are biased towards groups over-represented among elected politicians (namely older, elite males), we include additional measures that are widely perceived to be associated with quality and human capital, like years of education, professional experience, and IQ proxies. We roll the full set of indicators up into an equally weighted index, following Kling, Liebman and Katz (2007). See complete list of indicators in the Analysis section below.

Community Elicitation Data

We measure popularity among local constituents—as one dimension of representation—directly from the frequency with which individual names were put forward by household respondents during the structured community elicitation process. This dataset by construction includes all nominees, but will also include some SQ aspirants and incumbent Councillors (both of which will need to be matched on name and home ward location).

Administrative Data

To study the effects of the intervention on entry at multiple points along the political process, we use administrative records from parties and government.

Administrative data from the political parties includes: i) lists of all candidate applications received in the 14 district councils studied (i.e. the aspirant pool); and ii) official ranked lists of selected candidates submitted to ECSL (i.e. those put forward for election). As most of these lists do not include ward identifiers, we plan to complement the lists with information gathered via phone calls to party officials, applicants and candidates. We will further validate candidates' home ward by collecting voter registration location in our individual-level surveys. Note that we cannot run any of the causal estimates specified below (in Parts II, III and IV of the Analysis section) until this process of ward identification is completed. We are currently organizing with Innovations for Poverty Action (IPA) a field plan to conduct this work.

The key administrative data from ECSL is the official list of elected Local Councillors. As above, we plan to complement this list (which does not include ward identifiers) with phone calls and survey work to map each elected official to their home ward.

Analysis

We divide our proposed analysis into four parts: i) descriptive analysis that gauges whether the intervention did what it was intended to do; ii) causal analysis of the impacts of the intervention on candidate entry into the aspirant pool; iii) causal analysis of party responsiveness to the intervention and related impacts on selected candidates; and iv) estimation of potential spillover effects. We refer to descriptive analysis as questions (e.g., Part I Q1), and causal estimates as hypotheses (e.g., Part II H1).

In what follows, i denotes individual, w denotes ward, and c denotes constituency. Throughout the analysis we will consider a small number of dimensions for potential heterogeneous effects, namely: i) partisan stronghold, swing and weakhold areas; ii) gender; and iii) party.

Part I: Descriptive analysis of whether the intervention did what it was designed to do

In the spirit of a "first stage" analysis, this section sets out a series of empirical tests to evaluate whether the design and implementation of the Local Champions initiative established a reasonable foundation for subsequent analysis of causal impacts.

Q1: Does the intervention identify high quality potential candidates?

Regression analysis will compare the characteristics of community nominees (CN) to Local Councillors (LC) and status quo aspirants (SQ), using the following specification:

$$Q_{iws} = \beta_0 + \beta_1 \, CN_{iws} + \beta_2 \, LC_{iws} + \boldsymbol{s}_w + \varepsilon_{iws} \tag{1}$$

where Q is an index of quality measures, $\boldsymbol{s}$ is a vector of randomization strata (by district and competitiveness), and ε is an idiosyncratic error term. The sample of wards includes the 187 wards in the partial and full treatment groups where nominations and screening were conducted. The sample of nominees is restricted to the top picks per ward, or those who scored the highest on the screening, met eligibility criteria and were willing to participate (i.e., those who would have cleared the bar to have their profile shared with parties). Construction of the index follows Kling, Liebman and Katz (2007) by: orienting each variable so that higher values always indicate ''better'' outcomes; translating variables into standard deviation units by subtracting the mean and dividing by the standard deviation of the omitted group, which is SQ aspirants; imputing missing values at the respective respondent group mean; and giving equal weight to each variable in compiling the index. The estimand of interest is β_1, where $\beta_1 \geq 0$ indicates that the Local Champions intervention identified nominees who were at least as high quality as SQ aspirants. This analysis will be possible to conduct once SQ data collection is completed. We will also test whether $\beta_1 \geq \beta_2$, which would indicate that the intervention identified nominees that were at least as high quality as sitting Councillors.

Variables included in Q are as follows, where we flag indicators that predict performance outcomes in any of our three validation exercises (described above on page 8), with * denoting an indicator that predicts the performance of sitting Local Councillors, † denoting one that predicts the public spending performance of elected MPs, and + denoting one that predicts the quality of local development grant proposals developed by community members:

1. Human capital:
    a. Years of education
    b. Indicator for literacy and numeracy[*,+]
    c. Score in Ravens Test
    d. Score in digit memorization test
2. Work experience:
    a. Wage in previous job
    b. Indicator of experience in sectors like health, education, NGOs[*]
3. Local experience
    a. Number of ward development projects involved in before holding elected office[*]
    b. Number of ward community activities involved in before holding elected office
    c. Number of leadership roles in ward before holding elected office[*]
    d. Indicator for knowledge of NGOs working in ward[*]
4. Managerial capital
    a. Score in project proposal exercise[+]
    b. Indicator for experience managing projects (e.g. budgets, supervising people)
5. Conscientiousness – collected only for individuals in SQ and CN (not LC)
    a. Returned extra transport subsidy[†]

Q2: Does the intervention identify popular potential candidates?

While the answer to this question is largely "yes, by design," we will produce descriptive analysis of the average number (and percentage) of households who nominated a particular individual in CN, and compare these to rates for those in SQ and LC, by estimating Equation (1) for popularity outcomes.

Q3: Does the intervention identify new entrants into politics?

Here we will estimate a version of Equation (1) that uses measures of tenure of participation in politics as outcome variables. The primary measure is the likelihood that the individual has previously run for Local Council, where $\beta_1 \leq 0$, would suggest that the intervention found people who were less likely to be under the consideration of parties in absence of the intervention (note that the outcome is equal to 1 by construction for LCs). We will also run this for measures of connectedness (e.g., family connection to incumbent politicians or prominent party members) and measures associated with under-representation in politics (e.g., female, lower wealth).

Q4. Do the nominees enter politics?

For this we will produce summary statistics on the frequency with which nominees (i) agreed to have their information shared with parties, and (ii) filed an application with a party. For (i), willingness to share information with parties (if selected for the initiative) was collected at the end of the screening instrument for all nominees. For (ii), while all nominees were free to file an application, the top picks were given encouragement to do so as part of the treatment. Specifically, the research team called top picks to inform them that they were indeed top picks, that their profiles would be shared with parties, and encouraged them to apply before the relevant party's application deadline (which was announced at short notice by parties). We will run and report compliance statistics for these encouragement phone calls. Heterogeneity by party and gender is especially relevant for (ii), as the two parties charged different amounts and one waived fees for female candidates. We will also explore other observable characteristics that predict a positive response for these measures.

Q5. Did party leaders accept the nominee profiles?

The purpose of this measure is to evaluate party leader compliance with the information sharing component of the intervention. For the subsample of full treatment wards, we will report the frequency with which a party executive signed the ledger to confirm that he/she had received the profiles. Here we will also report the "hit rate" of how many of the full treatment wards had at least one nominee who cleared all steps involved in having their details shared with parties.

Part II: Causal analysis of impacts on candidate entry

This section estimates potential impacts of the intervention on the candidate pool, seeking to understand whether it was effective in increasing the size and quality of people available for parties to consider in advance of their candidate selection processes. Analyses will be run at the ward-level (which will only be possible once the ward identification process has been completed). Note that potential spillovers are not relevant here, as there were no limits on how many individuals could apply to the parties, so increasing applications from one ward does not detract from applications being filed from any other ward.

H1: The intervention expands the aspirant pool

For this first hypothesis we are interested in two measures related to geographic representation: (i) a binary indicator of whether there are any aspirants available for consideration from a given ward; and (ii) its continuous counterpart that measures the size of the aspirant pool per ward. We define an aspirant as someone who is registered to vote in a given ward and has filed a candidate application with a party. Outcome data comes from the district-level lists of applicants shared by the political parties, with subsequent validation checks on ward location as described above.

For the stronghold sample (of 250 wards), we will estimate:

$$Y_{ws} = \beta_0 + \beta_1 \, Nominations_{ws} + \beta_2 ShareProfiles_{ws} + \boldsymbol{s}_w + \varepsilon_{ws} \qquad (2)$$

where outcome Y captures the ward-level aspirant pool, $\boldsymbol{s}$ is a vector of randomization strata, and ε is an idiosyncratic error term. Coefficient estimates of interest are $\beta_1 \geq 0$, which would indicate that nominations plus screening expanded the aspirant pool, and $\beta_2 \geq 0$, which would suggest that the encouragement aspect of the profile component had an additional marginal effect on expanding the pool. For β_2 , note that applications were due before the profiles were delivered to parties, so it captures encouragement on the nominees' side (e.g., from knowing they were a top pick and that their profile would be shared), as opposed to any recruitment action taken by party leaders. For β_1, note that all nominees were informed during the screening process of how many households in their community had nominated them and were read a quotation from one about why the respondent thought they would be a good candidate. This kind of feedback could spur prosocial motivation to enter politics (see for example, Gulzar and Khan 2023).

The counterpoint regression for the full sample of 500 ward-party observations is:

$$Y_{wsp} = \beta_0 + \beta_1 \, Nominations_{wsp} + \beta_2 ShareProfiles_{wsp} + \boldsymbol{s}_w + \boldsymbol{p}_w + \varepsilon_{wsp} \qquad (3)$$

which adds party fixed effects $\boldsymbol{p}_w$ to Equation (2) and links each ward to two (independent) party-level treatment assignments. Coefficients of interest remain as defined above.

H2: The intervention enhances the quality of the aspirant pool

The second hypothesis tests whether aspirant entry induced by the intervention improves the quality of applicants available for parties to consider in a given ward. To do so, we replace the outcome in Equation (2) with two measures of quality: the average quality of the pool and the maximum quality observed in the pool. We construct a quality index as in Equation (1), however now standardizing with respect to the mean and standard deviation of aspirant quality in the control wards. Coefficients of interest remain as in Equation (2) and we will run for the both the stronghold sample of wards and full sample of ward-party observation. Analysis for impacts on quality cannot be run until both the ward identification process and the SQ survey data collection are completed.

Part III: Causal analysis of party responsiveness to the intervention

This section explores whether the intervention affected party leaders' selection of candidates. It considers both geographic representation and the quality of selected candidates. It further investigates whether any potential effects on candidate selection flow through to the set of elected Local Councillors. This analysis again depends on completing the ward identification process.

H3: The intervention enhances geographic representation on the candidate lists

To test this hypothesis, we estimate Equation (2) for three distinct outcome variables: i) a binary indicator for the presence of any candidate from a given ward on the relevant district-level list of candidates submitted by parties to the ECSL; ii) the continuous counterpart or number of candidates on the list from a given ward; and iii) the (inverse) rank of candidates from a given ward on the list, where lower numbers indicate a higher rank and likelihood of getting elected. The key coefficient of interest is now $\beta_2 \geq 0$, which would suggest that sharing profiles with party leaders increased the likelihood that they selected a candidate from treated wards. We will continue to also estimate $\beta_1 \geq 0$, which would indicate that nominations plus screening increased the likelihood that the parties selected a candidate from treated wards. These regressions will be estimated for both the stronghold sample of wards and full sample of ward-parties. Note that if the parties adhered somewhat to the old electoral system by nominating exactly two candidates per ward, then estimates for (i) and (ii) will be moot.

Note that this analysis does not depend on whether a selected candidate for a treated ward is one of the nominees identified by the intervention or not. One could imagine, for example, that the presence of a high quality nominee in the aspirant pool induces parties to select a higher quality status quo nominee than they would have otherwise. To unpack these multiple channels, we will estimate and report the share of top nominees who became candidates, for both nominations only and profile sharing.

H4: The intervention increased the quality of selected candidates

The hypothesis tests replicates the analysis outlined for H2 above but restricts attention to the sample of selected candidates. As such, it again replaces the outcome in Equation (2) with two measures of quality: the average quality of the pool and the maximum quality observed in the pool, while redefining the pool from aspirants to selected candidates representing a given ward. Standardize the quality index with respect to the mean and standard deviation of candidate quality select to represent control wards. Coefficient estimates of interest are $\beta_2 \geq 0$, which would suggest that sharing profiles with party leaders increased the likelihood that they selected a high quality candidate from treated wards; and $\beta_1 \geq 0$, which would indicate that nominations plus screening increased the likelihood that the parties selected a high quality candidate even in the absence of information provision. This analysis also depends on completing the SQ survey data collection.

H5: The intervention enhanced geographic representation in the elected Local Council

Testing this hypothesis will take a similar form to that for H3 above yet restricting attention to those candidates at the top of party lists who won a seat in the elected Council. We will estimate the regression for both the presence and number of elected representatives outcomes. Coefficient estimates of interest are $\beta_2 \geq 0$, which would suggest that sharing profiles with party leaders increased the likelihood that a treated ward gained representation in Council, and $\beta_1 \geq 0$, which would indicate that nominations plus screening increased the likelihood a treated ward is represented in Council in the absence of information provision. These regressions will be estimated for both the stronghold sample of wards and full sample of ward-parties.

H6: The intervention increased the quality of elected Councillors

This hypothesis test replicates the analysis outlined for H4 above but restricts attention to the quality of elected Councillors. As such, it again replaces the outcome in Equation (2) with the average and the maximum quality of elected Councillors. We will standardize the quality index with respect to the mean and standard deviation of elected Councillor quality representing control wards. Coefficient estimates of interest are $\beta_2 \geq 0$, which would suggest that sharing profiles increased the likelihood that treated wards were represented by high quality elected Councillors, and $\beta_1 \geq 0$, which would indicate that nominations plus screening improved the quality of elected officials representing treated wards without information provision.

Part IV: Estimation of potential spillover effects

A key issue with the switch from ward-level majoritarian elections to district block PR is it creates scope for potential interference between treatment and control wards when analyzing how parties responded to the receipt of nominee profiles, as in essence all wards are competing for representation on fixed-length district-level candidate lists. The presence of interference would introduce bias in the estimation of treatment effects for H3 through H6 as outlined above.

To see how bias could arise, consider first estimates for geographic representation in H3. Suppose that in the absence of treatment, parties would select exactly 2 candidates from each ward to include on the district list. Suppose further that when they received a nominee profile from a treated ward, they added that nominee to the list and removed a candidate from a control ward to maintain the specified length of the list (which recall is two times the number of wards in the district). In this scenario, the coefficient estimate for β_2 under H3 would be biased upwards, as it combines the positive effect observed for treated wards with the negative spillover effect on control wards.

On the other hand, partial interference could lead to downward bias for estimates of treatment effects on candidate quality in H4. Extending the scenario above, suppose that in the absence of treatment, parties select one high quality ($Q = 1$) and one low quality ($Q = 0$) candidate per ward. After seeing the profile, they add a second high quality candidate (the nominee) to a treated ward and drop a low quality candidate from a control ward. As a result, average quality in treated wards becomes 2/3 while in control wards it is equal to 1. In this case the treatment effect estimate would be biased downwards, and would be negative in sign, even though the intervention in fact succeeded in improving the quality of the aggregate pool (which under equal allocation of wards to treatment and control would have increased from ½ to ¾).

To explore the relevance of potential interference, we will leverage the saturation design at the constituency level. We illustrate the method for H3 and the outcome of number of selected candidates per ward on the district list. If we find no evidence of spillovers here, there is little cause for concern about bias in estimates for H3 or for the other three hypotheses. Moreover, if the candidate lists submitted by parties to ECSL adhere closely to two candidates per ward, spillovers are unlikely to matter. Yet if we do find evidence of interference, a similar specification can be applied to all four hypotheses.

To do so, we follow the approach in Baird et al (2018) where our randomized saturation design can be characterized by saturation vector $\prod = \{0, 0.33, 0.67\}$ and cluster share vector $f = \{0.27, 0.33, 0.40\}$. Let indicator $S_{wc} = 1$ indicate a ward that is a within-cluster control, i.e., a ward in a cluster with positive treatment saturation that did not have any nominee profile shared with party leaders. Let $L_c = 1$ indicate a constituency cluster c allocated to low saturation treatment ($p = 0.33$), and $H_c = 1$ indicate a cluster allocated to high saturation treatment ($p = 0.67$). We will estimate:

$$Y_{wcs} = \beta_0 + \beta_{1L} Nominations_{wcs} L_c + \beta_{1H} Nominations_{wcs} H_c + \gamma_{1L} S_{wc} L_c + +\gamma_{1H} S_{wc} H_c + \boldsymbol{\alpha_s} + \varepsilon_{wcs}$$

where $\gamma_{1L} \neq 0$ or $\gamma_{1H} \neq 0$ would indicate the presence of interference whereby the treatment of wards within a cluster has a spillover effect on control wards within the same cluster; $\beta_{1L} \geq 0$, $\beta_{1H} \geq 0$ would indicate positive intention-to-treat effects for treated wards in low, high saturation clusters; and $\gamma_{1L} < \gamma_{1H}$ would indicate the spillover effects are increasing with saturation. If the spillover effects are non-zero, the key estimate of interest for policy makers is the weighted averages $0.33\beta_{1L} + (1 - 0.33)\,\gamma_{1L}$ and $0.67\beta_{1H} + (1 - 0.67)\,\gamma_{1H}$ which are the total causal effect of the profile sharing nominations for each saturation level.

References

Baird, Sarah, J. Aislinn Bohren, Craig McIntosh, Berk Özler. 2018. "Optimal Design of Experiments in the Presence of Interference." *The Review of Economics and Statistics*, 100 (5): 844–860.

Casey, Katherine, Abou Bakarr Kamara, and Niccoló F. Meriggi. 2021. "An Experiment in Candidate Selection." American Economic Review, 111 (5): 1575-1612.

Casey, Katherine, Rachel Glennerster, Edward Miguel, Maarten Voors. 2023. "Skill Versus Voice in Local Development." *The Review of Economics and Statistics*, 105 (2): 311–326.

Gulzar, Saad and Muhammad Yasi Khan. 2023. "'Good Politicians': Experimental Evidence on Motivations for Political Candidacy and Government Performance." Manuscript.

Kling, Jeffrey R., Jeffrey B. Liebman, and Lawrence F. Katz. 2007. "Experimental Analysis of Neighborhood Effects," *Econometrica*, 75(1): 83-119.