The Distribution of Power: Decentralization and Favoritism in Energy Infrastructure

On-line Appendix

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C On-line Appendix: Data construction

C.1 Transformer and Meter Data

The location coordinates for some transformers are either missing or inaccurate. To merge the meter and transformer data sets with electoral and construction progress data, we develop a matching algorithm that combines GPS coordinates, names of administrative units, and location names. The number of transformers per ward ranges from 0 to 539 and averages 41. We also observe the list of 10,640 of these transformers that were selected for inclusion in LMCP Phase I, including whether each transformer was funded by the AfDB or the World Bank, and 5,893 that were selected for inclusion in LMCP Phase II funded by the AfDB. The number of meters per ward ranges from 0 to 59,071 and averages 4020.

- Cleaning transformer data
  - 2017 transformer list
    * Drop observations that have txno=="NA". This deletes 19 observations.
    * Drop observations that have txno=="not accessible". This deletes 2 observations.
    * Drop observations that have a DCScategory=="(Code 1) - H. V./M.V", which are high to medium voltage transformers, unless they have a reference number associated with LMCP, REA, or GPOBA. This deletes 2990 observations.
    * Drop observations with a duplicate txno: if two observations have the same txno, keep the one with the more recent dateFDBlastupdate.This removes 21 observations.
    * This leaves 60493 transformers from the 2017 data.
  - 2016 transformer list
    * Drop transformers that have txno==“not accessible”. This deletes 4 observations.
    * Drop transformers with missing transformer numbers. This deletes 9 observations.
    * Drop transformers that have txno=="0". This deletes 5 observations.
    * Drop transformers that have txno=="not indicated". This deletes 2 observations.
    * This leaves 52562 transformers from the 2016 data.
  - Merging transformers
    * The 2016 data have a significant number of duplicate transformer numbers. We resolve those as follows:
    * Drop duplicates with missing transformer names. This deletes 2 observations.
    * Merge with 2017 list on txno and keep duplicates where txname matches between years. This deletes 155 observations.
    * Keep duplicates where the 2016 coordinates are closer to the 2017 coordinates and where that distance is <1km. This deletes 34 observations.
    * Keep duplicates where the feeder name matches between years. This deletes 1 observation.
    * Delete duplicates where txno == txname. This deletes 3 observations.
    * Remaining 16 duplicate pairs are treated as unrecoverable and are dropped.
    * This leaves 52299 transformers from the post-duplicates 2016 data. We then merge with the 2017 data on txno, resulting in a final dataset of 63214 transformers.
- Cleaning meter data
  - 2019 meter list
    * Drop 41 meters with a missing account number.
    * Drop 294 observations which have the same contract activation date and the same serial number.
    * Drop 3442 observations that have the same serial number. If two observations have the same serial number, keep the observation with the more recent contract activation date.

- 2017 meter list
  - Drop 46 observations with the same installation date and same serial number.
  - Drop 269 observations that have the same serial number. If two observations have the same serial number, keep the observation with the more recent installation date.
- Merging meters
  - Coordinates
    - If the 2017 coordinates of a meter are outside the borders of Kenya, set the 2017 coordinates to missing. Do the same for 2019 coordinates.
    - If a meter is in both 2017 and 2019 data and doesn't have missing 2019 coordinates, choose the 2019 coordinates.
    - If a meter is in both 2017 and 2019 data and has missing 2019 coordinates but does not have missing 2017 coordinates, choose the 2017 coordinates.
    - If a meter is only in the 2019 data, choose the 2019 coordinates.
    - If a meter is only in the 2017 data, choose the 2017 coordinates.
  - Activation dates
    - Our 2019 meter data contains contract creation dates and our 2017 meter data contains installation dates, either of which usable as as a meter activation date. When both are available, we select the 2019 contract creation date. For only 1 meter are neither available, and we set its activation date as missing (and later mark the meter as non-LMCP).
    - After matching meters to wards, we use these activation dates to form a panel dataset of ward by month cumulative meter counts.
- LMCP meter definition (WB/AfDB Phase 1)
  - Our meter data contains reference markers for funding source, of which "LMCP" is an option. However, we do not use these in our analysis. This is because other funding sources (e.g., "WB", "GoK", "AfDB") could be reporting LMCP-funded meters, but could also be reporting meters from other residential electrification programs (such as KOSAP or GPOBA).
  - We instead define LMCP as based on three characteristics:
    - First, the meter activation date must be after January 1st, 2016
    - Second, the reference description must be non-missing and must not be clearly non-residential. Markers we exclude are "Meter separation", "New Application", "Additional load", "Temporary", "Transformer housing", "Underground cables", "Premium customer (25-1000 kVa)", "Large commercial (>1000 kVa)", "Rerouting", "Unknown", and "Streetlights".
    - Third, the tariff indicator must be "P0 - PREPAYMENT DOMESTIC" or missing. Other tariff indicators are possible for residential metering, but all meters installed through LMCP are prepaid.
- Matching meters to transformers
  - First, we attempt to match meters to transformers on listed txno. If either the meter or the transformer has no listed coordinates, confirm the match. If they both do and they are within 1km of one another, also confirm the match.
  - If they are further than 1km apart and the meter has coordinates, instead match the meter to the nearest transformer with coordinates. If that transformer is within 1km of the meter, confirm the match.
  - If the meter is further than 1km of all transformers with coordinates, leave the meter unmatched and drop it. This drops 52,069 meters.

- LMCP Transformer List Data
  - Phase I

    * For both AfDB Phase I and WB funded sites, we have received lists of transformers included in the program.
    * AfDB1 lists are as of 3/20/2017 and WB lists are as of 4/10/2018.
    * Both of these sets of lists are merged with the transformer master list on txno.
- AfDB Phase II
    * For AfDB Phase II funded sites, we received both a list of both transformers and the associated meters, which is as of 11/3/2022.
    * We perform a similar cleaning and matching process as above for meters and transformers.
        - For transformers, we drop 13 transformers with nonsensical/missing transformer numbers, then drop 7 duplicate pairs of transformer numbers based on missing installation dates. A further 15 duplicate pairs of transformer numbers are split and assigned a new index.
        - For meters, we drop 50 meters with nonsensical meter numbers. Geolocations are stored in inconsistent units both across and within lots, so we test a wide variety of orientations of GPS/UTM coordinates based on the columns of data. We validate the results of this exercise against the listed counties/constituencies/wards in the data, which leaves us with a dataset of 231124 meters with coordinates and 73516 without.
        - We merge meters to transformers on txno, then on site name. If both transformer candidates and the meter lack coordinates, we confirm the match preferring the match on txno. If we have coordinates for the meter and either tx candidates, we verify that they are within 1km of one another, and confirm matches (again preferring the match on txno). If neither is sufficiently close, match to the nearest transformer within the AfDB2 dataset (if it is within 1km of the meter). In total, 281523 out of 304640 meters were matched (92.4% of total).
    * We match between the datasets (main/phase 1 and AfDB phase 2) by:
        - First, match on txno. If the pair are within 1km of one another (or if one is missing coordinates), keep the match.
        - Among the transformers not yet matched, cycle through the following 3 steps until all transformers are matched or removed:
        - 1: Find closest main transformer to each AfDB2 transformer. Remove AfDB2 transformer if this distance is >1km.
        - 2: Find closest AfDB2 transformer to each main transformer. Remove main transformer if this distance is >1km.
        - 3: If a pair of an AfDB2 transformer and a main transformer mutually list each other as the closest, keep the match and remove both from the pool of transformers to be matched.
        - After this procedure is completed, all matched transformers and all unmatched main transformers are retained in the matched transformer dataset. 5391 of 5915 AfDB phase 2 transformers were matched into the main dataset (91.1%).
    * Note that none of the meters in the AfDB2 dataset can be matched to any of the meters in the main dataset because metering in this phase started after our latest snapshot was taken. They are aggregated separately when constructing ward and transformer level datasets.
    * We also record project completion dates for transformers that finished maximization before our AfDB2 snapshot was taken. We later combine these with the phase 1 construction progress data in creating our cross-sectional "Construction Completed" count.

C.2 Ward/Constituency Data, Sample, and Aggregation

For the 1,450 wards in Kenya, we obtain socioeconomic data from the 2009 census. We scrape ward-level results for the 2013 and 2017 presidential elections and the 2013 MP elections from the Independent Electoral and Boundaries Commissions Elections API. For these elections, data is missing for 185 wards, 0 wards, and 421 wards, respectively. At the constituency level, we also obtain equivalent (but more complete) electoral data and yearly CDF shares from 2013-2023.

We then restrict our attention to wards that are most eligible to have been targeted by LMCP. As mentioned in the main text, we remove areas targeted by REA's Kenya Off-Grid Solar Access Project, as they are too sparsely targeted to also have been targeted by LMCP in a meaningful way. These are the counties of Garissa, Isiolo, Kilifi, Kwale, Lamu, Mandera, Marsabit, Narok, Samburu, Taita Taveta, Tana River, Turkana, Wajir, and West Pokot (see map here). We also drop areas which are too dense to have been targeted by LMCP (and would have instead been targeted by urban slum electrification programs like GPOBA). This includes Nairobi and Mombasa counties, as well as "dense" wards that are equally or more population dense than these counties (cutoff of 3513 population per square kilometer). These are all visualized in Figure A5. As a part of our specification curve robustness checks (Figure D2 and Figure D3), we define "sparse" wards as those that are equally or less dense than the KOSAP areas - the population density cutoff is 15 population per square kilometer. We also define "(outlying) GPOBA" areas as those wards which were outside of Nairobi/Mombasa county, but were within 1km of a slum that was marked for GPOBA metering expansion around the same time as LMCP phase one (see pages 28-30 of this document) — there is significant overlap between these wards and the other high-density non-Nairobi/Mombasa wards we cut in our main specification. Overall, results are somewhat sensitive to the sample selected, but are generally still significant so long as both too-urban and too-rural areas are sufficiently trimmed.

To generate our final ward cross-section, we combine ward-level measurements with transformer and meter level outcomes aggregated according to the geolocations of the transformers/meters. For transformer and LMCP site counts, we simply sum the number of transformers and LMCP transformers in each ward. For construction progress data, we sum the number of WB/AfDB1 sites completed as of the latest date in each of the phase 1 construction progress reports and the number of AfDB2 sites completed as of the AfDB2 snapshot to get the number of completed sites in each ward in each ward. For LMCP meters, we sum the number of LMCP meters from the 2017/2019 snapshots (as defined above) and the number of AfDB phase 2 meters within each ward. The AfDB2 meters are not matched directly to the main snapshots because they were built after the latest snapshot were taken. Finally, for the land gradient covariate, which we measure at the transformer level using the 90-meter Shuttle Radar Topography Mission (SRTM) Global Digital Elevation Model, we take the average among transformers in each ward.

We also analyze similar results at the constituency level, primary to compare against other variables measured at that outcome (e.g., CDF shares, constituency-level election results). To do so, we first aggregate taking the raw sum of every count variable and the mean of every other variable weighted by ward population. We do this before dropping any wards whatsoever. Then, include only those constituencies wherein greater than 50% of the constituency population lives in a ward that is marked "rural" in our ward-level specification. The distribution of this percentage is heavily bimodal around 0% and 100%.

C.3 LMCP Progress Data

We have reports on the construction status of over 6,000 sites between May 2016 and July 2019. These reports vary in detail and in frequency. Some of them make explicit the construction status that the site is in at the time of the report. The stages are the following:

- Stage 1: Design pending approval
- Stage 2: Design approved
- Stage 3: Pole erection ongoing
- Stage 4: Pole erection complete
- Stage 5: Stringing ongoing
- Stage 6: Stringing complete
- Stage 7: Metering ongoing
- Stage 8: Metering complete

Sometimes a report doesn't explicitly name one of these stages, but for example reports a positive number of poles constructed, but zero lines and connections. We would classify that site as Stage 3. If a site is reported to have a positive number of poles and lines but no connections, we would classify it as Stage 5. If it is reported to have connections, we would classify it as Stage 7, unless the total number of possible connections is also available in which case it could be classified as a Stage 8 if the number of connections matches the total.

After classifying all possible reports, we have an unbalanced panel of 6,907 sites. Some of these have various reports, some of them only one. The next step is to geographically locate these sites.

We set $Construction = 1$ if a report confirms that at least pole erection is ongoing at the transformer site, and 0 if no construction has begun. $Stringing = 1$ if a report confirms that at least stringing of wires is ongoing, and 0 if construction has not progressed to stringing. These stages are cumulative: sites where stringing is complete (i.e. $stringing = 1$) will also have *construction* set to 1.

We linearly interpolate the status of transformers between reports. If a transformer is reported as undergoing stringing 4 weeks after being reported as commencing construction, the 4 weeks in between are interpolated to reflect increases of 0.25 sites in stringing each week. Any sharp increase in construction therefore represents actual progress in construction rather than the idiosyncratic timing of reports.

To verify the accuracy of contractors' progress reports, we compare the construction completion dates listed in contractors' progress reports with meter installation dates recorded in Kenya Power's customer database, as meter installation was supposed to occur soon after construction completion. Figure A8 plots a stacked difference-in-differences estimates of the number of meters installed in the 20 weeks before and after a contractor reports construction completion, relative to sites that were not yet completed during that period (Deshpande and Li, 2019; Cengiz et al., 2019; Goodman-Bacon, 2021). The estimation stacks 31 datasets matching the 31 distinct weeks during which at least one transformer had been recorded complete. To account for possible selection effects, the control group consists of sites where at least some stringing had been reported, but that never reached completion.

The figure shows that the relative number of meters increases significantly after $t = 0$, which is when the contractor first reports completion of the site. We take this as supporting evidence that the contractor's reports of construction completion are meaningful. Given that these two datasets come from independent sources—the meter activation dates from the Kenya Power infrastructure system, and the completion reports from contractors' manually compiled project reports—this strong relationship lends confidence to the accuracy of the data.

The result also shows that meters were generally not installed in bulk on the day of construction, but rather, the average number of meters at a completed site grows steadily, eventually reaching around 40 meters per site 20 weeks after the contractor reports the site is complete. It is therefore possible that households at some sites had to wait for four or five months from when pole erection and stringing had been completed until their home had a usable electricity connection. And, at some sites there is a slight increase in the number of meters even *before* the contractor reports completion, most likely due to some inaccuracies in the completion dates. For both of these reasons, we use Kenya Power's meter activation data as the primary final outcome in the primary construction timing analysis (e.g., Figure 1).

We also perform the following steps to construct a weekly panel of transformers:

- If there are two reports for a transformer in the same week, keep the report with the most advanced stage.
- If a report shows the a site 'reversed' a stage, ignore it and keep the most advanced stage. This may reflect inaccuracies in the data or instances where a step (e.g. stringing) was implemented more than once for a site.
- We fill the panel. Then, for sites for which the first report was Stage 1 or Stage 2 (so no construction yet), we assume all weeks prior to the report are whatever stage the first report was.
- We fill in the weeks between reports with the Stage reported in the earlier report. So if in week 5 site ABC is reported to be in Stage 3, and then in week 10 the site is reported to be in Stage 5, weeks 6 to 9 are filled in with Stage 3.
- When a site has no more future reports, we fill all the remaining weeks (until the last week of the panel), with the last stage that was reported.

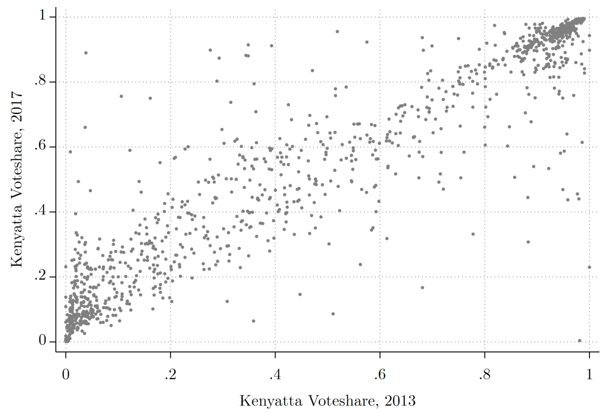
We then create three nested categories. If in a week a site is in Stage 3 or higher, is classified as being at least in **construction**. If it is reported to be in Stage 5 or higher, it is at least in **stringing**. Finally, a site must be reported as Stage 8 to be classified as **complete**. Each of these categories are coded as dummies. To make it clear, if a site has the dummy 'complete' equal to 1 in a given week, it must have the dummies 'construction' and 'stringing' equal to 1 as well.

If one were to analyze construction timing with this panel, it would be affected by the timing of reporting. The example previously given illustrates this. Site ABC will be coded as not being in stringing until week 9, and then in week 10 it will be coded as being in stringing. It is likely however that stringing began sometime between week 5 and 10. To prevent this, we perform the following interpolation: we fill in the weeks in between reports with a linear interpolation between the value of the dummy in the earlier report, and the value of the dummy in the later report. So going back to site ABC, the dummy construction would be equal to 1 in week 5 and week 10, so all weeks in between just have it equal to 1 as well. The same is the case for the complete dummy, but equal to 0 in that case. However, the dummy for stringing is equal to 0 in week 5, but equal to 1 in week 10. This means that the stringing variable will take the value of 0.2, 0.4, 0.6, and 0.8 in weeks 6, 7, 8, and 9 respectively. Once we aggregate observations at the ward level, whenever there are long gaps in reporting, this interpolation will produce smooth increments in the number of sites in construction, stringing, or completion.

Finally, another potential issue when interpreting construction timing, is that some sites have their first report after others do. So for example, if many sites in a ward report for the first time in a certain month a complete status, we would see a spike in completions, however they might have been completed well before the report date. To address this issue, we balance the panel, meaning we only keep transformers for which their first report was on or before the last week of April 2016, or sites for which the first report was after this date but reported a Stage 1 or 2 (so no construction yet), since we can safely say that they would have also been in Stage 1 or 2 in any date prior to the first report. After balancing the panel, we have 3,231 transformers left spanning 722 wards. This is used in Figure D8 and Figure D9.

D On-line Appendix D: Tables and Figures

Figure D1: Ward-level Kenyatta voteshares in 2013 and 2017 elections

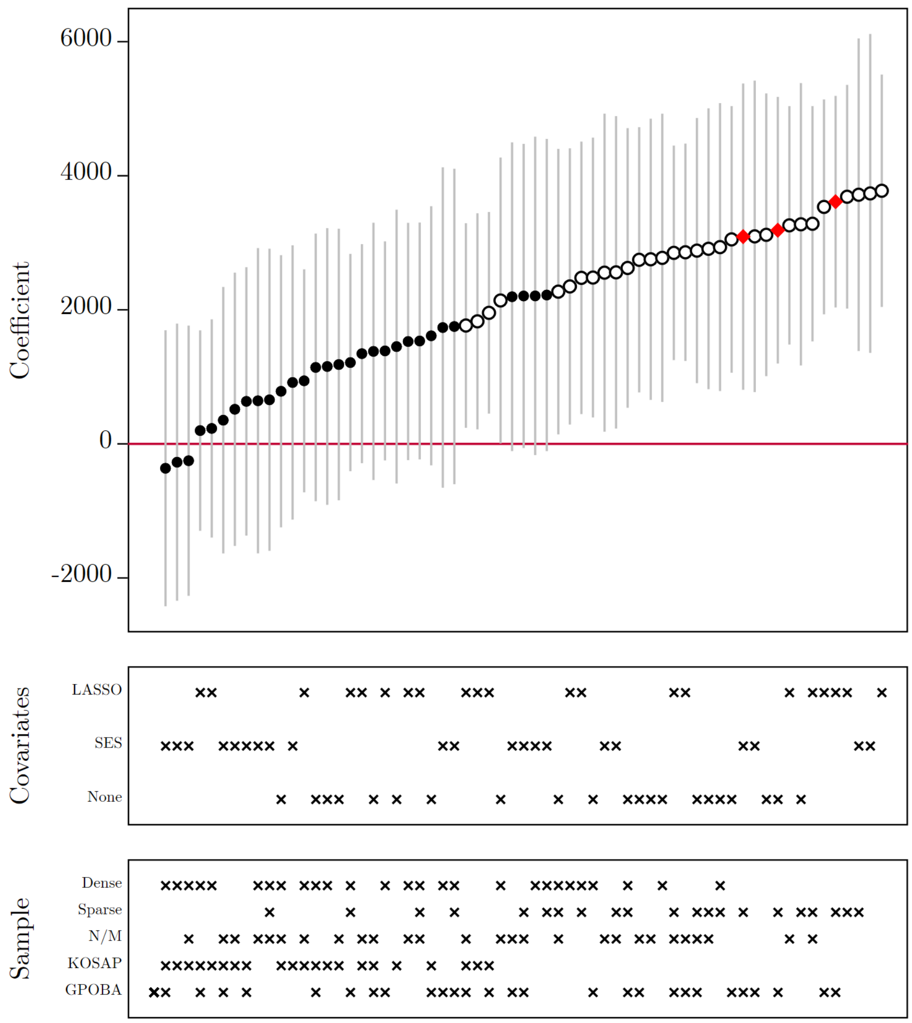


The x-axis shows Kenyatta's voteshare in the March 2013 presidential election across Kenya's 1,450 wards. The y-axis presents Kenyatta's voteshare in the August 2017 presidential election. This graph shows both the high degree of political polarization across wards and the persistence of this polarization across years.

D.1 Robustness: Main meters results

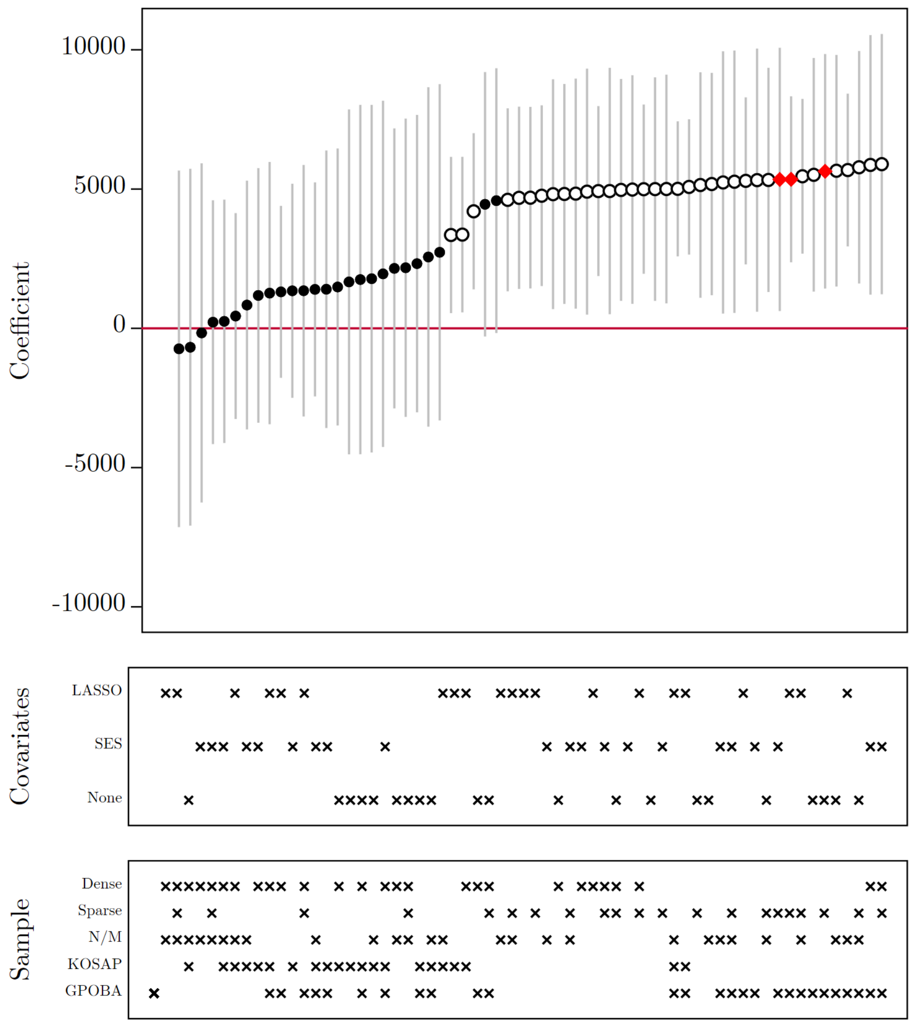
This section presents robustness analyses of Table 1.

Figure D2: Specification curve (ward-level)



Various combinations of sample definitions and controls to generate alternative versions of Columns 1–3 of Table 1. White circles represent specifications with coefficients significant at the 5% level, black circles represent specifications which are not. Red diamonds represent our three preferred specifications, shown in Table 1.

Figure D3: Specification curve (const-level)



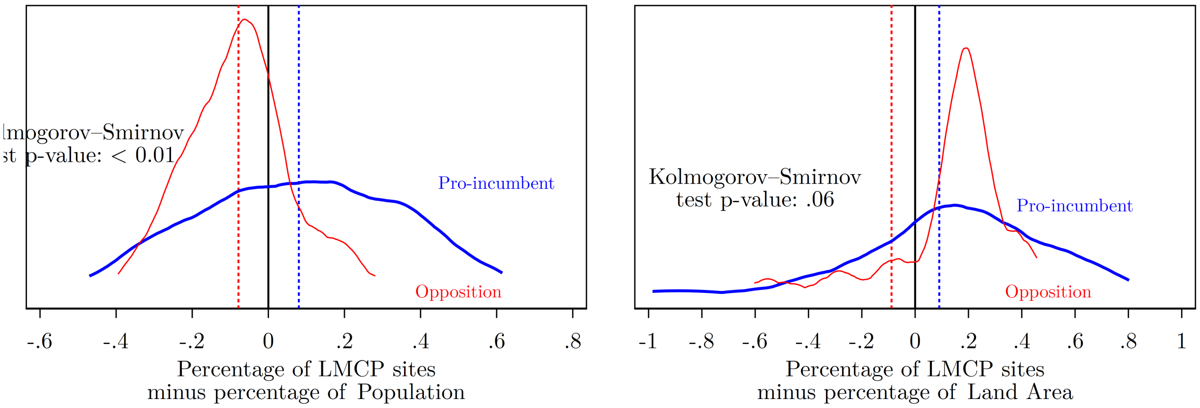
Various combinations of sample definitions and controls to generate alternative versions of Columns 4–6 of Table 1. White circles represent specifications with coefficients significant at the 5% level, black circles represent specifications which are not. Red diamonds represent out three preferred specifications, shown in Table 1.

D.2 Additional CDF analyses

This section presents robustness analyses for Figure 4.

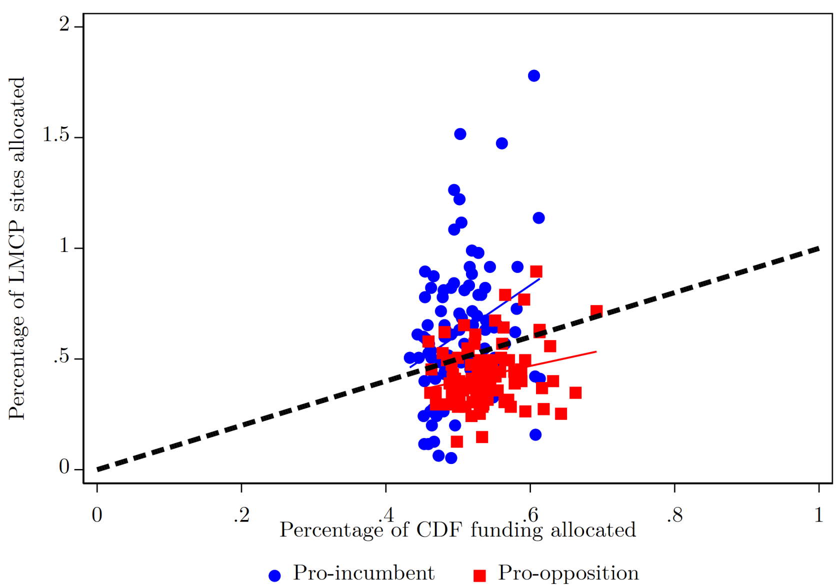
Figure D4: Relative LMCP site share allocation, by 2013 election result

(A) Relative to 2009 population share (B) Relative to land area share



Panel A plots the distribution of differences between the percentage of LMCP sites that a constituency was awarded and the share of total population in the 2009 census, separately for constituencies that voted pro-government in the 2013 presidential election and constituencies that that voted against the winner. Panel B plots the difference between the percentage of LMCP sites that a constituency was awarded and the share of land area, separately for constituencies that voted pro-government in the 2013 presidential election and constituencies that that voted against the winner. Vertical dashed lines present the sample means. Bottom- and top-coded at the 5th and 95th percentile.

Figure D5: LMCP sites share versus CDF share, by political alignment



For each constituency, we construct the number of LMCP sites as a share of all LMCP sites, and the amount of CDF funds allocated in 2014 as a share of all CDF funds. The sample is all constituencies without an urban ward. Points above the dashed 45-degree line indicates that for that constituency, the share of LMCP sites exceeds what would be expected based on the CDF allocation rule. Panel A of Figure 4 presents the distributions.

D.3 Core and Contested areas

This section presents robustness analyses for Table 2.

Table D1: Favoritism in Core Versus Swing Areas (using 75% as the core-swing cut-off)

	In absolute terms			Relative to CDF Allocation		
	(1)	(2)	(3)	(4)	(5)	(6)
Pro-Government Core (δ_1)	3609***	4013***	4543***	6693***	6776***	4589**
	(1098)	(1235)	(928)	(2156)	(2276)	(2075)
Pro-Government Swing (δ_2)	4315**	2845	2928*	4338	3454	3175
	(1963)	(2272)	(1613)	(3693)	(3261)	(2105)
Pro-Opposition Swing (δ_3)	2686*	2889**	2538**	3279	2916	1633
	(1530)	(1401)	(1258)	(2707)	(3041)	(2412)
Observations	911	911	911	193	193	193
Pro-Opposition Core Mean	14095	14095	14095	16125	16125	16125
p-val $\delta_1 = \delta_2 = \delta_3$	.73	.74	.28			
p-val $\delta_1 = \delta_2$	.72	.62	.34	.44	.29	.52
Controls	None	SES	LASSO	None	SES	LASSO
Sample	Wards	Wards	Wards	Consts	Consts	Consts

Columns 1, 2, and 3 are the same as in Table 2. Columns 4, 5, and 6 are at the constituency level relative to the CDF allocation using the same regression as in Table 1, but these estimates are noisier because only 8 of 193 constituencies are pro-government contested and only 18 are pro-opposition contested. SE clustered by constituency in parentheses. $^* \leq 0.10, ^{**} \leq .05, ^{***} \leq .01$.

Table D2: Favoritism in Core Versus Swing Areas (using 60% as the core-swing cut-off)

	In absolute terms			Relative to CDF Allocation		
	(1)	(2)	(3)	(4)	(5)	(6)
Pro-Government Core (δ_1)	3340***	3384***	3732***	5772**	5535**	5207***
	(1034)	(1190)	(865)	(2123)	(2592)	(1769)
Pro-Government Swing (δ_2)	4610*	4465*	3255	874	2992	4996**
	(2641)	(2301)	(2285)	(1259)	(3996)	(2270)
Pro-Opposition Swing (δ_3)	2936	3414**	1555	-7952	-27.1	644
	(2468)	(1714)	(1529)	(4977)	(3340)	(2684)
Observations	911	911	911	193	193	193
Pro-Opposition Core Mean	14316	14316	14316	16465	16465	16465
p-val $\delta_1 = \delta_2$	.63	.64	.84	.007	.57	.93
Controls	None	SES	LASSO	None	SES	LASSO
Sample	Wards	Wards	Wards	Consts	Consts	Consts

Same as Table D1 but using 50-60% as the "swing" group. Using this definition, 3 of 193 constituencies are pro-government contested and 2 are pro-opposition contested. SE clustered by constituency in parentheses. $^* \leq 0.10, ^{**} \leq .05, ^{***} \leq .01$.

Table D3: Favoritism in Core Versus Swing Areas (using 80% as the core-swing cut-off)

	In absolute terms			Relative to CDF Allocation		
	(1)	(2)	(3)	(4)	(5)	(6)
Pro-Government Core	3901***	4577***	4897***	7095***	7242***	5051**
(δ_1)	(1114)	(1177)	(926)	(2254)	(2300)	(2185)
Pro-Government Swing	3969**	2216	2859**	2973	2774	1005
(δ_2)	(1789)	(2097)	(1431)	(2932)	(2627)	(2362)
Pro-Opposition Swing	3306**	3438**	3248***	2608	1956	444
(δ_3)	(1486)	(1390)	(1132)	(2998)	(3390)	(2393)
Observations	911	911	911	193	193	193
Pro-Opposition Core Mean	13856	13856	13856	16139	16139	16139
p-val $\delta_1 = \delta_2$	.97	.23	.16	.062	.039	.083
Controls	None	SES	LASSO	None	SES	LASSO
Sample	Wards	Wards	Wards	Consts	Consts	Consts

Same as Table D1 but using 50-80% as the "swing" group. Using this definition, 13 of 193 constituencies are pro-government contested and 22 are pro-opposition contested. SE clustered by constituency in parentheses. $^{*} \leq 0.10,^{**} \leq .05,^{***} \leq .01$.

D.4 Robustness: Favoritism across construction stages

This section presents robustness analyses for Table 3.

Table D4: Favoritism across construction stages, no controls

		LMCP					
	Pre-existing Transformers	Site Selection		Construction		Meters	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Voted pro-govt in 2013	214***	.0165	50.6***	-.0241	30.4***	7.85	3188***
	(35.7)	(.0179)	(10.6)	(.0336)	(8.45)	(13.3)	(1008)
Observations	911	910	911	587	587	882	911
Opposition Mean	644.3	0.3	148.7	0.5	83.1	125.1	14443.6
Treatment Effect (%)	33.2	6.5	34.0	-4.5	36.6	6.3	22.1
Analysis		Marg.	Cumul.	Marg.	Cumul.	Marg.	Cumul.

Identical to Table 3, but with no control variables. SE clustered by constituency in parentheses. $^{*} \leq 0.10,^{**} \leq .05,^{***} \leq .01$.

Table D5: Favoritism across construction stages, PDS LASSO

	Pre-existing Transformers	LMCP					
		Site Selection		Construction		Meters	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Voted pro-govt in 2013	69.4**	.0645***	53.6***	-.0317	24.7***	-8.03	3100***
	(28.3)	(.0124)	(7.45)	(.0285)	(6.54)	(10.5)	(813)
Observations	911	910	911	587	587	882	911
Opposition Mean	644.3	0.3	148.7	0.5	83.1	125.1	14443.6
Treatment Effect (%)	10.8	25.4	36.0	-5.9	29.8	-6.4	21.5
Analysis		Marg.	Cumul.	Marg.	Cumul.	Marg.	Cumul.

Identical to Table 3, but using post-double selection LASSO to select covariates from all possible quadratic and cubic interactions of SES controls. SE clustered by constituency in parentheses. $^{*} \leq 0.10,^{**} \leq .05,^{***} \leq .01$.

Table D6: Favoritism across construction stages, unweighted

	Pre-existing Transformers	LMCP					
		Site Selection		Construction		Meters	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Voted pro-govt in 2013	116***	.0615***	66.9***	-.0525	28.6***	-10.1	3189***
	(42.3)	(.0182)	(11.1)	(.0399)	(9.72)	(10.4)	(1076)
Observations	911	913	911	587	587	885	911
Opposition Mean	644.3	0.3	148.7	0.5	83.1	125.1	14443.6
Treatment Effect (%)	18.0	24.2	45.0	-9.8	34.5	-8.1	22.1
Analysis		Marg.	Cumul.	Marg.	Cumul.	Marg.	Cumul.

Identical to Table 3, but not weighted by population. SE clustered by constituency in parentheses. $^{*} \leq 0.10,^{**} \leq .05,^{***} \leq .01$.

Table D7: Favoritism across construction stages, adjacent wards only

	Pre-existing Transformers	LMCP					
		Site Selection		Construction		Meters	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Voted pro-govt in 2013	58	.0504*	32**	.0422	32.2**	-24.3	511
	(65.9)	(.0274)	(15.5)	(.0566)	(14.1)	(16.3)	(1482)
Observations	239	239	239	149	149	228	239
Opposition Mean	706.0	0.2	149.2	0.5	79.1	119.7	13976.2
Treatment Effect (%)	8.2	21.8	21.4	8.2	40.7	-20.3	3.7
Analysis		Marg.	Cumul.	Marg.	Cumul.	Marg.	Cumul.

Identical to Table 3, but with adjacent wards only (as defined in Section 3). SE clustered by constituency in parentheses. $^{*} \leq 0.10,^{**} \leq .05,^{***} \leq .01$.

Table D8: Favoritism across construction stages, per capita

	Pre-existing Transformers	LMCP Site Selection		LMCP Construction		LMCP Meters	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Voted pro-govt in 2013	28.7***	.0539***	14.5***	-.0428	6.76***	-5.34	790***
	(10.4)	(.0178)	(2.78)	(.0415)	(2.58)	(11.1)	(290)
Observations	911	910	911	587	587	882	911
Opposition Mean	154.9	0.3	35.2	0.5	19.9	125.1	3511.0
Treatment Effect (%)	18.6	21.2	41.2	-8.0	34.0	-4.3	22.5
Analysis		Marg.	Cumul.	Marg.	Cumul.	Marg.	Cumul.

Identical to Table 3, but per capita instead of per household. SE clustered by constituency in parentheses. $^{*} \leq 0.10, ^{**} \leq .05, ^{***} \leq .01$.

Table D9: Favoritism across construction stages, with constituency fixed effects

	Pre-existing Transformers	LMCP Site Selection		LMCP Construction		LMCP Meters	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Voted pro-govt in 2013	86.2	.017	27.7	-.11**	-6.35	-21.8	1567
	(87.1)	(.0309)	(21.2)	(.0509)	(19.2)	(19.6)	(1552)
Observations	911	910	911	587	587	882	911
Opposition Mean	644.3	0.3	148.7	0.5	83.1	125.1	14443.6
Treatment Effect (%)	13.4	6.7	18.6	-20.6	-7.6	-17.4	10.8
Analysis		Marg.	Cumul.	Marg.	Cumul.	Marg.	Cumul.

Identical to Table 3, but with constituency fixed effects. SE clustered by constituency in parentheses. $^{*} \leq 0.10, ^{**} \leq .05, ^{***} \leq .01$.

Table D10: Deviation from the Constituency Development Fund Allocations

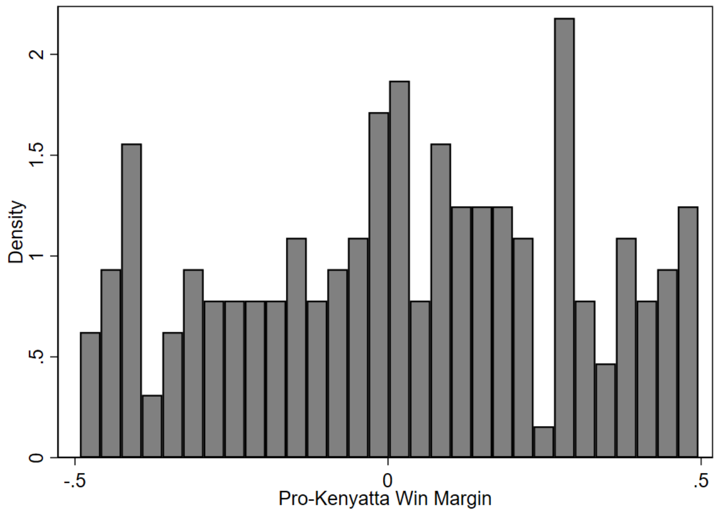
	Pre-existing Transformers		LMCP Site Selection		LMCP Construction		LMCP Meters	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Voted pro-govt in 2013	353.6***	N/A	75.9***	65.5***	42.7***	37.7**	5360.9**	4270.7**
	(82.3)		(18.6)	(19.7)	(14.3)	(14.6)	(1974.9)	(1921.4)
Observations	192		192	192	192	192	192	192
Opposition Mean	642.6		150.8	150.8	68.3	68.3	16532.5	16532.5
Pro-Gov Effect (%)	55.0		50.3	43.5	62.4	55.2	32.4	25.8
Comparison Allotment	2003	2016	2003	2016	2003	2016	2003	2016

Observations at the constituency level, weighted by constituency population. In column 1, y_i is the number of transformers in excess of what the CDF predicts; in columns 2–3, y_i is number of LMCP transformers in excess of what the CDF predicts; in columns 4–5, y_i is number of LMCP sites completed in excess of what the CDF predicts; in columns 6–7, y_i is number of LMCP meters in excess of what the CDF predicts; all per 100,000 households. Columns 1, 2, 4, and 6 use the 2003 CDF formula, whereas columns 3, 5, and 7 use the 2017 CDF formula. SE clustered by county in parentheses. $^{*} \leq 0.10, ^{**} \leq .05, ^{***} \leq .01$.

D.5 Member of Parliament alignment

This section presents robustness checks associated with Table 4.

Figure D6: 2013 Members of Parliament Win Margins



Note: The running variable—pro-Kenyatta win margin—represents the difference between the vote share of the best performing candidate in a race for Member of Parliament who was in the Jubilee coalition in the 2013 general elections and the best-performing candidate not in the Jubilee coalition. Each observation is a constituency.

Table D11: MP-alignment effects, no controls

		LMCP					
	Pre-existing Transformers	Site Selection		Construction		Meters	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Voted pro-govt in 2013	216***	.0074	44.8***	-.018	27.1***	18.2	3735***
	(38.1)	(.019)	(11.4)	(.0353)	(8.46)	(14.4)	(1037)
Voted pro-MP in 2013	29.6	-.012	-5.74	.0477	4.39	14.2	1084
	(33)	(.0145)	(9.2)	(.0316)	(7.31)	(11.2)	(887)
Observations	731	730	731	478	478	706	731
Opposition Mean	644.3	0.3	148.7	0.5	83.1	125.1	14443.6
Treatment Effect (%)	33.6	2.9	30.1	-3.4	32.7	14.5	25.9
MP Effect (%)	4.6	-4.7	-3.9	8.9	5.3	11.3	7.5
Analysis		Marg.	Cumul.	Marg.	Cumul.	Marg.	Cumul.

Identical to Table 4, but with no control variables. SE clustered by constituency in parentheses. $^{*} \leq 0.10, ^{**} \leq .05, ^{***} \leq .01$.

Table D12: MP-alignment effects, PDS LASSO

	Pre-existing Transformers	LMCP					
		Site Selection		Construction		Meters	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Voted pro-govt in 2013	70.6**	.0637***	51.6***	-.0286	25***	-4.6	3453***
	(32.1)	(.0137)	(8.35)	(.0287)	(6.8)	(12)	(866)
Voted pro-MP in 2013	25.8	.00723	4.89	.0458*	10.7*	-3.78	352
	(24.5)	(.0118)	(7.59)	(.0272)	(6.22)	(8.41)	(742)
Observations	731	730	731	478	478	706	731
Opposition Mean	644.3	0.3	148.7	0.5	83.1	125.1	14443.6
Treatment Effect (%)	11.0	25.1	34.7	-5.3	30.1	-3.7	23.9
MP Effect (%)	4.0	2.8	3.3	8.5	12.9	-3.0	2.4
Analysis		Marg.	Cumul.	Marg.	Cumul.	Marg.	Cumul.

Identical to Table 4, but using post-double selection LASSO to select covariates from all possible quadratic and cubic interactions of SES controls. SE clustered by constituency in parentheses. $^* \leq 0.10, ^{**} \leq .05, ^{***} \leq .01$.

Table D13: MP-alignment effects, unweighted

	Pre-existing Transformers	LMCP					
		Site Selection		Construction		Meters	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Voted pro-govt in 2013	111**	.061***	61.8***	-.0623	22.2**	-7.03	3269***
	(46.1)	(.0211)	(11.9)	(.0421)	(9.41)	(12.2)	(1108)
Voted pro-MP in 2013	19.9	.01	6.09	.0464	11.6*	-7.37	263
	(26)	(.0129)	(8.11)	(.0292)	(6.58)	(9.08)	(739)
Observations	731	733	731	478	478	709	731
Opposition Mean	644.3	0.3	148.7	0.5	83.1	125.1	14443.6
Treatment Effect (%)	17.3	24.0	41.6	-11.6	26.7	-5.6	22.6
MP Effect (%)	3.1	3.9	4.1	8.6	13.9	-5.9	1.8
Analysis		Marg.	Cumul.	Marg.	Cumul.	Marg.	Cumul.

Identical to Table 4, but not weighted by population. SE clustered by constituency in parentheses. $^* \leq 0.10, ^{**} \leq .05, ^{***} \leq .01$.

Table D14: MP-alignment effects, adjacent wards only

	Pre-existing Transformers	LMCP					
		Site Selection		Construction		Meters	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Voted pro-govt in 2013	64.3	.0718**	38.5**	.0199	27.9*	-28.7	727
	(74.3)	(.0334)	(17.5)	(.0592)	(14.4)	(18.6)	(1580)
Voted pro-MP in 2013	23.8	-.0161	-13.7	.0935*	17.9	5.93	1423
	(44.2)	(.0242)	(15.5)	(.0545)	(13.1)	(11.1)	(1301)
Observations	199	199	199	129	129	190	199
Opposition Mean	706.0	0.2	149.2	0.5	79.1	119.7	13976.2
Treatment Effect (%)	9.1	31.0	25.8	3.9	35.3	-23.9	5.2
MP Effect (%)	3.4	-7.0	-9.2	18.1	22.6	5.0	10.2
Analysis		Marg.	Cumul.	Marg.	Cumul.	Marg.	Cumul.

Identical to Table 4, but with adjacent wards only (as defined in Section 3). SE clustered by constituency in parentheses. $^{*} \leq 0.10,^{**} \leq .05,^{***} \leq .01$.

Table D15: MP-alignment effects, per capita

	Pre-existing Transformers	LMCP					
		Site Selection		Construction		Meters	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Voted pro-govt in 2013	26.8**	.0532***	13.5***	-.0533	4.97**	-2.21	780**
	(11.6)	(.0203)	(2.94)	(.0422)	(2.44)	(13)	(302)
Voted pro-MP in 2013	3.89	.00761	.825	.0505	2.96*	-4.78	133
	(6.51)	(.0125)	(2.02)	(.0307)	(1.69)	(8.91)	(198)
Observations	731	730	731	478	478	706	731
Opposition Mean	154.9	0.3	35.2	0.5	19.9	125.1	3511.0
Treatment Effect (%)	17.3	20.9	38.5	-9.9	25.0	-1.8	22.2
MP Effect (%)	2.5	3.0	2.3	9.4	14.9	-3.8	3.8
Analysis		Marg.	Cumul.	Marg.	Cumul.	Marg.	Cumul.

Identical to Table 4, but per capita instead of per household. SE clustered by constituency in parentheses. $^{*} \leq 0.10,^{**} \leq .05,^{***} \leq .01$.

Table D16: MP-alignment effects, without constituency fixed effects

	Pre-existing Transformers	LMCP					
		Site Selection		Construction		Meters	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Voted pro-govt in 2013	102**	.0532***	57.8***	-.0533	20.1**	-2.21	3084**
	(45.6)	(.0203)	(12)	(.0422)	(9.7)	(13)	(1197)
Voted pro-MP in 2013	17.7	.00761	4.04	.0505	11.9*	-4.78	428
	(26.2)	(.0125)	(8.16)	(.0307)	(6.65)	(8.91)	(793)
Observations	731	730	731	478	478	706	731
Opposition Mean	644.3	0.3	148.7	0.5	83.1	125.1	14443.6
Treatment Effect (%)	15.9	20.9	38.8	-9.9	24.2	-1.8	21.4
MP Effect (%)	2.7	3.0	2.7	9.4	14.4	-3.8	3.0
Analysis		Marg.	Cumul.	Marg.	Cumul.	Marg.	Cumul.

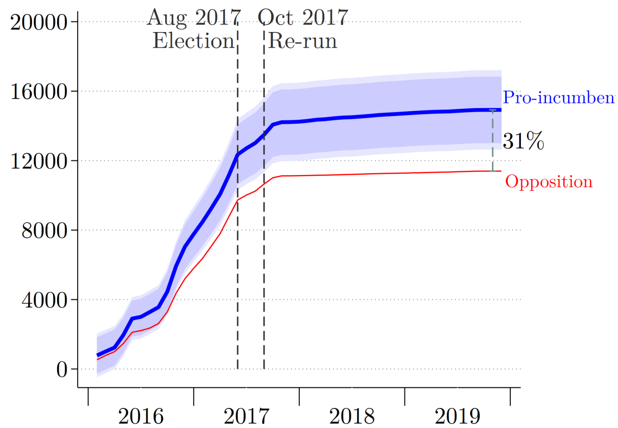
Identical to Table 4, but without constituency fixed effects. SE clustered by constituency in parentheses. $^{*} \leq 0.10,^{**} \leq .05,^{***} \leq .01$.

D.6 Panel data figures

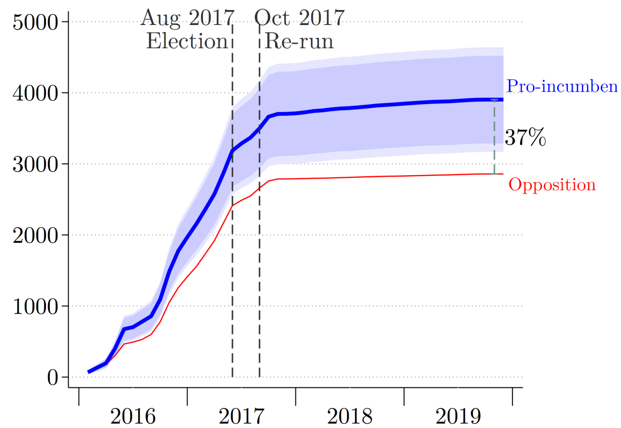
This section presents robustness checks associated with Figure 1 and Figure A4.

Figure D7: Number of meters activated in or after 2016 at LMCP sites per 1,000 households

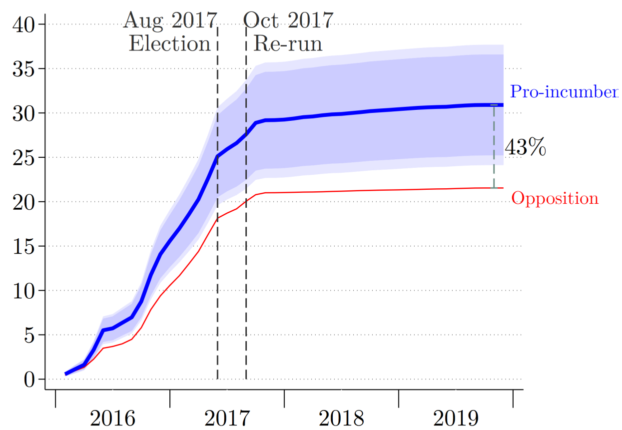
(A) Per 1,000 households, with controls



(B) Per 1,000 people



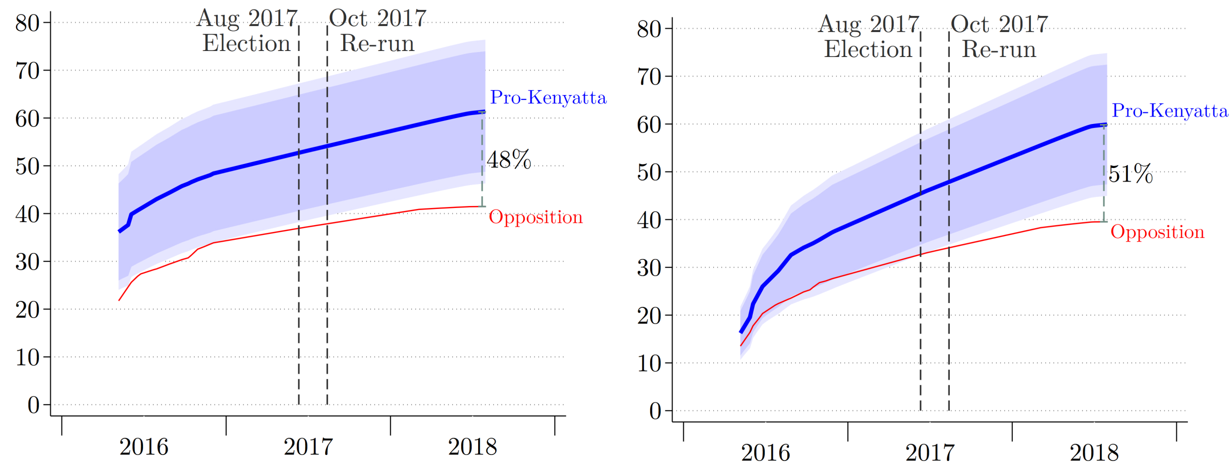
(C) Per 1% of CDF allocation, no controls



Results from the following regression: $y_{it} = \sum_{k=1}^{118} \gamma_k D_{it}^k + \sum_{k=1}^{118} \beta_k D_{it}^k * ProGovernment_i + \epsilon_{it}$. The red line plots the γ_k's while the blue line plots $\gamma_k + \beta_k$. The gap between the blue and red lines represents the difference between opposition and pro-government wards (β_k's). The darker (lighter) blue is the 90% (95%) confidence interval of the β_k's. The vertical line denotes the August 2017 Presidential election. Panel A includes socioeconomic controls as in Table 1. Figure A4 shows a version without controls. Endline estimates differ slightly from those in Table 3 and Table D8 because meter activation dates were unavailable for AfDB Phase 2 meters.

Figure D8: Construction progress per 100,000 households

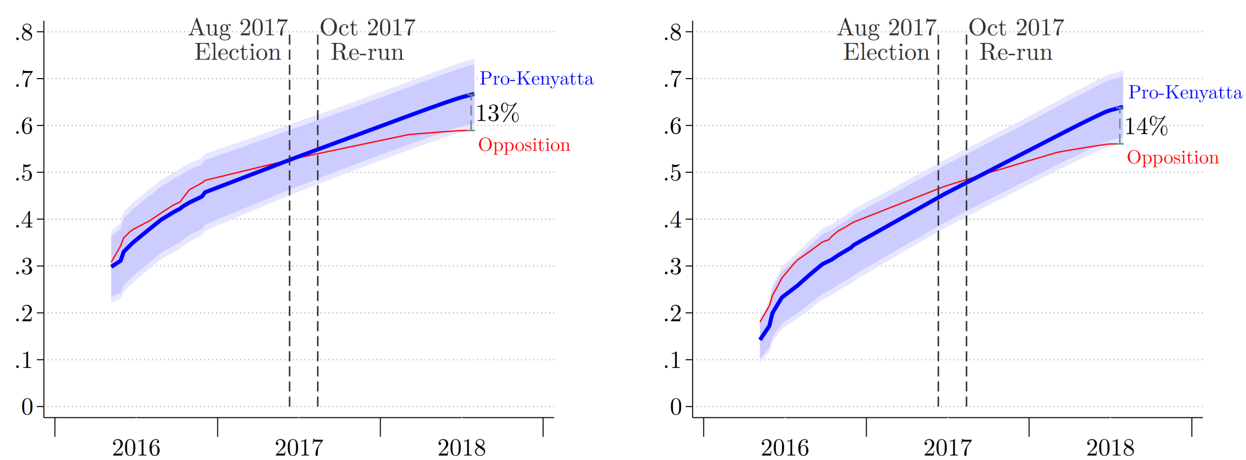
Panel A: Sites in construction — Panel B: Sites in stringing



Coefficients from the following regression, for the nationwide sample, weighted by households per ward: $y_{it} = \sum_{k=1}^{63} \gamma_k D_{it}^k + \sum_{k=1}^{63} \beta_k D_{it}^k * ProGovernment_i + \epsilon_{it}$. The red line plots the γ_k's (sites per 100,000 households in construction or stringing in opposition wards). The blue line plots $\gamma_k + \beta_k$ (meters per 100,000 households in pro-government wards). The blue shaded area is the confidence interval of the β_k's, the difference between pro-government and opposition wards. The darker blue is the 90% confidence interval, and the light blue is the 95% confidence interval. The dashed vertical lines represents the August 2017 Presidential election and the October 2017 re-run. The national construction progress sample has 468 pro-government wards (2,419 transformers) and 541 opposition wards (2,181 transformers).

Figure D9: Construction progress as a fraction of LMCP sites

(A) In construction — (B) Stringing



Coefficients from the following regression, for the nationwide sample, with number of sites that reached the construction and stringing stages as the outcome variables, weighted by households per ward: $y_{it} = \sum_{k=1}^{63} \gamma_k D_{it}^k + \sum_{k=1}^{63} \beta_k D_{it}^k * ProGovernment_i + \epsilon_{it}$. The red line plots the γ_k's, which are the share of sites that reached each stage in opposition wards. The blue line plots the γ_k's + β_k's, which are the share of sites that reached construction or stringing in pro-government wards. The darker blue is the 90% confidence interval, and the light blue is the 95% confidence interval, of the β_k's, the difference between pro-government and opposition wards. The dashed vertical lines represents the August 2017 Presidential election and the October 2017 re-run. The national construction progress sample has 468 pro-government wards (2,419 transformers) and 541 opposition wards (2,181 transformers).