The Distribution of Power: Decentralization and Favoritism in Public Infrastructure

Catherine D. Wolfram
Susanna B. Berkouwer
Felipe Vial
Eric Hsu
Oliver W. Kim
Edward Miguel

June 4, 2024

Latest version available **here**.

Abstract

Political favoritism can harm economic growth by distorting public investment. But how can researchers identify political bias without observing government objectives? Using granular infrastructure and electoral data, we leverage an institutional feature of Kenya's nationwide electrification program: a pre-existing transparent allocation formula. Despite constitutional reforms decentralizing fiscal expenditures, pro-government areas received 46% more electrified villages and 35% more household connections than allocated by the formula. Favoritism was exerted by national offices—not Members of Parliament or local construction managers. The benefits of central coordination, technical capacity, and economies of scale may expose infrastructure to continued political capture despite decentralization.

JEL codes: D72, H54, L94, O13, O18, O22, Q48

Authors are ⓡCertified Random. Wolfram: MIT Sloan School of Management and NBER (cwolfram@mit.edu); Berkouwer: The Wharton School, University of Pennsylvania and NBER (sberkou@wharton.upenn.edu); Vial: Uber Technologies (fvial@uber.com); Hsu: Y-RISE, Yale University (eric.hsu@yale.edu); Kim: Department of Economics, University of California, Berkeley (oliverwkim@berkeley.edu); Miguel: Department of Economics, University of California, Berkeley and NBER (emiguel@berkeley.edu). We thank Ken Opalo and numerous seminar participants for helpful comments and suggestions. We thank the DFID Economic Development and Institutions initiative for generous financial support. We thank Walter Mebane for generously sharing electoral data and Tavneet Suri for generously sharing data on M-PESA expansion. Andrew Hinchberger, Shivani Kaeley, Zachary Obstfeld, Nachiket Shah, Adam Streff, Kamen Velichkov, and Aidan Wang provided outstanding research assistance. Click to view the On-line Appendix.

1 Introduction

Hon. Temporary Deputy Speaker,
I want to talk about fair distribution of power. As a country, we do not have enough power. However, there are some areas that are more equal than others. It is important that Kenya Power does not have political patronage so that it can distribute power without fear or favour. We will definitely move on to the next level if that happens. We have talked about developing this economy and that can only happen if those things are put in place.

— Robert Mbui, Opposition Member of Parliament
Kenyan parliamentary debates, 10 July 2013 (Hansard, 2013)

There is a consensus among social scientists that ethnic and political favoritism has harmed economic development in Africa (Easterly and Levine, 1997; Herbst, 2000; Hodler and Raschky, 2014; Michalopoulos and Papaioannou, 2016). However, it can be difficult to distinguish favoritism from nonpartisan government objectives such as efficiency or equity. Imperfectly observing these objectives can lead researchers to misattribute correlations between public investment and political alignment—arising for legitimate reasons or coincidentally—to political favoritism. For instance, infrastructure investments may be most impactful in areas with rapid projected economic growth, but areas that are closely aligned with the government may also have higher projected growth for various reasons.

To quantify favoritism, this paper leverages a unique institutional feature of one of Kenya's largest public works programs: the $788 million Last Mile Connectivity Project (LMCP), an ambitious initiative launched in 2016 to connect all households to electricity.[1] The government announced that LMCP projects would be allocated across constituencies using the Constituency Development Fund formula, a transparent and equitable rule that had been agreed upon by opposing political parties more than a decade prior (Kenya Power, 2016). Comparing realized allocations against this legal benchmark allows us to more directly estimate political favoritism in the LMCP without having to make assumptions about the government's underlying policy objectives.

The Kenyan context is also useful for studying these issues in a setting of extensive fiscal decentralization, which is often proposed as an approach to curb political favoritism and advance democratization. A key determinant of political favoritism in many African countries has been control of the national executive (Burgess et al., 2015). Presidents often redirect resources towards their co-ethnic political supporters—the phrase "it's our turn to eat" captures a common attitude to securing the spoils of an election victory (Wrong, 2010). Decentralization aims to shift power towards local areas in order to better represent the interests of groups that are currently out of power (Faguet, 2014; Opalo, 2020; Hassan, 2020a). Kenya is a regional pioneer in this regard, having undergone major decentralizing reforms dubbed the "biggest political transformation since independence" in the early 2000s (Cheeseman, Lynch, and Willis, 2016). These include the 2003

[1] For comparison, Nairobi's expressway was projected to cost $504 million (KNHA, 2022). FY2021/2022 Kenyan government expenditure on secondary education was $521 million (Treasury of Kenya, 2021).

Constituency Development Fund (CDF) Act, which allocated 2.5% of national revenue to constituencies according to a simple and transparent formula, and a new constitution in 2010, which created 47 new popularly elected county governments and strengthened the legislature to create "arguably Africa's strongest parliament" (Opalo, 2014). With the LMCP occurring in the wake of these efforts to decentralize and democratize governance, the analysis in this paper serves to evaluate the success of these reforms in curbing political favoritism. In doing so, the paper aims to bring new evidence to a key question: how can states in Sub-Saharan Africa overcome favoritism in the distribution of public goods?

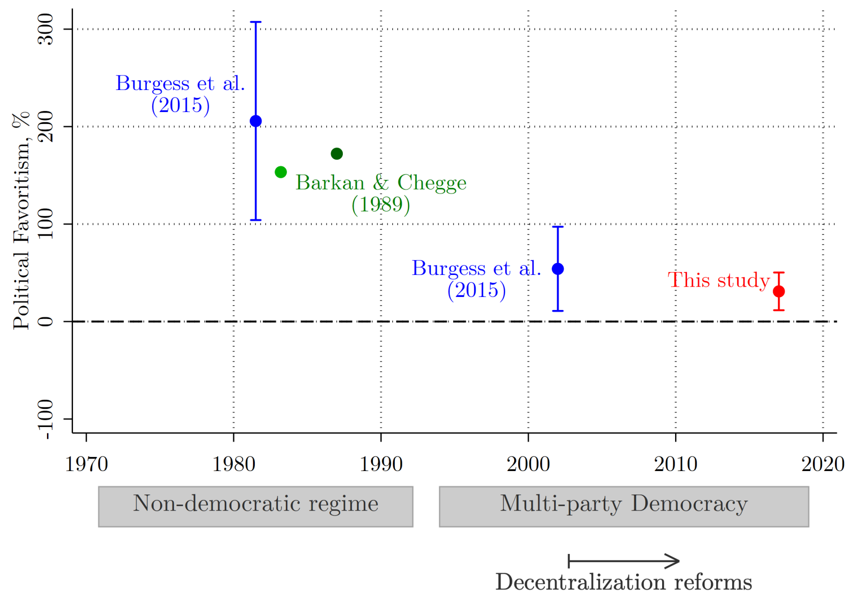
Decentralization was crucial in this context because distinct stages of the LMCP were influenced by different decision-makers and implementers, with varying degrees of connectedness to the central government. In particular, two parastatals—Kenya Power, the majority state-owned electric utility, and the Rural Electrification Authority—led initial transformer construction. To allocate LMCP projects within constituencies, Kenya Power worked with members of parliament (MPs), constituency-elected representatives with significant influence over local public finances but with limited technical expertise or experience in the electricity sector (Harris and Posner, 2019; Opalo, 2022b; Volkert and Klagge, 2022). On-the-ground construction was then contracted out in geographically clustered groups of sites to dozens of private contractors, who worked with regional Kenya Power offices (Wolfram et al., 2023).

The analyses use rich administrative data, including the universe of all of Kenya Power's 7.4 million electricity meters and 62,271 electrical transformers, as well as geo-located panel data on planning, construction, and meter activation at LMCP villages. We pair this with ward-level electoral data on presidential and parliamentary results from Kenya's 2013 and 2017 elections.

This paper has two main empirical findings. First, we statistically reject that LMCP sites were allocated using the CDF formula. Moreover, deviations from the formula align with political affiliation: constituencies that voted pro-government in the preceding election received 22% more LMCP sites than their CDF share, while opposition constituencies received 14% fewer. By 2019, pro-government wards had 35% more new meters per capita. This result is robust to using LASSO to select regression controls, using only geographically adjacent wards, and proxying for economic growth potential with mobile money penetration. Favoritism is strongest in core support wards, where the government received a large majority of the votes, but favoritism in swing wards is of similar magnitude regardless of whether the swing ward eventually voted for the government or the opposition.

While the political favoritism we estimate is statistically significant, Figure 1 shows that the magnitude is considerably smaller than historical levels of political favoritism in Kenya documented in other research. For instance, during periods of autocracy, districts with majorities co-ethnic with the president received fully double the road expenditures, and levels of favoritism were far higher in the early 2000's immediately after the transition to multi-party democracy but before the decentralization reforms discussed (Burgess et al., 2015). Kenya's extensive institutional reforms towards democratization and decentralization may have curbed the worst excesses of political and

Figure 1: Historical estimates of political favoritism in Kenya



Estimate for "this study" from Table 1. Estimates for Burgess et al. (2015) use results in Table 1 (Column 4, Panel B) on road expenditures per capita. Estimates for Barkan and Chege (1989) are on road expenditure (light green) and health expenditure (dark green). Figure A11 shows estimates for alignment with members of parliament.

ethnic favoritism, while not entirely eliminating it.

The paper's second main finding is that pro-government favoritism in LMCP is driven by nationally elected politicians rather than local representatives. Three main pieces of evidence support this finding. First, despite MPs' close involvement in Kenya Power's LMCP site selection process, wards within a constituency that align with the MP see similar levels of LMCP construction as wards that voted for a losing candidate. Second, using a close-election regression discontinuity design, we find that alignment of a constituency's MP with the winning presidential coalition does not affect its LMCP outcomes. Third, we do not detect favoritism during construction and meter activation, which were implemented and managed by geographically partitioned contractors and local utility employees. Instead, aggregate favoritism was driven by two earlier stages of the LMCP implemented by the national office: the construction of transformers, and the selection of LMCP sites.

These results highlight a fundamental tension in the decentralization of infrastructure (with similar issues arising for roads, railways, and information technology). Decentralization may be more difficult to fully implement in sectors that are primarily managed through national parastatals and therefore vulnerable to political capture, as national politicians facing electoral or other political incentives may protect their influence even at high cost. The process of decentralization furthermore may itself be subject to political capture, depending on the the entity responsible for allocation and implementation (Enikolopov and Zhuravskaya, 2007).

At the same time, continued centralized management of these sectors could provide technical, economic, or network benefits, which are crucial given the increasing financial strain faced by many African utilities (Blimpo and Cosgrove-Davies, 2019; Kojima and Trimble, 2016). Regional governments' technical or institutional capacity may lag behind the national government's, particularly in low-capacity states (Hassan, 2020a). Kenya Power and REA officials noted that the county governments created in the 2003 devolution reform generally lacked the 'skills, knowledge and experience' needed to implement electrification (Volkert and Klagge, 2022; Hassan, 2020b). Utilities are also often seen as natural monopolies—especially in low-capacity states where the national utility often remains vertically integrated across sectors that have clear natural monopoly characteristics (distribution) and sectors where this may be less true (generation)—resulting in potentially large economic efficiency gains from centralization (Prud'homme, 1995). Sectors with complex networks such as roads and pipelines can also benefit from central planning. While these factors complicate the decentralization of certain sectors, they also shed light on why other sectors where centralized service provision provides fewer benefits—such as agriculture, health care, and education—have been decentralized with some success in Kenya (Savage and Lumbasi, 2016).

The continued political influence in the electricity sector that we find has important implications for the global energy transition. Decarbonization will require replacing energy-consuming assets, such as gasoline vehicles and gas stoves, with lower carbon electric equivalents—commonly referred to as electrification—which in turn will require major investments in and expansions of national electricity grids. Solar, hydro, and wind generation at scale are often best located in areas that are far from demand and may therefore require transmission networks that span geographies (Martinot, 2016). Distortions in public resource allocation, including due to the clientelistic provision of electricity, may undermine electric utilities' ability to build the networks to manage these transitions. This paper joins a growing body of work studying the political influences on electric utilities (MacLean et al., 2016; Min, 2019; Briggs, 2021; Mahadevan, 2024).

These findings build on a rich literature on decentralization in low- and middle-income countries (Hassan, 2020a; Hassan, 2020b provide reviews). The economic dynamics we study can help shed light on the mixed results of decentralization in for example Indonesia since 1999 (Purwanto and Pramusinto, 2018) and in Latin America in the 1980s and 1990s (Campbell, 2004). For decades, advocates of decentralization have touted its potential benefits, including reducing intrastate conflict, lowering corruption, and checking the power of the central executive (Tiebout, 1956; Fisman and Gatti, 2002; Brancati, 2008; Opalo, 2014; Opalo, 2020). However, the overall empirical record of decentralization has been mixed, with some viewing decentralizing reforms in Kenya and elsewhere in Sub-Saharan Africa as less successful (Hassan, 2015; Dickovick, 2011). We furthermore contribute to a rich literature spanning economics and political science studying the political and bureaucratic impacts of decentralization (Hoffmann et al., 2017; Bardhan and Mookherjee, 2005; Bardhan, 2002).

Finally, this paper contributes to the large inter-disciplinary literature on political favoritism and the provision of public goods in Africa (Miguel and Gugerty, 2005; Marx, 2018; Barkan and Chege, 1989; Franck and Rainer, 2012; Francois, Rainer, and Trebbi, 2015). This paper also contributes to the empirical literature on the timing of spending around the election cycle (Nordhaus, 1975; Alesina and Roubini, 1992; Baskaran, Min, and Uppal, 2015).

2 Democratization, decentralization, and electrification in Kenya

Decentralization—a major feature of Kenyan democratization—has been described as Kenya's "biggest political transformation since independence" (Cheeseman, Lynch, and Willis, 2016). A key milestone in this process was the 2003 Constituency Development Fund (CDF) Act, which aimed to disburse resources across Kenya's 290 constituencies according to a transparent and equitable formula (Government of Kenya, 2010). A second milestone was the adoption of the 2010 Constitution after a national referendum, which created 47 counties with popularly elected governors and county assemblies. These legislative and constitutional changes devolved resources and power toward local politicians, with the intent to "diffuse, if not eliminate altogether, the ethnic tensions fuelled by perceptions of marginalization and exclusion" in national politics (Akech, 2010).

Around the time of these reforms, the Government of Kenya (GoK) began making universal access to electricity a national priority. In the 2009 census, only 20% of Kenyan households (and only 5% of rural households) had access to electricity.[2] GoK has since directed significant funding towards universal electrification. In 2015 it announced the Last Mile Connectivity Project (LMCP), which would connect millions of rural Kenyans to the grid between 2016–2022 at a cost of $788 million (REA, 2015; Kenya Power, 2018).

The 2010 Constitution assigned responsibility for electricity policies to both the national and the new county governments (GoK, 2010). These overlapping constitutional mandates created ambiguity about whether energy policy would be set and implemented nationally or locally (World Bank, 2017). In practice, Kenya Power—the country's electric utility, which is majority-owned by the Government of Kenya—was responsible for the implementation of the LMCP, leaving county governments with little control over implementation.

2.1 Kenya's political backdrop

In 2002, Kenya's main opposition party—led by Mwai Kibaki—won the presidential and parliamentary elections. Upon gaining power, opposition MPs—including Raila Odinga—moved to pass the 2003 CDF Act, with the goal of constraining future favoritism (Bagaka, 2010; UNODC, 2022).

Uhuru Kenyatta joined Kibaki's winning coalition in the 2007 election, which saw widespread violence after a disputed result: an estimated 1,500 Kenyans were killed (Leonard, Owuor, and George, 2009; Cheeseman, 2008). In the aftermath, key figures—including Kenyatta and William Ruto, who had been on opposite sides of the earlier violence but joined forces in the subsequent national election—were charged with crimes against humanity by the International Criminal Court. Their political alliance strengthened in the years after, forming what became known as the "coalition of the accused" (Shilaho, 2016; The Economist, 2013).

This paper's main explanatory variable is voting outcomes from the 2013 presidential election, which directly preceded the selection of LMCP sites. Uhuru Kenyatta won the March 2013 presidential election with an electoral coalition highly similar to Kibaki's, though Kenyatta's partnership

[2] Figure A1 shows the number of meters per household by wards per Kenya Power's residential meter data.

with Ruto also gained him significant support in the Rift Valley region, where Ruto's main political base resides. Odinga continued as Kenya's opposition leader in the 2007 and 2013 (and later 2017 and 2022) elections, with support located primarily in Nyanza and Western Kenya, while Kenyatta and Kibaki drew significant support from central Kenya, where voters co-ethnic with both candidates dominate (this is also reflected in the electoral map shown in Panel B of Figure 3). Despite increasing scrutiny surrounding ethnicity within public sector appointments (Amaya, 2016; Simson, 2018), the Kenya Power MDs appointed under Kenyatta in 2013 and in 2017 were both politically aligned with and coethnics of Ruto (Figure A2 provides an overview of appointments).

Kenya's rural electrification investments started with a program of transformer construction in 2008 under President Mwai Kibaki. Kenyatta subsequently expanded Kibaki's program, leveraging the growing network of transformers to target universal household electricity access. In a March 2017 State of the Nation address, Kenyatta stated:

> "To begin the walk towards industrialisation, we needed to drastically improve and expand our infrastructure, and to increase access to electricity... In 2013, we promised to provide access to electricity for 70% of all households by the end of 2017. Today, we have connected an additional 3.7 million new homes to electricity. We have more than doubled the total number of connections made since independence." (Kenyatta, 2017)

The LMCP accelerated in the year before the August 2017 presidential election, with more than a million new residential electricity meters installed over this period.

Kenyatta won the August 2017 election, but Kenya's Supreme Court annulled the results due to alleged irregularities, confirming both the strengths of Kenya's democracy (as the judiciary was able to force an election re-run) but also its limitations (the lack of fully transparent polls). After winning the November 2017 re-run, Kenyatta was sworn in to his second term on November 28, 2017.[3] Kenyatta's Jubilee Party won 140 out of 290 MP seats in the National Assembly, while Odinga's Orange Democratic Movement won 62.

Tensions continued after Kenyatta's inauguration, and Kenya appeared at risk for renewed electoral violence—until March 9, 2018, when Kenyatta and Odinga publicly announced a truce that would mark a significant realignment in Kenyan politics (Obonyo, 2020; Mwangi, 2019). Kenya Power's Managing Director was ousted and replaced with a political ally and coethnic of Odinga.

This paper's main analyses study the relationship between electrification placement and the 2013 election results, rather than the 2017 results, for two main reasons. First, the 2017 results might be endogenous to the placement of electricity infrastructure if electricity access influenced voting. Second, the spatial distribution of electoral support in Kenya is highly persistent over time: the 2013 and 2017 elections are correlated with an R^2 of 0.89 (Figure D1 provides a scatter plot). The 2013 election results therefore reflect the contemporaneous political landscape at play during the 2015–2017 rural electrification program.

[3]The October 2017 re-run was boycotted by the opposition. The August 2017 results, while also imperfect, thus better reflect the contours of regional electoral support and we use the August results in the analysis.

2.2 The evolution of the Constituency Development Fund formula

A central contribution of this paper is the estimation of favoritism against an existing benchmark (that had earlier been agreed upon by opposing political parties) through constituency development funds. The 2003 CDF Act specified a transparent formula to allocate public funds to constituencies. A potential concern is how the formula itself was developed, and this highlights the importance of the process by which decentralization allocates power.

The formula adopted in the 2003 CDF Act reflected government objectives for both equality and equity: 75% of CDF funding would be allocated in equal shares across all constituencies (regardless of population or other features) and 25% according to that constituency's share of national poverty (GoK, 2003). In early 2016, the legislature amended the allocation: each constituency would now receive an equal share (GoK, 2016). In 2022, the formula was amended again: 75% of CDF funding would be allocated in equal shares and 25% according to the number of wards in that constituency.

At face value, the 2003, 2016, and 2022 versions of the CDF formula all allocate resources using transparent and objective criteria. Realized CDF allocations largely followed the formulae prescribed in the various versions of the Act described above.[4] However, changes in CDF allocations over time also correlate with shifting electoral patterns. The original 2003 Act was pushed for by opposition MPs as a way to reduce perceived pro-government favoritism. It allocated disproportionately more funding to pro-opposition areas (column 1 of Table B1). This appears to be due to the fact that these areas were poorer on average (perhaps in part reflecting earlier bias towards pro-government areas), as the correlation weakens significantly when controlling for local socio-economic outcomes. In other words, the raw correlation between the original CDF allocation and pro-opposition political support may be a result of using a formula that is equitable (allocating more to poorer areas) but not equal (does not provide the same allotments across constituencies or individuals).

Conversely, pro-government MPs spearheaded changes to the formula in the 2016 Act and the 2022 amendment. The 2016 Act—implemented shortly before an election year—in practice increased the share of CDF funding received by constituencies that had voted pro-government in the previous election (columns 3 and 5 of Table B1). This may have played out in the favor of the incumbent during the 2017 election. The government presented these amendments as aiming to improve equality across constituencies, stating for example that "CDF cash should be shared equally for the sake of fairness" (The Star, 2016). However, the press took note that this would lower the amount of CDF funding available for the poorest constituencies (many of which vote pro-opposition), stating for example that the change "denies marginalised regions a greater share of the money" (The Star, 2016). This shift persisted with the 2022 amendment.

Still, these changes in the CDF formula over time are both economically and statistically small: they cannot explain the magnitude of political favoritism observed that we document in the LMCP, as noted below. Subsection 4.2 discusses this in more detail.

[4]This is especially evident in the high R^2 in Columns 2, 5, and 7 of Table B1.

2.3 Rural electrification and the Constituency Development Fund

Kenya's electricity grid has around 63,000 electrical transformers, which convert electricity from medium voltage down to low voltage (LV). The goal of the LMCP was to select several thousand of these transformers (which we label 'LMCP transformers' or 'LMCP sites') and then connect all households within 600 meters of each transformer, a process referred to as 'transformer maximization.' Most LMCP sites had between 20 and 100 unconnected households nearby.

The process of determining which households benefit from rural electrification through the LMCP program can be broken down into four stages, which jointly determine the number of LMCP household electricity meters per 100,000 households: (i) where to install new transformers, (ii) which transformers were selected for LMCP maximization, (iii) where construction of low voltage networks at the selected transformers progressed, and (iv) where household meters were activated. Equation 1 decomposes this aggregate measure of favoritism algebraically:

$$\begin{aligned}\frac{\text{\# LMCP household electricity meters}}{\text{100,000 households}} = &\left(\frac{\text{Total \# transformers}}{\text{100,000 households}}\right)\\ &\cdot\left(\frac{\text{\# LMCP transformer}}{\text{Total \# transformers}}\right)\\ &\cdot\left(\frac{\text{\# LMCP transformers with LV construction}}{\text{\# LMCP transformers}}\right)\\ &\cdot\left(\frac{\text{\# LMCP household electricity meters}}{\text{\# LMCP transformers with LV construction}}\right) \qquad (1)\end{aligned}$$

Stage 1: Transformer construction

The first major hurdle to increasing rural electricity access was the lack of transformers in rural areas. The Rural Electrification Authority (REA) 2008 Strategic Plan announced that REA would construct several thousand transformers across the country with the goal of connecting secondary schools, trading centers, and health and water centers to electricity (REA, 2008; Berkouwer, Lee, and Walker, 2018).

According to the Ministry of Energy, the construction of transformers was to be allocated across constituencies according to the CDF formula. Consider the following exchange from 2010:

> Evans Bulimo Akula, Opposition Member of Parliament for Khwisero:
> *Mr. Speaker, Sir, how many projects is the Ministry supposed to do in every constituency per year? For the last eight years, they have done only 11 projects.*
> [...]
> Charles Keter, Assistant Minister for Energy and Petroleum:
> [...] *Currently, we are using the CDF formula. The hon. Member will realise that in this financial year, he will get over Kshs15 million and we are doing about five projects. In the last financial year, he also got the same amount of money, that is, Kshs15 million*

which did three projects. Right now, the Ministry of Energy allocates funds using the CDF formula.

Kenyan parliamentary debates, 25 March 2010 (Hansard, 2010).

All told, the number of distribution transformers more than doubled between between 2007 and 2017.[5] As a result, millions of households living near transformers could be connected at relatively low marginal cost.

Stage 2: LMCP site selection

The second stage of the rural electrification process was the selection of LMCP transformer sites from among the set of transformers. For each constituency, Kenya Power and the relevant member of parliament exchanged a series of letters to jointly select which transformers would be maximized under LMCP. A total of 13,840 transformers were selected for maximization, with the goal of creating almost one million new grid connections, and the list of villages that had been selected to be part of the LMCP was shared publicly (Kenya Power, 2017; Kenya Power, 2015).

A key outcome in this study is the share of transformers in a given ward or constituency that were selected for the LMCP. Here again, Kenya Power publicly stated that it would allocate LMCP sites to constituencies according to the CDF formula. A "Last Mile Connectivity Program Q&A" section on Kenya Power's website reads (Figure A3 shows a screenshot):

Q: What criteria was used to choose transformers?
A: The selection of the 5,320 distribution transformers for the first phase was done using the CDF distribution formula and hence a few in each constituencies were selected. This was done in spirit of "equitable distribution of resources". This has also been applied to the subsequent phases. (Kenya Power, 2016).

Stage 3: Low-voltage network construction

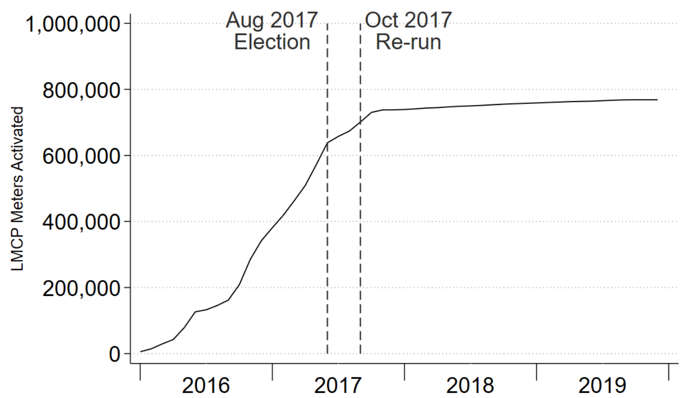
The third stage of rural electrification was completing construction at villages selected for the LMCP. Dedicated staff at Kenya Power's Nairobi headquarters implemented auctions and administered dozens of contracts with private contractors for the construction phase. These contractors—a mix of domestic and international firms—were responsible for designing an expanded local low-voltage electricity network, procuring materials (such as poles and conductors), and installing these materials. Installation consisted of three steps: erecting poles, stringing (wiring) poles, and connecting a drop cable from a pole to each customer.

Importantly, each installation contract awarded responsibility for implementing construction at LMCP sites in at most a handful of geographically clustered counties.[6] As a result, contractors

[5] Specifically, installed capacity of 11/0.415kV and 33/0.415kV distribution transformers increased from 3,515 MVA in June 2007 to 7,276 MVA in June 2017 (Kenya Power, 2012;2017).

[6] In LMCP contracts funded by the AfDB, the installer was also responsible for designs and procurement. In contracts funded by the World Bank, one contractor would conduct designs, a different one would provide materials,

Figure 2: LMCP household electricity meters



Count of LMCP meters (Section 3 defines an 'LMCP meter') over time. The vertical lines denote the August 2017 and October 2017 presidential elections. Figure A4 disaggregates construction per capita by political affiliation.

often had staff based in a regional city in or near their geographic cluster, who interacted more with local Kenya Power offices than with the central Nairobi office. This becomes a notable detail later when we discuss the role of decentralization.

Stage 4: Household electricity meter activation

The fourth and final stage of electrification was connecting a household to the grid by installing an electricity meter and activating it. While contractors were responsible for installing a meter and connecting a physical cable to each home, Kenya Power was responsible for household electricity meter activation. A crucial program feature that enabled LMCP to reach so many households was that beneficiaries were not required to pay an upfront deposit: per Kenya Power, "all the beneficiaries under this scheme will be connected whether they have paid the contribution or not" (Kenya Power, 2016). For households connected under the LMCP, the KES 15,000 (approx. USD 150) connection fee—already significantly lower than the standard KES 32,480 (approx. USD 350) fee, thanks to government and donor financing—could be paid by consumers in up to 36 installments of around USD 4 each. The monthly payments were supposed to have been automatically posted to households' electricity meters, but in practice, connection fees for many customers were never or only partly recovered (Alushula, 2018). This structure was later changed to a 20% upfront payment, with the balance recouped by dedicating 50% of households' monthly electricity expenditures to repaying the connection fee (AfDB, 2022).

Figure 2 plots the cumulative number of activated LMCP meters based on their activation dates from Kenya Power. Between the start of LMCP in 2016 and the October 2017 presidential election re-run, there was rapid progress in construction, with over 30,000 meters installed per month. However, after the August election and the October re-run there was a dramatic plateau in the pace of construction for at least two years. These patterns help motivate our investigation into

and the installer would do only the installation (Wolfram et al., 2023). Contracts funded by the AfDB and the WB were spatially interspersed and both nationally representative and this difference thus does not affect the political analysis. The results in the paper are similar when considering only AfDB sites or only WB sites.

the political drivers of electrification. In particular, the ramp-up in the lead-up to the election is consistent with ex ante strategic behavior designed to incentivize voting rather than a system of ex post rewards for areas that voted for the winning party (see Golden and Min, 2013 for a review on strategies in distributive politics and electoral cycles).

3 Data

A key feature of this paper is the granularity of the data on both grid infrastructure (provided by Kenya Power) and construction progress over time (provided by project contractors). Together, these data provide a comprehensive understanding of Kenya's rural electrification activities between 2008-2019. We merge these data with ward-level electoral outcomes from Kenya's March 2013 and August 2017 presidential elections.

3.1 Grid infrastructure and LMCP construction data

The grid infrastructure data provided by Kenya Power include the universe of Kenya's 7.4 million electricity meters and the 62,271 transformers that they were connected to as of December 2019, with geo-spatial coordinates and network connections for each meter and transformer. Meters and transformers span Kenya's 290 constituencies and 1,450 wards (each constituency contains around five wards). Since the LMCP was a program of transformer maximization, it deprioritized sparsely populated regions and urban regions: we therefore exclude these from the analyses.[7] The main analyses therefore use a sample of 911 rural wards that were the main focus of the LMCP (Figure A5). These 911 wards contain 42,135 transformers—including 9,284 out of the 11,934 transformers that were selected for the LMCP (78%)—and 948,063 household meters that are indicated as having been connected via a government electrification program since 2016.[8] For the remainder of the paper, we refer to these 911 wards as 'LMCP wards', the 9,284 transformers as 'LMCP sites', and these 948,063 electricity meters as 'LMCP meters'.

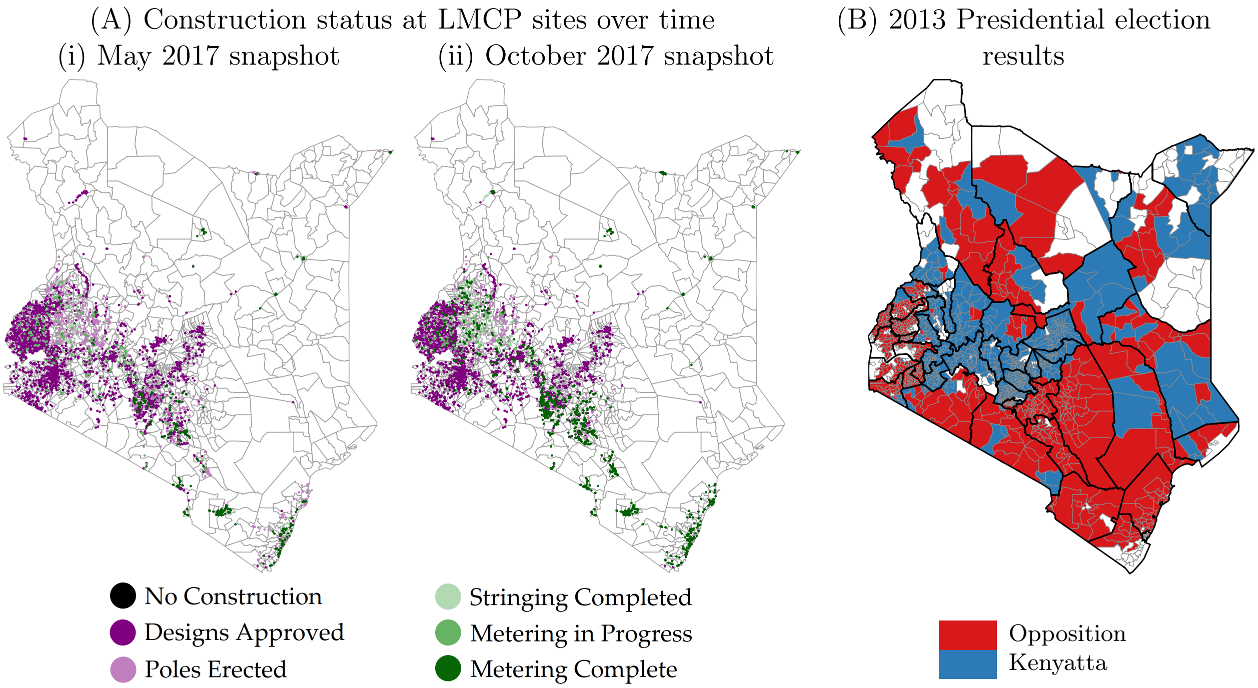
More than 99% of LMCP construction by 2019 was part of one of three programs that was co-financed by a major international funder: African Development Bank (AfDB) Phase I, AfDB Phase II, and World Bank (WB). The construction progress panel data consist of monthly transformer-level construction progress reports—which contractors were mandated to send to Kenya Power—for all LMCP sites that were financed through either AfDB Phase I or WB.[9] The data contain four markers of progress: the start of construction, pole installation, stringing of electrical cables, and

[7] We label counties targeted by REA's Kenya Off-Grid Solar Access Project as sparsely populated. In these remote areas, very few households lived within 600 meters of a transformer. We label wards in Nairobi or Mombasa, or with similar population density, as urban. By 2016, 84% of urban Kenya households were connected to electricity (WB, 2018). Figure D2 presents a specification curve with 63 variations of sample definitions. Results are not qualitatively sensitive to the sample definition.

[8] In line with Kenya Power explanations, we define this as having a pre-paid residential meter that was activated after 2015 as part of a government-funded scheme. Appendix C describes data construction in detail.

[9] We observe locations for all meters as of December 2019, but we only observe construction activity and activation dates for meters that had been installed by December 2017 as part of AfDB Phase I and WB. This limitation does not affect the main econometric analysis below.

Figure 3: Nationwide distribution of LMCP construction and 2013 election vote shares



Panel A shows two snapshots from monthly construction data, showing the status of construction at each LMCP transformer site. The full monthly panel data set spans from April 2017 to June 2019. Panel B shows 2013 presidential election results at the ward level, with county borders in thick black lines. Blue (red) wards had vote shares of over (under) 50% for Kenyatta. White wards are missing election data. Figure A7 presents the full gradient of vote shares and separates interior and border regions of support. Figure A8 maps the distribution of LMCP sites across pro-Kenyatta and opposition border areas.

meter installation. Panel A of Figure 3 shows two snapshots of these data. The fifth and final stage—metering activation, when electricity actually begins to flow to households—is completed by Kenya Power and thus not included in the contractor progress reports. Instead, we construct a panel dataset of meter activation using the activation dates from the Kenya Power data. Appendix C provides additional detail on data construction.

The various data sources generally align well. As an example, the meter activation database shows around 3 to 5 active electricity meters connected to each LMCP transformer prior to construction (Kenya Power officials confirmed that, prior to the LMCP, up to a handful of high-income households would often be connected to a rural transformers by paying the standard connection fee). There is a sharp rise of around 25–30 in the number of active meters that occurs in the weeks around when a contractor independently reports completion of construction at a site (Figure A6). This is in line with the expectations shared by Kenya Power in terms of how many unconnected households could likely be found within each site.

3.2 Electoral and demographic data

Panel B of Figure 3 displays ward-level results for Kenya's 2013 presidential election, obtained from the Independent Electoral and Boundaries Commission (IEBC) website. Blue wards are those where Kenyatta won over 50% of the vote, while red wards are those where Kenyatta won under 50% ('opposition').[10] Votes for Kenyatta's government were concentrated in Central Province and Rift Valley Province, the ethnic home areas of Kenyatta and Ruto, respectively, as discussed in Subsection 2.1. Electoral coalitions and geographic patterns in vote shares were very stable between 2013 and 2017 (Figure D1).

As a robustness check, we restrict the sample to wards bordering at least one ward that voted for the opposing candidate in the 2013 presidential election ('adjacent wards'), thus comparing only wards with relatively similar geographic and socioeconomic characteristics. This results in a sample of 451 adjacent wards (mapped in Figure A7).

3.3 Additional variables

We draw socio-economic controls from the 2009 Kenya Population and Housing Census, which was the most recent census before the launch of LMCP. These include population density, baseline unconnected electricity rates, and household asset proxies. In addition to these socio-economic controls, we include geographic controls for gradient and land area, as opposition wards have slightly less rugged terrain (as measured by a satellite-based gradient index) and larger land area, which could potentially affect construction costs.

We supplement these data with geo-tagged data on the roll-out of M-PESA mobile money agents. While Kenya Power was rolling out the LMCP, the private firm Safaricom was heavily expanding its network of M-PESA agents across the country between 2013–2015. We interpret these data as an indicator of private sector economic activity and investment.

4 Electrification and national politics

How much did Kenya's nationwide rural household electrification program favor areas that had voted for Uhuru Kenyatta, the winner of the previous presidential election? We first document the overall difference in household electrification using a standard selection-on-observables approach. Then, to distinguish favoritism from other possible government objectives, we evaluate realized allocations relative to the CDF formula; estimating political bias against this official policy benchmark allows us to avoid having to take a stance on the social welfare-maximizing allocation of electricity connections in Kenya.

[10] 2013 IEBC election data are missing for 185 out of 1,450 wards (13%), shown in white in Figure 3. These are primarily located in remote northern regions of the country with relatively small populations and fewer LMCP sites.

4.1 Selection-on-observables design

We first estimate the difference in electricity meters per 100,000 households between pro-government wards and opposition wards using the following regression:

$$y_i \quad = \quad \beta_0 + \beta_1 ProGovernment_i + \boldsymbol{\gamma}\mathbf{X_i} + \varepsilon_i \qquad (2)$$

where y_i is the number of government-subsidized household electricity meters per 100,000 households installed in ward i as of December 2019. (For comparison, Kenyan constituencies outside the major cities have an average population of around 27,000 households.) $ProGovernment_i$ equals 1 if ward i voted pro-Kenyatta in the 2013 presidential elections—as discussed in Subsection 2.1, the 2013 (not 2017) presidential elections result is the preferred explanatory variable because this could not have itself been affected by the 2015–2017 electrification activities. $\mathbf{X_i}$ is a vector of covariates that varies across regressions.

Column 1 of Table 1 presents results without any socio-economic or geographic controls. Wards in households that voted pro-Kenyatta in the 2013 election saw more than 3,000 more electricity meters per 100,000 households compared to wards that voted for the opposition. Relative to the 14,500 meters installed in opposition wards, this is a sizable 22% partisan gap. In other words, wards that voted pro-Kenyatta appear to have been significantly favored in the deployment of household electricity connections.

Of course, this uncontrolled regression may not accurately identify political favoritism if there are systematic differences between pro-Kenyatta and opposition areas. If, say, pro-Kenyatta areas are on average richer, and the economic returns of electrification increase with wealth, targeting pro-Kenyatta areas may be economically sensible. Large gaps in electrification rates that are correlated with political affiliation could be justified by a welfare-maximizing social planner.

To address this, Column 2 of Table 1 adds a large set of socio-economic and geographic controls (detailed in the table note). This does not substantially move the coefficient β_1. Similarly, Column 3 shows that using LASSO to flexibly select from quadratic and cubic transformations and double and triple interactions of these controls does not meaningfully alter the coefficient estimate. The basic finding persists: electoral wards that voted pro-Kenyatta in 2013 saw substantially more electricity metering than opposition-voting wards, on the order of around 21–25%. The stability of the coefficients after introducing a wide range of controls suggests that the observed political gaps do not merely reflect observed socio-economic or geographic differences. Results are qualitatively similar across a wide set of robustness checks.[11]

Political favoritism could be driven by expected growth rather than contemporaneous economic outcomes: the government may have used private information about the potential for economic growth, not captured in the census data, to allocate electrification projects. To test for this, we conduct a placebo test using data on the penetration of mobile money agents—which are widely used for financial transactions in Kenya (Berkouwer et al., 2023)—as a proxy for expected economic

[11] Column 2 is identical to Column 7 of Table 3, and similar to Column 7 in Table D6 (without population weighting), Table D7 (among only adjacent wards), Table D8 (per capita—not per household), and Column 1 of Table B4 (using panel data). Figure D2 presents a specification plot with 63 different specifications varying sample and controls.

Table 1: Political favoritism in household electricity connections per 100,000 households

	In absolute terms			Relative to CDF Allocation		
	(1)	(2)	(3)	(4)	(5)	(6)
Voted pro-govt in 2013	3188***	3092***	3613***	5639**	5285**	5045***
	(1008)	(1159)	(805)	(2062)	(2364)	(1609)
Observations	911	911	911	196	196	196
Opposition Mean	14444	14444	14444	16299	16299	16299
Effect Size (%)	22	21	25	35	32	31
Controls	None	SES	LASSO	None	SES	LASSO
Sample	Wards	Wards	Wards	Consts	Consts	Consts

In Columns 1–3, i is a ward and y_i is the number of government-subsidized household electricity meters per 100,000 households. In Column 4–6, i is a constituency, and y_i is that same number minus the hypothetical number had meters been allocated according to the CDF formula. Columns 2 and 5 control for land gradient, population density, baseline unconnected households, share adults with primary or secondary education, share adults who work for pay, dependency ratio, share households with an iron roof, population density, household size, mobile money agents as of 2013 per capita, and change in mobile money agents between 2013 and 2015 per capita. Column 3 uses post-double selection LASSO (Belloni, Chernozhukov, and C. Hansen, 2013; Ahrens, C. B. Hansen, and Schaffer, 2020) to flexibly select from a subset of quadratic and cubic interactions between this same set of variables. Table B2 presents the same analysis for LMCP sites per 100,000 households. Figure D2 and Figure D3 present specification plots with 63 different specifications varying sample and controls. $^* \leq 0.10,^{**} \leq .05,^{***} \leq .01$.

growth. If the LMCP was targeted based on economic growth potential, we would expect to see similar pro-Kenyatta bias in the allocation of mobile money agents across space. We repeat the analyses in Table 1 but replace the dependent variable with the change in M-PESA mobile money agents between 2013 and 2015. In contrast to the results for electricity connections, these estimates do not reveal favoritism toward pro-Kenyatta areas (Table B3). Similarly, the allocation of LMCP sites shows a pro-Kenyatta bias even when measured relative to the share of mobile money agents, or against the 2013-2015 growth in the number of mobile money agents (Figure A9). These results suggest that the pro-Kenyatta bias in LMCP sites is unlikely to simply be the result of underlying economic differences.

4.2 Leveraging the CDF allocation to identify favoritism

The results above indicate a strong bias towards pro-Kenyatta areas in Kenya's nationwide rural electrification program, even after controlling flexibly for a host of socio-economic and geographic characteristics. Still, a well-known limitation of using selection-on-observables approaches is that other unobserved factors could have driven the observed favoritism. For example, if the government has an idiosyncratic objective that is unobserved by the researcher, and this objective happens to correlate spatially with political affiliation, then differences that align with political affiliation may not reflect partisan favoritism. Distinguishing favoritism from unobserved welfare optimization (or other legitimate goals) is crucial when studying political favoritism in the allocation of public investment.

This paper addresses this common identification concern by leveraging a unique feature of the setting: a transparent, publicly announced benchmark in how LMCP sites would be allocated, which had earlier been agreed upon ex ante by opposing political parties. As discussed in Section 2, officials from the Ministry of Energy and Kenya Power publicly announced that transformers and LMCP sites would be allocated to constituencies according to the Constituency Development Fund (CDF) formula. LMCP sites were selected in 2015, when the 2003 CDF formula was in effect, which stated that 75% of CDF funding was to be allocated in equal shares across all constituencies while the remaining 25% based on each constituency's share of national poverty (GoK, 2003). Deviations from this CDF rule that are correlated with political affiliation can be interpreted as evidence of political favoritism.

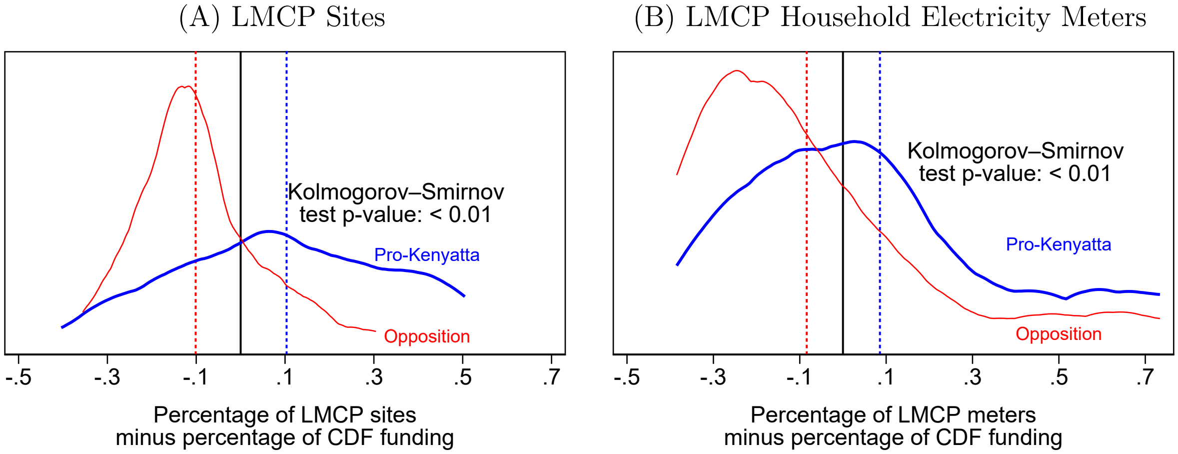
Columns 4, 5, and 6 of Table 1 measure the gap in electricity meters between constituencies that voted pro-Kenyatta in 2013 and constituencies that voted for the opposition, relative to the share of public funds each constituency was allocated per the CDF formula. Since constituency allocations are (by definition) only available at the constituency level, these estimates have fewer observations and the coefficient estimates are less precise. Still, Column 4 shows that constituencies that voted pro-Kenyatta in 2013 had over 5,500 more household electricity meters per 100,000 households relative to their CDF allocation than constituencies that voted for the opposition—a 35% gap compared to the opposition mean of around 16,000 meters per 100,000 households. This coefficient is stable after introducing the same set of socio-economic controls as for the wards (Column 5) and LASSO-selected quadratic and cubic transformations and triple-interactions of these controls (Column 6). Taken together, these results show that the allocation of electrification deviated strongly from its publicly stated benchmark, in favor of pro-Kenyatta areas.

Figure 4 documents that this difference is not driven by a small number of outlier constituencies, but rather is pervasive across the entire distribution. For each constituency, we compute an "allocation deviation": the share of LMCP sites a constituency was awarded minus its share of CDF funding. Had sites been allocated according to the CDF formula, allocation deviations would be concentrated at zero; positive values mean that the constituency was allocated more LMCP sites or meters than its CDF share; negative ones mean that constituencies were under-allocated. Figure 4 compares the distributions of allocation deviations between constituencies that voted pro-Kenyatta (blue) and opposition (red) in the 2013 presidential election.

Panel A shows that pro-Kenyatta constituencies were disproportionately allocated more LMCP sites—on average, 120% of the allocation they would have received under the CDF rule—while constituencies that voted for the opposition received on average only 81% of their allocation. Similarly, panel B shows that pro-Kenyatta constituencies saw significantly more LMCP household electricity meters than opposition constituencies, relative to their CDF allocations. For both outcomes, t-tests under the null that the means are equal and Kolmogorov-Smirnov tests under the null that the distributions are equal are rejected with p-value < 0.01. These results persist when comparing allocations to population (panel A of Figure D4), land area (panel B of Figure D4), or when using all wards nationwide instead of just the rural LMCP wards (Figure A10).

Taken together, these results provide strong evidence of pro-Kenyatta favoritism in the allocation of household electrification in Kenya, on the order of 20 to 35%. Crucially, by comparing the

Figure 4: Constituency LMCP site and meter shares relative to CDF shares by 2013 election result



A constituency's share of nationwide LMCP outcomes minus its share of CDF funding, by whether constituencies voted pro-Kenyatta in the 2013 presidential election, bottom- (top-) coded at the 5th (95th) percentile. Panel A shows LMCP sites selected. Panel B shows LMCP household meters activated. Vertical lines indicate sample means. Shares are normalized according to the same sample as in Table 1. Figure D5 presents a scatter plot version.

allocation of LMCP meters against the government's publicly stated method of allocating sites—the Constituency Development Fund (CDF) formula—we do not have to take a strong stance on efficiency or welfare-maximization: we can merely state that the Kenyan government, factoring in its own equity and efficiency goals, publicly committed to this allocation formula. Columns 4, 5, and 6 of Table 1 and Figure 4 provide strong evidence that the government deviated from this allocation formula, selecting significantly more LMCP sites and installing significantly more household electricity meters in pro-Kenyatta wards.

Figure 1 puts these findings in context by comparing them to other estimates of political favoritism in infrastructure allocation in Kenya exerted by the central executive in recent decades. While the favoritism we identify is economically and statistically meaningful, our estimates are significantly lower than those pertaining to favoritism between the 1970s through the early 2000s identified in Burgess et al. (2015) and Barkan and Chege (1989). This points to an encouraging continuing downward trend over time in the magnitude of favoritism, coinciding with political reforms that have strengthened democratic institutions and decentralized government functions.

4.3 Targeting core versus swing supporters

Political favoritism can manifest through different channels of electoral targeting. In 'swing' electoral areas, where the margins between political parties are small, parties may allocate more public goods in the belief that they can sway which party voters will support. In 'core' electoral areas, where a clear majority of voters supports one party, the objective may be to drum up electoral turn-out among committed partisans rather than swaying voters.

Was political favoritism in the LMCP targeted towards core or swing areas? We code wards where one party won 50–75% of the vote in the 2013 presidential elections as swing electoral regions,

Table 2: Electricity meters per 100,000 households in core and swing regions

	(1)	(2)	(3)
Pro-Government Core (δ_1)	3609***	4013***	4543***
	(1098)	(1235)	(928)
Pro-Government Swing (δ_2)	4315**	2845	2928*
	(1963)	(2272)	(1613)
Pro-Opposition Swing (δ_3)	2686*	2889**	2538**
	(1530)	(1401)	(1258)
Observations	911	911	911
Pro-Opposition Core Mean	14095	14095	14095
p-val $\delta_1 = \delta_2$	.72	.62	.34
Controls	None	SES	LASSO
Sample	Wards	Wards	Wards

Results from Equation 3. Samples and specifications are identical to those presented in Columns 1–3 of Table 1. Pro-Kenyatta Core are wards where the government received >75% of the presidential vote in the 2013 elections (414 wards). Pro-Kenyatta Swing: government received 50–75% (44 wards). Pro-Opposition Swing: opposition received 50–75% (81 wards). Omitted: Pro-Opposition Core (372 wards). SE clustered by constituency in parentheses. $^{*} \leq 0.10, ^{**} \leq .05, ^{***} \leq .01$.

and wards where a party won between 75–100% of the vote as core support regions.[12] Table 2 estimates how rates of electrification differ between these areas using the following equation, such that all coefficient estimates are relative to core opposition wards:

$$y_i \quad = \quad \delta_0 + \delta_1 ProGov_i \times Core_i + \delta_2 ProGov_i \times Swing_i + \delta_3 Opp_i \times Swing_i + \boldsymbol{\gamma}\mathbf{X_i} + \varepsilon_i \qquad (3)$$

Pro-Kenyatta core areas, pro-Kenyatta swing areas, and even opposition swing areas all see higher levels of household electrification than core opposition areas, on the order of 19%–32%. We cannot reject that the three areas all benefited from similar levels of electrification. This suggests that both core pro-Kenyatta areas and swing areas were targeted for greater electricity investments. The pattern also broadly persists when comparing against the CDF benchmark formula, although the estimates are noisier because the sample sizes are smaller when running regressions by constituency instead of by ward (Columns 4–6 of Table D1, Table D2 and Table D3).

4.4 Favoritism across the four construction stages

As discussed in Subsection 2.3, LMCP construction consisted of four stages: transformer construction, LMCP site selection, LMCP site construction, and household meter activation (Equation 1). These jointly determine the cumulative number of household electricity meters activated under the LMCP. Understanding how political favoritism differed across these construction stages may shed light on the mechanism through which political favoritism affected the final aggregate outcome.

Table 3 presents the effects of political favoritism at each stage of LMCP construction. There

[12] Swing areas are relatively scarce in this polarized political environment—comprising only 14% of wards in our analysis sample (23% nationally). Results are qualitatively robust to defining 'core' as having >60% or >80% of the presidential vote (Columns 1–3 of Table D2 and Table D3).

Table 3: Cumulative and marginal favoritism across the stages of the LMCP

	Pre-existing Transformers	LMCP					
		Site Selection		Construction		Meters	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Voted pro-govt in 2013	108***	.0539***	62.6***	-.0428	27.1***	-5.34	3092***
	(41.3)	(.0178)	(11.2)	(.0415)	(10.2)	(11.1)	(1159)
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 (%)	16.8	21.2	42.1	-8.0	32.6	-4.3	21.4
Analysis		Marg.	Cumul.	Marg.	Cumul.	Marg.	Cumul.

All regressions at the ward level, weighted by ward population, with same socioeconomic controls as in Table 1. For column 1, y_i is number of transformers per 100,000 households. For columns 2, 4, and 6, the regressions isolate the marginal impact of that particular stage. In column 2, y_i is proportion of transformers selected for LMCP; in column 4, y_i is LMCP sites completed per LMCP transformer; in column 6, y_i is LMCP meters per LMCP transformer. For columns 3, 5, and 7, the regressions are cumulative across stages of construction. In column 3, y_i is LMCP transformers; in column 5, y_i is LMCP sites completed; in column 7, y_i is LMCP meters; all per 100,000 households. SE clustered by constituency in parentheses. Results persist across a range of sample and regression specifications (Table D4 through Table D8). Table D9 adds constituency fixed effects. $^{*} \leq 0.10,^{**} \leq .05,^{***} \leq .01$.

is significant favoritism towards wards that voted pro-Kenyatta in 2013 in all stages of electricity construction. Column 1 indicates a 16.8% pro-Kenyatta bias in the placement of transformers prior to the start of the LMCP, as part of REA's activities in 2008-2016. This favoritism persists in the the selection of LMCP sites (column 3), the number of sites under construction as of June 2019 (column 5), and the number of household meters (column 7). The order of magnitude of favoritism is robust to a wide range of specifications.[13] Estimating these effects relative to the CDF formula shows quantitatively and qualitatively similar, and if anything slightly larger, results, with similar patterns of statistical significance (Table D10).[14]

However, this relatively constant *cumulative* effect may mask variation in the individual stages of construction. To examine whether aggregate favoritism originated in the transformer construction and selection process, or downstream in the maximization of LMCP sites, we decompose the cumulative effect into the marginal impacts during each stage of construction, conditional on attaining the previous stage. Columns 1, 2, 4, and 6 of Table 3 indicate that the bulk of cumulative favoritism is driven by pro-Kenyatta favoritism in the pre-LMCP stock of transformers (col. 1) and LMCP site selection (col. 2). We find little evidence of additional favoritism in the later stages of construction of site construction (col. 4) and provision of household meters (col. 6).

How can these results be reconciled with Kenya's extensive decentralization reforms? National-

[13]Specifically, results are qualitatively similar when dropping socio-economic controls (Table D4), using LASSO to select socio-economic controls (Table D5), not weighting by population (Table D6), only comparing adjacent wards (Table D7), and using per capita rather than per household (Table D8). Adding constituency fixed effects dampens the effects, indicating the results are driven by across-constituency rather than within-constituency targeting (Table D9). This makes sense since political affiliation correlates strongly across wards in the same constituency.

[14]We focus on the ward-level regressions, rather than the constituency-level regressions relative to the CDF formula because—for the marginal effects discussed in the next paragraph—it is mathematically nonsensical to estimate favoritism relative to both the CDF and the previous stage simultaneously.

level authorities had tighter control over the first two stages of the LMCP (initial transformer construction and the selection of LMCP sites): these activities were implemented by actors in national government, together with Kenya Power and the Rural Electrification Authority, which are both parastatals controlled by the national government. As a result, these stages may have been more subject to political pressure by the central executive. While the bulk of LMCP transformers were constructed between 2008 and 2012 under President Mwai Kibaki, geographic patterns of political support in this prior period are similar to those of his 2013 successor Uhuru Kenyatta.

Conversely, the final two stages—on-the-ground construction and meter installation—were implemented by local agents, one or more steps removed from the president's administration. LMCP site construction was implemented by private contractors and subcontractors, each of which was responsible for LMCP sites in a specific set of counties (Wolfram et al., 2023). After contracts had been awarded and administered, contractors interacted primarily with regional Kenya Power offices located in their geographic area of responsibility for the duration of the implementation period. Meter activation was completed by local Kenya Power offices. As a result, these latter stages may have been less easily influenced by the central government, and subject to stronger influence by local politicians.

Taken together, these findings suggest that aggregate political favoritism in Kenyan electrification at the household level is largely driven by stages of construction over which the central government had the most influence: the initial stock of pre-LMCP transformers and LMCP site selection. How can this be reconciled with Kenya's extensive post-2003 decentralization reforms, which aimed to limit the central government's influence in directing public expenditures? The next section seeks to disentangle the role of centrally and locally elected officials.

5 Centrally and locally elected officials

The pro-Kenyatta favoritism identified in the previous section is consistent with two broad hypotheses about the shortcomings of decentralization. One possibility is that decentralization successfully empowered local officials, but that these actors continued to enable or enact pro-Kenyatta favoritism. Another possibility is that decentralization did not empower local politicians sufficiently for them to be able to alter the centrally preferred allocation, and that power and resources remained concentrated *de facto* with national leaders.

To study these mechanisms, we focus on how Members of Parliament (MPs) shaped the implementation of the LMCP. MPs are the most politically influential locally elected officials and have close control over public funding—Harris and Posner (2019) and Opalo (2022a) both note how MPs largely determine how CDF funds are used within their constituencies. Volkert and Klagge (2022) observe that, based on interviews conducted in February 2020, Kenya Power and the rural electrification authority[15] officials expressed a preference for working with local MPs over county governments Despite the fact that MPs are technically national-level officials and spend much of

[15]The 2019 Energy Act created the Rural Electrification and Energy Corporation (REREC) as a successor of REA.

Table 4: Effects of MP alignment on LMCP stage outcomes (with constituency fixed effects)

	Pre-existing Transformers	LMCP					
		Site Selection		Construction		Meters	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Voted pro-govt in 2013	143	-.022	13.5	-.0908	-17.5	-17.8	1205
	(111)	(.0376)	(26.6)	(.0633)	(17)	(27.6)	(1700)
Voted pro-MP in 2013	-42.3	.0237*	1.43	.00613	.49	-6.39	-150
	(31.3)	(.0142)	(8.78)	(.0326)	(8.63)	(10.2)	(777)
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 (%)	22.2	-8.7	9.0	-16.9	-21.1	-14.2	8.3
MP Effect (%)	-6.6	9.3	1.0	1.1	0.6	-5.1	-1.0
Analysis		Marg.	Cumul.	Marg.	Cumul.	Marg.	Cumul.

Specifications are identical to those presented in Table 3 but with an additional independent variable and adding a constituency fixed effect to estimate impacts within constituency. 'Voted pro-MP in 2013'=1 if the ward voted for the winning MP in the 2013 constituency-level National Assembly elections.

the year in Nairobi, many interviewees expressed a view that MPs are seen as "representative of the people". MPs are one of the few locally elected offices that predate devolution, and unlike other local officials like senators or members of the county assembly, MPs often have close formal and informal links to Kenya Power and Kenya's rural electrification programs.

Additionally, early in the LMCP, Kenya Power and each constituency's MP exchanged a series of letters to jointly select the locations of transformers within each constituency. Through this process, MPs could have exerted influence on the selection of LMCP transformers.

MP favoritism may have taken two forms. First, MPs may have exerted bias when allocating LMCP sites to specific wards within their constituencies to favor wards that had voted for them in constituency elections. Interviewees of Volkert and Klagge (2022) reported that MPs decisions about where to implement REREC projects were "influenced by political intentions, especially the desire for re-election". Second, across constituencies, MPs aligned with the ruling party (Kenyatta's Jubilee coalition) at the national level may have been able to channel more resources to their constituencies relative to MPs aligned with the opposition coalition. We discuss these two hypotheses in turn.

5.1 Within-constituency MP favoritism

Do MPs favor the wards in their constituencies that voted for them in constituency-level MP elections? For wards indexed by i, we estimate the following equation:

$$y_{ic} = \theta_0 + \theta_1 ProGovernment_{ic} + \theta_2 ProMP_{ic} + \gamma X_{ic} + \gamma_c + \varepsilon_i \quad (4)$$

where $ProGovernment_i$ equals 1 if ward i voted pro-Kenyatta in the 2013 presidential elections (paralleling the analysis above) and $ProMP_i$ equals 1 if the MP candidate who got the most votes in ward i also won the overall constituency election. γ_c is a constituency fixed effect.

Table 4 presents the estimates of Equation 4, with the new MP coefficient θ_2 in the second row. Three of the four stages show no evidence that a ward having voted for its constituency MP affects that ward's LMCP outcomes. Column 2 shows marginally significant pro-MP favoritism in the selection of LMCP sites within a constituency: this is in line with Kenya Power and the MPs being jointly responsible for site selection (as discussed in Section 2.3). Still, the point estimate is considerably smaller than the presidential vote effect, and there is little evidence that areas that voted for their MP were favored in the final program outcome—the activation of household electricity meters (columns 6 and 7). Taken together, these results indicate that the main results presented above are not driven by MPs rewarding wards that voted for them in the 2013 election with more electrification. Note that the pro-government effects are estimated with far less precision due to the inclusion of constituency fixed effects given the limited variation in pro-government vote shares within a constituency, and are therefore generally less informative (and not the preferred specification to test for pro-government effects).

Results are similar in specifications that drop socioeconomic controls (Table D11), select controls using a LASSO procedure (Table D12), drop population weights (Table D13), use the adjacent wards sample (Table D14), use per-capita as opposed to per-household outcome measures (Table D15), or dropping constituency fixed effects (Table D16).

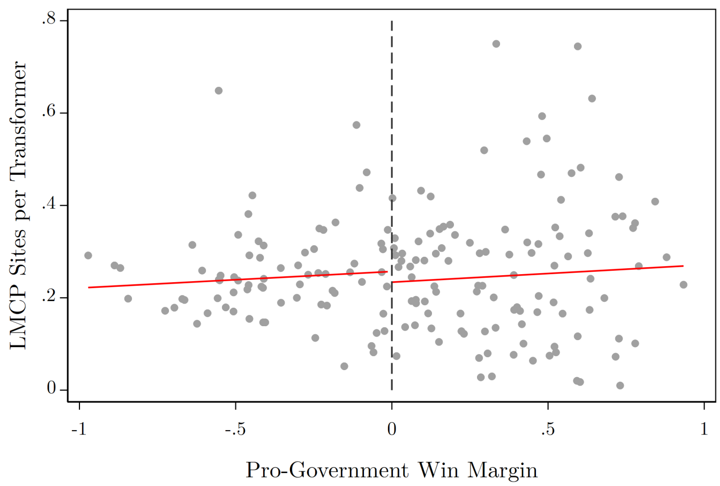
5.2 Across-constituency MP favoritism

Was there increased LMCP construction in constituencies with an MP who was aligned with the national government? To study this question, we use a close election regression discontinuity design. The running variable is the gap in vote share between the best-performing Jubilee coalition candidate and the best-performing non-Jubilee candidate in the 2013 MP elections. We observe if there is a discontinuity around 0 in the share of that constituency's transformers that were selected for the LMCP. Win margins in this context have a relatively smooth distribution, with little evidence of bunching and a notable mass of electoral outcomes near zero (Figure D6).

Figure 5 does not show a discontinuity at zero, indicating that electing an MP who was aligned with the central government did not meaningfully increase a constituency's share of transformers selected for LMCP. A robust regression discontinuity in the style of Calonico, Cattaneo, and Titiunik (2014) with linear trends fails to reject the absence of discontinuity with a p-value of 0.44. This departs from existing research on local politicians in the U.S. (Alesina, Baqir, and Easterly, 1999; Ferejohn, 1974), but is in line with Harris and Posner (2019) who study MPs in Kenya (see Figure A11 for a comparison). We similarly find no results when using the same regression discontinuity strategy with each stage of construction progress as the outcome (Figure A12).

It is worth noting that, by design, discontinuity estimates are identified off of constituencies where the electoral result was near the margin. MP alignment could increase a constituency's share of LMCP sites in core pro-government areas far from the discontinuity, which could contribute to the results presented in Section 4. However, given the strong overlap between MP and presidential voting, we are unable to disentangle these alternatives.

Figure 5: Share of constituency's transformers selected for LMCP



The running variable—pro-government win margin—represents the difference between the vote share of the best performing Jubilee candidate and the best-performing candidate not in the Jubilee coalition in the 2013 parliamentary elections. Linear trends on either side of the 0-margin line are weighted by constituency population. Figure A12 similarly shows no results for individual stages of construction.

5.3 Understanding decentralization

Taken together, the findings suggest that favoritism in the placement and progress of LMCP construction was not driven by clientelism exerted by MPs, but rather was a function of a region's vote in the presidential election. This is despite significant constitutional reforms during 2003–2010, in which local agencies had been awarded significant legal authority: under the 2010 Constitution, both county and national governments had mandates to oversee energy policy (World Bank, 2017).

In practice, significant political power in the electricity sector continued to reside with the central executive, revealing the vulnerability of large parastatals to political capture. Incentivized by electoral pressures or financially motivated corruption, national leaders, by retaining control over centralized infrastructure, can exploit this concentration of power to direct resources towards their political supporters. As discussed in Subsection 2.1, recent appointees at top management positions of Kenya Power have come from the political coalition of the incumbent president, reflecting the continued dominance of the executive in appointments. Hassan (2020a) observes that, in African countries, devolution has often had limited effects when legal mechanisms allow the national government to claim functions that fall under a local government's mandate.

At the same time, in key infrastructure sectors such as electricity—as well as, for example, telecommunications, roads, or railways—there may also be genuine technical, economic, or network benefits to centralization. Only two out of 52 utilities in Africa are able to fully recover their costs: 50 experience severe financial constraints (Blimpo and Cosgrove-Davies, 2019; Kojima and Trimble, 2016), in addition to facing increased pressure to provide low-cost, universal access to electricity and to improve service quality by investing in grid maintenance and upgrading (Burgess et al., 2020). These pressures could make continued centralized management of these sectors a sensible economic decision.

There are several such technical, economic, and network benefits. The expansion and management of infrastructure requires technical capacity, which local officials often lack. At the parliamentary level, the high turnover of MPs in Kenyan elections often inhibits the development of specialized expertise (Opalo, 2022b). Thus, despite its strong legal powers, in practice the legislature often defers to the executive branch on technical matters (Opalo, 2022b). Despite their constitutional mandate, county governments similarly lack technical expertise to implement electricity projects. In interviews with stakeholders from Kenya Power, the rural electrification authority, and the Kenyan government, Volkert and Klagge (2022) note that there was widespread agreement that "a lack of skills, knowledge and experience of the county governments, their staff and possibly also the MPs... is the main challenge for a devolved electrification governance." When the LMCP was launched, the new county governments had significantly less capacity than the long-established Ministry of Energy and Kenya Power. Sectors with complex networks furthermore benefit from a centrally designed spatial layout and management system. Larger independent system operators (ISOs) that pool many generation sources can better to minimize costs in wholesale electricity markets (Cicala, 2022). Economies of scale may furthermore generate natural monopolies in some sectors, for example in the nationwide procurement of materials required for expanding electricity networks (Wolfram et al., 2023).

These benefits are especially important given the global energy transition. The hydro, renewable, and geothermal sources that dominate electricity generation in East Africa are geographically constrained—unlike fossil fuel plants, which face fewer locational constraints - and are often best located far from demand centers. For example, Kenya's Lake Turkana Wind Power project—inaugurated in 2019 with operating capacity of 310MW, providing a 17% increase in the country's generation capacity—was sited in the far north of the country, where wind speeds are high, and thus required the additional completion of an additional 438 kilometers in transmission lines to link it with major cities. The rising share of renewables in the world's electricity mix will likely increase the importance of centrally managed generation and transmission networks.

The economic logic of large-scale infrastructure development may be in tension with the political logic of decentralization—the technical, economic, and operational benefits of centralization must be weighed against the risks and costs of an increased concentration of political power.

6 Conclusion

This paper evaluates political favoritism in the context of Kenya's $788 million program to connect all households to electricity. To objectively quantify favoritism, we leverage a unique institutional feature: the existence of an objective and transparent formula—the Constituency Development Fund (CDF) allocation rule—that had earlier been agreed upon by the incumbent government as well as the opposition. Through public and parliamentary communications, the government announced that electrification projects would be distributed across constituencies following the CDF allocation.

We document deviations from this rule that correlate with political alignment. Constituencies that voted for the president in 2013 received around 35% more household electricity connections than constituencies that voted for the opposition, relative to the allocation that the government had announced they would receive. These results persist when adding socio-economic controls or when testing a wide range of sample definitions. Still, the glass is half-full: as Figure 1 illustrates, the levels of favoritism documented in this study are far below those documented in earlier large-scale public programs in Kenya (Burgess et al., 2015) and less than many observers of Kenyan politics might predict. The continued strengthening of democratic norms, greater oversight from other actors such as the local media and foreign aid donors, and other recent political reforms may have all combined to generate a significant reduction in political favoritism in Kenya in recent decades.

We focus on one key such reform: decentralization. In the years leading up to the launch of the national electrification project, Kenya enacted major constitutional reforms that decentralized power away from the central executive and towards locally elected members of parliament and county governments, which were called the "biggest political transformation since independence" (Cheeseman, Lynch, and Willis, 2016) and created "arguably Africa's strongest parliament" (Opalo, 2014). Why does political favoritism persist despite decentralization in a largely democratic political system? Several observations support the hypothesis that decentralization reforms were not completely effective at reassigning power away from the central executive and towards locally-elected politicians. First, despite county and national governments having competing mandates for electricity planning in the 2010 constitution, the national government (including MPs) de facto largely implemented LMCP while county governments had no formal role in the program. Second, while locally elected MPs were consulted in the planning process, the data show little evidence that MPs allocated electrification programs in a clientelistic way: areas won by government-aligned MPs in close elections do not appear to benefit from more investment, and MPs did not appear to apply their influence to reward wards within their constituencies that voted for them. Third, a decomposition of the analysis across the various stages of the rural electrification process shows that overall favoritism was driven by the two stages that were most heavily influenced by the national government (rather than MPs or local contractors), namely, the installation of transformers and the selection of LMCP sites. These patterns are consistent with the central government retaining control over the energy parastatals because they serve as useful tools for exerting political influence.

Still, there are important potential benefits of centralized management. The central government may have greater technical expertise than local officials, or centralized management may benefit from economies of scale. In the presence of large network effects—for example, the design of the national electricity transmission grid—a centrally planned layout can generate large benefits. In these sectors—which include electricity generation or transmission, roads, telecommunications, manufacturing, or many others—the political benefits from decentralization must be weighed against the economic benefits of centralized management. Yet as we show in this paper, such centralization makes public investments vulnerable to political capture.

References

African Development Bank Group (2022). *Impact Evaluation of the AfDB-supported Kenya Last Mile Connectivity Project, Phase I, Summary Report*. IDEV Impact Evaluation.

Ahrens, A., C. B. Hansen, and M. E. Schaffer (2020). "lassopack: Model selection and prediction with regularized regression in Stata". *The Stata Journal* 20.1, pp. 176–235.

Akech, J. (2010). *Kenya: Institutional Reform in the New Constitution of Kenya*. International Center for Transitional Justice.

Alesina, A., R. Baqir, and W. Easterly (1999). "Public Goods and Ethnic Divisions". *The Quarterly Journal of Economics* 114.4, pp. 1243–1284.

Alesina, A. and N. Roubini (1992). "Political cycles in OECD economies". *The Review of Economic Studies* 59.4, pp. 663–688.

Alushula, P. (2018). *Connecting the poor hands Kenya Power Sh3bn debt*. Business Daily. URL: https://www.businessdailyafrica.com/bd/corporate/companies/connecting-the-poor-hands-kenya-power-sh3bn-debt--2229954 (visited on 12/13/2023).

Amaya, B. (2016). *Parastatal appointments should be open to all ethnicities*. The Standard. URL: https://www.standardmedia.co.ke/business/ureport/article/2000194787/parastatal-appointments-should-be-open-to-all-ethnicities.

Ayaga, W. (2016). *Poor constituencies lose out as major changes to CDF law passed*. The Star. URL: https://www.standardmedia.co.ke/article/2000214666/poor-constituencies-lose-out-as-major-changes-to-cdf-law-passed.

Bagaka, O. (2010). "An Institutionalized View on the Creation of the Constituency Development Fund in Kenya". *Kenya Studies Review* 1.2.

Bardhan, P. (2002). "Decentralization of Governance and Development". *Journal of Economic Perspectives* 16.4, pp. 185–205.

Bardhan, P. and D. Mookherjee (2005). "Decentralizing antipoverty program delivery in developing countries". *Journal of Public Economics* 89.4. Cornell - ISPE Conference on Public Finance and Development, pp. 675–704.

Barkan, J. D. and M. Chege (1989). "Decentralising the State: District Focus and the Politics of Reallocation in Kenya". *The Journal of Modern African Studies* 27.3, pp. 431–453.

Baskaran, T., B. Min, and Y. Uppal (2015). "Election cycles and electricity provision: Evidence from a quasi-experiment with Indian special elections". *Journal of Public Economics* 126, pp. 64–73.

Belloni, A., V. Chernozhukov, and C. Hansen (2013). "Inference on Treatment Effects after Selection among High-Dimensional Controls†". *The Review of Economic Studies* 81.2, pp. 608–650.

Berkouwer, S., P. Biscaye, E. Hsu, O. Kim, K. Lee, et al. (2023). "Money or Power? Choosing Covid-19 aid in Kenya". *Energy Economics* 127, p. 107036.

Berkouwer, S., K. Lee, and M. Walker (2018). "Secondary School Electrification in Western Kenya". AidData Working Paper 57.

Blimpo, M. P. and M. Cosgrove-Davies (2019). *Electricity Access in Sub-Saharan Africa: Uptake, Reliability, and Complementary Factors for Economic Impact*. Washington, DC: World Bank.

Brancati, D. (2008). *Peace by Design: Managing Intrastate Conflict through Decentralization*. Oxford University Press.

Briggs, R. (2021). "Power to Which People? Explaining how electrification targets voters across party rotations in Ghana". *World Development* 141.

Burgess, R., M. Greenstone, N. Ryan, and A. Sudarshan (2020). "The Consequences of Treating Electricity as a Right". *Journal of Economic Perspectives* 34.1, pp. 145–69.

Burgess, R., R. Jedwab, E. Miguel, A. Morjaria, and G. Padró i Miquel (2015). "The value of democracy: evidence from road building in Kenya". *American Economic Review* 105.6, pp. 1817–51.

Calonico, S., M. D. Cattaneo, and R. Titiunik (2014). "Robust Nonparametric Confidence Intervals for Regression-Discontinuity Designs". *Econometrica* 82.6, pp. 2295–2326.

Campbell, T. (2004). *The Quiet Revolution: Decentralization and the Rise of Political Participation in Latin American Cities*. University of Pittsburgh Press Digital Editions.

Cengiz, D., A. Dube, A. Lindner, and B. Zipperer (2019). "The Effect of Minimum Wages on Low-Wage Jobs". *The Quarterly Journal of Economics* 134.3, pp. 1405–1454.
Cheeseman, N. (2008). "The Kenyan Elections of 2007: An Introduction". *Journal of Eastern African Studies* 2.2, pp. 166–184.
Cheeseman, N., G. Lynch, and J. Willis (2016). "Decentralisation in Kenya: the governance of governors". *The Journal of Modern African Studies* 54.1, pp. 1–35.
Cicala, S. (2022). "Imperfect Markets versus Imperfect Regulation in US Electricity Generation". *American Economic Review* 112.2, pp. 409–41.
Deshpande, M. and Y. Li (2019). "Who Is Screened Out? Application Costs and the Targeting of Disability Programs". *American Economic Journal: Economic Policy* 11.4, pp. 213–248.
Dickovick, J. T. (2011). *Decentralization and recentralization in the developing world: Comparative studies from Africa and Latin America*. Penn State Press.
Easterly, W. and R. Levine (1997). "Africa's growth tragedy: policies and ethnic divisions". *The Quarterly Journal of Economics* 112.4, pp. 1203–1250.
Enikolopov, R. and E. Zhuravskaya (2007). "Decentralization and political institutions". *Journal of Public Economics* 91.11, pp. 2261–2290.
Faguet, J.-P. (2014). "Decentralization and Governance". *World Development* 53. Decentralization and Governance, pp. 2–13.
Ferejohn, J. A. (1974). *Pork Barrel Politics: Rivers and Harbors Legislation, 1947-1968*. Stanford University Press.
Fisman, R. and R. Gatti (2002). "Decentralization and corruption: evidence across countries". *Journal of Public Economics* 83.3, pp. 325–345.
Franck, R. and I. Rainer (2012). "Does the Leader's Ethnicity Matter? Ethnic Favoritism, Education, and Health in Sub-Saharan Africa". *American Political Science Review* 106.2, pp. 294–325.
Francois, P., I. Rainer, and F. Trebbi (2015). "How Is Power Shared in Africa?" *Econometrica* 83.2, pp. 465–503.
Golden, M. and B. Min (2013). "Distributive Politics Around the World". *Annual Review of Political Science* 16.1, pp. 73–99.
Goodman-Bacon, A. (2021). "Difference-in-differences with variation in treatment timing". *Journal of Econometrics* 225.2. Themed Issue: Treatment Effect 1, pp. 254–277.
Government of Kenya (2003). *Constituencies Development Fund Act*. Tech. rep.
— (2010a). *Constitution of Kenya, Fourth Schedule.*
— (2010b). *Public Expenditure Review: Policy for Prosperity 2010.* Nairobi: Ministry of State for Planning, National Development and Vision 2030. URL: https://www.planning.go.ke/kenya-vision-2030/.
— (2016). *The National Government Constituencies Development Fund Act, 2015*. Revised Edition 2015. URL: https://ngcdf.go.ke/wp-content/uploads/2022/03/Amended-Version-NationalGovernmentConstituenciesDevelopmentFundAct30of2015-updated-on-18-10_2016-converted.pdf.
— (2023). *Schedule of Budge Ceiling for Constituencies for the Financial Year 2023/2024*. Committee on National Government Constituencies Development Fund. URL: http://www.parliament.go.ke/sites/default/files/2023-08/Report%20of%20the%20National%20Government%20CDF%20Committee%20on%20Schedule%20of%20Budget%20Ceilings%20for%20Constituencies%20for%20the%20FY2023-24.pdf.
Harris, J. A. and D. N. Posner (2019). "(Under What Conditions) Do Politicians Reward Their Supporters? Evidence from Kenya's Constituencies Development Fund". *American Political Science Review* 113.1, pp. 123–139.
Hassan, M. (2015). "Continuity despite change: Kenya's new constitution and executive power". *Democratization* 22.4, pp. 587–609.
— (2020a). "Decentralization and Democratization"". In: *Handbook of Democratization in Africa.*
— (2020b). "The local politics of resource distribution". In: *The Oxford Handbook of Kenyan Politics.*

Herbst, J. (2000). *States and Power in Africa: Comparative Lessons in Authority and Control - Second Edition*. REV - Revised, 2. Vol. 149. Princeton University Press.

Hodler, R. and P. A. Raschky (2014). "Regional favoritism". *The Quarterly Journal of Economics* 129.2, pp. 995–1033.

Hoffmann, V., P. Jakiela, M. Kremer, R. Sheely, and M. Goodkin-Gold (2017). "There is No Place Like Home: Theory and Evidence on Decentralization and Politician Preferences". Working paper.

International Energy Agency; International Renewable Energy Agency; United Nations; World Bank Group; World Health Organization (2018). "Tracking SDG7 : The Energy Progress Report 2018."

Kenya National Highways Authority (2022). *Annual Report for the Financial Year 2021-2022*. URL: https://kenha.co.ke/wp-content/uploads/2023/07/KeNHa-ANNUAL-REPORT-2021-2022-FINAL-18-04-23.pdf.

Kenya Parliamentary Debates (2010). "Sitting : National Assembly : 2010 03 25 14 30 00". In: *[Hansard]*, p. 15.

— (2013). "Sitting : National Assembly : 2013 07 10 14 30 00". In: *[Hansard]*, p. 36.

Kenya Power (2012). *Kenya Power Annual Report and Financial Statements for the Year Ended 30 June 2012*. URL: https://kplc.co.ke/img/full/KpWY5QufBgyf_ANNUAL%20REPORT%20AND%20FINANCIAL%20STATEMENTS%202011-12%20EMAIL.pdf.

— (2015). *Transformer Listing - Final*. URL: https://kplc.co.ke/img/full/2nPEsH9Dge4K_Transformer%20Listing-%20Final.pdf (visited on 12/13/2023).

— (2016). *Last Mile Connectivity Program Q & A*. URL: https://www.kplc.co.ke/content/item/1694/last-mile-connectivity-program-q---a (visited on 11/01/2023).

— (2017). *Kenya Power Annual Report and Financial Statements for the Year Ended 30 June 2017*. URL: https://kplc.co.ke/AR2017/KPLC%202016%20-%202017%20Annual%20Report-.pdf.

— (2018). *Kenya Power Annual Report and Financial Statements for the Year Ended 30 June 2018*. URL: https://www.kplc.co.ke/AR2018/KPLC%20Annual%20Report%2017_12_2018_Wed.pdf.

Kenyatta, U. (2017). *Speech by His Excellency Hon. Uhuru Kenyatta, C.G.H., President of the Republic of Kenya and Commander in Chief of the Defence Forces During the 2017 State of the Nation Address, Parliament Buildings, Nairobi, 15th March 2017*. URL: https://www.president.go.ke/2017/03/19/speech-by-his-excellency-hon-uhuru-kenyatta-c-g-h-president-of-the-republic-of-kenya-and-commander-in-chief-of-the-defence-forces-during-the-2017-state-of-the-nation-address-parliament-buildings/.

Kojima, M. and C. Trimble (2016). *Making Power Affordable for Africa and Viable for Its Utilities*. World Bank.

Leonard, D. K., F. O. Owuor, and K. George (2009). "The political and institutional context of the 2007 Kenyan elections and reforms needed for the future". *Journal of African Elections* 8.1, pp. 71–107.

MacLean, L. M., C. Gore, J. N. Brass, and E. Baldwin (2016). "Expectations of power : the politics of state-building and access to electricity provision in Ghana and Uganda". *Journal of African Political Economy and Development* 1.1, pp. 103–134.

Mahadevan, M. (2024). "The Price of Power: Costs of Political Corruption in Indian Electricity". *American Economic Review*.

Martinot, E. (2016). "Grid Integration of Renewable Energy: Flexibility, Innovation, and Experience". *Annual Review of Environment and Resources* 41.Volume 41, 2016, pp. 223–251.

Marx, B. (2018). "Elections as Incentives: Project Completion and Visibility in African Politics". Working Paper.

Michalopoulos, S. and E. Papaioannou (2016). "The long-run effects of the scramble for Africa". *American Economic Review* 106.7, pp. 1802–48.

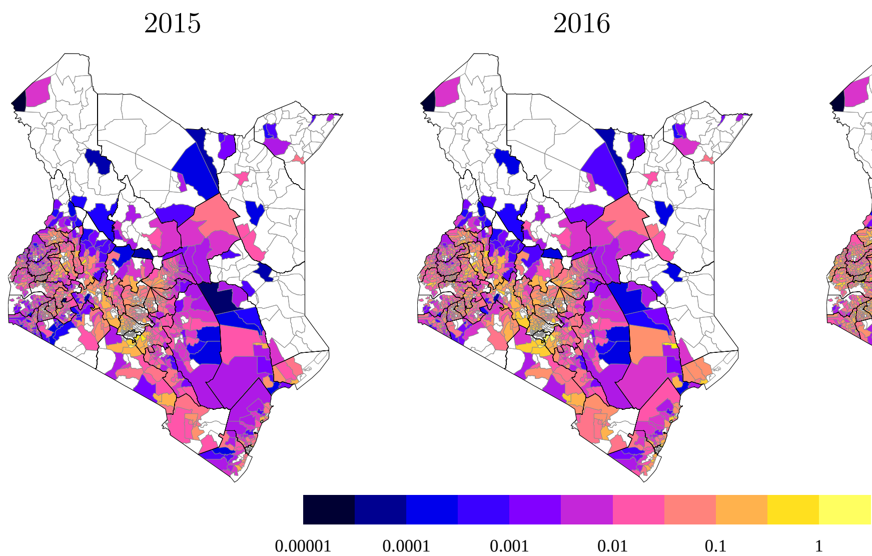
Miguel, E. and M. K. Gugerty (2005). "Ethnic diversity, social sanctions, and public goods in Kenya". *Journal of Public Economics* 89.11-12, pp. 2325–2368.

Min, B. (2019). "Political Favoritism and the Targeting of Power Outages". *International Growth Centre*.

Mwangi, P. (2019). *The handshake and what it really means*. The Daily Nation. URL: https://www.nation.co.ke/oped/opinion/The-handshake-and-what-it-really-means/440808-5038950-bqrd2fz/index.html (visited on 01/30/2020).
Nordhaus, W. D. (1975). "The political business cycle". *The Review of Economic Studies* 42.2, pp. 169–190.
Obonyo, O. (2020). *How Raila birthed enigmatic 'handshake'*. The Daily Nation. URL: https://www.nation.co.ke/news/politics/How-Raila-birthed-enigmatic--handshake-/1064-5436990-i347b0/index.html (visited on 01/30/2020).
Opalo, K. (2022a). "Formalizing clientelism in Kenya: From Harambee to the Constituency Development Fund". *World Development* 152, p. 105794.
Opalo, K. (2014). "The long road to institutionalization: the Kenyan Parliament and the 2013 elections". *Journal of Eastern African Studies* 8.1, pp. 63–77.
— (2020). "Constrained Presidential Power in Africa? Legislative Independence and Executive Rule Making in Kenya, 1963–2013". *British Journal of Political Science* 50.4, pp. 1341–1358.
— (2022b). "Leveraging legislative power: distributive politics and Committee work in Kenya's National Assembly". *The Journal of Legislative Studies* 28.4, pp. 513–532.
Prud'homme, R. (1995). "The Dangers of Decentralization". *The World Bank Research Observer* 10.2, pp. 201–220.
Purwanto, E. A. and A. Pramusinto (2018). "Decentralization and functional assignment in Indonesia: the case of health and education services". *Policy Studies* 39.6, pp. 589–606.
Rural Electrification Authority (2008). *Strategic Plan 2008-2012*.
— (2015). *Launch of the Last mile connectivity Project*. URL: https://kplc.co.ke/img/full/2nPEsH9Dge4K_Launch%20of%20the%20Last%20mile%20connectivity%20Project.pdf (visited on 05/01/2024).
Savage, A. and L. Lumbasi (2016). *The Impact of Decentralization in Kenya*. Tech. rep.
Shilaho, W. K. (2016). "Ethnic mobilisation and Kenya's foreign policy in the face of the International Criminal Court (ICC)". *Journal for Contemporary History* 41.1, pp. 103–125.
Simson, R. (2018). "Ethnic (in)equality in the public services of Kenya and Uganda". *African Affairs* 118.470, pp. 75–100.
The Economist (2013). *And the winner is...* URL: https://www.economist.com/middle-east-and-africa/2013/03/09/and-the-winner-is (visited on 12/13/2023).
The National Treasury of Kenya (2021). *The Budget Summary for the Fiscal Year 2021/22 and the Supporting Information*. URL: https://www.treasury.go.ke/budget-summary-of-revenue-expenditure/.
The World Bank (2017). "International Development Association Project Appraisal Document On A Proposed Credit In The Amount Of Eur 133.8 Million (US$150 Million Equivalent) To The Republic Of Kenya For An Off-grid Solar Access Project For Underserved Counties".
Tiebout, C. M. (1956). "A Pure Theory of Local Expenditures". *Journal of Political Economy* 64.5, pp. 416–424.
United Nations Office on Drugs and Crime (UNODC) (2022). *UNODC & GOPAC Pacific Regional Conference: Constituency Development Funds Conference Discussion Paper & Report*. Tech. rep.
United Nations, Department of Economic and Social Affairs, Population Division (2022). *World Population Prospects 2022*.
Volkert, M. and B. Klagge (2022). "Electrification and devolution in Kenya: Opportunities and challenges". *Energy for Sustainable Development* 71, pp. 541–553.
Wolfram, C., E. Miguel, E. Hsu, and S. Berkouwer (2023). "Donor Contracting Conditions and Public Procurement: Causal Evidence from Kenyan Electrification". NBER Working Paper #30948.
Wrong, M. (2010). *It's Our Turn To Eat*. New York, NY: HarperCollins.

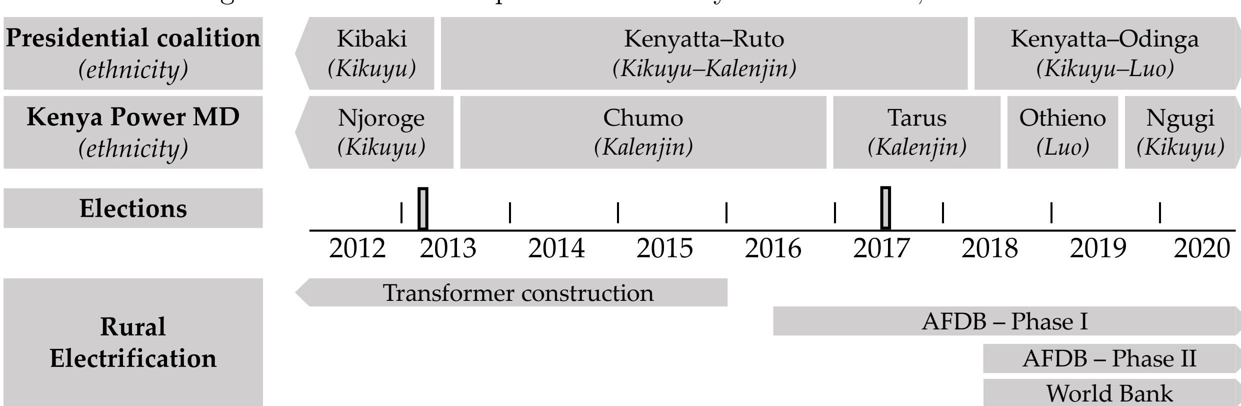
A Appendix Figures

Figure A1: Residential meters per household by ward (log)



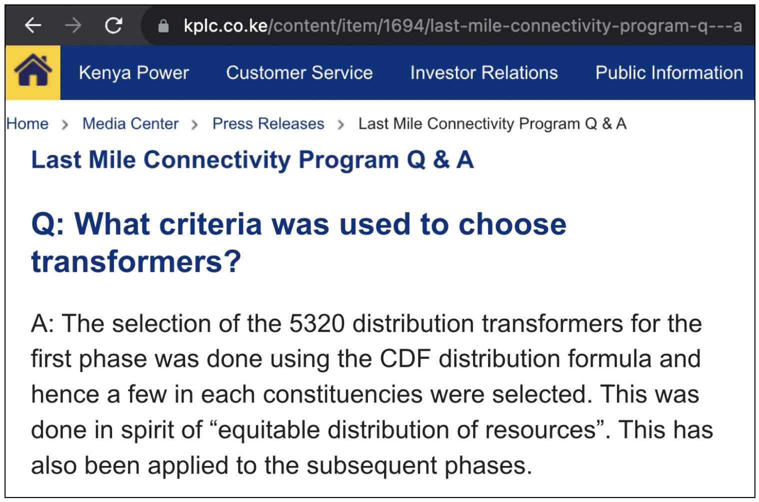
Ward-level population comes from the 2009 census after applying a uniform growth rate based on country-level population growth from UN WPP (UN, 2022). Units are residential meters per household, with shading following a log10 scale. White wards contain no residential meters in our dataset or are missing 2009 population data.

Figure A2: Timeline of political and Kenya Power events, 2013-2022



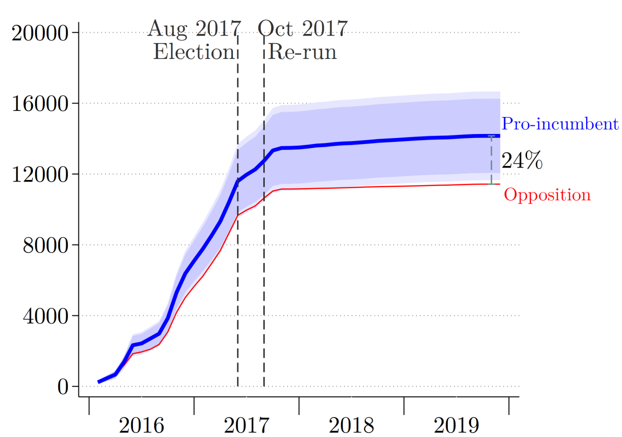
Timeline of Kenyan presidential terms, Kenya Power managing director appointments (MD), elections, and rural electrification. Kenyatta was inaugurated on April 9th, 2013 and again on November 28th, 2017. The 'Handshake' between Kenyatta and Odinga took place on March 9th, 2018.

Figure A3: Kenya power website announcement



The Kenya Power website announced that LMCP transformers would be allocated to constituencies according to the Constituency Development Fund (CDF) formula. Source: Kenya Power (2016).

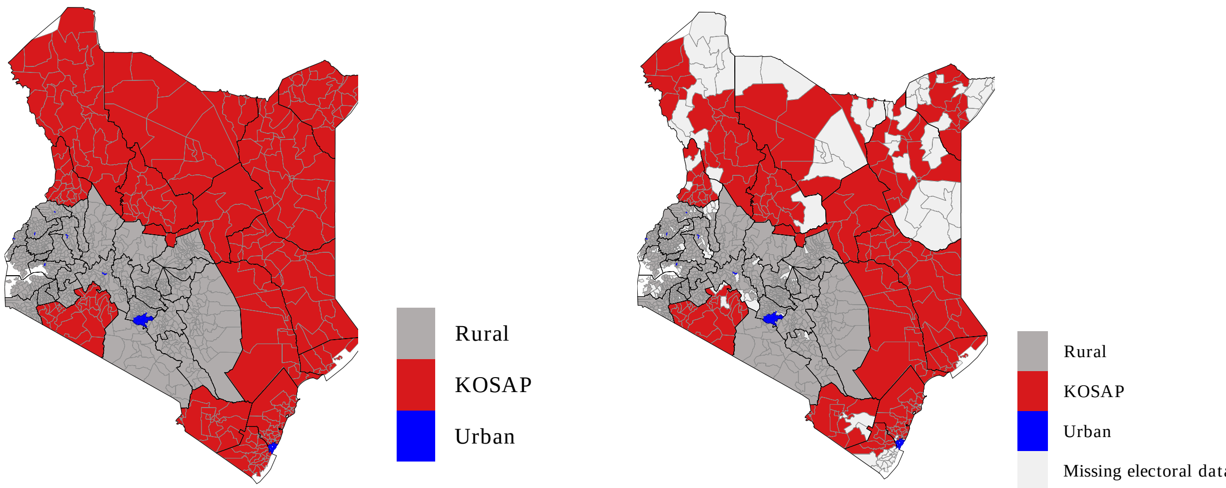
Figure A4: Number of meters activated in or after 2016 at LMCP sites per 100,000 households



Results from the following regression: $y_{it} = \sum_{k=1}^{118} \gamma_k D_{it}^k + \sum_{k=1}^{118} \beta_k D_{it}^k * ProGovernment_i + \epsilon_{it}$ (no socio-economic controls). 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. Figure 2 shows a version without political breakdown in absolute terms. Figure D7 provides versions with controls, per capita, and per CDF allocation. Figure D9 and Figure D8 provide versions for construction progress. Table B4 presents equivalent regression results.

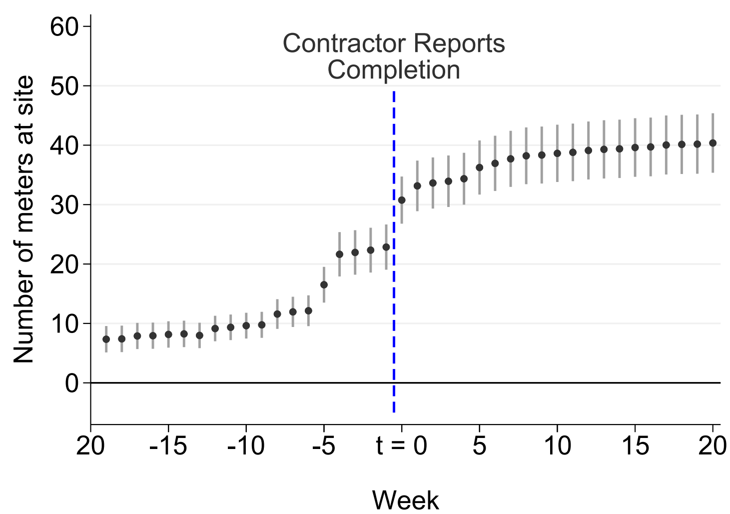
Figure A5: Main sample specification: omitted urban and sparse areas

(A) All wards (B) Only wards with electoral data



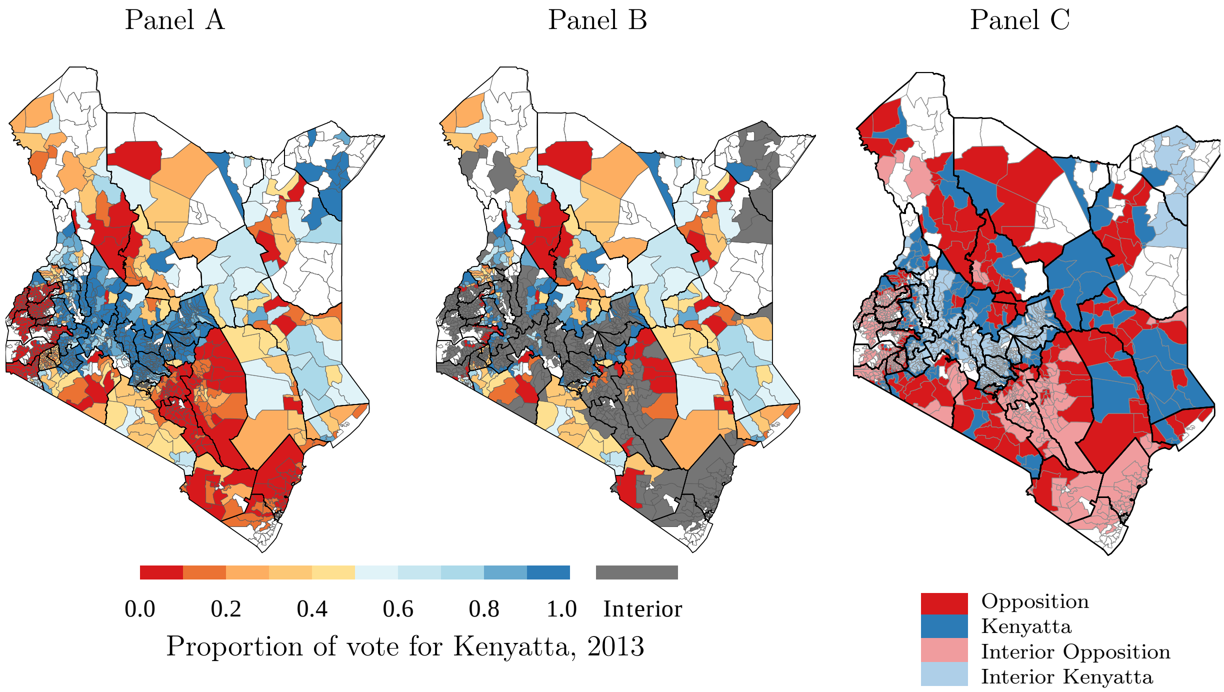
Wards labelled "rural" (in gray) form the main sample of LMCP wards (see Section 3 for a detailed description of sample construction). Wards shaded red are in counties targeted by KOSAP, an off-grid solar electrification project. Wards shaded blue are within Nairobi and Mombasa counties or are in a ward with an equal or greater population density (3,513 population per square km). Wards shaded white in Panel B are missing 2013 election data.

Figure A6: Meters activated in Kenya Power infrastructure database relative to when contractors report construction completion



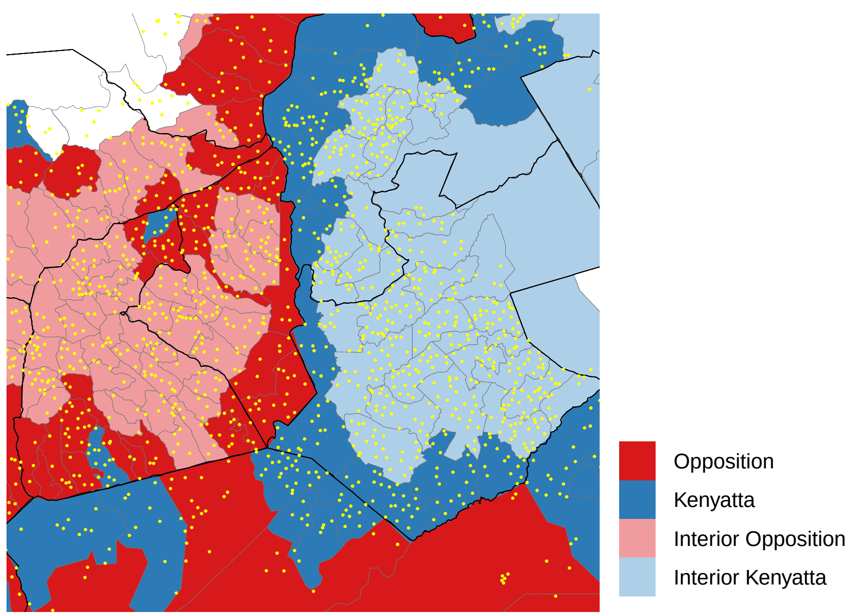
This figure combines Kenya Power's meter data with construction progress data at the transformer level provided by independent contractors. In the weeks after a contractor reports construction at a particular transformer to have been complete, the number of meters that Kenya Power identifies as going on-line increases sharply up to on average 40, in line with estimates of the number of unconnected households living within 600 meters of each LMCP transformer (as discussed in Subsection 2.3). Point estimates and standard errors from 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).

Figure A7: 2013 Kenya presidential election results



Blue wards had vote shares of over 50% for Kenyatta. Red wards had vote shares under 50% for Kenyatta. White wards are missing election data. Panel A shows 2013 presidential election results at the ward level. Panel B shows the same, but 'interior' wards—which only border similarly aligned wards—are greyed out. Panel C shows a binary version, with adjacent wards shown in dark.

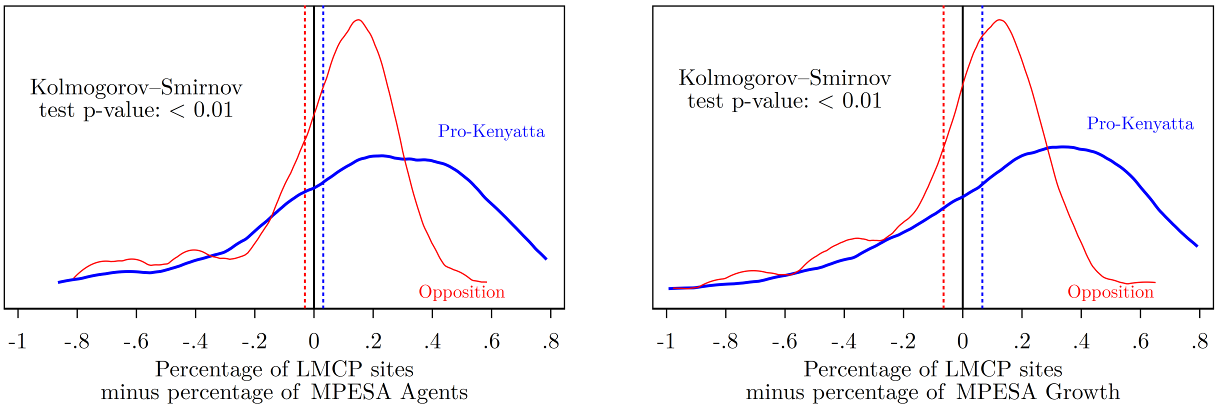
Figure A8: Adjacent wards with LMCP sites (example area)



Region mapped contains primarily Bomet, Kisii, Nyamira, Kericho counties. Blue (red) wards had vote shares of over (under) 50% for Kenyatta. White wards are missing election data. Darker (lighter) wards represent adjacent (interior) wards. Yellow dots show the locations of transformers which were selected for maximization under LMCP.

Figure A9: Constituency LMCP site shares relative to mobile money shares by 2013 election result

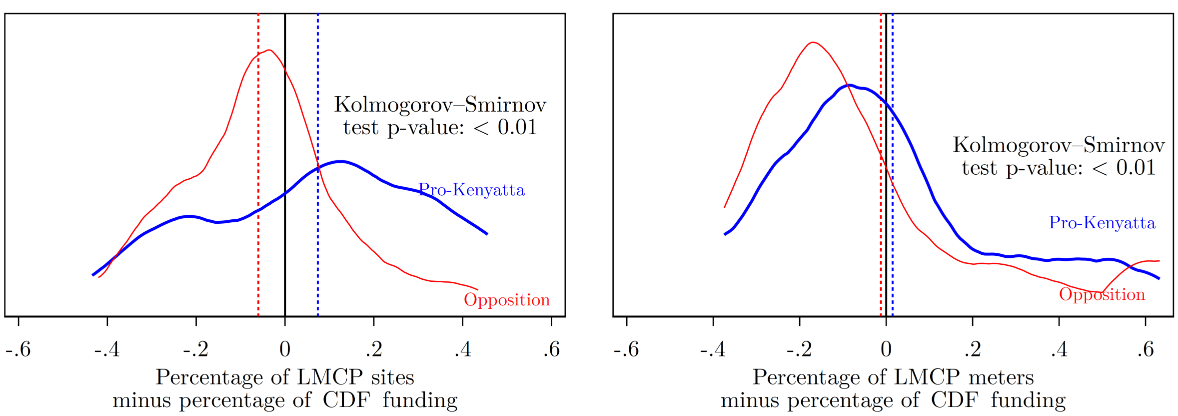
(A) Relative to mobile money agent share (B) Relative to 2013-2015 growth in share



Differences between a constituency's percentage of LMCP sites minus its share of mobile money agents (panel A) or its share of new mobile money agents in 2014/2015 (panel B), by whether constituencies voted pro-government in the 2013 presidential election, bottom- (top-) coded at the 5th (95th) percentile. Both panels include only rural constituencies. Vertical dashed lines present the sample means.

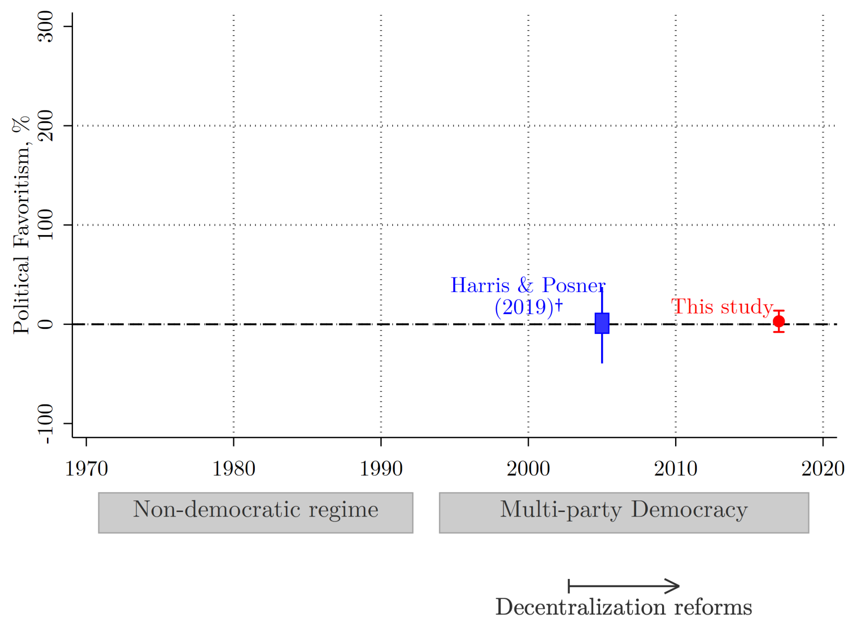
Figure A10: LMCP outcomes relative to CDF shares by 2013 election result (nationwide sample)

Panel (A) LMCP Sites Panel (B) LMCP Household Electricity Meters



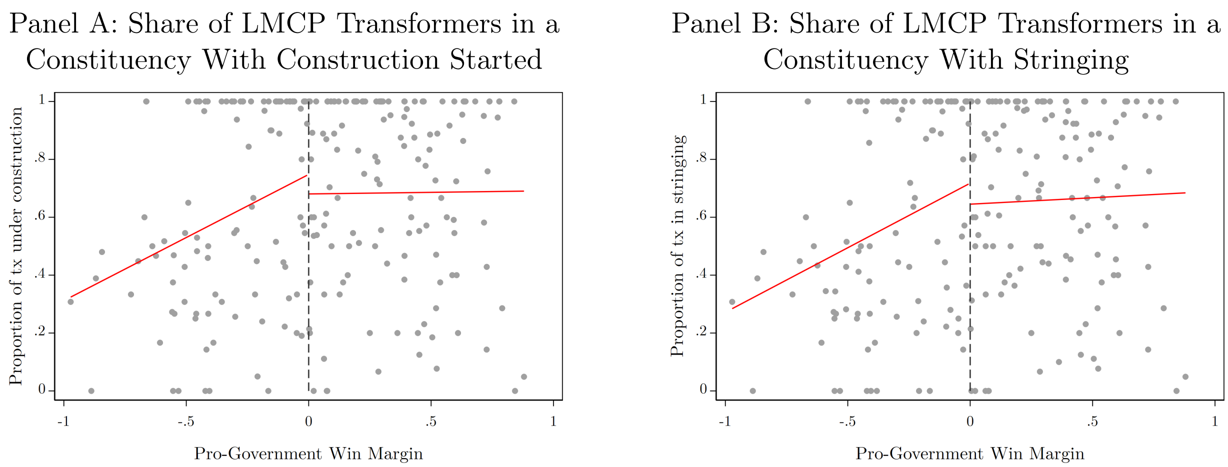
This figure shows the same as Figure 4 but for all wards nationwide. A constituency's percentage of LMCP sites minus its share of CDF funding, by whether constituencies voted pro-government in the 2013 presidential election, bottom- (top-) coded at the 5th (95th) percentile. Vertical lines indicate sample means.

Figure A11: Estimates of favoritism (by alignment with Member of Parliament)



Estimates for this study taken from Column 7 of Table 4. †: Box and whisker plot based on estimates of favoritism in each constituency, as reported in Harris and Posner (2019). Figure 1 shows estimates for alignment with the president.

Figure A12: Share of constituency's LMCP transformers with construction progress



Note: Similar to Figure 5 but using two main construction outcomes as the main outcome variables. Panel A shows the fraction of a constituency's LMCP transformers where construction started. Panel B shows the fraction of a constituency's LMCP transformers where stringing had been completed.

B Appendix Tables

Table B1: Determinants of Constituency Development Fund allocations to constituencies over time

	2003–2015			2016–2021		2022–	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Constant	9.29***	8.48***	6.83***	9.36	9.36	10.01***	7.64***
	(0.10)	(0.21)	(0.41)	(.)	(.)	(0.05)	(0.00)
2013 Kenyatta voteshare (%)	-0.50***	-0.01	-0.22	0.00	0.00	0.01	-0.00
	(0.17)	(0.11)	(0.18)	(.)	(.)	(0.09)	(0.00)
Poverty index (2009)		0.36***			0.00		0.00***
		(0.03)			(.)		(0.00)
Poverty index (2005)			1.47***				
			(0.29)				
Population		0.54***	0.03		0.00		-0.00
		(0.08)	(0.13)		(.)		(0.00)
Ward count		0.11**	0.32***		0.00		0.47***
		(0.04)	(0.07)		(.)		(0.00)
Observations	290	286	229	290	286	289	285
Mean	9.1	9.1	9.1	9.4	9.4	10.0	10.0
R2	0.03	0.71	0.28	.	.	0.00	1.00

Columns 1–3, 4–5, and 6–7 use the allocations (hundred thousands 2016 USD) from 2013, 2017, and 2022, respectively, but allocations were proportional in each period. Ward counts from 2013 administrative boundaries, consistent with those used by the 2023-24 NG-CDF Committee (GoK, 2023). The R^2 in Columns (2) and (3) of do not equal 1 because the exact constituency poverty index formula is not public. We approximate it using 2005 and 2009 Census Data. For Column (7), the regression is not perfectly multicollinear because of minor rounding in the allocations. $^{*} \leq 0.10, ^{**} \leq .05, ^{***} \leq .01$.

Table B2: Political favoritism in LMCP sites per 100,000 households

	In absolute terms			Relative to CDF Allocation		
	(1)	(2)	(3)	(4)	(5)	(6)
Voted pro-govt in 2013	50.6***	62.6***	58.7***	69.4***	63.7***	63.4***
	(10.6)	(11.2)	(8.13)	(18.4)	(19.4)	(12.1)
Observations	911	911	911	196	196	196
Opposition Mean	149	149	149	151	151	151
Effect Size (%)	34	42	39	46	42	42
Controls	None	SES	LASSO	None	SES	LASSO
Sample	Wards	Wards	Wards	Consts	Consts	Consts

In Columns 1–3, y_i is the number of LMCP sites per 100,000 households. In Column 4–6, y_i is the same but minus the hypothetical number had meters been allocated according to the CDF. Columns 2 and 5 controls for land gradient, population density, baseline unconnected households, share adults with primary or secondary education, share adults who work for pay, dependency ratio, share households with an iron roof, population density, household size, mobile money agents as of 2013 per capita, and change in mobile money agents between 2013 and 2015 per capita. Column 3 uses post-double selection LASSO (Belloni, Chernozhukov, and C. Hansen, 2013; Ahrens, C. B. Hansen, and Schaffer, 2020) to flexibly select from a subset of quadratic and cubic interactions between this same set of variables. Table 1 presents the same analysis for LMCP meters per 100k households. $^{*} \leq 0.10, ^{**} \leq .05, ^{***} \leq .01$.

Table B3: Placebo Test: Political Favoritism in Rollout of New M-Pesa Agents (2013-2015)

	In absolute terms			Relative to CDF Allocation		
	(1)	(2)	(3)	(4)	(5)	(6)
Voted pro-govt in 2013	16.3	-75.4	-83.5	54.9	-50	-11.4
	(37.6)	(58.8)	(58.5)	(48.5)	(58.3)	(52.9)
Observations	911	911	911	196	196	196
Opposition Mean	291	291	291	319	319	319
Effect Size (%)	5.6	-26	-29	17	-16	-3.6
Controls	None	SES	LASSO	None	SES	LASSO
Sample	Wards	Wards	Wards	Consts	Consts	Consts

In Columns 1–3, y_i is the number of new M-PESA agents added in 2013-2015 per 100,000 households. In Column 4, y_i is the same but minus the hypothetical number had agents been allocated according to the CDF. Sample in all regressions excludes urban wards and KOSAP wards. Columns 2 controls for land gradient, population density, baseline unconnected households, share adults with primary or secondary education, share adults who work for pay, dependency ratio, share households with an iron roof, population density, household size, mobile money agents as of 2013 per capita, and change in mobile money agents between 2013 and 2015 per capita. Column 3 uses LASSO to flexibly select from a subset of quadratic and triple interactions between this same set of variables. Column 4 does not include socio-economic controls. $^{*} \leq 0.10, ^{**} \leq .05, ^{***} \leq .01$.

Table B4: Favoritism in LMCP (meter panel data)

	(1)
Pro-Govt Effect, Dec 2016	1359.35**
	(641.52)
Pro-Govt Effect, Dec 2017	2325.01*
	(1228.72)
Pro-Govt Effect, Dec 2018	2622.13**
	(1255.64)
Pro-Govt Effect, Dec 2019	2728.60**
	(1268.26)
Observations	42624
Opposition Mean, Dec 2016	5022.30
Opposition Mean, Dec 2017	11154.30
Opposition Mean, Dec 2018	11304.63
Opposition Mean, Dec 2019	11428.82

Results from the following regression: $y_{it} = \sum_{k=1}^{118} \gamma_k D_{it}^k + \sum_{k=1}^{118} \beta_k D_{it}^k * ProGovernment_i + \epsilon_{it}$. Listed coefficients are estimated β_k values; listed opposition means are estimated γ_k values. The estimates in this table correspond to Figure A4. Estimates are in units of meters per 100,000 households.