The Distribution of Power: Favoritism, Efficiency, and Equity in Energy Infrastructure

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Abstract

Existing research demonstrates that political favoritism distorts the allocation of public investments. This paper builds on this rich literature by modeling the welfare gains from public investment under the observed, politically motivated allocation, comparing it to several counterfactual scenarios. Using granular infrastructure, electoral, and census data on Kenya's national electricity grid access project, we first show that areas with majority pro-government vote shares received 35-42% more household and village electrification relative to the formula legislated to promote equity. Surprisingly, we estimate that this deviation *increased* total consumer surplus by 2%. This came at the expense of opposition voters, who received 21% less surplus gain from the program on average than they would have if the allocation had followed the legislated formula. The observed deviation from the legislated formula also disproportionately disadvantaged households in the poorest income quintile, who received 12% less surplus. We then show that the counterfactual surplus-maximizing allocation is in fact politically neutral. Thus even though the observed deviation from the legislated formula increased total surplus in this context, political bias in the observed allocation cannot be justified on the basis of surplus maximization alone, and must be weighed against the potentially adverse long-term welfare impacts of heightened political and economic inequality.

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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)

When citizens vote largely along ethnic-party lines, electoral accountability can be limited and public services may serve as tools for patronage. In Sub-Saharan Africa, the popular phrase "it's our turn to eat" captures how a presidential election can lead to spoils for the supporters of the winner (Wrong, 2010). A large literature has quantified this type of political bias across a host of settings—see for example Burgess et al. (2015), Franck and Rainer (2012), Dickens (2018), Harris and Posner (2019), Asher and Novosad (2017), Francois, Rainer, and Trebbi (2015), Do, Nguyen, and Tran (2017), Pande (2003), and Rouanet, Tallec, and Alonzo (2025)—but most stop short of quantifying aggregate impacts on economic surplus. When considering the allocation of goods and public services, one might implicitly assume that, by deviating from a 'fair' allocation, political favoritism reduces aggregate welfare. However, depending on how the 'fair' counterfactual is defined, a politically motivated deviation could in theory increase total economic surplus or advance equity goals, depending on the characteristics and needs of the winning party's supporters.

This study makes progress on this subject by quantifying political favoritism and then integrating the resulting estimates into a formally grounded economic analysis to assess its impacts on the magnitude and distribution of total surplus. This allows us to disentangle the degree to which political favoritism might be justifiable from a social welfare perspective. In particular, this paper estimates favoritism and its effects on efficiency and equity in the context of Kenya's Last Mile Connectivity Project (LMCP), an ambitious initiative launched in 2016 to connect all households to electricity—and, at a cost of $788 million, one of Kenya's largest public works programs.[1]

In the early 2000s, Kenya underwent major decentralizing reforms dubbed the "biggest political transformation since independence" (Cheeseman, Lynch, and Willis, 2016), creating "arguably Africa's strongest parliament" (Opalo, 2014) and making it one of Africa's most democratic countries (Figure A1). These reforms include the 2003 Constituency Development Fund (CDF) Act, in which opposing political parties ratified a transparent formula to disburse treasury funds equally and equitably across Kenya's 290 constituencies. In 2010, Kenya's Assistant Minister for Energy and Petroleum stated in Parliament that the ministry allocated funding for rural electrification "using the CDF formula" (Hansard, 2010). Kenya Power, the government-controlled electric utility,

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

later confirmed that "selection of the 5,320 distribution transformers for the [LMCP] was done using the CDF distribution formula" (Kenya Power, 2016).

We combine village-level panel data on LMCP construction progress with the universe of Kenya Power's 7.4 million electricity meters and 62,271 electrical substations. We match these with granular results from Kenya's 2013 and 2017 presidential and parliamentary elections by administrative ward. This unusually rich data environment allows us to first estimate marginal favoritism relative to the CDF rule across four distinct stages of the electrification program: transformer construction, LMCP site selection, grid extension, and household meter activation. We then integrate the results into estimates of consumer surplus that incorporate Kenya National Bureau of Statistics microdata on income and electricity consumption across Kenya's 1,450 wards, electricity tariff data, and off-the-shelf demand elasticities. This approach allows us to estimate consumer surplus across the population under the observed allocation and three counterfactual scenarios, namely: the intended CDF allocation, the surplus-maximizing allocation, and a politically neutral surplus-maximizing allocation. By not assuming that the benchmark CDF allocation is welfare-maximizing, we allow for the more nuanced possibility that political favoritism can in some contexts even *increase* welfare. We then evaluate cost heterogeneity in construction by analyzing the actual contracts signed between Kenya Power and dozens of private sector contractors.

The first main result is that constituencies that voted pro-government in the preceding election received significantly more LMCP sites than their CDF share, while opposition constituencies received significantly fewer. As a result, by 2019 pro-government wards had 35% more new electricity meters per capita. These results are robust to a wide range of specifications and controls, including census data and measures of private sector economic activity. Favoritism is strongest in core support wards (where the government received at least 75% of the vote), but also large and significant in more heavily contested swing wards, regardless of whether they eventually voted for the government or the opposition.

In terms of mechanisms, the data are consistent with political favoritism being exerted primarily by central government officials. Pro-government areas saw 17% more initial construction of transformers, which was managed by the Ministry of Energy between 2008 and 2016. Kenya Power's selection of LMCP sites from among the set of existing transformers expanded the gap to a 42% difference in LMCP sites. The results show no evidence of subnational favoritism: within a constituency, wards that voted for or against the MP see similar levels of LMCP construction, and a close-election regression discontinuity design finds that presidential alignment of a constituency's MP does not affect electrification. Network construction and meter activation, which were managed locally, also exhibit no favoritism. These results suggest Kenya's constitutional decentralization reforms did not in practice successfully decentralize the electricity sector, despite local governments having been given an explicit mandate to conduct electricity planning.

The second main result is that the deviation from the announced policy rule *increased* aggregate consumer surplus. This possibly counterintuitive result comes from the disproportionate allocation of electricity meters towards higher-income households, who consume more electricity on average and thus experience higher consumer surplus once connected. A stylized model presents intuition for this result and explores other contexts where it may hold. Given Kenya's high income inequality, relaxing the need for near equal distribution across constituencies by deviating from the CDF enables the targeting of constituencies with richer unconnected households, who generate larger returns to electrification.

This empirical finding raises a critical question: was favoritism justified on the basis of surplus maximization, or could these efficiency gains have been achieved without political bias? We first show that construction costs are statistically indistinguishable across voting regions, suggesting that any differential welfare gains by political affiliation are caused entirely by differences in consumer surplus. Still, if connecting a pro-government voter generates a larger consumer surplus gain than connecting an opposition voter, then political favoritism could be justifiable on the grounds of surplus maximization. However, we find no heterogeneity in the returns to electrification by political affiliation.

To evaluate these dynamics more rigorously, we generate several counterfactual allocations, guided by a conceptual framework that models the heterogeneous surplus gains from electricity access. We first implement a national-level counterfactual simulation to recover the surplus maximizing allocation of connections. This shows essentially no political favoritism towards government supporters. In fact, constraining the surplus maximization algorithm to only consider politically neutral allocations only marginally decreases surplus relative to this maximum. We also allow for the possibility that the planner's social welfare function does not have uniform weights across the income distribution, but might prefer, for example, a pro-poor allocation. Even under this scenario, none of the surplus maximizing allocations feature pro-government bias. The political bias in the observed allocation of electricity connections therefore does not appear to be justified on the basis of surplus maximization alone. Finally, we use generalized methods of moments (GMM) to recover the planner's welfare weights implied by the observed allocation of electricity connections. We allow these weights to vary by household income and local voting patterns, as well as their interaction. The parameter estimates indicate significant pro-government favoritism as well as a progressive allocation with respect to income, i.e., towards poor households. The negative interaction term suggests that the planner places greater weight on poorer households in pro-government areas.

The modest aggregate surplus gain from political favoritism (relative to the legislated CDF allocation) must be weighed against its political and distributional implications. Relative to the CDF allocation, opposition voters captured 10% less surplus while pro-government voters captured 13% more surplus, generating significant political inequity. The observed allocation also exacerbated income inequality relative to the announced allocation, with the poorest income quintile gaining 12% less surplus than they would have had the legislative formula been followed. As implemented, the program generated 1.3 times more connections and 2.9 times more consumer surplus for the highest income quintile than for the lowest income quintile. This regressivity directly undermined the equity goals underlying the CDF, which the public statements suggested the electrification program was following. More speculatively, to the extent that political and economic inequality undermines long-term economic growth, any modest gain in aggregate economic surplus from the observed political favoritism may not be worth the political discontent it could generate through the highly visible uneven distribution of resources. At the same time, the social welfare maximizing allocation implies far more public investment in electricity connections to wealthy households, which could also exacerbate inequality and understandably generate political resentment.

A longstanding literature quantifies political favoritism in the provision of public goods and services to government supporters and opposition groups across a range of contexts (such as Ferejohn (1974), Michalopoulos and Papaioannou (2016), Curto-Grau, Solé-Ollé, and Sorribas-Navarro (2018), Harris and Posner (2019), Asher and Novosad (2017), Ferraz and Finan (2008), and Rouanet, Tallec, and Alonzo (2025)), as well as contexts where political alignment is largely coethnic such as Casey (2015), Burgess et al. (2015), Franck and Rainer (2012), Posner (2005), Dickens (2018), and Francois, Rainer, and Trebbi (2015). However, few papers evaluate the welfare consequences of political favoritism. This paper expands this literature by integrating estimates of political bias into a formally grounded notion of economic surplus to evaluate the impacts of such favoritism on both efficiency and equity goals. We show that even though the observed politically biased allocation of electricity connections in Kenya appears to increase social welfare relative to the legislated CDF formula, it generates substantial regional inequality and falls far short of the social welfare maximizing allocation. But there do not appear to be easy policy answers here, as even the social welfare maximizing allocation strongly favors wealthier households (who use more electricity), and could generate a populist backlash.

Understanding the consequences of political favoritism in the energy sector is especially critical as ambitious global decarbonization goals drive trillions of dollars of investment into electric grids (IEA, 2024). In particular, low- and middle-income contexts often face potential tensions between equity and efficiency goals: many utilities are under pressure to provide affordable, universal access to electricity (Burgess et al., 2020; Blimpo and Cosgrove-Davies, 2019), with many offering costly, inefficient, and often politically motivated subsidies (Mahadevan, 2024; Kojima and Trimble, 2016). Kenya is a useful context to study the interplay of these issues: Kenya Power has grown from having fewer than 1 million residential customers in 2008 to 9.7 million by 2024 (Kenya Power, 2013, 2024), and Kenya is a regional leader in decarbonization, with 20th-percentile emissions of CO_2 per dollar of GDP (Kenya Power, 2023; World Bank, 2016) and 89% of its grid powered by hydropower, geothermal, and wind.

Energy infrastructure is part of a broad class of public investments whose economic returns appear to *increase* with the incomes of the recipient, creating an inherent efficiency-equity trade-off. Research on place-based policies often highlights this trade-off: public expenditures on, for example, broadband, airports, electric vehicle charging stations, or higher education often generate larger welfare gains when implemented in wealthier places (Glaeser, 2008; Gaubert et al., 2025; Muehlegger and Rapson, 2022). Benabou (2000), Guerreiro, Rebelo, and Teles (2021), and Herwartz and Theilen (2017) have similarly identified a class of public investments that generate large aggregate welfare gains for society but worsen outcomes for the poor. Even cash transfers can exhibit regressive returns when the poor face structural barriers to accessing capital or education (Haushofer et al., 2025; Daruich and Fernández, 2024). While these papers have noted the possibility for the efficiency-equity tradeoff, we quantify its extent. While we find that political favoritism was not justifiable on the grounds of surplus maximization in this paper, it may be the case in other settings where recipients' incomes and political alignment are more strongly correlated. Given this inherent trade-off, another possibility is to shift public expenditure towards other sectors where the efficiency-equity trade-off favors the poor, which may be the case for health and human capital investments.

Finally, given that the electrification program was implemented in the wake of a major decentralization reform in Kenya, this research contributes to a body of work on the effects of decentralization.[2] The results highlight the role of institutional design in effective decentralization: given the continued centralized management of the power sector in most countries, these results may have implications for the political economy of the global energy transition.

2 Electrification in Kenya

In 2009, only 23% of all Kenyan households and 5% of rural households had access to grid electricity.[3] The Government of Kenya (GoK) has since directed significant funding towards universal electrification. Following the 2008 launch of the Rural Electrification Authority's project to electrify thousands of public facilities, in 2016 the GoK announced the Last Mile Connectivity Project (LMCP). The LMCP aimed to connect millions of rural Kenyans to the grid between 2016 and 2022 at a cost of USD 788 million (REA, 2015; Kenya Power, 2018). These programs, which raised household electricity access to more than 50% by 2019, took place largely after major, government-wide decentralization reforms had taken place between 2003 and 2010. This section discusses these developments in more detail.

2.1 Decentralization and the Constituency Development Fund

Decentralization—the re-allocation of political and fiscal power away from the central executive—has been a major feature of Kenyan democratization, and has helped make Kenya's democratic institutions among the strongest in Sub-Saharan Africa (Figure A1). A key milestone in the reform process was the 2003 Constituency Development Fund (CDF) Act, enacted after President Arap Moi's 24-year rule came to an end in 2002 when Kenya's main opposition party—led by Mwai Kibaki—had won the presidential and parliamentary elections. The CDF Act was supported by members of both government and opposition parties—including Raila Odinga, the subsequent leader

[2]See Ostrom, Tiebout, and Warren (1961), Prud'homme (1995), Fisman and Gatti (2002), Brancati (2008), Fedelino and Ter-Minassian (2010), Alatas et al. (2012), Opalo (2014), Mookherjee (2015), Savage and Lumbasi (2016), Rodríguez (2018), Opalo (2020), Hassan (2020b), Hassan (2020a), Hamidi and Puspita (2022), Rajasekhar (2021), and Faguet and Pal (2023).

[3]These calculations use Kenya Power meter data. Figure A2 shows the number of meters per household by wards per Kenya Power's residential meter data. Other data sources sometimes count solar lanterns as electricity access and thus generate higher estimates.

of the opposition in the 2007, 2013, and 2017 national elections—to help constrain future political favoritism.

Kenya had 210 constituencies at the time, with significant economic and social heterogeneity: populations alone, for example, ranged from just over 100,000 in the smallest constituency to more than a million in the largest. The CDF Act was designed to increase equity: specifically, to "promote the national values of human dignity, equity, social justice, inclusiveness, equality, human rights, non-discrimination and protection" and to "provide for a public finance system that promotes an equitable society and in particular expenditure that promotes equitable development of the country" (GoK, 2016). To do so, the Act established a transparent formula: 75% of CDF funding would be allocated in equal shares across all constituencies (regardless of population) and 25% according to that constituency's share of national poverty (GoK, 2003). A 2016 revised version amended the allocation: each constituency would now receive an equal share, though in practice this change in the formula was both economically and statistically small (GoK, 2016).[4] In a recent review, the Minister for Energy described the 2003 CDF Act as "one of the greatest innovations that we have done in this Parliament" (GoK, 2024).

A second milestone of decentralization was the adoption of the 2010 Constitution after a national referendum. Among other reforms, it created an entirely new layer of government: 47 counties with significant political and fiscal independence. This included popularly elected governors for the first time, as well as county assemblies elected across 1,450 newly created electoral wards. The new constitution also increased the number of constituencies from 210 to 290. These legislative and constitutional changes devolved resources and power toward local politicians, with the intent to "diffuse, if not eliminate altogether, the ethnic tensions fueled by perceptions of marginalization and exclusion" in national politics (Akech, 2010).

2.2 Kenya's political backdrop

Uhuru Kenyatta was the incumbent president during the launch of the LMCP in 2015. He had earlier joined Kibaki's winning coalition in the 2007 election, which, after a disputed result, saw widespread violence in which 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 previously been on opposite sides but joined forces in the subsequent 2013 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).

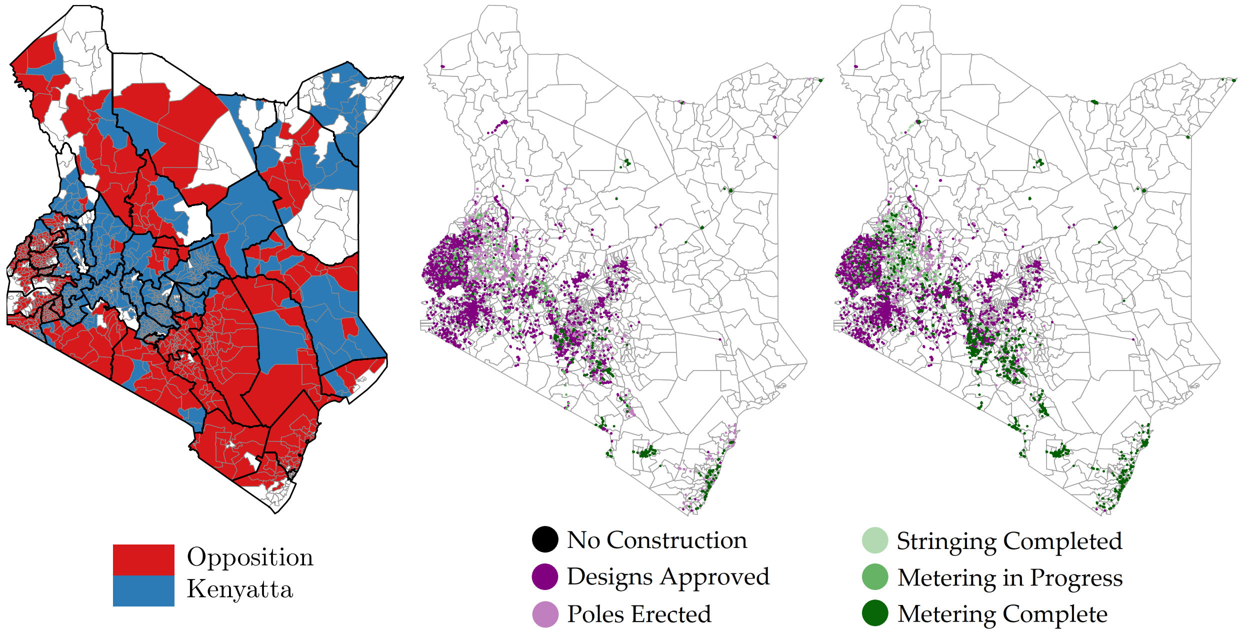
This main explanatory variables in this paper's analysis are voting outcomes from the 2013 presidential election, which preceded the selection of LMCP sites. Uhuru Kenyatta won the March 2013 presidential election with an electoral coalition similar to Kibaki's in 2002 and 2007, drawing significant support from central Kenya. Kenyatta's partnership with Ruto also gained him significant

[4] After controlling for basic census variables, allocations are uncorrelated with political affiliation, while without controls, they lean very slightly towards pro-opposition areas, which tend to be somewhat poorer (Table B1).

Figure 1: 2013 election vote shares and nationwide distribution of LMCP construction

(A) 2013 Presidential election results — (B) Construction status at LMCP sites over time

(i) May 2017 snapshot — *(ii) October 2017 snapshot*



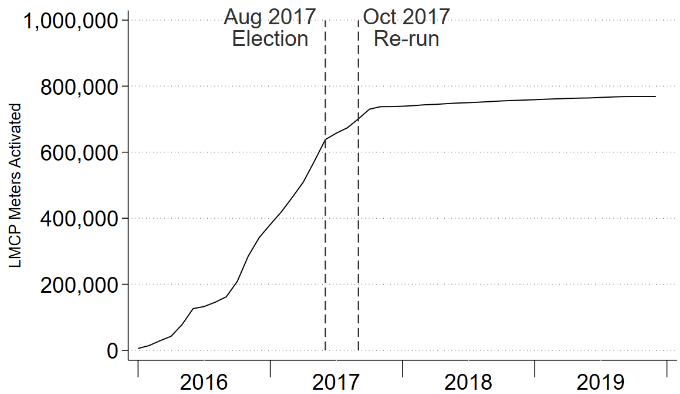
Note: Panel A shows 2013 presidential election results at the ward level, with county borders in thick black lines: blue (red) wards had vote shares of over (under) 50% for Kenyatta, white wards are missing election data. (Figure A4 presents the full distribution of vote shares and separates interior and border regions of support; Figure A5 maps the distribution of LMCP sites in an example border area). Panel B 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.

support in the west-central Rift Valley region, where Ruto's main political base resides. Raila Odinga led Kenya's opposition with support located primarily in western regions of Kenya and some urban centers. The electoral map in panel A of Figure 1 shows this geographic variation.

In 2008 President Kibaki had launched a program to connect public buildings such as schools and health centers to electricity. After being elected in 2013, Kenyatta expanded this program to target universal household electricity access. Despite increasing scrutiny surrounding ethnicity within public sector appointments (Amaya, 2016; Simson, 2018), both Kenya Power managing directors appointed under Kenyatta in 2013 and in 2017 were politically aligned with his coalition (Figure A3 provides an overview of appointments). Electrification efforts accelerated in the year before the August 2017 presidential election, with more than a million new residential electricity meters installed over this period. 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)

Figure 2: Household electricity meters activated under the Last Mile Connectivity Project



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 A7 disaggregates construction per capita by political affiliation.

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).[5] After winning the November 2017 re-run, Kenyatta was sworn in to his second term on November 28, 2017. Kenyatta's Jubilee Party won 140 out of 290 MP seats in the National Assembly, while Odinga's Orange Democratic Movement won 62.

This paper's main analyses study the relationship between electrification project 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 those investments 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 A6). The 2013 election results thus reflect the prevailing political landscape during the 2016–2017 rural electrification program.

Figure 2 plots the cumulative number of activated LMCP meters based on their activation dates provided by 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 activated per month. However, after the August election and the October re-run there was a noticeable plateau in the pace of construction for at least two years. These patterns suggest the presence of political forces—in particular, the ramp-up before the election is consistent with strategic behavior designed to incentivize voting *ex ante* (Golden and Min, 2013).

2.3 Rural electrification in Kenya

Kenya's approach to nationwide electrification consisted of a three-pronged strategy. Urban and peri-urban households were to receive approximately 17% of new connections; because of the high population density in cities these households were connect at a lower cost of around USD 15 (World

[5]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 these are used in the analysis.

Bank, 2016, 2010). In the remote and sparsely populated areas of northern and eastern Kenya, far beyond the reach of the grid, REA implemented the Kenyan Off-grid Solar Access Project (KOSAP) with the goal of using solar and other alternative energy sources (World Bank, 2017).

The bulk of new connections, however, were planned for rural areas with medium population densities and some degree of grid access. In 2008, Kenya's electricity grid had around 30,000 electrical transformers. Transformers convert medium voltage electricity down to low voltage (LV), which can be used by households and businesses. Between 2008–2015, thousands more transformers were installed across the country, but many households located close to the transformers remained unconnected (Lee et al., 2016). This greatly reduced the marginal cost of household connections, and motivated the launch of the 'Last Mile' Connectivity Project (LMCP), aimed at bridging the final gap between households and the grid. In 2016, several thousand transformers were selected for the LMCP (termed 'LMCP transformers' or 'LMCP sites'). The LMCP's goal was to leverage economies of scale and connect all households within 600 meters of a transformer in a single process referred to as 'transformer maximization'. Most LMCP sites contained between 20 to 100 unconnected households. This section describes the four stages of this process in more detail. Panel B of Figure 1 shows the geographic distribution of construction progress across these four stages.

Stage 1: The installation of new transformers

The first major hurdle to increasing rural electricity access was the lack of transformers in rural areas. In its 2008 Strategic Plan, the Rural Electrification Authority (REA) announced that it would install thousands of 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). In part as a result, the number of distribution transformers nationally more than doubled: 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).

Stage 2: The selection of LMCP sites from among the nationwide set of transformers

Based on primary reads of original correspondence between Kenya Power and individual members of parliament, we determined that Kenya Power first set a target budget for each constituency. Kenya Power then reached out to each constituency's member of parliament and exchanged a series of letters to jointly select which transformers in that constituency would be included in the LMCP. A total of 13,840 transformers were selected for maximization. The list of these LMCP villages was shared publicly (Kenya Power, 2017; Kenya Power, 2015).

Stage 3: The construction of low voltage network expansions at LMCP sites

Construction at villages selected for the LMCP was outsourced to private contractors, with staff at Kenya Power's Nairobi headquarters implementing auctions and administering dozens of contracts (Wolfram et al., 2023). The selected contractors—a mix of domestic and international firms—were responsible for designing low-voltage network expansions, procuring materials (such as poles and conductors), and installing them. Installation consisted of three steps: erecting poles, stringing (wiring) poles, and connecting a drop cable from a pole to each customer.

Importantly, implementation contracts were segregated geographically, with each contract assigning responsibility for LMCP sites in at most a handful of geographically clustered counties.[6] As a result, contractors often had staff based in smaller cities, who interacted primarily with local Kenya Power offices. This becomes a notable detail later when discussing the role of decentralization.

Stage 4: The activation of household electricity meters at sites with construction

Connecting a household to the grid requires both physically installing a meter and activating it with a customer account. While contractors were responsible for the physical connection and meter installation, Kenya Power was responsible for meter activation.

Program beneficiaries were not required to pay an upfront deposit: per Kenya Power, "all the beneficiaries under this scheme will be connected" (Kenya Power, 2016). While there was a nominal connection fee of Ksh 15,000 (∼USD 150)—significantly lower than the standard Ksh 35,000 (∼USD 350) fee, thanks to government and donor financing—households connected under the LMCP could pay this in up to 36 monthly installments of around USD 4 each; in practice many fees were never recovered: in survey data, more than half of households report never having been told that they would need to pay Kenya Power for the connection (Berkouwer, Lee, and Walker, 2018).[7] At the average site only 7% of households were not connected: the modal reason was being absent on the day construction was done.

Cumulative electrification

The marginal impacts across these four stages determine the cumulative number of LMCP household electricity meters per 100,000 households. Equation 1 formalizes this measure of electrification:

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

[6] Both the African Development Bank (AfDB) and World Bank (WB) were major donors. The contracts funded by the AfDB and the WB were spatially interspersed and both broadly nationally representative and this difference thus does not affect the political analysis (Wolfram et al., 2023). The results in this paper are similar when considering only AfDB sites or only WB sites.

[7] 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).

2.4 Use of the CDF formula to allocate electricity grid investments

A central contribution of this paper is estimating favoritism against a counterfactual that reflects the government's apparent welfare goals. Over a period of several years, the Ministry of Energy consistently stated that in order to achieve an equitable allocation of rural electrification investments, expenditures for both the construction of transformers and for household connections were to follow the 2003 Constituency Development Fund (CDF) formula, which had been determined well before REA and LMCP electrification programs launched in 2008 and 2015. Consider the following exchange during a 2010 parliamentary session, at the start of REA's transformer construction program:

> Evans Bulimo Akula, Opposition Member of Parliament:
> *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:
> [...] *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).

The LMCP was similarly described as a policy to advance economic equity. A "Last Mile Connectivity Program Q&A" section on Kenya Power's website for example stated that "the selection of the 5320 distribution transformers for the first phase was done using the CDF distribution formula" and that this was done "in the spirit of equitable distribution of resources" (Figure A8).

In 2016, President Kenyatta stated, "Every Kenyan who needs electricity must be connected. The days when electricity was a preserve for the well to do is long gone. The approach we are taking will bring equality," with Charles Keter, Assistant Minister for Energy and Petroleum, adding, "Previously electricity was a privilege enjoyed by the rich people now the President has instructed us to ensure that we do not segregate" (Bungane, 2016). This was motivated by development goals for the lowest-income Kenyans, with the GoK saying for example that "improved access to energy sources especially electricity improves human development conditions" (Ministry of Energy, 2015) and that "accelerating the pace of electrification in line with the government's target of 70 percent electrification by 2017 can contribute to eliminating extreme poverty" (Treasury, 2020).

In a parliamentary session in Nairobi in 2016, an opposition member of the senate asked "why the Government is discriminating against sections of the public in terms of the allocation," in response to which a member of government provided the following statement:

> Senator Mwakulegwa, Vice-Chairperson in the Standing Committee on Energy:
> *The company is not discriminating against any section of the public in terms of their*

location... The company has ensured that the ongoing projects are supported by donors and the Government and are spread throughout the constituencies and counties using the Constituencies Development Fund (CDF) distribution formula.

Kenyan parliamentary debates, 14 June 2016 (Hansard, 2016).

Throughout this period, Kenya Power's public materials also all stated that it would allocate LMCP sites to constituencies according to the CDF formula: Kenya Power's electrification information web page, for example, stated that "selection of the distribution transformers for the Last Mile project was based on the Government Constituency Development Fund criteria for resource allocation" (Kenya Power, 2024).

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 LMCP project contractors). We combine this with detailed ward-level electoral data, constituency-level household income and electricity spending data, and county- and national-level expenditures in the energy sector. Together, these data provide a detailed understanding of Kenya's rural electrification activities, electoral outcomes, and public expenditures between 2008-2019, across Kenya's 47 counties, 290 constituencies, and 1,450 electoral wards.

3.1 Grid infrastructure and LMCP construction data

The grid infrastructure data provided by Kenya Power include the universe of Kenya's 7 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, spanning all of Kenya (Table B2 provides summary statistics). Since the LMCP was a program of transformer maximization, it deprioritized sparsely populated regions and densely populated urban regions, and we exclude these from the analyses.[8] The main analyses thus focus on a sample of 911 rural wards that were the main focus of the LMCP (Figure A9). These 911 wards contain 42,135 transformers—including 9,284 out of the 11,934 transformers that were selected for the LMCP (78%)—and 840,548 household meters that are indicated as having been connected via a government electrification program since 2016.[9] For the remainder of the paper, we refer to these 911 wards as 'LMCP wards', the 9,284 transformers as 'LMCP sites', and these 840,548 electricity meters as 'LMCP meters'.

More than 99% of LMCP construction by 2019 was part of one of three programs co-financed with major international funders: African Development Bank (AfDB) Phase I, AfDB Phase II,

[8]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 A12 presents a specification curve with 63 variations of sample definitions. Results are not qualitatively sensitive to the sample definition.

[9]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.

and World Bank (WB), which through the end of 2019 incurred a combined cost of $343 million (Auditor-General, 2023). 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.[10] The data contain four markers of progress: the start of construction, pole installation, stringing of electrical cables, and meter installation. Panel B of Figure 1 shows two snapshots of these data. The activation of household meters—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. We also obtained copies of the signed contracts between Kenya Power and all of the contractors, allowing us to estimate heterogeneity in construction costs.

The various data sources generally align well. As an example, the meter activation database shows on average three to five household connections prior to construction, with a sharp rise of around 25–30 newly activated meters in the weeks around when a contractor independently reports completion of construction at a site (Figure A10). This is in line with Kenya Power's ex ante expectations around the likely number of ex ante connected and unconnected households at each site. (Kenya Power officials confirmed that, prior to the LMCP, up to a handful of high-income households would have been connected by paying the standard connection fee).

3.2 Electoral data

Panel A of Figure 1 displays ward-level results for Kenya's 2013 presidential election, obtained from the Independent Electoral and Boundaries Commission website. Blue wards are those where Kenyatta won over 50% of the vote, while red wards are those where the opposition won over 50%.[11] Votes for Kenyatta's government were concentrated in central and west-central Kenya, covering the ethnic home areas of Kenyatta and Ruto, as discussed in Subsection 2.2. Electoral coalitions and geographic patterns in vote shares were stable between 2013 and 2017 (Figure A6).

As a robustness check, we restrict the sample to wards that geographically border at least one ward that voted for the opposing candidate in the 2013 presidential election, thus comparing only wards with relatively similar geographic and socioeconomic characteristics. This also accounts for baseline differences in the extent of the national grid, which can affect the cost and feasibility of local network extensions. This results in a sample of 451 adjacent wards (panel C of Figure A4).

3.3 Demographic and socio-economic data

The welfare analysis uses data from the Kenya National Bureau of Statistics, which are published at the ward level (KNBS, 2009). We use ward-level measures of household consumption and GINI

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

[11] 2013 election data are missing for 185 out of 1,450 wards (13%), shown in white in Figure 1. These are primarily located in remote northern regions of the country with relatively small populations and fewer LMCP sites.

indices to simulate household-level inequality and connections, following the literature in assuming a Pareto distribution for income (Lubrano, 2017). To estimate the Lorenz curve we define the distribution's shape parameter α as a function of the GINI index ($g = \frac{1}{2\alpha-1}$) and calculate the cumulative share of income $L(p)$ for each percentile $p \in [0, 1]$:

$$L(p) = 1 - (1-p)^{(\alpha-1)/\alpha}$$

We calibrate these to ward-level minimum and mean household incomes.

Reassuringly, ward-level electrification rates per the 2009 census are highly correlated with the rates we compute using the Kenya Power meter data and ward-level household count after adjusting for population growth ($R^2 = 0.75$ at the ward level, 0.83 at the constituency level; Figure A11). We use the 2016 Kenya Integrated Household Budget Survey (KIHBS, 2016) to recover the pre-LMCP relationship between income and household propensity to have an electricity connection and to map incomes to estimated electricity expenditures conditional on having a connection, both at the household level.

Mapping electricity expenditures to electricity consumption is less straightforward: Kenyan electricity tariffs saw significant changes over this time period, with for example announcements about monthly fixed charges and monthly connection deductions that frequently did not align with on-the-ground reports of actual purchases. To map electricity expenditures to electricity consumption among the rural Kenyan population, we use electricity payment receipts, which record both the total cost and the number electricity units purchased in any given transaction. These reflected an average price of USD 0.18 per kWh at the time (Berkouwer et al., 2023).

3.4 Additional data

We draw additional ward-level socio-economic controls from the 2009 Kenya Population and Housing Census, which was the most recent census before the launch of LMCP (GoK, 2009). These include population density, baseline share of households that are unconnected to the grid, and household asset proxies. In addition to these socio-economic controls, we include geographic controls for land gradient and land area, as on average 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.

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

To understand the extent of decentralization in public expenditures in Kenya, we collect realized 2015 Constituency Development Fund (CDF) allocations (GoK, 2015) as well as total and energy-specific sub-national government expenditures (Kenya's Office of the Controller of Budget, 2022) for each county (Figure A31). At the national level we collect data on 2021–2022 ministerial expenditures by the ministries of health, agriculture and livestock, education, water and sanitation, roads and transport, and energy (GoK, 2022).

4 Favoritism in the rural electrification program

How much did Kenya's household electrification program favor areas that voted for Kenyatta, the winner of the previous presidential election? We first document the overall difference in household electrification using a selection-on-observables approach. Then, to distinguish favoritism from other possible government objectives, we evaluate the observed allocation relative to the Constituency Development Fund (CDF) formula.

4.1 Selection-on-observables estimation

We estimate the difference in electricity meters per 100,000 households between pro-government wards and opposition wards as follows:

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

where y_i is the number of government-subsidized household electricity meters per 100,000 households activated in ward i as of December 2019. (For scale, 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 2.2, the 2013 presidential elections result is the preferred explanatory variable (rather than 2017). $\mathbf{X_i}$ is a vector of covariates that varies across regressions.

Column 1 of Table 1 presents results without any socio-economic or geographic controls. Wards that voted pro-Kenyatta in the 2013 election saw more than 3,000 more active electricity meters per 100,000 households compared to wards that voted for the opposition. Relative to the 14,500 meters activated in opposition wards, this is a sizable 21% 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 initial regression may not accurately identify political favoritism if there are systematic differences between pro-Kenyatta and opposition areas that could account for uneven rates of electrification. 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. Gaps in electrification rates that are correlated with political affiliation could in that case be justified by a welfare-maximizing social planner, as discussed further below.

To begin 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. Similarly, Column 3 shows that using LASSO to flexibly select from the quadratic and cubic transformations and double and triple interactions of these controls does not meaningfully alter the coefficient estimate. It moves the point estimate slightly—which may be expected since government support is correlated with certain socio-economic outcomes—but the magnitude remains similar.

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, with standard errors clustered by constituency. 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 Constituency Development Fund (CDF) formula. Columns 2 and 5 control for land gradient, population density, baseline share of households that are unconnected, share adults with primary or secondary education, share adults who work for pay, dependency ratio, share households with an iron roof, 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 Hansen, 2013; Ahrens, Hansen, and Schaffer, 2020) to flexibly select from a subset of quadratic and cubic terms and interactions between this same set of variables. Table B4 presents the same analysis for LMCP sites per 100,000 households. Figure A12 presents two specification plots with 63 different specifications each varying sample and controls. $^{*} \leq 0.10, ^{**} \leq .05, ^{***} \leq .01$.

The main finding persists: electoral wards that voted pro-Kenyatta in 2013 saw substantially more electricity metering than opposition-voting wards, on the order of between 21–25%. The stability of the coefficients even when 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.[12]

Even though favoritism does not appear to be correlated with contemporaneous economic outcomes, it could still be driven by other factors, such as expected growth: the government may have used private information about the potential for economic growth, not captured in the census data, to allocate electrification projects. To assess this possibility, we conduct a placebo test using data on the penetration of M-PESA mobile money agents—which are widely used for financial transactions in Kenya—as a proxy for expected growth in local economic activity. M-PESA expansion should reflect private sector expectations about regional growth trajectories. If electrification was targeted based on economic growth potential, the allocation of mobile money agents across space would thus exhibit similar pro-Kenyatta bias.

Repeating the analyses in Table 1 but replacing the dependent variable with the change in M-PESA mobile money agents between 2013 and 2015, M-PESA expansions do not appear to favor pro-Kenyatta areas (Table B5). 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 A13). Taken together, these results suggest that the

[12] For instance, Column 2 of Table 1 is similar to favoritism estimates in Table B3 (using panel data) and Column 7 in Table B9 (without population weighting), Table B10 (among only adjacent wards), and Table B11 (per capita). Figure A12 plots 63 different specifications varying sample, controls, and level of analysis.

pro-Kenyatta bias in LMCP sites is unlikely to be driven by underlying differences in the levels or growth of economic activity.

4.2 Estimating favoritism against the Constituency Development Fund formula

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 favoritism. For example, if the government has an idiosyncratic objective function 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.

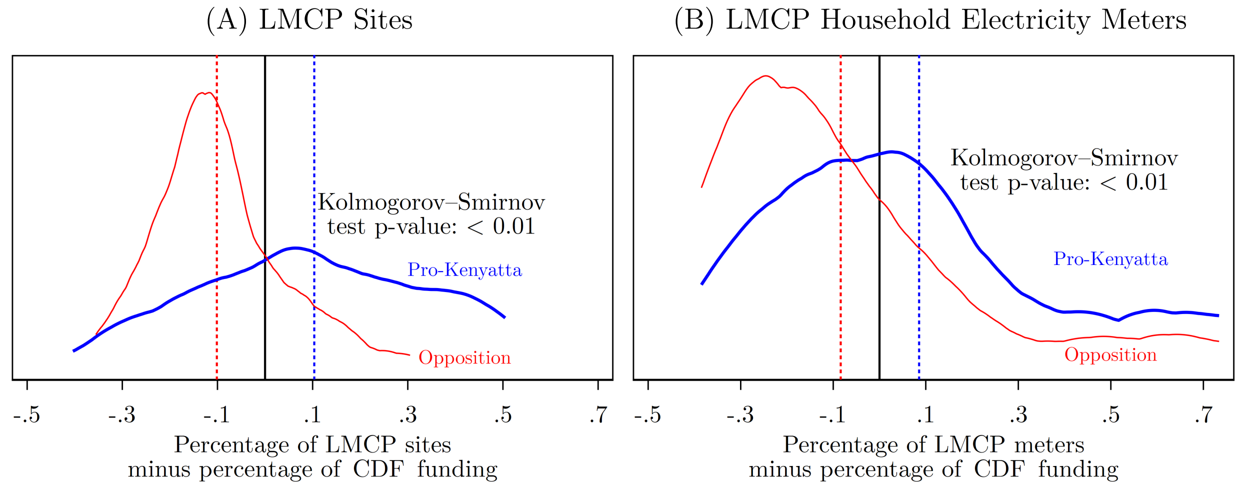
This paper addresses this common identification concern by leveraging a unique feature of the setting: a transparent, equitable, and well-known benchmark against which to measure favoritism. As discussed in Subsection 2.1 and Subsection 2.4, officials from the Ministry of Energy and Kenya Power publicly announced that the well-known Constituency Development Fund (CDF) formula was to determine the allocation of LMCP funds across constituencies. Since there were no systematic construction cost differences (as we discuss in Subsection 6.4), this suggests that the allocation of transformer construction and LMCP connections should also follow the CDF formula.

LMCP sites were selected in 2015, when the original 2003 CDF formula was in effect, which stated that 75% of CDF funding was to be split in equal shares across all constituencies, with the remaining 25% allocated based on each constituency's share of national poverty (GoK, 2003). Given the government's commitment to following the non-partisan CDF rule, deviations that are correlated with political affiliation are natural to interpret 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. The analysis mirrors columns 1, 2, and 3 except the dependent variable is the number of household electricity meters per 100,000 households minus the hypothetical number of meters per 100,000 households had meters been allocated according to 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 again 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 meaningfully from its publicly stated benchmark, in favor of pro-Kenyatta areas.

To examine whether this effect is driven by outliers or persists across the distribution, we define

Figure 3: Constituency LMCP shares relative to Constituency Development Fund (CDF) shares by 2013 election result



A constituency's share of nationwide LMCP outcomes minus its share of Constituency Development Fund (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. These patterns hold when plotting residuals after controlling for the same socio-economic controls as Column 2 of Table 1 (Figure A14). Figure A17 presents a scatter plot version.

each constituency's 'allocation deviation' as the share of LMCP sites a constituency was awarded minus its share of CDF funding. Had sites been allocated exactly 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.

Figure 3 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, 110% of the allocation they would have received under the CDF rule—while constituencies that voted for the opposition received on average only 90% of their allocation. Similarly, panel B shows that pro-Kenyatta constituencies saw significantly more active 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. Plotting the residuals after controlling for socio-economic characteristics shows a slightly narrower distribution but an almost identical difference (Figure A14). The results persist when using all wards nationwide instead of just LMCP wards (Figure A15) and when comparing allocations to population or to land area (Figure A16).

Columns 4, 5, and 6 of Table 1 and Figure 3 provide evidence that the government selected significantly more LMCP sites and activated significantly more household electricity meters in pro-Kenyatta wards relative to the CDF formula. Taken together, these results indicate that there was substantial pro-Kenyatta favoritism in the allocation of household electrification in Kenya, on the order of 20% to 35%.

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

	In absolute terms		
	(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 $\delta_1 = \delta_2 = \delta_3$	.73	.74	.28
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. $^* \leq 0.10, ^{**} \leq .05, ^{***} \leq .01$. Results are qualitatively similar under alternative assumptions (Table B6, Table B7, Table B8).

While these levels of favoritism are economically and statistically meaningful, the 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) (Figure A18). This points to an encouraging continuing downward trend over time in the magnitude of political favoritism, coinciding with major reforms that have strengthened democratic institutions and decentralized government functions.

4.3 Targeting core versus swing supporters

Political favoritism can operate through different approaches to electoral targeting. In 'swing' electoral areas, where the margins between political parties are relatively small, parties may allocate public investment 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 or to reward them for past support.

Was political favoritism in electrification targeted towards core or swing areas? We define swing regions to be wards where one party won 50–75% of the vote in the 2013 presidential elections, and core support regions as wards where a party won between 75–100% of the vote.[13] The following equation estimates how electrification allocations differ between these areas, such that coefficient

[13] Even with this generous definition swing areas are relatively scarce in this polarized political environment, comprising only 14% of wards in the analysis sample (23% nationally).

estimates are relative to core opposition wards:

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

Table 2 indicates that pro-Kenyatta core areas received the largest number of electrification connections. That said, pro-Kenyatta swing areas and opposition swing areas also see higher levels of household electrification than core opposition areas (the omitted category), on the order of 18%–21% higher, and we cannot reject that the three areas all benefited from similar levels of electrification. Results are qualitatively robust to defining 'core' as having >60% or >80% of the presidential vote (Table B7, Table B8). The pattern also broadly persists when comparing against the CDF benchmark formula, although the estimates are noisier when running regressions by constituency instead of by ward (Columns 4–6 of Table B6, Table B7 and Table B8).

5 National and subnational favoritism

What is the role of decentralization in the pro-Kenyatta favoritism identified in the previous section? The findings presented above are consistent with two broad hypotheses. One possibility is that decentralization successfully empowered local officials but 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.

We evaluate the roles of national and sub-national officials in two ways. First, we evaluate marginal favoritism across the four stages of rural electrification, which were implemented by different levels of government. Second, we assess how members of parliament shaped implementation.

5.1 Favoritism across the four stages of electrification

As discussed in Subsection 2.3, rural electrification consisted of four stages. Understanding how political favoritism differed across these stages can shed light on the underlying mechanisms.

Crucially, national-level authorities had tight control over the first two stages of rural electrification: transformer installation and the selection of LMCP sites. These activities were implemented by 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.

Conversely, local officials one or more steps removed from the president's administration were responsible for implementing the final two stages: local network construction and meter activation. Local network construction was implemented by private contractors, 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

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

	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 and standard errors clustered by constituency. 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. Results persist across a range of sample and regression specifications (Table B9 through Table B15). $^{*} \leq 0.10, ^{**} \leq .05, ^{***} \leq .01$.

easily influenced by the central government, and subject to stronger influence by local politicians.

To examine where aggregate favoritism originated, we decompose the cumulative effect into the marginal impacts during each stage, conditional on attaining the previous stage. Table 3 presents the results. Column 1 indicates a 17% pro-Kenyatta bias in the placement of transformers between 2008-2016, prior to the start of the LMCP. Column 2 indicates that the selection of LMCP sites from among the set of transformers further exacerbated this difference by 21%, for a cumulative (compounded) difference of 42% in the number of LMCP sites. The bulk of cumulative favoritism thus is driven by these first two stages. Columns 4 and 6 show little evidence of additional favoritism in local network construction and the activation of household meters, with the marginal impacts if anything attenuating the overall difference slightly. Still, the favoritism exerted in the initial stages leads to significant favoritism in all stages of the program. The order of magnitude of favoritism is robust to a wide range of specifications.[14] Estimating the effects in columns 1, 3, 5, and 7 relative to the Constituency Development Fund (CDF) formula shows quantitatively and qualitatively similar (and if anything slightly larger) effects, with similar patterns of statistical significance (Table B15).[15]

Taken together, aggregate political favoritism in Kenyan electrification at the household level appears entirely driven by stages that were largely controlled by the central government, namely, the initial stock of pre-LMCP transformers and LMCP site selection. There appears to be no

[14]Specifically, results are qualitatively similar when not weighting by population (Table B9), only comparing adjacent wards (Table B10), using per capita rather than per household (Table B11), dropping socio-economic controls (Table B12), and using LASSO to select socio-economic controls (Table B13). Adding constituency fixed effects dampens the effects, indicating the results are driven by across-constituency rather than within-constituency targeting (Table B14). This makes sense since political affiliation correlates strongly across wards in the same constituency.

[15]We focus on the ward-level regressions, rather than the constituency-level regressions relative to the CDF formula because—for the marginal effects—estimating favoritism relative to both the CDF and the previous stage simultaneously is undefined.

statistically significant favoritism in the latter stages of construction, which were managed locally.

5.2 Members of Parliament

Each of Kenya's 290 constituencies is represented in the national legislature by an elected Member of Parliament (MP). What role did MPs play in allocating LMCP funds? MPs are locally elected officials, likely giving them an incentive to advocate for local interests. However, their power to do so may vary depending on their alignment with nationally elected politicians. Volkert and Klagge (2022) observe that, based on interviews conducted in February 2020, Kenya Power and REA officials often expressed a preference for working with local MPs over county governments.[16] MPs furthermore have some control over local public spending: Harris and Posner (2019) and Opalo (2022a) both note how MPs largely determine how CDF funds are used within their constituencies. Although MPs are technically national-level officials and spend much of the year in Nairobi, many interviewees stated that MPs are seen as "representative[s] of the people." MPs are one of the few locally elected offices that predate Kenya's recent devolution reforms, and unlike other local officials (e.g., senators or members of the county assembly), MPs often have close formal and informal links to Kenya Power and REA. As discussed in Subsection 2.3, Kenya Power and each constituency's MP jointly selected the locations of transformers within each constituency, giving MPs the ability to directly exert influence on the process.

MP favoritism may have taken at least two forms. While neither can fully account for the aggregate levels of favoritism we observe, these are the most likely channels through which local politicians could have exerted political influence. First, MPs may have exerted bias when allocating LMCP sites to specific wards within their constituencies to favor those wards that had voted for them in constituency elections. Kenya Power and REA employees interviewed by Volkert and Klagge (2022) reported that MPs decisions about where to implement REA projects were "influenced by political intentions, especially the desire for re-election". While these would not contribute to the cross-constituency results we estimate in Columns 4, 5, and 6 of Table 1, they could have contributed partly to the ward-level regression results in Table 3 and in Columns 1, 2, and 3 of Table 1. Second, across constituencies, MPs aligned with the pro-Kenyatta ruling party at the national level may have been able to channel more resources to their constituencies relative to MPs aligned with the opposition coalition. The next two sections evaluate these two hypotheses in turn.

5.2.1 Within-constituency favoritism

Do MPs favor the wards in their constituencies that voted for them with more LMCP projects? For wards indexed by i, Table 4 presents estimates from the following equation, with the new MP coefficient (θ_2) in the second row:

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

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

Table 4: Effects of MP alignment on stage outcomes

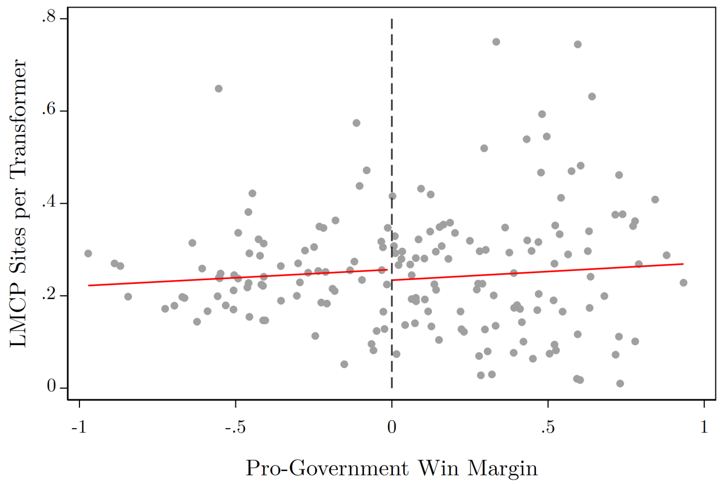
	Pre-existing Transformers	LMCP					
		Site Selection		Construction		Meters	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Voted pro-govt in 2013	143	-.022	13.5	-.0908	-17.5	-17.8	1205
	(111)	(.0376)	(26.6)	(.0633)	(17)	(27.6)	(1700)
Voted pro-MP in 2013	-42.3	.0237*	1.43	.00613	.49	-6.39	-150
	(31.3)	(.0142)	(8.78)	(.0326)	(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.

All regressions are at the ward level, weighted by ward population. Socioeconomic controls are as in Table 1, with the addition of constituency fixed effects. 'Voted pro-MP in 2013'=1 if the ward voted for the winning MP in the 2013 constituency-level National Assembly elections. For column 1, y_i is number of transformers per 100,000 households. Columns 2, 4, and 6 isolate the marginal impact of each 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. Columns 3, 5, and 7, estimate cumulative effects across stages. 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 are in parentheses.

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 with the most votes in ward i also won the overall constituency election. γ_c is a constituency fixed effect.

Three of the four stages show no evidence that a ward having voted for the overall winning MP affects that ward's electrification outcomes, when compared to a ward in the same constituency that did not vote for the overall winning MP. Column 2 shows marginally significant pro-MP favoritism in the selection of LMCP sites within a constituency, a pattern in line with Kenya Power and the MPs being jointly responsible for site selection (as discussed in Subsection 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 projects (the estimates are slightly noisier due to the inclusion of constituency fixed effects). Results are similar in specifications that drop socioeconomic controls (Table B16), select controls using a LASSO procedure (Table B17), drop population weights (Table B18), use the adjacent wards sample (Table B19), use per-capita as opposed to per-household outcome measures (Table B20), or dropping constituency fixed effects (Table B21).

Figure 4: 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 pro-Kenyatta coalition (Jubilee) candidate and the best-performing candidate not in the pro-Kenyatta coalition in the 2013 parliamentary elections. Linear trends on either side of the 0-margin line are weighted by constituency population. A sharp discontinuity test yields a coefficient of 0.03 which fails to reject (*s.e.*=0.04). The results are qualitatively the same for construction outcomes (Figure A19).

5.2.2 Across-constituency favoritism

Was there increased electrification in constituencies that elected an MP politically aligned with Kenya's President? To evaluate this, Figure 4 presents a close election regression discontinuity design. The running variable is the gap in vote share between the best-performing pro-Kenyatta coalition candidate and the best-performing non-coalition candidate in the 2013 MP elections. 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 A20).

Figure 4 does not show a meaningful 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 null of no 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 (Figure A18). Using the same regression discontinuity strategy with each of the four stages as the outcome similarly shows no effects (Figure A19).

By design, discontinuity estimates are identified off of constituencies where the electoral result was near the margin. MP races saw more close wins than would be suggested by presidential voting results, partly due to the presence of candidates from multiple competing parties. 32% of constituencies saw a win margin of less than 20 percentage points. 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 substantial correlation between MP and presidential voting patterns, we are unable to readily disentangle these alternatives.

6 Surplus estimation: Intuition and empirical approach

The previous sections presented evidence that the allocation of rural electrification projects favored pro-government constituencies relative to the Constituency Development Fund formula. How did this deviation affect economic surplus? Sections Subsection 6.1 and Subsection 6.2 presents a simple framework that guides an empirical exercise to estimate impacts on economic surplus and then describes the empirical approach. Subsection 6.3 then describes an approach to back out the surplus-maximizing social planner's implied welfare weights that are consistent with the observed allocation of meters. Section 7 presents the results.

6.1 Theoretical intuition

Many public investments—such as broadband, airports, and electricity connections—do not generate utility directly. Rather, they enable agents to consume goods that generate utility—such as internet, travel, and lighting. These types of public investment often generate larger surplus gains to higher-income agents, for whom the infrastructure enables higher levels of consumption. This pattern of regressive surplus gain has been documented across a host of public investments.[17]

In the context of electricity connections, Lee, Miguel, and Wolfram (2020a) document that low-income households may not be able to afford much more than a lightbulb and a phone charger, two appliances that many Kenyans already owned anyway, and that they may charge using solar power (for instance, 50% of Kenyans own a solar light) or alternative electricity delivery mechanisms (some Kenyans use car batteries as a source of electricity within their homes). High-income households, on the other hand, more often purchase larger appliances such as televisions, refrigerators, irons, and fans, or start income-generating businesses. The model and empirics are agnostic as to whether income heterogeneity reflects differences in income or differences in attributes correlated with income, such as access to credit, education, and markets.

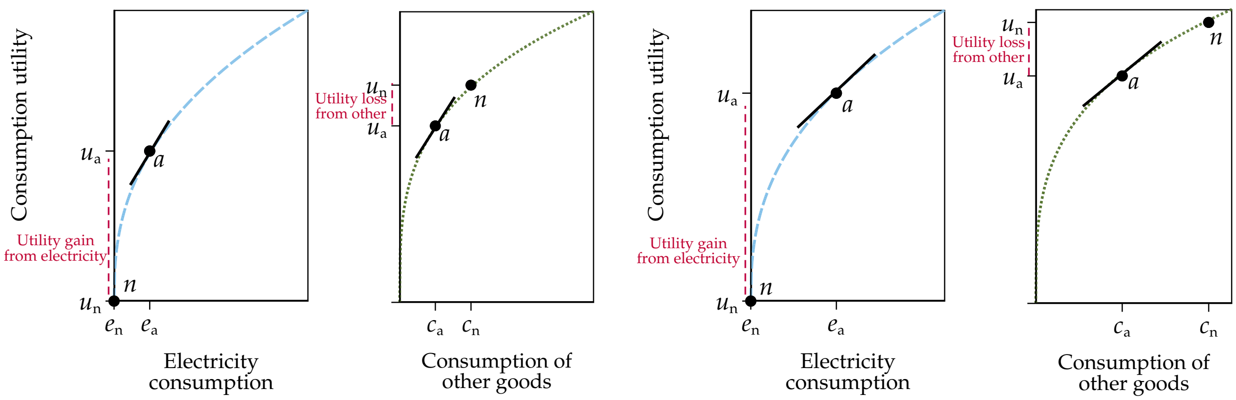
Figure 5 illustrates with a simple example how the increased surplus from electricity access can vary by income. Consider an agent endowed with either high or low income such that $Y_L < Y_H$. The agent can consume two goods, electricity e and outside consumption c. With no access to electricity, the agent spends all their income on the other good, such that $e_n = 0$ and $c_n = Y_i$. Utility is additively separable and weakly concave in each component, so when the planner provides the agent with electricity access, the agent equalizes the marginal utilities of both goods. The net utility gain is $U = u_e(e_a) + u_c(c_a) - u_c(c_n)$, which by the curvature of the utility function is greater for high income agents than for low income agents (proof in Appendix C).

For simplicity, and since LMCP households were connected without an upfront fee, we assume that acquiring an electricity connection does not affect income (which is also consistent with the findings in Lee, Miguel, and Wolfram, 2020b). Rather, this exercise can be thought of as asking how much additional surplus is generated when the price per unit of electricity falls from a high level

[17] See for example Glaeser (2008), Gaubert et al. (2025), Benabou (2000), Guerreiro, Rebelo, and Teles (2021), Herwartz and Theilen (2017), Haushofer et al. (2025), and Daruich and Fernández (2024).

Figure 5: Utility gain from connecting low-income and high-income agents

(A) Low-income agent (B) High-income agent



Note: With no electricity access (n), the agent consumes no electricity ($e_n = 0$) and spends all their money on other goods ($c_n = Y$). With electricity access (a), the agent consumes electricity and other goods to the point where their marginal utilities equal (identified by parallel tangents). By the curvature of the utility curve, utility with access exceeds utility without access, by an amount that increases with income.

(that leads to zero consumption) down to the observed price. Acquiring a free electricity connection can be thought of as equivalent to such a price drop.

6.2 Estimation and simulation of aggregate surplus

Estimating the utility gain from an electricity connection requires data on joint distributions of income and electricity consumption in each constituency, as well as data on the incomes of unconnected households. Constructing these distributions for the set of ex ante unconnected households requires first estimating the joint distribution of income and electricity access within each constituency and (conditional on being connected) the relationship between income and electricity consumption among rural households (Figure A21). As described in Subsection 3.3, these exercises primarily use micro-data collected by the Kenyan National Bureau of Statistics. Since the KNBS does not collect income per se, and since aggregate household consumption is widely thought to be a higher-quality and more stable measure of household well-being, we use consumption as a proxy for income and our primary measure of socioeconomic well-being.[18] The conversion of electricity spending (in Ksh) to electricity consumption (in kWh) uses an average electricity price of USD 0.18 per kWh, recovered from observed electricity purchasing data (Berkouwer et al., 2023).[19]

Finally, we apply a price elasticity of electricity consumption of $\epsilon_D = -0.3$, 10% annual electricity spending growth, and assume a linear approximation for the electricity demand function to calculate the consumer surplus derived from electricity consumption (similar to Lee, Miguel,

[18] Income data are often systematically under-reported, and are also more time-varying than consumption which tends to be smoothed, and thus less accurately capture a household's long-term economic well-being. See Deaton (1997), Browning, Crossley, and Winter (2014), and Carletto, Tiberti, and Zezza (2021) for more rigorous treatments of these measurement concerns, and Silber (2023) for a recent research methods handbook.

[19] The composition and levels of Kenyan electricity tariffs vary frequently over this time period; using the observed receipts data is thus more reliable than attempting to recover price data directly.

and Wolfram, 2020b; Mahadevan, 2024; Burlig and Preonas, 2024). We assume that not having an electricity connection generates zero additional surplus and that an electricity connection only generates surplus through the consumption of electricity. Aggregate surplus is defined as the net present value of 30 years of consumption, discounted at 15% per year. These assumptions yield an estimated 22.5 USD in aggregate consumer surplus per 1 kWh consumed monthly over the lifetime of the connection. The qualitative results are robust to alternative assumptions of demand elasticity and electricity spending growth (Figure A26, Figure A27, Table B23).

Surplus gains under this approach approximate the compensating variation required to make a household indifferent between having an electricity connection versus no electricity connection plus cash. In the absence of income effects in electricity consumption, Hicksian and Marshallian demand for electricity would coincide, and surplus gains under this approach would exactly reflect the compensating variation (Mas-Colell, Whinston, and Green, 1995).

Using these estimates, we simulate gains in aggregate surplus under four scenarios, each of which allocates electricity connections to exactly 840,548 households (the observed number of LMCP meters): the observed allocation, the Constituency Development Fund (CDF) allocation, a politically neutral surplus-maximizing allocation, and an unconstrained surplus-maximizing allocation. Under all four scenarios, we assume that a household's probability of already being connected before the LMCP is consistent with observed pre-LMCP connection rates by income for each constituency (though as stated above, the results are robust to alternative assumptions).

The observed and CDF allocations use allocations of LMCP meters across constituencies that mirror those used for Table 1. Within each constituency, both of these scenarios assume that the propensity of an unconnected household to be connected through the LMCP is random, following the LMCP's stated goal of connecting 'all Kenyans' to electricity without regard to socioeconomic status. We apply realizations at the household level by constituency vote share, assuming pro-Kenyatta and opposition voters have identical income distributions within each constituency.[20,21] The two surplus-maximization scenarios assign connections to households who were ex ante unconnected but are expected to generate the largest surplus gains from connection, regardless of which constituencies these households reside in. Given the model set-up, in practice these are simply the highest-income households. Under the politically neutral surplus maximization scenario, the allocations under consideration are restricted to those where the percentage of unconnected pro-Kenyatta households that receive a meter must be equal to the percentage of unconnected opposition households that receive a meter.

Formally, the simulations proceed as follows. Characterize households i by income such that total utility is $\int_0^N u(y(i))di$ where $y(\cdot)$ is income, which following the literature is assumed Pareto

[20] The results are qualitatively unchanged when estimating results at the constituency level, mirroring Section 4, rather than allocating surplus proportionally to each constituency's vote share (Panel B of Figure A27).

[21] While household-level data almost never contains political voting data, at the ward level there is a weak and noisy correlation between income and political affiliation. Among unconnected households within a constituency, an increase in Kenyatta vote share from 25% to 75% is associated with just a 1.5% decrease in annual household consumption (Figure A22). If anything this assumption would therefore seem to bias the approach against finding evidence of political favoritism impacting welfare.

distributed within constituencies (Lubrano, 2017). Without LMCP, the probability of being connected to electricity $Pr(\cdot)$ is an increasing function of income.[22] Assume that share of consumption going to electricity is a log-linear function of total consumption (non-homothetic preferences),[23] and that utility of electricity consumption is quasi-separable from other consumption:

$$u(c_i^{nonelec}, c_i^{elec}) = v(c_i^{nonelec}) + w(c_i^{elec})$$

If a household is connected to the electricity grid, it maximizes utility over both $c_i^{nonelec}$ and c_i^{elec} subject to its budget constraint. If a household is not connected to the electricity grid, it is constrained to $c^{elec} = 0$. For simplicity, we do not model any income gains from obtaining an electricity connection, assuming that any income gains are second order and consistent with evidence from (Lee, Miguel, and Wolfram, 2020b). We quantify the utility gain from connecting households in a given set $\mathbb{I}$:

$$\int_{i\in\mathbb{I}} \Big[max\{u(c_i^{nonelec}, c_i^{elec})\} - max\{u(c_i^{nonelec}, 0)\}\Big]\, di$$

It can be shown that when $v(\cdot)$ is the identity function, consumer surplus from electricity demand is equal to the gain in utility from an electricity connection. In general, however, these are not equivalent and we consider consumer surplus as an approximation to utility gain.[24]

Following (Lee, Miguel, and Wolfram, 2020b), we assume that households with different income all have linear demand for electricity with identical elasticities of demand at the quantity demanded. Assuming that $v(\cdot)$ is a linear function, we can interpret total consumer surplus from the electricity consumption of newly electrified households as the utility gain generated by those connections.

6.3 Estimation of implied welfare weights

To back out welfare weights that are consistent with the observed allocation of meters, we write a model in which the social planner maximizes the total weighted surplus experienced by all households that receive a connection. Household weights are permitted to be a flexible function of income and political alignment, and the planner incurs a penalty that grows with deviations from the announced allocation. We can then calibrate the model to match moments from the observed allocation.

Let constituencies be denoted by $k \in \mathbb{K}$. Each constituency k has n_k ex-ante unconnected

[22] For the quantitative exercise we consider two possible functions C. First, we consider an increasing function estimated using microdata from the 2015-2016 Kenya Integrated household Budget Survey. Second, we consider the following function, where $\underline{I}$ is an income threshold that is determined at the ward level:

$$Pr(I) = \begin{cases} 1 & \text{if } I \geq \underline{I}, \\ 0 & \text{if } I < \underline{I} \end{cases}$$

We assume for simplicity that aggregate consumption c_{agg} and income are linearly related.

[23] Also estimated using microdata from the 2015-2016 Kenya Integrated household Budget Survey

[24] In this framework, utility gain for household i from getting an electricity connection is $max\{u(c_i^{nonelec}, c_i^{elec})\} - max\{u(c_i^{nonelec}, 0)$. Whereas consumer surplus is defined by the condition: $u(c_i^{nonelec*} - CS, c_i^{elec*}) = u(y, 0)$, where $c^{nonelec*}$ and c^{elec*} are optimal consumption choices with an electricity connection. That is, consumer surplus can be thought of as *'how much less the agent would have to spend on non-electricity consumption to return to utility without an electricity connection'*.

households denoted by $i = c_1, ..., c_{N_k}$. Let $N := \sum_k n_k$. Household i has exogenous income y_i, which maps into the surplus gain from a connection Δ_i as described in Subsection 6.2. Political affiliation of household i is represented by $pro_i \in \{0,1\}$, where 1 represents pro-Kenyatta and 0 represents opposition. This is a priori assigned randomly based on the vote-share in each constituency, with income quintile among all ex-ante unconnected households $q_i \in \{1,\ldots,5\}$. Let $a_i^{obs}, a_i^{cdf}, a_i \in \{0,1\}$ denote whether they are allocated a connection under the observed allocation, the CDF allocation, and the model-implied allocation, respectively.

For each allocation scheme we compute three (untargeted) moments. Favoritism is defined as the difference in percentage connected between pro-Kenyatta and opposition households, given by:

$$m_{\text{fav}} = 100 \times \left(\frac{\sum_i a_i \cdot \mathbb{1}\{pro_i = 1\}}{\sum_i \mathbb{1}\{pro_i = 1\}} - \frac{\sum_i a_i \cdot \mathbb{1}\{pro_i = 0\}}{\sum_i \mathbb{1}\{pro_i = 0\}} \right). \tag{5}$$

Regressivity is the ratio of percentage connected in the 5th income quintile relative to 20%

$$m_{\text{regress}} = \Big(\frac{\sum_i a_i \cdot \mathbb{1}\{q_i = 5\}}{\sum_i a_i} \Big) \Big/ 0.2. \tag{6}$$

The difference in regressivity between pro-Kenyatta and opposition households is given by:

$$m_{\text{diff-regress}} = 100 \times \left(\Big(\frac{\sum_i a_i \cdot \mathbb{1}\{pro_i = 1, q_i = 5\}}{\sum_i a_i \cdot \mathbb{1}\{pro_i = 1\}} \Big/ 0.2 \Big) - \Big(\frac{\sum_i a_i \cdot \mathbb{1}\{pro_i = 0, q_i = 5\}}{\sum_i a_i \cdot \mathbb{1}\{pro_i = 0\}} \Big/ 0.2 \Big) \right) \tag{7}$$

We define $m^c_{\text{dist}} = 100 \times \frac{\left(\sum_{i=c_1}^{c n_k} a_i\right) - \left(\sum_{i=c_1}^{c n_k} a_i^{obs}\right)}{n_k}$ as the percentage point difference in allocated meters in constituency k. We use this to construct the Euclidian distance from a simulated allocation to the observed allocation as:

$$f_{\text{dist}} = \left(\sum_k (m^c_{\text{dist}})^2 \right)^{\frac{1}{2}} \tag{8}$$

The surplus-maximizing planner has a fixed number of meters $M < N$ to allocate across constituencies $k \in \mathbb{K}$. For each constituency k with n_k unconnected households, the planner decides an integer allocation $A_k \in \{0, 1, ..., n_k\}$ such that $\sum_k A_k = M$. Within each constituency, meters are randomly assigned to unconnected households, as an approximation to the LMCP's aim of connecting all unconnected households near maximized transformers regardless of income.

The planner can weigh household surplus differentially by political affiliation and income, governed by three skewness parameters:

$$\theta = (\theta_{\text{pro}}, \theta_{\text{income}}, \theta_{\text{pro*income}})$$

Let $N_{\text{pro}} = \sum_i \mathbb{1}\{\text{pro}_i = 1\}$ and $N_{\text{opp}} = \sum_i \mathbb{1}\{\text{pro}_i = 0\}$ be the total number of unconnected pro-Kenyatta and opposition households. Their total weights are defined as:

$$W_{\text{pro}}(\theta) = \frac{(1 + \theta_{\text{pro}}) \cdot N_{\text{pro}}}{(1 + \theta_{\text{pro}}) \cdot N_{\text{pro}} + N_{\text{opp}}} \cdot N$$

With $W_{\text{opp}}(\theta) = N - W_{\text{pro}}(\theta)$. Finally, with $\bar{y}$ and σ_y as the mean and standard deviation of unconnected household income, we rescale a household income z-score within pro-Kenyatta and opposition groups so that they sum to group totals. Let $t_j(\theta) = \exp\left(z_i \cdot (\theta_{\text{income}} + \theta_{\text{pro*income}} \cdot \text{pro}_i)\right)$. Then define household weights as:

$$w_i(\theta) = \begin{cases} t_j(\theta) \cdot \dfrac{W_{\text{pro}}(\theta)}{\sum_{j:pro_j=1} t_j(\theta)}, & \text{if } pro_i = 1 \\ t_j(\theta) \cdot \dfrac{W_{\text{opp}}(\theta)}{\sum_{j:pro_j=0} t_j(\theta)}, & \text{if } pro_i = 0 \end{cases} \tag{9}$$

Let $i \in \{1, ..., n_k\}$ index households in constituency k. Let π_k be a random ordering/permutation of $\{1, ..., n_k\}$. Let weighted household surplus be $\Delta_i^{wtd}(\theta) = w_i(\theta) \cdot \Delta_i$. The cumulative surplus function in the number of allocated meters M is then:

$$S_k(M|\theta, \pi_k) = \sum_{s=1}^{M} \Delta_{\pi_k(s)}^{wtd}(\theta)$$

We further impose a penalty for deviating from the announced constituency-level CDF allocations. We are agnostic as to the source of this penalty: this could represent bureaucratic procedures, international donor oversight, media scrutiny, or political constraints. For each constituency k, let A_k^{cdf} be the number of allocated meters under the CDF allocation. The penalty parameter λ then governs a quadratic penalty function in the number of meters p deviated from the CDF allocation:

$$F_k(p|\lambda) = 100 \times \lambda \times \frac{(p - A_k^{cdf})^2}{2n_k}$$

With $\bar{\Delta}_k^{wtd}(\theta)$ denoting the average weighted household surplus in constituency k given skewness parameters θ, denote the planner's problem as follows:

$$\arg \max_{\{A_k : k \in \mathbb{K}\}} A_k \times \bar{\Delta}_k^{wtd}(\theta) - F_k(A_k|\lambda) \tag{10}$$

For each constituency's model-implied allocation A_k and observed allocation A_k^{obs}, define the percent point difference in the connection rate $m^c_{\text{distance}} = 100 \times \frac{A_k - A_k^{obs}}{n_k}$ and define $\hat{m}(\lambda, \theta) = (m^1_{\text{distance}}, ..., m^C_{\text{distance}})^\top$. Using GMM we then solve for penalty and skewness parameters (λ, θ) that minimize:

$$(\hat{\lambda}, \hat{\theta}) \in \arg \min_{\lambda, \theta} \left\{ \hat{m}(\lambda, \theta)^\top W \hat{m}(\lambda, \theta) \right\} \tag{11}$$

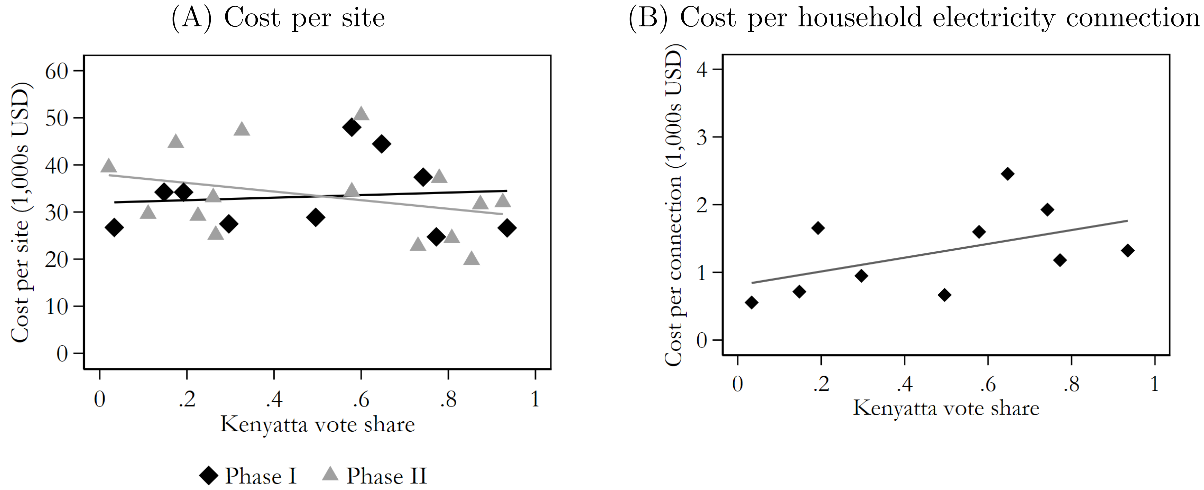
Figure A23 shows that the model reasonably approximates the observed allocation.

6.4 Cost

Estimating aggregate surplus requires estimating both consumer surplus and supplier costs. Even if consumer surplus does not vary with political affiliation, political favoritism might still be justifiable if construction costs were systematically lower in pro-government areas than in opposition ones. For example, if opposition areas are hillier than pro-government areas, increasing construction costs, then favoring pro-government regions might have increased total surplus.

To evaluate this, we use cost data from the 25 contracts signed between Kenya Power and construction firms. As discussed in Subsection 2.3, construction for the LMCP was conducted

Figure 6: Cost estimates across 25 construction contracts



Note: At most LMCP sites that saw at least some construction, Kenya Power connected between 10-100 households. Household-level connection costs are only available for Phase I. In panel A, the 95% confidence intervals for the slope coefficients are [-19, 29] and [-24, 8]. In panel B, the 95% confidence interval is [-0.7, 2.6].

entirely by private sector contractors. Firms were awarded contracts to connect all unconnected households at a set of designated LMCP sites in a geographic cluster of two to six counties. Most contracts were "turn-key", covering all aspects of construction, from the creation of electrical designs to expand the local grid, to the procurement of materials, to the actual on-the-ground construction (Wolfram et al., 2023). Ten turn-key phase I contracts were signed in 2015 and fifteen phase II were signed in 2017. Helpfully, contracts' geographic clusters largely followed political boundaries, allowing us to compare costs across political regions.

We define cost per site as the contract's total cost divided by the total number of LMCP sites across the counties specified in the contract. Panel A of Figure 6 compares cost per site with the aggregate pro-Kenyatta vote share for the corresponding geographical region, for all 25 construction contracts. Panel B complements these data with meter count data to calculate the average cost per household electricity connection.[25] It is reassuring that the estimated cost per household matches previous estimates in the same context (Lee, Miguel, and Wolfram, 2020b).

Political affiliation and construction costs per site are not meaningfully correlated (Panel A). There is also no strong correlation between political affiliation and cost per connection (Panel B). Pro-Kenyatta regions face slightly higher costs per connection, but the slope is not statistically different than zero, and if anything this would justify a bias *against* pro-Kenyatta wards. Given the fact that construction costs tend to decline with the number of connections, this cannot be explained by the larger number of connections in pro-Kenyatta regions. LMCP sites in wards that voted for Kenyatta also exhibit similar distances to major towns, land gradient, and nighttime radiance compared to pro-opposition areas, suggesting that there are no meaningful underlying characteristics that might cause substantial differences in construction cost (Figure A24). If anything, pro-Kenyatta

[25] The data only identify meter counts for Phase I sites.

wards appear slightly hillier than opposition wards, which would again imply a *higher* cost per connection.

These results are somewhat imprecisely estimated, so we refrain from incorporating cost estimates into the surplus calculations. Still, the lack of a clear correlation suggests that any cost differences correlated with political affiliation are not a major determinant of aggregate surplus.

7 Surplus estimation: Results

Subsection 7.1 first documents that the realized allocation generates higher total welfare than the pre-announced allocation. Subsection 7.2 documents that pro-Government voters captured more than just the total surplus gain, with opposition voters receiving *lower* surplus than they would have under the announced allocation. Subsection 7.3 uses Generalized Method of Moments (GMM) to recover the welfare weights embedded in the planner's objective function as implied by the realized allocation, allowing for heterogeneous weights varying by income, political affiliation, and their interaction.

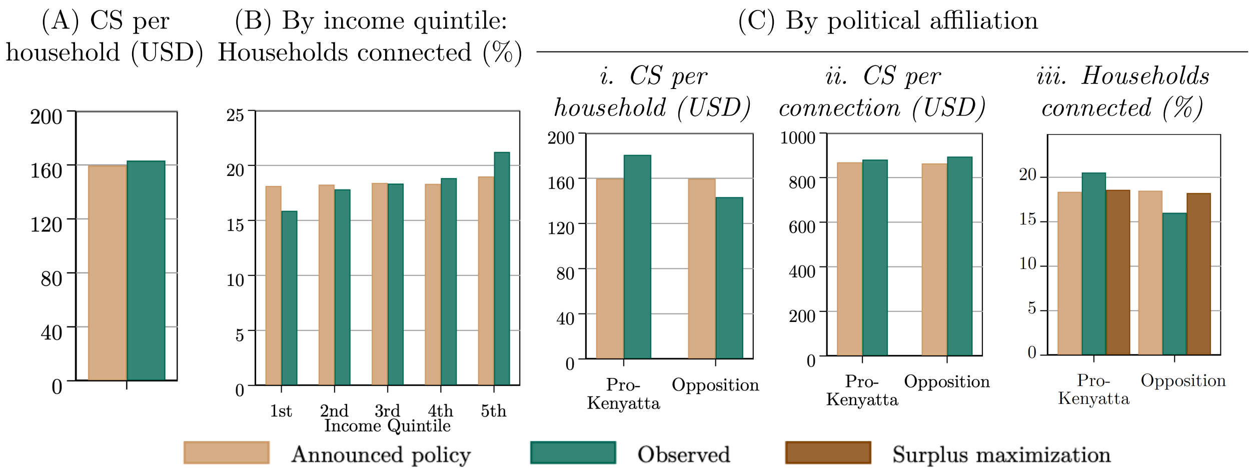
7.1 Total consumer surplus

Figure 7 and Table 5 present the surplus estimation results. To start, we find that total surplus was 2.3% *higher* under the observed allocation than under the Constituency Development Fund (CDF) allocation. Thus political favoritism does not necessarily decrease welfare; in this context, favoritism increased total economic surplus by a small amount.

This aggregate surplus increase resulted from an increase in regressivity. Panel B of Figure 7 shows that the CDF rule would have assigned largely similar connection probabilities to all unconnected households, regardless of income. Instead, the observed allocation assigned 34% more connections to households in the highest-income quintile of unconnected households than to the lowest-income quintile. Connecting a higher-income household generates a larger surplus gain than connecting a lower-income household, thus increasing aggregate surplus. However, it decreased surplus for the poor, who received 12% less surplus under the observed allocation than what they would have received under the CDF allocation.

Regressivity in the number of connections is exacerbated by the fact that lower-income households gain less surplus from being connected. The CDF formula would have allocated equal numbers of connections across all income quintiles of unconnected households, but would have generated 2.3 times more surplus for the highest than for the lowest quintile. The observed allocation generated 1.3 times more connections and 2.9 times more surplus for the highest quintile (Figure A25). This is partly driven by significant economic inequality across constituencies: in the data we use, per capita income is four times higher in the 90th percentile constituency than in the 10th percentile constituency, and 20 times higher in the wealthiest constituency than in the poorest constituency. Deviating from the CDF enables the targeting of constituencies with more rich households, who generate larger returns to electrification. The observed deviation thus generated higher surplus but

Figure 7: Consumer surplus (CS) and connections by political favoritism and allocative efficiency



Note: Panel A shows aggregate consumer surplus per ex ante unconnected household (USD). Panel B shows the number of ex ante unconnected households connected through LMCP (%), by income quintile. Panel C (i) shows consumer surplus per ex ante unconnected household (USD). Panel C (iii) shows the percentage of unconnected households connected through LMCP (%) The announced policy was to allocate connections according to the Constituency Development Fund (CDF) formula. Panel A shows no significant difference in consumer surplus per connection. Panel B shows that the observed allocation favored pro-Kenyatta voters relative to both the CDF allocation as well as to the surplus-maximizing allocation, suggesting political bias in this context cannot be justified on the basis of surplus maximization. Panel C shows that consumer surplus per ex ante unconnected household in USD under the observed allocation and a counterfactual allocation that follows the CDF formula. Subsection 6.2 details the methodology.

undermined the stated goals of the CDF and of the LMCP.

It is worth noting that there is significant uncertainty around the levels of total economic surplus the program will generate, even when relative differences in surplus are robust to different assumptions. For example, under the observed scenario, assuming a demand elasticity of -0.3, the LMCP's 343 million USD investment generated either a -3% or 117% aggregate return depending on whether over the next 30 years rural household electricity demand stays constant or grows by 10% per year (Table B23). This reflects real uncertainty in growth trajectories. Nevertheless, under both sets of assumptions, the realized allocation generates slightly more surplus than the CDF would have.

7.2 Political favoritism

Panel C of Figure 7 disaggregates outcomes by political affiliation. Panel C(i) indicates that consumer surplus for opposition voters was 10% *lower* under the observed outcome than under the CDF allocation, while among pro-government voters it was 13% higher. Thus, it is not just that the 2.3% increase in surplus was captured entirely by pro-Kenyatta voters: the favoritism gap reflects both gains in surplus accruing to pro-Kenyatta households and losses in total surplus accruing to opposition households. Under a range of assumptions, the observed distribution exhibits a 18.3% to 26.5% bias towards pro-Kenyatta households (Figure A26, Figure A27).[26] For comparison, estimates of favoritism under the CDF allocation range from just −5.2% to 0.8%.

[26] We define favoritism as the surplus per pro-Kenyatta household minus the surplus per opposition household, divided by the surplus per opposition household.

Table 5: Consumer surplus, political favoritism, and regressivity across four allocations

	Total Consumer Surplus (Million USD)	Political Favoritism (%)	Regressivity (Ratio)
(a) Uniform Welfare Weight			
Announced Policy Allocation	728.1	-0.1	1.0
Observed Allocation	744.9	4.5	1.2
Surplus-Maximizing Allocation - Politically Neutral	1041.3	-0.0	5.0
Surplus-Maximizing Allocation	1041.3	0.3	5.0
(b) Pro-Poor Welfare Weight $\propto$ (1 / Household Income)			
Announced Policy Allocation	693.7	-0.1	1.0
Observed Allocation	678.0	4.5	1.2
Surplus-Maximizing Allocation - Politically Neutral	976.2	-0.0	0.0
Surplus-Maximizing Allocation	976.3	-1.7	0.0
(c) Pro-Rich Welfare Weight $\propto$ Household Income			
Announced Policy Allocation	754.7	-0.1	1.0
Observed Allocation	803.2	4.5	1.2
Surplus-Maximizing Allocation - Politically Neutral	1843.6	-0.0	5.0
Surplus-Maximizing Allocation	1843.6	0.3	5.0

Note: The announced policy was to allocate connections according to the Constituency Development Fund formula. The third row maximizes surplus subject to the constraint that equal fractions of unconnected pro-government and opposition voters get connected. Political favoritism represents the percentage point difference between previously unconnected pro-Kenyatta and opposition households who received connection through LMCP. Regressivity is the fraction of previously unconnected households that receive connection through LMCP that are in the highest income quintile of unconnected households, divided by 20%, which would be the equitable allocation. Estimates of political favoritism and regressivity do not vary by welfare weight and are thus the same for the first two rows across the three panels. Welfare weights sum to the total number of households. The reported total consumer surplus is a weighted sum. Figure A28 presents these dimensions visually. Table B23 shows additional outcomes and assumptions.

Can this level of political favoritism be justified? Consumer surplus per unconnected household captures both the surplus gain per connection and the fraction of households connected. Political favoritism might be justifiable on the basis of surplus maximization if, for example, the average surplus generated per connection was higher among pro-Kenyatta voters than opposition voters. However, there is little evidence of this. Panel C(*ii*) of Figure 7 plots the average consumer surplus per connection among pro-Kenyatta and opposition voters separately. If anything, the average gain in surplus per connection is slightly higher among opposition voters. Panel C(*iii*) shows that differences in aggregate surplus are driven primarily by differences in the fraction of unconnected households who were connected under the LMCP. We similarly see no heterogeneity in regressivity by political affiliation (Figure A29).

To further examine whether political favoritism can be economically justifiable on the basis of surplus maximization, Table 5 uses the model to evaluate two additional scenarios: (1) an unconstrained surplus maximizing allocation, and (2) a politically neutral surplus maximizing allocation. The unconstrained surplus-maximizing allocation shows almost no favoritism. In the observed allocation, pro-Kenyatta areas see substantially more connections when compared with the unconstrained surplus-maximizing benchmark. This suggests that the observed allocation's political bias therefore cannot be motivated by surplus maximization alone. Even constraining the possible set of allocations to those that are politically neutral yields a surplus gain that is 99.99% as large as what can be achieved under the unconstrained surplus-maximizing allocation. That is, enforcing political neutrality in allocation of grid connection in this context would not meaningfully lower total economic surplus.

Finally, it could be that the planner is using non-uniform welfare weights, and that favoritism could be justifiable from a welfare-maximization perspective under an alternative welfare weighting scheme. These weights could reflect the government's political or social objectives—for instance, a preference to help the poor.

The uniform weight scenario presented in Panel A of Table 5 is the same as considered above. The announced policy allocation (the CDF) is almost politically neutral, while the observed allocation skews pro-Kenyatta. The surplus-maximizing allocation under equal welfare weights is fairly regressive, with five times as many connections received by the top income quintile compared to the bottom quintile.

Panels B and C of Table 5 consider allocations under alternative sets of weights representing pro-poor and pro-rich social planner preferences, respectively. Pro-poor welfare weights are derived using the linear *inverse* of household income. The government's goal in connecting low-income Kenyans was to promote human development, rather than simply maximizing aggregate surplus (Subsection 2.4). This goal can be justified from a welfare perspective if the social planner has a welfare function that places higher weight on lower-income individuals, or if lower-income individuals face market frictions such as credit constraints, and/or if the planner faces a constraint on transfers to enact its preferred income distribution.

Using pro-poor weights, the surplus-maximizing allocation is moderately pro-opposition, with 1.73 percentage points more unconnected opposition households receiving connections. Moreover, with inverse income weights, the regressivity of the previous allocations disappears—the top income quintile receives no connections. In addition, it's worth noting that, after imposing pro-poor welfare weights, the observed allocation produces *less* consumer surplus than the announced CDF allocation—the opposite of all other weighting scenarios.

Finally, we consider pro-rich welfare weights. Under standard welfare theorem conditions, the competitive market allocation is equivalent to the allocation that maximizes a hypothetical social welfare function where consumer utility is weighted by the inverse of the marginal utility of income. (Intuitively, in a market allocation those with the most income can consume the most, and contribute the most to aggregate utility.) We use weights that are linearly proportional to household income, which we justify following Negishi (1960). The linear weights thus correspond to the implicit weights of a market allocation under the standard case of log utility.[27] Under these pro-rich weights, the

[27]If I_i is income of consumer i, and w_i is the Negishi (1960) welfare weight, $u_i(x_i) \equiv \ln(x_i) \implies u'(I_i) = 1/I_i \implies w_i \equiv 1/U'(I_i) = I_i$.

Table 6: Aggregate moments from observed and counterfactual allocations

Scenario	Untargeted Moments				Parameter Estimates			
	Favoritism (p.p.)	Regressivity (Ratio)	Differential Regressivity (p.p.)	Distance to Observed Allocation	θ_{pro}	θ_{income}	$\theta_{\text{pro-income}}$	λ
Observed	4.53	1.15	-8.05	0.00	-	-	-	-
Model-Implied	4.70	1.16	-10.94	181.74	0.07	-0.14	-0.09	2.61

Note: Favoritism is the percentage point difference between ex-ante unconnected pro-Kenyatta and opposition households who received connection through LMCP. Regressivity is the fraction of ex-ante unconnected households that receive connection through LMCP that are in the highest income quintile of unconnected households, divided by 20%, which would be the equitable allocation. Differential regressivity is the percentage point difference in regressivity between ex-ante pro-Kenyatta and opposition households. Results are similar under alternative assumptions (Table B22).

surplus-maximizing allocation remains largely politically neutral. Moreover, unsurprisingly, the surplus-maximizing allocation is again highly regressive, with the top income quintile receiving 5 times the connections of the bottom quintile.

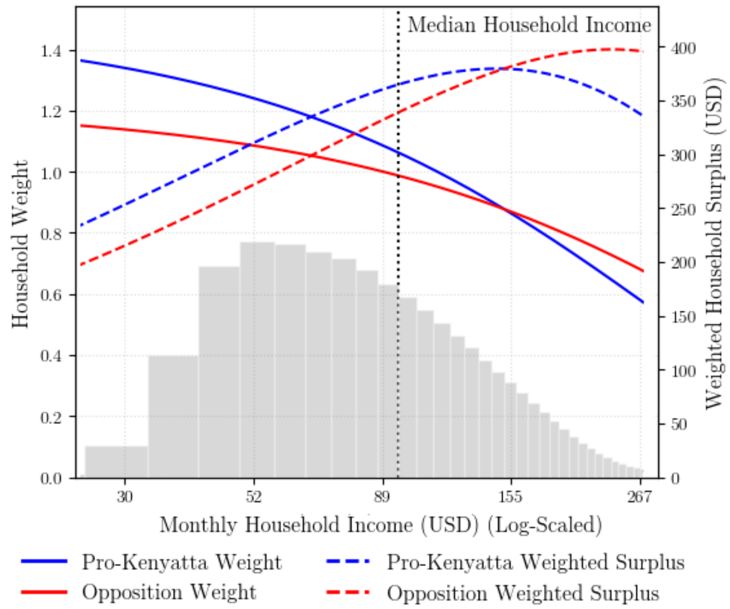
Taken together, these results suggest that political favoritism emerges as largely *orthogonal* to economic considerations. The observed, politically biased allocation does not resemble the pre-announced policy or the surplus-maximizing scenario. Alternative welfare weights ranging from pro-poor and pro-rich preferences are also unable to recreate the observed pro-Kenyatta bias, suggesting that it is not the choice of welfare weights per se that drives the main results.

7.3 Recovering the planner's implicit welfare weights

We next back out the hypothetical social planner's welfare weights that rationalize the observed allocation of meters. As described in Subsection 6.3, we simulate a model where a social planner allocates meters to maximize social surplus. The key parameters are θ_{pro}, θ_{income}, and $\theta_{\text{pro-income}}$, with λ capturing the penalty from deviating from the constituency-level CDF allocations. Concretely, pro-Kenyatta households receive θ_{pro} more weight than opposition households. Households that are one standard deviation above the mean income receive θ_{income} (if opposition) or $\theta_{\text{income}} + \theta_{\text{pro-income}}$ (if pro-Kenyatta) more weight than a household at the mean income given the same political affiliation.

Table 6 presents the parameters, estimated using Generalized Method of Moments (GMM). We are able to closely match both the favoritism and the regressivity of the observed allocation, both untargeted moments. We find higher implied weight for pro-Kenyatta users, ($\theta_{\text{pro}} > 0$), and lower-income users particularly in pro-Kenyatta areas ($\theta_{\text{income}} < 0$, $\theta_{\text{pro-income}} < 0$). Using the estimated θ_{pro}, Figure 8 presents the welfare weights for each group across the income distribution (solid lines), as well as the weighted surplus by income (dashed lines, where richer households receive more surplus from each connection). The results show that lower-income households are weighted more heavily, especially in pro-Kenyatta areas, but that overall surplus is still generally increasing in income for households in both political groups.

Figure 8: Per-household weight and weighted surplus in model-implied allocation



Note: Model-implied welfare weights across the income distribution by political affiliation. The implied distribution of funding allocation appears to be pro-poor and pro-Kenyatta. Surplus is increasing in income because connecting a higher-income household generates more surplus than connecting a lower-income household. Figure A30 shows that the results are similar under alternative assumptions.

8 Policy discussion

The preceding sections documented favoritism in Kenya's rural electrification program, and measured its welfare implications. However, the question remains of how favoritism was able to persist despite significant constitutional decentralization reforms, which helped Kenya become one of Africa's most democratic societies (Figure A1). While answering this question is beyond the scope of this paper, we discuss some plausible explanations.

Dozens of countries have enacted political and fiscal decentralization in recent decades, including India, Indonesia, Mexico, China, and Nigeria, with heterogeneous implementations and results across countries and sectors.[28] Yet Kenya's energy sector remains disproportionately centralized: only 1% of total public spending is disbursed by county governments, with 99% by the Ministry of Energy. Kenya's energy sector is 16 times more centralized than its health sector and 10 times more than its agriculture sector (Figure A32).

How did this continued centralized management of the power sector unfold? First, the 2010 constitution assigned responsibility for energy policy to both the national and the new county governments (GoK, 2010). These overlapping mandates created ambiguity about whether energy policy would be managed nationally or subnationally (WB, 2017). As a result, the central executive could retain significant political power in the electricity sector, frequently appointing top management

[28]See Rajasekhar (2021), Hamidi and Puspita (2022), Rodríguez (2018), Fedelino and Ter-Minassian (2010), and Faguet and Pal (2023).

Kenya Power positions from its political coalition and leaving county governments with little control over implementation. Indeed, in many African countries, devolution can have limited effects when legal mechanisms allow the national government to claim functions that fall under a local government's mandate (Hassan, 2020a).

At the parliamentary level, the high turnover of MPs in Kenyan elections often inhibits the development of specialized expertise, causing the legislature to often defer to the executive branch on technical matters (Opalo, 2022b). Compared with central agencies such as Kenya Power and the Rural Electrification Authority, county governments had significantly less technical expertise to implement electricity projects (Volkert and Klagge, 2022).

8.1 Favoritism in the global energy transition

Electrification—replacing technologies like steel production, gasoline vehicles, and charcoal cookstoves with electric substitutes—is a key mode of decarbonization, and one that will increase the importance of the electric grid for the global economy (IEA, 2024). In low-and middle-income countries (LMICs), these intensive margin pressures will be exacerbated by extensive margin growth: more than 600 million people in Africa alone still lack access to electricity.

In the U.S., more than 250 companies own transmission lines serving over 4,000 distribution utilities (NAICS, 2024). Yet, across 46 African countries, 42 (91%) have a single nationwide transmission company and 38 (83%) have a single nationwide distribution company. More than 90% of these monopolies are majority government-owned (Table B24). Centrally managed grids might more efficiently deploy generation and expand transmission networks by overcoming regulatory and coordination bottlenecks and pooling power generators to minimize generation costs (Cicala, 2021; Cicala, 2022; Welton, 2024; Botterud et al., 2024). At the same time, continued centralized management may increase the energy sector's vulnerability to political capture, threatening mistargeting and state capture of public resources (Briggs, 2021; Min, 2019; Mahadevan, 2024). Despite the technical efficiency gains from centralization, continued centralized management of the electricity sector may make it more vulnerable to political favoritism.

8.2 Political accountability in Kenya

This paper's main estimates of political favoritism range between 35 to 42%. While substantial in magnitude, this is smaller than the 100%–300% bias that Kenya experienced between 1964–2002, when Kenya was largely under autocratic rule (Burgess et al., 2015; Barkan and Chege, 1989). Thus, the glass is half-full: the levels of political favoritism documented in this study are far below those documented in earlier large-scale public programs in Kenya (Figure A18).

What can explain the stark contrast between earlier and current periods? A leading explanation is Kenya's democratic progress in the 2000s and early 2010s (Opalo, 2020; Burgess et al., 2015). Multiparty elections decreased the incidence of unilateral executive actions, offering evidence of increased legislative checks on executive authority. The Polity IV measure of democracy increased from 4 in 2001 ('anocracy') to 9 in 2013 ('consolidated democracy').

An independent media can also be a strong driver of democratization (Strömberg, 2015; Egorov and Sonin, 2024). The LMCP was highly publicized as a national government endeavor, and the list of sites was publicly announced in national and local news. Kenya has a relatively free press, consistently ranking at around the 65th percentile among lower-middle income countries in terms of press freedom (WPI, 2022).

9 Conclusion

This paper studies the effects of political favoritism in the context of Kenya's $788 million national electrification project. The analysis uses fine-grained electricity infrastructure and network construction data, combined with ward-level electoral outcomes and administrative data on household income and electricity consumption. The primary estimates of favoritism compare the observed allocation against an objective and transparent formula—the Constituency Development Fund (CDF) allocation rule—that had been agreed upon by pro-government and opposition members of parliament more than a decade prior to the project's launch in the spirit of promoting equity.

Even in this relatively democratic context, we find evidence of significant levels of political favoritism: constituencies that had earlier voted for the president received around 35 to 42% more household electricity connections than constituencies that voted for the opposition, relative to the official allocation that the government had committed to. A decomposition of the various stages of rural electrification shows that favoritism was driven by the two stages that were implemented centrally, and that there was no sign of favoritism in stages that were implemented locally. While locally elected MPs were consulted in the planning process, there is little evidence that they allocated electrification programs in a clientelistic way.

This paper makes a significant contribution to the existing literature on political favoritism by integrating the political favoritism results into a formal framework of economic surplus. By contrasting observed allocations with counterfactual policies, this allows us to evaluate the implications of political favoritism for efficiency and equity goals. Perhaps surprisingly, we estimate that the observed allocation generated *more* economic surplus than what would have been generated under the government's official policy allocation (the CDF formula). Furthermore we simulate what the surplus maximizing allocation would look like and it is coincides with neither the official policy rule nor with equal allocation across all households. This is a departure from some existing literature that has assumed that any deviations from the stated rule or the benchmark of equal allocations are evidence of social welfare lowering political favoritism.

The findings also offer a more nuanced perspective on the trade-off between efficiency and equity, applicable to a broad class of public programs whose returns increase with the incomes of the recipient. Political favoritism in the context of this program served to lower the aggregate surplus gain generated for households that voted for the opposition and for the country's poor, pointing to significant political and economic inequities in how the surplus gains were distributed. In addition, even greater aggregate surplus gains could have been achieved without introducing any political bias at all. In other words, the political favoritism we document appears unjustified both in terms of achieving either efficiency or equity goals in this context. While our estimates show a moderate increase in economic surplus in the short-term due to the deviation from the official program allocation, the inequality that it induces between pro-government and pro-opposition areas may lead to substantial political discontent that could undermine political legitimacy and ultimately put pressure on democratic institutions. Likewise, the social welfare maximizing allocation leads to starkly greater public investments favoring wealthy households, which may have similarly negative political consequences. More speculatively, these adverse institutional consequences might generate long-run social costs that outweigh the modest economic surplus gains.

In the coming decades, decarbonization efforts will require trillions of dollars in new investments globally to accommodate growing demand for electrical power and expanded renewable energy generation. This paper's findings underscore potential political economy difficulties in managing these investments and highlight the limitations of decentralization for constraining political favoritism in the clean energy transition.

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