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Does Decentralization Promote Poverty Alleviation? Evidence from Kenya's Constituencies Development Fund

J. Andrew Harris
New York University Abu Dhabi

Daniel N. Posner
University of California, Los Angeles

Abstract
Decentralization is thought to facilitate poverty reduction by giving power over resource distribution to officials with local knowledge about where resources are most needed. However, decentralization also implies less oversight and greater opportunities for local officials to divert resources for political or personal ends. We investigate this tradeoff by exploring the degree to which Kenya's premier decentralized development program—the Constituency Development Fund——targets the poor. Using a detailed spatial dataset of 32,000 CDF projects and data on the local distribution of poverty within Kenyan constituencies, we find that most MPs do not target the poor in their distribution of CDF projects. In places where they do, this tends to be in constituencies that are more rural, not too large, and, in keeping with the findings in Harris and Posner (2019), where the poor and non-poor are spatially segregated from one another. These factors all point to the feasibility of poverty-based targeting, rather than, as most of the literature emphasizes, political actors' motivation to pursue such a strategy. In addition to these substantive findings, we also make a methodological contribution by underscoring how aggregation to the administrative unit may truncate important variation within geographic areas, and how a point-level analysis may avoid these pitfalls.

Author Information

J. Andrew Harris
Division of Social Science
New York University Abu Dhabi
andy.harris@nyu.edu

Daniel N. Posner
Department of Political Science
University of California, Los Angeles
dposner@polisci.ucla.edu

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Introduction

When the Constituencies Development Fund (CDF) Act was passed by Kenya's parliament in 2003, it was heralded as a major tool for poverty alleviation. The language of the Act, which provided for 2.5 percent of all ordinary government revenues to be redistributed to the country's 210 electoral constituencies, emphasized that the purpose of this decentralization of allocative authority was to "ensure that a specific portion of the national annual budget is devoted to the constituencies for purposes of development *and in particular in the fight against poverty* [emphasis added] at the constituency level" (Government of Kenya 2003). Contributors to the parliamentary debates on the legislation almost uniformly echoed this objective. One Member of Parliament (MP) described the bill as heralding "a new dawn in this country" that "will help uplift the poor conditions...[and] alleviate the poverty that is deep rooted down in some of the constituencies."[1] The Minister of Finance introduced the second reading of the bill by referring to it as an extremely important piece of legislation that will "assist in alleviating poverty by ensuring that the poorest of the poor have a voice in determining what projects they want to do. It will also enable Hon. Members to assist the government in channeling whatever development funds there are to the right areas in their constituencies because they know the problems in depth."[2] Another supporter of the bill emphasized that "the shoe owner knows where it pinches most. The people in the grassroots know the problems affecting them. Therefore, if they are financed in this manner, they will know where to put that little resource effectively [...] It should not pass through the Permanent Secretaries in various ministries where they would start planning and doing things which are not applicable or beneficial to the people at the grassroots."[3]

These arguments reflect several of the major theoretical rationales for decentralization in the academic literature (Bardhan 2002; Treisman 2007; Mansuri and Rao 2013; Faguet 2014). Chief among them is the idea that, by putting decision-making power over local resource distribution in the hands of the elected officials who are closest to the people (in the case of the CDF Act, MPs elected in single member constituencies), decentralization

[1] Hon. Betty Tett, Assistant Minister for Local Government, Parliamentary Debates 27 November 2003.

[2] Hon. David Mwiraria, Minister of Finance, Parliamentary Debates, 27 November 2003.

[3] Hon. Capt. Eustace Mbuba Ntwiga, MP for Nithi, Parliamentary Debates, 23 October 2002.

will ensure that development projects are located in the places where they are most needed. This is because locally elected officials have better information about local needs than decision makers located far away in centralized bureaucracies, and also because the behavior of these officials is more readily observed by the communities they serve, thus making the officials more accountable.

The theoretical reasons to think that decentralization will aid in targeting the poor are, however, in tension with the concern that local officials may be more readily captured by the socially connected or politically valuable, or by actors who are able to provide favors or kickbacks in return for the allocation (Crook 2003; Galasso and Ravallion 2005; Mansuri and Rao 2013; Hoffmann et al. 2017). Proximity to the *wananchi* may provide access to local information, but it also implies distance from the central government and the national press—and hence less oversight, higher levels of malfeasance, and patterns of targeting that may be less favorable for the poor than the theory would lead us to expect.

We examine this trade-off between local information and local capture in the context of the first five years of Kenya's CDF program. Leveraging unique data on the precise geo-locations of 32,000 CDF projects initiated during this period, along with fine-grained data on the local distribution of poverty, we employ spatial modeling techniques to investigate whether MPs allocated CDF projects to areas with greater numbers of poor people. We find little evidence that they did. Instead, we find that, once we have controlled for other factors that may explain project placement such as local population density, distance to paved roads, coethnicity with the MP, and levels of local support for the MP in the prior election, local poverty rates are *negatively* associated with CDF project placement in most constituencies. Where MPs do target CDF resources to poorer areas, this tends to occur in smaller, less urban constituencies and where the MP is affiliated with the ruling political coalition. We also find, in keeping with the results in Harris and Posner (2019), that targeting the poor is significantly more likely in settings where the poor and non-poor are spatially segregated from one another. These findings speak to the importance of factors that affect the *feasibility* of targeting the poor, and stand in contrast to accounts emphasizing the incentives for political actors to adopt pro-poor distribution strategies.

Beyond these empirical results, the paper makes several broader contributions. A first contribution is to the literature analyzing the origins and impact of constituency development funds (Keefer and Khemani 2009; Baskin and Mezey 2014; Malik 2019), as well as to the subset of this literature that focuses explicitly on the Kenyan case (Kimenyi 2005; Bagaka 2009; Nyamori 2009; Nyaguthii and Oyugi 2013; Ndii 2014; Ngacho and Das 2014; Harris 2017). Our paper complements this prior, largely qualitative, work by bringing rich quantitative data to bear on the question of how politicians use the funds that CDF programs make available to them.

The paper also relates to the literature investigating the impact of decentralization on poverty alleviation (Alderman 2002; Crook 2003; Bardhan and Mookherjee 2005; Galasso and Ravallion 2005; Bardhan and Mookherjee 2006; Alatas et al. 2012; Carlitz 2017; Basurto et al. 2020). Although our analysis does not permit comparisons across units that were and were not decentralized, and although we do not test directly whether resources that were not targeted to the poor were stolen or captured by local elites, our evidence does shed light on whether the opportunities afforded by decentralization are seized upon by political actors to better target the poor. In this respect, our work is similar to most other efforts in the literature that take decentralization as a given and study whether the outcomes observed under such a system accord with theoretical expectations. In keeping with the results of most other studies, our findings suggest that decentralization is not associated with high rates of targeting poor areas with development resources.

The paper also speaks to the literature on aid targeting (Briggs 2014; Jablonski 2014; Öhler and Nunnenkamp 2014; Nunnenkamp et al. 2016; Briggs 2017; Öhler et al. 2019; Dipendra 2020; Wayoro and Ndikumana 2020)—especially the subset of that literature that employs highly disaggregated local data on project placement alongside covariates measured at the micro-level (Chhibber and Jensenius 2016; Carlitz 2017; Hoffmann et al. 2017; Briggs 2018a,b; Ejdemyr et al. 2018; Murray 2020). While our study joins these others in leveraging highly disaggregated data, the degree of disaggregation offered by our point-level empirical approach (described below) goes well beyond that of other research. For example, the analysis presented in Briggs (2018b) employs 0.5 x 0.5 degree grid cells as its unit of analysis. There are approximately 234 such grid cells in Kenya (including those that span the borders between Kenya and its neighbors). Our main analysis, by contrast, is built on an analysis of more than 32,000 point-level observations, allowing us to understand the determinants of project placement across continuous space. As we describe below, this extremely high degree of disaggregation allows for much more precise and meaningful estimates of the local relationship between poverty rates and patterns of

CDF project placement.

Our study also contributes to the aid targeting literature by studying the distribution of development funds within nearly 200 distinct constituency-level units, rather than, as is usually the case in such analyses, within a single country. This makes it possible to investigate the ways in which both local conditions and the characteristics of the political actors making the allocation decisions shape the ways in which development funds are targeted. As we demonstrate, such factors are critically important in explaining when and where MPs target the poor with their CDF funds.

Finally, our study contributes to the growing literature on political geography (Enos 2017; Jusko 2017; Ejdemyr et al. 2018; Rickard 2018; Rodden 2019) by demonstrating the critical importance of the spatial distribution of poor people in explaining distributive patterns. As in Harris and Posner (2019), our findings suggest that analyses that fail to incorporate the spatial distribution of key groups may generate misleading conclusions about how distributive politics operates.

The Constituencies Development Fund (CDF) Program in Kenya

During the period we study (2003-2007), Kenya's national CDF Fund provided each MP with an average of $316,709 per year to be used for any project whose "prospective benefits are available to a widespread cross-section of the inhabitants of a particular area" (Government of Kenya 2003). These funds, which were distributed equally to each constituency with some adjustments based on each constituency's poverty rate, underwrote an average of 157 projects per constituency (min= 11; max= 425).[4]

Although CDF funds were technically disbursed from the central government to constituency-level CDF committees, their local distribution was effectively controlled by the MP, who determined which projects were funded and where they were located.[5] The CDF program thus presented each MP with a large, annually replenished, exogenously determined sum of money that, subject to minimal restrictions, could be allocated within his constituency with nearly total discretion.[6] This provides an ideal opportunity to observe whether po-

[4]Further details of the CDF program's origins and details are provided in Harris and Posner (2019).

[5]Hornsby (2013) describes the MP's powers to distribute CDF funds during this period as "almost unchecked."

[6]Only three percent of the MPs in our sample are female, so we use the male pronoun throughout for

litical actors to whom decision making authority has been decentralized distribute the resources they control with an eye toward poverty reduction. And since we can observe such distribution decisions in 196 separate contexts, we can also draw important lessons about the conditions under which they pursue such a strategy.[7]

Data

To assess whether MPs use their CDF allocations to help their poorest constituents, we estimate the spatial association between CDF project placement and local poverty rates. This requires geo-coded data on both project locations and local poverty rates, as well as fine-grained spatial data on the other covariates we include in our analyses.

CDF Project Locations

The CDF project data we utilize come from the annual reports that MPs are required to submit to the national CDF Board. These reports provide project names (e.g., Mwachema borehole; Olopito Dam repair; Chitago Primary School refurbishment), information about the activity completed, and the amount of money allocated to the project in that year. The reports do not, however, provide geo-coordinates of project loctions. We estimate these locations by matching the project names to the names of facilities for which point or polygon data are available—for example, schools, market towns, health centers, or water/irrigation features. Using this approach, we were able to match 60 percent of all 32,699 CDF projects in our data set to an exact geo-referenced point. In cases where we were not able to match a project to a specific point, we randomly placed the project at a point within the smallest unit to which we could assign it, with the probability of placing the project at each point in the unit proportional to the estimated population density at that point. In roughly a third of these cases, the unit to which we match the project has an area of 1 square kilometer or less; in another another 12.5 percent of cases, it was an area of 2.5 kilometers or less—both well inside the radius within which residents would benefit from most projects. In all, 80 percent of projects were placed within an area smaller than

simplicity.

[7] Kenya had 210 constituencies during the period we study. However, fourteen constituencies are excluded from the analysis due to lack of data on CDF projects.

0.5 percent of the total constituency area and 88.3 percent within an area smaller than 5 percent of the constituency area.

To account for measurement error in our imputation of project locations, we created 21 separate data sets of imputed project locations and ran all of the analyses in which project locations are the dependent variable on each of these 21 separate data sets. The results we report below are the average coefficient estimates of these 21 separate regressions, with standard errors calculated following the procedures discussed in King et al. (2001).

In the first set of analyses we present below, we aggregate project locations to the sublocation level. In the later analyses, we use the precise point-level estimates of project locations.

Explanatory Variables

We use data described by Tatem et al. (2015) to create constituency-level rasters containing estimates of the number of people living in poverty in each one-square kilometer grid cell. We do this by combining information from a population density raster (Linard et al. 2012) with information from the Kenya 1km poverty raster, which reports the proportion of individuals in a grid square below the poverty line. To arrive at a count of those falling below the poverty line for each grid square, we reproject the poverty data to match that of the population density raster and then multiply the poverty raster by the population density raster.

In some of the analyses we present below, we also control for a series of other factors that we have reason to believe may shape the distribution of CDF funds. The first of these covariates is population density, which we measure using data from Linard et al. (2012), as noted. Population density may matter for project allocations insofar as MPs seek to help the greatest number of people and/or avoid placing projects where very few will benefit. We also utilize the World Bank/Kenya Ministry of Roads and Public Works dataset (Government of Kenya 2006) to create a raster identifying the square of the distance from each point in each constituency to a paved road. Since projects located closer to paved roads are cheaper to build, and since MPs have incentives to try to stretch their limited budgets, we might expect areas located closer to paved roads to receive more CDF projects.[8] Controlling for distance to roads is also appropriate because most CDF projects involve repairs or upgrades to existing infrastructure—schools, clinics, water points, etc.—and most such infrastructure is located close to roads.

MPs may also seek to use the CDF funds to favor their ethnic kin and/or reward their political supporters. We control for the former using polling station-level estimates of ethnic demographics from Harris (2015) and linking them to a geo-referenced polling station dataset.[9] We combine these two data sources to create rasters for each constituency identifying the estimated number of the MP's coethnics at each point in each constituency. We test for the MP's partisan connection to voters at every point in the constituency using similarly constructed data built from polling station-level electoral returns from Kenya's 2002 parliamentary elections. These elections took place a year before the launch of the CDF program and can thus be taken as exogenous to any effects that the program might have subsequently had on election outcomes.

Although our main objective in this paper is to estimate the spatial association between poverty and project placement, a secondary aim is to demonstrate the value and power of disaggregated data in understanding how benefits are targeted to constituents. To this end, we begin with an analysis aggregated to the sub-location level—the smallest administrative unit in Kenya—representing the functional limit of an aggregated polygon-based approach to the study of targeting. Then, we contrast these results with our findings using point-level data.

A Sublocation-Level Analysis of Pro-Poor Targeting

Investigating whether CDF funds are used to target the poor requires analyzing project allocation decisions at the constituency level, since this is the level at which decisions are made about which CDF projects will be funded and where they will be placed. As a first cut, we aggregate our data to the sublocation level, estimating within each constituency whether sublocations with higher poverty rates receive more CDF projects.[10]

[8] This expectation accords with the finding in the aid targeting literature that development aid tends to be channeled disproportionately to places that are more easily accessible (Brass 2012; Briggs 2019).

[9] See Harris and Posner (2019, Appendix B) for detail on this data construction process.

[10] Kenya contains roughly 6,000 sublocations, with an average of about 30 per constituency (min = 6; max = 101). Sublocations have a median area of about 15 square kilometers (min < 1 sq. km.; max > 4,500 sq.

This approach is in keeping with other studies of aid targeting and distributive politics, which aggregate their analyses to various administrative units: the district (Weinstein 2011; Burgess et al. 2015; Masaki 2018), the constituency (Jablonski 2014), the village (Chhibber and Jensenius 2016; Hoffmann et al. 2017), the ward (Carlitz 2017), or the census enumeration area (Ejdemyr et al. 2018; Briggs 2018a).[11]

Figure 1 plots the distribution of CDF projects allocated to each sublocation in each constituency, grouped by province. As the Figure makes clear, most constituencies exhibit significant variation in the number of CDF projects allocated to each sublocation, ranging from zero projects in many sublocations to more than thirty in a handful of others. Figure 2 presents parallel plots of sublocation-level poverty rates in each constituency, again with constituencies grouped by province. As in Figure 1, Figure 2 shows that most constituencies exhibit significant variation in sublocation-level poverty rates. For our purposes, the relevant question is whether these patterns of variation in poverty and in project allocation within constituencies are correlated. Do sublocations with higher poverty rates receive more CDF projects?

To answer this question, we regress the number of CDF projects in each sublocation on sublocation-level poverty rates. As shown in Figure 3, we find a robust negative relationship: poorer sublocations receive *fewer* CDF projects. Our results hold whether or not we measure CDF projects in each sublocation with a count variable or with an indicator of whether the sublocation received any CDF projects at all and whether we operationalize poverty as the share of the population in the sublocation living below the poverty line or whether the sublocation's poverty rate is above or below the median in the constituency.[12] The results suggest strongly that MPs do not target CDF projects to the poorest sublocations.

km.) and a median population of about 3,700 (min < 10; max > 120,000.), according to 2009 census data.

[11] Briggs (2018b) takes a slightly different approach, aggregating not to a pre-existing administrative unit but to the 0.5 x 0.5 degree grid square.

[12] The results are also robust to including or excluding constituency fixed effects. The results shown in Figure 3 are from models that include constituency fixed effects.

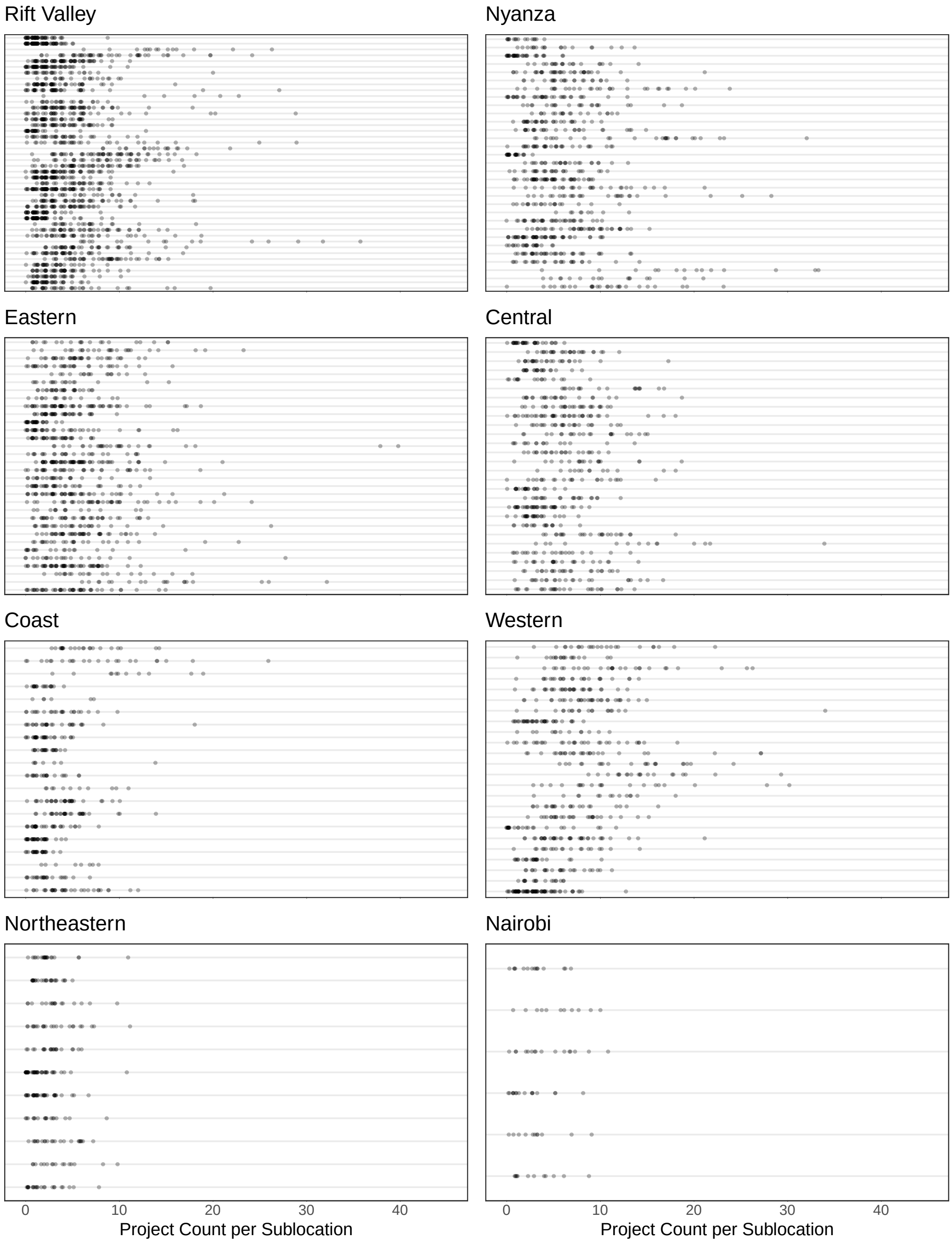

Figure 1: Lineplot of sublocation-level project counts by constituency, sorted by province, 2003-2007. Tick marks indicate the number of CDF projects allocated to each sublocation.

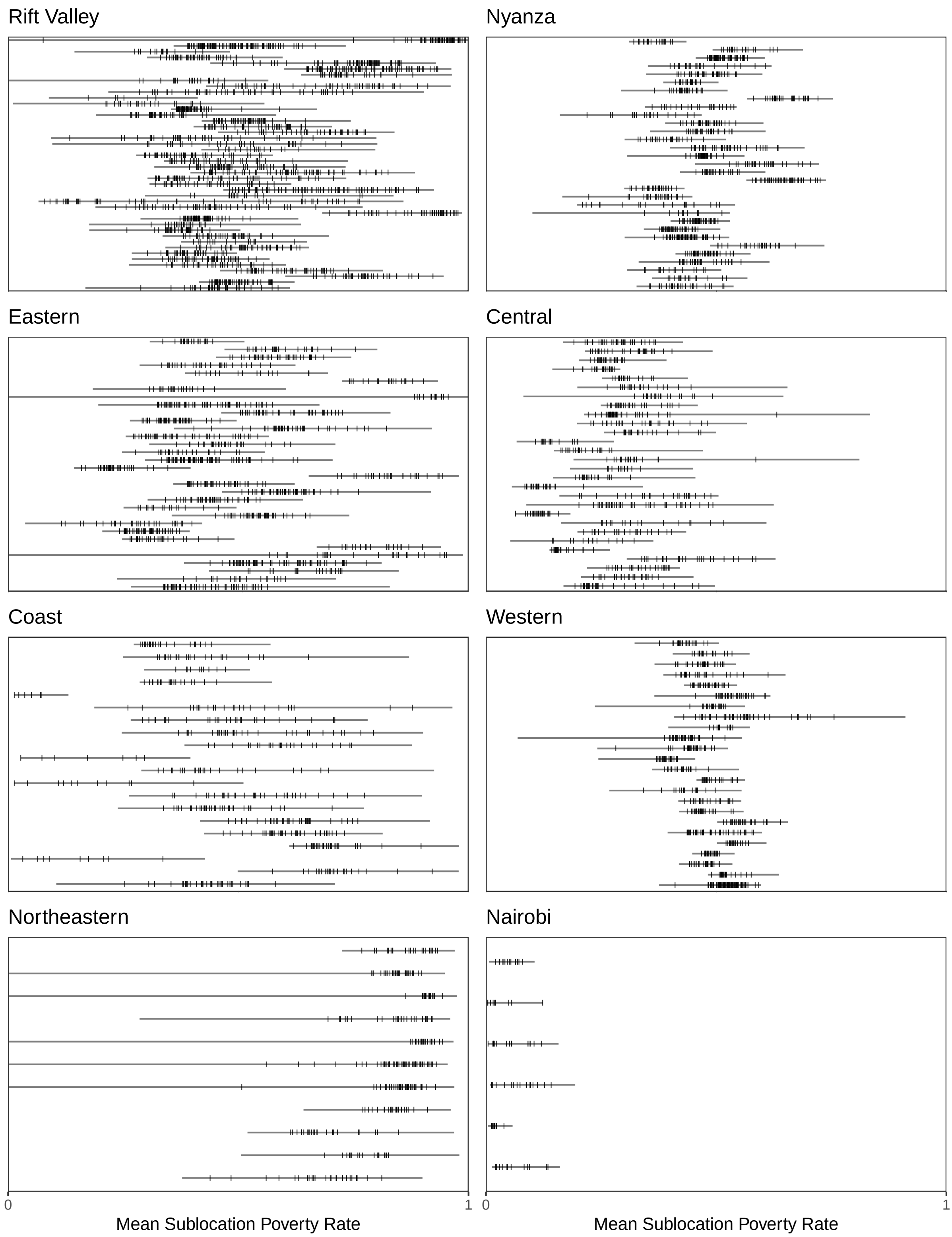

Figure 2: Lineplot of sublocation-level poverty rates by constituency, sorted by province. Tick marks indicate the share of the population in the sublocation living below the poverty line.

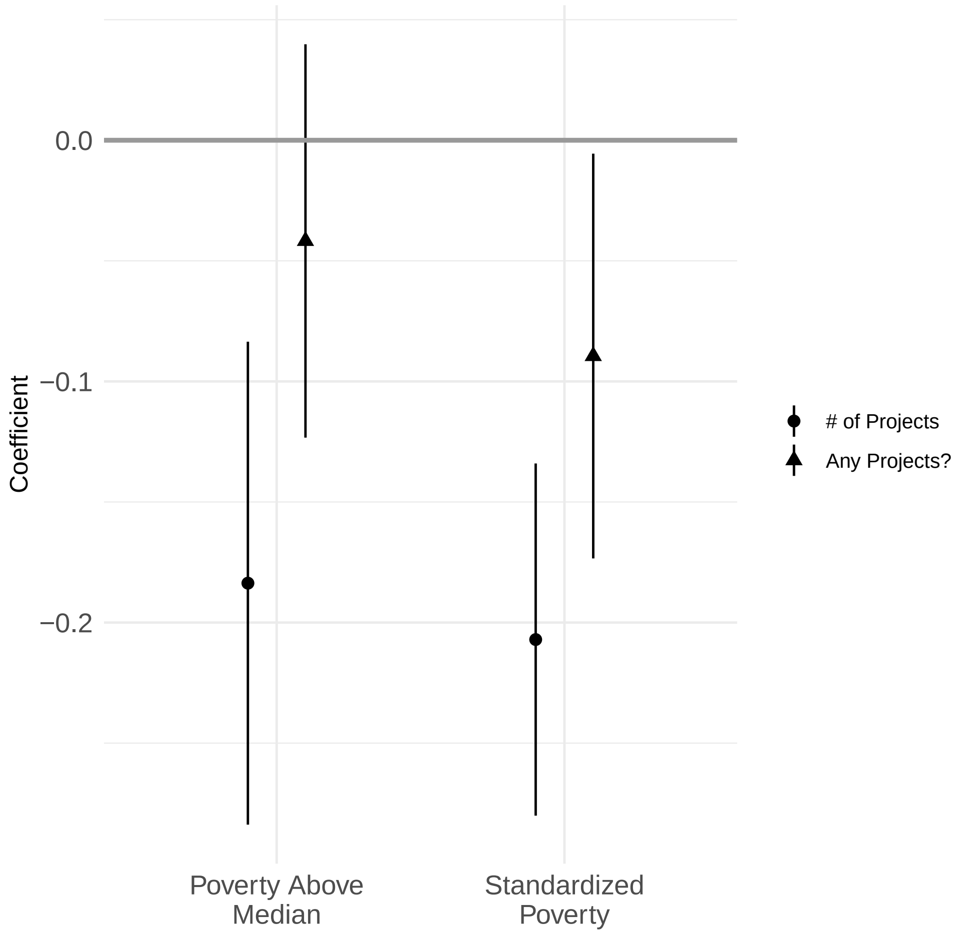

Figure 3: Predicting CDF project outcomes using poverty rates. The plotted coefficients show that CDF project placement, whether measured as a count or an indicator of project presence within a sublocation, exhibits a negative relationship with average sublocation poverty rates.

Several factors caution against reading too much into these findings, however. First, the analysis does not control for sublocation population or proximity to roads, which earlier work has found to be important in shaping where CDF projects are placed (Harris and Posner 2019).[13] In addition, the analysis does not consider political or ethnic factors that may have caused CDF projects to have been placed in some sublocations rather than others, perhaps overriding considerations of poverty alleviation. Ideally, we would want to estimate the relationship between poverty and project placement net of these factors.[14]

Second, the aggregation of poverty rates and CDF project counts to the sublocation level may obscure significant within-sublocation variation.[15] In Figure 2, the horizontal lines represent the full range of pixel-level poverty rates in each constituency, while the tick marks indicate the average poverty estimates at the sublocation level. In most constituencies, the horizontal line extends well beyond the range of the tick marks, indicating that there is a great deal of variation in poverty rates within sublocations that is not captured in the aggregated sublocation-level figures. Given this hidden within-sublocation variation, we cannot rule out the possibility that, consistent with a commitment to alleviating poverty, MPs may in fact have placed CDF projects in the poorer areas of each sublocation, even if they did not place more projects in poorer sublocations. Aggregated

[13] Indeed, when we regress the sublocation level poverty headcount on the number of CDF projects, we find a significant positive relationship (see Appendix B, Figure B1). While it might be tempting to interpret this as evidence that MPs are targeting the poor, a more likely explanation is that MPs are putting projects in more populated sublocations, which, because of the generally high levels of poverty everywhere, happen to have large numbers of poor people.

[14] Briggs (2018b) argues that, for a purely descriptive analysis of whether poorer people are more likely to get CDF projects, one would not want to include control variables, noting that "aid can help the poor only if it reaches the poor—and from this point of view it does not matter if the mechanism causing it to reach the poor is something other than poverty" (134). However, our question of interest is not whether poor people get CDF projects but whether MPs target the poor when they decide where to place those projects. We are interested in an allocation decision rather than a descriptive outcome. Our view is that we can only understand this allocation decision if we can rule out the other explanations that we have reason to believe also affect MPs' choices regarding project placement (such as seeking to reduce the cost of locating a project in a particular place, seeking to reward supporters or coethnics, or seeking to maximize the number of people who will benefit from the project, irrespective of their poverty).

[15] This relates to the well-known modifiable unit area problem, in which continuous spatial phenomena (e.g., population density) are aggregated into discrete units like sublocations (Wong 2004). See Gerell (2017) for an empirical examination.

sub-location level analyses obscures this possibility by averaging over actual variation within a sublocation—variation which can be numerically and substantively important.

Figure 4, which displays CDF project locations and local poverty rates estimated at the point-level in two sublocations in Nyakach Constituency, demonstrates how much is missed by aggregating to the sublocation. In the analysis summarized in Figure 3, the only relevant information about these two sublocations is the number of CDF projects they each contain (12 and 15 projects, respectively) and their average poverty rates. The analysis ignores the fact that, in both sublocations, the eastern side is poorer than the western side (indicated by the darker shading). If MPs are allocating projects with an eye toward poverty reduction, we would expect more projects to be located in the eastern portion of each sublocation than in the west. Aggregating to the sub-location level makes it impossible to test this key observable implication.

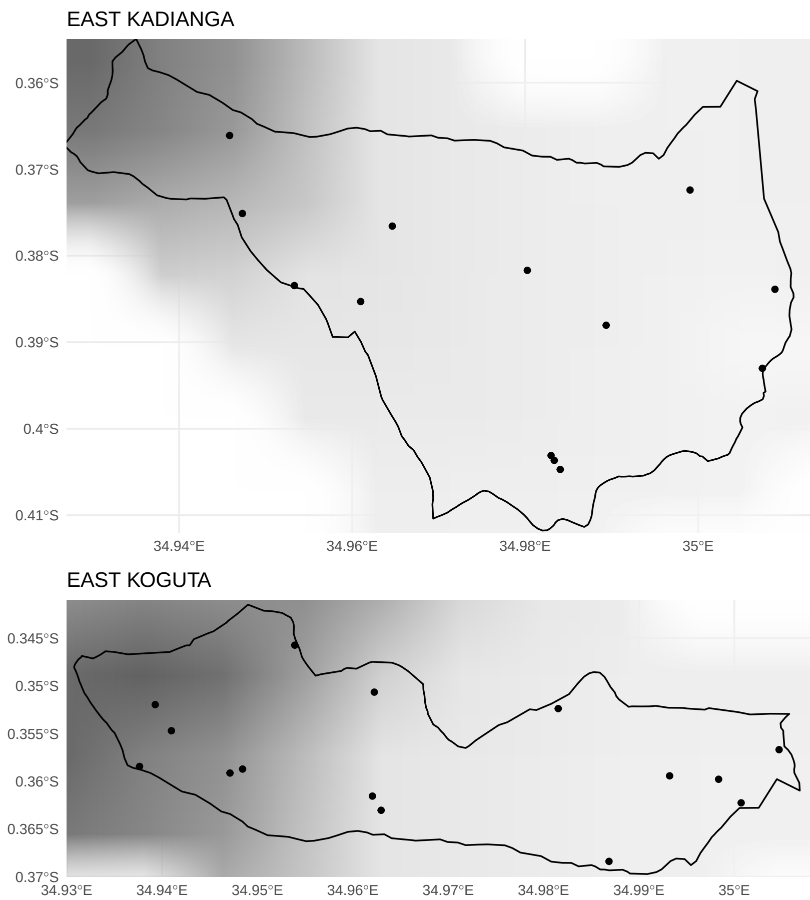

Figure 4: Project placement and variation in local poverty rates. Darker shading indicates higher poverty rates.

We also observe that the projects are not spread evenly across the space of each sublocation. In some instances they are bunched right on top of one another (implying that some areas of the sublocation are receiving lots of benefits, while other areas are not). In addition, many of the projects are located right on the sublocation boundary—often because sublocation boundaries are defined by roads and because projects, which tend to be sited at schools, clinics, or other infrastructure, tend to be located close to roads. The implication is that the benefits of many projects are consumed equally by people residing in adjacent sublocations, raising questions about the logic of assigning "credit" for poverty alleviation to just one jurisdiction.

These considerations point to the desirability of investigating the link between poverty and CDF project placement without aggregating project counts and poverty rates to the level of artificial administrative units like sublocations. If MPs were only able to target projects to broad sections of their constituency (as they might if they were building a bridge or a new road that served a wide area), then analyzing patterns of project distribution at the sublocation level might make sense. But most CDF projects are small in scale—a dispensary; a cattle dip; a refurbished classroom or a new latrine at a primary school—and provide benefits only for the populations living within a short distance from them. This implies the desirability of undertaking one's analysis of project placement at the most fine-grained level possible. Furthermore, to the extent that MPs make their decisions about where to place CDF projects in response to information about local poverty rates, this information unfolds in the continuous space of their geographic constituency (and even within and across sub-locations, as illustrated in Figure 4). Aggregation to higher-level administration units thus hides important and theoretically interesting variation from analysis.

A Point-Level Analysis of Pro-Poor Targeting

Our solution to these aggregation problems is to leverage the point-level data we have gathered, treating the distribution of CDF projects as a Poisson point process that varies across space as a function of the local poverty levels and other covariates (Gatrell et al. 1996; Diggle 2013).[16] While point process models have long been used in fields like

[16] Technical details of the Poisson point process model are provided in Appendix A. For a more thorough discussion of the approach, and an application to the question of whether MPs use CDF funds to favor their supporters, see Harris and Posner (2019).

ecology (e.g., Warton and Shepherd 2010) and seismology (e.g., Ogata 1999), such models have only more recently been adopted by social scientists to study topics such as policing (Baudains et al. 2019), crime (Mohler et al. 2011), and political violence (Warren 2015; Reeder 2018).

As discussed in Harris and Posner (2019), a complexity that arises from the move to a point-level analysis is that many areas in Kenya are uninhabited, or very nearly so. Since CDF projects are very unlikely to be placed where there are no people, this skewed population distribution generates a strong mechanical correlation between population density and the number of people living in poverty when measured at the pixel level. To deal with this problem, we regress, in each constituency, (the log of) population density on the number of people living in poverty, and then use the residuals from these regressions in lieu of our direct measure of local poverty (we do similarly with the other population-based covariates we include in our models as well). This allows us to interpret the estimated spatial association between project placement and the number of people living in poverty as capturing the effect of the part of our local poverty measure that is not due to population density.[17]

Constituency-Level Analysis

Figure 5 presents the results of our point-level analysis of the spatial relationship between poverty rates and CDF project placement. Each boxplot presents the constituency-level estimates for each of the 196 constituencies for which we have data.[18] The first column in Figure 5 presents the bivariate constituency-level relationships between project locations and (residualized) poverty. The second through fifth columns add controls, respectively,

[17] This choice is predicated on how population is spread across space. As in most countries, humans in Kenya tend to cluster in towns, villages, and cities, meaning that much of the countryside is very sparsely populated. As a result, a simple approach using the numbers of people below the poverty line means that this variable will show a high correlation with other population-related variables. The sign change on the estimates in Figure 3 and Appendix B, Figure B1 provides one example of this empirical issue. The residualization approached used here and in Harris and Posner (2019) provides one way to address this issue.

[18] As noted earlier, these constituency-level estimates are the average of 21 separate regressions, each using a slightly different set of imputed project locations, thus explicitly taking spatial measurement uncertainty into account.

for population density, the (square of the) distance to paved roads, the (residualized) number of coethnics living in the area, and the (residualized) number of people living in the area that voted for the MP in the last election. The final column presents the association between project placement and (residualized) poverty, conditional on all four of these additional covariates.

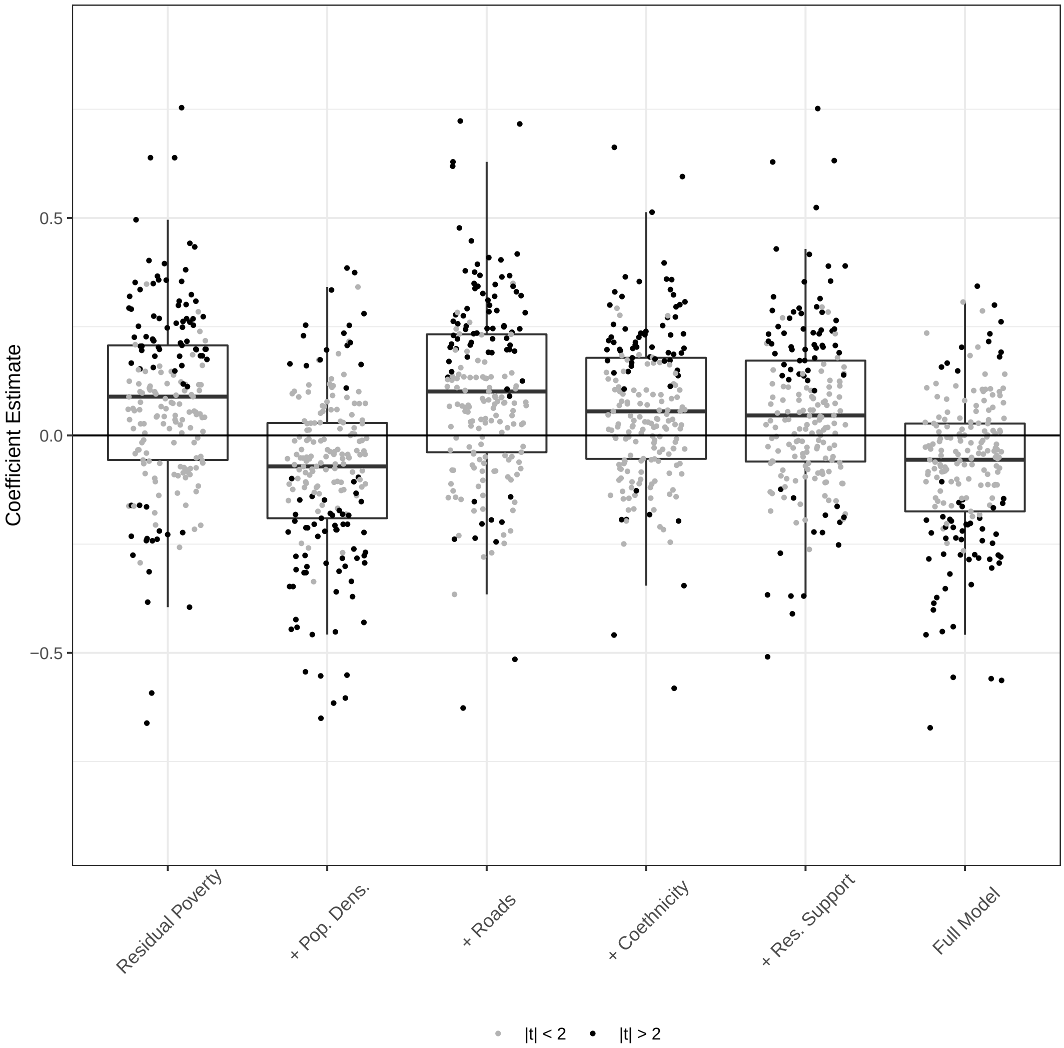

Figure 5: The impact of local poverty on CDF project placement. Each dot represents a constituency-level coefficient estimate, with coefficients that are statistically different from zero (with a $t-$statistic > 2) plotted in black and those not significantly different from zero plotted in grey. The left-most boxplot shows the bivariate relationship between project placement and (residualized) poverty. The next four present the relationships between project placement and (residualized) poverty, controlling for the listed covariate. The right-most boxplot shows the relationship between the project placement and (residualized) poverty, controlling for all of the covariates added in columns 2-5.

The estimates reported in the first column indicate a positive relationship in most constituencies between poverty rates and CDF project placement (although the relationship in the median constituency, indicated by the dark horizontal bar in the middle of the boxplot, is not statistically significant at conventional levels). Viewed alongside the results of the sublocation-level analysis, which found a robust *negative* relationship between poverty and project locations in the bivariate regressions, these findings underscore the extent to which the aggregated analysis misses a good deal of within-sublocation targeting.

Beyond this general finding, the patterns in column 1 also suggest significant heterogeneity in the extent to which MPs target the poor with CDF projects. While we find a significant positive association between local poverty and CDF project placement in some constituencies, we find a significant negative association in others. Meanwhile, in a large number of constituencies (indicated by the grey dots), there is no statistically significant relationship at all between the rate of poverty in an area and its likelihood of receiving a CDF project.[19]

The other columns in Figure 5 show what happens to the bivariate relationship between poverty and CDF project placement when additional controls are added to the analysis. Although conditioning on (the square of the) distance to paved roads, coethnicity with the MP, and levels of political support in the last election (columns 3-5) does not significantly change the distribution of outcomes vis-a-vis the biviariate relationship depicted in column 1, the addition of a control for population density (column 2) alters the results sufficiently to flip the sign of the relationship between poverty and project placement in the median constituency. This change carries over to the full model (column 6), which reports the results of the analysis that includes all four additional covariates. When we control for population density, distance to roads, coethnicity with the MP, and levels of political support for the MP in the last election, the relationship between poverty and CDF project placement is negative (although not statistically significant) in the median constituency.

Yet, as with the bivariate results reported in column 1, this finding belies considerable cross-constituency variation. Once we have controlled for these other factors that shape where MPs place CDF projects, many MPs would appear not to target the poor—notwithstanding the rhetoric about poverty alleviation that accompanied the launch of the

[19]This pattern of heterogeneity in targeting of the poor is similar to that found in Galasso and Ravallion (2005).

CDF program. However, against this general trend, we do see a significant positive relationship between poverty and CDF project placement in a handful of constituencies. What accounts for these differences? Why do MPs seem to adopt pro-poor distribution strategies in their allocation of CDF resources in some constituencies but not others?

Cross-Constituency Analysis

Theory and local knowledge of the Kenyan case point to several factors that may account for the cross-constituency variation we observe in whether MPs target the poor with their CDF funds. A first variable to consider is the MP's gender. Recent research in Africa finds that both female parliamentarians and women in general attach greater importance to poverty alleviation than their male counterparts (Gottlieb et al. 2018; Clayton et al. 2019). We might therefore expect female MPs to be more likely to use their CDF funds to target the poor.

A second potentially relevant factor is the vote margin in the prior election. Close vote margins imply greater electoral competitiveness, which in turn implies stronger incentives for incumbent MPs to be strategic in how they deploy the resources they control to maximize their chances of re-election. As Bates (1987) notes, "public officials are frequently less concerned with using public resources in a way that is economically efficient than they are with using then in a way that is politically expedient." What matters, Bates (1987) underscores, is that the resources are used "as an instrument for building a rural political constituency." To the extent that channeling CDF projects to the poor is at cross purposes with building such a political constituency, closer vote margins may be associated with a weaker relationship between poverty and project placement.

A third factor that may shape the extent to which MPs target the poor is the MP's membership in the ruling political coalition. Although CDF resources represent a considerable source of funding for local public goods provision, they are not the only source. Central government ministries also spends millions of dollars a year on roads, schools, health facilities, and other local infrastructure. To the extent that MPs with ties to the ruling coalition have a greater ability to direct how central government funds are deployed within their constituencies, they may be able to use these resources to help secure their re-election, thus freeing up CDF funds for poverty alleviation. This would lead us to expect a closer relationship between poverty levels and project placement in constituencies controlled by ruling party MPs. Alternatively, having some control over ministry-based funding could lead ruling party MPs to use those central government resources to target the poor, freeing up CDF funds to win votes. This would imply lower levels of targeting the poor. Or, MPs might use some mixture of these two strategies. As a result, we have no strong expectation about the sign of this coefficient.

A fourth potentially relevant factor is the constituency's ethnic heterogeneity. A significant body of research suggests that public officials in Kenya tend to distribute goods with an eye toward rewarding their coethnics (Barkan and Chege 1989; Burgess et al. 2015; Kramon and Posner 2016). To the extent that the expectations underlying such behavior are stronger in ethnically mixed environments, where group comparisons are more relevant (Tajfel and Turner 1979), we might expect to find a stronger tendency toward ethnic allocations in more ethnically heterogeneous settings. And to the extent that the impetus to channel CDF projects toward one's coethnics conflicts with the impetus to channel projects to the poor, we may expect to find weaker patterns of pro-poor targeting in ethnically heterogeneous constituencies.

An additional set of factors speaks less to politicians' motivations to use their CDF funds to target the poor than to the feasibility of pursuing such a pro-poor strategy. For example, targeting the poor may be especially challenging in very large constituencies of Northeastern, Coast, and the northern parts of Eastern and Rift Valley Provinces, where the poorest constituents tend to live in remote areas that are difficult to reach with CDF projects. It may also be challenging in very urban constituencies, where poverty is much less pronounced and where the poor and the non-poor are interspersed with one another, making it difficult to target the poor without also putting projects in close proximity to those who are better off.[20] This latter consideration suggests a broader factor that may be relevant outside of urban constituencies as well: whether the poor and the non-poor are spatially segregated from one another.[21] Harris and Posner (2019) find that the segregation of a Kenyan MP's political supporters and opponents matters critically

[20] According to data from Kenya's 2008-09 Demographic and Health Survey (Kenya National Bureau of Statistics and ICF Macro 2010), 78.5 percent of urban residents are in the highest wealth quintile, compared to just 6 percent of rural residents.

[21] We measure segregation using the spatial information theory index described in Reardon and O'Sullivan (2004).

for the MP's ability to reward his supporters, and Ejdemyr et al. (2018) find similarly with respect to the ability of Malawian MPs to favor their coethnics. It stands to reason that an analogous logic may apply for politicians seeking to channel CDF projects to the poor.

We test these hypotheses by regressing the constituency-level conditional association between project placement and poverty rates, as depicted in the "full model" column in Figure 5, on variables capturing the seven factors just discussed. We present bivariate and multivariate models using weighted least squares to account for the fact that our outcome variable is an estimated coefficient with a standard error (Lewis and Linzer 2005).[22] We divide all continuous covariates by two standard deviations to facilitate direct comparison with dichotomous covariates (Gelman 2008). Our results are presented in Table 1.

Notwithstanding the strong evidence that women are more concerned with poverty alleviation than men, we find no statistically significant impact of an MP's gender on pro-poor targeting. If anything, we find some evidence that constituencies with female MPs have weaker associations between poverty and CDF project locations. We caution, however, that this result is driven by a very small number of female MPs in our sample—just six—so we hesitate to read too much into this finding.

We find no evidence that the vote margin in the last election affects whether MPs use the CDF resources they control to target the poor. This null result may stem from the fact that Kenyan MPs are rarely secure in their re-election likelihoods. While political parties are very adept at retaining the seats they have won in past elections, the candidates who occupy those seats tend to change from contest to contest, largely because parties decline to renominate incumbent MPs more than 60 percent of the time (Choi 2020). This implies that, in the Kenyan setting, the margin of victory may not, in fact, be a good proxy for whether or not a seat is "safe" from the point of view of the incumbent, and thus not a strong predictor of the MP's behavior while in office. Almost all Kenyan MPs need to be thinking about their re-election and, as Choi (2020) suggests, this may have more to do with winning the support of the party that controls the re-nomination process than with winning the support of voters through poverty alleviation or other strategies.

We do find robust evidence that membership in the ruling coalition matters. MPs

[22] An alternative specification using ordinary least squares is presented in Appendix B, Table B1.

Table 1: What factors are associated with targeting the poor?

	Targeting of projects to poor areas								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Female MP	−0.11							−0.13	−0.11
	(0.09)							(0.09)	(0.08)
Vote margin in last election		0.03						0.03	0.001
		(0.03)						(0.03)	(0.02)
Member of ruling coalition			0.05^{*}					0.05^{*}	0.08^{***}
			(0.03)					(0.03)	(0.02)
Ethnic heterogeneity				−0.56				−0.08	−0.35
				(0.42)				(0.44)	(0.38)
Constituency area					-0.03^{*}			-0.04^{**}	-0.10^{***}
					(0.01)			(0.02)	(0.02)
Urban						−0.09		-0.19^{**}	-0.33^{***}
						(0.07)		(0.07)	(0.07)
Segregation of poor							0.09^{***}		0.19^{***}
							(0.02)		(0.02)
Observations	196	196	196	196	196	196	196	196	196
R^2	0.03	0.03	0.04	0.04	0.05	0.04	0.11	0.11	0.33
Adjusted R^2	−0.01	−0.01	0.003	−0.01	0.005	−0.01	0.07	0.04	0.28

Note: All models include province fixed effects and are estimated via weighted least squares. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

who are affiliated with the ruling party are significantly more likely to favor the poor in their allocation of CDF projects. Combined with the finding in Harris and Posner (2019) that MPs affiliated with the ruling coalition are less likely to target their supporters, this pattern is consistent with a strategy of prioritizing re-election over helping the poor. Ruling party MPs, who have influence over the distribution of central government ministry funds by virtue of their membership in the governing coalition, use these ministry resources to reward their political allies, leaving their CDF funds available for targeting the poor. MPs outside of the ruling coalition, who lack access to these alternative development resources, use their CDF funds for strategic political ends, and thus neglect the poor in their distribution strategies. We find no evidence, however, that MPs operating in more ethnically heterogeneous constituencies behave any differently from their counterparts in more homogeneous constituencies with respect to targeting the poor with CDF funds.

The last three factors we investigate—whether the constituency is large or urban and whether the poor are spatially segregated from the non-poor—are all statistically significant in the multivariate models, suggesting that the *feasibility* of targeting the poor may matter more than whether the MP is motivated to try. We find that CDF projects are much less likely to be targeted toward the poor in large constituencies, likely because of the challenges in targeting anyone in constituencies that are vast and sparsely settled, combined with the special challenges of targeting the poor, who tend to live in remote locations. We also find that CDF projects are more likely to be targeted toward the poor in rural than in urban constituencies, largely because, as suggested earlier, it is challenging to separate the poor from the non-poor in densely packed urban settings where poverty rates are quite narrowly distributed. A comparison of the bottom two panels in Figure 2, which show the lineplots of sublocation-level poverty rates in Northeastern Province (the area of the country with the largest constituencies) and Nairobi (the area with the most urban constituencies), helps make this point clearly. In Northeastern, which contains several second-tier urban areas (e.g., Garissa, Wajir, Moyale) with relatively low poverty rates and large expanses of rural territory with high poverty rates, we see wide variation in pixel-level poverty rates, with most sublocation averages bunched toward the upper edges of the scale. In Nairobi, we see the opposite: very little variation in poverty rates, with most pixels bunched at the lower end of the spectrum, indicating generally low poverty rates in most sublocations. Both of these situations create challenges for MPs to target the poor—and for our ability to identify such targeting given our strategy of looking for spatial associations between local poverty rates and CDF project locations.

We also find that constituencies in which the poor are segregated from the non-poor are significantly more likely to have positive associations between poverty and CDF project placement. As indicated by the seven-fold increase in the adjusted R-squared when we add the *segregation of poor* variable to our analysis, the spatial segregation of the poor matters a lot. The implication, which echoes the findings in Harris and Posner (2019) and Ejdemyr et al. (2018), is that analyses that fail to include such spatial variables may generate incomplete, and possibly misleading, conclusions about how politics operates.

Conclusion

The spatial patterns explored in our analyses speak to the degree to which Kenyan politicians have taken advantage of the decentralized power they were given over the distribution of CDF resources to target the poorest areas of their constituencies. Our finding that MPs generally do not use this discretion to target the poor is in keeping both with the empirical literature on decentralization and poverty reduction (see Mansuri and Rao (2013) for a summary) and with the broader literature on the motivations of political actors in settings like Kenya (e.g., Bates 1981). What is more novel is our demonstration of the extent to which MPs' poverty targeting behavior is fundamentally constrained by human geography.

Most of the literature on distributive politics emphasizes the *motivations* of politicians to target one constituency rather than another. Our results underscore the importance of also examining the extent to which politicians have the *opportunity* to target particular constituencies—and the degree to which the distribution of people in space fundamentally shapes this opportunity. Our analyses suggest that the poor are underserved not just because politicians lack incentives to target them with development resources but because they are challenging to reach.[23]

Our research underscores the power of highly disaggregated, point-level data to generate important insights about distributive politics. We nonetheless acknowledge the lim-

[23] Briggs (2019) makes a similar point with respect to the targeting of World Bank project aid.

itations of making inferences about complex processes on the ground based on associations in data collected remotely in an observational study—even when using detailed, comprehensive data like our own. For example, an alternative explanation for our finding of a weak relationship between local poverty rates and CDF project placement is that the poor are unable to mobilize to demand that projects be located in their areas (Baird et al. 2013).[24] To the extent that this alternative explanation holds, the lack of evidence for pro-poor targeting of CDF funds by MPs stems from demand- rather than supply-side forces.[25] Detailed case study research into this, and other, hypotheses would complement our quantitative analyses and deepen our understanding of the links between poverty and CDF resource distribution.

Our findings are also limited by our singular measure of poverty, which captures the number of people living below the poverty line in a given area with no consideration of how far those people are below the poverty line. Although we think it highly unlikely, we cannot rule out the possibility that MPs, while not putting CDF project in places with large numbers of poor people, are nonetheless channeling projects to places where the poorest of the poor reside. As with the above limitation, deeper qualitative case studies aimed at understanding the complex objectives of politicians may better elucidate whether and how MPs understand the goal of poverty alleviation.

These limitations notwithstanding, our analyses offer insight into the impact of decentralization on poverty alleviation. They also illustrate some of the fundamental insights we owe to Robert Bates. Perhaps chief among them is the idea that politicians rarely behave as social planners. Rather, political expedience often rules the day (Bates 1987). That this insight seems obvious from the present is testament to the fundamental importance of Bates' contributions. While our reading of Bates often focuses on "big ideas" like these, re-reading some of Bates' less well-known early work shows that the ideas we focus on in this paper are as relevant now as they were then—including the insight that population segregation interacts with political incentives to shape distributive strategies (Bates 1978).

[24]While CDF allocation decisions are made by the MP and his CDF committee, community members may also, and frequently do, apply for projects.

[25]We note that such an explanation runs counter to the assumption in the decentralization literature that local political actors should know where the poorest are located, even without being told so by them.

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A Technical Details of the Point Process Model

The discussion here closely follows Baddeley (2010). The observed data in our analysis are the locations of n CDF projects, $x = \{x_1, ..., x_n\}$, whose spatial distribution is a realization of the point process X in a given constituency R; $x \in R$. The Poisson process model estimates parameters of the intensity function for all locations $u \in R$. The intensity function is:

$$E\left[N(X \cap B)\right] = \int_B \lambda(u)du$$

where $E\left[N(X \cap B)\right]$ is the expected number of points in B, a region within R. For R we can estimate the intensity as the count of points in x divided by the area of R. This is the intensity in the entire constituency. Point patterns may not occur with uniform intensity, since some areas of a constituency likely receive more projects than others.

We define $\lambda(u)$ is the intensity of a local Poisson process at location u. Note that covariates Z are measured at every point in R. The stochastic component of the model is defined as:

$$X \sim \text{Poisson}(\lambda(u))$$

The systematic component of the model is defined as:

$$\lambda(u) = e^{Z(u)\beta}$$

The assumptions for the point process model are familiar to regular users of standard generalized linear models. First, the observations (project locations and dummy points) are independent of one another. While this is rarely strictly true in any kind of data, we constructed our data in a way to better fit this assumption. We counted only unique project locations, rather than treating each individual project in a given year as a separate project. For instance, if CDF funds went to projects at Huduma Primary School in several years (e.g., to build several new classrooms across several years or if a single project had a funding allocation recorded over multiple years in the CDF database), we represent this as a single project in our dataset. Second, the intensity function (reporting the propensity for an area u to receive projects) is log-linear in the spatial covariates, as is standard in the Poisson generalized linear model and given the non-negative nature of count-type data. Renner et al. (2015) discusses these modeling assumptions in more detail.

$Z(u)$ are the values of spatial covariates at location u; these are defined at every point in the study area (in this case, in each of the 196 constituencies), and stored as high-resolution raster data. Our definition of units of analysis for estimation in this framework follow from the point nature of the data. Two kinds of points are used to estimate the intensity λ as a function of spatial covariates: points representing actual project locations and "dummy" points representing "pseudo-absences," or places without a project. Modeling continuous space is not computationally feasible, so we break up continuous space using the dummy point scheme. This combined set of points form a quadrature scheme that breaks up the area of analysis R into disjoint spatial units ("tiles") that can be analyzed using familiar Poisson log-linear regression.

We make two choices regarding the model defaults in our analysis. Although these choices do not affect the substantive results, we report them here for transparency. First, we face a choice regarding the number of dummy points to include in each constituency-level point process model. A higher number of dummy points leads to a more stable estimate, but at significant computational cost. Ideally, we would set the density of dummy points identically for all constituencies. However, this approach would lead to a computationally impractical number of dummy points for large constituencies (e.g., virtually anywhere in North Eastern Province). As a result, we vary the number of dummy points used as a flexible function of constituency area. To do so, we calculate the bounding box of the constituency (in meters), and set a quantity Q equal to the longest dimension of that bounding box divided by 100. Then we set the spacing of dummy points equal to max(Q, 250). This ensures that, for large constituencies, we retain a relatively fine grid of dummy points (ensuring high approximation of two-dimensional space). For small urban constituencies, this ensures that the dummy points are spaced 250 meters apart.

The second choice regards the methods for estimating the parameters of interest. Options include maximum pseudolikelihood, logistic likelihood, variational Bayes likelihood, and the Huang-Ogata method. We use the maximum pseudolikelihood method, as it is equivalent to the maximum likelihood in the case of Poisson regression and is unbiased in the presence of a large number of dummy points (such as the number we specify). See Baddeley and Turner (2000) and Baddeley and Turner (2005) for further details.

We estimate all models using the `spatstat` package in `R` (Baddeley et al. 2015).

B Additional Figures and Tables

Table B1: What factors are associated with targeting the poor?

	Targeting of projects to poor areas								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Female MP	-0.09							-0.12	-0.11^{*}
	(0.07)							(0.07)	(0.06)
Vote margin in prior election		0.02						0.02	-0.0003
		(0.03)						(0.03)	(0.02)
Member of ruling coalition			0.06^{**}					0.06^{**}	0.09^{***}
			(0.03)					(0.03)	(0.02)
Ethnic heterogeneity				-0.79				-0.32	-0.58
				(0.48)				(0.48)	(0.42)
Constituency area					-0.05^{***}			-0.06^{***}	-0.11^{***}
					(0.01)			(0.02)	(0.02)
Urban						-0.02		-0.17^{**}	-0.33^{***}
						(0.06)		(0.07)	(0.06)
Segregation of poor							0.11^{***}		0.20^{***}
							(0.03)		(0.02)
Observations	196	196	196	196	196	196	196	196	196
R^2	0.02	0.02	0.04	0.03	0.06	0.01	0.10	0.12	0.35
Adjusted R^2	-0.02	-0.03	-0.01	-0.01	0.02	-0.03	0.06	0.06	0.30

Note: All models include province fixed effects and are estimated via ordinary least squares. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

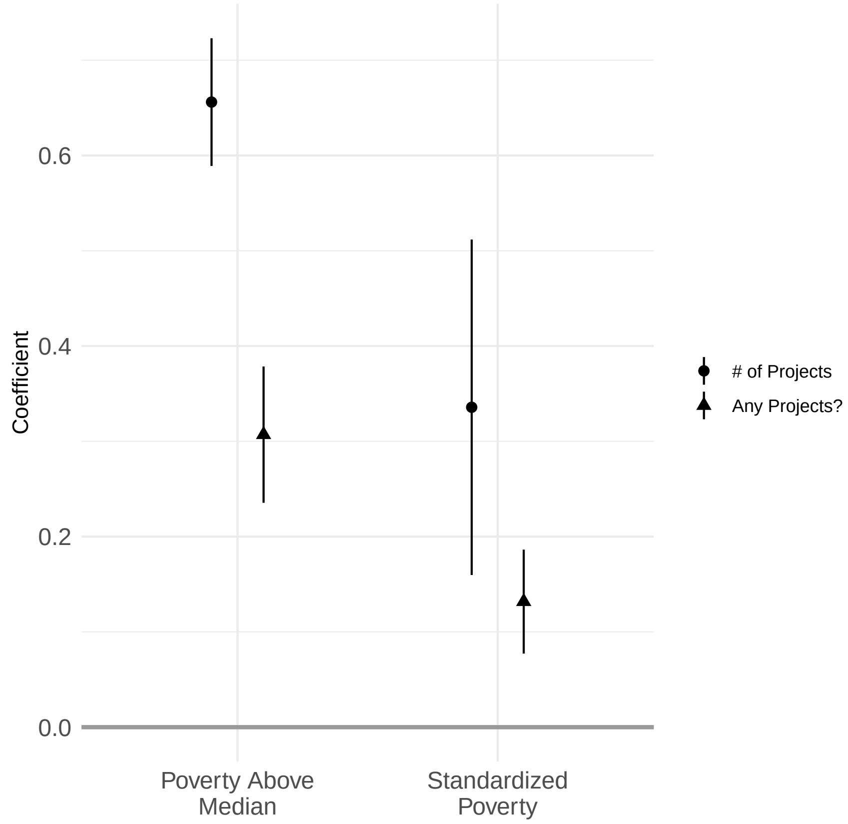

Figure B1: Predicting CDF project outcomes using poverty headcounts. The plotted coefficients show that CDF project placement, whether measured as a count or an indicator of project presence within a sublocation, exhibits a positive relationship with average sublocation poverty headcounts.