Lost in Aggregation – Recasting neighborhood effects on political participation

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June 18, 2018

Abstract

Using a unique geo-located household survey in Malawi, we explore how to best account for neighborhood effects on political participation, namely voting in presidential elections. We show how the magnitude of these effects varies along a continuum of neighborhood size. Rather than defining arbitrary neighborhood boundaries, defining them as the number of residents co-located with the respondents in a certain radius (N) and produce multiple effect size for multiple ranges of N. We then demonstrate that the neighborhood sizes for which the measured effect on the voting is decreasing is dependent on parties and reaches farer than the immediate neighborhood.

Keywords: aggregation bias; neighborhood effects; survey data; political participation

1 Introduction

In this paper, we illustrate the issue of neighborhood aggregation in political science by using the example of political participation. While conventional wisdom contends that neighborhood effects influence participation, the literature only focuses on static units of aggregation. In empirical studies, the spatial units used to test these propositions are typically defined at a level of aggregation that is coarse and exceeds what is generally conceptualized as "neighborhood" by geographers (Deng 2016).

Our approach is to avoid testing neighborhood effects using fixed, arbitrary geographical or administrative data, but instead to locate statistically the specific geographical scope that is associated with a particular type of neighborhood effect. Doing so requires a flexible approach to the empirical construction of neighborhoods. We do so by leveraging a detailed data representative survey conducted in Malawi in 2016 that includes geo-located household data suitable for re-aggregation at any level chosen by researchers. Our data draw on a survey conducted in 2016 in Malawi with over 8000 respondents. Since the precise geo-location of each respondent was collected, one can easily calculate whether and how each respondent's neighbors, who were also interviewed in the study, voted in the 2014 Malawi elections. We can thus use this survey to demonstrate the differences between "conventional" and "egocentric" approaches to the measurement of neighborhood effects. And hence test whether neighborhoods defined as micro-communities (or sub-villages) have a greater or smaller impact on voting than more expansive conceptualizations of neighborhood, such as units comparable in size to typical villages, or even to larger entities that span village boundaries.

The correct identification of neighborhoods is of utmost importance when theorizing about the effect of "neighborhoods" on voting behavior. We use a data driven dynamic spatial aggregation approach by which we calculate egocentric neighborhoods similar to Andersson and Malmberg (2015) and Duncan et al. (2013). The simple intuition behind this approach is that the social context of an individual is not necessarily coterminous with administrative delineations. In fact, results based on these seemingly obvious levels of aggregation may be misleading. Estimates of the magnitude of neighborhood effects may be biased downward if the concept of "neighborhood" is too expansive (a case of aggregation bias). Conversely if the size of local units is exceedingly small, true effects may not be detectable empirically (disaggregation bias). Thus, getting the size of the neighborhood "right" is the key to properly capturing and measuring neighborhood effects.

2 Literature review

The debate about the impact of "neighborhoods" on voting behavior dates as far back as the early 1920s, when political scientists began to hypothesize that many individual acts are in part influenced by the behavior and beliefs of other members of one's community (Foladare 1968). The decision to vote–and for whom to vote–has been a focal point of political science research, but the question of neighborhood effects has greatly divided the scholarship. The literature can be differentiated between the question of turnout (what influences individuals to vote in the first place) (Cho, Gimpel, and Dyck 2006; Estrada-Correa and Johnson 2012; Gimpel, Dyck, and Shaw 2004; Sinclair, McConnell, and Green 2012) and electoral choice (who do individuals vote for when they show up at the polls) (David and Van Hamme 2011; Ichino and Nathan 2013; Leigh 2005; Pattie and Johnston 2000; Gent, Jansen, and Smits 2014; Westinen 2014). All of these studies find an effect of neighborhoods on voting behavior, except for (Sinclair, McConnell, and Green 2012) who use an experimental instead of an observational design. They find evidence that the treatment (a motivational post card to take part in the upcoming election) has an effect on other non-treated household members, but not on other households that reside in the same zip code.

While Ichino and Nathan's study (2013) about voting preferences and local ethnicity in Ghana is an exception,[1] most studies deal with elections in advanced industrial democracies: Australia (Leigh 2005), Belgium (David and Van Hamme 2011), Finland (Westinen 2014), the Netherlands (Gent, Jansen, and Smits 2014), the United States (Sinclair, McConnell, and Green 2012; Gimpel, Dyck, and Shaw 2004; Cho, Gimpel, and Dyck 2006; Estrada-Correa and Johnson 2012), or the UK (Pattie and Johnston 2000).

Furthermore, the definition of neighborhood is often not driven by theory, but is derived instead by the nature of the data that are readily available, typically of the administrative sort. Therefore, aggregation by polling stations (Pattie and Johnston 2000; Gent, Jansen, and Smits 2014),[2] postal codes (Leigh 2005; Sinclair, McConnell, and Green 2012; Estrada-Correa and Johnson 2012), municipal or even higher levels of administration (David and Van Hamme 2011; Westinen 2014; Gent, Jansen, and Smits 2014) polling station or census blocks (Gimpel, Dyck, and Shaw 2004) are common practices. This atheoretical selection is criticized by Weaver (2014) as the uncertain geographical context

[1] Note that Simiyu (2010) is investigating whether candidates have a higher probability of being elected when they are residents in their constituency in Kenya.

[2] Ichino and Nathan (2013) draw a 30km buffer zone around the polling station.

problem (Kwan 2012a, 2012b): even when the closest 500 persons are defined as a neighborhood, the unit remains an arbitrary construct that does not necessarily reflect the social context in which a person lives. Furthermore, social contexts are not fixed. How one acts and perceives one's neighborhood can change over time. Change can be voluntary (e.g. switching to home delivery services rather than personally visiting the nearest supermarket), or involuntary, for instance if the said supermarket closes due to a decrease in demand. When a local meeting point vanishes, its disappearance also affects the very notion of the neighborhood effect: the possibility of connecting with neighbors is reduced, which erodes social cohesion (Deng 2016, 232).

3 Elusive neighborhoods

When we turn to the developing world, the question of neighborhood effects is in many ways more complex. Most countries of the Global South have not been immune to the trend towards greater urbanization, or the communications revolution, but resource constraints among the less affluent communities has tied billions of people to rural land, often in the very communities where they were born or moved into upon marriage. Rising levels of urbanization is taking place in many countries, but this process tends to push residents into dense urban neighborhoods that lack adequate transportation infrastructure necessary for commuting, which produces neighborhoods where residential life and employment are closely entwined. High costs of urban life combined with underemployment tend to depress mobility among urban residents, particularly the poorer ones. Thus, "neighborhoods" – in their spatial-geographical form – retain a far stronger significance in the daily lives of both urban and rural residents of the developing world.

Relying on data aggregated at the municipal (or other) level of spatial aggregation is likely to result in biased estimates of the "true" neighborhood effects. The modifiable areal unit problem (MAUP) is well-known in the geographic literature (Gehlke and Biehl 1934; Openshaw and Taylor 1979; Wong 2009), and can be parsed into two main issues. First is the scaling effect, which describes the bias introduced by aggregating data to a larger spatial entity; the second one is the aggregation effect, which biases results by selecting different shapes of spatial entities. Fotheringham and Wong demonstrated how the MAUP introduces bias in multivariate statistical analysis. Figure 1 A shows four ideal-type villages that do not overlap. When aggregating individuals (who are represented by points) to the village level, one may bias the subsequent analysis because the

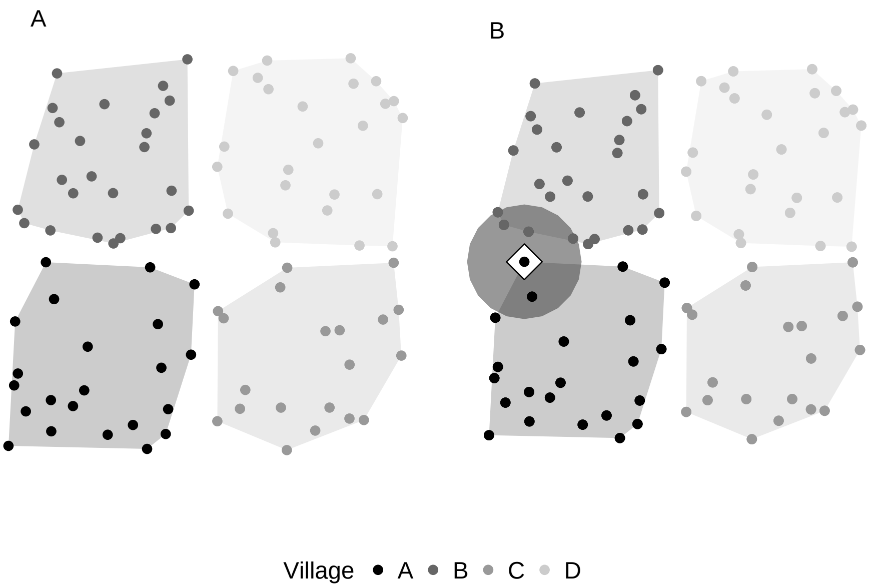

Figure 1: Idealized layout of four non-overlapping villages. Points represent individuals whereas areas indicated villages. Panel B shows the egocentric neighborhood of one individual (diamond).

data is unnecessarily aggregated to a higher spatial level – assuming that the research question is targeting individuals.

Panel B in Figure 1 demonstrates an egocentric neighborhood for the individual indicated by the diamond shape. Andersson and Malmberg (2015) measure egocentric neighborhoods by taking the same number of nearest neighbors for each individual. Similarly, Duncan et al. (2013) measure the distance to the closest five tobacco retailers for each individual in their study of the accessibility of tobacco retailers. Andersson and Malmberg (2015) state that they not only circumvent the MAUP but also the issue of uncertain geographic contexts (Kwan 2012b). The latter is criticized by Weaver (2014) since the nearest neighbors do not reflect the real social context of each individual. Furthermore, the claim that the MAUP is also not a biasing threat in this approach is questionable. The nearest neighbors are measures that vary by individual, but are still a spatial aggregate in nature. Other approaches such as letting respondents draw a map of their neighborhood, are compelling but costly (Coulton et al. 2001). Research on questions such as pollution depend much more on the actual movement of respondents and thus require collecting observable data about everyday behavior. However, this approach is less suitable for face-to-face surveys that often cover a wide range of topics. Additionally, these methods cannot be implemented once fieldwork has been completed. The method proposed by Andersson and Malmberg (2015) and Duncan et al. (2013) is thus more suitable for addressing the issue of neighborhood effect.

4 Political System in Malawi

Shortly after Malawi's independence in 1964, then president Hastings Banda introduced a one party system which was only abolished in 1993. The first multiparty election led to a turnover of power to Bakili Muluzi who was the chairman of United Democratic Front (UDF). His successor Bingu wa Mutharika quit the UDF shortly after his election in 2004 and founded the Democratic Progressive Party (DPP). Mutharika died during his second term in 2012, and thus vice-president Joyce Banda–who had been expelled from the DPP in 2010–assumed the presidency. Despite the promising opinion polls at the beginning of her presidency, a corruption scandal that erupted in 2013 eroded her support, allowing Binguwa Muathrika's brother–Peter Mutharika–to defeat Joyce Banda in the 2014 elections, the fifth round of multi-party election since democratization in 1994 (Dulani and Dionne 2014).

In 2014, Malawian voters filled a "triparpite ballot", in which they voted concurrently for president, members of parliament, as well as (for the first time) local councilors. Turnout was around 71% and 27% of the members of parliament do not belong to any party (Dulani and Dionne 2014).

5 Data

The Governance and Local Development Project implemented the Local Governance Performance Index (LGPI) Survey in Malawi in the spring of 2016. The data consists of a random probability sample of adults, stratified along the three land-use legal regimes: matrilineal and patrilineal, land-tenure regimes as well as urban zones where land-use rights are derived from laws established in the colonial period. Primary sampling units consisted of "Traditional Authorities" (TAs), *de facto* local government that stand between the district level and the village. Since patrilineal groups are relatively rare, TAs with such system were oversampled. In each sampled TA, four enumeration areas (EAs) defined by the Malawian Statistical Agency for the latest population census (similar to census tracts in the U.S. Census Bureau) form the secondary sampling units and were randomly selected. Again, four villages are randomly selected from each sampled EA. In the villages, enumerators followed a random walk pattern to select approximately 20 households. The final respondent in each household was selected through the “Kish grid” method.

In addition to the data collected in face-to-face interviews, the survey teams also recorded the geo-location of each household during fieldwork. By design, the LGPI project seeks to collect information from a relatively large number of respondents in each primary sampling unit in order to obtain reliable estimates of the quality of governance in each region. Such heavily clustered data is thus especially suitable for research on spatial effects, since many of each respondent’s ‘neighbors’ were also interviewed, located in the immediate vicinity of the respondent, within the same village, or within the same Traditional Authority, but in different villages.

In contrast to the stylized representation of Figure 1, Malawian villages are not neatly clustered or sharply spatially separated, as the map of respondents from two sampled villages demonstrate (Figure 2). It is apparent for this case (as well as the overall distribution of LGPI villages) that data aggregation on village level may be misleading. In the sample, the average distance between two villages, measured as the mean distance between two respondents from different villages, is 287 kilometers. However, due to the design of the sample that covers the entire territory of Malawi, this figure is not very meaningful. More importantly, the distance between every village and its closest neighboring village never exceeds 19 kilometers. On average, the shortest distance between two villages is 561 meters. The mean distance between respondents from the same village is 410 meters, whereas the mean distance between respondents and their nearest neighbor is only 9 meters. The mean maximum distance between respondents and their farthest sampled co-villager is 1216 meters.

6 Empirical Strategy

We are interested in estimating the relative impact of two sets of predictors of a dependent variable of interest, **Y**. **X** represents a set of individual-level covariates, whereas **Neighborhood** captures neighborhood-level variables aggregated at a given geographical level. This allows to estimate models where **Neighborhood** is evaluated at different degrees of aggregation:

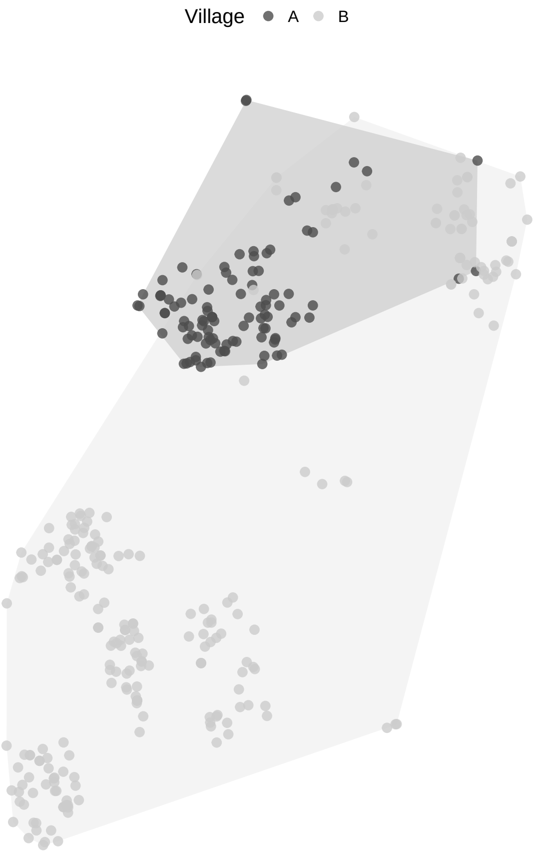

Figure 2: Two overlapping villages with respondents (actual data).

$$Y_i = \beta X_i + \gamma Neighborhood_{ij} + \epsilon \tag{1}$$

where j represents the radius determining the aggregation of the **Neighborhood** variable for each respondent i. **X** is a set of individual-level covariates with corresponding βs that are likely to influence the level of **Y**. **Neighborhood** includes the aggregation of all respondents n lying in a given radius j who voted for a given political party. Large and significant γ coefficients suggest the existence of a neighborhood effect, in the sense that the political preferences of i's neighbors influence i's vote choice.

We select 100 meter as the smallest radius and increase it in 100 meter steps until the size is 1 kilometer. Then we increase the step size to 500 meter until we reach 10 kilometers. We aggregate the vote share of respondents lying

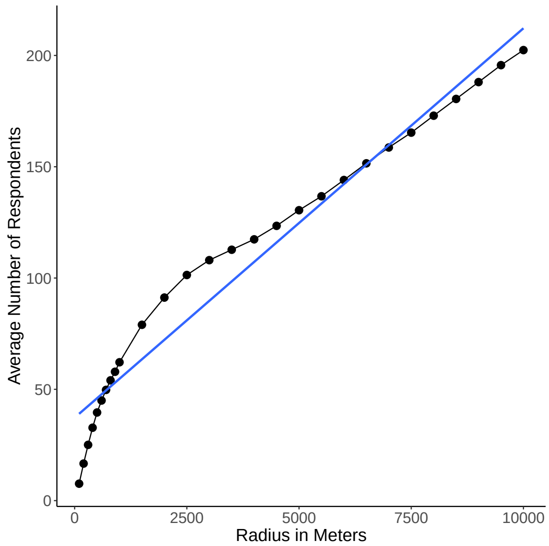

Figure 3: Increase in average number of respondents by radius.

inside of a specific radius for a particular party. We investigate four different parties. The Democratic Progressive Party ($Vote\_DPP$) whose candidate Peter Mutharika won the elections, the Malawi Congress Party ($Vote\_MCP$) with Lazarus Chakwera, the People's Party ($Vote\_PP$), who provided the incumbent, Joyce Banda, and the United Democratic Front ($Vote\_UDF$) with Atupele Muluzi. All four variables are dichotomous and coded 1 if the respondent voted for the candidate and 0 otherwise. Figure 3 shows that the upper limit of 10 kilometer is still justified because the number of respondents included in the radius is still increasing even though with not a steep slope as for the smaller radii.

Individual-level variables include gender, age, education, and an index of key possessions in the household as a proxy for household wealth. $Female$ is coded 1 if the respondent is a woman and 0 otherwise. Age is the age of the respondent in years. $Asset\_Index$ was computed through a multiple correspondence analysis based on four items that a household may own (motor vehicle, mobile telephone, radio, and bicycle). A higher value indicates more assets, and thus the wealthier it is likely to be. The variable $Education$ is an ordinal variable ranging from 1 to 4 wherein 1 indicates the lowest level of education.[3]. Furthermore, we add two orthogonal village level modernization indices ($Modernization1$ and

[3]The variable collapses the answers "no formal education" and "informal education only" into the first category. The value two is assigned for respondents who have some primary schooling, and three for respondents who completed primary education. All levels above primary are collapsed into the highest category, due to the fact that only 18% of respondents possess a level of education that exceeds primary.

$Modernization2$). These indices are created by using the first two dimensions of a principal component analysis on variables drawn from surveys with village heads.[4]

We rely on weighted OLS and therefore estimate a linear probability model, which circumvents the problem that the maximum likelihood estimation with many fixed effects often fail to converge. The problem of out-of-bounds predictions of LPMs is of minor importance here since because we are not focused on forecasting the dependent variable.

Obviously, our sets of independent variables can only serve as proxy for neighborhood effects. After all it is based on the same question as the dependent variable, but measured across a range of nearby other respondents whose preferences are likely to influence voter choice. We cannot claim a causal connection for different reasons. First, The LGPI in Malawi was conducted almost two years after the election. We only measure post-treatment conditions and cannot disentangle possible reverse causality issues (is the respondent influenced by neighbors, or were some neighbors influenced by the respondent's preference?). Furthermore, we are using information from other respondents to the same survey in the same cluster as measures of neighborhood effects. Finally, retrospective answers about vote choice may result in systematic measurement error due to social desirability bias. Respondents might feel the need to claim that they voted for the winning party.

7 Results

Regression estimates are presented in graphic form in figures 4, 5, 6, and 7. Panel A shows random effects, while panel B includes village fixed effects that absorb unobserved village-level influences that might bias the results. The dark segments represent the 95% confidence interval and each segment consists of 61 models. If the segment crosses the red null line, the neighborhood variable is not significant in that model. The darker the area the more confidence intervals of different models overlap. The segments of the variable of interest with a radius larger than 1 kilometer are kept in dark-blue. The white area in the middle represents the minimum and maximum estimate of the coefficient.

The results suggest that the political preferences of neighbors are strongly correlated with voter choice. Regardless of the chosen political party, the baseline

[4]The indices combine self reported access to electricity as well as distance to nearest health center, maternity center, to water, to district center, to road, and to school.

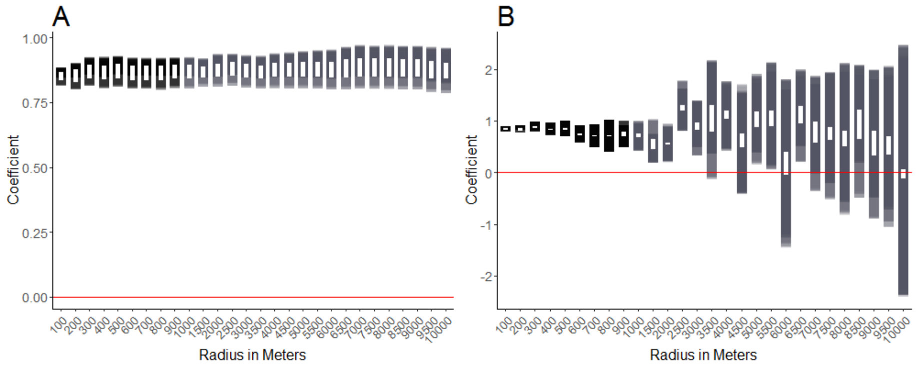

Figure 4: Coefficients of neighborhood variable for DPP. Segments represent the 95% confidence intervals. The darker the interval the more models overlap. The white area inside the intervals spans from the smallest to the largest coefficient for each radius. Panel A are with out village fixed effects and panel B includes fixed effects.

random effects model show strong positive and significant effects for the whole range of conceptualizations of neighborhood size (Panel A). However, the magnitude of the effect is not identical across parties. For DDP voters, the coefficients for neighborhood effects hover around .75, while they are closer to 1 for other political parties. All four figures show a similar stable pattern as distance away from the respondent increases. In contrasts to other parties, the results for the People's Party (whose lead candidate Joyce Banda failed to win reelection) suggest weaker effects as one draws larger circles to define neighborhoods around respondents. Adding village fixed effects (Panel b) in order to account for omitted village-level variables, we find that the effect is similar to panel A in all models for close distances, but typically fails to reach statistical significance with larger conceptualizations of neighborhood– about from 1.5 kms and higher for UDF and PP, 2 kms for MCP, and 3.5 kilometers for DPP.

These findings are consistent with the view that highly localized social institutions influence voter choice. Respondents seem to be influenced to vote just like their immediate neighbors, while incorporating the political preferences of residents who live farther afield do not change the basis result. Thus, to the extent that neighborhoods matter, it is conditions within rather than outside villages that influenced election outcomes in Malawi in 2014. The People's Party results are more peculiar, but shed light on dynamics that may explain President Banda's defeat at the polls. As for other parties, we detect strong immediate neighborhood effects for the PP, but weaker ones farther distance are used. This suggests that PP voting was highly particuliaristic. Voters living close to PP voters in their village voted for the PP, but the presence to more

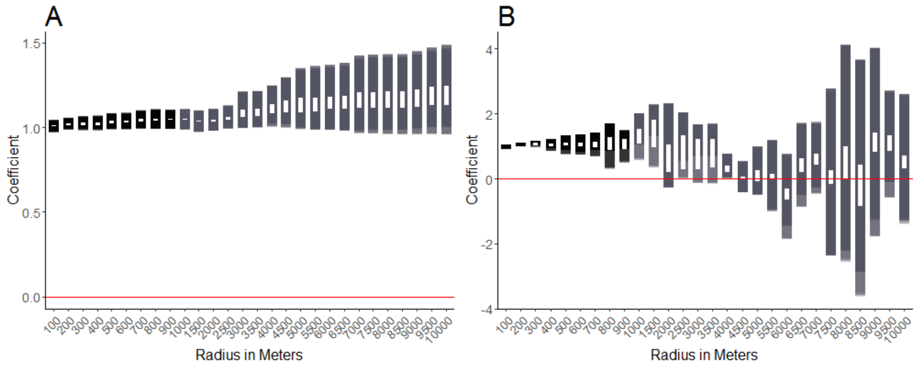

Figure 5: Coefficients of neighborhood variable for MCP. Segments represent the 95% confidence intervals. The darker the interval the more models overlap. The white area inside the intervals spans from the smallest to the largest coefficient for each radius. Panel A are with out village fixed effects and panel B includes fixed effects.

distant PP supports leader to weaker levels of support, sign that the party was not as cohesive as others, especially the DPP for which we find no such trend. We are mindful that strong geographic patterns in party support are at work. Figure 8 shows the density of the four parties in our sample. There are strong geographic clusters for DPP in the South, PP in the North, MCP in the center, and UDF in the center South. Even though our models so far absorbs a great deal of this clustering through village-level fixed effects, the geographic clusters for party support seem to be wider in scope. We plan on exploring other types of local effects (including ethnicity) in further iterations of our analysis.

8 Preliminary Conclusions

The ability to cheaply collect and use precise localization data for all respondents in surveys opens new horizons for political and social research. In the absence of geo-spatial information, researchers have been forced to use whatever level of administrative aggregation that was readily available and lacked the ability to identify the scope of the community for which "neighborhood effects" may be the strongest. In this paper, we present an early effort to loosen this constraint by testing models explicitly for a range of plausible conceptualizations of neighborhoods. In future iterations of this paper, we intend to test our modeling approach on a wider range of dependent variables. We will also include richer combinations of neighborhoods, aggregated for a wider set of co-variates. We can for instance imagine that the partisan preference of close

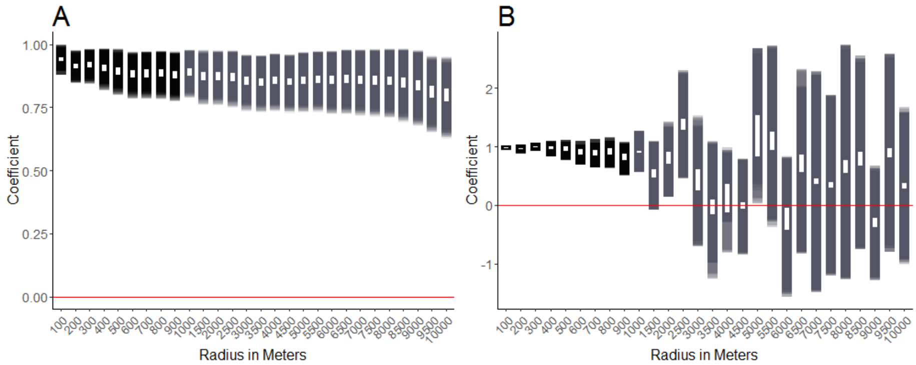

Figure 6: Coefficients of neighborhood variable for PP. Segments represent the 95% confidence intervals. The darker the interval the more models overlap. The white area inside the intervals spans from the smallest to the largest coefficient for each radius. Panel A are with out village fixed effects and panel B includes fixed effects.

neighbors is a key driver of individual voter choice, but it is also also plausible to posit that political-economic forces that operate across wider communities also have a concurrent and distinctive impact on voter choice. Testing such effects for N possible neighborhood scopes and P geographically aggregated covariates requires estimating at least NxP models.

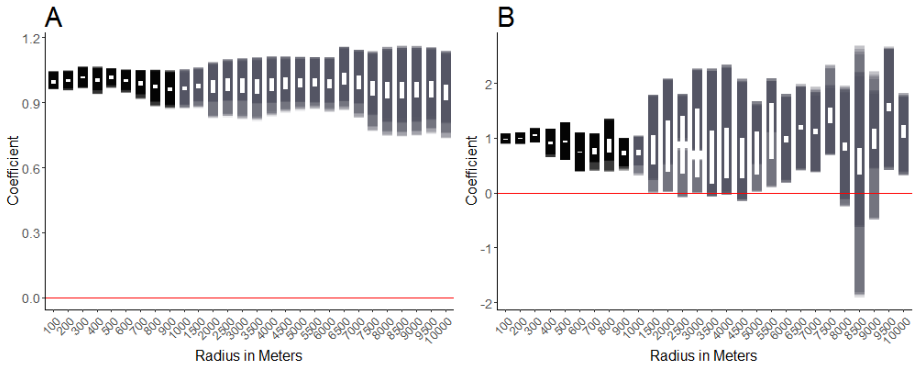

Figure 7: Coefficients of neighborhood variable for UDF. Segments represent the 95% confidence intervals. The darker the interval the more models overlap. The white area inside the intervals spans from the smallest to the largest coefficient for each radius. Panel A are with out village fixed effects and panel B includes fixed effects.

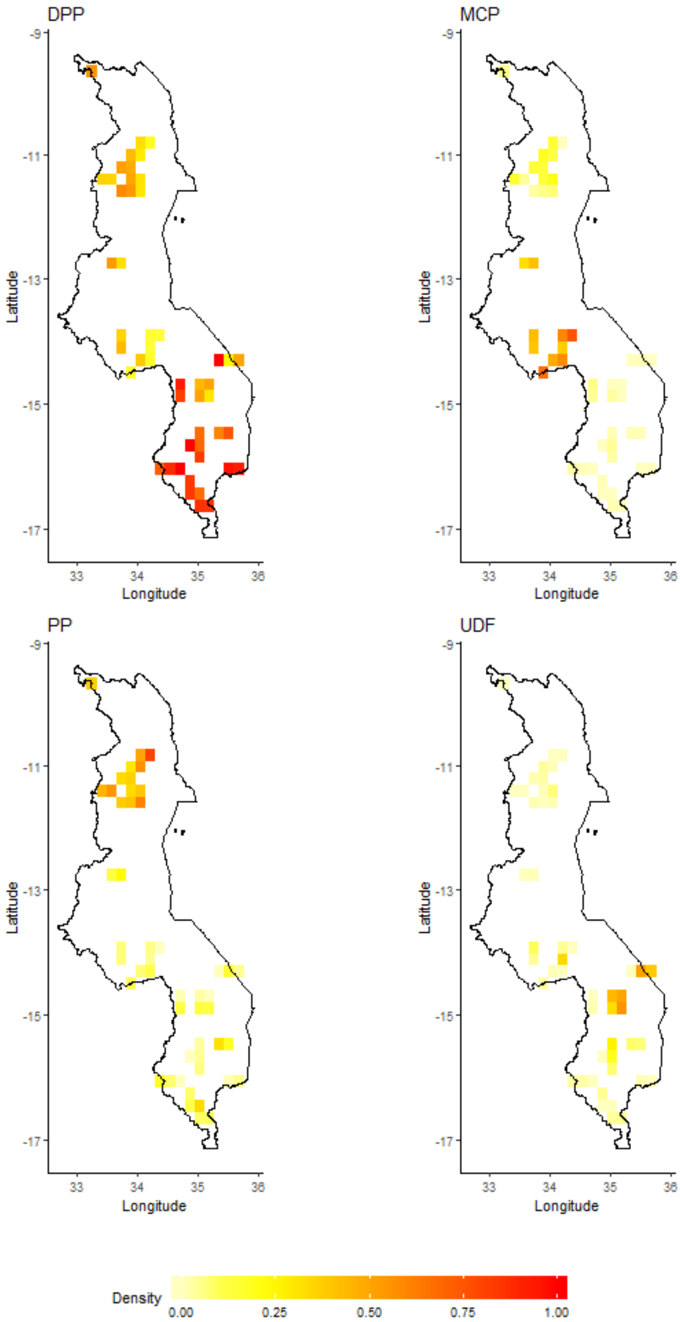

Figure 8: Density of voters by party.

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