Closing the vaccination gap – heterogenous effects of immunization campaigns in Kenya

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INTRODUCTION

- Vaccines are effective in saving the lives and preventing diseases estimated to be responsible for nearly 25 percent of deaths of children under the age of five worldwide, saving more than 6 million children every year.
- Immunization campaigns have improved health outcomes in Africa, resulting in a reduction in measles deaths by 89 percent between 2000 and 2016 and annual deaths by 2.5 million.
- The government of Kenya has developed national policy guidelines for public vaccination programs in accordance with the second National Health Sector Strategic Plan 2005-2012 (NHSSP II). This strategic plan for an enhanced nationwide immunization program recommends children by age 12 months receive bacillus Calmette–Guerin (BCG), polio, pentavalent, and measles vaccines.
- Africa persistently has the lowest rate of childhood vaccination worldwide despite the expansion of vaccine coverage in Africa and worldwide.

OBJECTIVES

- We address the issue of under-vaccination of children by identifying and assessing the heterogenous effects of an immunization campaign on and the determinants in caretakers' decisions to vaccinate their children.
- We analyze a unique dataset, observing vaccination decisions and the socio-economic status of residents in rural Western Kenya to determine whether the vaccination campaign significantly increased household decisions to vaccinate children.
- Our aims are twofold:
  1) identify the high-risk groups from which the most effective impacts of vaccination campaigns are expected
  2) offer policymakers insights that can serve as focuses for policy measures to successfully reduce the vaccination gap in the target population group.

DATA

- We analyze socio-economic survey (SES) data generated under the population-based surveillance conducted by the Kenya Medical Research Institute (KEMRI) in cooperation with the Centers for Disease Control and Prevention (CDC) Kenya and Washington State University (WSU).
- The SES data collected from 2014 to 2017 was combined with data from CDC Kenya's Household Morbidity Surveillance. This comprehensive socio-economic data includes information for 1,500 rural households in Western Kenya collected on a quarterly basis.

METHODOLOGY

- This study adopts recent machine learning (ML) tools developed by Athey and Imbens (2017) and Wager and Athey (2017) to explore the heterogenous effects of vaccination programs on vaccination decision based on socio-economic status of residents in Western Kenya.
- A causal tree algorithm splits observations into subgroups, referred to as leaves, where observations share similar attributes X_i within the leaf while minimizing the mean squared error (MSE). The treatment effects are estimated by obtaining the differences in the means of estimated outcomes for leaves.
- This technique has the advantage of isolating the most responsive covariates without limiting the model to the initial identification. This is a unique data-driven approach when observing many potential covariates in terms of the sample size (Burkett, 2018).
- Conditional average treatment effects of campaigns can be estimated as

$$\tau(x) = E[Y_i(1) - Y_i(0) | X_i = x]$$

  where $Y_i(1)$ indicates an individual received the treatment, $Y_i(0)$ an individual is allocated to the control group, and X_j characteristics.
- In obtaining consistent estimates of the program effects, we assume that the unconfoundedness condition is met because the vaccination programs were randomly provided to the residents: $Y_i(1), Y_i(0) \perp T_i | X_i$, where T_i indicates the treatment provision. We also assume that the probability of treatment provision given a set of covariates is less than one,

$$0 < \Pr(T_i = 1 | X_i = x) < 1, \forall\, x.$$

- For the robustness check, we performed the difference-in-difference (DID) analysis to estimate the treatment effect.

RESULTS

- Figure 1 presents an overview of the association between covariates and the vaccination decision. Table 2 contains the percentage of observations for the selected variables for each quartile of estimated treatment effects. These variables are converted to binary and category forms based on the splitting criteria used in constructing trees.
- Overall the causal forest algorithm identifies the use of certain demographic characteristics in determining treatment effects. Vaccination campaigns are most effective (i.e. Quartile 4) for parents with lower levels of education and for fathers in the age group between 24 and 35 or above 55. The households most responsive to the vaccination campaigns include those with the characteristics of spending less for health care and education.
- Access to mass communication outlets is also an important attribute to detect heterogeneity in campaign effects. More than 87 percent of the respondents do not own a TV while only 18 percent do not own a mobile phone. Those who do not own phones also do not own TVs. Most of those who do not own either also do not possess electronic communication outlets (i.e. radio, computer) and rely on village elders to receive information relevant to public health. The phone value variable indicates the expected market value of an owned phone assessed by a respondent. The results suggest that those who do not own mobiles or own low value phones are positively responsive to vaccination campaigns.
- The tree algorithm selected two additional splitting variables, the amount of owned land by acres and of bean harvest acres, to explain the variations in vaccination decisions. The splitting points are 1.5 acres of owned land and 0.7 acres of bean harvest land, implying those who possess more land than these points are not responsive to vaccination campaigns.
- These results indicate that vaccination campaigns can be implemented by targeting groups with certain demographics characteristics and indicators such as ownership of a certain amount of land and electronic communication outlets.

Figure 1. Single tree

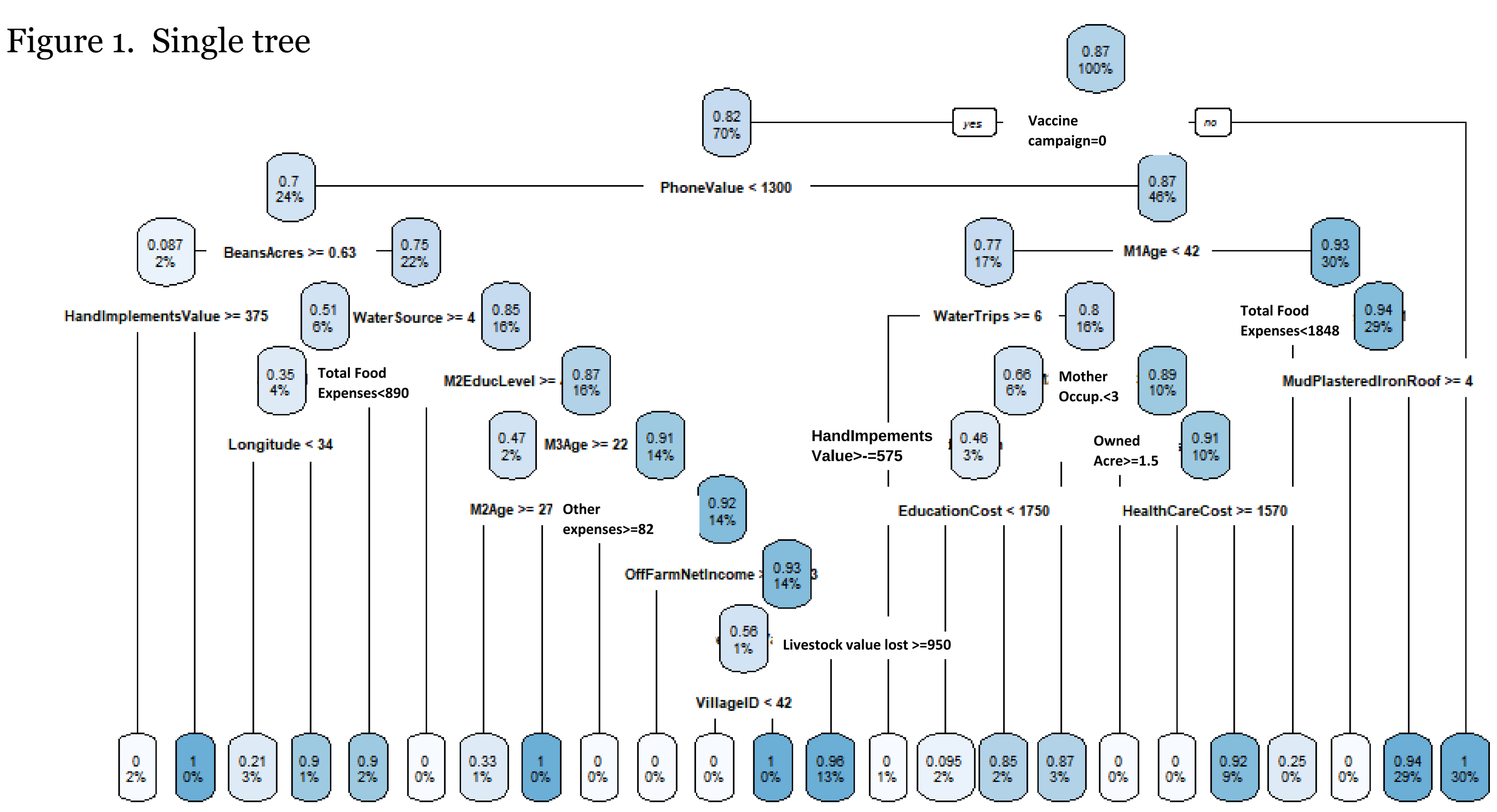

Table 1. Important variables used in constructing trees

predictors	Increase in MSE of predictions	predictors	Increase in MSE of predictions
Vaccine campaign	91.72	OffFarmNetIncome	19.96
Total Food Expenses	31.82	Mother's education	19.58
Phone Value	28.83	Father's net income	18.89
Longitude	27.99	Water Source	18.54
VillageID	27.87	TotalHHMembers	18.12
Beans Acres	27.59	HandImplementsValue	17.84
Mother's age	22.43	Education Cost	17.45
OtherExpenses	21.31	Radio Value	16.66
Father's age	20.88	Total Goats	16.46
SorghumPlantedArea	20.03	HandImplements	16.43

Table 2. Treatment effects (TE) and percentages of households by TE quartiles

Variables		**Average estimated treatment effect**	**Quartile 1(%)**	**Quartile 2(%)**	**Quartile 3(%)**	**Quartile 4(%)**
Phone value	Below KES 1300	0.352	2.69	7.82	10.51	12.96
	Above KES 1300	0.304	22.33	17.20	14.51	11.98
Owned acre	Below 1.5 acre	0.321	23.72	25.02	25.02	24.94
	Above 1.5 acre	0.255	1.30	0.00	0.00	0.00
Beans acre	Below 0.7 acre	0.320	22.90	24.37	24.69	23.06
	Above 0.7 acre	0.321	2.12	0.65	0.33	1.87
Father's age	0-24	0.308	0.41	0.33	0.81	0.00
	25-34	0.323	4.56	4.97	9.05	5.79
	35-44	0.325	3.91	4.97	5.05	4.89
	45-54	0.297	8.88	6.93	3.02	3.83
	55 above	0.333	7.25	7.82	7.09	10.43
Mother's age	0-24	0.337	3.99	11.33	11.57	12.22
	25-34	0.314	5.95	3.99	5.87	4.32
	35-44	0.308	7.33	4.48	4.07	3.67
	45-54	0.296	5.46	3.02	1.71	2.77
	55 above	0.327	2.28	2.20	1.79	1.96
Father's education	Below bachelor's degree	0.322	19.80	20.95	20.62	21.03
	Above bachelor's degree	0.315	5.22	4.07	4.40	3.91
Mother's education	Below bachelor's degree	0.324	19.56	17.93	20.54	21.11
	Above bachelor's degree	0.306	5.46	7.09	4.48	3.83
Health Care Cost	Below KES 1500	0.322	23.39	22.58	24.12	24.78
	Above KES 1500	0.289	1.63	2.44	0.90	0.16
Education Cost	Below KES 1500	0.334	23.39	22.58	24.12	24.78
	Above KES 1500	0.296	1.63	2.44	0.90	0.16

CONCLUSIONS

- The results highlight that the provision of vaccination campaigns targeting and prioritizing specific groups of the population can effectively reduce vaccination gaps for certain populations within the budget for implementing the campaign.
- To achieve the goal of universal vaccination of children, the government can optimize the use of its resources by targeting high risk groups and prioritizing them for vaccination. Coordinating the vaccination service delivery with stratified priorities based on the expected impact of the vaccinations can reduce risk of outbreaks in areas with known herd-immunity or life-threatening diseases.

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