1 Supplemental Information for:

Title: Micro-level structural poverty estimates for southern and eastern Africa

Authors: Elizabeth J. Tennant, Yating Ru, Peizan Sheng, David S. Matteson, and Christopher B. Barrett

Working Paper (please do not cite or distribute)

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Data Supplement

Household data cleaning and pre-processing

Household surveys suffer from missing data and measurement error, and these data quality issues may vary systematically with the country and specific survey. Uganda has the highest prevalence of missing values; approximately half of the sample households have at least one missing data field, often consumption expenditure, land, livestock, or other agricultural assets. For Ethiopia, Malawi, and Tanzania 4% - 14% of households are missing necessary data fields. We do not detect patterns of imbalance across households with or without missing data. Observations with missing data are dropped. We also use winsorization to replace extreme values, truncating at the 99th percentile. This removes outliers, especially those that appear erroneous (e.g., owning 124 computers or 111 bicycles). Some rare assets are converted to dummy variables, such as: irrigated land, boats, ploughs, tractors, harvesters, and sprayers.

Asset wealth

We construct our asset wealth index from a common set of assets surveyed in the Living Standards and Measurement Surveys (LSMS). These include tropical livestock units, total land area, irrigated land area, number of rooms per person, number of ploughs, radios, TVs, bicycles, motorcycles, and cellphones, as well as access to electricity, improved drinking water, improved toilet facilities, and improved materials for roof, wall, and floor. Several of these variables are recoded following the relevant literature. For example, tropical livestock units convert all livestock to common units based on (an assumed, based on species) live weight of 250kg per TLU (Rothman-Ostrow et al., 2020). Designations of improved or unimproved facilities or materials are based on DHS standards (Croft et al., 2018). These same re-coding procedures are used to process the asset variables prior to use in the structural consumption modeling.

To construct a single continuous asset index from these variables, we draw on procedures used to calculate the Demographic and Health Surveys Relative Wealth Index (RWI) (Rutstein and Johnson, 2004; Rutstein, 2008) and the International Wealth Index (IWI) (Smits and Steendijk, 2015). A common wealth score across the full study area is first calculated, as well as separate urban and rural wealth scores. The common scores, which exclude assets that may have divergent relationship with wealth in rural vs. urban areas, are then used to calibrate the separate urban and rural models.

Consumption expenditures

Consumption expenditure aggregates are pre-computed in the LSMS surveys, but typically provided in nominal local currency values. We convert these values to a common currency and equalize their purchasing power over countries and years using purchasing power parity (PPP) adjustments.[1] We adjust all consumption expenditures to 2011 PPP dollars per capita per day as follows:

$$\text{Real consumption (\$/day/person)} = \frac{\text{Consumption in local currency}}{\text{PPP conversion factor} \times \text{hhsize} \times 365} \tag{1}$$

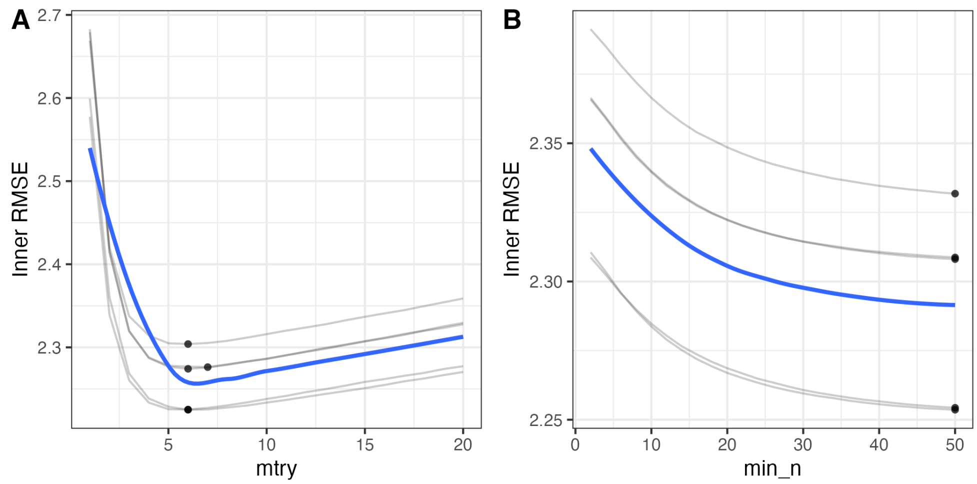
Asset to Consumption Modeling

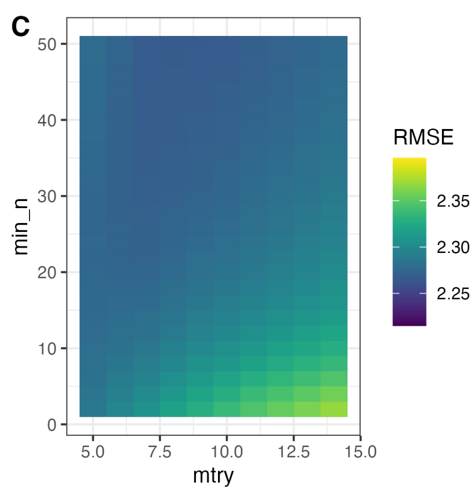
Model tuning

The structural consumption models utilize a shared set of hyper-parameters: an $mtry = 8$, a $min\_n = 30$, and the number of $trees = 1000$. These were selected based on grid search using nested re-sampling of the training data for a single 80%-20% split of each permutation of the study area (individual country, pooled, and LOCO). Re-tuning the household models for every data-split of the cluster-level analysis, as we do in the second stage of the analysis, would be computationally untenable. Based on the generally small differences in model performance across the hyperparameter grids (see Appendix Figures 1-9) we anticipate that this would not substantially aid model performance. For those interested in replicating this approach but without the computational resources for a similar grid search, we note that performance does not appear to be highly sensitive to the hyperparameters and that solid performance is achieved with software defaults.

[1] We use the World Bank's PPP conversion factor, private consumption (LCU per international \$), available at: https://data.worldbank.org/indicator/PA.NUS.PRVT.PP

Supplementary Figures

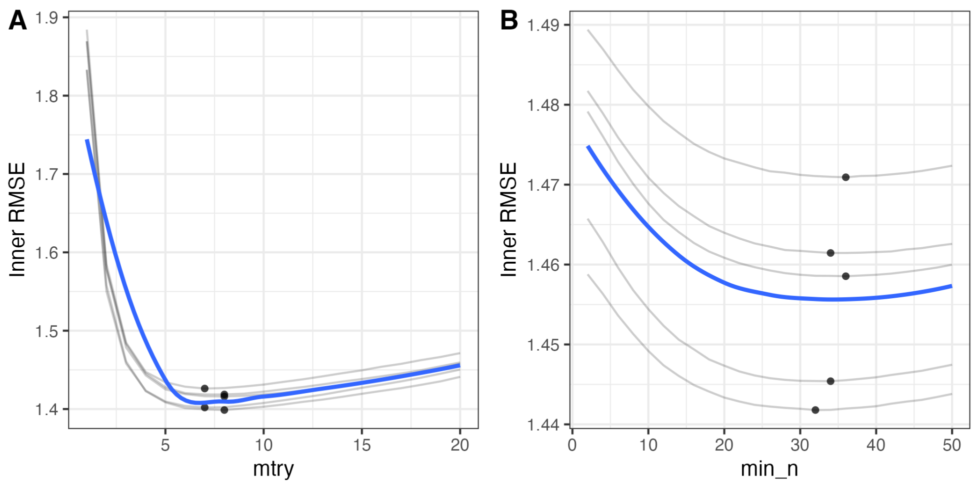


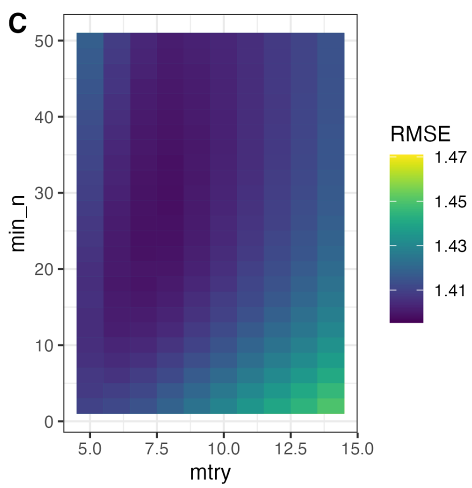


D

mtry	min_n	Inner RMSE (mean)	Outer RMSE
8	50	2.294	2.153
9	50	2.215	2.486
8	50	2.218	2.295
8	50	2.266	2.640
8	48	2.267	2.702

Figure 1: Results of grid search of hyperparameters for random forest structural poverty estimation for **Ethiopia**.





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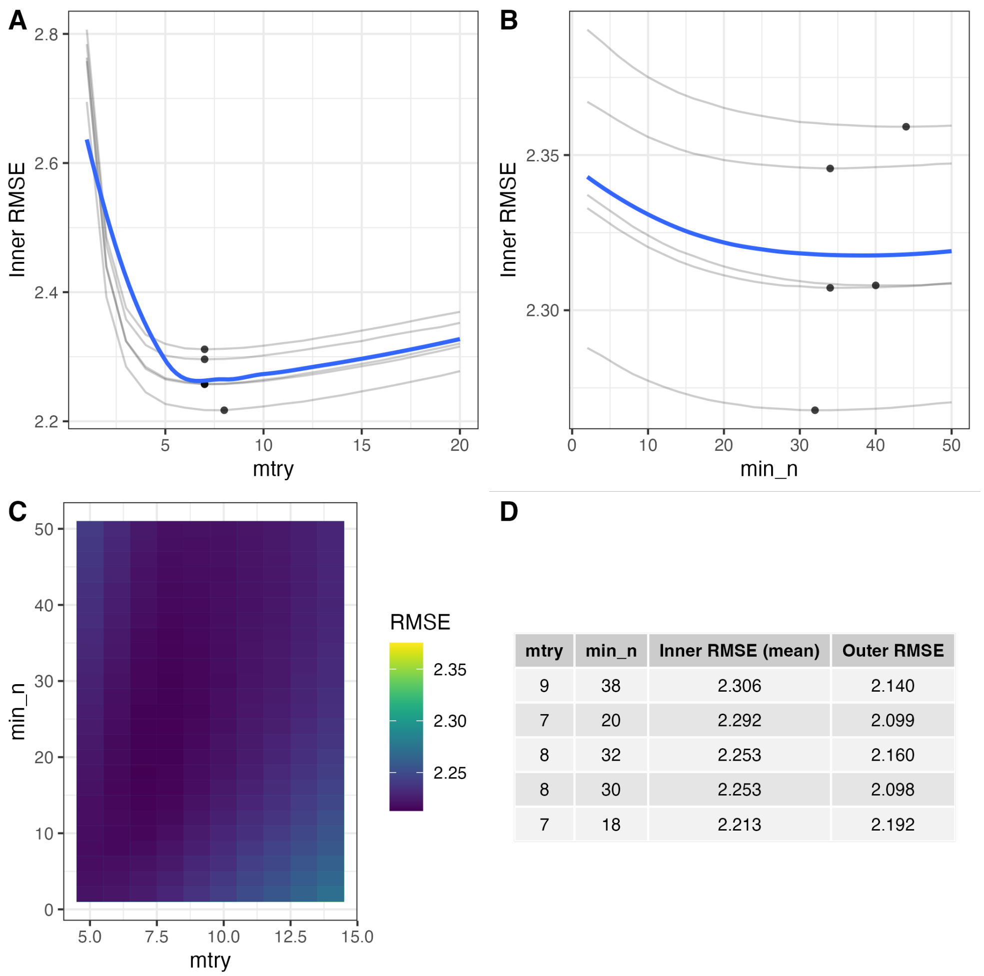
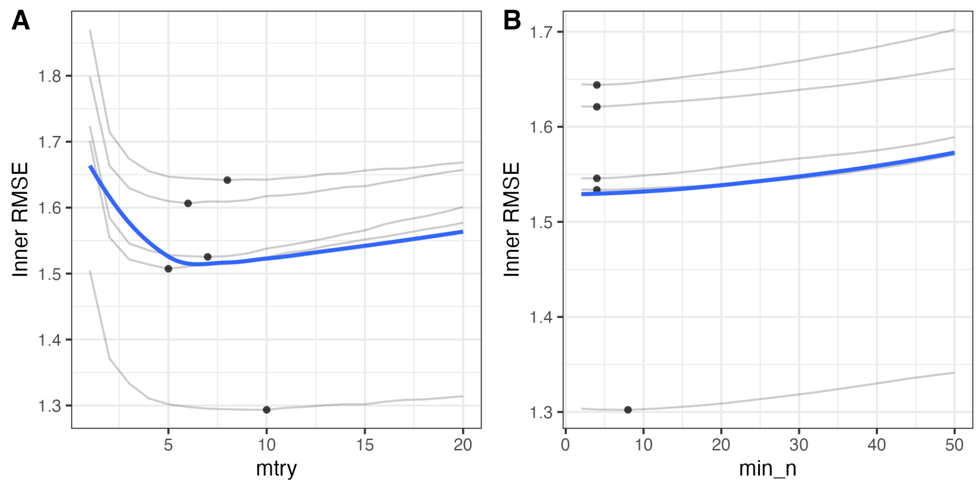
mtry	min_n	Inner RMSE (mean)	Outer RMSE
8	28	1.415	1.326
8	26	1.423	1.362
8	28	1.395	1.506
8	30	1.412	1.420
8	28	1.398	1.431

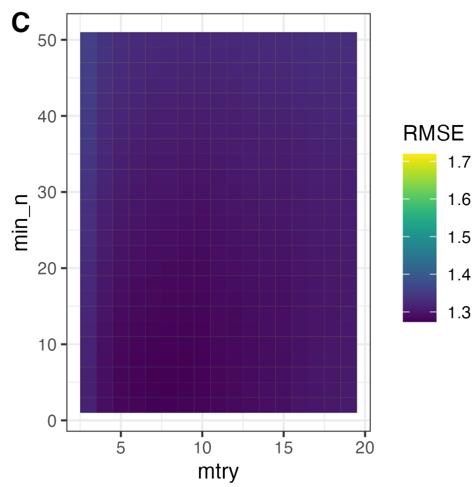
Figure 2: Results of grid search of hyperparameters for random forest structural poverty estimation for **Malawi**.



mtry	min_n	Inner RMSE (mean)	Outer RMSE
9	38	2.306	2.140
7	20	2.292	2.099
8	32	2.253	2.160
8	30	2.253	2.098
7	18	2.213	2.192

Figure 3: Results of grid search of hyperparameters for random forest structural poverty estimation for **Tanzania**.





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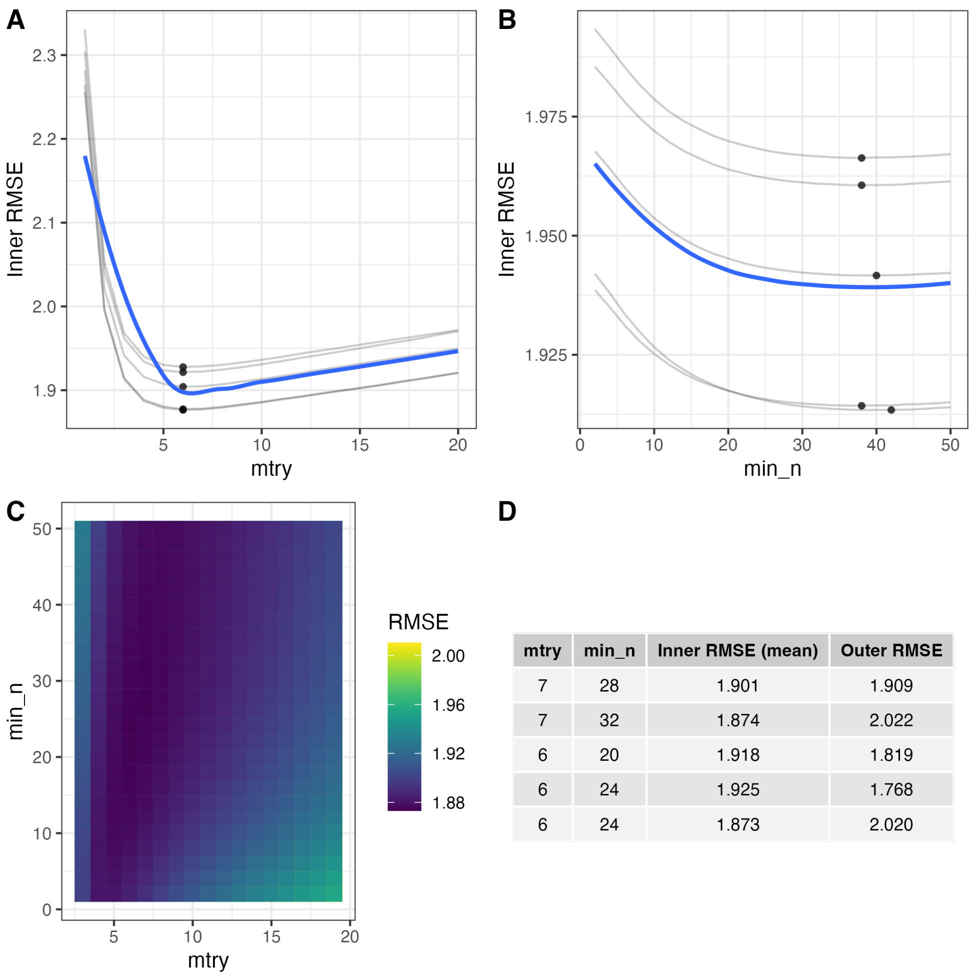
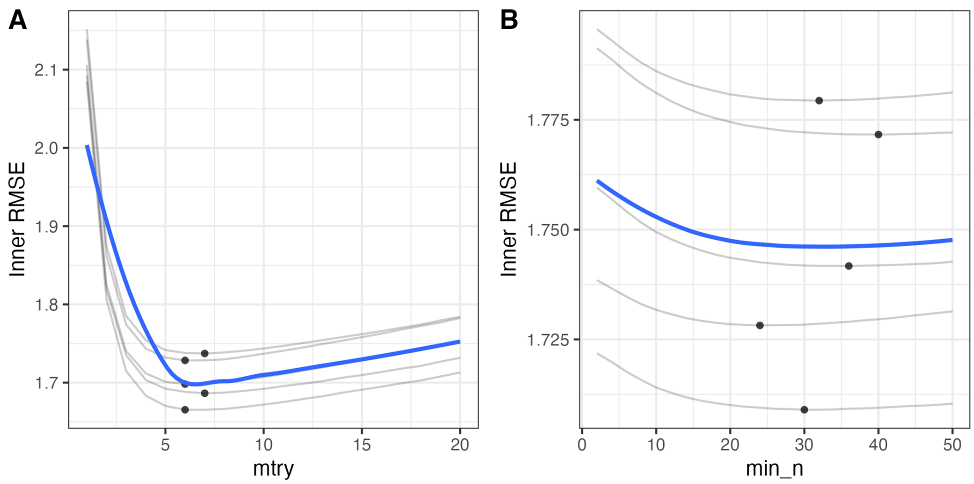
mtry	min_n	Inner RMSE (mean)	Outer RMSE
5	2	1.498	1.744
6	4	1.582	1.253
5	2	1.477	1.842
6	4	1.611	1.328
8	4	1.274	1.569

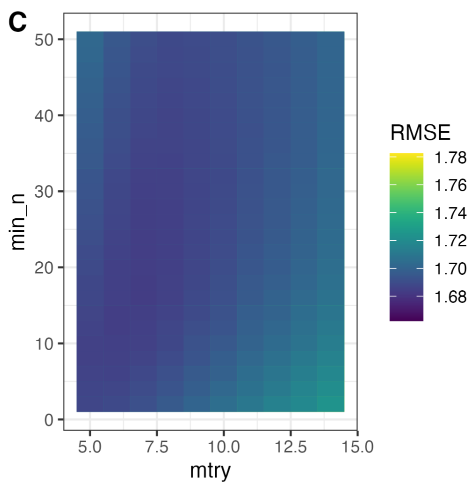
Figure 4: Results of grid search of hyperparameters for random forest structural poverty estimation for **Uganda**.



mtry	min_n	Inner RMSE (mean)	Outer RMSE
7	28	1.901	1.909
7	32	1.874	2.022
6	20	1.918	1.819
6	24	1.925	1.768
6	24	1.873	2.020

Figure 5: Results of grid search of hyperparameters for random forest structural poverty estimation for **Pooled model (all countries)**.





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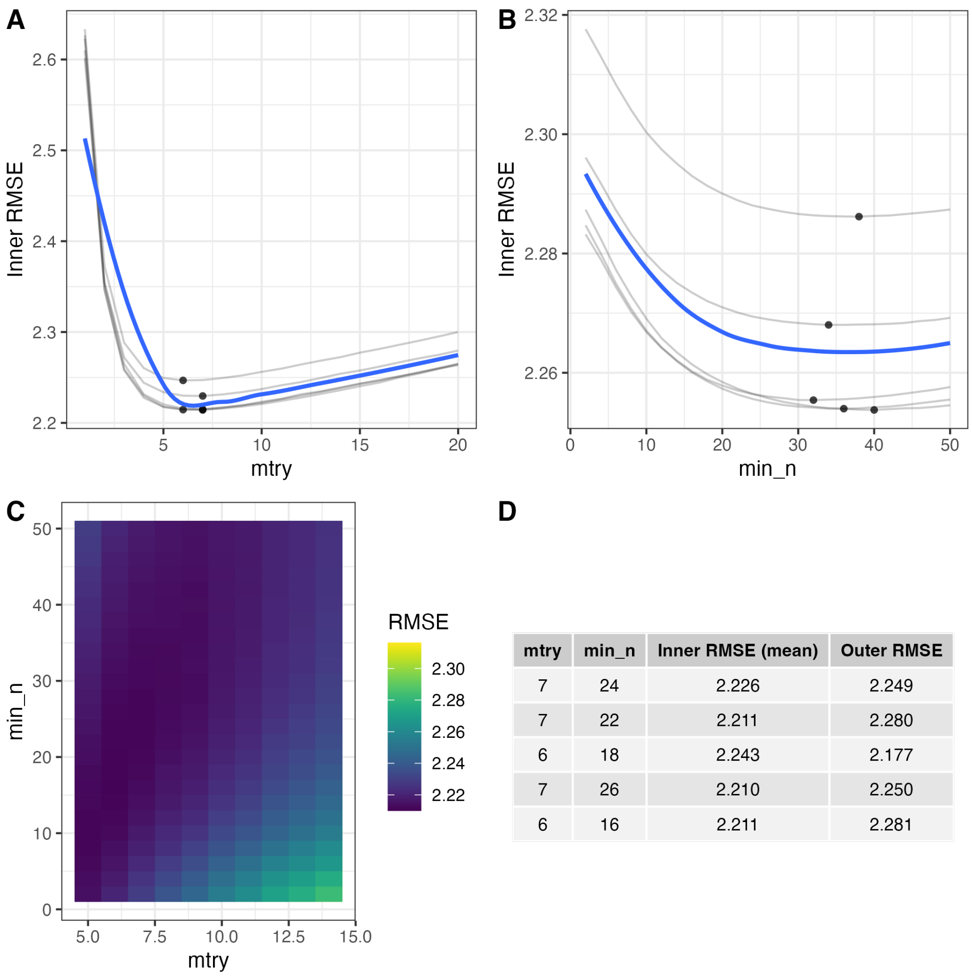
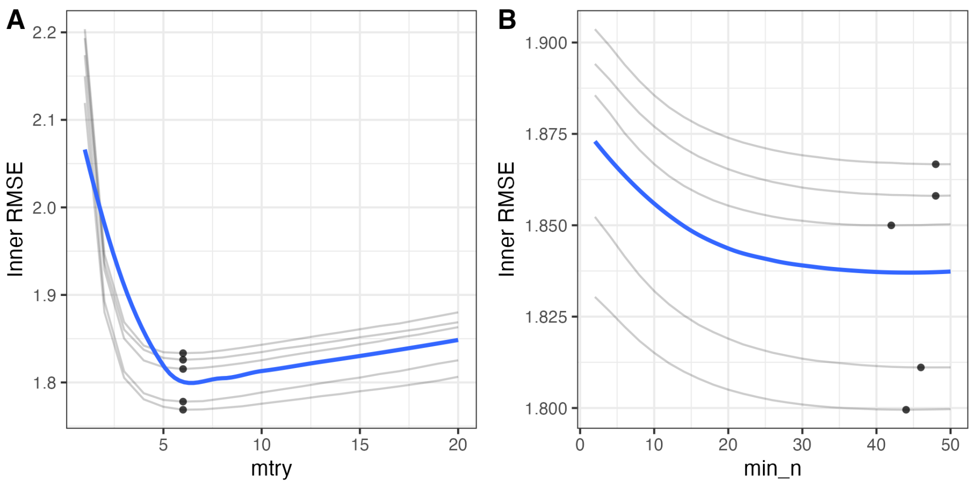
mtry	min_n	Inner RMSE (mean)	Outer RMSE
7	20	1.734	1.588
6	14	1.662	1.854
7	28	1.725	1.643
6	20	1.695	1.735
7	18	1.683	1.771

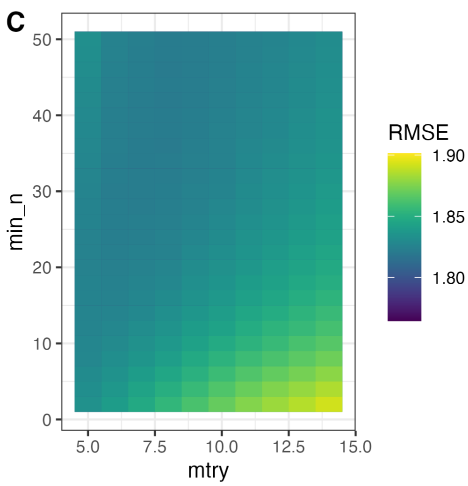
Figure 6: Results of grid search of hyperparameters for random forest structural poverty estimation for **Leave-one-country-out (Ethiopia)**.



mtry	min_n	Inner RMSE (mean)	Outer RMSE
7	24	2.226	2.249
7	22	2.211	2.280
6	18	2.243	2.177
7	26	2.210	2.250
6	16	2.211	2.281

Figure 7: Results of grid search of hyperparameters for random forest structural poverty estimation for **Leave-one-country-out (Malawi)**.

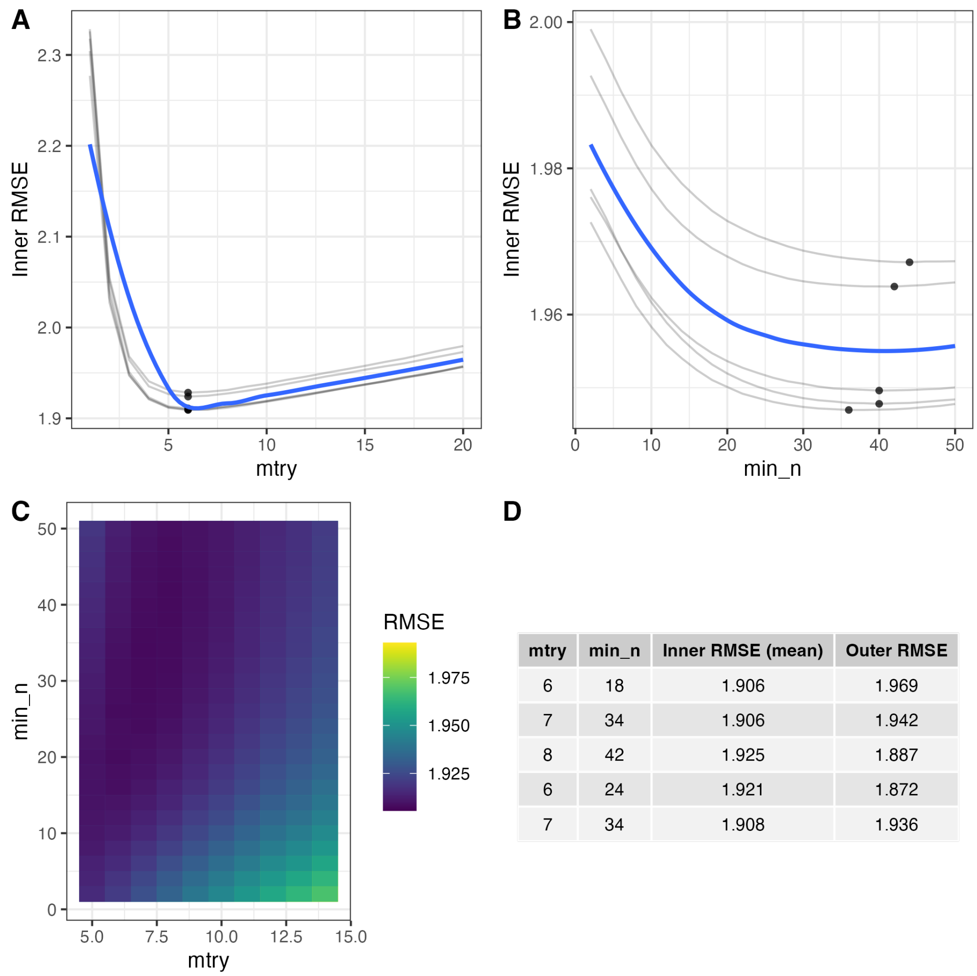




D

mtry	min_n	Inner RMSE (mean)	Outer RMSE
7	38	1.828	1.668
7	34	1.764	1.963
7	40	1.772	1.878
6	30	1.811	1.740
8	42	1.821	1.734

Figure 8: Results of grid search of hyperparameters for random forest structural poverty estimation for **Leave-one-country-out (Tanzania)**.



mtry	min_n	Inner RMSE (mean)	Outer RMSE
6	18	1.906	1.969
7	34	1.906	1.942
8	42	1.925	1.887
6	24	1.921	1.872
7	34	1.908	1.936

Figure 9: Results of grid search of hyperparameters for random forest structural poverty estimation for **Leave-one-country-out (Uganda)**.

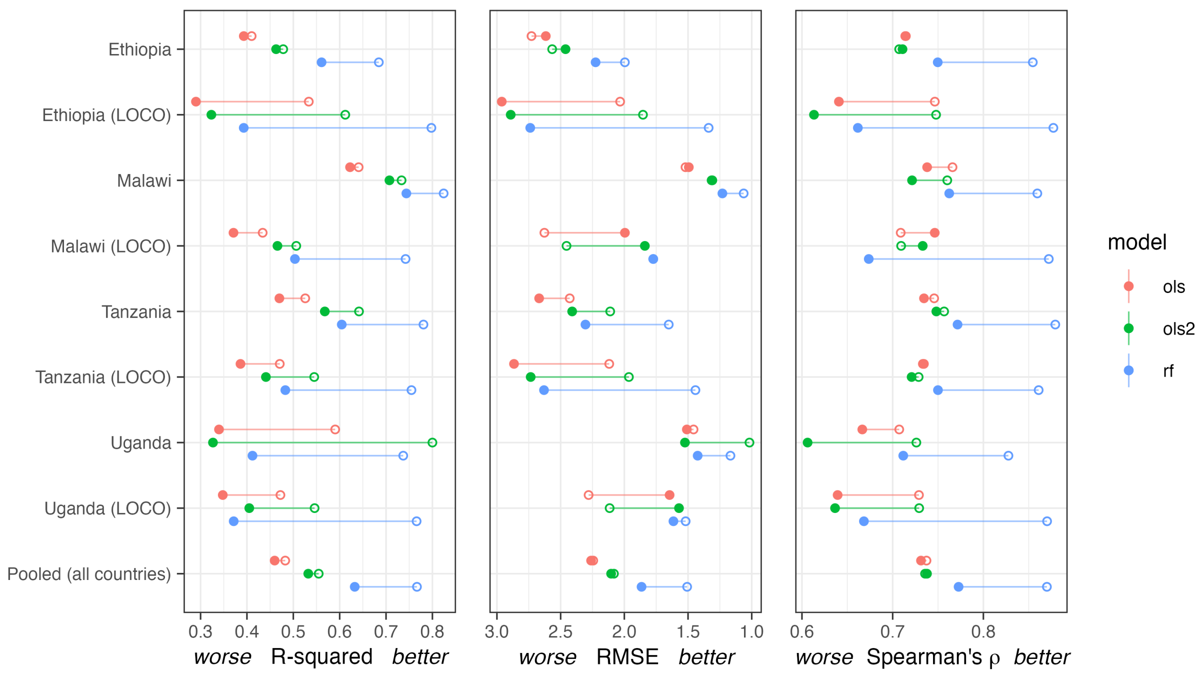


Figure 10: Comparison of measures of fit for continuous models of structural poverty. The solid circle indicates the fit statistic in the test data, the open circle in the training set, and the line is the difference between these. Wider lines therefore indicate larger differences in fit between the training and test data. Country models are based on training and test data from that country. Leave-one-country-out (LOCO) models are trained on the pooled dataset excluding that country (which serves as the test set).

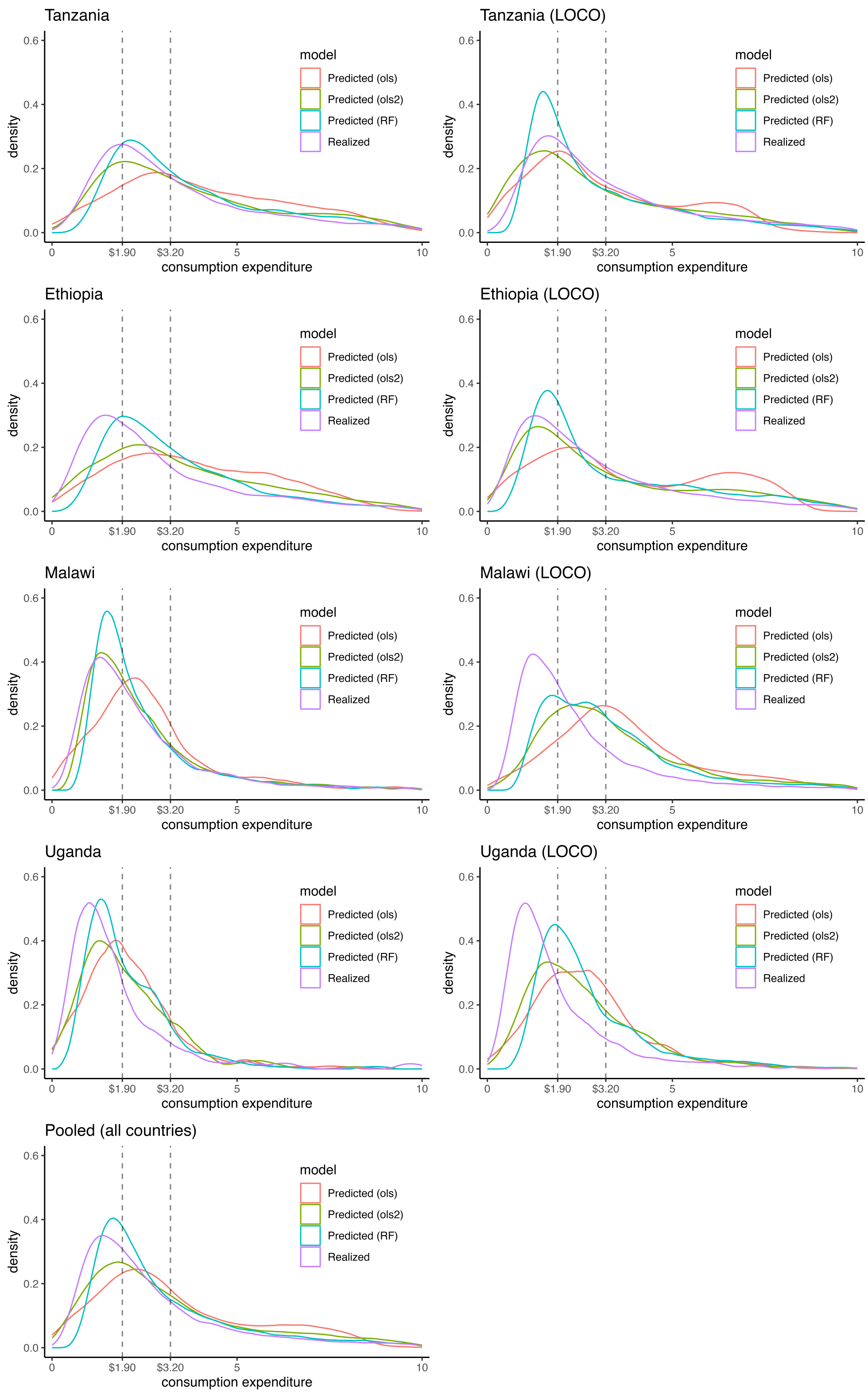


Figure 11: Kernel density plots of predicted versus realized consumption expenditures.

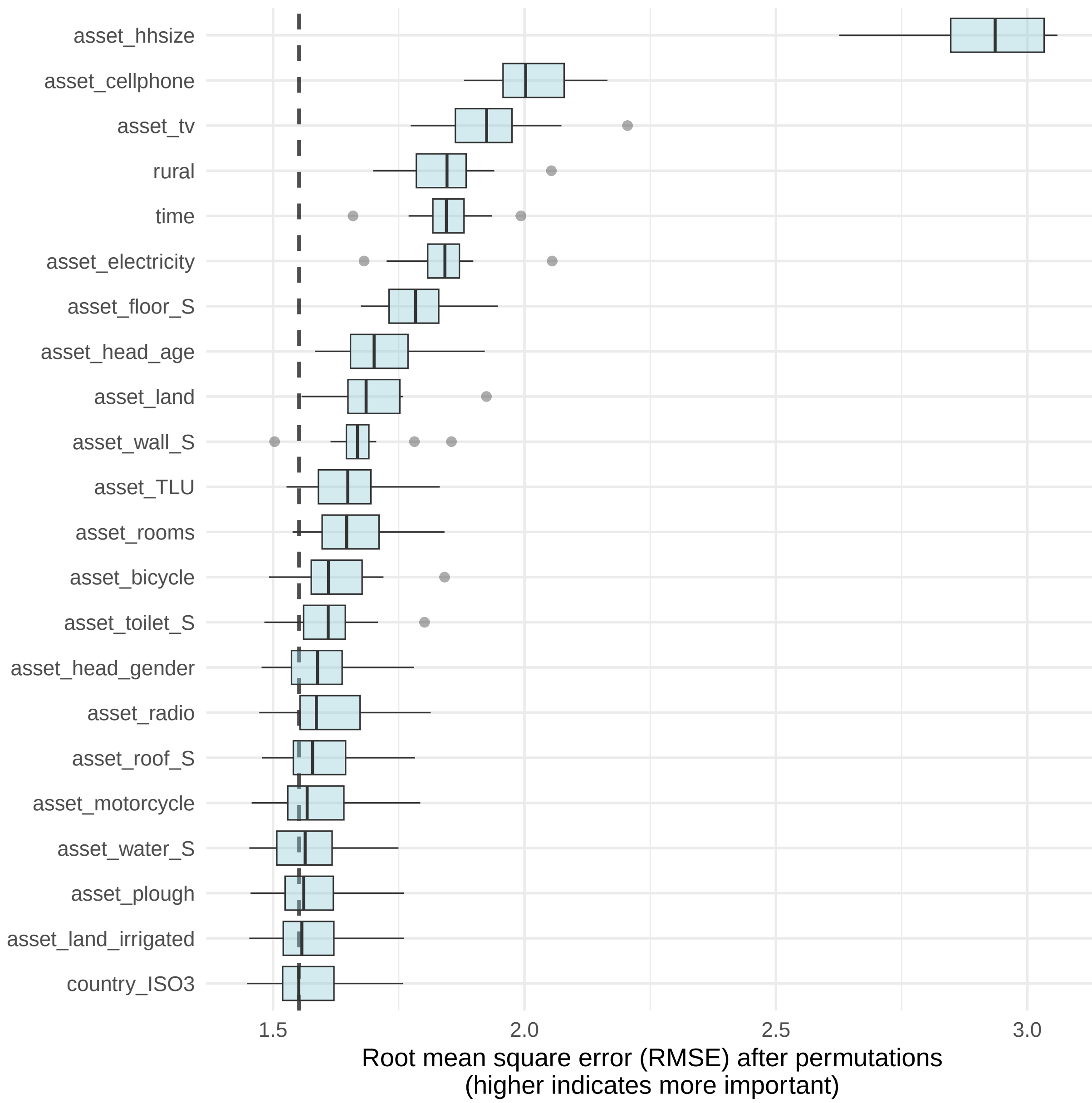


Figure 12: Feature importance for pooled, 1st stage (household asset-consumption) Random Forest regression model.

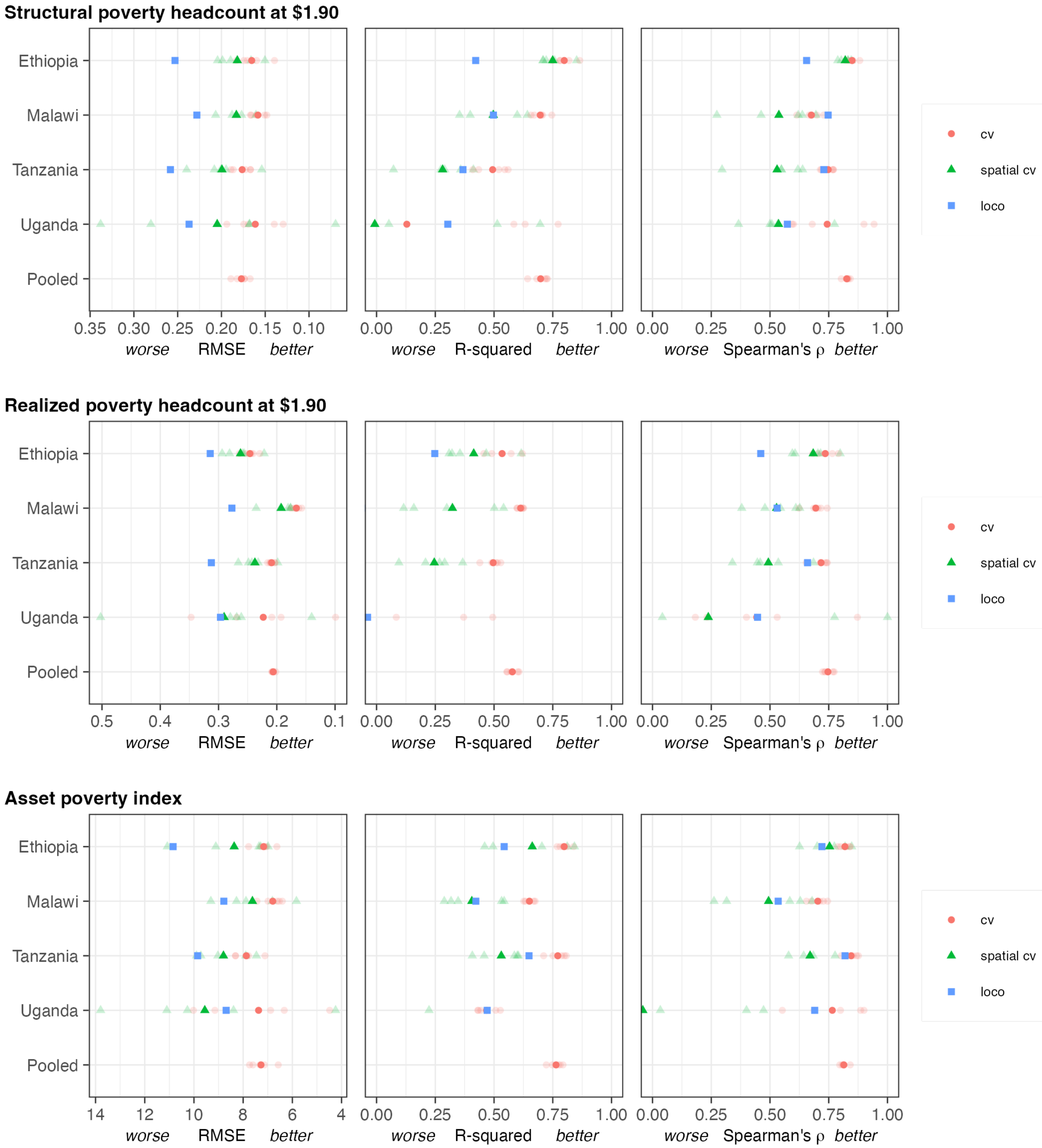


Figure 13: Performance of EO-Structural Poverty models in test set, for the: Poverty Headcount (P^0) at a poverty line of $z = \$1.90$. For cross-validated models, the bold symbol indicates mean performance of the shown folds. Country models are based on training and test data from that country. Leave-one-country-out (LOCO) models are trained on the pooled dataset excluding that country, which serves as the test set.

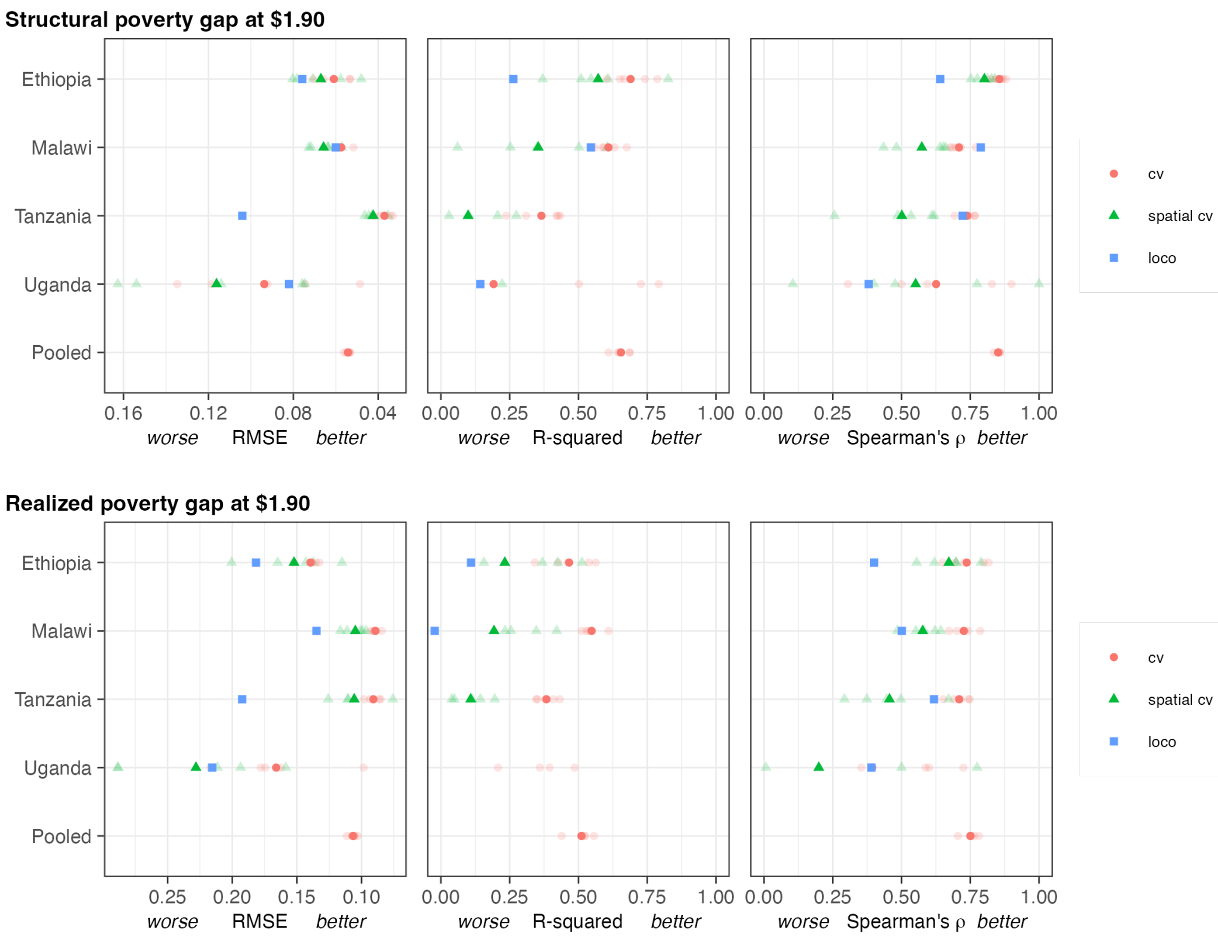


Figure 14: Performance of EO-Structucal Poverty models in test set, for the: Poverty Gap (P^1) at a poverty line of $z = \$1.90$. For cross-validated models, the bold symbol indicates mean performance of the shown folds. Country models are based on training and test data from that country. Leave-one-country-out (LOCO) models are trained on the pooled dataset excluding that country, which serves as the test set.

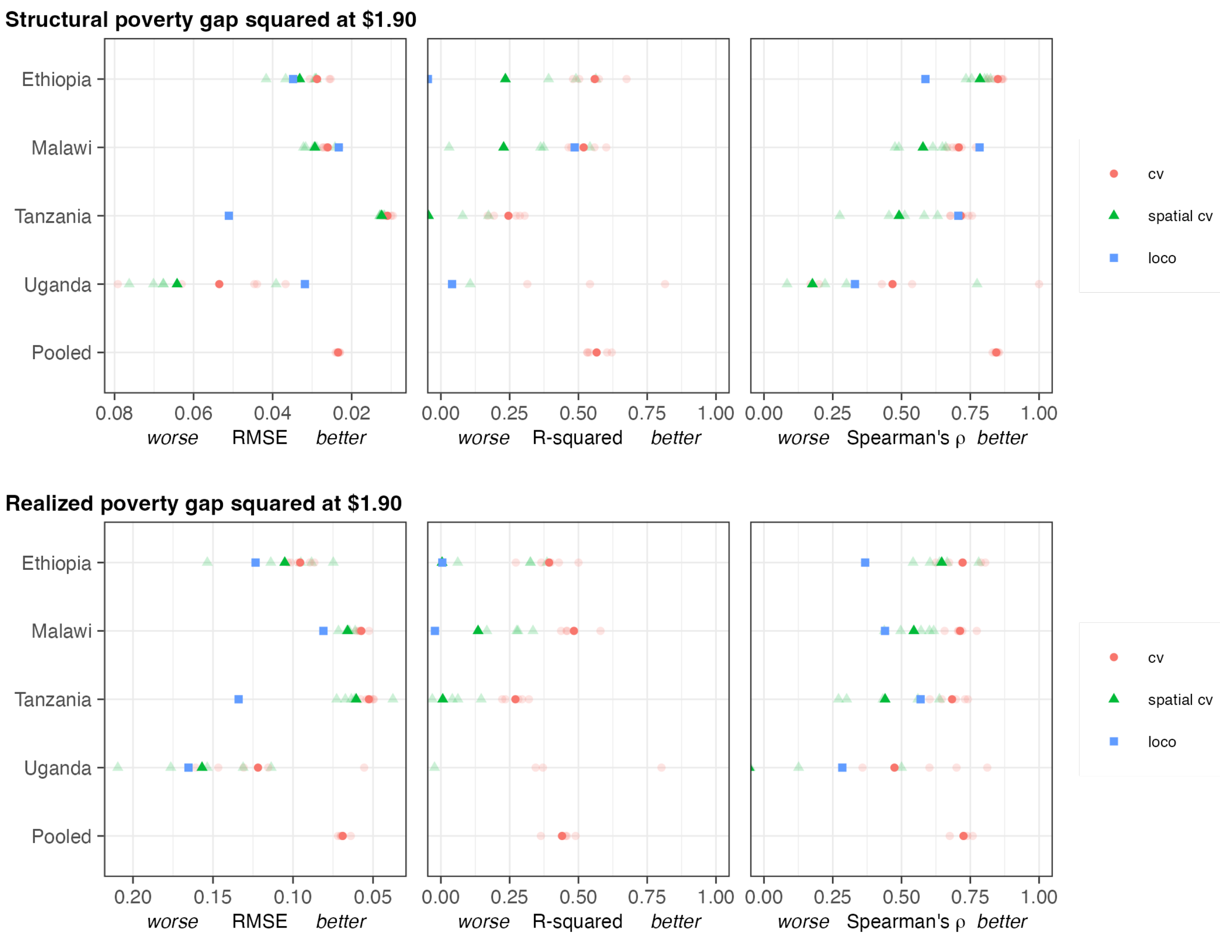


Figure 15: Performance of EO-Structual Poverty models in test set, for the: Poverty Gap Squared (P^2) at a poverty line of $z = \$1.90$. For cross-validated models, the bold symbol indicates mean performance of the shown folds. Country models are based on training and test data from that country. Leave-one-country-out (LOCO) models are trained on the pooled dataset excluding that country, which serves as the test set.

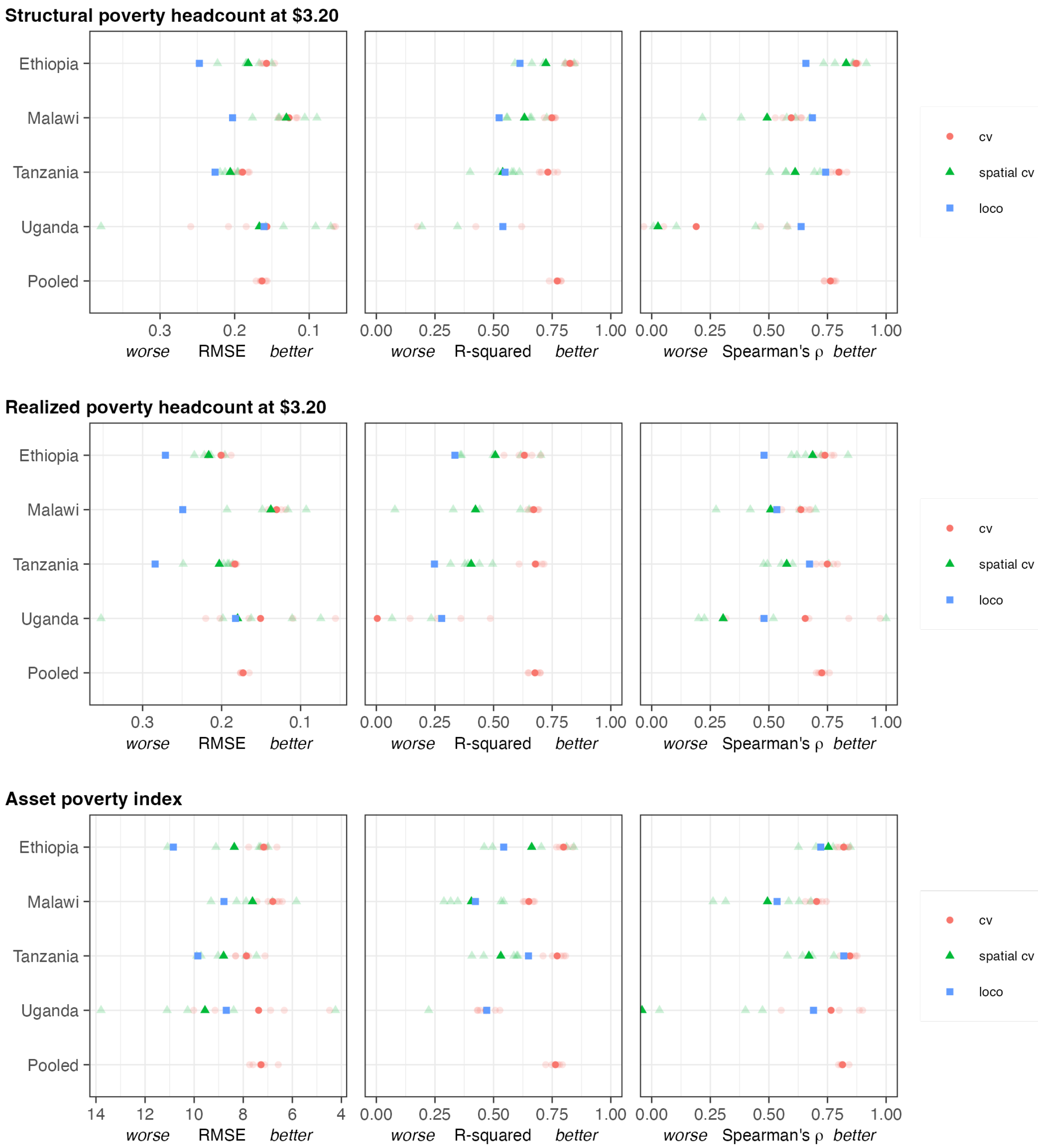


Figure 16: Performance of EO-Structural Poverty models in test set, for the: Poverty Headcount (P^0) at a poverty line of $z = \$3.20$. For cross-validated models, the bold symbol indicates mean performance of the shown folds. Country models are based on training and test data from that country. Leave-one-country-out (LOCO) models are trained on the pooled dataset excluding that country, which serves as the test set.

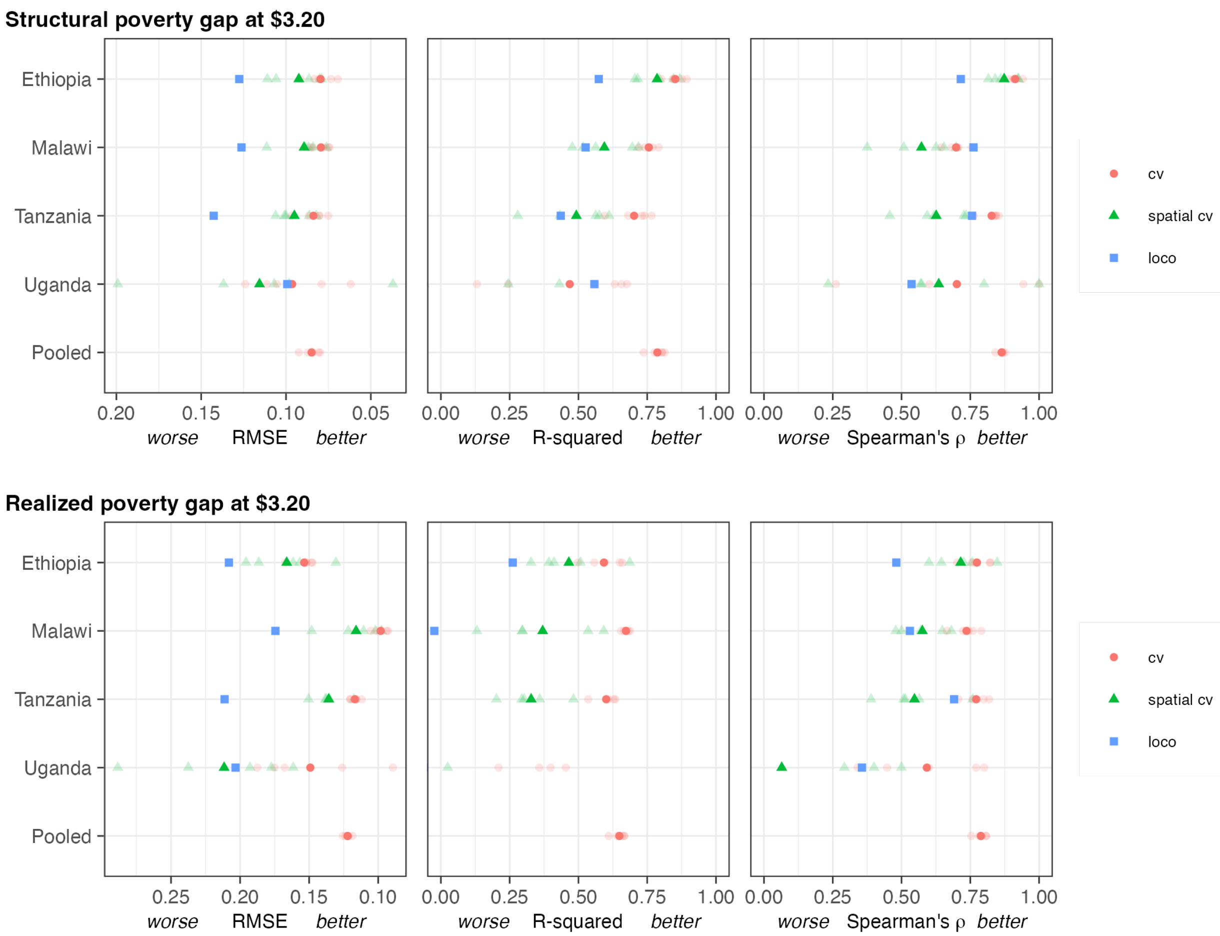


Figure 17: Performance of EO-Structual Poverty models in test set, for the: Poverty Gap (P^1) at a poverty line of $z = \$3.20$. For cross-validated models, the bold symbol indicates mean performance of the shown folds. Country models are based on training and test data from that country. Leave-one-country-out (LOCO) models are trained on the pooled dataset excluding that country, which serves as the test set.

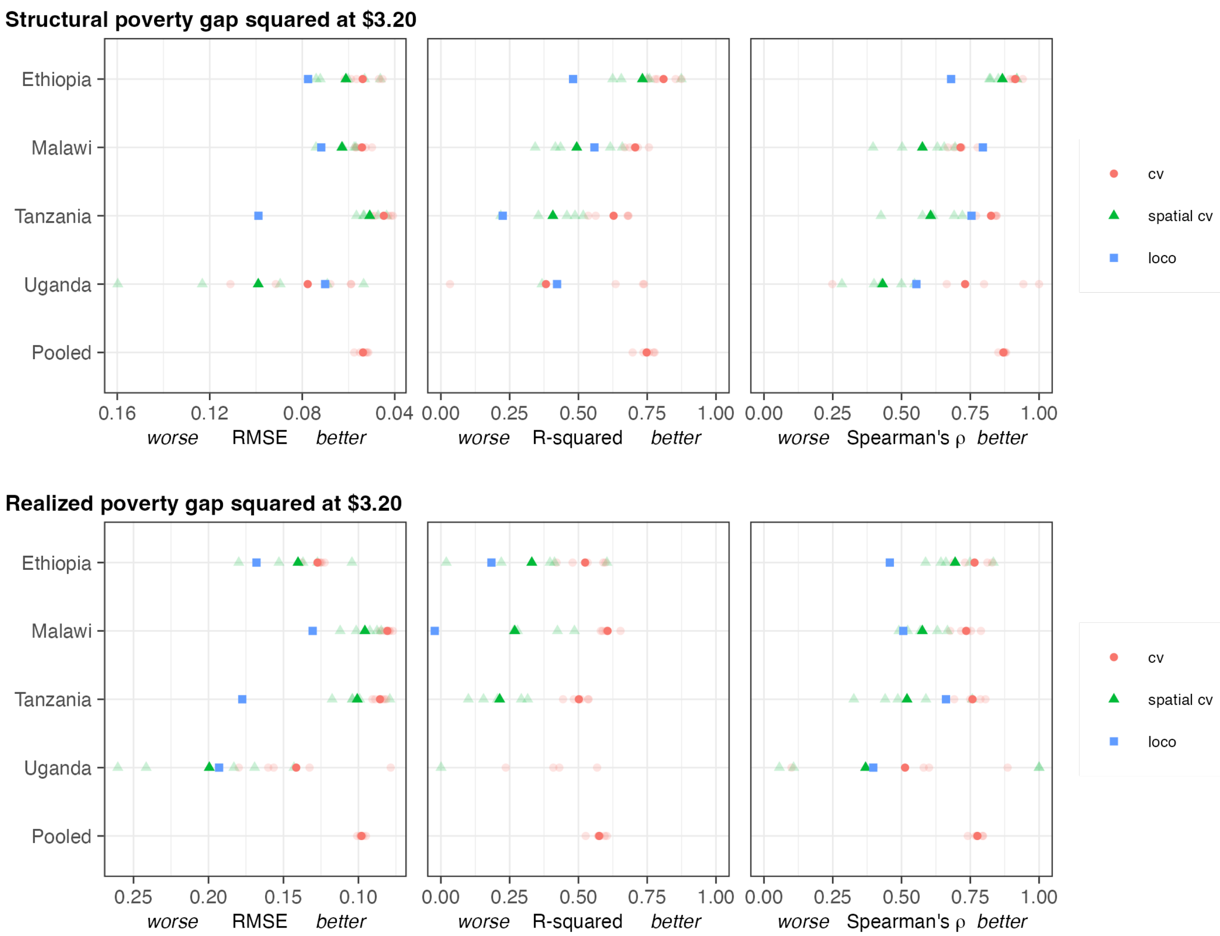


Figure 18: Performance of EO-Structual Poverty models in test set, for the: Poverty Gap Squared (P^2) at a poverty line of $z = \$3.20$. For cross-validated models, the bold symbol indicates mean performance of the shown folds. Country models are based on training and test data from that country. Leave-one-country-out (LOCO) models are trained on the pooled dataset excluding that country, which serves as the test set.

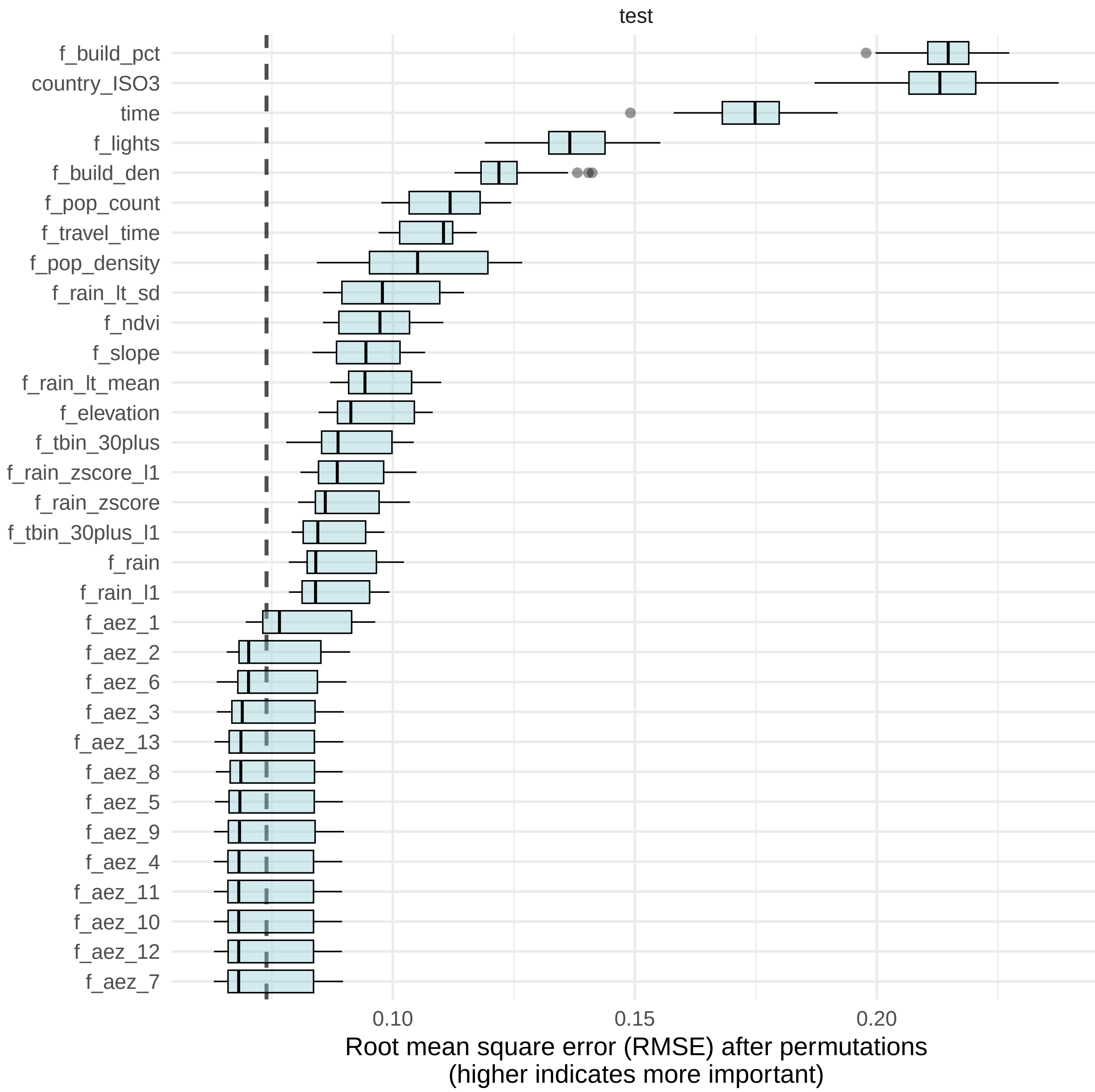


Figure 19: Feature importance for pooled, 2nd stage (EO–structural poverty) Random Forest regression model. Feature importance is averaged across the five folds.

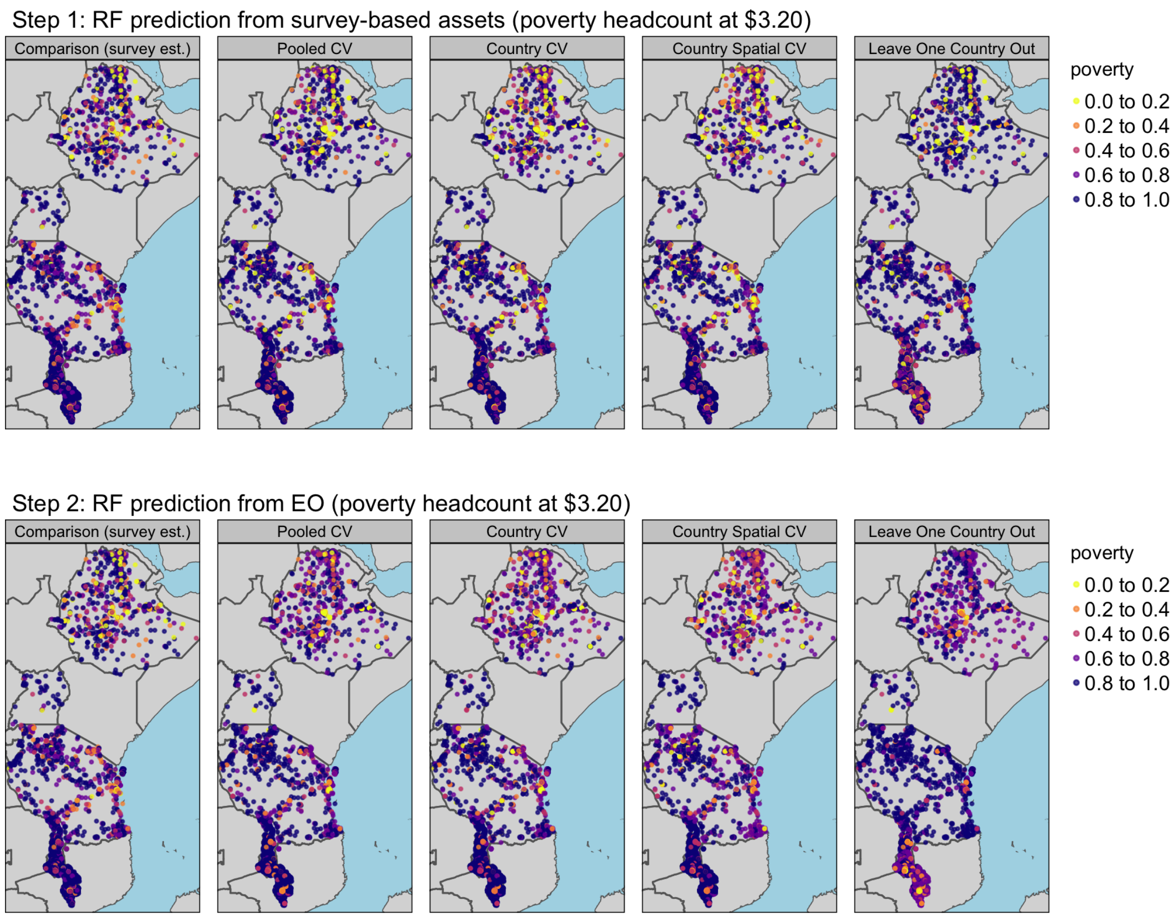


Figure 20: Maps of Poverty Headcount (P_0) at the $3.20 poverty line. For comparison, the leftmost panel for each row are EA poverty rates estimated directly from realized consumption in the survey data. The remaining panels on the top row are predictions from the asset-consumption models into the test sets (combining model results from cross-validation). The corresponding maps in the bottom row are predicted from EO data trained on the structural poverty estimates.

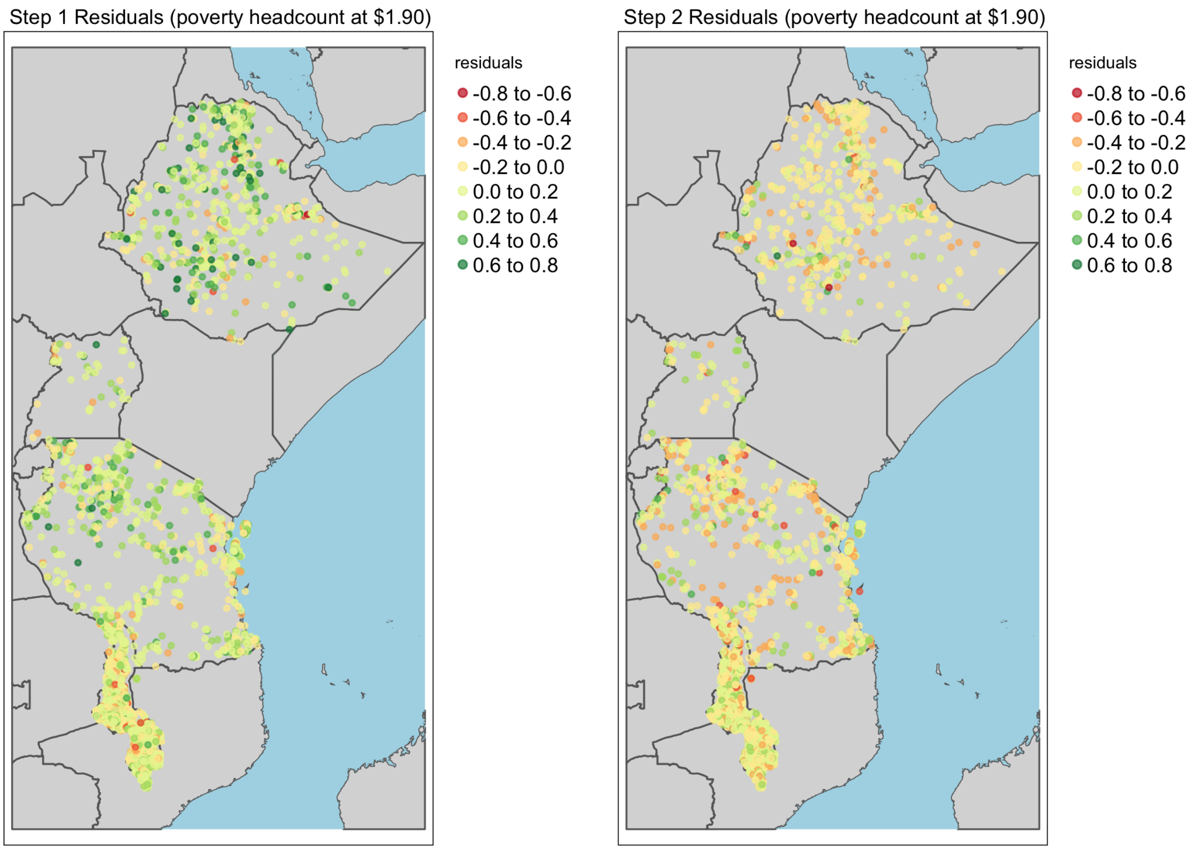


Figure 21: Residual maps for structural poverty at the $1.90 per person per day extreme poverty line, using the pooled (multi-country) dataset with standard cross-validation. The left-hand panel plots the difference between the aggregated (EA-level) first stage structural poverty estimates and realized poverty estimates. The right-hand panel plots the difference between the second stage and first stage structural poverty estimates.

Supplementary Tables

Table A1: Correlation across 1st stage asset variables (pooled, all-country dataset)

	TLU	land	land_irrig.	electr.	radio	tv	bicycle	motorcycle	cellphone	plough	rooms	roof_S	wall_S	floor_S	water_S	toilet_S	head_gender	head_age	hhsize
TLU	1.00	0.43	0.08	-0.05	0.09	-0.08	0.13	0.07	0.02	0.44	0.02	-0.03	-0.16	-0.11	-0.16	-0.11	0.09	0.10	0.29
land	0.43	1.00	0.07	-0.16	0.18	-0.13	0.24	0.10	0.00	0.26	0.15	-0.06	-0.11	-0.14	-0.19	-0.13	0.11	0.15	0.29
land_irrigated	0.08	0.07	1.00	0.01	0.01	-0.04	-0.02	0.00	-0.02	0.18	-0.03	0.01	-0.07	-0.05	-0.04	-0.03	0.03	0.02	0.05
electricity	-0.05	-0.16	0.01	1.00	0.08	0.63	-0.09	0.09	0.45	0.02	0.00	0.40	0.10	0.46	0.19	0.25	0.01	-0.07	-0.06
radio	0.09	0.18	0.01	0.08	1.00	0.17	0.28	0.14	0.27	-0.02	0.20	0.17	0.10	0.19	0.00	0.12	0.18	0.01	0.15
tv	-0.08	-0.13	-0.04	0.63	0.17	1.00	0.07	0.16	0.54	-0.12	0.16	0.35	0.24	0.52	0.18	0.29	0.05	-0.04	0.01
bicycle	0.13	0.24	-0.02	-0.09	0.28	0.07	1.00	0.14	0.19	-0.06	0.27	0.07	0.16	0.07	0.01	0.03	0.20	0.03	0.24
motorcycle	0.07	0.10	0.00	0.09	0.14	0.16	0.14	1.00	0.18	-0.01	0.12	0.11	0.09	0.13	0.03	0.04	0.09	-0.01	0.09
cellphone	0.02	0.00	-0.02	0.45	0.27	0.54	0.19	0.18	1.00	-0.08	0.27	0.40	0.26	0.49	0.17	0.24	0.13	-0.04	0.20
plough	0.44	0.26	0.18	0.02	-0.02	-0.12	-0.06	-0.01	-0.08	1.00	-0.10	-0.03	-0.26	-0.18	-0.14	-0.10	0.11	0.07	0.18
rooms	0.02	0.15	-0.03	0.00	0.20	0.16	0.27	0.12	0.27	-0.10	1.00	0.26	0.33	0.20	0.07	0.10	0.06	0.19	0.31
roof_S	-0.03	-0.06	0.01	0.40	0.17	0.35	0.07	0.11	0.40	-0.03	0.26	1.00	0.37	0.54	0.20	0.24	0.02	0.02	0.01
wall_S	-0.16	-0.11	-0.07	0.10	0.10	0.24	0.16	0.09	0.26	-0.26	0.33	0.37	1.00	0.42	0.20	0.22	0.02	0.00	0.00
floor_S	-0.11	-0.14	-0.05	0.46	0.19	0.52	0.07	0.13	0.49	-0.18	0.20	0.54	0.42	1.00	0.22	0.33	0.03	-0.04	-0.03
water_S	-0.16	-0.19	-0.04	0.19	0.00	0.18	0.01	0.03	0.17	-0.14	0.07	0.20	0.20	0.22	1.00	0.15	-0.04	-0.04	-0.09
toilet_S	-0.11	-0.13	-0.03	0.25	0.12	0.29	0.03	0.04	0.24	-0.10	0.10	0.24	0.22	0.33	0.15	1.00	0.04	-0.04	-0.03
head_gender	0.09	0.11	0.03	0.01	0.18	0.05	0.20	0.09	0.13	0.11	0.06	0.02	0.02	0.03	-0.04	0.04	1.00	-0.13	0.21
head_age	0.10	0.15	0.02	-0.07	0.01	-0.04	0.03	-0.01	-0.04	0.07	0.19	0.02	0.00	-0.04	-0.04	-0.04	-0.13	1.00	0.11
hhsize	0.29	0.29	0.05	-0.06	0.15	0.01	0.24	0.09	0.20	0.18	0.31	0.01	0.00	-0.03	-0.09	-0.03	0.21	0.11	1.00

Notes: This table is based on the pooled, all-country and all-year dataset and therefore only contains assets common to all surveys.

Table A2: Summary out-of-sample performance for EO-based OLS-1 models

A. Poverty Measures

Predictand	Validation	Average R-squared P_r	Average R-squared P_s	Average RMSE P_r	Average RMSE P_s	Average Spearman's ρ P_r	Average Spearman's ρ P_s
P^0 $z = \$1.90$	country cv	0.412	0.456	0.231	0.213	0.632	0.648
	country spatial cv	0.051	0.159	0.271	0.235	0.399	0.520
	pooled cv	0.448	0.523	0.235	0.229	0.650	0.742
	pooled leave-country-out	-0.512	0.020	0.353	0.303	0.363	0.467
P^1 $z = \$1.90$	country cv	0.291	0.319	0.109	0.074	0.637	0.657
	country spatial cv	-0.049	0.051	0.122	0.076	0.467	0.510
	pooled cv	0.354	0.474	0.122	0.069	0.624	0.741
	pooled leave-country-out	-0.415	-0.082	0.200	0.092	0.344	0.409
P^2 $z = \$1.90$	country cv	0.198	0.194	0.076	0.032	0.614	0.642
	country spatial cv	-0.017	0.044	0.079	0.035	0.455	0.509
	pooled cv	0.281	0.398	0.078	0.028	0.593	0.718
	pooled leave-country-out	-0.297	-0.150	0.125	0.036	0.328	0.378
P^0 $z = \$3.20$	country cv	0.570	0.669	0.204	0.202	0.636	0.715
	country spatial cv	0.235	0.399	0.236	0.238	0.401	0.524
	pooled cv	0.582	0.674	0.196	0.195	0.649	0.702
	pooled leave-country-out	0.112	0.301	0.297	0.270	0.444	0.522
P^1 $z = \$3.20$	country cv	0.509	0.609	0.135	0.107	0.674	0.677
	country spatial cv	0.118	0.282	0.162	0.122	0.466	0.577
	pooled cv	0.505	0.639	0.145	0.113	0.678	0.791
	pooled leave-country-out	-0.533	0.209	0.227	0.164	0.401	0.480
P^2 $z = \$3.20$	country cv	0.395	0.516	0.104	0.068	0.664	0.683
	country spatial cv	0.030	0.229	0.117	0.072	0.485	0.565
	pooled cv	0.421	0.581	0.114	0.071	0.653	0.790
	pooled leave-country-out	-0.478	0.084	0.193	0.101	0.375	0.463

B. Asset Wealth Index

Predictand	Validation	R-squared	RMSE	Spearman's ρ
$\bar{A}$	country cv	0.574	9.400	0.668
	country spatial cv	0.204	10.893	0.505
	pooled cv	0.647	9.102	0.723
	pooled leave-country-out	0.333	10.534	0.609

Notes: Diagnostic statistics are averaged over folds and geographies.

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