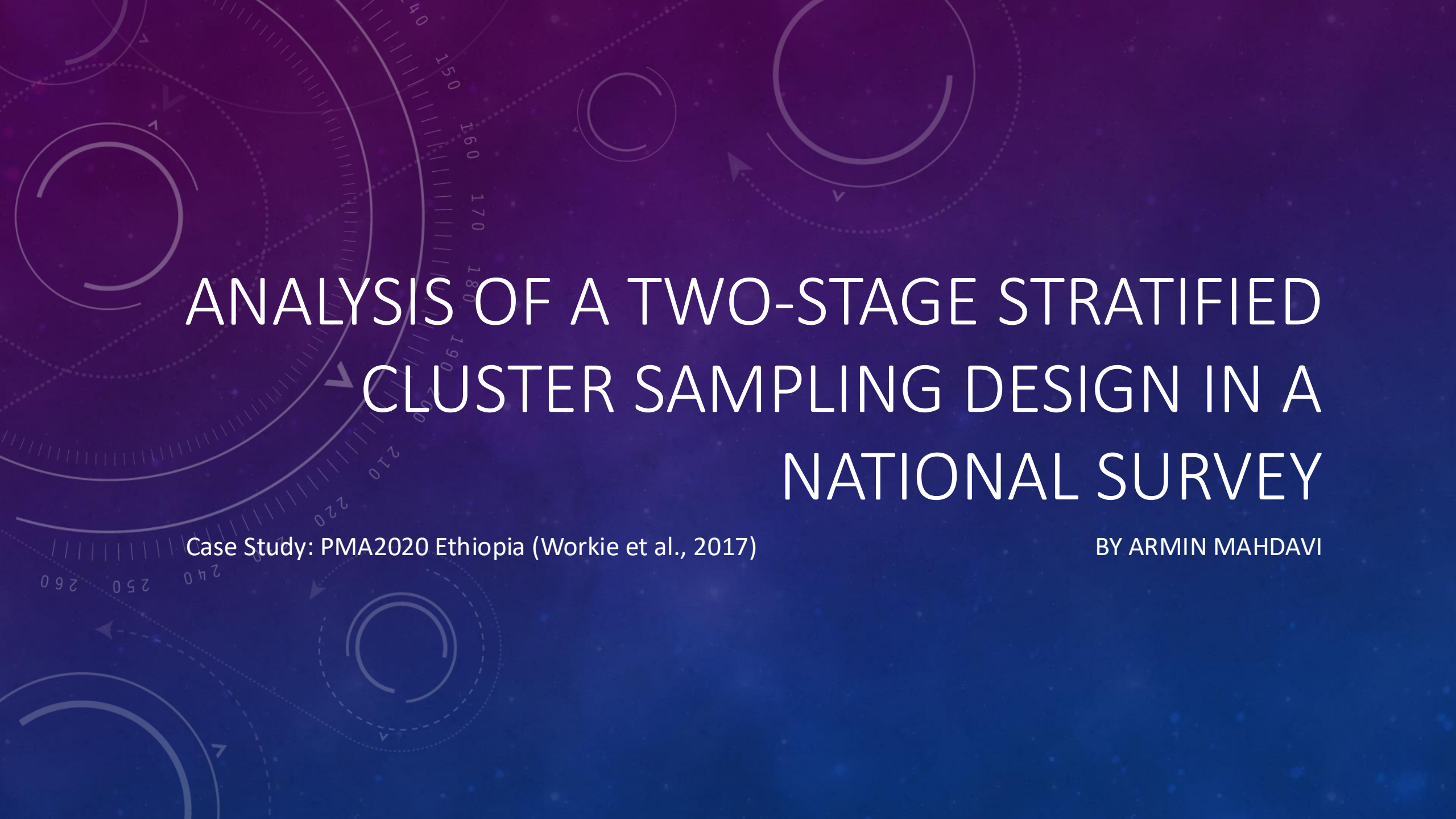




ANALYSIS OF A TWO-STAGE STRATIFIED CLUSTER SAMPLING DESIGN IN A NATIONAL SURVEY

Case Study: PMA2020 Ethiopia (Workie et al., 2017)

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STUDY OVERVIEW

Full title: A binary logistic regression model with complex sampling design of unmet need for family planning among all women aged (15-49) in Ethiopia.

- Population: Women aged 15–49 in Ethiopia
 - Sample size: $n = 7,494$
 - Outcome: Unmet need for family planning (binary)
 - 1= unmet need, 0=no unmet need.
 - All other background characteristics of the women were categorical
 - Objective: to estimate prevalence and factors associated with said unmet needs of family planning.
 - Specific parameter: population log-odds of unmet need among Ethiopian women aged 15-49.

SAMPLING DESIGN OVERVIEW

- Data Utilized: PMA2020 Round 4 Survey, a national conducted survey in Ethiopia, conducted in April 2016.
 - Performance Monitoring for Action, collaboration between Addis Ababa U and John Hopkins U.
- Two-stage stratified cluster sampling design
 - Stage 1: 221 Enumeration Areas (PSUs, clusters, or neighborhoods) Primary Sampling Unit = PSU
 - Stage 2: 35 households per EA (SRS within cluster)
 - Eligible women interviewed
 - Broad representation ensured but also introduced clustering effects via Stage 1.

SAMPLING FRAME

- Central Statistical Agency's master sampling frame of enumeration areas (221 EAs selected).

STRATIFICATION

- PMA2020 population divided into strata
 - Improves precision
 - Ensures subgroup representation
 - Changes variance estimation structure

WHY SAMPLING DESIGN MATTERS

- Classical regression assumes IID sampling,
 - Independent (one observation's outcome isn't influencing another observation's outcome)
 - Equal selection probabilities
 - Simple Random Sampling (SRS)
 - Survey used stratification, clustering, multistage sampling

CLUSTERING AND INTRA-CLASS CORRELATION

- Women within same EA correlated
 - Design Effect: $Deff = 1 + (n - 1)\rho$
 - Inflates variance relative to SRS
 - Ignoring clustering underestimates Standard errors!
 - $SE_{cluster} = \sqrt{Deff} \cdot SE_{SRS}$
 - Deff =1 same as ...

- Example: $\rho = 0.2$, given the nature of these clusters,

And given $n=35$, $Deff=2.79$ so the clustering SE increases by a factor of 2.79

Measures variance inflation when combined with cluster size via within-cluster similarity.

n = average cluster size (35)

ρ = intra-class correlation coefficient (ICC).

$\rho = 1 \rightarrow$ all group members are identical

$\rho = 0 \rightarrow$ none of the group members are identical (SRS)

CLUSTERING AND INTRA-CLASS CORRELATION

- Effective sample size to consider,
- design effect “affects” effective sample size:
- $n_{eff} = \frac{n}{Deff}$
- With $n=7,494$, the “effective” sample size that can provide useful independent information is reduced by design effect value. This is because of ICC

ρ = intra-class correlation coefficient (ICC).

If women within clusters (same EA) are very similar the coefficient is higher → higher DE.
This means a larger sample is now required to maintain same power of useful independent information.

IF SIMPLE RANDOM SAMPLING (SRS) WAS USED?

CONSIDERATION	EFFECT BY SRS	EFFECT BY TWO-STAGE CLUSTER
COST	HIGHER	LOWER
VARIANCE	LOWER	HIGHER
INDEPENDENCE	YES	NO
WEIGHTING	NOT NEEDED	NEEDED

WHY STANDARD LOGISTIC REGRESSION IS UNSUITABLE

Our logistic regression model is :

$$\text{logit}(\pi(\vec{X})) = \log\left(\frac{\pi(\vec{X})}{1 - \pi(\vec{X})}\right) = \beta_0 + \beta_1 X_1 + \dots + \beta_k X_k$$

- $\text{logit}(P(Y=1|X)) = \beta_0 + \beta_1 X_1 + \dots + \beta_p X_p$
 - Requires independence (cluster sampling violates)
 - Requires equal probability sampling
 - Estimator coefficients may remain consistent

COMPLEX OR SURVEY-ADJUSTED LOGISTIC REGRESSION (PSEUDO-LIKELIHOOD)

- Incorporates sampling weights
 - Accounts for clustering (PSU)
 - Accounts for stratification
 - Accounts for nonresponse adjustment

Base Weight: $w_i = 1 / \pi_i$

π_i = selection probability

Corrects unequal probability sampling

provides population-representative estimates

Higher selection probability $\rightarrow$ less weight contribution and vice versa

- Variance estimated via first-order Taylor linearization at the PSU level.
 - Approximates sampling distribution of $\hat{\beta}$ to estimate its variance.
 - Accounts for clustering
- B-weighted information matrix (bread)
- M-cluster-level variation (meat)

Sandwich estimate of $\text{cov}(\hat{\beta})$

$$\widehat{\text{cov}}(\hat{\beta}) = \hat{B}^{-1} \hat{M} \hat{B}^{-1}$$

$$\hat{B} = \sum_{i=1}^N \hat{D}_i \hat{V}_i^{-1} \hat{D}_i \quad \text{bread}$$

$$\hat{M} = \sum_{i=1}^N \hat{D}_i \hat{V}_i^{-1} \left\{ (Y_i - \hat{\mu}_i)(Y_i - \hat{\mu}_i) \right\} \hat{V}_i^{-1} \hat{D}_i \quad \text{meat}$$

Consistent estimate of the true
Covariance matrix of Y

HOW IS STANDARD ERROR AFFECTED? POINT ESTIMATES?

- All 7494 women interviewed for standard logistic regression assumes independent information. But with cluster sampling, women might likely be similar within same EAs. Design effect inflates variance.
- Less independent information available → variance of point estimates increases
 - Ignoring clustering underestimates Standard errors!
 - $SE_{cluster} = \sqrt{Deff} \cdot SE_{SRS}$
- Conditional mean model is unaffected.
- Point estimates themselves however, are often not changed.
 - Example of what that would look like:

Logistic Regression	$\hat{\beta}$	SE	p-value
Normal/naive	~same	lower	<0.05
Survey-adjusted	~same	higher	<0.05

SURVEY-WEIGHTED ESTIMATING EQUATION

- $\sum_{i=1}^n w_i X_i (Y_i - \mu_i) = 0$
- Where,
- $\mu_i = \text{logit}^{-1}(X_i^T \cdot \beta)$
- Survey logistic regression uses weighted score equation to solve for parameter estimates. This weight component reflects unequal selection probabilities mentioned earlier.

KEY RESULTS, VIA ODDS RATIOS

- Inference is design-adjusted
- Adjusted Odds Ratios Findings (of unmet family planning needs):
 - Urban residence ↓ odds
 - Young age ↑ odds
 - Currently married ↑ odds
 - Higher education ↓ odds
 - More births ↓ unmet need

The key determinants of unmet need FP in Ethiopia were residence, age, marital-status, education, household members, birth-events and number of under-5 children.

Government should take immediate steps to address the causes of high unmet need for family planning among women.

Table 5 Factors associated with unmet need for FP among aged (15-49) in Ethiopia, March to April, 2016

Variables		Total Unmet Need		COR (95% CI)	AOR (95% CI)	Over all P-value
		No	Yes n (%)			
Place of Residence	Urban	1672	130(7.2)	0.33 (0.273, 0.399)*	0.717 (0.556, 0.924)*	<0.0001
	Rural	4605	1087(19.1)	1	1	
Age in groups	15-24	2766	313(10.2)	0.466 (0.397, 0.547)*	2.266 (1.644, 3.123)*	<0.0001
	25-34	1906	514(21.2)	1.112 (0.959, 1.288)	1.237 (0.989, 1.547)	
	35+	1605	390(19.5)	1	1	
Marital Status	Currently married	3549	1121(24.0)	19.5 (13.648, 27.863)*	8.077 (5.21, 12.523)*	<0.0001
	Living with man	87	25(22.3)	17.4 (9.857, 30.718)*	7.344 (3.654, 14.761)*	
	Divorced/separated	488	28(5.4)	3.492 (2.077, 5.87)*	1.498 (0.825, 2.722)	
	Widow	189	12(6.0)	3.785 (1.900, 7.542)*	1.434 (0.663, 3.103)	
Never married	1962	32(1.6)	1	1		
	Never	2418	701(22.5)	4.816 (2.182, 10.628)*	0.323 (0.186, 0.559)*	
highest level of school attended	Primary	2479	406(14.1)	2.724 (1.231, 6.026)*	0.417 (0.240, 0.726)*	<0.0001
	Secondary	1076	93(8.0)	1.434 (0.635, 3.241)	0.499 (0.278, 0.896)*	
	Technical	191	10(5.0)	0.907 (0.332, 2.476)	0.460 (0.184, 1.150)	
	Higher	109	7(6.0)	1	1	

REPERCUSSIONS OF COMPLEX DESIGN OMISSION

- Underestimated standard errors
 - Inflated Type I error
 - Different conclusions
 - Potential policy misinterpretation

DESIGN STRENGTHS

- National representativeness
 - Cost-efficient implementation
 - Made region estimates possible
 - Design-consistent inference

LIMITATIONS

- Stratification variable not explicitly described in article
 - Perhaps due to PMA2020 protocol
- Specifics of weight construction and design effect value not provided
- Was FPC used? Not provided.

BROADER STATISTICAL IMPLICATIONS AND CONCLUSION

- Design-based vs Model-based inference
 - Survey logistic regression (inference-protected) vs Multilevel modeling (can model cluster variation)
 - Finite population inference
 - Public health policy implications
- Proper use of multistage stratified sampling
 - Correct survey-weighted logistic regression
 - Valid design-adjusted inference
 - Population of Ethiopian women in 2016 is fixed and known

CITATIONS

- Workie, D. L., Zike, D. T., Fenta, H. M., & Mekonnen, M. A. (2017). A binary logistic regression model with complex sampling design of unmet need for family planning among all women aged (15-49) in Ethiopia. *African Health Sciences*, 17(3), 637–646. <https://doi.org/10.4314/ahs.v17i3.6>
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QUESTION TIME