

7.6 Cluster Sampling with Unequal Cluster Sizes

- Suppose the N cluster sizes M_1, M_2, \dots, M_N are not all equal and that a one-stage cluster sample of n primary sampling units (PSUs) is taken with the goal of estimating t or \bar{y}_U .
- Let M_i and t_i ($i = 1, 2, \dots, n$) be the sizes and totals of the n sampled PSUs. Let $m = \sum_{i=1}^n M_i$ be the total number of secondary sampling units (SSUs) in the sample.
- We will review three methods of estimating \bar{y}_U and t given the unequal cluster sizes. These methods are based on two representations of the population mean \bar{y}_U .

(i) \bar{y}_U as a population ratio:

$$\bar{y}_U = \frac{\sum_{i=1}^N t_i}{\sum_{i=1}^N M_i} = \frac{\sum_{i=1}^N t_i}{M_0} \quad (89)$$

expresses \bar{y}_U as the ratio of the total of the primary sampling unit values to the total number of secondary sampling units.

(ii) \bar{y}_U as a mean cluster total:

$$\bar{y}_U = \left(\frac{N}{M_0} \right) \sum_{i=1}^N \frac{t_i}{N} \quad (90)$$

expresses \bar{y}_U as a multiple of the mean of the cluster totals.

Method 1: The sample cluster ratio: Suppose a SRS of clusters is selected without replacement. Substitution of sample values into (89) provides the following ratio estimator for \bar{y}_U :

$$\widehat{\bar{y}}_{Uc(1)} = \frac{\sum_{i=1}^n t_i}{\sum_{i=1}^n M_i} = \frac{\sum_{i=1}^n t_i}{m} = r_{clus}$$

which is the ratio of the sum of the sampled cluster totals to the sum of the sampled cluster sizes. Thus, the ratio-based estimator for t is

$$\widehat{t}_{c(1)} = M_0 \widehat{\bar{y}}_{Uc(1)} = M_0 r_{clus}$$

- $\widehat{\bar{y}}_{Uc(1)}$ is a special case of the SRS ratio estimator presented in Section 5 of the course notes (with $y_i = t_i$ and $x_i = M_i$). Thus, $\widehat{\bar{y}}_{Uc(1)}$ is biased with the bias $\rightarrow 0$ as n increases.
- There are no closed-forms for the true variances of $\widehat{\bar{y}}_{Uc(1)}$ and $\widehat{t}_{c(1)}$. However, approximations are given in Section 5 of the course notes.
- Estimators of the variances ($\widehat{V}(\widehat{t}_{c(1)})$ and $\widehat{V}(\widehat{\bar{y}}_{Uc(1)})$) are in Section 5 of the course notes.
- If M_0 is not known, $\widehat{V}(\widehat{\bar{y}}_{Uc(1)})$ can be estimated by replacing M_0 with the estimate $\widehat{M}_0 \approx Nm/n$. Then dividing \widehat{M}_0^2 (instead of M_0^2) provides an estimate of $\widehat{V}(\widehat{\bar{y}}_{Uc(1)})$.
- Furthermore, when estimating t , multiply $\widehat{\bar{y}}_{Uc(1)}$ by \widehat{M}_0 and $\widehat{V}(\widehat{\bar{y}}_{Uc(1)})$ by \widehat{M}_0^2 .

Figure 10: Cluster Sampling with Unequal-Sized Cluster

The mean $\bar{y}_U = 33.385$. There are $M_0 = 400$ secondary sampling units and $N = 49$ primary sampling units (clusters). There are 9 clusters of size $M_i = 16$, 24 clusters of size $M_i = 8$, and 16 clusters of size $M_i = 4$. The boldfaced values represent the SSUs in the sample.

18	20	15	20	20	15	19	18	24	23	20	26	29	28	28	31	31	34	28	32
13	20	16	20	15	23	19	26	21	21	24	30	23	26	25	33	31	28	32	38
16	18	20	24	25	26	22	23	26	26	22	27	25	25	34	28	37	36	38	31
17	17	16	22	21	23	22	27	27	24	28	32	29	33	27	37	37	38	35	33
15	19	23	17	21	23	21	23	24	25	31	26	32	34	32	33	31	31	36	37
21	24	20	21	28	26	30	22	31	25	29	29	27	30	29	37	35	32	38	43
23	17	24	25	24	27	31	29	31	34	27	36	29	29	34	39	37	37	40	36
18	24	21	25	27	22	32	32	31	26	28	34	34	37	35	34	38	38	37	40
22	26	28	26	24	29	33	26	27	27	34	31	39	32	36	38	37	40	44	43
23	27	28	29	26	32	25	31	35	34	32	33	37	32	42	40	40	37	42	44
23	21	31	23	30	27	31	30	32	35	30	40	32	37	37	36	40	44	44	40
26	29	31	26	30	31	34	36	30	38	36	32	38	38	37	42	42	41	40	49
28	24	28	27	26	31	32	29	32	33	38	34	39	38	40	37	41	43	42	43
32	25	31	32	29	29	35	38	38	32	36	35	39	42	39	40	44	42	41	45
27	29	35	28	35	35	31	40	35	37	38	44	40	40	47	39	49	48	51	49
30	29	32	32	33	30	36	38	42	36	35	38	44	47	45	49	41	43	44	51
28	35	35	34	34	33	41	33	34	35	39	44	44	48	44	50	49	48	53	54
29	33	32	36	39	33	33	34	35	42	46	47	48	47	46	45	44	52	54	55
28	37	38	37	33	33	34	37	45	40	39	42	42	46	47	48	52	47	46	53
38	39	39	37	34	38	39	45	39	42	45	41	44	51	46	50	52	51	51	53

M_i	t_i	$\bar{y}_i = t_i/M_i$	M_i	t_i	$\bar{y}_i = t_i/M_i$
16	401	25.0625	16	337	21.0625
8	279	34.8750	8	321	40.1250
8	280	35.0000	4	171	42.7500
4	187	46.7500	4	216	54.0000

$$m = 68 \quad \sum t_i = 2192 \quad \bar{y} = 274 \quad \bar{\bar{y}} = 37.453125$$

Method 2: The cluster sample total: Suppose a SRS of clusters is selected without replacement. Substitution of sample values into (90) provides the following unbiased estimator for \bar{y}_U :

$$\widehat{\bar{y}}_{Uc(2)} = \frac{N}{M_0} \frac{\sum_{i=1}^n t_i}{n} = \frac{N}{nM_0} \sum_{i=1}^n t_i$$

- The variance $V(\widehat{\bar{y}}_{Uc(2)}) = \frac{(N-n)N}{n(N-1)M_0^2} \sum_{i=1}^N (t_i - \bar{t}_i)^2 = \frac{(N-n)N}{nM_0^2} S_t^2$

where S_t^2 is the population variance of the t_i values.

- An estimate of this variance is given by

$$\widehat{V}(\widehat{\bar{y}}_{Uc(2)}) = \frac{(N-n)N}{n(n-1)M_0^2} \sum_{i=1}^n (t_i - \bar{y})^2 = \frac{(N-n)N}{nM_0^2} s_t^2. \quad (91)$$

where s_t^2 is the sample variance of the sampled t_i values.

- To estimate t , multiply $\widehat{\bar{y}}_{Uc(2)}$ by M_0 . For estimated variances, multiply $\widehat{V}(\widehat{\bar{y}}_{Uc(2)})$ by M_0^2 .
- If M_0 is not known, we can substitute of $\widehat{M}_0 = Nm/n$ into (91) and get:

$$\widehat{V}(\widehat{\bar{y}}_{Uc(2)}) = \frac{(N-n)n}{(n-1)Nm^2} \sum_{i=1}^n (t_i - \bar{y})^2 = \frac{(N-n)n}{Nm^2} s_t^2. \quad (92)$$

- For Methods 1 and 2, if a SRS of clusters is taken with replacement, then the estimator formulas for t and \bar{y}_U remain unchanged, but the variance formulas need to be adjusted. Simply replace $N(N-n)$ with N^2 in the numerators of the estimated variance formulas.

Confidence Intervals

- A confidence interval for \bar{y}_U using either Method 1 ($k = 1$) or Method 2 ($k = 2$) is:

$$\widehat{\bar{y}}_{Uc(k)} \pm t^* \sqrt{\widehat{V}(\widehat{\bar{y}}_{Uc(k)})} \quad \text{for } k = a, b \quad (93)$$

where t^* is the upper $\alpha/2$ critical value from the $t(n-1)$ distribution.

Method 3: Primary sampling units selected with pps:

Suppose that the primary sampling units (PSUs) are selected with replacement with draw-by-draw selection probabilities (p_i) proportional to the sizes of the PSUs, $p_i = M_i/M_0$.

One way to select the PSUs when each of M_i 's (the sizes of the PSUs) is known is to

1. Generate N intervals $(0, M_1]$, $(M_1, M_1 + M_2]$, $(M_1 + M_2, M_1 + M_2 + M_3]$, \dots , $(M_1 + \dots + M_{N-1}, M_0]$.
2. Generate a random number U between 0 and M_0 . Pick the interval that contains U . If this is the i^{th} interval, then select cluster i .
3. Repeat this n times.

Another way to construct the sampling design if each of the M_0 secondary sampling units can be listed in a sampling frame:

1. Select n SSUs (say, u_1, u_2, \dots, u_n) from the M_0 in the population using simple random sampling with replacement. That is, select n numbers with replacement from $\{1, 2, \dots, M_0\}$. Let u_i ($i = 1, 2, \dots, n$) be the corresponding n secondary sampling units.
2. Then for each u_i ($i = 1, 2, \dots, n$), sample all SSUs in the cluster containing u_i .

Thus, a PSU is selected every time any of its SSUs is selected.

- Now we can use either the Horvitz-Thompson estimator (Figure 11) or the Hansen-Hurwitz estimator (Figure 12), and their associated variance estimators discussed in Section 6 of the course notes.

Figure 11: Horvitz-Thompson Estimation with Selection Probabilities Proportional to Cluster Size

The mean $\bar{y}_U = 33.385$. There are $M_0 = 400$ secondary sampling units and $M_0 = 49$ primary sampling units (clusters). There are 9 clusters with $M_i = 16$, 24 clusters with $M_i = 8$, and 16 clusters with $M_i = 4$. Five clusters were sampled with replacement. One cluster was sampled twice. The boldfaced values are in the sample.

				Sampled ↓ twice ↓											
18	20	15	20	20	15	19	18	24	23	20	26	29	28	28	31
13	20	16	20	15	23	19	26	21	21	24	30	23	26	25	33
16	18	20	24	25	26	22	23	26	26	22	27	25	25	34	28
17	17	16	22	21	23	22	27	27	24	28	32	29	33	27	37
15	19	23	17	21	23	21	23	24	25	31	26	32	34	32	33
21	24	20	21	28	26	30	22	31	25	29	29	27	30	29	37
23	17	24	25	24	27	31	29	31	34	27	36	29	29	34	39
18	24	21	25	27	22	32	32	31	26	28	34	34	37	35	34
22	26	28	26	24	29	33	26	27	27	34	31	39	32	36	38
23	27	28	29	26	32	25	31	35	34	32	33	37	32	42	40
23	21	31	23	30	27	31	30	32	35	30	40	32	37	37	36
26	29	31	26	30	31	34	36	30	38	36	32	38	38	37	42
28	24	28	27	26	31	32	29	32	33	38	34	39	38	40	37
32	25	31	32	29	29	35	38	38	32	36	35	39	42	39	40
27	29	35	28	35	35	31	40	35	37	38	44	40	40	47	39
30	29	32	32	33	30	36	38	42	36	35	38	44	47	45	49
28	35	35	34	34	33	41	33	34	35	39	44	44	48	44	50
29	33	32	36	39	33	33	34	35	42	46	47	48	47	46	45
28	37	38	37	33	33	34	37	45	40	39	42	42	46	47	48
38	39	39	37	34	38	39	45	39	42	45	41	44	51	46	50

i	t_i	M_i	$p_i = M_i/M_0$	$\pi_i = 1 - (1 - p_i)^5$
1	344	16	16/400=.04	$1 - .96^5 = .184627302$
2	252	8	8/400=.02	$1 - .98^5 = .096079203$
3	278	8	8/400=.02	$1 - .98^5 = .096079203$
4	181	4	4/400=.01	$1 - .99^5 = .049009950$

$$\pi_{12} = \pi_{13} = [1 - (.96^5)] + [1 - (.98^5)] - [1 - (.94^5)] = .0146105270$$

$$\pi_{14} = [1 - (.96^5)] + [1 - (.99^5)] - [1 - (.95^5)] = .00741819$$

$$\pi_{24} = \pi_{34} = [1 - (.98^5)] + [1 - (.99^5)] - [1 - (.97^5)] = .003823179$$

$$\pi_{23} = [1 - (.98^5)] + [1 - (.98^5)] - [1 - (.96^5)] = .007531104$$

Figure 12: Hansen-Hurwitz Estimation with Selection Probabilities Proportional to Cluster Size

In Figure 11, the total abundance is $t = 13354$. There are $M_0 = 400$ secondary sampling units and $M_0 = 49$ primary sampling units (clusters). There are 9 clusters with $M_i = 16$, 24 clusters with $M_i = 8$, and 16 clusters with $M_i = 4$. The cluster totals t_i for the clusters in Figure 11 are summarized in the figure below. Also included is a cluster label (1 to 49). Eight clusters were sampled with replacement. The sampled units are 2, 6, 6, 16, 25, 30, 32, and 44. Note that cluster 6 was sampled twice. The boldfaced values are in the sample.

<i>1</i>	<i>2</i>	<i>3</i>	<i>10</i>	<i>11</i>	<i>12</i>	<i>13</i>
292	(344)	401	218	243	272	267
<i>4</i>	<i>5</i>	<i>6</i>	<i>14</i>	<i>15</i>	<i>16</i>	<i>17</i>
337	418	((467))	252	273	(279)	307
<i>7</i>	<i>8</i>	<i>9</i>	<i>18</i>	<i>19</i>	<i>20</i>	<i>21</i>
419	475	526	285	308	321	346
<i>22</i>	<i>26</i>	<i>30</i>	<i>34</i>	<i>35</i>	<i>36</i>	<i>37</i>
227	249	(278)	158	156	170	171
<i>23</i>	<i>27</i>	<i>31</i>	<i>38</i>	<i>39</i>	<i>40</i>	<i>41</i>
242	278	305	171	180	181	195
<i>24</i>	<i>28</i>	<i>32</i>	<i>42</i>	<i>43</i>	<i>44</i>	<i>45</i>
262	280	(322)	187	185	(193)	216
<i>25</i>	<i>29</i>	<i>33</i>	<i>46</i>	<i>47</i>	<i>48</i>	<i>49</i>
(293)	293	333	333	183	191	203

Unit i	t_i	p_i	t_i/p_i
2	344	.04	8600
6	467	.04	11675
6	467	.04	11675
16	279	.02	13950
25	293	.02	14650
30	278	.02	13900
32	322	.02	16100
44	193	.01	19300
			109850

7.6.1 Using R and SAS for estimation with unequal cluster sizes

R code for analysis of Figure 10 data: Methods 1 and 2

```
library(survey)
source("c:/courses/st446/rcode/confintt.r")

# Cluster sample with unequal-size clusters (Figure 10)

M0 = 400
N = 49
n = 8
y <- c(401,337,279,321,280,171,187,216)
clusterid <- c(1,2,3,4,5,6,7,8)

# Method 1: SRS of clusters using cluster ratios

fpc1 <- c(rep(N,n))
Mvec <- c(16,16,8,8,8,4,4,4)
ratio_ttl <- M0*y
ratio_mn <- y

Fig10 <- data.frame(cbind(fpc1,ratio_ttl,ratio_mn,Mvec))
Fig10

# Create the sampling design
dsgn10 <- svydesign(data=Fig10,id=~1,fpc=~fpc1)

# Method 1: Estimation of the population mean

estmean1 <- svyratio(~ratio_mn,~Mvec,design=dsgn10)
confint.t(estmean1,tdf=n-1,level=.95)

# Method 1: Estimation of the population total

esttotal1 <- svyratio(~ratio_ttl,~Mvec,design=dsgn10)
confint.t(esttotal1,tdf=n-1,level=.95)

# Method 2: SRS of clusters using cluster totals

fpc2 <- c(rep(N,8))
wgt2a <- c(rep(N/n,n))
wgt2b <- wgt2a/M0
#wgt2b <- c(rep(N/(n*M0),n))

Fig10a <- data.frame(cbind(clusterid,y,wgt2a,wgt2b,fpc2))
Fig10a
dsgn10a <-svydesign(ids=~clusterid,weights=~wgt2a,fpc=~fpc2,data=Fig10a)
dsgn10b <-svydesign(ids=~clusterid,weights=~wgt2b,fpc=~fpc2,data=Fig10a)

# Method 2: Estimation of population total

esttotal2 <- svytotal(~y,design=dsgn10a)
print(esttotal2,digits=15)
confint.t(esttotal2,level=.95,tdf=n-1)

# Method 2: Estimation of population mean

estmean2 <- svytotal(~y,design=dsgn10b)
print(estmean2,digits=15)
confint.t(estmean2,level=.95,tdf=n-1)
```

R output for analysis of Figure 10 data: Methods 1 and 2

Method 1: SRS of clusters using cluster ratios

	fpc1	ratio_ttl	ratio_mn	Mvec
1	49	160400	401	16
2	49	134800	337	16
3	49	111600	279	8
4	49	128400	321	8
5	49	112000	280	8
6	49	68400	171	4
7	49	74800	187	4
8	49	86400	216	4

> # Method 1: Estimation of the population mean

```
mean( ratio_mn/Mvec ) = 32.23529
SE( ratio_mn/Mvec ) = 3.60282
```

```
Two-Tailed CI for ratio_mn/Mvec where alpha = 0.05 with 7 df
  2.5 %      97.5 %
23.71598    40.75460
```

> # Method 1: Estimation of the population total

```
mean( ratio_ttl/Mvec ) = 12894.11765
SE( ratio_ttl/Mvec ) = 1441.12717
```

```
Two-Tailed CI for ratio_ttl/Mvec where alpha = 0.05 with 7 df
  2.5 %      97.5 %
9486.39340    16301.84189
```

> # Method 2: SRS of clusters using cluster totals

	clusterid	y	wgt2a	wgt2b	fpc2
1	1	401	6.125	0.0153125	49
2	2	337	6.125	0.0153125	49
3	3	279	6.125	0.0153125	49
4	4	321	6.125	0.0153125	49
5	5	280	6.125	0.0153125	49
6	6	171	6.125	0.0153125	49
7	7	187	6.125	0.0153125	49
8	8	216	6.125	0.0153125	49

> # Method 2: Estimation of population total

```
mean( y ) = 13426.00000
SE( y ) = 1255.09810
```

```
Two-Tailed CI for y where alpha = 0.05 with 7 df
  2.5 %      97.5 %
10458.16459    16393.83541
```

> # Method 2: Estimation of population mean

```
mean( y ) = 33.56500
SE( y ) = 3.13775
```

```
Two-Tailed CI for y where alpha = 0.05 with 7 df
  2.5 %      97.5 %
26.14541    40.98459
```

SAS code for analysis of Figure 10 data (Supplemental)

```

data in;
  NN = 49;
  MO = 400;
  n = 8;
input _cluster Mi y @@;
  t = MO*y;
datalines;
  1 16 401   2 16 337   3  8 279   4  8 321
  5  8 280   6  4 171   7  4 187   8  4 216
;
TITLE 'SRS of clusters with replacement-- Figure 10';

PROC SURVEYMEANS DATA=in TOTAL=49 ;
  VAR y;
  RATIO y/Mi;
  RATIO t/mi;
TITLE2 'The sample cluster ratio method: Method 1';

DATA in; SET in;
  ytotal = y*NN;
  ymean  = ytotal/MO;
  wgt = 1/MO;

PROC SURVEYMEANS DATA=in TOTAL=49 ;
  WEIGHT wgt;
  VAR ytotal ymean;
TITLE2 'The cluster sample total method: Method 2';
run;

```

SAS output for analysis of Figure 10 data

SRS of clusters with replacement-- Figure 10
The sample cluster ratio method: Method 1

The SURVEYMEANS Procedure
Data Summary

Number of Observations 8

Statistics

Variable	N	Mean	Std Error of Mean	95% CL for Mean	
y	8	274.000000	25.614247	213.4319	334.568
Mi	8	8.500000	1.612406	4.6873	12.313
t	8	109600	10246	85372.7721	133827.228

Ratio Analysis

Numerator	Denominator	N	Ratio	Std Err
y	Mi	8	32.235294	3.602818

95% CL for Ratio

Numerator	Denominator	95% CL for Ratio
y	Mi	23.7159835 40.7546047

Ratio Analysis

Numerator	Denominator	N	Ratio	Std Err
t	Mi	8	12894	1441.127165

95% CL for Ratio

Numerator	Denominator	95% CL for Ratio
t	Mi	9486.39340 16301.8419

SRS of clusters with replacement-- Figure 10
The cluster sample total method: Method 2

The SURVEYMEANS Procedure

Data Summary
Number of Observations 8
Sum of Weights 0.02

Variable	N	Statistics			
		Mean	Std Error of Mean	95% CL for Mean	
ytotat	8	13426	1255.098104	10458.1646	16393.8354
ymean	8	33.565000	3.137745	26.1454	40.9846

Using R and SAS for Hansen-Hurwitz Estimation (Method 3) for Figure 12 data

R code for Hansen-Hurwitz Estimation for Figure 12 data

```
library(survey)
source("c:/courses/st446/rcode/confintt.r")

# Cluster sample with unequal-size clusters (Figure 12)

M0 = 400
N = 49
n = 8
y <- c(344,467,467,279,293,278,322,193)
Mvec <- c(16,16,16,8,8,8,8,4)

# Method 3: Sampling proportional to size with replacement

p <- Mvec/M0
t <- y/p
t2 <- t/M0

Fig10c <- data.frame(t,t2)
Fig10c
dsgn10c <- svydesign(ids=~1,data=Fig10c)

# Method 3: Estimation of population total

esttotal3 <- svymean(~t,design=dsgn10c)
print(esttotal3,digits=15)
confint.t(esttotal3,level=.95,tdf=n-1)

# Method 3: Estimation of population mean

estmean3 <- svymean(~t2,design=dsgn10c)
print(estmean3,digits=15)
confint.t(estmean3,level=.95,tdf=n-1)
```

R output for Hansen-Hurwitz Estimation for Figure 12 data

```
> # Cluster sample with unequal-size clusters (Figure 12)
> # Method 3: Sampling proportional to size with replacement
```

```
      t      t2
1  8600 21.5000
2 11675 29.1875
3 11675 29.1875
4 13950 34.8750
5 14650 36.6250
6 13900 34.7500
7 16100 40.2500
8 19300 48.2500
```

```
> # Method 3: Estimation of population total
```

```
-----
mean( t ) = 13731.25000
SE( t ) = 1136.47668
```

```
Two-Tailed CI for t where alpha = 0.05 with 7 df
      2.5 %      97.5 %
11043.90968    16418.59032
-----
```

```
> # Method 3: Estimation of population mean
```

```
-----
mean( t2 ) = 34.32812
SE( t2 ) = 2.84119
```

```
Two-Tailed CI for t2 where alpha = 0.05 with 7 df
      2.5 %      97.5 %
27.60977    41.04648
-----
```

SAS code for Hansen-Hurwitz Estimation for Figure 12 data (supplemental)

```
data in;
  M0 = 400;
input _cluster Mi y @@;
  p = Mi/M0;    t = y/p;    ymean = t/M0;
datalines;
1 16 344  2 16 467  3 16 467  4  8 279
5  8 293  6  8 278  7  8 322  8  4 193
;
PROC SURVEYMEANS DATA=in MEAN CLM ;
  VAR t ymean;
TITLE 'PPS sampling of clusters with replacement-- Figure 12 -- Method 3';
run;
```

SAS output for Hansen-Hurwitz Estimation for Figure 12 data (supplemental)

PPS sampling of clusters with replacement-- Figure 12 -- Method 3

The SURVEYMEANS Procedure

Data Summary

Number of Observations 8

Statistics

Variable	Mean	Std Error of Mean	95% CL for Mean	
t	13731	1136.476679	11043.9097	16418.5903
ymean	34.328125	2.841192	27.6098	41.0465

7.7 Attribute Proportion Estimation using Cluster Sampling

- Instead of studying a quantitative measure associated with sampling units, we often are interested in an attribute (a qualitative characteristic). Statistically, the goal is to estimate a proportion. The **population proportion** p is the proportion of population units having that attribute.
- Examples: the proportion of females (or males) in an animal population, the proportion of consumers who own motorcycles, the proportion of married couples with at least 1 child. . .
- If a one-stage cluster sample is taken, then how do we estimate p ?

7.7.1 Estimating p with Equal Cluster Sizes

- Statistically, we use an indicator function that assigns a y_{ij} value to secondary sampling unit j in primary sampling unit (cluster) i as follows:

$$\begin{aligned} y_{ij} &= 1 && \text{if unit } j \text{ in cluster } i \text{ possesses the attribute} \\ &= 0 && \text{otherwise} \end{aligned}$$

Then $t = \sum_{i=1}^N \sum_{j=1}^M y_{ij}$ = the total number of SSUs in the population that possess the attribute. By definition, the population proportion p is

$$p = \frac{t}{MN} = \frac{t}{M_0}$$

where $M_i = M$ for each cluster, and the proportion for cluster i is

$$p_i = \frac{1}{M} \sum_{j=1}^M y_{ij}.$$

- By taking a one-stage cluster sample of n equal-sized clusters, we can estimate p as the weighted average of the sampled cluster proportions:

$$\hat{p}_c = \frac{\sum_{i=1}^n p_i}{n}.$$

- \hat{p}_c is an unbiased estimator of p , and the variance of \hat{p}_c is

$$V(\hat{p}_c) = \left(\frac{N-n}{nN} \right) \sum_{i=1}^N \frac{(p_i - p)^2}{N-1} = \left(\frac{1-f}{n} \right) \sum_{i=1}^N \frac{(p_i - p)^2}{N-1} \quad (94)$$

where $f = n/N$ = the proportion of clusters sampled.

- Because p is unknown, we use \hat{p}_c as an estimate of p to get the unbiased estimator of $V(\hat{p}_c)$:

$$\hat{V}(\hat{p}_c) = \left(\frac{N-n}{nN} \right) \sum_{i=1}^n \frac{(p_i - \hat{p}_c)^2}{n-1} = \left(\frac{1-f}{n} \right) \sum_{i=1}^n \frac{(p_i - \hat{p}_c)^2}{n-1} \quad (95)$$

7.7.2 Estimating p with Unequal Cluster Sizes

- Suppose the cluster sizes are not all equal. Let M_i be the number of secondary sampling units (SSUs) in cluster i and $t_i = \sum_{j=1}^{M_i} y_{ij}$ = the cluster i total.
- By taking a one-stage cluster sample of n clusters from a population with unequal-sized clusters, we estimate p as the proportion of sampled SSUs that possess the attribute:

$$\hat{p}_c = \frac{\sum_{i=1}^n t_i}{\sum_{i=1}^n M_i}.$$

- Note that \hat{p}_c is a ratio estimator. Therefore, it is a biased estimator. The bias, however, tends to be small for large $\sum_{i=1}^n M_i$.
- The variance $V(\hat{p}_c)$ is approximated by:

$$V(\hat{p}_c) \approx \left(\frac{1-f}{n\bar{M}_0^2} \right) \frac{\sum_{i=1}^N (t_i - pM_i)^2}{N-1} \quad (96)$$

where $\bar{M}_0 = \sum_{i=1}^N M_i / N$ = the average number of elements per cluster in the population.

- Because p is unknown, we use \hat{p}_c as an estimate to get the unbiased estimator of $V(\hat{p}_c)$:

$$\begin{aligned} \hat{V}(\hat{p}_c) &\approx \left(\frac{1-f}{n\bar{m}^2} \right) \frac{\sum_{i=1}^n (t_i - \hat{p}_c M_i)^2}{n-1} \\ &= \left(\frac{1-f}{n\bar{m}^2} \right) \frac{\sum_{i=1}^n t_i^2 - 2\hat{p}_c \sum_{i=1}^n t_i M_i + \hat{p}_c^2 \sum_{i=1}^n M_i^2}{n-1} \end{aligned} \quad (97)$$

where $\bar{m} = \sum_{i=1}^n M_i / n$ = the average number of elements per cluster in the sample.

Additional References

- Bellhouse, D.R. (1988) Systematic sampling. *Handbook of Statistics, Vol. 6 (Sampling)*. 125-145. Eds: Krishnaiah and Rao. Elsevier Science Publishers. Amsterdam.
- Murthy, M.N. and Rao, T.J. (1988) Systematic sampling with illustrative examples. *Handbook of Statistics, Vol. 6 (Sampling)*. 147-185. Eds: Krishnaiah and Rao. Elsevier Science Publishers. Amsterdam.
- Wolter, K.M. (1984) An investigation of some estimators of variance for systematic sampling. *J. of the American Statistical Association*. **79** 781-790.

Example of cluster sampling of attributes with unequal size clusters:

A simple random sample of $n = 30$ households (clusters) was drawn from a health district in Baltimore (USA) that contains $N = 15,000$ households. Using the following data, estimate the proportion p of people in this health district that visited a doctor last year.

Household Number	Household Size (M_i)	Number who visited doctor last year (t_i)	Household Number	Household Size (M_i)	Number who visited doctor last year (t_i)
1	5	5	16	6	0
2	3	2	17	3	3
3	2	0	18	3	0
4	3	0	19	3	0
5	4	0	20	4	0
6	3	0	21	2	0
7	7	0	22	4	4
8	3	1	23	5	2
9	4	0	24	4	0
10	3	1	25	3	3
11	4	2	26	3	0
12	3	0	27	1	0
13	2	2	28	4	2
14	3	0	29	4	2
15	2	0	30	4	1
Totals				104	30

7.7.3 Using R and SAS for proportion estimation with unequal-sized clusters

R code for proportion estimation with unequal-sized clusters

```
library(survey)
source("c:/courses/st446/rcode/confintt.r")

# Cluster sample with unequal-size clusters - proportion estimation)

N = 15000
n = 30

Mvec <- c(5,6,3,3,2,3,3,3,4,4,3,2,7,4,3,5,4,4,3,3,4,3,3,1,2,4,3,4,2,4)
y <- c(5,0,2,3,0,0,0,0,0,0,0,0,0,4,1,2,0,0,1,3,2,0,0,0,2,2,0,2,0,1)
fpc <- c(rep(N,n))

propest <- data.frame(cbind(fpc,y,Mvec))

# Create the sampling design
dsgn <- svydesign(data=propest,id=~1,fpc=~fpc)

estmean1 <- svyratio(~y,~Mvec,design=dsgn)
confint.t(estmean1,tdf=n-1,level=.95)
```

R output for proportion estimation with unequal-sized clusters

```
-----
mean( y/Mvec ) = 0.28846
SE( y/Mvec ) = 0.07208
Two-Tailed CI for y/Mvec where alpha = 0.05 with 29 df
      2.5 %      97.5 %
0.14105      0.43587
-----
```

SAS code for proportion estimation with unequal-sized clusters (supplemental)

```
data in;
  n = 30;
  NN = 15000;
  m = 104;
input _cluster Mi y @@;
datalines;
 1 5 5   2 6 0   3 3 2   4 3 3   5 2 0   6 3 0
 7 3 0   8 3 0   9 4 0  10 4 0  11 3 0  12 2 0
13 7 0  14 4 4  15 3 1  16 5 2  17 4 0  18 4 0
19 3 1  20 3 3  21 4 2  22 3 0  23 3 0  24 1 0
25 2 2  26 4 2  27 3 0  28 4 2  29 2 0  30 4 1
;
PROC SURVEYMEANS DATA=in TOTAL = 15000 MEAN CLM ;
  VAR y;
  RATIO y/Mi;
TITLE 'SRS of clusters without replacement-- Estimating p for household
data';
run;
```

SAS output for proportion estimation with unequal-sized clusters (supplemental)

SRS of clusters without replacement-- Estimating p for household data

The SURVEYMEANS Procedure

Statistics

Variable	Mean	Std Error of Mean	95% CL for Mean	
y	1.000000	0.253454	0.48162776	1.51837224
Mi	3.466667	0.223297	3.00997205	3.92336128

Ratio Analysis

Numerator	Denominator	Ratio	Std Err	
y	Mi	0.288462	0.072076	<-- for proportion p

Numerator	Denominator	95% CL for Ratio		
y	Mi	0.14104945	0.43587362	<-- for proportion p