Sampling People, Records, & Networks

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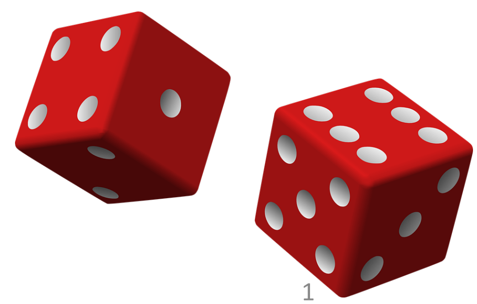

Unit 3

- 1 Simple complex
- 2 deff & roh
- 3 2-stage sampling
- 4 Designing 2-stage samples
- 5 Unequal sized clusters
- 6 Subsampling

- Unit 1: Sampling as a research tool
- Unit 2: Mere randomization
- Unit 3: Saving money
  - Lecture 1: Simple complex sampling – choosing entire clusters
  - Lecture 2: Design effects & intraclass correlation
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- Unit 4: Being more efficient
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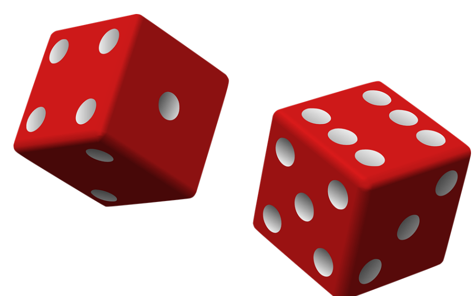
- Unit 6: Some extensions & applications



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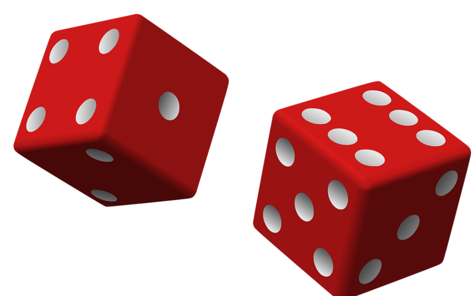

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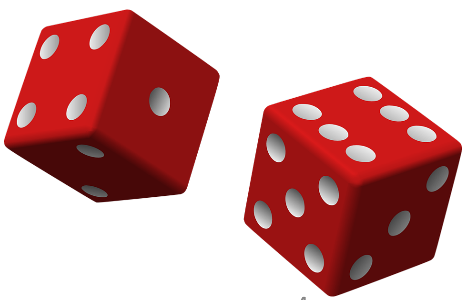

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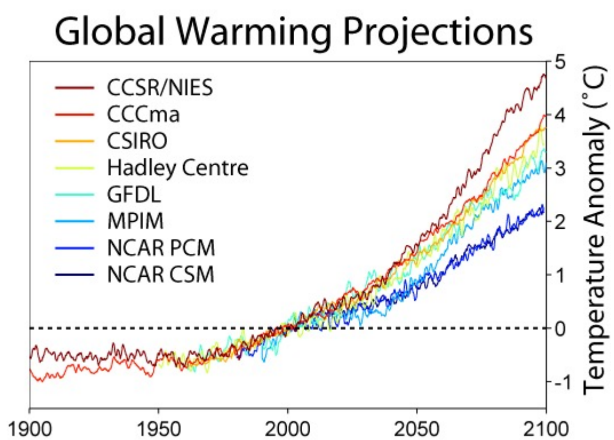
- **Projecting design effects**
- Design effects and sample size
- Projecting standard errors and confidence intervals

A. Suppose the sample described in Exercise 4 (with n = 2,400 and a = 60) is to be repeated with a smaller sample of n =1,200 and in only a = 30 equal-sized clusters

Project (say what is expected) how large the sampling variance of p will be under this new design.



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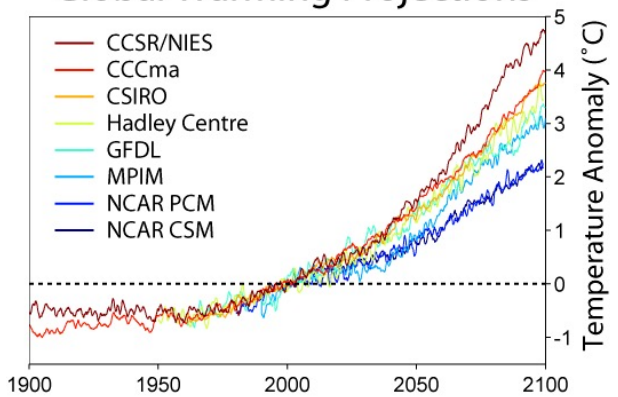
B. Now suppose the reduced size of *n* = 1,200 is retained, but we want to consider *a* = 60 equal-sized clusters.

Project (say what is expected) how large the sampling variance of *p* will be under this new design.

Global Warming Projections



- **Projecting design effects**
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1. **For A), compute the simple random sampling variance**

$$\text{var}_{SRS}(p) = \frac{p(1-p)}{n-1}$$

2. **Computed the design effect**

$$deff(p) = 1 + (b-1)roh = 1 + (40-1)roh$$

3. **Compute the projected sampling variance**

$$\text{var}(p) = \text{var}_{SRS}(p) \times deff(p) =$$

4. **For B), repeat steps 1-3 for the second design, replacing b = 40 with b = 20 in Step 2 above.**

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For A), n = 1200 for a = 30 and b = 40.

$$\mathrm{var}(p) = deff(p) \times \mathrm{var}_{SRS}(p)$$

Here,

$$deff(p) = 2.1795$$

Thus, using the design effect and new SRS variance, we can obtain *var*(*p*) under the new design.

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And, ignoring the *fpc*,

$$\mathrm{var}_{SRS}\left(p\right)=\frac{p\left(1-p\right)}{n}=\frac{0.4\times 0.6}{1,200}=0.0002$$

Then,

$$\mathrm{var}\left(p\right)=2.1795\times\boxed{0.0002}=0.0004358$$

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For B), when a = 60 and b = 20 for n = 1200,

$$deff\,(p) = 1 + (20 - 1)(0.03024) = 1.575$$

$$\text{var}\left(p\right) = 1.575 \times \boxed{0.0002} = 0.0003150$$

- **Projecting design effects**
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n	*a*	*b*	*deff*	*var(p)*
2400	60	40	2.1795	.000218
1200	30	40	2.1795	.000436
1200	60	20	1.5750	.000315

- Projecting design effects
- **Design effects and sample size**
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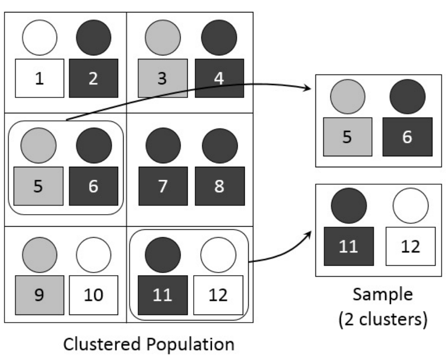
- **Design effects, when projected, can also help us determine sample size in cluster sampling**



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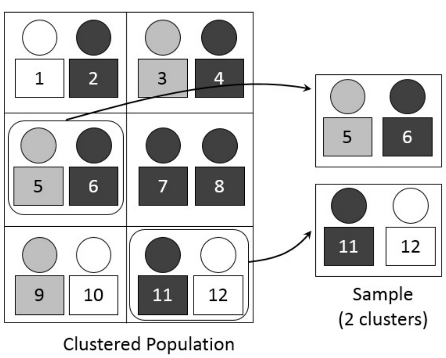
- **Design effects, when projected, can also help us determine sample size in cluster sampling**
- **Cluster sampling increases variances by a factor**

$$deff(p) = 1 + (b-1)roh$$

compared to SRS



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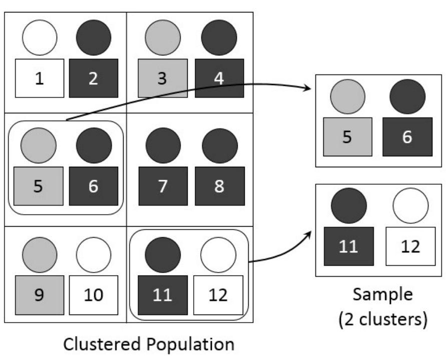

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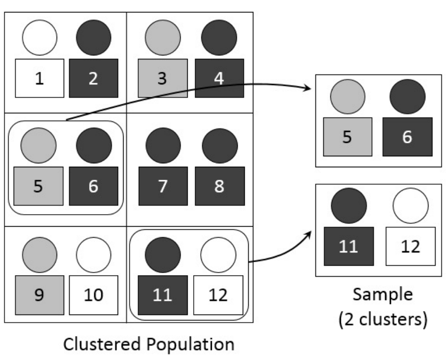

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- **Let's 'offset' this increase by increasing sample size by**

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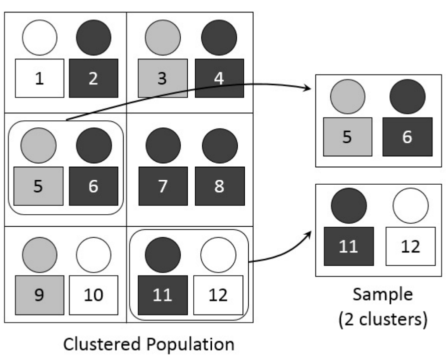
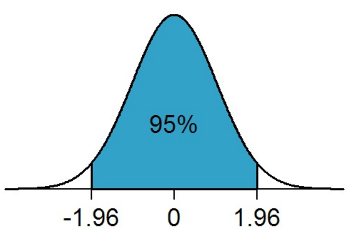
- **That is, compute an SRS sample size and inflate it by a design effect …**



- **For example, suppose, for our proportion p = 0.4 we want a 95% confidence interval (0.37,0.43)**



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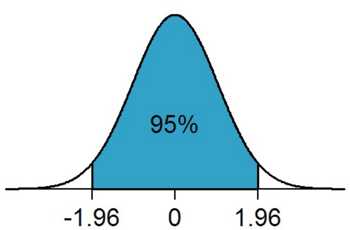
- This is a "margin of error" of 0.03 …



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- For example, suppose, for our proportion $p = 0.4$ we want a 95% confidence interval (0.37,0.43)
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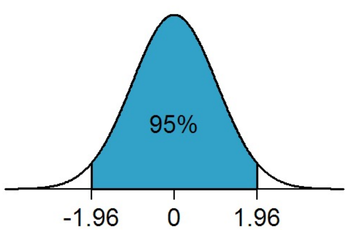

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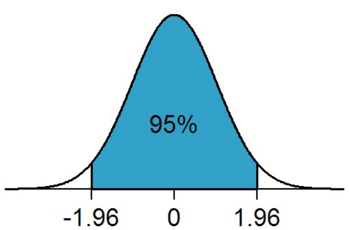
- Or a standard error of 0.015 ...
- Which for a proportion yields an SRS sample size

$$n_{SRS} = \frac{S^2}{\left[se(p)\right]^2} = \frac{(0.4)(1-0.4)}{\left[0.015\right]^2} = 1066.67$$



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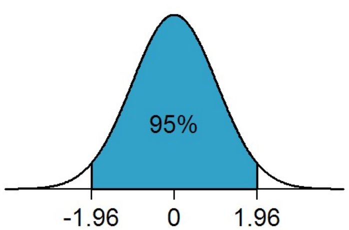
$$n_{SRS} = \frac{S^2}{\left[se\left(p\right)\right]^2} = \frac{\left(0.4\right)\left(1-0.4\right)}{\left[0.015\right]^2} = 1066.67$$

- If the cluster sample has *deff* = 2.1795, the sample size for the cluster sample would be

$$n = n_{SRS} \times deff\left(p\right) = 1066.67 \times 2.1795 \approx 2{,}325$$



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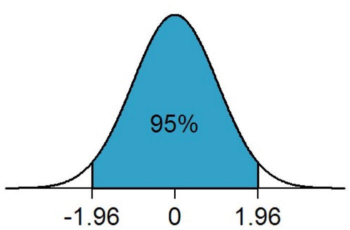
- **We can take the variance projection one step further, and project what a 95% confidence interval would look like …**



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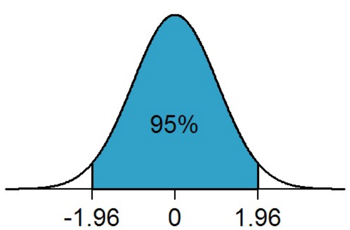
… the 95% confidence interval, using the 'Normal' distribution multiplier, is

$$\left(0.4 - 1.96 \times \sqrt{0.000315}, 0.4 + 1.96 \times \sqrt{0.000315}\right)$$

$$\left(0.365, 0.435\right)$$



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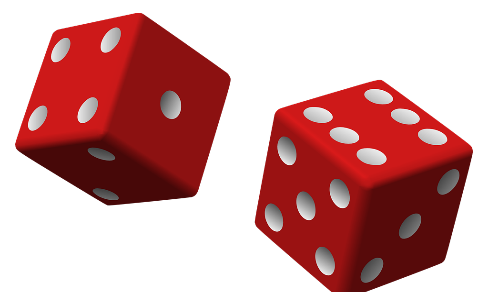

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