

METHODS OF QUANTITATIVE  
DATA ANALYSIS  
MSR Course, 2011-2012

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Lecture 1.2: Inferential Statistics

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# IS and DS lingo

- Standard error
- Confidence level
- Confidence interval
- Probability level
- Significance (alpha) level
- Statistically significant
- T-test / t-value
- F-test
- Chi-squared test
- Alpha / beta (type I/II) error
- Mean, median, mode
- Standard deviation
- Percentile scores
- Z-scores
- Association, correlation
- Regression
- Variance, explained variance

# IS

- IS is about DS.
- IS adds to descriptive statistics (such as (difference in) means, standard deviation, regression- and correlation coefficients) on sample data, how these statistics would be in the population.
- Note that population statistics are fixed (but unknown), the uncertainty is in the sample.

# What if there is no (good) sample?

- IS assumes (simple) random sampling.
- If there is no random sample, IS quantities have no literal interpretation, they are only ‘metaphors’.
  - What could we have said about the population if the observations would have constituted a simple random sample?
- I still find this a very valuable point of view. Others disagree.
- NOTE: If there is no simple random sample, is does not mean that there is no sampling error. You just cannot model it exactly.

# Benchmark: simple random sampling (SRS)

- Random: lottery determines inclusion in the sample.
- Simple: there is only one single draw.
- Almost all IS quantities are calculated assuming SRS.
- In practical sampling SRS is hardly ever used.
- Techniques for handling complex random sampling: multi-level analyses, robust estimation, weights.

# Random, but not simple

- Systematic sampling with random begin
- Multistage clustered sampling
- Stratified sampling
- PPS sampling
- Evaluation of these sampling schemes requires specialized statistical programs (STATA).

# Non-random sampling

- Quota sampling
- Snowball sampling
- Convenience sampling
- Purposive sampling
- IS for these procedures is at best metaphorical

# Sampling distributions

- Take any DS quantity:  $P$ ,  $M$ ,  $SD$ ,  $R$ ,  $B$  or whatever.
- Assume a (fixed) population value.
- Draw an infinite number of samples (SRS) of size  $N$  and calculate the sample quantity:  $p$ ,  $m$ ,  $sd$ ,  $r$ ,  $b$  or whatever.
- The frequency distribution of all the sample quantities together is called the sampling distribution.



# Sampling distributions

- Have a normal (symmetric, bell-shaped) form
  - If population distribution is normal, or
  - If  $N$  is large ( $> 30$ )
  - Note that normality arises with larger  $N$  in the sample, irrespective of the nature of the distribution in the population.
- Have a t-distribution, when:
  - Sample is small / distribution is very non-normal.
- The (expected) mean of the sampling distribution is the population value of the DS quantity of interest.
- The (expected) standard deviation (SD) of the sampling distribution can be derived mathematically. It always contains an element that resembles  $1/\sqrt{N}$ : The higher  $N$ , the smaller the SD of the sampling distribution.

# SE

- The SD of the sampling distribution is called the Standard Error (SE) and is often printed in computer outputs.
- SE denotes the variation of a statistic when many samples (of size  $N$ ) would be drawn from the population.
- Important SE's:  $P$ ,  $M$ ,  $M1-M2$ ,  $R$ ,  $B$ .
- Most simple SE is that of the pearson correlation:  $1/\sqrt{N}$ .

# SE's in regression

- It is useful to study the formula's for SE's of simple and partial regression coefficients:
- $SE(B) = \text{SQRT}(SS(Y-\hat{Y}) / SS(X)*(N-2))$
- $SE(B) = \text{SQRT}(SS(Y-\hat{Y}) / SS(X)*(1-R_x^2)*(N-k-1))$
- Elements:
  - $SS(Y-\hat{Y})$ : residual variation in Y
  - $SS(X)$ : Variation of X
  - $(1-R_x^2)$ : VIF = explained variance in  $X_i$  by remaining  $X_k$
  - $(N-k-1)$ : degrees of freedom

# Implications

- Sampling variability goes up:
  - With smaller N
  - With more X variables
  - When X-variables are stronger correlated (=‘collinearity’)
  - When X-variable explain less variance in Y.
- These are all fundamental lessons in research design.

# Confidence intervals (CI)

- If we know the (normal) shape of the sampling distribution and SE, we can estimate the population value  $S$  of the statistic from the sample.
- The best estimate of the statistic  $S$  is its value  $s$  in the sample.
- The uncertainty in the estimate is formulated as a (95%) confidence interval:  $S = s \pm 2*SE$ .
- Again: the variation is among the samples, not in the population value. Each sample will give you a different estimate and in the long run 95% of the CI's will contain the population value.

# Significance testing

- (Significance) testing is a (binary) test whether a sample statistics could have been produced by a hypothetical population value, called the null-hypothesis ( $H_0$ ).
- $H_0$  usually assumes that a population statistic is 0, but this is not necessary.
- Statistical testing is the decision whether the sample statistic lies inside or outside the confidence interval of the population value specified in  $H_0$ .

# Confidence level $1-\alpha$

- Confidence levels are chosen by the researcher.  $\alpha$  is the chosen probability that the conclusion (population value is in CI) will be wrong.
- This is called the type I error: rejecting  $H_0$  while it is correct.
- If we increase  $1-\alpha$ , then we will be wrong less often, but we will also be less informative.
- $1-\alpha$  is conventionally very often chosen at 95%. This is arbitrary, but it could never be, say, 50%.

# $\alpha$ -errors

- A  $\alpha$ -error (or type I error) occurs when the  $H_0$  is true, but we reject the  $H_0$  (i.e. decide that the sample statistic is significant).
- We make  $\alpha$ -errors in  $\alpha\%$  (say: 5%) of all decisions. This is NOT influenced by the size of the sample.
- The only way to avoid making so much  $\alpha$ -errors is by choosing  $\alpha$  at a lower level.
- In practice, researchers (should) care very little about this type of error.



# Probability values

- Using the sampling distribution of the  $H_0$ , we can calculate the probability that the sample statistic would arise.
- This probability ( $p$ ) is calculated by computer programs and printed in the output. The SPSS header for this is “Sig.”.
- If the probability is lower than the significance level  $\alpha$ , we reject the  $H_0$  and call the sample result “statistically significant”.
- We will be wrong in  $\alpha\%$  of the case and commit an alpha-error (type I error): reject the  $H_0$ , while it is correct.
- We know in advance how often we will make an  $\alpha$ -error, but NOT when we make it.

# T-test

- We can compare the probability to the significance levels, or alternatively calculate:
- $\text{Effect} / \text{SE} = t$
- If  $t > 2$  or  $t < -2$ , we call the result statistically significant.
- Exact evaluation of  $t$  depends upon degrees of freedom, but this matters only for small samples.
- Most computer programs print both  $p$  and  $t$ .

# One- and two-tailed

- Computer programs usually calculate two tailed probability levels: what is the probability that the sample statistic or its negative counterpart would arise if  $H_0$  is true?
- This is so because computer programs cannot know the expected direction of a result.
- However, researchers usually have a one-tailed interest: they have an directional alternative hypothesis in mind.
- One-tailed probabilities are just half the two-tailed ones.
- The decision about one/two tailed is in the mind of the researcher.

# $\beta$ -errors

- A  $\beta$ -error (or type II error) occurs when the  $H_0$  is not true (but some alternative hypotheses  $H_1$ ), but we accept ('do not reject') the  $H_0$  (i.e. decide that the sample statistic is not significant)
- If we do not have a fixed  $H_1$ , the size of  $\beta$  cannot be calculated. However, we do know some circumstances in which  $\beta$  becomes smaller / larger.
- The ability to avoid  $\beta$ -errors is called the statistical power of a test [*onderscheidingsvermogen*]. Power =  $1 - \beta$ .
- $\beta$ -errors are usually of greater concern than  $\alpha$ -errors.

# When is $\beta$ smaller?

- $\beta$  is smaller:
  - With larger sample size  $N$
  - With more extreme  $H_1$
  - With higher alpha
  - In one-sided problems
  - With better measurement, also higher level of measurement
  - With stronger designs: matching, repeated observations / panel, paired observations, higher explained variance
  - With better samples (SRS or better).

# Problems with significance testing

- Significance testing leads to a binary decision (yes/no), but our research often requires nuances.
- Significance level is arbitrarily set (at, say, 5%).
- It all depends on SRS assumptions.
- Statistical significance is not relevance.
- In the end, we know more about  $H_0$  than about  $H_1$  – and we know very little about  $\beta$ .