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JOHNS HOPKINS
BLOOMBERG
SCHOOL *of* PUBLIC HEALTH

Section D

Simple Linear Regression Model: Estimating the Regression Equation—Accounting for Uncertainty in the Estimates

Example: Hemoglobin and Packed Cell Volume

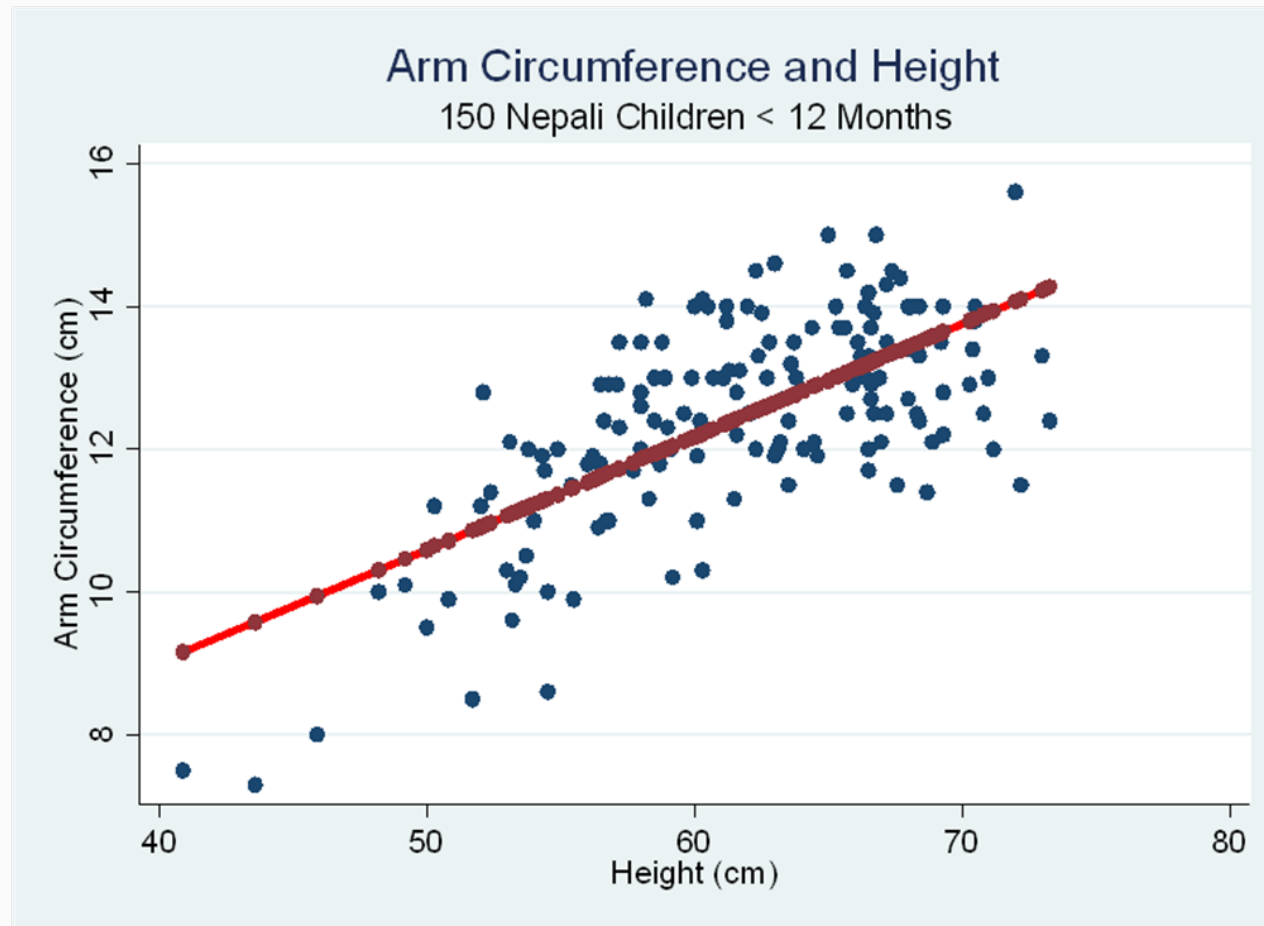
- So in the last section, we showed the results from several simple linear regression models
- For example, when relating arm circumference to height using a random sample of 150 Nepali children < 12 months old, I told you that the resulting regression equation was . . .

$$\hat{y} = 2.7 + 0.16x$$

- I told you this came from Stata—and will show you how to do regression with Stata shortly—but how does Stata estimate this equation?

Example: Arm Circumference and Height

- There must be some algorithm that will always yield the same results for the same data set

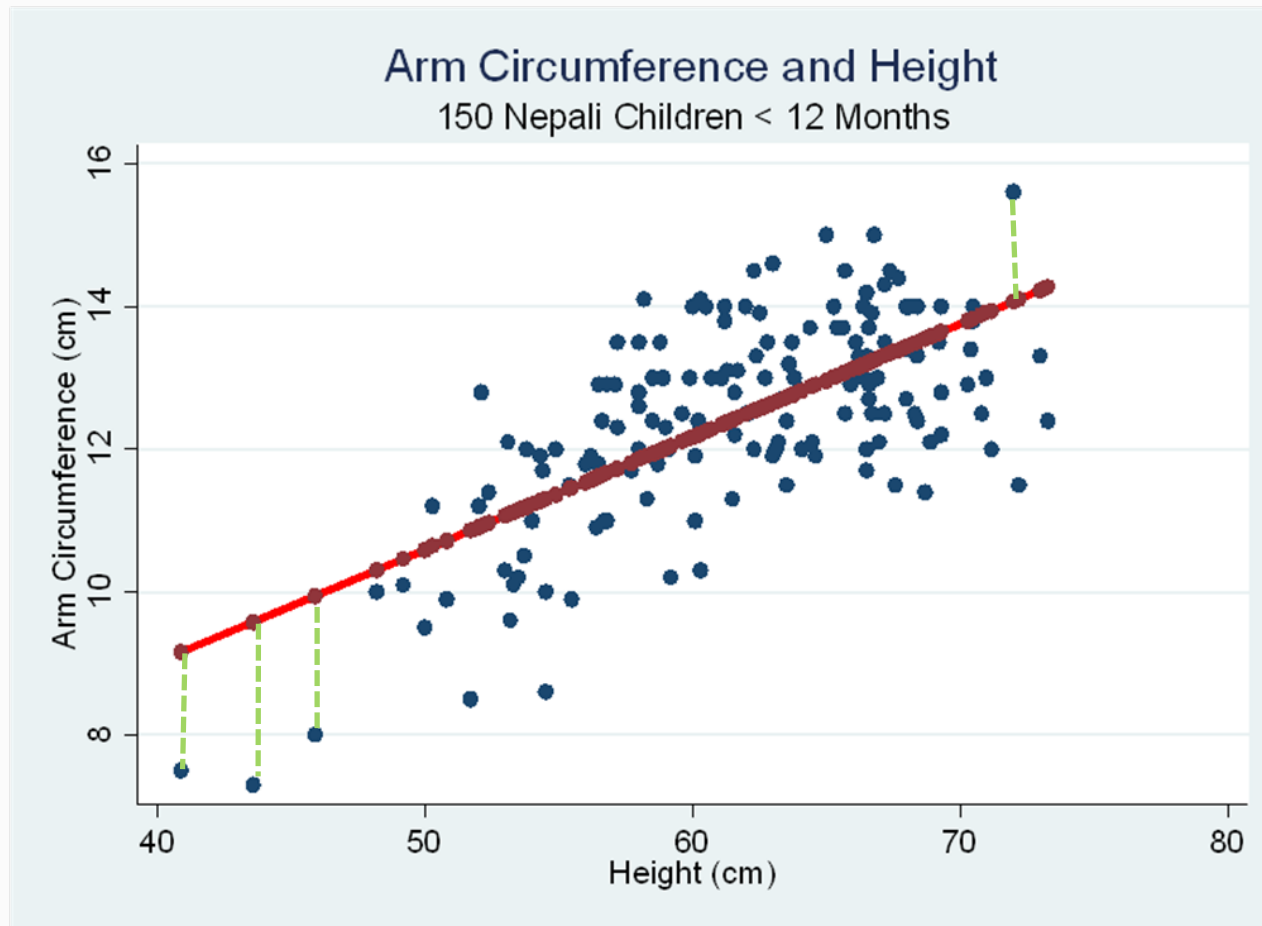


Example: Arm Circumference and Height

- The algorithm to estimate the equation of the line is called the “least squares” estimation
- The idea is to find the line that gets “closest” to all of the points in the sample
- How to define closeness to multiple points?
 - In regression, closeness is defined as the cumulative squared distance between each point’s y-value and the corresponding value of \hat{y} for that point’s x
 - In other words the squared distance between an observed y-value and the estimated y-value for all points with the same value of x

Example: Arm Circumference and Height

- Each distance is $y - \hat{y} = y - (\hat{\beta}_0 + \hat{B}_1x)$: this is computed for each data point in the sample



Example: Arm Circumference and Height

- The algorithm to estimate the equation of the line is called the “least squares” estimation
- The values chosen for $\hat{\beta}_0$ and $\hat{\beta}_1$ are the values that minimize the cumulative distances squared:

$$\min \left[\sum_{i=1}^n \left(y_i - (\hat{\beta}_0 + \hat{\beta}_1 x_i) \right)^2 \right]$$

Example: Arm Circumference and Height

- The values chosen for $\hat{\beta}_0$ and $\hat{\beta}_1$ are just estimates based on a single sample
 - If you were to have a different random sample of 150 Nepal children from the same population of <12 month olds, the resulting estimate would likely be different (i.e., the values that minimized the cumulative squared distance from this second sample of points would likely be different)
- As such, all regression coefficients have an associated standard error that can be used to make statements about the true relationship between mean y and x (for example, the true slope β_1) based on a single sample

Example: Arm Circumference and Height

- The estimated regression equation relating arm circumference to height using a random samples of 150 Nepali children < 12 months old, I told you that the resulting regression equation was . . .

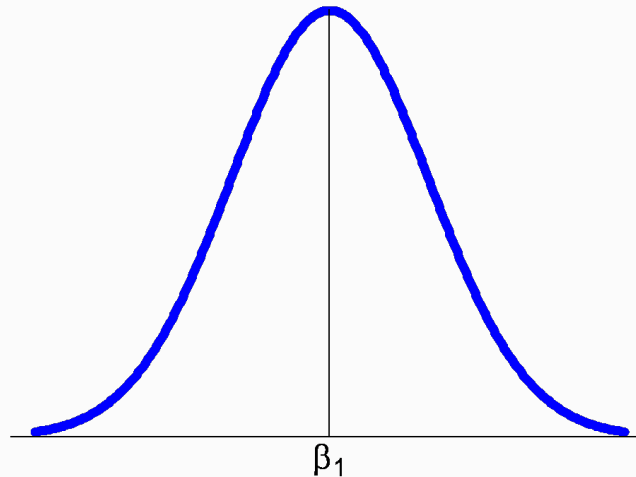
$$\hat{y} = 2.7 + 0.16x$$

$$\hat{\beta}_1 = 0.16 \text{ and } SE(\hat{\beta}_1) = 0.014$$

$$\hat{\beta}_0 = 2.70 \text{ and } SE(\hat{\beta}_0) = 0.88$$

Example: Arm Circumference and Height

- Random sampling behavior of estimated regression coefficients is normal for large samples ($n > 60$), and centered at true values



- As such, we can use the same ideas to create 95% CIs and get p-values

Example: Arm Circumference and Height

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$$\hat{\beta}_1 = 0.16 \text{ and } SE(\hat{\beta}_1) = 0.014$$

- 95% CI for β_1

$$\hat{\beta}_1 \pm 2 \times SE(\hat{\beta}_1) \rightarrow 0.16 \pm 2 \times 0.014 \approx (0.13, 0.19)$$

Example: Arm Circumference and Height

- p-value for testing:

- $H_0: \beta_1 = 0$

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- Assume the null is true and calculate standardized “distance” of $\hat{\beta}_1$ from 0

$$t = \frac{\hat{\beta}_1 - 0}{\widehat{SE}(\beta_1)} = \frac{\hat{\beta}_1}{\widehat{SE}(\beta_1)} = \frac{0.16}{.014} \approx 11.4$$

- P-value is the probability of being 11.4 or more standard errors away from mean of 0 on a normal curve: very low in this example, $p < .001$

Summarizing Findings: Arm Circumference and Height

- This research used simple linear regression to estimate the magnitude of the association between arm circumference and height in Nepali children less than 12 months old, using data on a random sample of 150
- A statistically significant positive association was found ($p < .001$)
- The results estimate that two groups of such children who differ by 1 cm in height will differ on average by 0.16 cm in arm circumference (95% CI 0.13 cm to 0.19 cm)

Summarizing Findings: Arm Circumference and Height

- Finally: Stata!
- If you have your “y” and “x” values entered in Stata, then to do linear regression use the regress command:
 - regress y x
- Data snippet from Stata

```
+-----+
| armcirc  height |
|-----|
1. |      12    71.2 |
2. |     9.9    55.5 |
3. |    12.5    70.8 |
4. |    11.2     52 |
5. |    14.1    58.2 |
+-----+
```

Using Stat: Arm Circumference and Height

- regress armcirc height

```
. regress armcirc height
```

Source	SS	df	MS			
Model	148.874597	1	148.874597	Number of obs	=	150
Residual	177.263335	148	1.19772523	F(1, 148)	=	124.30
Total	326.137932	149	2.18884518	Prob > F	=	0.0000
				R-squared	=	0.4565
				Adj R-squared	=	0.4528
				Root MSE	=	1.0944

armcirc	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
height	.1579469	.0141671	11.15	0.000	.1299511	.1859428
_cons	2.695906	.8774225	3.07	0.003	.9620116	4.4298

$$\hat{y} = 2.7 + 0.16x$$

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$$\hat{y} = 2.7 + 0.16x$$

Example 2: Arm Circumference and Height

- Give an estimate and 95% CI for the mean difference in arm circumference for children 60 cm tall compared to children 50 cm tall

- From previous set we know this estimated mean difference is

$$(60 - 50) \times \hat{\beta}_1 = 10\hat{\beta}_1 = 10 \times 0.16 = 1.6 \text{ cm}$$

- How to get standard error? Well as it turns out:

$$SE(10\hat{\beta}_1) = 10 \times SE(\hat{\beta}_1)$$

$$SE(10\hat{\beta}_1) = 10 \times 0.014 = 0.14$$

- 95% CI for the mean difference

$$10\hat{\beta}_1 \pm 2SE(10\hat{\beta}_1)$$

$$1.6 \pm 2 \times 0.14$$

Example 2: Hemoglobin and “Packed Cell Volume”

- Equation of regression line relating estimated mean Hemoglobin (g/dL) to packed cell volume: from Stata

$$\hat{y} = 5.77 + 0.20x$$

- Snippet of data in Stata

```
+-----+
|   Hb   PCV |
|-----|
1. | 13.5   35 |
2. | 10.5   30 |
3. |  9.6   25 |
4. | 13.5   35 |
5. |  12    35 |
+-----+
```

Example 2: Hemoglobin and “Packed Cell Volume”

- regress Hb PCV

```
. regress Hb PCV
```

Source	SS	df	MS			
Model	53.7803079	1	53.7803079	Number of obs =	21	
Residual	51.5711174	19	2.71426934	F(1, 19) =	19.81	
Total	105.351425	20	5.26757126	Prob > F =	0.0003	
				R-squared =	0.5105	
				Adj R-squared =	0.4847	
				Root MSE =	1.6475	

Hb	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
PCV	.2033502	.0456835	4.45	0.000	.1077335	.2989668
_cons	5.77645	1.913624	3.02	0.007	1.771188	9.781712

Example 2: Hemoglobin and “Packed Cell Volume”

- Same idea with computation of 95% CI and p-value as we saw before
- However, with small ($n < 60$) samples, a slight change analogous to what we did with means and differences in means before
- Sampling distribution of regression coefficients not quite normal, but follow a t-distribution with $n-2$ degrees of freedom
- 95% for β_1

$$\hat{\beta}_1 \pm t_{.95, n-2} \times SE(\hat{\beta}_1)$$

- In this example

$$\hat{\beta}_1 \pm t_{.95, 19} \times SE(\hat{\beta}_1) \rightarrow 0.20 \pm 2.09 \times .046 \approx (0.10, 0.30)$$

Example: Hemoglobin and “Packed Cell Volume”

- p-value for testing:
 - $H_0: \beta_1 = 0$
 - $H_0: \beta_1 = 0$
- Assume the null is true and calculate standardized “distance” of $\hat{\beta}_1$ from 0

$$t = \frac{\hat{\beta}_1 - 0}{SE(\hat{\beta}_1)} = \frac{\hat{\beta}_1}{SE(\hat{\beta}_1)} = \frac{0.20}{.046} \approx 4.35$$

- P-value is the probability of being 4.35 or more standard errors away from mean of 0 on a t curve with 19 degrees of freedom: very low in this example, $p < .001$

Interpreting Result of 95% CI

- So, the estimated slope is 0.2 with 95% CI 0.10 to 0.30
- How to interpret results?
 - Based on a sample of 21 subjects, we estimated that PCV(%) is positively associated with hemoglobin levels
 - We estimated that a one-percent increase in PCV is associated with a 0.2 g/dL increase in hemoglobin on average
 - Accounting for sampling variability, this mean increase could be as small as 0.10 g/dL, or as large as 0.3 g/dL in the population of all such subjects

Interpreting Result of 95% CI

- In other words:
 - We estimated that the average difference in hemoglobin levels for two groups of subjects who differ by one-percent in PCV to be 0.2 g/dL on average (higher PCV group relative to lower)
 - Accounting for sampling variability, the mean difference could be as small as 0.10 g/dL, or as large as 0.3 g/dL, in the population of all subjects

What about Intercepts?

- In this section, all examples have confidence intervals for the slope, and multiples of the slope
- We can also create confidence intervals/p-values for the intercept in the same manner (and Stata presents it in the output)
- However as we noted in the previous section, many times the intercept is just a placeholder and does not describe a useful quantity: as such, 95% CIs and p-values are not always relevant