Introduction to Econometrics (4th Edition)

by

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Solutions to Odd-Numbered End-of-Chapter Exercises: Chapter 18

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18.1. (a) Suppose there are n observations. Let b_1 be an arbitrary estimator of β_1. Given the estimator b_1, the sum of squared errors for the given regression model is

$$\sum_{i=1}^{n}(Y_i - b_1 X_i)^2.$$

$\hat{\beta}_1^{RLS}$, the restricted least squares estimator of β_1, minimizes the sum of squared errors. That is, $\hat{\beta}_1^{RLS}$ satisfies the first order condition for the minimization which requires the derivative of the sum of squared errors with respect to b_1 equals zero:

$$\sum_{i=1}^{n} 2(Y_i - b_1 X_i)(-X_i) = 0.$$

Solving for b_1 from the first order condition leads to the restricted least squares estimator

$$\hat{\beta}_1^{RLS} = \frac{\sum_{i=1}^{n} X_i Y_i}{\sum_{i=1}^{n} X_i^2}.$$

(b) We show first that $\hat{\beta}_1^{RLS}$ is unbiased. We can represent the restricted least squares estimator $\hat{\beta}_1^{RLS}$ in terms of the regressors and errors:

$$\hat{\beta}_1^{RLS} = \frac{\sum_{i=1}^{n} X_i Y_i}{\sum_{i=1}^{n} X_i^2} = \frac{\sum_{i=1}^{n} X_i(\beta_1 X_i + u_i)}{\sum_{i=1}^{n} X_i^2} = \beta_1 + \frac{\sum_{i=1}^{n} X_i u_i}{\sum_{i=1}^{n} X_i^2}.$$

Thus

$$E(\hat{\beta}_1^{RLS}) = \beta_1 + E\left(\frac{\sum_{i=1}^{n} X_i u_i}{\sum_{i=1}^{n} X_i^2}\right) = \beta_1 + E\left[\frac{\sum_{i=1}^{n} X_i E(u_i | X_1, \quad, X_n)}{\sum_{i=1}^{n} X_i^2}\right] = \beta_1,$$

where the second equality follows by using the law of iterated expectations, and the third equality follows from

$$\frac{\sum_{i=1}^{n} X_i E(u_i | X_1, \quad, X_n)}{\sum_{i=1}^{n} X_i^2} = 0$$

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18.1 (continued)

because the observations are i.i.d. and $E(u_i|X_i) = 0$. (Note, $E(u_i|X_1,\ldots, X_n) = E(u_i|X_i)$ because the observations are i.i.d.

Under assumptions 1-3 of Key Concept 18.1, $\hat{\beta}_1^{RLS}$ is asymptotically normally distributed. The large sample normal approximation to the limiting distribution of $\hat{\beta}_1^{RLS}$ follows from considering

$$\hat{\beta}_1^{RLS} - \beta_1 = \frac{\sum_{i=1}^n X_i u_i}{\sum_{i=1}^n X_i^2} = \frac{\frac{1}{n}\sum_{i=1}^n X_i u_i}{\frac{1}{n}\sum_{i=1}^n X_i^2}.$$

Consider first the numerator which is the sample average of $v_i = X_i u_i$. By assumption 1 of Key Concept 18.1, v_i has mean zero: $E(X_i u_i) = E[X_i E(u_i|X_i)] = 0$. By assumption 2, v_i is i.i.d. By assumption 3, var(v_i) is finite. Let $\bar{v} = \frac{1}{n}\sum_{i=1}^n X_i u_i$, then $\sigma_{\bar{v}}^2 = \sigma_v^2/n$. Using the central limit theorem, the sample average

$$\bar{v}/\sigma_{\bar{v}} = \frac{1}{\sigma_v \sqrt{n}} \sum_{i=1}^n v_i \xrightarrow{d} N(0, 1)$$

or

$$\frac{1}{\sqrt{n}} \sum_{i=1}^n X_i u_i \xrightarrow{d} N(0, \sigma_v^2).$$

For the denominator, X_i^2 is i.i.d. with finite second variance (because X has a finite fourth moment), so that by the law of large numbers

$$\frac{1}{n} \sum_{i=1}^n X_i^2 \xrightarrow{p} E(X^2).$$

Combining the results on the numerator and the denominator and applying Slutsky’s theorem lead to

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18.1 (continued)

$$\sqrt{n}(\hat{\beta}_1^{RLS} - \beta_u) = \frac{\frac{1}{\sqrt{n}}\sum_{i=1}^n X_i u_i}{\frac{1}{n}\sum_{i=1}^n X_i^2} \xrightarrow{d} N\left(0, \frac{\text{var}(X_i u_i)}{E(X^2)}\right).$$

(c) $\hat{\beta}_1^{RLS}$ is a linear estimator:

$$\hat{\beta}_1^{RLS} = \frac{\sum_{i=1}^n X_i Y_i}{\sum_{i=1}^n X_i^2} = \sum_{i=1}^n a_i Y_i, \qquad \text{where } a_i = \frac{X_i}{\sum_{i=1}^n X_i^2}.$$

The weight a_i ($i = 1,\ldots, n$) depends on $X_1,\ldots, X_n$ but not on $Y_1,\ldots, Y_n$.

Thus

$$\hat{\beta}_1^{RLS} = \beta_1 + \frac{\sum_{i=1}^n X_i u_i}{\sum_{i=1}^n X_i^2}.$$

$\hat{\beta}_1^{RLS}$ is conditionally unbiased because

$$\begin{aligned} E(\hat{\beta}_1^{RLS}|X_1,\ldots, X_n &= E\left(\beta_1 + \frac{\sum_{i=1}^n X_i u_i}{\sum_{i=1}^n X_i^2}|X_1,\ldots, X_n\right) \\ &= \beta_1 + E\left(\frac{\sum_{i=1}^n X_i u_i}{\sum_{i=1}^n X_i^2}|X_1,\ldots, X_n\right) \\ &= \beta_1. \end{aligned}$$

The final equality used the fact that

$$E\left(\frac{\sum_{i=1}^n X_i u_i}{\sum_{i=1}^n X_i^2}|X_1,\ldots, X_n\right) = \frac{\sum_{i=1}^n X_i E(u_i|X_1,\ldots, X_n)}{\sum_{i=1}^n X_i^2} = 0$$

because the observations are i.i.d. and E $(u_i|X_i) = 0$.

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18.1 (continued)

(d) The conditional variance of $\hat{\beta}_1^{RLS}$, given $X_1,\ldots, X_n$, is

$$\begin{aligned}\text{var}(\hat{\beta}_1^{RLS}|X1,\ldots, X_n) &= \text{var}\left(\beta_1 + \frac{\sum_{i=1}^n X_i u_i}{\sum_{i=1}^n X_i^2}|X_1,\ldots, X_n\right)\\ &= \frac{\sum_{i=1}^n X_i^2 \,\text{var}(u_i|X_1,\ldots, X_n)}{(\sum_{i=1}^n X_i^2)^2}\\ &= \frac{\sum_{i=1}^n X_i^2 \sigma_u^2}{(\sum_{i=1}^n X_i^2)^2}\\ &= \frac{\sigma_u^2}{\sum_{i=1}^n X_i^2}.\end{aligned}$$

(e) The conditional variance of the OLS estimator $\hat{\beta}_1$ is

$$\text{var}(\hat{\beta}_1|X_1, \quad , X_n) = \frac{\sigma_u^2}{\sum_{i=1}^n (X_i - \bar{X})^2}.$$

Since

$$\sum_{i=1}^n (X_i - \bar{X})^2 = \sum_{i=1}^n X_i^2 - 2\bar{X}\sum_{i=1}^n X_i + n\bar{X}^2 = \sum_{i=1}^n X_i^2 - n\bar{X}^2 < \sum_{i=1}^n X_i^2,$$

the OLS estimator has a larger conditional variance:
$\text{var}(\bar{\beta}_1|X_1, \quad , X_n) > \text{var}(\hat{\beta}_1^{RLS}|X_1, \quad , X_n).$
The restricted least squares estimator $\hat{\beta}_1^{RLS}$ is more efficient.

(f) Under assumption 5 of Key Concept 18.1, conditional on $X_1,\ldots, X_n$, $\hat{\beta}_1^{RLS}$ is normally distributed since it is a weighted average of normally distributed variables u_i:

$$\hat{\beta}_1^{RLS} = \beta_1 + \frac{\sum_{i=1}^n X_i u_i}{\sum_{i=1}^n X_i^2}.$$

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18.1 (continued)

Using the conditional mean and conditional variance of $\hat{\beta}_1^{RLS}$ derived in parts (c) and (d) respectively, the sampling distribution of $\hat{\beta}_1^{RLS}$, conditional on $X_1,\ldots, X_n$, is

$$\hat{\beta}_1^{RLS} \sim N\left(\beta_1, \frac{\sigma_u^2}{\sum_{i=1}^n X_i^2}\right).$$

(g) The estimator

$$\tilde{\beta}_1 = \frac{\sum_{i=1}^n Y_i}{\sum_{i=1}^n X_i} = \frac{\sum_{i=1}^n (\beta_1 X_i + u_i)}{\sum_{i=1}^n X_i} = \beta_1 + \frac{\sum_{i=1}^n u_i}{\sum_{i=1}^n X_i}$$

The conditional variance is

$$\begin{aligned}\text{var}(\tilde{\beta}_1|X_1,\ldots, X_n) &= \text{var}\left(\beta_1 + \frac{\sum_{i=1}^n u_i}{\sum_{i=1}^n X_i}|X_1,\ldots, X_n\right)\\ &= \frac{\sum_{i=1}^n \text{var}(u_i|X_1,\ldots, X_n)}{(\sum_{i=1}^n X_i)^2}\\ &= \frac{n\sigma_u^2}{(\sum_{i=1}^n X_i)^2}.\end{aligned}$$

The difference in the conditional variance of $\tilde{\beta}_1$ and $\hat{\beta}_1^{RLS}$ is

$$\text{var}(\tilde{\beta}_1|X_1,\ldots, X_n) - \text{var}(\hat{\beta}_1^{RLS}|X_1,\ldots, X_n) = \frac{n\sigma_u^2}{(\sum_{i=1}^n X_i)^2} - \frac{\sigma_u^2}{\sum_{i=1}^n X_i^2}.$$

In order to prove $\text{var}(\tilde{\beta}_1|X_1,\ldots, X_n) \geq \text{var}(\hat{\beta}_1^{RLS}|X_1,\ldots, X_n)$, we need to show

$$\frac{n}{(\sum_{i=1}^n X_i)^2} \geq \frac{1}{\sum_{i=1}^n X_i^2}$$

or equivalently

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18.1 (continued)

$$n\sum_{i=1}^{n} X_i^2 \geq \left(\sum_{i=1}^{n} X_i\right)^2.$$

This inequality comes directly by applying the Cauchy-Schwartz inequality

$$\left[\sum_{i=1}^{n}(a_i \cdot b_i)\right]^2 \leq \sum_{i=1}^{n} a_i^2 \cdot \sum_{i=1}^{n} b_i^2$$

which implies

$$\left(\sum_{i=1}^{n} X_i\right)^2 = \left(\sum_{i=1}^{n} 1 \cdot X_i\right)^2 \leq \sum_{i=1}^{n} 1^2 \cdot \sum_{i=1}^{n} X_i^2 = n\sum_{i=1}^{n} X_i^2.$$

That is $n\Sigma_{i=1}^{n} X_i^2 \geq (\Sigma_{x=1}^{n} X_i)^2$, or $\mathrm{var}(\tilde{\beta}_1 | X_1,\ldots, X_n) \geq \mathrm{var}(\hat{\beta}_1^{RLS} | X_1,\ldots, X_n)$.

Note: because $\tilde{\beta}_1$ is linear and conditionally unbiased, the result $\mathrm{var}(\tilde{\beta}_1 | X_1,\ldots, X_n) \geq \mathrm{var}(\hat{\beta}_1^{RLS} | X_1,\ldots, X_n)$ follows directly from the Gauss-Markov theorem.

18.3. (a) Using Equation (18.19), we have

$$\begin{aligned}\sqrt{n}(\hat{\beta}_1-\beta_1) &= \sqrt{n}\,\frac{\frac{1}{n}\sum_{i=1}^{n}(X_i-\bar{X})u_i}{\frac{1}{n}\sum_{i=1}^{n}(X_i-\bar{X})^2}\\ &= \sqrt{n}\,\frac{\frac{1}{n}\sum_{i=1}^{n}[(X_i-\mu_X)-(\bar{X}-\mu_X)]u_i}{\frac{1}{n}\sum_{i=1}^{n}(X_i-\bar{X})^2}\\ &= \frac{\sqrt{\frac{1}{n}}\sum_{i=1}^{n}(X_i-\mu_X)u_i}{\frac{1}{n}\sum_{i=1}^{n}(X_i-\bar{X})^2}-\frac{(\bar{X}-\mu_X)\sqrt{\frac{1}{n}}\sum_{i=1}^{n}u_i}{\frac{1}{n}\sum_{i=1}^{n}(X_i-\bar{X})^2}\\ &= \frac{\sqrt{\frac{1}{n}}\sum_{i=1}^{n}v_i}{\frac{1}{n}\sum_{i=1}^{n}(X_i-\bar{X})^2}-\frac{(\bar{X}-\mu_X)\sqrt{\frac{1}{n}\sum_{i=1}^{n}u_i}}{\frac{1}{n}\sum_{i=1}^{n}(X_i-\bar{X})^2}\end{aligned}$$

by defining $v_i - (X_i - \mu_X)u_i$.

(b) The random variables $u_1,\ldots, u_n$ are i.i.d. with mean $\mu_u = 0$ and variance $0<\sigma_u^2<\infty$. By the central limit theorem,

$$\frac{\sqrt{n}(\bar{u}-\mu_u)}{\sigma_u}=\frac{\sqrt{\frac{1}{n}}\sum_{i=1}^{n}u_i}{\sigma_u}\xrightarrow{d} N(0,\ 1).$$

The law of large numbers implies $\bar{X}\xrightarrow{p}\mu_{X_2}$, or $\bar{X}-\mu_X\xrightarrow{p}0$. By the consistency of sample variance, $\frac{1}{n}\Sigma_{i=1}^{n}(X_i-\bar{X})^2$converges in probability to population variance, var(X_i), which is finite and non-zero. The result then follows from Slutsky's theorem.

(c) The random variable $v_i = (X_i - \mu_X)\, u_i$ has finite variance:

$$\begin{aligned}\text{var}(v_i) &= \text{var}[(X_i-\mu_X)\mu_i]\\ &\le E[(X_i-\mu_X)^2u_i^2]\\ &\le \sqrt{E[(X_i-\mu_X)^4]}E[(u_i)^4]<\infty.\end{aligned}$$

The inequality follows by applying the Cauchy-Schwartz inequality, and the second inequality follows because of the finite fourth moments for (X_i, u_i). The finite variance along with the fact that v_i has mean zero (by assumption 1 of Key Concept 18.1) and v_i is i.i.d. (by assumption 2) implies that the sample average $\bar{v}$ satisfies the requirements of the central limit theorem. Thus,

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18.3 (continued)

$$\frac{\bar{v}}{\sigma_{\bar{v}}} = \frac{\sqrt{\frac{1}{n}}\sum_{i=1}^{n} v_i}{\sigma_v}$$

satisfies the central limit theorem.

(d) Applying the central limit theorem, we have

$$\frac{\sqrt{\frac{1}{n}}\sum_{i=1}^{n} v_i}{\sigma_v} \xrightarrow{d} N(0, 1).$$

Because the sample variance is a consistent estimator of the population variance, we have

$$\frac{\frac{1}{n}\sum_{i=1}^{n}(X_i - \bar{X})^2}{\text{var}(X_i)} \xrightarrow{p} 1.$$

Using Slutsky's theorem,

$$\frac{\frac{\frac{1}{n}\sum_{i=1}^{n} v_t}{\sigma_v}}{\frac{\frac{1}{n}\sum_{i=1}^{n}(X_t - \bar{X})^2}{\sigma_X^2}} \xrightarrow{d} N(0,1),$$

or equivalently

$$\frac{\sqrt{\frac{1}{n}}\sum_{i=1}^{n} v_i}{\frac{1}{n}\sum_{i=1}^{n}(X_i - \bar{X})^2} \xrightarrow{d} N\left(0, \frac{\text{var}(v_i)}{[\text{var}(X_i)]^2}\right).$$

Thus

$$\sqrt{n}(\hat{\beta}_1 - \beta_1) = \frac{\sqrt{\frac{1}{n}}\sum_{i=1}^{n} v_i}{\frac{1}{n}\sum_{i=1}^{n}(X_i - \bar{X})^2} - \frac{(\bar{X} - \mu_X)\sqrt{\frac{1}{n}}\sum_{i=1}^{n} u_i}{\frac{1}{n}\sum_{i=1}^{n}(X_i - \bar{X})^2}$$
$$\xrightarrow{d} N\left(0, \frac{\text{var}(v_i)}{[\text{var}(X_i)]^2}\right)$$

since the second term for $\sqrt{n}(\hat{\beta}_1 - \beta_1)$ converges in probability to zero as shown in part (b).

18.5. Let $a = W^2$. Then $\text{var}(a) = \text{E}(a^2) - \text{E}(a)^2 = \text{E}(W^4) - \text{E}(W^2)^2 \geq 0$.

Thus $\text{E}(W^2) \leq [E(W^4)]^{1/2}$, and the result follows.

18.7. (a) The joint probability distribution function of u_i, u_j, X_i, X_j is $f(u_i, u_j, X_i, X_j)$. The conditional probability distribution function of u_i and X_i given u_j and X_j is $f(u_i, X_i | u_j, X_j)$. Since u_i, X_i, $i = 1,\ldots, n$ are i.i.d., $f(u_i, X_i | u_j, X_j) = f(u_i, X_i)$. By definition of the conditional probability distribution function, we have

$$\begin{aligned} f(u_i, u_j, X_i, X_j) &= f(u_i, X_i | u_j, X_j) f(u_j, X_j) \\ &= f(u_i, X_i) f(u_j, X_j). \end{aligned}$$

(b) The conditional probability distribution function of u_i and u_j given X_i and X_j equals

$$f(u_i, u_j | X_i, X_j) = \frac{f(u_i, u_j, X_i, X_j)}{f(X_i, X_j)} = \frac{f(u_i, X_i) f(u_j, X_j)}{f(X_i) f(X_j)} = f(u_i | X_i) f(u_j | X_j).$$

The first and third equalities used the definition of the conditional probability distribution function. The second equality used the conclusion the from part (a) and the independence between X_i and X_j. Substituting

$$f(u_i, u_j | X_i, X_j) = f(u_i | X_i) f(u_j | X_j)$$

into the definition of the conditional expectation, we have

$$\begin{aligned} E(u_i u_j | X_i, X_j) &= \int\int u_i u_j f(u_i, u_j | X_i, X_j)\, du_i du_j \\ &= \int\int u_i u_j f(u_i | X_i) f(u_j | X_j) du_i du_j \\ &= \int u_i f(u_i | X_i) du_i \int u_j f(u_j | X_j) du_j \\ &= E(u_i | X_i) E(u_j | X_j). \end{aligned}$$

(c) Let $Q = (X_1, X_2,\ldots, X_{i-1}, X_{i+1},\ldots, X_n)$, so that $f(u_i | X_1,\ldots, X_n) = f(u_i | X_i, Q)$. Write

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18.7 (continued)

$$
\begin{aligned}
f(u_i|X_i, Q) &= \frac{f(u_i, X_i, Q)}{f(X_i, Q)} \\
&= \frac{f(u_i, X_i)f(Q)}{f(X_i)f(Q)} \\
&= \frac{f(u_i, X_i)}{f(X_i)} \\
&= f(u_i|X_i)
\end{aligned}
$$

where the first equality uses the definition of the conditional density, the second uses the fact that (u_i, X_i) and Q are independent, and the final equality uses the definition of the conditional density. The result then follows directly.

(d) An argument like that used in (c) implies

$$f(u_i u_j|X_i, \quad X_n) = f(u_i u_j|X_i, X_j)$$

and the result then follows from part (b).

18.9. We need to prove

$$\frac{1}{n}\sum_{i=1}^{n}[(X_i-\bar{X})^2\hat{u}_i^2-(X_i-\mu_X)^2u_i^2]\xrightarrow{p}0.$$

Using the identity $\bar{X}=\mu_X+(\bar{X}-\mu_X)$,

$$\frac{1}{n}\sum_{i=1}^{n}[(X_i-\bar{X})^2\hat{u}_i^2-(X_i-\mu_X)^2u_i^2]=(\bar{X}-\mu_X)^2\frac{1}{n}\sum_{i=1}^{n}\hat{u}_i^2$$
$$-2(\bar{X}-\mu_X)\frac{1}{n}\sum_{i=1}^{n}(X_i-\mu_X)\hat{u}_i^2$$
$$+\frac{1}{n}\sum_{i=1}^{n}(X_i-\mu_X)^2(\hat{u}_i^2-u_i^2).$$

The definition of $\hat{u}_i$ implies

$$\hat{u}_i^2=u_i^2+(\hat{\beta}_0-\beta_0)^2+(\hat{\beta}_1-\beta_1)^2X_i^2-2u_i(\hat{\beta}_0-\beta_0)$$
$$-2u_i(\hat{\beta}_1-\beta_1)X_i+2(\hat{\beta}_0-\beta_0)(\hat{\beta}_1-\beta_1)X_i.$$

Substituting this into the expression for $\frac{1}{n}\Sigma_{i=1}^{n}[(X_i-\bar{X})^2\hat{u}_i^2-(X_i-\mu_X)^2u_i^2]$ yields a series of terms each of which can be written as a_nb_n where $a_n\xrightarrow{p}0$ and $b_n=\frac{1}{n}\Sigma_{i=1}^{n}X_i^ru_i^s$ where *r* and *s* are integers. For example, $a_n=(\bar{X}-\mu_X)$, $a_n=(\hat{\beta}_1-\beta_1)$ and so forth. The result then follows from Slutksy's theorem if $\frac{1}{n}\Sigma_{i=1}^{n}X_i^ru_i^s\xrightarrow{p}d$ where *d* is a finite constant. Let $w_i=X_i^ru_i^s$ and note that w_i is i.i.d. The law of large numbers can then be used for the desired result if $E(w_i^2)<\infty$. There are two cases that need to be addressed. In the first, both *r* and *s* are non-zero. In this case write

$$E(w_i^2)=E(X_i^{2r}u_i^{2s})<\sqrt{[E(X_i^{4r})][E(u_i^{4s})]}$$

and this term is finite if *r* and *s* are less than 2. Inspection of the terms shows that this is true. In the second case, either *r* = 0 or *s* = 0. In this case the result follows directly if the non-zero exponent (*r* or *s*) is less than 4. Inspection of the terms shows that this is true.

18.11. $\mu_{Y|X} = \mu_Y + (\sigma_{XY} / \sigma_X^2)(x - \mu_X)$.

(a) Using the hint and equation (18.38)

$$f_{Y|X=x}(y) = \frac{1}{\sqrt{\sigma_Y^2(1-\rho_{XY}^2)}}\frac{1}{\sqrt{2\pi}}$$
$$\times \exp\left(\frac{1}{-2(1-\rho_{XY}^2)}\left(\left(\frac{x-\mu_X}{\sigma_X}\right)^2 - 2\rho_{XY}\left(\frac{x-\mu_X}{\sigma_X}\right)\left(\frac{y-\mu_Y}{\sigma_Y}\right) + \left(\frac{y-\mu_Y}{\sigma_Y}\right)^2\right) + \frac{1}{2}\left(\frac{x-\mu_X}{\sigma_X}\right)^2\right).$$

Simplifying yields the desired expression.

(b) The result follows by noting that $f_{Y|X=x}(y)$ is a normal density (see equation (18.36)) with $\mu = \mu_{T|X}$ and $\sigma^2 = \sigma_{Y|X}^2$.

(c) Let $b = \sigma_{XY}/\sigma_X^2$ and $a = \mu_Y - b\mu_X$.

18.13 (a) The answer is provided by equation (13.10) and the discussion following the equation. The result was also shown in Exercise 13.10, and the approach used in the exercise is discussed in part (b).

(b) Write the regression model as $Y_i = \beta_0 + \beta_1 X_i + v_i$, where $\beta_0 = E(\beta_{0i})$, $\beta_1 = E(\beta_{1i})$, and $v_i = u_i + (\beta_{0i} - \beta_0) + (\beta_{1i} - \beta_1)X_i$. Notice that

$$E(v_i \mid X_i) = E(u_i|X_i) + E(\beta_{0i} - \beta_0| X_i) + X_i E(\beta_{1i} - \beta_1|X_i) = 0$$

because β_{0i} and β_{1i} are independent of X_i. Because $E(v_i \mid X_i) = 0$, the OLS regression of Y_i on X_i will provide consistent estimates of $\beta_0 = E(\beta_{0i})$ and $\beta_1 = E(\beta_{1i})$. Recall that the weighted least squares estimator is the OLS estimator of Y_i/σ_i onto $1/\sigma_i$ and X_i/σ_i , where $\sigma_i = \sqrt{\theta_0 + \theta_1 X_i^2}$. Write this regression as

$$Y_i / \sigma_i = \beta_0 (1/\sigma_i) + \beta_1 (X_i / \sigma_i) + v_i / \sigma_i.$$

This regression has two regressors, $1/\sigma_i$ and X_i/σ_i. Because these regressors depend only on X_i, $E(v_i|X_i) = 0$ implies that $E(v_i/\sigma_i \mid (1/\sigma_i), X_i/\sigma_i) = 0$. Thus, weighted least squares provides a consistent estimator of $\beta_0 = E(\beta_{0i})$ and $\beta_1 = E(\beta_{1i})$.

18.15

(a) Write $W = \sum_{i=1}^{n} Z_i^2$ where $Z_i \sim N(0,1)$. From the law of large numbers

$W/n \xrightarrow{d} E(Z_i^2) = 1$.

(b) The numerator is $N(0,1)$ and the denominator converges in probability to 1. The result follows from Slutsky's theorem (equation (18.9)).

(c) V/m is distributed χ_m^2 / m and the denominator converges in probability to 1. The result follows from Slutsky's theorem (equation (18.9)).