

Problem 1

Part a. The QUAD regression is of the form

$$price = \beta_1 + \beta_2 size + \beta_3 size^2 + u \implies \widehat{price} = -174.13 + 292.01 size + 17.40 size^2.$$

The marginal effect of size on sales is therefore

$$\frac{d\widehat{price}}{dsize} = 292.01 + 2 \times 17.40 size.$$

The marginal effect at the mean is found by plugging in the mean of size, 2.04, into the preceding equation, which gives

$$\frac{d\widehat{price}}{dsize}(2.04) = 292.01 + 2 \times 17.40(2.04) = 363.$$

Part b. The regression DUMMIES omits dummy variable `d3`, and therefore below-quality is the reference category. We can then conclude that an average-quality diamond, as indicated by `d2`, sells more by \$1.55, on average.

Part c. An above-average quality diamond sells for 3.98 more than a below-average one, and an average diamond sells for 1.55 more than a below-average one, therefore the above-average diamond sells for more than an average quality diamond by $3.98 - 1.55 = \$2.43$.

Part d. The overall significance test is specified as

$$H_0 : \beta_{size} = \beta_{d1} = \beta_{d2} = 0,$$

$$H_1 : \text{at least one of } \beta_{size}, \beta_{d1}, \beta_{d2} \neq 0.$$

Stata gives us the F -statistic for an overall significance test, here 662.090. There are $n = 48$ observations, $k = 4$ things being estimated (because we also estimate the constant), and we make $q = 3$ restrictions to test overall significance. Therefore we look at critical value $F_{0.05;3,48-4}$, given in Stata output as 2.8164658. The F -statistic is way bigger than the critical value so we reject the null that the regression is insignificant in favor of the alternative that the regression is significant overall.

Part e. We want to do an F -test but only for variables d_1 and d_2 , not for the overall regression. Thus we are testing

$$H_0 : \beta_{d1} = \beta_{d2} = 0,$$

$$H_A : \text{at least one of } \beta_{d1}, \beta_{d2} \neq 0.$$

The unrestricted model has $RSS_u = 46491.43$; the restricted model has $RSS_r = 46635.67$; the number of things being estimated in the unrestricted model is $k = 4$; the number of restrictions being tested is $q = 2$; and the sample size of $n = 48$. Therefore the F -statistic is

$$F = \frac{(RSS_r - RSS_u)/q}{RSS_u/(n - k)} = \frac{(46635.67 - 46491.43)/2}{46491.43/44} \approx 0.068.$$

Under the null, F here is drawn from $F_{q,n-k}$ distribution. Therefore the critical value we use is $F_{0.05;2,44} = 3.209278$. Our F -statistic is less than the critical value, which means we fail to reject the null. In other words, the dummies d_1 and d_2 are jointly statistically insignificant at 5% significance.

Part f. We have three categories of diamond: below, average, and above average qualities. Therefore we only include dummy variables for two of the three categories to avoid the dummy variable trap, a source of perfect multicollinearity.

Part g. The measure of fit that controls for model size is the adjusted R^2 , shown in the table as `r2_a`. Here it looks like the linear or quadratic regressions are marginally better than the one with dummies.¹ Looks like the log-log regression is better than the log-linear regression. But recall that we cannot compare models with different dependent variables, e.g. we can't compare the quadratic regression to the log-linear regression.

Part h. The log-linear regression has interpretation

$$\% \Delta price = 100 \beta_{size} \times \Delta size \implies \% \Delta price = 67.9 \times \Delta size$$

In words, an increase in size by 1 unit is associated with an increase in price by 67.9%.

¹Model LINHET includes heteroskedasticity-robust standard errors, but that does not affect goodness of fit. So for this question we treat it the same as model LINEAR.

Part i. The log-log regression has interpretation

$$\% \Delta price = \beta_{size} \times \% \Delta x \implies \% \Delta price = 1.50 \times \% \Delta x.$$

In words, an increase in size by 1% is associated with an increase in price by 1.50%.

Part j. When we estimate a log-linear model, we can make predictions

$$\widehat{\log(y)} = b_1 + b_2 x.$$

It is tempting to then transform the equation so we can predict y instead of $\log(y)$. That is, it is tempting to predict

$$\hat{y} = e^{b_1 + b_2 x}.$$

This leads to biased predictions of y , however, which is the problem you should see.

Assuming the zero conditional mean holds, $E[u|x] = 0$ implies that u and x are uncorrelated. Transforming the estimated log-linear form implies that

$$y = e^{\beta_1 + \beta_2 x + u}.$$

Now taking the conditional mean gives

$$\begin{aligned} E[y|x] &= E[e^{\beta_1 + \beta_2 x + u}|x] \\ &= E[e^{\beta_1 + \beta_2 x} e^u | x] \\ &= e^{\beta_1 + \beta_2 x} E[e^u | x]. \end{aligned}$$

However, $E[u|x] = 0$ does not imply that $E[e^u|x] = 1$, so in general it is the case that

$$E[y|x] \neq e^{\beta_1 + \beta_2 x}.$$

That is why we use the correction term $e^{s_e^2/2}$ if we want to transform in such a way, where s_e is the standard error of the log-linear regression. (This correction requires normally distributed errors and homoskedasticity to be valid.) That is, we can use prediction

$$\hat{y} = e^{s_e^2/2} e^{b_1 + b_2 x}$$

if the conditions are met.

Problem 2

Part a. We simply plug $tv = 100$ into the estimated regression to get

$$\widehat{sales} = 7032.60 + 47.54(100) = 11786.60.$$

Part b. In the regression as shown, dummy **region1** suggests that being in region 1 reduces sales by \$404.47 compared to being in region 3; and being in region 2 reduces sales by \$308.80 compared to being in region 3.

If instead we do the regression with **region2** and **region3**, then the associated coefficients are in comparison to region 1. We know from above that region 2 has sales higher than region 1 by $404.47 - 308.80 = \$95.67$. And we know that region 3 has sales higher than region 1 by \$404.47. These differences are the respective coefficients, then, and *that's all that changes*.

Problem 3

If there were any perfect multicollinearity, then the regression wouldn't have even been able to run. To see this, recall that the formula for coefficient estimates is given by

$$b_j = \frac{\sum_{i=1}^n \tilde{x}_{ji}(y_i - \bar{y})}{\sum_{i=1}^n \tilde{x}_{ji}^2},$$

where \tilde{x}_{ji} is the residual you get from regressing x_j on all of the other regressors. If x_j exhibits perfect multicollinearity with other regressors – that is, if x_j exhibits a perfect linear relationship with other regressors – then the residual \tilde{x}_{ij} would always be zero. Since the denominator is zero, b_j is then undefined and we are doomed.²

Problem 4

Dummy variable $gender = 1$ when we're talking about women, so the average wage for women is $20 - 4 \times 1 = 16$. On the other hand, $gender = 0$ when we're talking about men, so the average wage for men is $20 - 4 \times 0 = 20$.

²If there were imperfect but high multicollinearity, then we would expect large standard errors and therefore small t -statistics and high p -values – and therefore we would never be able to reject any nulls ever. But all of the p -values are really small, so it appears as though multicollinearity is not a problem.

Problem 5

The Rule of 72 says that for net annual percentage rate r , it takes approximately $72/r$ years for the value to double. Here we are told that it takes $72/r = 4$ years for an investment to double, so the investment must have approximately a $72/4 = 18$ percent annual rate of return.

Another example. If the rate of annual GDP growth is 2%, then it takes approximately $72/2 = 36$ years for GDP to double.

Problem 6

- (a) Unbiased. OLS 1 and 2 do not involve any requirements about sample size.
- (b) Unbiased. An irrelevant regressor increases standard errors a little bit, but estimates are still unbiased.
- (c) Biased if w is correlated with either x or z . If w is uncorrelated with both, then still unbiased.
- (d) Unbiased because the correlation between x and z is not 1 (nor -1), so there is not a perfect linear relationship between x and z and therefore everything is fine. (But like in part b, we might have large standard errors.) In other words, this is a case of high but not *perfect* multicollinearity.
- (e) Unbiased. The default standard errors will not be valid, however.
- (f) Unbiased. The default standard errors will not be valid, however.