

Answer Key to final exam

1.  $Y_t = \beta_0 + \beta_1 X_t + u_t \quad t = 1, 2, \dots, N \quad (1)$

$E(u_t) = 0 \quad \text{and} \quad V(u_t) = \sigma^2 \quad \text{Cov}(u_t, u_{t+z}) = 0$

a) Show that the model in (1) with the assumptions given that the OLS estimators of  $\beta_0$  &  $\beta_1$  are unbiased.

$$\hat{\beta}_1 = \frac{\sum_{i=1}^N (x_i - \bar{x})(y_i - \bar{y})}{\sum_{i=1}^N (x_i - \bar{x})^2} = \frac{\sum_{i=1}^N (x_i - \bar{x})y_i}{\sum_{i=1}^N (x_i - \bar{x})(x_i)} = \frac{\sum_{i=1}^N (x_i - \bar{x})(\beta_0 + \beta_1 x_i + u_i)}{\sum_{i=1}^N (x_i - \bar{x})(x_i)}$$

$$= \frac{\beta_0 \sum_{i=1}^N (x_i - \bar{x}) + \beta_1 \sum_{i=1}^N (x_i - \bar{x})(x_i) + \sum_{i=1}^N (x_i - \bar{x})u_i}{\sum_{i=1}^N (x_i - \bar{x})(x_i)} = 0 + \beta_1 + \frac{\sum_{i=1}^N (x_i - \bar{x})u_i}{\sum_{i=1}^N (x_i - \bar{x})(x_i)}$$

$$E(\hat{\beta}_1) = \beta_1 + \frac{\sum_{i=1}^N (x_i - \bar{x}) E(u_i)}{\sum_{i=1}^N (x_i - \bar{x})(x_i)} = \beta_1 \quad \text{so } \hat{\beta}_1 \text{ unbiased} \quad (6)$$

$$\hat{\beta}_0 = \bar{y} - \hat{\beta}_1 \bar{x} = \beta_0 + \beta_1 \bar{x} + \bar{u} - \hat{\beta}_1 \bar{x}$$

(2)

$$E(\hat{\beta}_0) = \beta_0 + \beta_1 \bar{x} + 0 - E(\hat{\beta}_1) \bar{x} = \beta_0 + \beta_1 \bar{x} - \beta_1 \bar{x} = \beta_0 \quad \text{so } \hat{\beta}_0 \text{ unbiased}$$

b) if  $E(u_t) = 0$  but  $V(u_t | X_t) = \sigma^2 X_t^2$   $t=1, 2, \dots, n$

$\hat{\beta}_0$  &  $\hat{\beta}_1$  are still unbiased because the variance of  $u_t$  does not affect the parameter estimates only the standard errors. This can be seen from the proof in a) which is the same proof to show  $\hat{\beta}_0$  &  $\hat{\beta}_1$  unbiased when heteroscedasticity is present.

To estimate  $\beta_0$  &  $\beta_1$  more efficiently we would use WLS

1: Take original model  $Y_t = \beta_0 + \beta_1 X_t + u_t$  where  $V(u_t | X_t) = \sigma^2 X_t^2$  and create weights  $w_t = \sqrt{X_t^2} = X_t$

2: Divide both sides of model by  $w_t$

$$Y_t^* = \frac{Y_t}{X_t} = \beta_0 \left( \frac{1}{X_t} \right) + \beta_1 + \frac{u_t}{X_t} = \beta_0 X_t^* + \beta_1 + \varepsilon_t \quad V(\varepsilon_t | X_t) = \sigma^2$$

3: Perform OLS on this transformed model and  $\hat{\beta}_0$  &  $\hat{\beta}_1$  will be BLUE

⑥

c) You suspect that  $V(u_t | X_t) = \sigma_t^2$

(i) Use white test

1: Run OLS on (1) and find  $\hat{u}_t$

2: Square  $\hat{u}_t$  and regress on all  $x$ 's, cross products, and squared terms. That is  $\hat{u}_t^2 = \delta_0 + \delta_1 X_t + \delta_2 X_t^2 + v_t$

⑤

3: Use OLS on this regression and save  $R_v^2$ .

4: Use F or LM statistic to test  $H_0: \delta_1 = \delta_2 = 0$  against

$H_1: H_0$  false

$$F_v = \frac{R_v^2 / 2}{(1 - R_v^2) / (n - 3)}$$

$$LM_v = n R_v^2$$

$$F \sim F(2, n - 3)$$

$$LM_v \sim \chi^2_2$$

ii) Assuming that we find evidence of Heteroscedasticity we can still obtain heteroscedasticity corrected standard errors of the OLS estimators  $\hat{\beta}_0$  &  $\hat{\beta}_1$ .

$$s.e.(\hat{\beta}_1) = \sqrt{\frac{\sum_{i=1}^N (x_i - \bar{x})(\hat{u}_i)^2}{\left(\sum_{i=1}^N (x_i - \bar{x})^2\right)^2}} \quad (3)$$

For the standard error of  $\beta_0$  corrected for heteroscedasticity we do the following procedure.

1: run OLS to  $Y = \beta_0 + \beta_1 X + u$  and keep fitted residuals  $\hat{u}_i$ .

2: run OLS to  $z = \delta_0 + v$  and keep fitted residuals  $\hat{v}_i$ .

3: Find  $s.e.(\hat{\beta}_0)$  as  $\sqrt{\frac{\sum_{i=1}^N \hat{v}_i \hat{u}_i^2}{\sum_{i=1}^N \hat{v}_i^2}} \quad (2)$

d) Let the model be  $Y_i = \beta_0 + \beta_1 X_i + u_i$  where  $Y_i$  is a dummy variable

Then  $Y = 1$  w/ probability  $p$   
 $Y = 0$  w/ probability  $1-p$ .

$$E(Y) = p \quad E(Y_i) = \beta_0 + \beta_1 X_i$$

$$V(Y) = E((Y-p)^2) = E(Y^2) - (E(Y))^2 = p - p^2 = p(1-p)$$

$$V(Y_i) = E(\beta_0 + \beta_1 X_i + u_i - (\beta_0 + \beta_1 X_i))^2 = E(u_i^2) = p(1-p) \quad (6)$$

Since we do not know  $p$  we estimate it. Therefore  $E(Y_i) = \hat{p}_i = \hat{\beta}_0 + \hat{\beta}_1 X_i$

Thus  $v(u_i) = \hat{p}(1-\hat{p}) = (\hat{\beta}_0 + \hat{\beta}_1 x_i)(1 - \hat{\beta}_0 - \hat{\beta}_1 x_i)$  which is not constant. ④

1: To estimate this model we estimate the model by OLS and find the fitted values.  $\hat{p}_i = \hat{\beta}_0 + \hat{\beta}_1 \hat{x}_i$

2: We create weights equal to  $w_i = \sqrt{\hat{p}_i(1-\hat{p}_i)}$

3: We weight the model as  $\frac{Y_i}{w_i} = \beta_0/w_i + \beta_1 \frac{x_i}{w_i} + \frac{u_i}{w_i}$

4: We estimate this model using OLS, where our error term satisfies all of the Gauss-Markov assumptions. ④

e) Consider the same model (1) but now  $u_t = \rho u_{t-1} + \varepsilon_t$   $|\rho| < 1$  and  $\varepsilon_t$  is iid(0,  $\sigma^2$ ).

Using the same argument in a)  $\hat{\beta}_0$  &  $\hat{\beta}_1$  are unbiased ②

• If  $\rho$  was known then we estimate  $\beta_0$  &  $\beta_1$  by adjusting the model as  $Y_t^* = \beta_0^* + \beta_1 X_t^* + \varepsilon_t$

$$Y_t^* = Y_t - \rho Y_{t-1}$$

$$\beta_0^* = \beta_0(1-\rho)$$

$$X_t^* = X_t - \rho X_{t-1}$$

$$\varepsilon_t = u_t - \rho u_{t-1}$$

If we run OLS on this model we get

$\hat{\beta}_0^*$  &  $\hat{\beta}_1^*$ . To recover  $\hat{\beta}_0$  we use

$$\hat{\beta}_0 = \frac{\hat{\beta}_0^*}{1-\rho}$$

⑤

1: If  $\rho$  is not known then we estimate model (1) by OLS and keep the residuals  $\hat{u}_t$ .

2: we run the auxiliary regression  $\hat{u}_t = \rho \hat{u}_{t-1} + \varepsilon_t$  and find  $\hat{\rho}$

3: we construct  $Y_t^* = Y_t - \hat{\rho} Y_{t-1}$   
 $X_t^* = X_t - \hat{\rho} X_{t-1}$  and regress  $Y_t^*$  on  $X_t^*$  and an intercept

4: we take the residuals from the regression in 3 and go to step 2: run these steps until  $\hat{\rho}$  from consecutive iterations is less than some pre-specified level.

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f) let  $X_t$  be measured with error so that  $X_t = X_t^* - v_t$  and the true model is  $Y_t = \beta_0 + \beta_1 X_t^* + u_t = \beta_0 + \beta_1 X_t + \beta_1 v_t + u_t = \beta_0 + \beta_1 X_t + \varepsilon_t$

$$\hat{\beta}_1 = \beta_1 + \frac{\sum_{i=1}^n (x_i - \bar{x}) \varepsilon_i}{\sum_{i=1}^n (x_i - \bar{x})^2} \rightarrow E(\hat{\beta}_1) = \beta_1 + \frac{\sum_{i=1}^n E[(x_i - \bar{x}) \varepsilon_i]}{\sum_{i=1}^n (x_i - \bar{x})^2}$$

if  $E((x_i - \bar{x}) \varepsilon_i) = 0$  then  $\hat{\beta}_1$  is unbiased. However  $E(x_i \varepsilon_i) \neq 0$

so  $E((x_i - \bar{x}) \varepsilon_i) \neq 0$ .  $E(x_i \varepsilon_i) = E((X_t^* - v_t)(\beta_1 v_t + u_t)) = E(X_t^* \beta_1 v_t) - E(\beta_1 v_t^2) + E(X_t^* u_t) - E(u_t X_t) \neq 0$

since  $-E(\beta_1 v_t^2) = -\beta_1^2 \text{Var}(v_t) = -\alpha \sigma^2 \neq 0$

So  $\hat{\beta}_1$  is biased when there is measurement error. 6

$$2. \quad Y = \alpha_1 + \alpha_2 D_1 + \alpha_3 X + \alpha_4 (D_1 * X) + u$$

$D_1 = 1$  when state legislature is run by Democrats; 0 otherwise

$$Y = \beta_1 + \beta_2 D_2 + \beta_3 X + \beta_4 (D_2 * X) + v$$

$D_2 = 1$  when state legislature is not run by Democrats; 0 otherwise

Obtain estimates of the  $\alpha$ 's from estimates of the  $\beta$ 's

$$Y = \hat{\beta}_1 + \hat{\beta}_2 D_2 + \hat{\beta}_3 X + \hat{\beta}_4 D_2 * X$$

when  $D_1$  on  $D_2$  off

$$\hat{\alpha}_1 + \hat{\alpha}_2 = \hat{\beta}_1$$

$$\hat{\alpha}_1 = \hat{\beta}_1 + \hat{\beta}_2$$

$$\hat{\alpha}_3 = \hat{\beta}_3 + \hat{\beta}_4$$

$$\hat{\alpha}_3 + \hat{\alpha}_4 = \hat{\beta}_3 \rightarrow \hat{\beta}_3 + \hat{\beta}_4 + \hat{\alpha}_4 = \hat{\beta}_3$$

$$\rightarrow \hat{\alpha}_4 = -\hat{\beta}_4$$

$$\text{so } \hat{\beta}_1 + \hat{\beta}_2 + \hat{\alpha}_2 = \hat{\beta}_1$$

$$\hat{\alpha}_2 = \hat{\beta}_1 - \hat{\beta}_1 - \hat{\beta}_2 = -\hat{\beta}_2$$

$\hat{\alpha}_1 = \hat{\beta}_1 + \hat{\beta}_2$	②
$\hat{\alpha}_2 = -\hat{\beta}_2$	③
$\hat{\alpha}_3 = \hat{\beta}_3 + \hat{\beta}_4$	②
$\hat{\alpha}_4 = -\hat{\beta}_4$	②

$$Y_e = \hat{\alpha}_1 + \hat{\alpha}_2 D_1 + \hat{\alpha}_3 X + \hat{\alpha}_4 D_1 X$$

$$= \hat{\alpha}_1 + \hat{\alpha}_2 (1 - D_2) + \hat{\alpha}_3 X + \hat{\alpha}_4 (1 - D_2) X$$

$$= (\hat{\alpha}_1 + \hat{\alpha}_2) - \hat{\alpha}_2 D_2 + (\hat{\alpha}_3 + \hat{\alpha}_4) X - \hat{\alpha}_4 D_2 X$$

$$= \hat{\beta}_1 + \hat{\beta}_2 D_2 + \hat{\beta}_3 X + \hat{\beta}_4 D_2 X$$

3.

a) Model D - Q, Y, P are all in logs

$D82=D86=0$  1960-1981 Price elasticity =  $-.371$  ②  
 Income elasticity =  $.732$  ②

$D82=1$   $D86=0$  1982-1985 Price elasticity =  $-.371 + .288 = -.083$  ②  
 Income elasticity =  $.732 - 2.602 = -1.87$  ②

$D82=D86=1$  1986-1988 Price elasticity =  $-3.71 + .288 = -.083$  ②  
 Income Elasticity =  $.732 - 2.602 + 3.248 = 1.428$  ②

b) Find  $R^2$  for Models A-D

$$\bar{R}^2 = 1 - \frac{(1-R^2)(n-1)}{n-k-1} \Rightarrow 1 - \bar{R}^2 = \frac{(1-R^2)(n-1)}{n-k-1}$$

$$\frac{(1-\bar{R}^2)(n-1)}{(n-1)} = 1-R^2 \Rightarrow R^2 = 1 - \frac{(1-\bar{R}^2)(n-1)}{(n-1)}$$

For all models A-D  $n = 29$

Model A:  $\bar{R}^2 = .921$   $R^2 = 1 - \frac{(1-.921)(28)}{28} = 1 - \frac{(0.079)(28)}{28} = 1 - \frac{2.212}{28}$   
 $k = 8$

$R^2 = 1 - .079 = .921$  ②

Model B:  $\bar{R}^2 = .859$   $R^2 = 1 - \frac{(1-.859)(28)}{28} = 1 - \frac{(.141)(28)}{28} = 1 - \frac{3.948}{28}$   
 $k = 6$

$R^2 = 1 - .141 = .859$  ②

$$\text{Model C: } \bar{R}^2 = .852 \quad R^2 = 1 - \frac{(1 - .852)(24)}{28} = 1 - \frac{(.148)(24)}{28} = 1 - \frac{3.552}{28}$$

$$k = 4$$

$$R^2 = 1 - .1269 = .8731 \quad \textcircled{2}$$

$$\text{Model D: } \bar{R}^2 = .921 \quad R^2 = 1 - \frac{(1 - .921)(21)}{28} = 1 - \frac{(.079)(21)}{28} = 1 - \frac{1.659}{28}$$

$$k = 7$$

$$R^2 = 1 - .0593 = .9407 \quad \textcircled{2}$$

c) i) test the null that price & income elasticities for 1960-1981, 1982-1985, & 1986-1988 are the same

The restricted model is C the unrestricted model is A

$$H_0: \beta_5 = \beta_6 = \beta_8 = \beta_9 = 0$$

$H_1: H_0$  false

$$F = \frac{(.04195 - .0186) / 4}{.0186 / (29 - 9)} = \frac{.02335 / 4}{.0186 / 20} = \frac{.005838}{.00093} = 6.2774$$

This test statistic is distributed  $F(4, 20)$ . If we look for the 1% critical value for a  $F(4, 20)$  distribution, call  $F_c$ , then if  $F > F_c$  we reject  $H_0$  and conclude that the price elasticities and income elasticities are not the same across periods.



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ii) Test that the income elasticities are constant over time but the price elasticities are not

H The restricted model is B the unrestricted is A

$$H_0: \beta_5 = \beta_6 = 0$$

$$H_1: H_0 \text{ false}$$

$$G = \frac{(.0364 - .0186)/2}{.0186 / (24-9)} = \frac{.0178/2}{.0186/20} = \frac{.0089}{.00093} = 9.5699$$

$G \sim F(2, 20)$ . If we look at the 1% critical value for a  $F(2, 20)$  distribution and see that  $G > F_c$  then we reject the null and claim that both income elasticities as well as price elasticities are differing over time.

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