



### **ECON2271**

### **Business Econometrics**

**Or: Practical Econometrics for Beginners** 

Week 7: Multivariate Regression (ii)

## **Topic 3(ii): Multivariate Regression** *Agenda and learning outcomes*



Topic 3: Multivariate Regression: (continuous Y, different types of X)

$$Y = b_0 + b_1 X_1 + b_2 X_2 + b_3 X_3 + ... + b_n X_n + e$$

Part (i): Essentials: (recap)

- a) Model specification:
  - > Understand how model specification affects the interpretation of model coefficients.
  - > Be aware of key model specification criteria
  - > Specification and robustness

Part (ii): Extensions:

- b) Allowing for heterogeneity in associations (interaction terms):
  - > Understand when, why and how allow for differences in associations between X and Y;
  - ➤ being able to correctly interpret relevant model estimates.
- c) Using alternative estimation techniques to cope with endogenous regressors
  - > Students able to explain how 2SLS works
  - > Students able to perform 2SLS estimation and interpret results correctly



#### A recap of Multivariate Regression Essentials:

- How does model specification affect estimated coefficients and how we interpret them?
  - E.g. Consider this general model: LifeSatisfaction = f(Education, Income, X)
  - My key interest here is in understanding the relationship between education and life satisfaction.
  - In theory, education is expected to be positively associated with life satisfaction. However, much of this association is expected to occur via income: people with higher education earn higher incomes, on average, and therefore we expect them to have higher life satisfaction. But are there additional benefits of education, beside the benefits which occur via higher income?
  - If I estimate the model without income, the education variable absorbs variation in income, so
    the education coefficient will reflect the association between education and life satisfaction,
    including any effects that occur via higher incomes. Hence, I cannot be sure whether this
    parameter really reflects the effect of education or the effect of income.
  - By including income as well as education I can evaluate the pure association between education and life satisfaction,
  - Here, X represents a vector of variables which I include in order to account for other things
    which could cause bias in key model parameters if I omit them. This might include various
    demographic variables, labour market characteristics, and anything else I think I should account
    for. That is: these are my

# **Topic 3(ii): Multivariate Regression** *a) Multivariate regression essentials*



### A recap of Multivariate Regression Essentials:

- How do we identify the correct model specification?
  - There is no black&white rulebook to follow here. The model specification deemed to be most appropriate will depend on a number of factors:
    - What is the objective of the research? What are you REALLY trying to find out?
    - What data do you have access to? (obviously a constraint...)
    - · What does theory propose?
    - · What does the existing literature suggest?
    - What are you prepared to assume about key relationships?
    - What do the data tell you?



#### A recap of Multivariate Regression Essentials:

- How do we identify the correct model specification?
  - Studenmund distils four key specification criteria:
    - 1. Theory: Is the variable's place in the equation unambiguous and theoretically sound?
    - t-Test: Is the variable's estimated coefficient significant in the expected direction (i.e. correct sign)?
    - 3.  $\bar{R}^2$ : Does the overall fit of the equation (adjusted for degrees of freedom) improve when the variable is added to the equation?
    - 4. Bias: Do other variables' coefficients change significantly when the variable is added to the equation?

# **Topic 3(ii): Multivariate Regression** *a) Multivariate regression essentials*



### A recap of Multivariate Regression Essentials:

- Specification and robustness
  - Often, we observe that a key model parameter is quite sensitive to model specification. This
    raises a number of questions:
    - 1. What is the source of this sensitivity? Which variables are causing the model parameter to change?
    - 2. What is the intuitive explanation behind this sensitivity?
    - 3. With that in mind, what is the most appropriate model specification?



#### A recap of Multivariate Regression Essentials:

- Specification and robustness
  - We also use alternative model specifications to check our robust our baseline results are.
  - For example: Say you are working in the productivity commission and are asked to estimate the relationship between wealth and health using cross-sectional data. You estimate a significant positive relationship between wealth and health. Your supervisor is sceptical, however, and asks: How robust is this estimate?
  - A robust estimate is one that is not sensitive to alternative model specifications, methods of measurement, and data sources. If there really is a positive relationship between wealth and health, then we should be able to observe this:
    - Regardless of what control variables are included.
    - Regardless of how health and wealth is measured.
    - Regardless of which data set you use.
  - So you need to be sure you're measuring what you think you are measuring, and not something else.

### **Topic 3(ii): Multivariate Regression** *a) Multivariate regression essentials*



Source	SS	df	df MS Number of obs			= 14,879 = 465.01
Model	1732222.35	10	173222.23		), 14000) ) > F	= 465.01 = 0.0000
Residual	5538560.38		372.51549			= 0.2382
					· .	= 0.2377
Total	Total 7270782.72 14,87		8 488.693556 R		t MSE	= 19.301
ph	Coef.	Std. Err.	t	P> t	[95% Conf	. Interval]
lnwealth	1.816976	.0970777	18.72	0.000	1.626692	2.007261
hs	2.003178	.526927	3.80	0.000	.9703362	3.03602
vt	.9350519	.4258943	2.20	0.028	.1002465	1.769857
ug	3.050033	.4936564	6.18	0.000	2.082406	4.017661
pg	3.766319	.7822309	4.81	0.000	2.23305	5.299588
lnreinc	1.328053	.2264577	5.86	0.000	.8841683	1.771938
age	3921182	.0101397	-38.67	0.000	4119932	3722431
marrdef	1.489094	.3597226	4.14	0.000	.7839936	2.194195
ue	-4.509817	.8520219	-5.29	0.000	-6.179885	-2.839749
nil	-9.147464	.4030142	-22.70	0.000	-9.937421	-8.357506
_cons	56.27447	2.391308	23.53	0.000	51.58721	60.96173

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#### A recap of Multivariate Regression Essentials:

#### · Specification and robustness

- For example, your supervisor may ask whether there is some omitted variable bias here: people who accumulate wealth faster than others may have some sort of characteristics that also promotes good health behaviours.
  - > If you have information about personality characteristics, you can include these in your model as additional controls and see whether the estimated wealth-coefficient changes.
- Or, your supervisor may be critical of your health and/or wealth variables: could your estimates be affected by bias from measurement error?
  - > Investigate the basis for these concerns: how exactly are these variables measured?
  - > Find alternative measures of health (maybe something more objective, like BMI?)
  - ➤ Find alternative measures of wealth (maybe home value?). Is the lin-log specification reasonable?
- Or, your supervisor may be critical of your sample. How representative are these data?
  - > Find alternative samples and estimate your model based on those data.

			-		=		-	pnemote	
Source	SS	df	MS	Numb	er of obs	=	13,090		
				- F(15	, 13074)	=	328.14		
Model	1768438.27	15	117895.88	4 Prob	> F	=	0.0000		
Residual	4697259.41	13,074	359.282	5 R-sc	quared	=	0.2735		
				- Adj	R-squared	=	0.2727		
Total	6465697.68	13,089	493.979	5 Root	MSE	=	18.955		
ph	Coef.	Std. Err.	t	P> t	[95% Cc	nf.	Interval]		
lnwealth	1.778926	.1061554	16.76	0.000	1.57084	16	1.987006		
hs	1.945465	.5651678	3.44	0.001	.837653	8	3.053276		
vt	1.180441	.4514458	2.61	0.009	.295541	4	2.06534		
uq	2.520112	.5291261	4.76	0.000	1.48294	18	3.557276		
pq	3.733946	.8239828	4.53	0.000	2.1188	32	5.349072		
lnreinc	1.369488	.2370122	5.78	0.000	.904909	3	1.834066		
age	4499304	.011433	-39.35	0.000	472340	7	42752		
marrdef	1.603539	.3816161	4.20	0.000	.855516	52	2.351562		
ue	-3.057277	.9570725	-3.19	0.001	-4.93327	8	-1.181275		
nil	-8.794305	.4262293	-20.63	0.000	-9.62977	7	-7.958834		
pnextrv	.5476807	.1597488	3.43	0.001	.234549	9	.8608115		
pnagree	.426691	.2021037	2.11	0.035	.030538	84	.8228436		
pnconsc	1.548499	.1816136	8.53	0.000	1.19251	.1	1.904488		
pnemote	2.866799	.1762728	16.26	0.000	2.52127	8	3.212319		
pnopene	2429965	.1760103	-1.38	0.167	588002	1	.1020092		
_cons	32.3876	2.834419	11.43	0.000	26.8317	3	37.94348		

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A recap of Multivariate Regression Essentials:

- · Specification and robustness
  - Should the model include personality variables? Why/ why not?

- Is the association between wealth and health robust with respect to whether or not we control for differences in these personality characteristics?

### **Topic 3(ii): Multivariate Regression** *b) Interaction Terms*



**Interaction terms:** In a standard regression model, Y = b0 + b1X + u, we estimate one relationship between X and Y, which is captured by the X-coefficient (b1).

- Suppose we suspect that the relationship between X and Y varies systematically for different groups.
  - For example, maybe the relationship between income and financial satisfaction differs between men and women? How do we test this?
  - We could estimate the same model twice, once for men then for women, and then compare the income coefficient.
  - However, it would be neat to estimate the difference between the income coefficient for men and women in the same model. For various reasons...
  - So, instead of:

 $FS_i = b_0 + b_1(InY) + b_iX_{ii} + u_i$  estimated for men and women separately...

- We estimate:

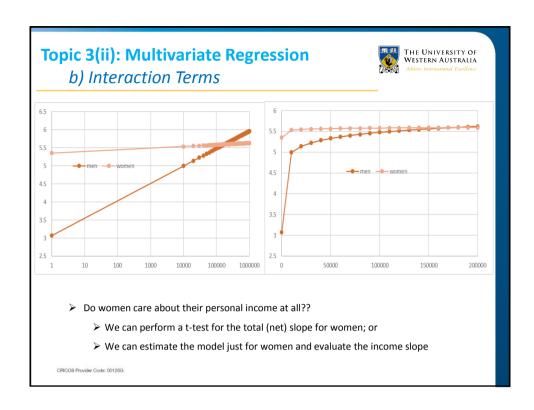
 $FS_i = b_0 + b_1(InY) + b_2(InY)(female) + \mathbf{b}_i \mathbf{X}_{ii} + \mathbf{u}_i$  estimated for everyone.

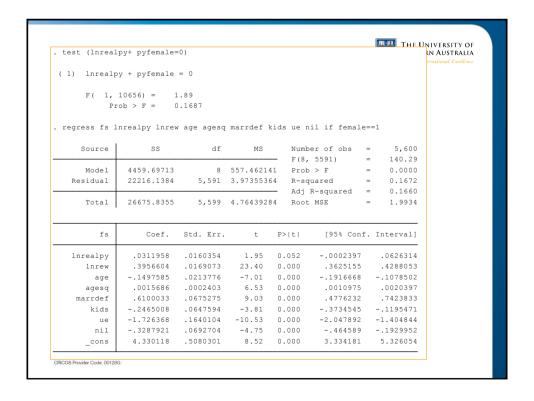
. gen pyfemale=female\*(lnrealpy) (2 missing values generated) . regress fs lnrealpy pyfemale female lnrew age agesq marrdef kids ue nil Number of obs MS F(10, 10656) 242.52 10 913.775362 Prob > F 9137.75362 0.0000 0.1854 Residual 40149.584 10,656 3.76779129 R-squared Adj R-squared = 0.1846 1.9411 49287.3376 10,666 4.62097671 Root MSE Total Coef. Std. Err. t P>|t| [95% Conf. Interval] lnrealpy .2094968 .0211668 9.90 0.000 .1680059 .2509877 -.238209 -.1390908 -.1886499 .0252828 -7.46 0.000 pvfemale 1.702585 .2945464 female 2.279951 7.74 0.000 2.857317 .0123933 32.43 0.000 .4018594 .3775662 .4261525 lnrew  $-.1829727 \qquad .0151252 \qquad -12.10 \qquad 0.000 \qquad -.2126209 \qquad -.1533245$ age .0019246 .0001697 11.34 0.000 .5379621 .0490265 10.97 0.000 .001592 .0022572 agesg marrdef .4418611 .6340631 -.2305425 .0451601 -5.11 0.000 -.3190646 -.1420204 kids .108816 -... .05445 -7.75 0.000 7 74 0.000 -1.80793 .108816 -16.61 0.000 -2.021229 -1.59463 -.4221049 0.000 -.5288371 nil -.3153726 3.071175 .3968713 cons 2.293234 3.849117

### **Topic 3(ii): Multivariate Regression** *b) Interaction Terms*



- > Is the relationship between income and financial satisfaction different for women, compared to for men?
  - ➤ Oh yes!
    - ➤ The coefficient for *female* is positive and statistically significant, estimated at 2.28.
      - ➤ Hence, the intercept term is 2.28 higher for women than for men
      - ➤ The intercept term for men is the \_cons coefficient = 3.07
      - > So the intercept term for women =
    - > The coefficient for *pyfemale* is negative and statistically significant, estimated at -0.19
      - > Hence, the slope parameter is lower for women than for men
      - The slope parameter for men is the Inrealpy coefficient = 0.21
      - > So the slope parameter for women =





### **Topic 3(ii): Multivariate Regression** *b) Interaction Terms*



- > Do women care about their personal income at all??
  - > The F-test is a joint hypothesis test, testing the null hypothesis that the sum of the two slope coefficients equals zero, i.e. that the total (net) association between income and financial satisfaction = 0 for females.
    - > p-value > 0.05
    - > Apparently, women's financial satisfaction is not significantly related to their own personal income...
  - ➤ When we estimate the model for women only, the income coefficient is very small (0.03) and not statistically significant at the 95% level of confidence.
  - ➤ What is going on??

# **Topic 3(ii): Multivariate Regression** *c) 2-Stage Least Squares Estimation*



### The problem of endogenous regressors (recap):

- Let's say we want to estimate how income (Y) affects health (H). That is, we want to estimate how
  a change in income will change health, all other things held constant:
  - $H_i = b_0 + b_1(\ln Y_i) + b_i X_i + u_i$
  - Recall: The income variable (InY) will be endogenous if:
    - The model omits an important variable which is correlated both with income and health:
    - There causality runs in both directions (reverse causality); or
    - The data suffers from non-random measurement error (e.g. people with high income systematically under-report their income).
  - Any of these things will cause income to be correlated with the error term.
  - This will again cause the income coefficient  $(b_1)$  to be biased.
  - This happens because the income coefficient will capture the total association between income and health.
    - If health has a positive effect on income, and income has a positive effect on health, b<sub>1</sub> will capture both of these effects and be biased upward.
    - If, for argument's sake, health has a negative effect on income, and income has a
      positive effect on health, b<sub>1</sub> will capture the net effect and be biased downward

### **Topic 3(ii): Multivariate Regression** *c) 2-Stage Least Squares Estimation*



2-Stage Least Squares Estimation: (text reference: Gujarati Ch 20, Section 20.4)

- Estimating how income explains health (b<sub>1</sub>):
  - $\rightarrow$   $H_i = b_0 + b_1 \ln Y_i + b_2 X_i + u_i$ ; but  $\ln Y_i = b_3 + b_4 H_i + b_5 Z_i + e_i$
  - We need to be able to separate out the effect of H on Y to correctly estimate the effect of Y on H.
  - We may be able to use 2-Stage Least Squares (2SLS), which involves constructive an instrumental variable (IV) within the model:
    - Stage 1 construct an IV for Y by regressing Y on all exogenous variables in the model:

$$Y_i = \hat{b}_6 + \hat{b}_7 \mathbf{X}_i + \hat{b}_8 \mathbf{Z}_i + \mathbf{v}_i$$

- $\Rightarrow$   $\hat{Y}_i$  = the IV for Y = the part of Y explained by X's and Z's (but not by H; hopefully, that part of the variation, which we don't want to include, is contained in the error term  $v_i$ )
- 2. Stage 2 estimate  $H_i = b_9 + b_{10}\hat{Y}_i + b_{11}X_i + e_i$
- If this all goes to plan, the b<sub>10</sub> estimate is now an unbiased ("pure") estimate of the effect of Y on H.
- > BUT: this depends on how well the first stage (reduced form) regression is estimated.

### Topic 3(ii): Multivariate Regression c) 2-Stage Least Squares Estimation



#### 2-Stage Least Squares Estimation:

- Let's try...:
  - $\rightarrow$   $H_i = b_0 + b_1 \ln Y_i + b_2 X_i + u_i$ ; but  $\ln Y_i = b_3 + b_4 H_i + b_5 Z_i + e_i$
  - We need to identify the set of exogenous explanatory variables for health (X) and income (Z). These can overlap, but they can't be equivalent: Z must include at least one variable which is not included in X.
  - Hard to find a variable that explains income but should not be included in the health model...
  - ➤ Here is one possibility: personal income is quite different for married women with children than others, all other things held constant. However, if we compare the health of two women who are otherwise comparable but where one is married with kids and the other is not, one would not expect their health to be all that different. Hence, we can try to generate dummies to identify gender/marital status/kids combinations, and include these in Z but not in X.

#### THE UNIVERSITY OF WESTERN AUSTRALIA Achieve International Excellence Code and first-stage regression... . ivregress 2sls ph age agesq marrdef hs vt ug pg (lnrealpy = marrfemkids marrmalekids), first First-stage regressions Number of obs 9.919 F( 9, 9909) 76.70 Prob > F 0.0000 R-squared 0.0651 Adj R-squared 0.0643 Root MSE 1.5632 Coef. Std. Err. t P>|t| [95% Conf. Interval] lnrealpv .0635932 .0123313 5.16 0.000 .0394212 .0877652 age .0001378 agesg -.0007622 -5.53 0.000 -.0010323 -.0004922 marrdef -.1514424 .0421208 -3.60 0.000 -.2340076 -.0688771 hs .3246656 .0585747 5.54 0.000 .2098472 .439484 vt .3925045 .044327 8.85 0.000 .3056144 .4793945 .6537438 .7480557 .0481133 15.55 0.000 .8423677 ug pg .826885 .0697852 11.85 0.000 .6900918 .9636782 -.3543979 -.4482989 .0479037 -9.36 0.000 -.5422 marrfemkids .5107121 .0482655 10.58 0.000 .4161018 .6053223 marrmalekids 8.884731 .2645168 33.59 0.000 8.366224 9.403237 cons CRICOS Provider Code: 00126G

#### THE UNIVERSITY OF WESTERN AUSTRALIA Second-stage: the 2SLS regression Instrumental variables (2SLS) regression Number of obs = 9,919 Wald chi2(8) 932.21 Prob > chi2 0.0000 R-squared 0 0948 Root MSE 19.896 Coef. Std. Err. z P>|z| [95% Conf. Interval] .1680228 lnrealpy 1.565239 .7128784 2.20 0.028 2.962455 -.1745518 .1609002 0.278 -.4899104 -1.08 .1408069 age -.0020708 .001788 -1.16 0.247 -.0055752 .0014337 agesq 5.437294 .5016244 10.84 0.000 4.454129 6.42046 marrdef 5.22169 .7783838 6.71 3.696086 6.747294 0.000 hs vt 3.821847 .6421972 5.95 0.000 2.563164 5.08053 7.04732 .8047281 5.470082 8.624558 ug 8.76 0.000 8.938279 1.070978 0.000 6.8392 pq 8.35 11.03736 \_cons 63.70818 7.053942 9.03 0.000 49.88271 77.53365 Instrumented: lnrealpy Instruments: age agesq marrdef hs vt ug pg marrfemkids marrmalekids CRICOS Provider Code: 00126G

#### Compare this to the standard OLS regression:



Source	SS	df	MS	N	umber of obs	=	9,921
				F	(8, 9912)	=	130.09
Model	412185.903	8	51523.2379	P	rob > F	=	0.0000
Residual	3925645.9	9,912	396.049828	R	-squared	=	0.0950
				- A	dj R-squared	=	0.0943
Total	4337831.8	9,920	437.281432	R	oot MSE	=	19.901
ph	Coef.	Std. Err.	t	P> t		f	Interval
	0001.			27   0			
lnrealpy	1.343885	.1258804	10.68	0.00	0 1.097133		1.59063
age	1559312	.1533726	-1.02	0.30	94565726		.1447102
agesq	0022838	.0016943	-1.35	0.17	8005605		.0010374
marrdef	5.412142	.490818	11.03	0.00	0 4.450039		6.374245
hs	5.293894	.7466961	7.09	0.00	0 3.830218		6.75757
vt	3.913244	.566136	6.91	0.00	0 2.803502		5.022985
ug	7.210399	.619329	11.64	0.00	0 5.996388		8.42441
pg	9.124533	.8946471	10.20	0.00	0 7.370843		10.87822
cons	65.5571	3.498783	18.74	0.00	0 58.69877		72.41543

CRICOS Provider Code: 00126G

## **Topic 3(ii): Multivariate Regression** *c) 2-Stage Least Squares Estimation*



### What did we find?

- If we have correctly identified what variables are exogenous and endogenous, and not broken
  any other rules, then this experiment appears to show that there really is a positive effect of
  income on health, even when we try to instrument income by using what we think is a set of
  exogenous variables.
- However, the first-stage regression is not great... so our instrument (the estimate of PH from the first-stage regression) is pretty weak. This is not a good thing.
- This was just an illustration of how it is supposed to work. It's hard to come up with a really good
  example that works really well, but textbooks do provide some.