

Lecture 2a: Model building I (VER 14.4, 14.6-7)

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● Learning objectives

- ★ understand how to model different type of variables
- ★ review confounding and interaction in regression models
- ★ interpret regression model coefficients

● Exercises

- ★ review exercise 1 linear regression
- ★ Monday - lab: exercise 2 linear regression

● Quiz 1

Predictors (X variables)

● Categorical

- ★ nominal – values represent “levels” (no numerical meaning)
- ★ ordinal – values represent ordered levels
- ★ must be re-coded
 - ➔ indicator or dummy variables

● Continuous (quantitative)

- ★ scaling
- ★ assumption of linearity

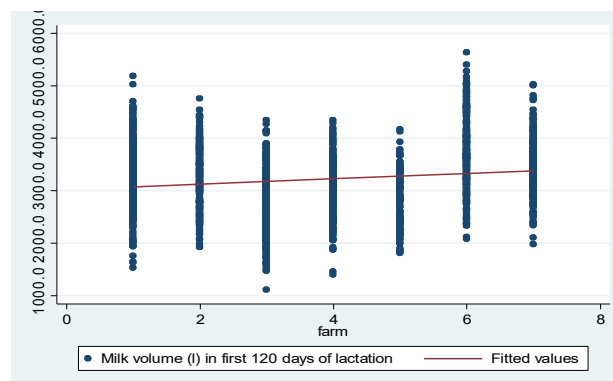
Categorical predictors

- Nominal (and sometimes ordinal) predictors with more than two levels should not be used as numeric

```
. table farm_id, c(mean milk120)
```

farm_id	mean(milk120)

1	3357.8
2	3279.3
3	2778.6
4	3032.5
5	2838.2
6	3730.6
7	3435.8



```
. regress milk120 farm
```

milk120	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	

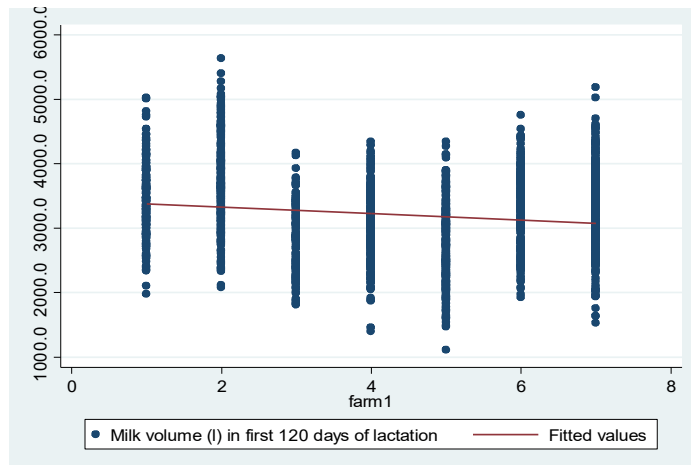
farm	50.90872	8.848643	5.75	0.000	33.552	68.26543
_cons	3026.143	37.27521	81.18	0.000	2953.028	3099.259

```
. list farm_id milk120 farm1_id
```

```

+-----+
| farm_id milk120 farm1_id |
+-----+
1. |      1      3357.8      7 |
2. |      2      3279.3      6 |
3. |      3      2778.6      5 |
4. |      4      3032.5      4 |
5. |      5      2838.2      3 |
+-----+
6. |      6      3730.6      2 |
7. |      7      3435.8      1 |
+-----+

```



milk120	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
farm1	-50.90872	8.848643	-5.75	0.000	-68.26543	-33.552
_cons	3433.413	41.84204	82.06	0.000	3351.339	3515.487

Indicator variables

- Convert nominal or ordinal variables to a set of dichotomous variables or indicator variables
 - ★ assign observations to one of two categories (usually 0 and 1)
 - ★ $j-1$ indicator variables are required in the regression model
- One level is referent (or baseline) level

Obs. #	parity	parity_1	parity_2	parity_3
1	1	1	0	0
2	2	0	1	0
3	3	0	0	1

- Choice of referent (base) level
 - ★ biological sense and ease of interpretation
 - ★ reasonable sample size
 - ★ Stata - default smallest values as base category (help *fvvarlist*)
 - ★ Changing referent no effect on overall model fit (eg same R^2)
 - ★ All in / all out
- Example daisy2red- parity as an ordinal variable
 - ★ regress milk120 i.parity

milk120	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
parity						
2	708.2134	43.74086	16.19	0.000	622.4149	794.0118
3	789.8435	45.94638	17.19	0.000	699.7189	879.9681
4	848.5137	50.96418	16.65	0.000	748.5467	948.4808
5	787.6091	56.22915	14.01	0.000	677.3147	897.9035
6	878.1606	79.09305	11.10	0.000	723.0183	1033.303
7	925.9548	305.0416	3.04	0.002	327.6106	1524.299
_cons	2639.645	30.2407	87.29	0.000	2580.328	2698.963

- ★ compare with simple average

Parity	Avg milk120	Indicator variables
1	2639.7	2639.7*
2	3347.9	708.2
3	3429.5	789.8
4	3488.2	848.5
5	3427.3	787.6
6	3517.8	878.2
7	3562.6	925.9
*intercept (or _cons)		

Continuous predictors

Improving the “interpretation” of X variables

● Scaling X variables

★ limited range of plausible values

- ➡ effects only the constant (not the coefficient for the variable – slope)
- ➡ subtract min. plausible value (eg. parity)

```
. regress milk120 parity
...output omitted
```

milk120	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
parity	178.347	11.01266	16.19	0.000	156.7455	199.9484
_cons	2727.08	34.33991	79.41	0.000	2659.722	2794.438

```
. gen parity_1=parity-1
```

```
. reg milk120 parity_1
....output omitted
```

milk120	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
parity_1	178.347	11.01266	16.19	0.000	156.7455	199.9484
_cons	2905.427	25.23474	115.14	0.000	2855.928	2954.925

★ subtract the central value (eg. mean) (centring)

- ➡ helps to reduce collinearity with quadratic and interaction terms

```
. reg milk120 c.herd_size##c.herd_size
```

milk120	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
herd_size	28.73126	1.993023	14.42	0.000	24.82192	32.6406
c.herd_size#c.herd_size	-.0608255	.0041101	-14.80	0.000	-.0688875	-.0527634
_cons	66.06488	231.8877	0.28	0.776	-388.7858	520.9155

```
. estat vce, corr -> correlation = -0.9907
```

```
. summ herd_size
```

```
.gen hrdsz_ctr=herd_size - 251
. reg milk120 c.hrdsz_ctr#c.hrdsz_ctr
```

	milk120	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
	hrdsz_ctr	-1.803116	.2847073	-6.33	0.000	-2.361573	-1.244659
	c.hrdsz_ctr#c.hrdsz_ctr	-.0608255	.0041101	-14.80	0.000	-.0688875	-.0527634
	_cons	3445.547	22.80494	151.09	0.000	3400.815	3490.279

```
. estat vce, corr -> correlation = 0.3115
```

★ scale of measurement (eg grams or kg)

- ➡ look at range and IQR and establish acceptable values
- ➡ avoid very small regression coefficients
- ➡ example: herd size (mean=251; min=125; max=333)

```
. reg milk120 herd_size
```

	milk120	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
	herd_size	-.49048	.2891242	-1.70	0.090	-1.057601	.0766405
	_cons	3338.164	74.69789	44.69	0.000	3191.643	3484.685

```
. gen herdsz_100=herd_size/100 /*rescale herd_size so coef are larger*/
```

```
. reg milk120 herdsz_100
```

	milk120	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
	herdsz_100	-49.04796	28.91242	-1.70	0.090	-105.76	7.664098
	_cons	3338.164	74.69789	44.69	0.000	3191.643	3484.685

Detecting confounding (VER 13.5)

● Review

★ components: Y (outcome), E (exposure) and Z (measured or unmeasured confounder)

★ criteria

- ➡ Z must be a risk factor of Y (in E-, because risk must not be caused by E→Y)
- ➡ Z must be associated with E
 - cohort - start follow up period
 - if constant during follow up -> look for unconditional assoc. Z→E
 - case-control - in controls (represent source population if no selection bias)
- ➡ Z must not be the result of E or the result of Y

★ causal model

Vaginal
Discharge

Herd

WPC

● Assessment of confounding

★ when three criteria are met

★ difference between crude and adjusted effect/association changes substantially

➡ $(\text{crude} - \text{adjusted}) / \text{crude}$

➡ eg. $\pm 20-30\%$

● Example - change in regression coefficient

```
. reg wpc i.vag_disch          /* vag_disch adds 12 days, P=0.04 */
```

wp	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
vag_disch						
yes	11.99647	5.846716	2.05	0.040	.5282858	23.46465
_cons	68.17426	1.334494	51.09	0.000	65.55669	70.79184

```
. reg wpc i.herd if vag_disch==0 /*herd is associated with WPC*/
```

Source	SS	df	MS	Number of obs	=	1,492
Model	223706.812	6	37284.4686	F(6, 1485)	=	14.92
Residual	3711781.88	1,485	2499.51642	Prob > F	=	0.0000
				R-squared	=	0.0568
				Adj R-squared	=	0.0530
Total	3935488.69	1,491	2639.4961	Root MSE	=	49.995

wp	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
herd						
2	-7.455598	4.572715	-1.63	0.103	-16.42527	1.51407
3	12.30396	4.184586	2.94	0.003	4.095636	20.51229
4	-20.0733	4.70619	-4.27	0.000	-29.30479	-10.84181
5	-21.78125	5.489853	-3.97	0.000	-32.54994	-11.01256
106	-15.40129	4.618509	-3.33	0.001	-24.46079	-6.341796
119	-17.26021	5.05679	-3.41	0.001	-27.17942	-7.341
_cons	75.1583	3.106548	24.19	0.000	69.06461	81.25199

```
. tab herd vag_disch, chi row /* herd is associated with vag_disc*/
```

Herd Number	Vaginal discharge observed		Total
	no	yes	
3	318 98.76	4 1.24	322 100.00
...output omitted			
106	214 84.58	39 15.42	253 100.00
Total	1,492 94.79	82 5.21	1,574 100.00

Pearson chi2(6) = 74.2267 Pr = 0.000

```
. reg wpc i.vag_disch i.herd
```

Source	SS	df	MS	Number of obs	=	1,574
Model	252509.59	7	36072.7985	F(7, 1566)	=	14.35
Residual	3935580.97	1,566	2513.14238	Prob > F	=	0.0000
				R-squared	=	0.0603
				Adj R-squared	=	0.0561
Total	4188090.56	1,573	2662.48605	Root MSE	=	50.131

wpc	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
vag_disch						
yes	17.81936	5.825177	3.06	0.002	6.393393	29.24533
herd						
2	-8.178615	4.509228	-1.81	0.070	-17.02338	.6661455
3	11.71303	4.133611	2.83	0.005	3.605039	19.82103
4	-20.74627	4.653654	-4.46	0.000	-29.87432	-11.61823
5	-22.15954	5.359351	-4.13	0.000	-32.6718	-11.64728
106	-18.18881	4.422295	-4.11	0.000	-26.86305	-9.514562
119	-17.85657	4.920293	-3.63	0.000	-27.50763	-8.205518
_cons	75.97555	3.052377	24.89	0.000	69.98837	81.96272

Confounding and collinearity

- Confounding => collinearity

- ★ example: bwt - smoking (only for example, not for model building)

- ➡ cig_2, cig_3 on bwt

- ★ two models

- ➡ 1) $E = \text{cig_2}$

- ➡ 2) $E = \text{cig_3}$

- ★ causal diagrams / criteria

- Model 1

- ★ cig_3 is not a confounder

- ★ cig_3 intervening variable

- ★ cig_3 highly correlated with cig_2 -> keep cig_2

- Model 2

- ★ cig_2 meets (partially) confounding criteria

- ★ change of coefficient?

Detecting and modelling interaction

Reasons

★ identify subgroups

➡ eg. Which groups treat / benefit

★ mechanism on the outcome

➡ eg. Why the effect is different

★ model fit - statistical

Cross-product term

★ eg. `stata = i.vag_disch##i.rp`

examples 14.9, 14.10 and 14.11

Interaction between 2 dichotomous predictors

```
. reg wpc i.vag_disch##i.rp
```

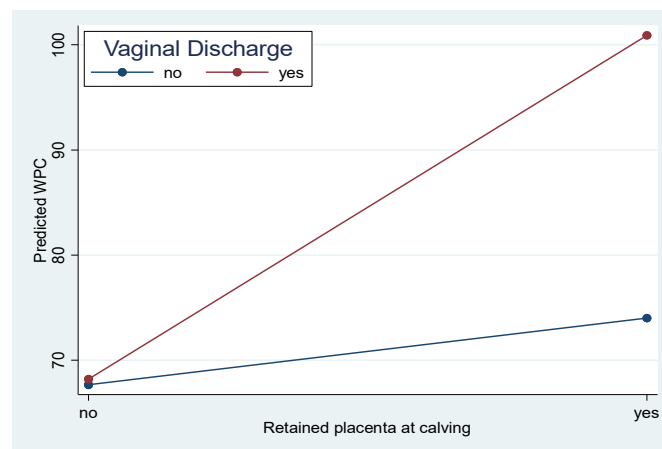
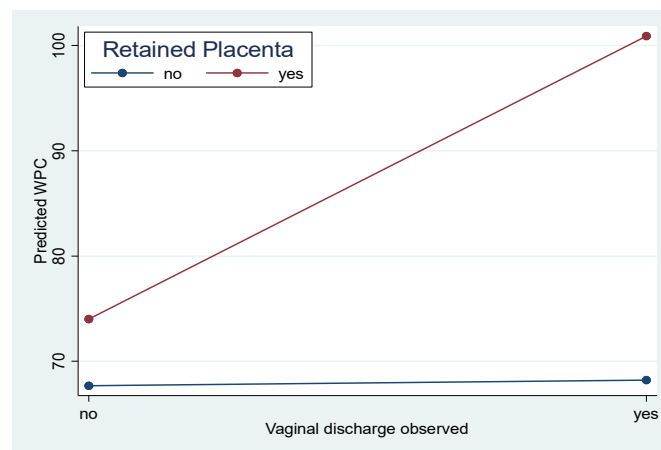
Source	SS	df	MS	Number of obs = 1574		
Model	35915.9774	3	11971.9925	F(3, 1570) = 4.53		
Residual	4152174.58	1570	2644.69719	Prob > F = 0.0036		
				R-squared = 0.0086		
				Adj R-squared = 0.0067		
Total	4188090.56	1573	2662.48605	Root MSE = 51.427		

wpc	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
1.vag_disch	.5429296	7.265382	0.07	0.940	-13.70794	14.7938
1.rp	6.339794	4.914322	1.29	0.197	-3.299531	15.97912
vag_disch#rp						
1 1	26.34867	12.77367	2.06	0.039	1.293414	51.40392
_cons	67.66861	1.387883	48.76	0.000	64.94631	70.39091

```
. table vag_disch rp, c(mean wpc) // display wpc means by vag_dich and rp
```

Vaginal discharge observed	Retained placenta at calving	
	no	yes
no	67.66861	74.0084
yes	68.21154	100.9

● Interaction plots (margins command - later)

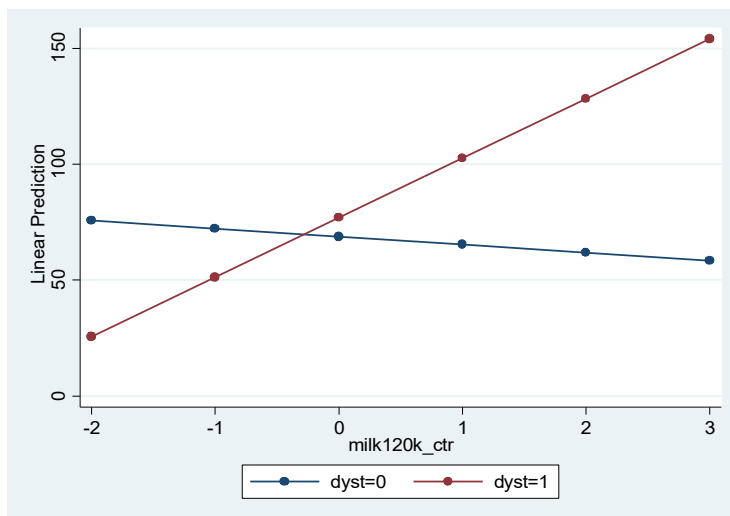


Interaction between a dichotomous and a continuous predictor

```
. reg wpc i.dyst##c.milk120k_ctr
```

...output ommitted

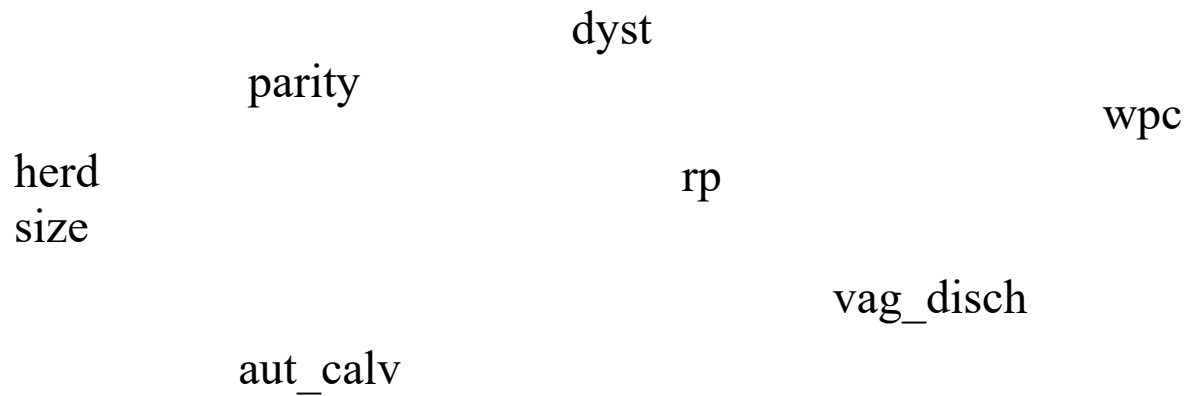
	wpc	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
dyst						
yes		8.20714	5.718528	1.44	0.151	-3.00983 19.42411
milk120k_ctr		-3.446531	1.928535	-1.79	0.074	-7.229379 .3363161
dyst#c.milk120k_ctr						
yes		29.14238	9.468101	3.08	0.002	10.57057 47.71419
_cons		68.75682	1.357147	50.66	0.000	66.09475 71.41888



Interaction between 2 continuous predictors

- eg. `reg wpc c.parity_1##c.milk120k_ctr`
- Two way interactions between continuous predictors are difficult to interpret, and, whenever significant, should be evaluated by fitting a range of possible values for both predictors.
- ★ be sure that predictions are within range of the data

Causal interpretation (VER 14.7)



● Graphical assessment confounding

★ draw causal diagram

➡ nodes=variables; arrow=causal relations

➡ time on horizontal axis (right most recent)

★ identify [and remove] intermediate variables

★ identify potential confounders

★ identify collider variables

➡ controlling for the effect of 2 variables (eg. dyst) will create an spurious association between them (eg. between herd size and parity)

```
. reg wpc c.hs100_ctr##c.hs100_ctr parity_1 i.aut_calv i.twin i.dyst
i.rp##vag_disch, vsquish
```

Source	SS	df	MS	Number of obs	=	1,574
Model	296062.694	9	32895.8549	F(9, 1564)	=	13.22
Residual	3892027.86	1,564	2488.50886	Prob > F	=	0.0000
				R-squared	=	0.0707
				Adj R-squared	=	0.0653
Total	4188090.56	1,573	2662.48605	Root MSE	=	49.885

wpc	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
hs100_ctr	19.85708	2.163397	9.18	0.000	15.61361	24.10054
c.hs100_ctr#						
c.hs100_ctr	11.13827	3.111145	3.58	0.000	5.035817	17.24073
parity_1	1.13721	.8583103	1.32	0.185	-.5463501	2.82077
1.aut_calv	-8.263839	2.537751	-3.26	0.001	-13.24159	-3.286086
twin						
yes	20.68314	9.845165	2.10	0.036	1.37203	39.99425
dyst						
yes	11.70041	5.462576	2.14	0.032	.985666	22.41516
rp						
yes	5.98687	4.811976	1.24	0.214	-3.451734	15.42547
vag_disch						
yes	1.228196	7.161395	0.17	0.864	-12.81875	15.27514
rp#vag_disch						
yes#yes	22.85194	12.51605	1.83	0.068	-1.698056	47.40194
_cons	64.33029	2.634114	24.42	0.000	59.16352	69.49705

➤ herd_size

➤ parity

➤ aut_calv

➤ twin

➤ dyst

➤ rp

➤ vag_disch

Confounding and Interaction (ME, Last et al 2021)

- “effect heterogeneity” vs “causal interaction”
- causal interaction – control for confounders for each factor of the interaction
- impact on decisions about interventions
- regression models doesn't differentiate between them

Assessing linearity

- Assumption about nature of relationship between X and Y
 - ★ note: the following are all discussed in more detail under Model Building (Chapter 15)
- **Detecting non-linearity – in final model**
 - ★ plot residuals vs fitted values (see L1a)
 - ➔ simultaneous evaluation of all predictors
 - ➔ plot of residuals vs predictor (see L1a)
- **Detecting non-linearity – before / during model building**
 - ★ smoothed scatter plot of outcome vs predictor
 - ★ explore polynomial functions of X
 - ★ transformation of X
 - ★ categorization of predictor
 - ➔ indicator dummy variable
 - ➔ compare categorical and linear variables

Stata Factor-Notation basics

- For predictors x , z and outcome y
 - ★ $i.x$ = categorical effect of x (x must be integer)
 - ★ $c.x$ = continuous effect (slope) of x (x must be numerical)
 - ★ Stata default depends on command
 - ➔ `reg y x = reg y c.x` (default is $c.x$)
 - ➔ `anova y x = anova y i.x` (default is $i.x$)
- Combined effects
 - ★ $c.x##c.x$ = continuous terms for x and x^2
 - ★ interaction
 - ➔ `x#z = interaction x * z;`
 - ➔ in all commands the default is `x#z = i.x#i.z`
 - ➔ `c.x#c.z` = need to use "c" for continuous variables
 - ➔ always `x##z = x z x#z`
- Factor terms can be used in tests
 - ★ `testparm i.x`
 - ★ `testparm c.x##c.x` (test $c.x$ and $c.x#c.x$)
 - ★ `testparm c.x#c.x` (test $c.x#c.x$)