

# FIE401: Financial Econometrics

## Non-linear Functional Form: Interactions

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## Non-Linear Functional Form (i)

- ▶ The regression functions so far have been linear in the xs.
- ▶ But the linear approximation is not always a good one.
- ▶ The multiple regression model can handle regression functions that are non-linear in one or more xs.
- ▶ Linear regression = Linear in parameters!

## Non-Linear Functional Form (ii)

If a relation between  $y$  and  $x$  is non-linear:

- ▶ The effect on  $y$  of a unit change in  $x$  depends on the value of  $x$  – that is, the marginal effect of  $x$  is not constant.
- ▶ A linear regression is misspecified: the functional form is wrong.
- ▶ The estimator of the effect on  $y$  of  $x$  is biased.
- ▶ The solution is to estimate a regression function that is non-linear in  $x$ .

## Example: Test Scores

Are test scores completely determined by class size?

Is the relationship between test scores and independent variables linear?

- ▶ testscr: test scores
- ▶ str: student-to-teacher ratio
- ▶ el\_pct: proportion of English learners

## Interactions Between Independent Variables

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_1 \times x_2 + u$$

- ▶ Interaction between two binary variables.
- ▶ Interaction between binary and continuous variable.
- ▶ Interaction between two continuous variables.

## Interactions Between Two Binary Variables

$$y = \beta_0 + \beta_1 D_1 + \beta_2 D_2 + u$$

- ▶  $D_1$  and  $D_2$  are binary variables (dummy variables).
- ▶  $\beta_1$  is the effect of changing  $D_1 = 0$  to  $D_1 = 1$ .
- ▶ In this specification, this effect does not depend on the value of  $D_2$ .

To allow the effect of changing  $D_1$  to depend on  $D_2$ , include the “interaction term”  $D_1 \times D_2$  as a regressor:

$$y = \beta_0 + \beta_1 D_1 + \beta_2 D_2 + \beta_3 D_1 \times D_2 + u$$

## Interpreting Coefficients

$$y = \beta_0 + \beta_1 D_1 + \beta_2 D_2 + \beta_3 D_1 \times D_2 + u$$

- ▶ Compare the various combinations of values  $D_1$  and  $D_2$ .
- ▶  $E(y|D_1 = 0, D_2 = 0) = \beta_0$ .
- ▶  $E(y|D_1 = 0, D_2 = 1) = \beta_0 + \beta_2$ .
- ▶  $E(y|D_1 = 1, D_2 = 0) = \beta_0 + \beta_1$ .
- ▶  $E(y|D_1 = 1, D_2 = 1) = \beta_0 + \beta_1 + \beta_2 + \beta_3$ .
- ▶  $\beta_3$  is an incremental effect of changing  $D_1$  from 0 to 1 when  $D_2 = 1$ .

## Example: Test Scores and Class Size

$$\widehat{testscr} = 664.14 - 1.91\text{large\_class} - 18.16\text{high\_el} - 3.49\text{large\_class} \times \text{high\_el}$$

```
#load necessary packages
require(car);
require(lmtest);
#load data
load("M:/Projects/FIE401/data/data_lectures/School.Rdata");
#define dummies
School$large_class<- (School$str>=20)*1;
School$high_el<- (School$el_pct>=10)*1;
#run regression
fit<-lm(testscr~large_class+high_el+high_el*large_class,
        data=School);
#summary of the regression
#robust to heteroskedasticity
coeftest(fit,vcov=hccm);
```

## Example: Test Scores and Class Size

```
##  
## t test of coefficients:  
##  
##  
##  
## (Intercept)      664.1433     1.3908 477.5271 < 2.2e-16 ***  
## large_class       -1.9078     1.9416 -0.9826    0.3264  
## high_el          -18.1629     2.3575 -7.7042 9.739e-14 ***  
## large_class:high_el -3.4943     3.1384 -1.1134    0.2662  
## ---  
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

## Example: Test Scores and Class Size

- ▶ Generate cross-tabulation for large class and high percentage of English learners.

```
#load necessary packages
require(dplyr);
#load data
load("M:/Projects/FIE401/data/data_lectures/School.Rdata")
#define small class
School$large_class<- (School$str>=20)*1;
School$high_el<- (School$el_pct>=10)*1;
Summary<-School %>%
  group_by(large_class,high_el) %>%
  summarise(Mean = mean(testscr, na.rm=TRUE));
print(Summary);
```

## Example: Test Scores and Class Size

```
## # A tibble: 4 x 3
## # Groups:   large_class [2]
##   large_class high_el  Mean
##       <dbl>    <dbl> <dbl>
## 1         0        0  664.
## 2         0        1  646.
## 3         1        0  662.
## 4         1        1  641.
```

## Interactions Between Binary and Continuous Variables

$$y = \beta_0 + \beta_1 x + \beta_2 D + u$$

- ▶  $D$  is binary variables (dummy variables).
- ▶  $x$  is continuous variable.
- ▶  $\beta_1$  is the effect on  $y$  of a unit increase in  $x$ .
- ▶ In this specification, this effect does not depend on the value of  $D$ .

To allow the effect of changing  $x$  to depend on  $D$ , include the “interaction term”  $D \times x$  as a regressor:

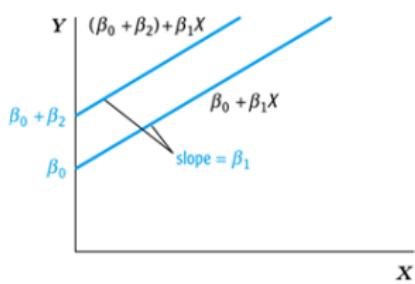
$$y = \beta_0 + \beta_1 x + \beta_2 D + \beta_3 D \times x + u$$

## Binary and Continuous Interactions: Two Regression Lines

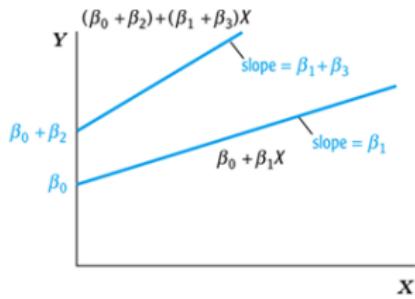
$$y = \beta_0 + \beta_1 x + \beta_2 D + \beta_3 D \times x + u$$

- ▶ When  $D_i = 0$ :  $y = \beta_0 + \beta_1 x + u$ .
- ▶ When  $D_i = 1$ :  $y = (\beta_0 + \beta_2) + (\beta_1 + \beta_3)x + u$ .
- ▶ By playing with specification of the regression equation we can have regression lines that are different:
  - ▶ Both in slopes and intercepts (current specification).
  - ▶ In slopes only (drop  $\beta_2 D$  from regression equation).
  - ▶ In intercepts only (drop  $\beta_3 D \times x$  from regression equation).

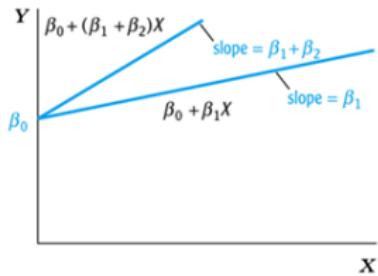
# Binary and Continuous Interactions



(a) Different intercepts, same slope



(b) Different intercepts, different slopes



(c) Same intercept, different slopes

## Interpreting Coefficients

$$y = \beta_0 + \beta_1 x + \beta_2 D + \beta_3 D \times x + u$$

- ▶ Compute  $y$  before and after change in  $x$ .
- ▶ Before:  $y = \beta_0 + \beta_1 x + \beta_2 D + \beta_3 D \times x$ .
- ▶ After:  $y + \Delta y = \beta_0 + \beta_1(x + \Delta x) + \beta_2 D + \beta_3 D \times (x + \Delta x)$ .
- ▶ Subtract “before” from “after”.
- ▶  $\Delta y = \beta_1 \Delta x + \beta_3 D \times \Delta x$ .
- ▶  $\frac{\Delta y}{\Delta x} = \beta_1 + \beta_3 D$ .
- ▶ The effect of  $x$  depends on  $D$ .
- ▶  $\beta_3$  = increment to the effect of  $x$ , when  $D = 1$ .

## Hypothesis Tests

$$y = \beta_0 + \beta_1 x + \beta_2 D + \beta_3 D \times x + u$$

- ▶ The two regression lines have the same slope  $H0: \beta_3 = 0$ .
- ▶ The two regression lines have the same intercept  $H0: \beta_2 = 0$ .
- ▶ The two regression lines are the same  $H0: \beta_2 = \beta_3 = 0$ .

## Example: Test Scores and Class Size

$$\widehat{testscr} = 682.25 - 0.97str + 5.64high\_el - 1.28str \times high\_el$$

```
#load necessary packages
require(car);
require(lmtest);
#load data
load("M:/Projects/FIE401/data/data_lectures/School.Rdata");
#define dummies
School$high_el<- (School$el_pct>=10)*1;
#run regression
fit<-lm(testscr~str+high_el+high_el*str,
         data=School);
#summary of the regression
#robust to heteroskedasticity
coeftest(fit,vcov=hccm);
```

## Example: Test Scores and Class Size

```
##  
## t test of coefficients:  
##  
##           Estimate Std. Error t value Pr(>|t|)  
## (Intercept) 682.24584   12.07126 56.5182 <2e-16 ***  
## str         -0.96846    0.59943 -1.6156  0.1069  
## high_el      5.63914   19.88866  0.2835  0.7769  
## str:high_el -1.27661   0.98557 -1.2953  0.1959  
## ---  
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

## Example: Test Scores and Class Size

- ▶ Regression for high and low percentage of English learners have the same slope  $H_0: \beta_3 = 0$  ( $high\_el \times str$ ).
  - ▶ Cannot be rejected.
- ▶ Regression for high and low percentage of English learners have the same intercept  $H_0: \beta_2 = 0$  ( $high\_el$ ).
  - ▶ Cannot be rejected.
- ▶ Regression for high and low percentage of English learners are the same  $H_0: \beta_2 = \beta_3 = 0$  ( $high\_el \times str$  and  $high\_el$ ).

```
myH0<-c("high_el=0","str:high_el=0");  
linearHypothesis(fit,myH0,vcov=hccm);
```

- ▶  $p\text{-value} < 2.2e-16$
- ▶ Rejected.

## Interactions Between Two Continuous Variables

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + u$$

- ▶  $x_1$  and  $x_2$  are continuous variables.
- ▶ As specified, the effect of  $x_1$  does not depend on  $x_2$ .
- ▶ As specified, the effect of  $x_2$  does not depend on  $x_1$ .
- ▶ To allow the effect of  $x_1$  to depend on  $x_2$ , include the “interaction term”  $x_1 \times x_2$  as a regressor:

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_1 \times x_2 + u$$

## Interpreting Coefficients

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_1 \times x_2 + u$$

- ▶ Compute  $y$  before and after change in  $x_1$ .
- ▶ Before:  $y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_1 \times x_2$ .
- ▶ After:  
$$y + \Delta y = \beta_0 + \beta_1(x_1 + \Delta x_1) + \beta_2 x_2 + \beta_3(x_1 + \Delta x_1) \times x_2.$$
- ▶ Subtract "before" from "after".  
$$\Delta y = \beta_1 \Delta x_1 + \beta_3 \Delta x_1 \times x_2.$$
- ▶  $\frac{\Delta y}{\Delta x} = \beta_1 + \beta_3 x_2$ .
- ▶ The effect of  $x_1$  depends on  $x_2$ .
- ▶  $\beta_3$  = increment to the effect of  $x_1$  from a unit change in  $x_2$ .
- ▶ Rarely used in practice due to complicated interpretation.

## Summary Interactions

- ▶ Three cases depending on whether we consider interactions between two binary variables, between one binary variable and one continuous variable, and between two continuous variables.
- ▶ Estimation and inference proceed in the same way as in the linear multiple regression model.
- ▶ The interpretation of coefficients differs from case to case.
- ▶ Interpretation of the coefficients is model-specific, but the general rule is to compute effects by comparing “before” and “after” cases.
- ▶ Many non-linear specifications are possible, so you must use judgment:
  - ▶ What non-linear effect you want to analyze?
  - ▶ What makes sense in your application?

## Textbook

- ▶ Non-linear regression functions: Chapter 8, Stock and Watson, Introduction to Econometrics, Global Edition, 4th edition