

ch15: Multiple Regression

3 Nov 2011
BUSI275
Dr. Sean Ho

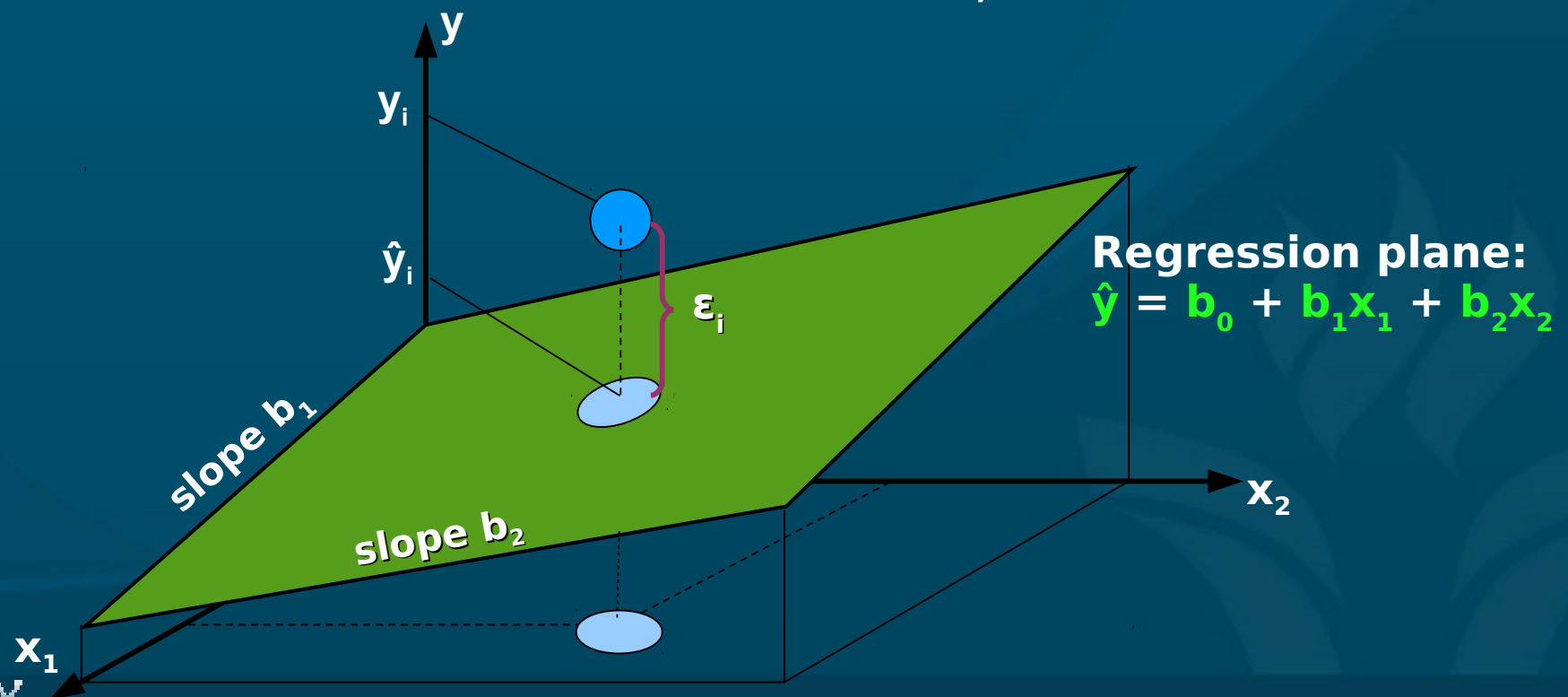
- **HW7** due Tues
- Please download:
17-Hawlings.xls

Outline for today

- Multiple regression **model**
 - Running it in **Excel**
 - **Interpreting** output
- **Unique** contributions of predictors
 - **Automated** predictor selection
- **Moderation** (interaction of predictors)
 - How to **test** for it
- Regression **diagnostics**: checking assumptions
 - **Transforming** variables

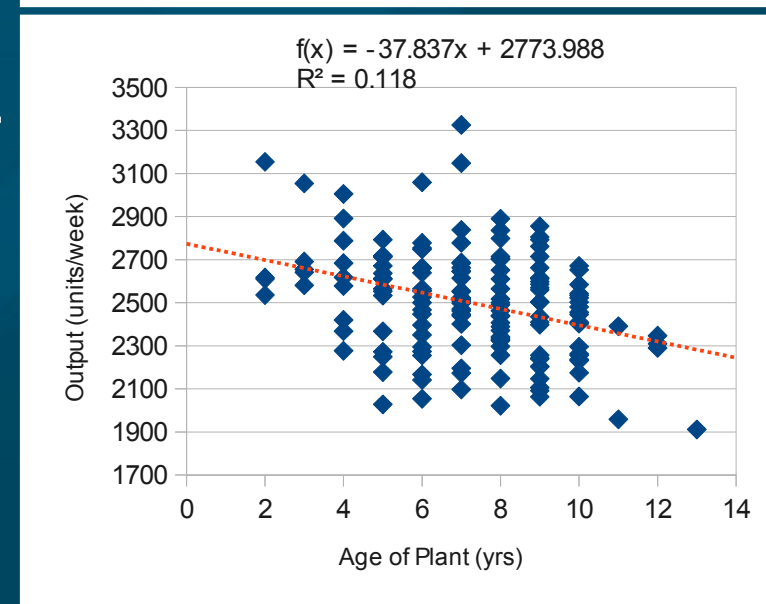
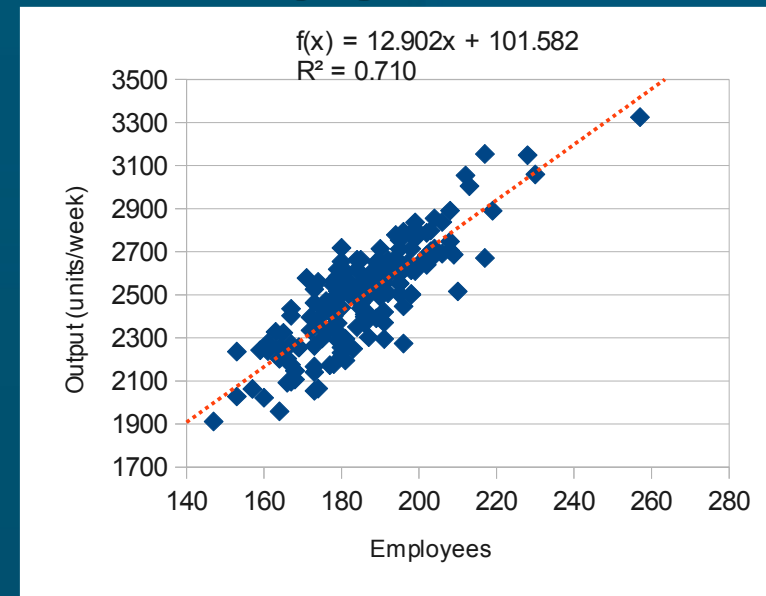
Multiple regression

- 1 outcome (scale), k predictors (scale)
- Linear model: hyperplane
 - $\hat{y} = b_0 + b_1x_1 + b_2x_2 + \dots + b_kx_k$
- Residuals still assumed normal, homoscedastic



Multiple regression in Excel

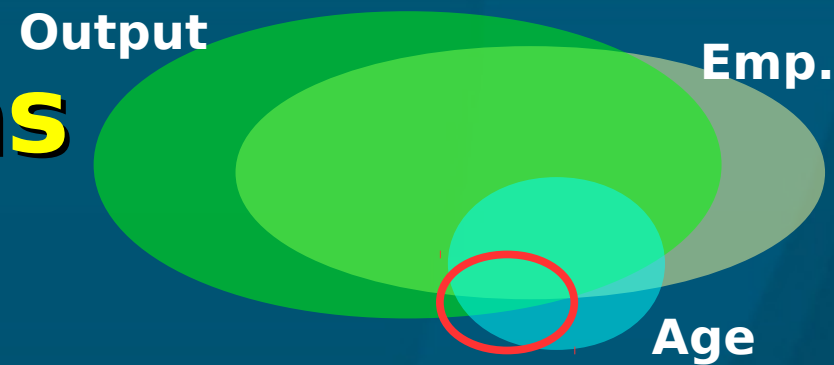
- Dataset: 17-Hawlins.xls
- DV (y): Output (units/wk)
- IV (x_1): Employees
- IV (x_2): Age of Plant (yrs)
- Pairwise **scatters** are helpful
 - Note R^2 for each predictor
- Data → Analysis → Regression
 - Y Range: B1:B160
 - X Range: C1:D160
 - Check “Labels” and “Standardized Residuals”



Interpreting the output

- R Square (R^2): fraction of DV var explained
 - Adjusted R^2 compensates for adding more IVs
- ANOVA table: F , p , and dfs
 - “Number of employees and plant age significantly predicted output:
 $R^2 = .72, F(2, 156) = 200.7, p < .001.$ ”
- Coefficient table:
 - For each predictor: slope b_i , t-score, and p
 - Both slopes are significantly nonzero
- Standardized residuals: z-scores
 - Can use to look for observations that don't fit the model (e.g., $|z| > 3$)

Unique contributions



- From the **Employees scatter**, it predicts **Output** pretty well ($R^2 = 71\%$)
- **Age?** **Not** so well ($R^2 = 12\%$)
- When use **both** together, why is R^2 only **72%**?
 - Most of the **12%** of variability in **Output** explained by **Age** is **shared variability**:
 - **Age** doesn't tell us much more about **Output** than we already knew from **Employees**
 - **Age's unique contribution** is only **1%**
- Compare regression using **all predictors** against regression using **all except Age**

Drawing conclusions

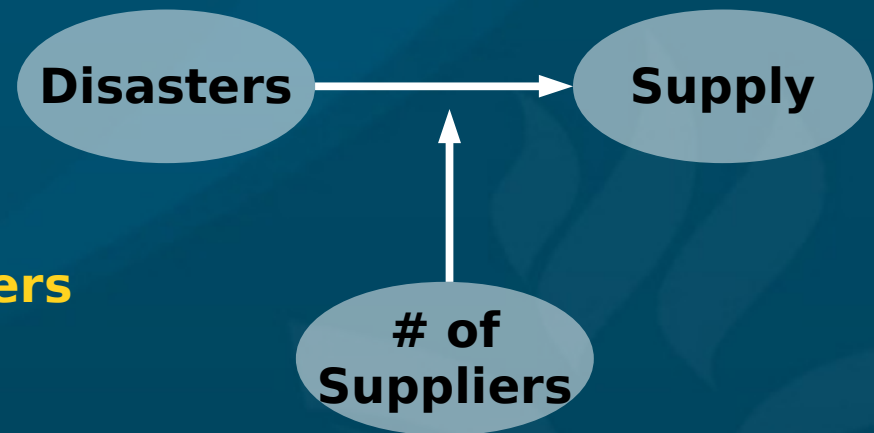
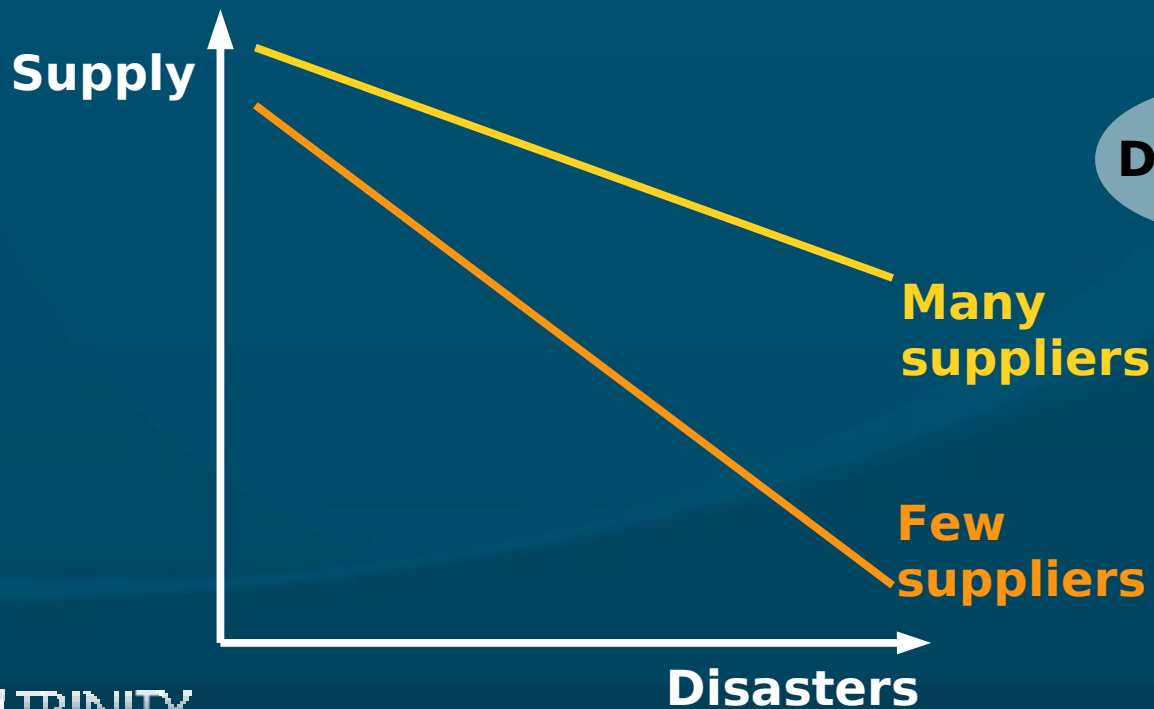
- We see that **Employees** and **Age** do significantly predict **Output** (global F test), and
 - Each predictor does contribute **significantly** (t -tests on slope), but
 - The **unique** contribution of **Age** is very small, so
 - **Most** of the predictive power is in the number of **employees**.
-
- In a formal **write-up**, you usually want to include details such as R^2 , F , dfs , and p , for those who understand the statistics.

Automated predictor selection

- “Best subsets” regression uses several runs with different combinations of predictors to try to find the set that predicts best while using the fewest predictors
 - Parsimony: simpler model to understand
- “Stepwise” regression adds/removes 1 predictor at a time to try to do the same
 - Backward: eliminate the least significant IV
 - Forward: add the next most significant IV
- Only in PHStat add-on, or SPSS, Stata, R, etc.

Moderation

- **Moderator**: a predictor that affects the **strength** of another predictor's **influence** on the outcome
 - **Interacts** with the other predictor
- E.g., natural **disasters** may affect your **supply**, but having multiple **suppliers** **buffers** the effect



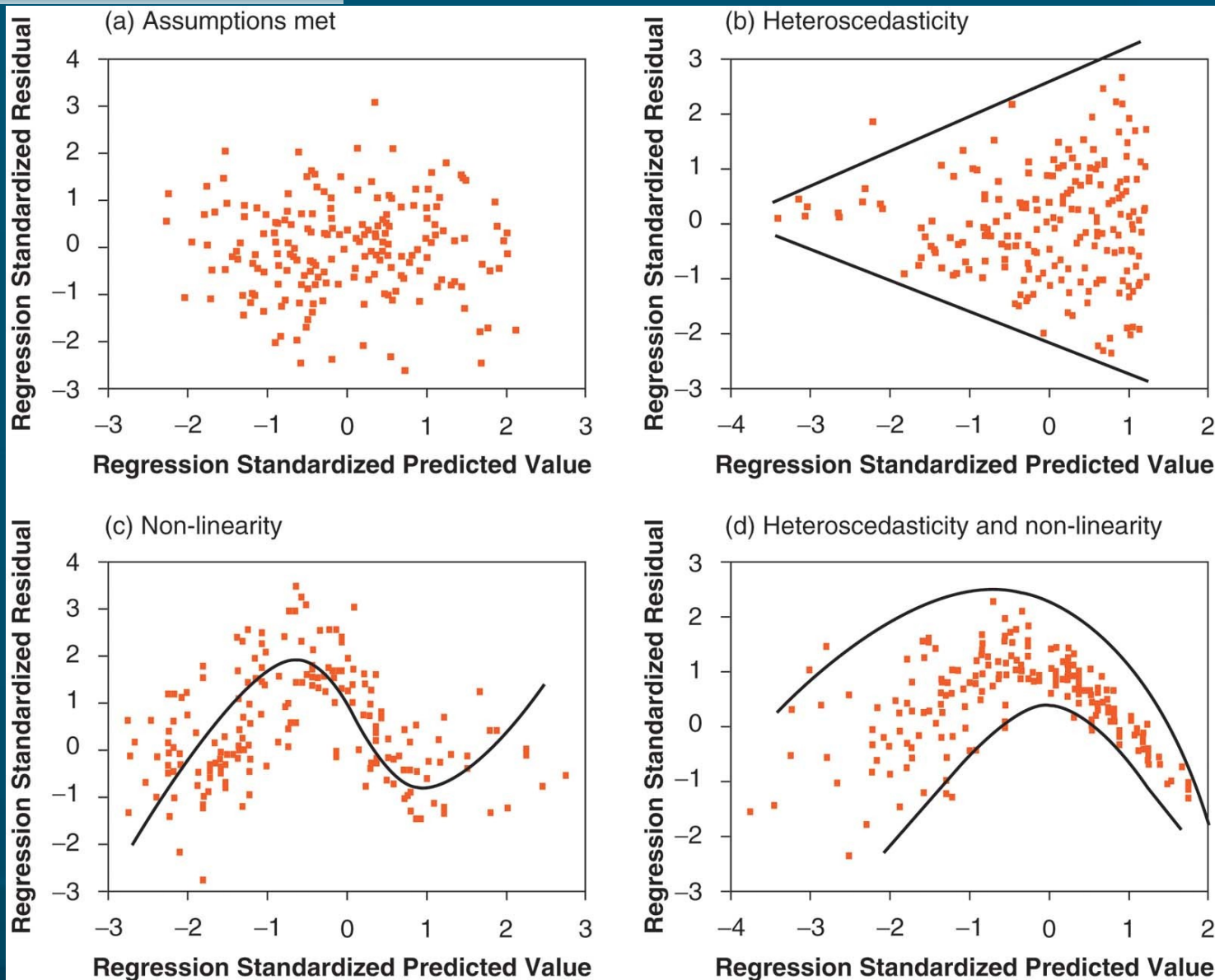
Testing for moderation

- How do we know if predictors are interacting?
- Add an interaction term to the regression:
 - $\hat{y} = b_0 + b_1x_1 + b_2x_2 + b_{12}x_1x_2$
- In Excel, centre both IVs (subtract their means), then make a 3rd column with the product
 - Include it in the regression as if it were an IV
- Check the *t*-test to see if the slope (b_{12}) of the interaction term is significantly nonzero
- If so, check R^2 both with and without the interaction term to see the size of its effect
- Also 3-way ($x_1x_2x_3$) and higher interactions!

Diagnostics: check assumptions

- Normality of residuals:
 - Check histogram of standardized residuals
- Homoscedasticity:
 - Residual plot: residuals vs. predicted values
 - Look for any odd or “fan shaped” patterns
- Linearity: curves on the residual plot
 - Try adding x_1^2 or x_2^2 , etc. to the model
 - And/or apply transforms to variables
- Indep. of residuals (time series are usually bad)
- Collinearity of IVs: check correlations of IVs
- Outliers / influential points: see residual plot

Homoscedasticity & linearity



Transforms

- Some variables (either IVs or DV) may be so heavily **skewed** that they break assumptions (esp. **heteroscedasticity** and **nonlinearity**)
- You can try applying a **transform** to make them roughly more **symmetric** or normal
 - But strict normality is not required
 - E.g., **log(income)** is usually more normal
- The family of **power transforms** includes:
 - \sqrt{x} , x^2 , $1/x$, $x^{-5.2}$, etc., as well as **log(x)**
 - May need to **shift** ($x+c$) or **reflect** ($c-x$) first
 - The **Box-Cox** procedure “automatically” selects a power transform for your variable

TODO

- HW7 (ch10,14): due Tue 8 Nov
- Projects:
 - Acquire **data** if you haven't already
 - ◆ If waiting for REB: try making up **toy** data so you can get started on analysis
 - Background **research** for likely predictors of your outcome variable
 - Read ahead on your chosen method of **analysis** (regression, time-series, logistic, etc.)