

III. Simple Regression.

- A. Introduction
- B. Population Regression Equation
- C. Sample Regression Equation
- D. Ordinary Least Squares
- E. Classical Regression Model.
- F. Properties of OLS Estimators (**BLUE**)
- G. Estimator for  $\sigma^2$
- H. Inference
- I. Goodness of Fit
- J. Forecasting or Prediction

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I. Goodness of Fit

- 1. Objective – a summary measure that tells us how well our model “fits the data.”
  - 2. Measures for the Dependent Variable:
    - $Y_i$ : observed value – an actual value for the dependent variable observed in our sample.
    - $\bar{Y}$ : the sample mean – used when Y does not depend upon X.
    - $\hat{Y}_i$ : The SRF – used when Y depends on X, use SRF to estimate the population mean of Y at each level of X.
- (Illustrate each of these on the graph.)

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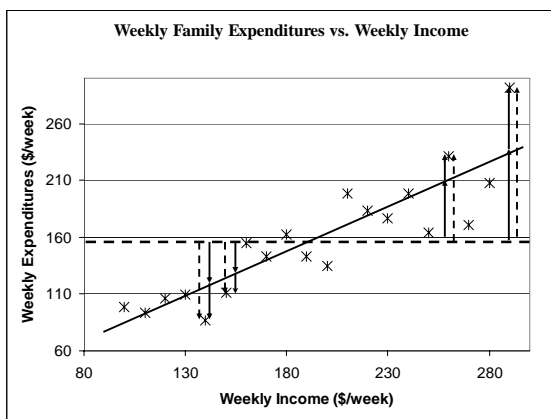
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### 3. Sums of Squares

- We want to know how we did on average.
- But, summing deviations always gives zero.
- Square them! Then sum:

$$\sum (Y_i - \bar{Y})^2 - \text{Total Sum of Squares (TSS)}$$

$$\sum (\hat{Y}_i - \bar{Y})^2 - \text{Explained Sum of Squares (ESS)}$$

$$\sum (Y_i - \hat{Y}_i)^2 - \text{Residual Sum of Squares (RSS)}$$

The Sums of Squared Deviations always add-up:

$$\sum (Y_i - \bar{Y})^2 = \sum (\hat{Y}_i - \bar{Y})^2 + \sum (Y_i - \hat{Y}_i)^2$$

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### 4. R<sup>2</sup> a measure of Goodness of Fit.

- What we have: **TSS = ESS + RSS**
- Form a ratio:
- Interpretation:
- Range of possible R<sup>2</sup> values:

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### Dan's Sample Regression Function (SRF) for Used 2004 Accords.



ANOVA

	df	SS	MS	F	Significance F
Regression	1	64053691.1	64053691	10.68	0.0029
Residual	28	167986040.4	5999501		
Total	29	232039731.5			

	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%
Intercept	23191.85	1022.62	22.68	0.00	21097.10	25286.60
Miles	-0.1050	0.0321	-3.267	0.0029	-0.1708	-0.0392

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**IV. Multiple Regression.**

- A. Introduction
- B. CRM
- C. Estimation
- D. Interpretation of Parameter Estimates
- E. Properties of Estimators

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**IV. Multiple Regression**

**A. Introduction.**

1. **Multiple regression** – measure the effects of several independent variables on the dependent variable.
2. Write a multiple regression population regression equation.

**Example: Demand –**

**Example: Salary inequities –**

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**B. Classical Regression Model** – again the assumptions, and we add one.

1.  $Y_i = \beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + \dots + \beta_k X_{ki} + u_i$ .
2. *The Xs are not random variables.*
3.  $E[u | X_i] = 0$ .
4.  $Var(u | X_i) = \sigma^2$ .
5.  $Cov(u_i, u_j) = E[u_i u_j] = 0$ .
6.  $u \sim$  *Normally.*
7. *No perfect linear associations among Xs.*

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**C. Estimation of population parameters.**

1. How? What method??
2. Process: Describe in words.

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**D. Interpretation of Parameter Estimates.**

1. Partial Effects – we now have several variables affecting Y. Each X has a *partial effect on Y*.

**Example:**  $Y = f(X_1, X_2)$

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2. Experimental vs Social Sciences

- **Experimental Sciences** – in physical and biological sciences, factors are physically held constant.

What do we do in econometrics?

- Gather data from individuals (markets, firms, etc.) **after choices have been made.**
- **Holding other factors constant** – we have to include them in the model.

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3. Specification Bias

- This is what happens when **we don't hold other factors constant**.
- Suppose  $Y$  is **truly** affected by  $X_1$  and  $X_2$ .

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**Specification Bias** – what happens when we omit an important variable from our model.

**Truth:**  $Y_i = \beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + u_i$

**You specify:**  $Y_i = \alpha_0 + \alpha_1 X_{1i} + u_i$

**Estimator:**  $\hat{\alpha}_1 = \frac{\sum x_{1i} Y_i}{\sum x_{1i}^2}$

Evaluate using the true model to see the effects of the **specification mistake**: **Bias**

$$E[\hat{\alpha}_1] = \beta_1 + \beta_2 \frac{\sum x_{1i} X_{2i}}{\sum x_{1i}^2}$$

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**Regression Analysis: sales versus prose, pcarn, dinc**

The regression equation is  
 $\text{sales} = 13355 - 3628 \text{ prose} + 2634 \text{ pcarn} - 19.3 \text{ dinc}$

Predictor	Coef	SE Coef	T	P
Constant	13355	6485	2.06	0.062
prose	-3628.2	635.6	-5.71	0.000
pcarn	2634	1013	2.60	0.023
dinc	-19.25	30.69	-0.63	0.542

S = 1076.29 R-Sq = 77.8% R-Sq(adj) = 72.2%

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### What if we don't hold other factors constant?

#### Regression Analysis: sales versus prose

The regression equation is  
sales = 16899 - 2979 prose

Predictor	Coef	SE Coef	T	P
Constant	16899	1985	8.52	0.000
prose	-2978.5	630.0	-4.73	0.000

S = 1312.19    R-Sq = 61.5%    R-Sq(adj) = 58.7%

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### E. Properties of OLS Estimators

- 1. Linear:** The OLS estimators are still linear estimators.
- 2. Unbiased:** If CRMAs # 1 – 3 are correct, the OLS estimators are unbiased estimators.  
$$E[\hat{\beta}_1] = \beta_1$$
- 3. Minimum Variance:** If CRMAs # 1 – 5 are correct, the OLS estimators are the **Best Linear Unbiased Estimators**.

(Gauss-Markov Theorem)

Draw a graph illustrating properties 2 & 3.

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