

# Example 1 of econometric analysis: the Market Model

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# Recap: framework for estimating $\beta_i$

- We want to estimate the following linear relationship:

$$r_i = r_f + \beta_i(r_M - r_f)$$

Equivalent statement:

$$r_i - r_f = \beta_i(r_M - r_f)$$

- Form of the econometric model:

$$Y_i = \alpha + \beta_i X_i + \epsilon_i$$

- What are the null hypotheses?

1. If  $Y_i = r_i, X_i = r_M - r_f$

$$H_0 : \beta_i = 1; H_a : \beta \neq 1$$

$$H_0 : \alpha = r_f; H_a : \alpha \neq r_f - \text{not well posed}$$

2. If  $Y_i = r_i - r_f, X_i = r_M - r_f$

$$H_0 : \beta_i = 1; H_a : \beta \neq 1$$

$$H_0 : \alpha = 0; H_a : \alpha \neq 0$$

# Estimate the market model for a security

- Time period for analysis: Jan 1 2003 to Dec 31 2007
- Frequency of data: monthly
- Fully diversified portfolio: NSE-50 market index.
- Any stock – it is not important that it is in the stock index or not.  
Our examples: Infosys Technologies, ICICI Bank
- Calculate monthly returns for the stocks and the index:

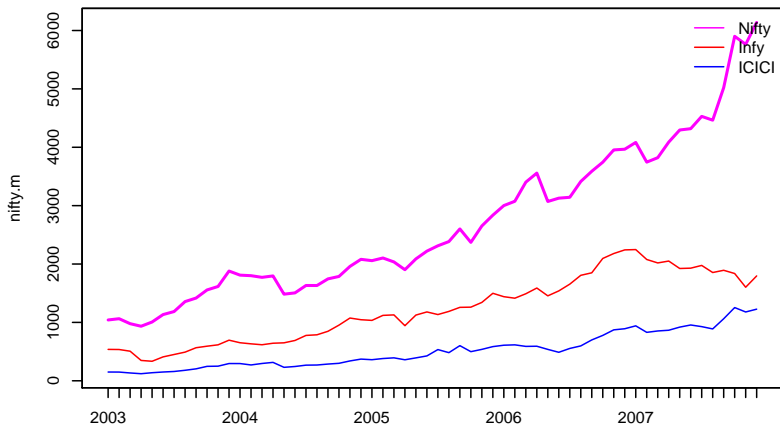
$$r_i = 100 * (\log P_1 - \log P_0)$$

where  $P_0$  is the price at the start of the month.  $P_1$  is the price at the end of the month.

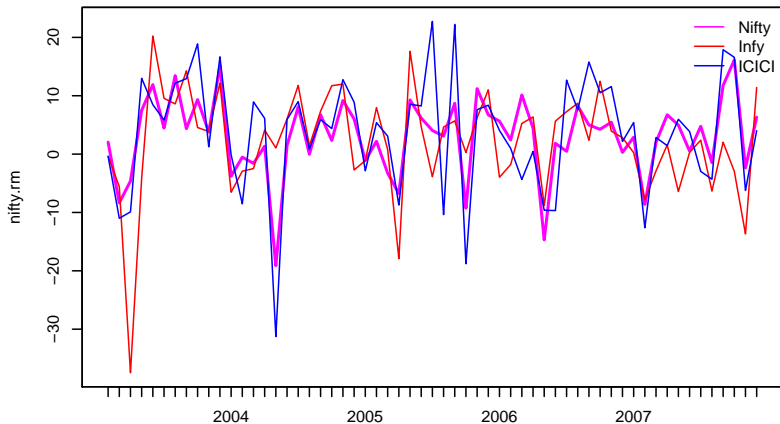
- $r_f$  is the three-month interest rate set by the RBI.
- Use OLS to estimate beta for Infosys and ICICI Bank assuming the single index market model is the best model for  $E(r_i)$ .

# Regression results for ICICI Bank returns

# Recap: Distribution of prices



# Recap: Distribution of $\partial$ returns



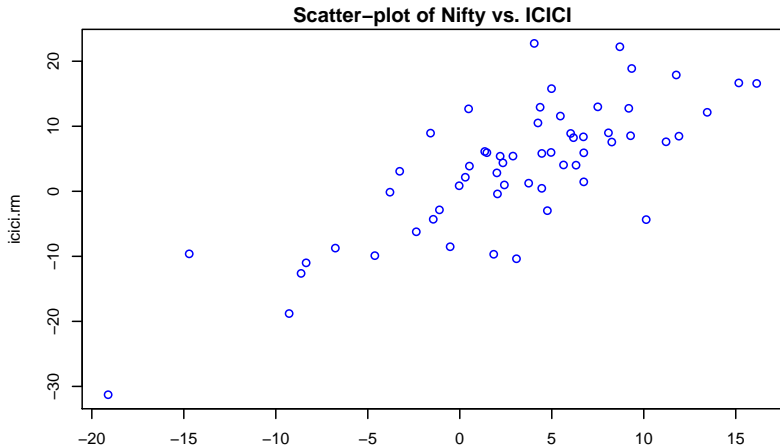
# Statistical tests for normality: ICICI Bank

- Summary statistics for monthly data

	ICICI Bank
Mean	3.5629
Std. Dev.	10.1755
Skewness	-0.7185 (5.16)
Kurtosis	3.975 (2.377)
N = 60	

- $\chi^2(1)$ , 0.05% level of significance = 3.84, 0.01% = 6.63
- $\chi^2(2)$ , 0.05% level of significance = 5.99, 0.01% = 9.21
- Significantly different from a normal distribution – will it affect the OLS estimation? How?
- Will MLE be a better estimation tool here? Not if we don't know the exact form of the distribution.

# Distribution of Nifty returns vs. ICICI Bank returns





# ICICI Bank regression results

- ICICI Bank:  $r_{\text{icicibank}} - r_f = \alpha_0 + \beta_{\text{icicibank}}(r_{\text{Nifty}} - r_f) + \epsilon$
- Regression results:

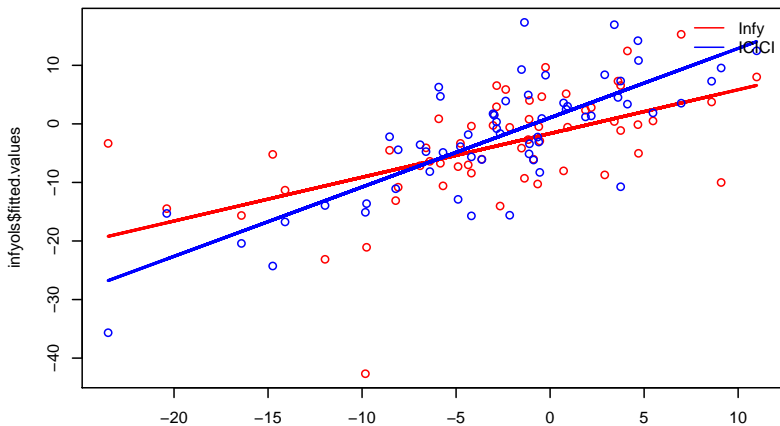
	ICICI Bank		Infosys Tech	
	Estimate	Std. Error	Estimate	Std. Error
(Intercept)	1.0513	0.9030	-1.6413	1.0974
Market returns	1.1837	0.1247	0.7474	0.1516
F-stat(1, 57) =	90.05		24.31	
prob value =	2.5e-13		7.5e-6	
R <sup>2</sup> =	0.6124		0.2989	
Adj R <sup>2</sup> =	0.6056		0.2866	
$\sigma_\epsilon^2$ =	7.757		6.383	

- Model:  $E(r_{\text{icicibank}} - r_f) = 1.1837(r_{\text{Nifty}} - r_f)$

# Interpreting the regression results

- On average, ICICI Bank price move by 1.2% when the market returns are 1%.  
In comparison: on average, Infosys returns move 0.75% with a 1% move in the market portfolio.
- Market returns captures 61% of the variation in ICICI Bank returns.  
But it captures only 30% of variation in Infosys Technologies.

# The regression lines for Infosys Tech and ICICI Bank



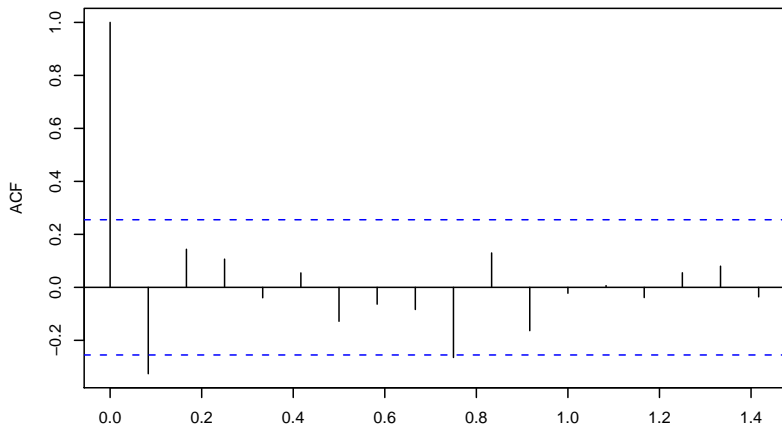
# Error analysis for ICICI Bank

- Characteristics of  $\epsilon$ .

	Y	$\epsilon$
Mean	3.562	0.000
Std. Dev. 10.176		
Skewness	-0.718 (5.162)	0.106 (0.113)
Kurtosis	3.975 (2.377)	3.442 (0.488)
60 observations		

- Correlation between  $(r_M, \epsilon) = -6.93e - 18$
- Serial dependence in  $\epsilon$ : autocorrelation coefficient function of  $\epsilon$ .

# Serial dependence in errors



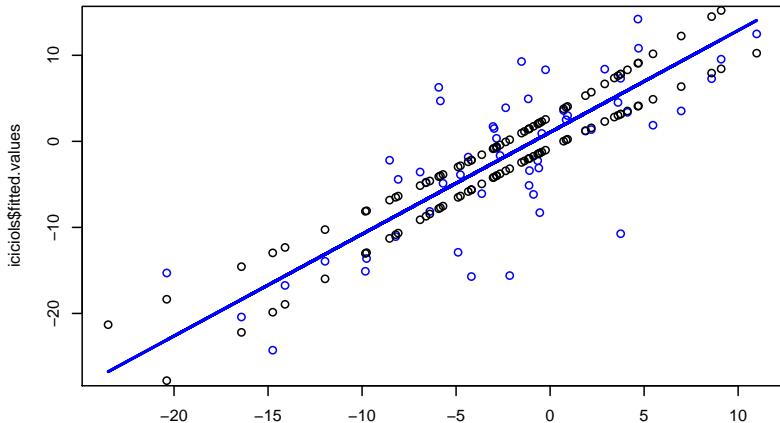
# Model prediction for ICICI Bank returns

- $E(r_i - r_f) = \hat{\alpha} + \hat{\beta}_i E(r_M - r_f)$
- For a move in excess market index returns of 1%, what is the expected excess returns on ICICI Bank?
- $\hat{\beta}_i = 1.18, (r_M - r_f) = 1\%$
- $E(r_i - r_f) = 1.18 * 1 = 1.0513 + 1.18 = 2.2313\%$
- The 95% confidence interval: 0.3198 – 4.1502%
- Suppose we ignore the  $\hat{\alpha}$ .
- Then,  $E(r_i - r_f) = 1.18\%$  with  $\text{var}(E(r_i - r_f))$

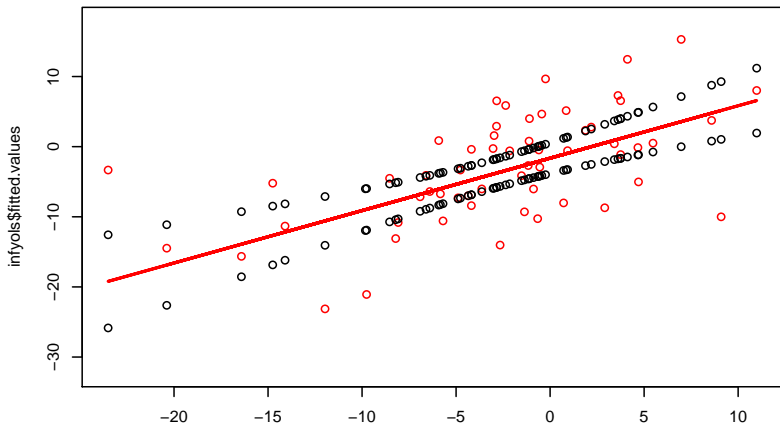
$$1 \times \text{var}(\hat{\beta}_i) = \sigma_e / \sqrt{N} \sigma_X = 0.1215$$

- Then, the 95% confidence interval becomes:  
0.9417 – 1.418

# Predictions and the 95% CI bands: ICICI Bank



# Predictions and the 95% CI bands: Infosys Tech





# HW: Model prediction for Infosys Technologies

- **HW:** For the same period data, what is the  $E(r_i - r_f)$  for Infosys Technologies?
- What is the 95% CI for the prediction with and without the  $\alpha$ ?
- Find the monthly returns that Infosys Technologies actually obtained in January 2008.  
How well did the model's 95% prediction fare?

# Transformation of the data and implication on the results

# Changing the scale of the dependent variable

- We have the model:  $Y_t = \alpha + \beta X_t + u_t$
- What if we accidentally create  $Y_{t^*} = 1000Y_t$  and run the regression instead?
- Impact: New equation on  $Y_{t^*} = 1000Y_t$

$$\begin{aligned}\Rightarrow Y_{t^*} &= 1000(\alpha + \beta X_t + u_t) \\ &= 1000\alpha + 1000\beta X_t + 1000u_t\end{aligned}$$

$$\Rightarrow Y_{t^*} = \alpha' + \beta' X_t + u_{t^*}$$

$$\Rightarrow \hat{\alpha}' = 1000\hat{\alpha}$$

$$\hat{\beta}' = 1000\hat{\beta}$$

$$\hat{\sigma}_{u_{t^*}} = 1000\sigma_{u_t}$$

- The impact on the regression results:
  - Standard error of regression  $\times 1000$
  - Standard error of regression co-efficient  $\times 1000$
  - But t-stats,  $R^2$ , F-stats are not changed because they are ratios. Scale measures cancel out.
- **Conclusion:** When  $Y_t$  is changed by K, values of ALL required co-efficients by K.

# Changing the scale of one independent variable

- Say we mistakenly transform  $X'_t = \frac{X_t}{100}$
- Impact on the estimation:

$$\begin{aligned} Y_t &= \alpha + \beta X_t + u_t \\ &= \alpha + \beta_{100} \frac{X_t}{100} + u_t \\ &= \alpha + \beta' X'_t + u_t \end{aligned}$$

- $\hat{\beta}' = 100\hat{\beta}$
- Standard Error of  $\hat{\beta}'$  also increases by 100
- But t-stats remain unchanged.
- **Conclusion:**
  - 1 Only the transformed variable's coefficient is affected.
  - 2 t-stats, ESS,  $R^2$ , F all remain unchanged
- Important for data combinations with diverse ranges of scale: Some  $X$  might take real values from 0 to 1. Simultaneously others can take values above 10,000.

Also useful to detect *errors* during data entry: the scale of estimated coefficients appear different from expected values.

# Example: Market model for Infosys against $(r_m - r_f)/100$

- $Y_t = (r_{\text{infosys}} - r_f)$
- $X_t = (r_{\text{nifty}} - r_f)$
- $X_t^* = (r_{\text{nifty}} - r_f)/100$
- Statistical features:

	$X_t$	$X_t^*$
Mean	-2.6922	-0.0269
Std Dev	6.777	0.06777
Skewness	-0.703	-0.7033
Kurtosis	3.8276	3.8276

# Regression results: $Y = f(X^*)$

	Infosys Tech			
	Estimate	Std. Error	Estimate	Std. Error
Intercept	-1.6413	1.0974	-1.50	0.1403
Market returns*	74.7377	15.1594	4.93	0.0000

F-stat(1, 57) = 90.05

prob value = 2.5e-13

$R^2 = 0.2989$

Adj  $R^2 = 0.2866$

Residual Std. Err: 7.825

# Example: Market model for Infosys with

$$(r_{\text{infosys}} - r_f)/100$$

- $Y_t = (r_{\text{infosys}} - r_f)$
- $Y_t^* = (r_{\text{infosys}} - r_f)/100$
- $X_t = (r_{\text{nifty}} - r_f)$
- Statistical features:

	$Y_t$	$Y_t^*$
Mean	-2.6922	-0.0269
Std Dev	6.777	0.06777
Skewness	-0.703	-0.7033
Kurtosis	3.8276	3.8276

# Regression results: $Y = f(X^*)$

	Infosys Tech			
	Estimate	Std. Error	Estimate	Std. Error
Intercept	-1.6413	1.0974	-1.50	0.1403
Market returns*	74.7377	15.1594	4.93	0.0000

F-stat(1, 57) = 90.05

prob value = 2.5e-13

$R^2 = 0.2989$

Adj  $R^2 = 0.2866$

Residual Std. Err: 7.825