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## Level 2 - Formula Sheet

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## Quantitative Methods

### LM1: Basics of Multiple Regression and Underlying Assumptions

LOS: Formulate a MR equation

**General Equation:**  $Y = b_0 + b_1X_1 + b_2X_2 + \dots + b_nX_n$

<b>k</b>	Slope Coefficients
<b>K + 1</b>	Coefficients
<b>df</b>	Degrees of Freedom = $n - (k + 1) = n - k - 1$
<b><math>X_1, X_2 \dots X_n</math></b>	Partial Regression Coefficients

**Dummy Variables:** Take the value of 0 or 1. Use  $n - 1$  dummy variables. If all dummy variables = 0, then the regression represents the  $i^{th}$  condition (i.e. the intercept).

**Log-log Regression:**  $\ln(Y) = b_0 + b_1\ln(X_1) + b_2\ln(X_2) + \dots + b_n\ln(X_n)$

### LM2: Evaluating Regression Model Fit and Interpreting Model Results

LOS: Measures of goodness of fit

**R-Squared:**  $R^2 = \frac{SSR}{SST}$

**Adjusted R-Squared:**  $\bar{R}^2 = 1 - \left(\frac{n-1}{n-k-1}\right) (1 - R^2)$

or: 
$$\bar{R}^2 = 1 - \left[ \frac{SSE / (n - k - 1)}{SST / (n - 1)} \right]$$

**Akaike's information criterion:**  $n \ln \left( \frac{SSE}{n} \right) + 2(k + 1)$

**Schwarz's Bayesian information criterion:**  $n \ln \left( \frac{SSE}{n} \right) + \ln(n)(k + 1)$

**Testing Joint Hypotheses for Coefficients:** 
$$F = \frac{(SSE \text{ restricted model} - SSE \text{ unrestricted}) / q}{SSE \text{ unrestricted model} / (n - k - 1)}$$



**LM3: Model Misspecification**

*LOS: Heteroskedasticity and Serial Correlation*

**Breusch-Pagan test for conditional heteroskedasticity:**

$$\varepsilon^2 = b_0 + b_1X_1 + b_2X_2 + \dots + b_nX_n$$

- If no conditional heteroskedasticity,  $R^2$  will be very low
- $H_0$  : no conditional heteroskedasticity
- $nR^2 \sim \chi^2$ , df = number of independent variables, then compare with  $\chi_c^2$  (one-tailed test)
- Do not want to reject  $H_0$

**Durbin-Watson test for SC:**

$$DW \approx 2(1 - r)$$

$$r = \text{corr}(\hat{\varepsilon}_t, \hat{\varepsilon}_{t-1})$$

- $H_0$ : DW = 2
- $DW \approx 2(1 - r)$  where  $r = \text{corr}(\hat{\varepsilon}_t, \hat{\varepsilon}_{t-1})$
- Reject  $H_0$  if  $DW < d_L$
- Do not reject  $H_0$  if  $DW > d_U$

**Breusch-Godfrey test for SC:**

**Original regression:**

$$y_t = b_0 + b_1X_{1t} + b_2X_{2t} + u_t$$

$$\hat{u}_t = a_0 + a_1X_{1t} + a_2X_{2t} + p_1u_{t-1} + e_t$$

- $H_0$  : No serial correlation
- Chi-square test statistic for lag = 1
- F stat with n-p-k-1 degrees of freedom for  $p > 1$

*LOS: Explain multicollinearity*

**Variance Inflation Factor (VIF) test for MC:**

$$VIF_j = \frac{1}{1 - R_j^2}$$

- $R_j^2$  is calculated by regressing each independent variable against the k-1 other independent variables
- $VIF_j > 5$  warrants investigation
- $VIF_j > 10$  indicates serious multicollinearity

**LM4: Extensions of Multiple Regression**

*LOS: Formulate and interpret a logistic regression model*

**Logistic Regression:**

$$\ln \frac{P}{(1-P)} = b_0 + b_1X_1 + b_2X_2 + \dots + b_nX_n + \varepsilon$$

$$P = \frac{1}{1 + \exp\left[-(b_0 + b_1X_1 + b_2X_2 + \dots + b_nX_n)\right]}$$



**LM5: Time Series Analysis**

*LOS: Calculate and evaluate trend models*

**Linear:**  $y_t = b_0 + b_1t + \epsilon_t$

If SC, DW  $\neq$  2, SE biased downwards

**Log-linear:**  $\ln(y_t) = b_0 + b_1t + \epsilon_t$

- $b_1$**  Trend Coefficient
- $t$**  Time
- $\epsilon_t$**  Error Term

*LOS: Describe the structure of AR(p)*

**AR(1)**  $x_t = b_0 + b_1x_{t-1} + \epsilon_t$

**AR(2)**  $x_t = b_0 + b_1x_{t-1} + b_2x_{t-2} + \epsilon_t$

**AR(p)**  $x_t = b_0 + b_1x_{t-1} + b_2x_{t-2} + \dots + b_px_{t-p} + \epsilon_t$

**Covariance Stationary**

- Constant mean, variance and Covariance( $x_t, x_{t-s}$ ) in all periods. If  $b_1 < 1$ , then the series is mean reverting and is Covariance stationary. All Cov. St. T have a finite mean reverting level. If not, then move on to first-differencing.
- Cannot use the DW statistic anymore to test for SC (once the model has as IV that is a lagged value of the DV). Use the t-statistics of the autocorrelations of the error terms.

*LOS: Calculate mean-reverting level*

$$x_t = \frac{b_0}{(1 - b_1)}$$

*LOS: Calculate the root mean squared error*

The square root of the average squared error:

$$RMSE = \sqrt{\frac{\sum \epsilon^2}{n}}$$

The smaller the RMSE, the more accurate the model.

*LOS: Unit roots, random walks*

**Random Walk:**  $b_0 = 0$  and  $b_1 = 1$

**After first differencing:**

$b_0 = 0$  and  $b_1 = 0$

(Cov. St., but no forecasting power)

- Cannot estimate an AR(1) on a random walk
- Test for a RW: Dickey-Fuller
- $H_0: g = 0$ ,  $H_a: g < 0$ , where  $g = (b_1 - 1)$

**Random Walk with drift:**  $b_0 \neq 0$

LOS: ARCH models

$$\hat{\epsilon}_t^2 = a_0 + a_1 \hat{\epsilon}_{t-1}^2 + \mu$$

Test:  $H_0: a_1 = 0$  versus  $H_a: a_1 \neq 0$

Rejecting  $H_0$  implies ARCH(1)

Thus, if  $a_1 = 0$ , we have constant variance

LOS: Two time-series

**Engle-Granger DF test:**  $(\epsilon_t - \epsilon_{t-1}) = b_0 + g\epsilon_{t-1} + \mu$

- $H_0: g = 0, H_a: g = 1$
- Reject  $H_0$ , regression output is OK.

DV and IV are both TS

Neither TS has a unit root	No issues	All else, not OK
Both have a unit root but are cointegrated		

LM6: Machine Learning

LOS: supervised versus unsupervised

