

Understanding and Interpreting Multiple Linear Regression Output in Excel

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[Multiple linear regression](#) is an indispensable tool in [statistical modeling](#), utilized across numerous disciplines--from finance to social science--to meticulously analyze the causal relationships between a single outcome (response) variable and two or more [predictor variables](#). Mastering the interpretation of this powerful technique is fundamental for accurate data analysis.

This extensive guide serves as an expert resource detailing the necessary steps to interpret every critical metric produced when executing a multiple linear regression model within **Microsoft Excel**. We aim to demystify the output, ensuring users can confidently validate their models, assess variable significance, and derive actionable insights from complex datasets.

Understanding Multiple Linear Regression Output

The regression analysis feature in Excel organizes its comprehensive results into three distinct, yet interconnected, segments: the Summary of Regression Statistics, the Analysis of Variance ([ANOVA](#)) table, and the detailed Coefficient Output. Effective interpretation necessitates a structured approach, understanding how these numerical values collectively determine the model's viability, explanatory power, and the significance of individual predictors.

A common challenge for new analysts is translating the dense statistical terminology into practical, real-world conclusions. This guide tackles that challenge head-on, providing a systematic, step-by-step walkthrough of each section, ensuring that statistical values are clearly linked to the scenario being investigated.

Setting Up the Foundational Regression Example

To effectively illustrate the process of interpretation, we will utilize a practical, educational example. Our objective is to ascertain whether a student's final score on a college entrance exam (the [response variable](#)) is statistically influenced by two primary factors: the **total number of hours spent studying** and the **quantity of preparatory exams taken**. These two factors constitute our [predictor variables](#).

By applying [multiple linear regression](#), we construct a predictive model designed to quantify the marginal impact of each predictor on the resultant exam score. This process is essential for forecasting future outcomes and rigorously assessing the comparative importance and significance of each hypothesized influence.

The following visual output represents the standard regression report generated by **Microsoft Excel**, derived from our hypothetical sample dataset comprising 20 student observations:

D	E	F	G	H	I	J	K
SUMMARY OUTPUT							
<i>Regression Statistics</i>							
Multiple R	0.857						
R Square	0.734						
Adjusted R Square	0.703						
Standard Error	5.366						
Observations	20						
ANOVA							
	<i>df</i>	<i>SS</i>	<i>MS</i>	<i>F</i>	<i>Significance F</i>		
Regression	2	1350.76	675.38	23.46	0.00		
Residual	17	489.44	28.79				
Total	19	1840.20					
	<i>Coefficients</i>	<i>Standard Error</i>	<i>t Stat</i>	<i>P-value</i>	<i>Lower 95%</i>	<i>Upper 95%</i>	
Intercept	67.67	2.82	24.03	0.00	61.73	73.61	
hours	5.56	0.90	6.18	0.00	3.66	7.45	
prep_exams	-0.60	0.91	-0.66	0.52	-2.53	1.33	

Interpreting the Regression Statistics (Model Fit)

The initial output segment provides essential descriptive statistics and metrics related to the overall goodness-of-fit of the model. These values offer an immediate, high-level assessment of how successfully the established linear model accounts for the observed variability inherent in the response data.

Multiple R (0.857): This statistic is the multiple correlation coefficient, measuring the magnitude of the linear relationship between the response variable (exam score) and the combined influence of all predictor variables. A value approaching 1.0 signifies a robust positive linear correlation, strongly suggesting that the chosen predictors are highly effective in explaining the variation observed in the outcome.

R Square (0.734): Also known as the [coefficient of determination](#), R Square is arguably the most fundamental measure of explanatory power. It quantifies the precise proportion of the total variance in the response variable that is mathematically predictable from the set of explanatory variables included in the model. In our educational context, 73.4% of the variation in the students' exam scores can be directly attributed to, or explained by, the combined effects of study hours and prep exams taken.

Adjusted R Square (0.703): This metric is a refinement of R Square. The Adjusted R Square accounts for both the total number of predictors in the model and the sample size. It is critical because it introduces a penalty for including superfluous or weak variables, thereby offering a more conservative and reliable estimate of the model's true explanatory power. Analysts frequently use the adjusted value when comparing the efficacy of different models that contain varying numbers of independent variables.

Standard Error (5.366): The [standard error](#) of the regression quantifies the average magnitude of the estimation error. Conceptually, it represents the average distance that the actual observed data points deviate from the mathematically fitted regression line. Lower values are highly desirable, indicating that the model's predictions are tightly clustered around the observed scores. Here, the average prediction error is 5.366 units.

Observations (20): This simply denotes the total number of data points, or the sample size (N), utilized by Excel to calculate and fit the parameters of the regression model.

Analyzing the ANOVA Table (Overall Model Significance)

The second critical section, the Analysis of Variance ([ANOVA](#)) table, provides the necessary framework for rigorous [hypothesis testing](#) regarding the utility of the regression model as a whole. Specifically, this test evaluates the null hypothesis that all population regression [coefficients](#) are simultaneously equal to zero. If the null hypothesis holds true, it implies that none of the independent variables possess a meaningful linear relationship with the dependent variable.

The ANOVA output focuses heavily on two interconnected statistical results: the F statistic and the corresponding Significance F value (or p-value). These metrics collectively determine whether the model is deemed statistically useful for predictive purposes.

F Statistic (23.46): The F statistic serves as the primary test statistic for assessing overall model significance. It is calculated by taking the ratio of the Mean Square (MS) attributed to the Regression (explained variance) to the MS of the Residual (unexplained error). A significantly larger [F statistic](#) indicates that the model is successfully explaining substantially more variance than the inherent error, thereby lending strong support to the model's overall utility.

Significance F (0.0000): This value represents the [p-value](#) associated with the overall [F statistic](#). It is used to determine if the collective set of predictors results in a statistically significant relationship with the response variable. We traditionally compare this value against a predefined alpha (α) level, typically set at 0.05.

In the context of our example, the Significance F value is reported as 0.0000, which is dramatically lower than the conventional threshold of $\alpha = 0.05$. Based on this outcome, we confidently

reject the null hypothesis. This rejection provides robust evidence that the combination of study hours and prep exams has a highly significant association with the exam score, validating the overall usefulness of the regression model for predictive analysis.

Examining the Coefficients and P-values (Individual Variable Significance)

The final and most detailed section of the Excel output focuses on the individual contributions of the intercept and each predictor, enabling analysts to isolate and understand the unique predictive power of every variable within the model structure.

The **Coefficients** column provides the specific numerical values required to formulate the estimated regression equation. Each coefficient quantifies the expected marginal change in the response variable resulting from a one-unit increase in that specific predictor, provided that all other explanatory variables are held constant--a critical statistical assumption known as *ceteris paribus*.

Intercept Coefficient (67.67): This value represents the baseline prediction: the estimated score a student would achieve if all predictor variables were set to zero. Specifically, a student who reported zero hours of study and zero preparatory exams is expected to receive a baseline exam score of **67.67**.

Hours Studied Coefficient (5.56): This positive coefficient indicates a direct relationship. For every additional hour dedicated to studying, the student's exam score is predicted to increase by 5.56 points, assuming the number of prep exams remains unchanged.

Prep Exams Taken Coefficient (-0.60): This counter-intuitive negative coefficient suggests that for every additional prep exam taken, the predicted exam score decreases by 0.60 points, holding study hours constant. However, the true importance of this coefficient must be assessed alongside its accompanying [p-value](#), which determines if this observed effect is statistically meaningful or merely random noise.

The **P-values** column is derived from individual t-tests for each coefficient, and it is paramount for determining the individual statistical relevance of each predictor. We use these p-values to test whether the individual population coefficient is significantly different from zero.

The p-value for **Hours Studied** is 0.00. Given that this value is far below the conventional $\alpha = 0.05$ threshold, we emphatically conclude that hours studied is a highly significant predictor of the final exam score.

Conversely, the p-value for **Prep Exams Taken** is 0.52. Since 0.52 is substantially greater than 0.05, we must conclude that the number of prep exams taken is **not statistically significant** at the 5% level. This finding suggests that once the strong effect of study hours is already accounted for,

taking extra prep exams provides no meaningful or reliable additional predictive power regarding the score.

Constructing and Utilizing the Estimated Regression Equation

The derived [coefficients](#) from the Excel output are the essential building blocks for formulating the explicit estimated regression equation, which serves as the predictive model for future estimations. The foundational structure of a multiple regression equation is defined as:

$$\text{Predicted Y} = \text{Intercept} + (\text{Coefficient 1} * X1) + (\text{Coefficient 2} * X2) + \dots$$

Incorporating the specific numerical results obtained from our Excel analysis, the estimated regression equation designed to predict exam scores is:

$$\text{Exam score} = 67.67 + 5.56 * (\text{hours studied}) - 0.60 * (\text{prep exams taken})$$

This powerful equation can now be deployed to estimate a student's expected score based on their specific preparation inputs. For instance, consider calculating the predicted score for a hypothetical student who studies for three hours and completes one preparatory exam:

$$\text{Calculation: Exam score} = 67.67 + 5.56 * (3) - 0.60 * (1) = 67.67 + 16.68 - 0.60 = 83.75$$

Based on the model, the predicted outcome is that this student is expected to achieve an exam score of **83.75**.

Next Steps and Model Refinement (Parsimony)

A critical phase immediately following the initial interpretation is the refinement of the statistical model. Because the predictor variable **prep exams taken** was conclusively identified as statistically non-significant (p-value of 0.52), standard statistical practice often mandates its removal from the model to achieve greater parsimony.

The inclusion of non-significant predictors can introduce unnecessary complexity, potentially inflate the calculated [standard error](#), and mask the true underlying relationships. Even though the overall F-test confirmed the model's significance, this result was driven almost entirely by the strong, significant effect of **hours studied**, effectively overshadowing the weak contribution of the prep exams variable.

In this specific analytical scenario, the expert recommendation is to simplify the approach. A subsequent analysis should utilize a simpler model--a simple linear regression--employing only **hours studied** as the sole explanatory variable. This refinement creates a more robust, efficient, and easily interpretable model focused exclusively on the statistically meaningful insight provided

by the strongest predictor.

Additional Resources for Advanced Regression Analysis

For analysts seeking to transition beyond foundational interpretation and deepen their expertise in advanced statistical concepts related to regression modeling, including diagnostics, assumption testing, and validation, the following topics are highly recommended for detailed study:

Understanding the challenges of [Multicollinearity](#) and its systemic impact on model stability and coefficient estimates.

Methodologies for testing crucial assumptions, such as Homoscedasticity and Normality of Residuals.

Clarifying the fundamental difference between statistical correlation and true causal inference in predictive modeling.