A Primer on Forecasting Business Performance

There are two common approaches to forecasting: qualitative and quantitative. Qualitative forecasting methods are important when historical data is not available. These methods include the Delphi and market share approaches. The Delphi method involves solicitation of expert opinion. The market share method entails making an estimate of the current size of the total market and its future growth rate. The analyst must then assume the firm's future market share and how long it likely to take the firm to achieve that penetration. Consequently, a firm's sales for a given year can be projected by multiplying the assumed market share by the projected size of the market in that year.

The focus in this appendix will be on using quantitative methods analyzing historical time series to determine causal relationships between variables to project financial statements for target and acquiring companies. Other topics such as alternative regression models, model specification, the purpose of various types of test statistics, and the limitations of regression analysis are also addressed. Hanke and Wichern (2005) and Marks and Samuelson (2003) provide more rigorous treatments of this subject.

The Art of Forecasting

For purposes of business valuation, key determinants of future valuation cash flows include unit sales, costs and selling prices. To project these factors, it is necessary to determine the key drivers behind their growth. For example, increases in auto sales may be a result of increasing consumer personal disposable income, while costs may be affected by changes in wage rates and other input expenses. Future selling prices may reflect an increase or decrease in intra-industry price competition. The drivers vary by the type of industry and business.

In general, the annual forecast period should be long enough so that the analyst is comfortable projecting growth to the sustainable growth period. For very high growth or cyclical companies, the analyst may need forecast periods of ten years or more to reach a period reflecting sustainable growth for the firm. Whether the analyst should use 3, 5, 10 or more years of annual projections before assuming a sustainable growth period depends largely on how much confidence the analyst has in longer-term forecasts. The perceived credibility of any forecast depends on the reasonableness of the underlying assumptions. Ultimately, what forecasting is all about is translating the underlying assumptions into the numbers they imply. Some of the most critical forecast assumptions relate to the analyst's opinion about the firm's future growth rate in sales and profit relative to the industry's overall growth rate and how long it can be sustained.

General Guidelines for Sales and Profit Forecasting

The process of projecting cash flows involves a 2-step procedure. First, the analyst should determine the factors affecting the historical growth rate of cash flows. For revenue, such factors would be the firm's pricing power and factors affecting unit sales such as income growth, price elasticity of demand, demographics, credit availability, new market entrants, etc. Factors affecting the cost of sales include wage rates, degree of unionization, productivity growth, the firm's reinvestment rate, etc. Other factors influencing both revenue and costs could include the regulatory environment, macroeconomic changes, and fluctuations in exchange rates.

Second, the analyst should make assumptions about how, if at all, the factors that determined historical growth might change in the future. If the historical determinants of cash flow growth are not expected to change, simple extrapolation using the historical growth rate is appropriate. Otherwise, adjust the future growth rate for expected changes in the factors affecting the growth in cash flow. How factors might change depends on answer to a variety of questions. How will the future regulatory environment change? Are there likely to be new market entrants, substitute products or emerging technologies? If so, how will these factors impact product pricing and the growth in unit sales? What is the outlook for the domestic and global economies?
<B>Time Series Analysis (Seasonal, Irregular, Cyclical and Secular)<B>
Time series models identify patterns in a single variable over time. Time-series patterns can be broken down into four major categories: trend, business cycles, seasonal variation, and irregular or random fluctuations. A trend or secular movement is a steady movement in an economic variable overtime. Superimposed on such trends are periodic business cycles or periods of accelerating or decelerating/declining growth in the economy. Seasonal variation refers to shorter cycles that depend on the time of the year, the season, or other conditions. For example, tourism, tax preparation services, ice cream, and clothing sales are affected by seasonal factors. Irregular movements are due to random or unpredictable factors such as droughts, strikes, wars, spikes in commodity prices, etc. .

Understanding historical trends are generally the most useful for long-term forecasting. If the analyst is confident that the causal relationship between variables historically is likely to continue into the future, the analyst may simply extrapolate this trend growth rate from the base or initial year of the forecast. Growth rates can be readily calculated based on the historical experience of the firm or industry. The average annual growth rate, g, for a time series extending from time, t_1, to t_n can be calculated by solving the following equation:

$$g = (t_n/t_1)^{1/n} - 1 \qquad (7\text{-}19)$$

Care should be taken to discard aberrant data points resulting from infrequent or nonrecurring events such as labor shortages or droughts. Such data points distort the growth rate. Aberrant data points will be apparent by plotting the data. The length of the historical time period used in the analysis should be long enough to encompass one full business cycle (i.e., recession and recovery). Otherwise, the extrapolation may be distorted if the starting or ending point for calculating the average annual growth rate occurs when the economy is growing at above or below its trend rate of growth.

Analysts are often confronted with less than a full year's worth of data for the base year of the forecast period. For example, the fourth quarter for public companies is often not reported until April or May of the following year. Consequently, the analyst must estimate the full year based on three quarters of data. Assuming little seasonality in the data, if we have data on the first three quarters of the year, full year sales (S) can be estimated as $(S_1+S_2+S_3)/.75$, where $(S_1 + S_2 + S_3)$ represents the dollar value of sales during the first three quarters. Suppose sales in the fourth quarter have historically accounted for 40 percent of annual sales, full year sales can be estimated as (S1+S2+S3)/.6. This relationship can be generalized as follows:

$$S = \sum_{i=1}^{n-1} S_i \;/\; (1 - (S_n/S)_h) \qquad (7\text{-}20)$$

where S_i represents the dollar value of sales in the ith period of the year and n is equal to 1 to 3 periods for quarterly data and 1 to 11 for monthly data. $(S_n/S)_h$ is the ith period historical percentage of total sales.

Alternative Time Series Regression Models

Regression analysis is a statistical technique that estimates the mathematical or causal relationship between a dependent and independent variables. In analyzing mergers and acquisitions, regression analysis may be used to forecast sales and costs that provide the basis for projecting cash flow used in discounted cash flow valuation. The basic assumption in time series regression analysis is that the factors that have influenced patterns of activity in the past will continue to do so in about the same way in the future. If the analyst feels comfortable with this assumption, she should then plot the data and observe its tendencies over time. Plotting the data enables the analyst to determine whether there is a long-term upward or downward trend. Linear regression involves the relationship between a dependent variable (Y) and a single independent variable (X). Multiple regression models use several explanatory or independent variables (X_1, X_2, X_3, …X_n) to predict the value of the dependent variable.

Simple Linear Regression Model

A simple linear regression model may be expressed as follows:

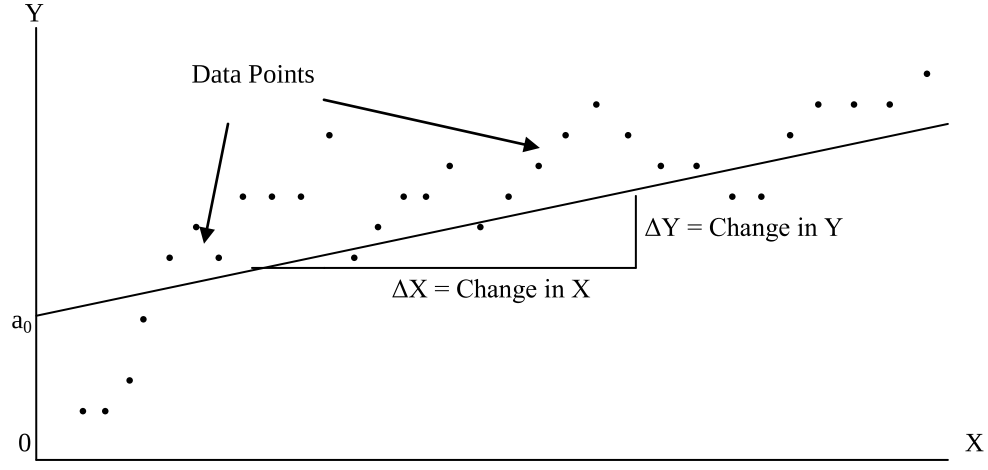
$$Y_i = a_0 + b_1X_i + \varepsilon_i \qquad (7\text{-}21)$$

where

a_0 = Y intercept for the data sample
b_1 = Slope for the data sample
ε_i = Random error in Y for observation i

Note that a_0 and b_1 in equation 7-21 are estimates derived from a data sample taken from the total data population of the true values of the intercept, A_0, and the regression coefficient, $ß_1$. The upward sloping regression line in Figure 7-1 is that which minimizes the sum of the squared deviations between the values given by the line and the actual data points. Squaring the deviations prevents negative deviations from offsetting positive ones. Furthermore, the larger deviations have a greater influence, because they are squared. In this model, the slope of the line represents the expected change in Y per unit change in X. The Y intercept a_0 represents the average value of Y when X equals 0. ε_i represents the random error in Y for each observation, i, that occurs. ε_i represents the difference between the actual value of Y and $\hat{Y}$, the value estimated by the equation $Y_i = a_0 + b_1X_i$.

Figure 7-1. Linear Relationship between Y and X



Quadratic Regression

A linear time trend is not the only equation that can be used to fit the past data. The quadratic form can be expressed as follows:

$$Y_i = a_0 + b_1X_1 + b_2X_2^2 + \varepsilon_i \tag{7-22}$$

where a positive value of b_2 implies an increasing rate of growth in Y_i over time. In contrast, if b_2 is negative, Y_i tends to grow more slowly over time. The quadratic equation includes the linear equation as a special case when $b_2 = 0$.

Exponential smoothing

Another commonly estimated specification is the exponential form

$$Y_i = br^t \tag{7-23}$$

where coefficients b and r are to be estimated. Note that the coefficient r is raised to the power t. If r is greater than 1, Y_i grows proportionately more with the passage of time. For example, if r equals 1.06, Y_i grows by 6 percent annually. Alternatively, if r is less than one, Yi decreases proportionately. If r equals .92, Y_i falls by 8 percent annually.

Test Statistics

Simple linear regression analysis (see equation 7-21) focuses on finding the straight-line that fits the data best. The best fit is defined as that straight-line for which the differences between the actual and estimated values of Y_i are minimized. Total variation in estimated Y, $\hat{Y}$, about its average value can be decomposed into two components: explained and unexplained or residual variance. Explained variation is that portion of total variation in Y that can be explained or accounted for by variation or changes in independent variables in the equation. That portion of total variance that cannot be explained by changes in the independent variables is called unexplained variance.

A number of statistical indicators exist to assist in the determination of which model best fits the historical data. These indicators are called "goodness of fit" statistics. Other statistics help to determine the overall statistical significance of each independent variable (i.e., t-statistics), all independent variables as a group (i.e., F-statistics), and all independents variables plus the intercept (i.e., P-statistics). Statistical significance implies that there is an identifiable and measurable relationship between the dependent and independent variables that is not simply due to chance or coincidence. Statistical significance may be measured at the 5% level. Statistical significance at this level or lower allows the analyst to reject the "null hypothesis" that the estimated intercept, a_0, and regression coefficients, b_i, are different from zero. T-statistics can be used to construct "confidence intervals." Within such intervals, the analyst can be relatively confident that the true value of the intercept and regression coefficients lie within a specific range and that the estimated values of the intercept and regression coefficients lie at the midpoint of that range. See Table 7-4 for a summary of commonly used test statistics.

Table 7-4. Common Regression Test Statistics

Statistic	Description
Goodness of Fit	
R value	Degree of correlation between the dependent and independent variable. R =1 indicates perfect correlation. R values fall between -1 (negative or inverse correlation) and +1 (positive or direct correlation).
Multiple R	Degree of correlation between the dependent and all of the independent variables.
R^2	Measures the percentage of variation in the dependent variable that is explained by the independent variables, (i.e., explained variation in Y/total variation in Y).
Adjusted R^2	Removes spurious correlation that can result from adding more independent variables to the equation.
Analysis of Variance (ANOVA)	
SS (Sum of Squares)	The sum of squared differences between each observed Y value and the average value of Y.
Standard Error of Estimate	Measures the variability of the actual values of Y around the predicted values, for given values of X_i.
Standard deviation	Square root of the variance of a_0 or b_i.
Statistical Significance	
t-statistic[1]	A measure of the likelihood that there is a causal relationship between Y and X. In general, for t values greater than 2.0, the analyst can be 95% certain that the estimated values of a_0 or bi are different from zero.
Confidence interval	Interval within which the true value of b, ß, lies within a range of ± 2.5% of the estimated value b. This interval may be constructed as the estimated value of b ± $t_{.025}$ $S_ß$, where $t_{.025}$ is the value from a standard t-Table and $S_ß$ is the

	standard deviation of b. A confidence level of 95% is approximately ± 2 standard deviations from the estimate..
P-value (i.e., the probability value)	P represents the level at which we can reject the null hypothesis that $a_0 = 0$ and $b_i = 0$. P-values of .05 or .01 are typically viewed as rejections of the null hypothesis. At these levels, (1 – P) is the level of statistical significance of the y-intercept and the independent variable (s) and suggests a strong rejection of the null hypothesis.
F-test[1]	A test of whether the independent variables as a group explain a statistically significant portion of the variation in Y. It is estimated as the ratio of the explained to the unexplained variance. Therefore, the larger the value the more statistically significant the set of independent variables. In general, for 2-5 independent variables and 10 to 20 observations, F values > 4.5 are statistically significant.
[1]T and F statistics are found in most statistics textbooks. See Berenson, Levine and Stephan (1999) or Hanke and Wichern (2005)	

Model Specification

A model is an approximation of the perceived relationship between dependent and independent variables. Model specification refers to the direction of causation (i.e., which is the dependent variable), the initial identification of the possible variables whose variation is likely to explain changes in the dependent variable, and the form of the variables (e.g., linear or non-linear). See Exhibit 7-12 for a generic specification of hypothetical models for forecasting sales, cost of sales, product/service selling prices, and profit margins.

Exhibit 7-12. Examples of Model Specification

Unit Sales (S) Forecasting Model: $S = f((-P_{own}/P_{sub}), +INC, -i, +W, +POP, +Tastes, X_i)$

where

P_{own} = Product/service's own price
P_{sub} = Price of substitute products or services
INC = Consumer personal disposable income (After-tax cash flow if the firm is selling to businesses)
i = Interest rates (i.e., cost of borrowing)
W = Household wealth (Corporate net worth if the firm is selling to businesses)
POP = Population (Number of potential business customers if the firm is selling to businesses)
Tastes = Consumer tastes or personal preferences
Xi = Other variables specific to the firm (e.g., patent protection for pharmaceutical companies, which limits the number of competitors)

Cost of Sales (COS) Forecasting Model: COS = f(+S, +W, -Prod, +PUR, +i) where

W = Wages, salaries, commissions, bonuses, and benefits
Prod = Some measure of productivity (e.g., output/hour or output per employee)
PUR = Purchased materials

Selling Price (SP) Forecasting Model: SP = f(+S, $+P_{sub}$, +COS)

Profit Margin (PM) Forecasting Model: PM = f(+S, +SP, -COS)

Note: The positive or negative sign associated with each variable represents the hypothesized direction of correlation between the dependent and independent variable.

Limitations to Regression Analysis

Insufficient data often results in an increase in forecast error, as the limited data is inadequate to capture the true causal relationship between the variables. Moreover, factors affecting changes in the dependent variable historically often change during the forecast period. Such factors include the emergence of new products and competitors, increasing costs due to rising raw material prices, increased government regulation, or unionization of the firm's labor force. Finally, a forecast using a regression equation may result in erroneous projections because the assumptions underlying the future values of the independent variables are incorrect.