



Hedge Effectiveness Testing

Using Regression Analysis



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When companies use derivative instruments to hedge economic exposures, they generally want to apply special hedge accounting. Without this special treatment, derivative gains or losses and the gains or losses associated with the risk being hedged would hit earnings in different time periods. The resulting income volatility masks the objectives of the hedging strategy; and with hedge accounting, this volatility may be largely avoidable. Hedge accounting is elective, but the problem is that companies must qualify for this treatment.

Perhaps the most onerous requirement to qualify for hedge accounting is that the derivative's results must be expected to be "highly effective"

in offsetting the changes in fair value or cash flows associated with the risk being hedged. Besides requiring a company to make this assessment prospectively, Statement of Financial Accounting Standards No. 133, *Accounting for Derivative Instruments and Hedging Activities* (SFAS 133) also requires a retrospective assessment to be made on an ongoing basis — at each reporting period, and no less frequently than quarterly.

FAS 133 does not prescribe a single method for assessing hedge effectiveness; and in fact, different methods for prospective and retrospective testing are permitted. What is required, however, is that the selected approach must be reasonable; it must also be consistent with the company's risk



management strategy; it must be documented at the inception of the hedging relationship; and it must be consistently applied throughout the term of the hedge. Further, although different methods may be used for different hedges, a company must be able to justify the use of different methodologies for similar hedges.

The simplest approach to assessing hedge effectiveness is the “dollar offset” method. Under this method, the change in the value of the derivative is compared to the change in the value of the hedged item. In practice, the term “highly effective” is interpreted to mean that this ratio takes on a value within a range of 80-120 percent.

The drawback to this method, however, is that it is often difficult to achieve high effectiveness consistently, from period to period¹; and failing the hedge effectiveness test precludes the use of hedge accounting. However, Derivative Implementation Group (DIG) Issue E7, *Methodology to Assess Effectiveness of Fair Value and Cash Flow Hedges*, permits companies to use regression or other statistical methods to test hedge effectiveness, thereby possibly permitting hedge accounting when the dollar offset method would otherwise disallow it.

Terminology

Regression analysis is a statistical technique that provides quantitative information about the relationship between two or more variables. In the context of FAS 133, the need to show that a derivative will be highly effective translates to

showing that the price (or interest rate or currency exchange rate) associated with the hedged item bears a close relationship to the price associated with the hedging derivative.² Simple regression (i.e., a regression designed to explain the relationship between two variables) provides a summary statistic, the correlation coefficient, which quantifies the closeness of the relationship.

Correlation coefficients may range in value from -1.0 to +1.0, where 1.0 is indicative of a case where the two respective variables, X and Y, are perfectly correlated. That is, X and Y perform perfectly in a linear relationship such that the data behave consistently and perfectly, according to the following equation:

$$\text{EQUATION (1): } Y = aX + b$$

In this equation *a* is the slope coefficient and *b* is the intercept; and the regression program provides numerical values for these two parameters.

If the correlation coefficient is -1.0, X and Y are said to be perfectly inversely correlated. The regression equation would show that the value of the slope coefficient, *a*, in such a case would be negative, such that larger values for X would consistently be associated with smaller values for Y, and vice versa.

A correlation coefficient equal to zero suggests that no reliable linear relationship between X and Y exists. Rather, the relationship between these two variables is perfectly random. In this case *a* would have a value not statistically different from zero.

A related concept to the correlation coefficient is the coefficient of determination, or the R-Squared. The R-Squared is found simply by squaring the correlation coefficient, so the possible range of the R-Squared statistic is from zero to one. While FAS 133 does not specify how to distinguish highly effective hedges from those that are less effective, in practice, highly effective is interpreted to describe a hedging relationship where the R-Square is of at least 0.80.

Using a Regression Program

Most regression programs are fairly easy to use if the data are given. Collecting and preparing the data, however, requires some time and thought.

To perform the analysis, data for the X and Y variables must be collected — data relating to the price (or interest rate or currency exchange rate) associated with the hedged item and the hedging derivative, respectively. In assembling these data, the analyst must make judgments about the time span of the data (i.e., the time between the first and the last observations) and the frequency (i.e., daily, weekly, monthly, etc.).

Often, however, the decision may default to whatever data are available. In any case, for statistically reliable results, 25-30 observations should be considered to be the bare minimum requirement; and if this threshold cannot be met, an alternative to regression analysis should be explored.

Clearly, if daily data were available, the company only would have to collect data for

a little more than a month to meet the minimum requirements, but a larger data set, starting at an earlier point in time, would definitely be preferred. Ideally, the company should try to incorporate as much *relevant* information as possible. Determining what is relevant requires considerable judgment. This judgment should incorporate a perspective as to what *has* happened and what *could* happen, to the extent possible and practical.

For instance, in choosing a time span, if earlier data were thought to be unrepresentative of the current price relationship — say, because of some structural change in the market (e.g., a change in tax treatment or a new regulatory regime) — it would be appropriate to use a shorter, more recent data set. Put another way, a company should not use historical data that may not represent current or future market conditions.

On the other hand, too short a time period might be equally problematic. For example, suppose over the last several months interest rates were relatively stable. A regression analysis based on this short time span would offer a poor indication of how a hedge might perform when interest rates become more volatile.

An Example

Consider the case where a company wants to assess whether a pay fixed /receive 3-month LIBOR (i.e., the London Interbank Offer Rate on Eurodollar deposits) interest rate swap could be used to hedge the variable interest expense associated with a prime-based loan. Under the terms of the loan, the



Exhibit 1. Setting up a Spreadsheet

	A	B	C	D	E
1	Date	ED-bid	Prime	LIBOR	Avg Prime
2	1.2.97	5.44	8.25	5.468	8.277
3	1.3.97	5.44	8.25	5.468	8.281
4	1.6.97	5.44	8.25	5.468	8.285
5	1.7.97	5.44	8.25	5.468	8.289
6	1.8.97	5.44	8.25	5.468	8.393
7	1.9.97	5.44	8.25	5.468	8.297
8	1.10.97	5.44	8.25	5.468	8.301
9	1.13.97	5.44	8.25	5.468	8.305
10	1.14.97	5.44	8.25	5.468	8.309
11	1.14.97	5.44	8.25	5.468	8.313
12	1.16.97	5.44	8.25	5.468	8.316
⋮	⋮	⋮	⋮	⋮	⋮
1189	9.26.01	2.51	6.00	2.538	5.219

interest rate is reset whenever the prime rate changes.

Interest on the swap is reset on the first business day of each calendar quarter. Ideally, the client should find these two data series, but sometimes the “right” data (i.e., the data that precisely correspond to the price, interest rate, or currency that is under consideration) simply do not exist. In that case a close substitute will have to suffice.

Other times, seemingly similar data may be readily available — often for free — while “better” data may be available for a price. Here, the trade-off needs to be evaluated on a case-by-case basis.

Returning to the example at hand, LIBOR is the interest rate underlying the variable interest exposure, and therefore the company would want to collect an historical time series for LIBOR. The company evaluating this hedge might refer to the Federal Reserve System’s H15 report for historical interest rates.³ Unfortunately, despite being an especially popular

benchmark interest rate, these data seem to be available only on a paid subscription basis.

It is important to understand exactly what the data used in a regression represent, and the explanatory footnotes in the H15 report provide this information. While the H15 report does not provide a price history of LIBOR, it does have data on *bid* rates for 3-month Eurodollar deposits.

LIBOR, however, as earlier noted, stands for the London Interbank *Offer* Rate of the Eurodollar deposit market. What is at issue here is the spread between the bid and the offer. This spread tends to vary — but only slightly — typically ranging between 1/16 and 1/8 of a percent.

Those with greater market experience are obviously in a better position to gauge whether this compromise is acceptable or not; and sometimes, consultation might be needed to make the required determination. In the current example, because the spread between the bids and offers for

Eurodollar deposits tend to range between 1/16 and 1/8 of a percent, and this spread is only a tiny fraction of the level of interest rates, we have constructed a proxy series for LIBOR by adding a spread of 0.0009375 (= 3/32nds of a percent) to the bid rate.⁴

Both series from the H15 report are available by business day, week, month, and annually. A closer look at the footnotes, however, shows that the weekly data are not directly comparable, as the Eurodollar deposit rates reflect averages for weeks ending on Fridays, while the prime rates reflect averages for weeks ending on Wednesdays. Monthly and annual data are comparable, reflecting averages rates over the same time periods.

At this point it is important to fully appreciate the way the interest expense under the prime-rate-based loan and the swap’s cash flow settlements are calculated. For the swap, LIBOR on any rate setting date determines the cash flow requirement relevant to the coming three months.

For example, assuming quarterly cash flow settlements, if LIBOR is set on January 15, the associated cash flow for this interest rate will be made three months later on April 15⁵ (assuming this date is a working business day). Alternatively, the interest on a prime-rate-based loan generally is adjusted immediately with a change in the prime rate, such that the effective interest rate is the average prime rate throughout the term.

To construct appropriate data for the regression analysis, we start by importing the business day data for the two series into an Excel® spreadsheet. On some business days, one or the other of the series may be missing data, generally because of banking holidays. Our adjusted data set spans January 2, 1997, through December 31, 2001, including only those dates for which both price series are reported.

Exhibit 1 shows an abbreviated Excel® spreadsheet. Columns A, B, and C show the dates, the Eurodollar bid rates and the prime rate, respectively — the unaltered original data from the H15 release. Column D is the estimated LIBOR, found by adding 3/32nds of a basis point to the rates shown in Column B. Column E shows the average prime rates over the coming three months. Reflecting the fact that rates are not quoted for weekends and holidays, the average prime rate calculation assumes that each quarter has 63 business days.⁶

With the data arrayed in this way, the regression tool may be employed. All that is required is to specify the data in columns D and E for the X and Y variables, respectively. Note that



because of the averaging requirement, the data used in the regression run only through the September 26, 2001 observation.

As far as the R-Square Statistic is concerned, the order is not important (i.e., LIBOR may serve as the X variable and Avg Prime may be Y, or vice versa). The order does matter in terms of the resulting parameter estimates for *a* and *b*. Exhibit 2 shows the sample results from an Excel® regression package, where LIBOR served as the Y variable, and Avg Prime served as the X variable.

Multiple R is the same as the correlation coefficient. Squaring this value then gives the R-Square, which is the key statistic for the purposes of hedge effectiveness testing.

Another statistic related to the R-Square is the adjusted R-Square. In cases where only two variables are compared, the adjusted R-Square and the R-Square will be identical.⁷

At the bottom of this table, the intercept and slope

Exhibit 2. Sample Regression Output (LIBOR = Y Variable)								
SUMMARY OUTPUT								
Regression Statistics								
Multiple R	0.975							
R Square	0.950							
Adj. R Square	0.950							
Standard Error	0.176							
Observations	1188							
ANOVA								
	df	SS	MS	F	Signit F			
Regression	1	692.620	692.620	22373.488	0.000			
Residual	1185	36.550	0.031					
Total	1167	729.171						
					Lower 95%	Upper 95%	Lower 95%	Upper 95%
	Coeffs	Std Error	t Stat	P-Value				
Intercept	-2.208	0.052	-42.676	0.000	-2.310	-2.107	-2.310	-2.107
X Variable 1	0.932	0.006	149.915	0.000	0.920	0.944	0.920	0.944

coefficients are given (-2.208 and 0.932 respectively). Thus, according to the regression results, the relationship between LIBOR and the average prime rate can be expressed by the following equation:

EQUATION (2): LIBOR = 0.932 Avg Prime – 2.208

One might expect that if equation (2) were the “true” equation relating the average prime rate to LIBOR (remember, the regression equation only estimates the true relationship), then we should be able to rearrange the terms in Equation (2) and solve for LIBOR. The result would be the following:

EQUATION (3): Avg Prime = 1.073 LIBOR + 2.370

However, if we re-run the regression, this time specifying Avg Prime as the Y variable, we get something else. (See Exhibit 3.) Specifically:

EQUATION (4): Avg Prime = 1.019 LIBOR + 2.666

The discrepancy arises because the regression analysis has two distinct objectives in mind for the two respective trials. That is, in the first case, where the average prime rate is the Y variable, the regression provides estimates for parameters *a* and *b* that minimize the differences between the observed LIBORs and those predicted by the regression equation. In the second case, the regression line minimizes the difference between the observed Avg Primes and the Avg Primes predicted by the regression equation.

To illustrate, Exhibit 4 shows a plot of the pairs of data

Exhibit 2. Sample Regression Output (Avg Prime = Y Variable)								
SUMMARY OUTPUT								
Regression Statistics								
Multiple R	0.975							
R Square	0.950							
Adj. R Square	0.950							
Standard Error	0.184							
Observations	1188							
ANOVA								
	df	SS	MS	F	Signit F			
Regression	1	757.597	757.597	22474.488	0.000			
Residual	1186	39.979	0.034					
Total	1187	797.576						
					Lower 95%	Upper 95%	Lower 95%	Upper 95%
	Coeffs	Std Error	t Stat	P-Value				
Intercept	-2.666	0.036	70.440	0.000	2.592	2.740	2.592	2.740
X Variable 1	1.019	0.007	149.915	0.000	1.006	1.033	1.006	1.033



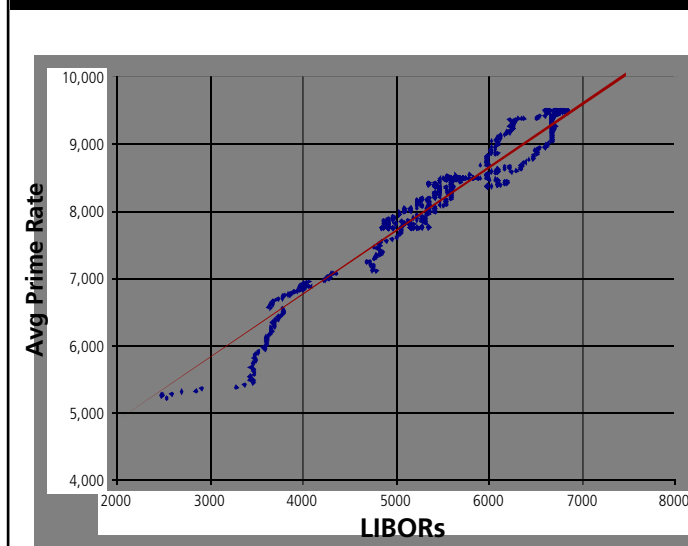
— LIBOR and the average prime rate for all dates between January 2, 1997 and September 26, 2001. In this case, the average prime rate is shown as the Y variable. Alternatively, the second regression result minimizes the horizontal differences between the dots and the solid line. These are two different objectives, and therefore they result in two different regression equations.

In the Long Run

SFAS 133 requires testing for hedge effectiveness both prospectively and retrospectively. Testing is not required on an ongoing basis, but at least quarterly. We recommend that regression be used for the prospective test and dollar offset for retrospective tests. We make these recommendations even though we expect the dollar offset retrospective test may likely fail with high frequency.

In the event that the retrospective dollar offset ratio falls between 0.80 and 1.20, this

Exhibit 4. Scatter Diagram




result validates the expectation of high effectiveness, and hedge accounting may be applied. In this case, no additional prospective regressions analysis would be needed. However, if the dollar offset retrospective test fails, DIG Issue E7 permits a company to continue hedge accounting without interruption, *so long as the prospective regression test satisfied anew and thus the hedging relationship may*

still be expected to be highly effective on a go-forward basis. Thus, assuming this updated regression again “passes,” the failure of the dollar offset ratio retrospective test would not prohibit hedge accounting.

The revised regression analysis would necessarily have to incorporate the recent observations from the period just passed; and the documentation would have to be specific about

how the data set will be altered. For instance, the analyst may either extend the original data set or re-run the regression using a constant number of observations (i.e., dropping off the older data points and adding the newer). Either approach is acceptable, as long as the procedure is fully documented and followed consistently.

In the long run, we expect that this approach to allow for hedge accounting to be applied with the fewest interruptions. 

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Endnotes

¹ See Kawaller, I.G., “The 80/125 Problem,” *Derivatives Strategy*, March 2001 for a more detailed discussion of some of the shortcomings of applying dollar offset method for testing hedge effectiveness.

² Paragraph 75 of FAS 133 asserts that if the price of the hedged item and the price of the hedging derivative are highly correlated, it is reasonable to expect the hedge to be “highly effective” in offsetting price changes. For an expanded discussion of the validity of this point, see Kawaller, I.G. and Paul Koch, “Meeting the ‘Highly Effective Expectation’ Criterion for Hedge Accounting,” *The Journal of Derivatives*, Summer 2000.

³ See <http://www.federalreserve.gov/releases/H15/data.htm#top>.

⁴ Using the unadjusted bid rates (as apposed to this adjusted series) would yield the same R-Square statistic. On the other hand, the adjustment would affect the intercept parameter, *b*, in the regression equation.

⁵ Sometimes, the swap documentation will distinguish between a “trade date” and a “value date.” The trade date is the date at which an interest rate is determined, but the value date is the start of the period for which the interest rate applies. In Eurodollar deposit market, the normal convention calls for the value date to follow the trade date by two business days, and the swap documentation may adopt this convention. If that were true in the case of the current example, cash settlements would occur on three-month anniversaries of the value date, rather than on three-month anniversaries of the trade date.

⁶ Because the columns are truncated, the average prime rates cannot be validated. Column E reflects the fact that the prime rate rose to 8.50 percent on March 26, 1997 and remained at that higher rate until September 30, 1998, as they reflect the fact that the prime rate increased.

⁷ Formally, the R-Square is said to measure the proportion of the total variance that is explained by the linear equation. If other right-hand side variables are introduced in the equation, the R-Square would necessarily increase. The *adjusted* R-Square, makes a correction to the R-Square statistic, such that adjusted R-Squares are comparable, irrespective of the number of right-hand side variables. In other words, the adjusted R-Square is a statistic that reveals whether the inclusion of additional right hand side variable adds to the explanatory capability of the equation. As the sample size expands, however, adjusted R-Squares will tend to converge to the unadjusted R-Square. In the example shown, the difference is lost in the rounding.