ESTIMATING ECONOMIC LOSS FOR THE MULTI-PRODUCT BUSINESS

I. Introduction:

The basic model for estimating economic losses to a company that has some type of business interruption in well documented in the forensic literature. A summary of much of this literature is contained in Gaughan [2000]. Whether the loss occurs because of some type of natural disaster, such as a fire, flood or hurricane [i.e., an insurance loss], or is caused by the actions of another party [a potential tort claim], does not alter the general method used to measure the damages. The basic damage is the loss of revenues less the incremental costs associated with producing the prodcut or service that was not sold, plus or minus some other factors that are summarized in Gaughan [2000], and elsewhere in the forensic literature.

The basic normally model begins with the estimation of lost revenues over some past, current, and/or future time period. The nature of the loss with respect to time depends on whether the loss period is over (i.e., a "closed" loss); is currently continuing from the past into a future with an estimated ending time (i.e., and "open" loss); or, is a permanent loss with a closure of the business.[1]

Typically, forensic economists use some type of time series model or econometric model to estimate the lost revenues. The economist then subtracts the attendant incremental costs to arrive at the what is generally termed the "lost profits," and makes other adjustments to the lost profits to take into account other expenditures the injured firm may have made to continue in business during and after the event which caused the business interruption.

II. Economic Models of Business Interruption Loss:

The estimation of revenue losses over time can usually be accomplished by using one of two general classifications of economic models:

1. Time series models

2. Econometric models

Both types of models require, at a minimum, some data about the past history of periodic sales or revenues, as well as history about the profit margins or incremental costs of production or costs of service to determine the lost profits.[2] In the case of econometric models, other data about relevant causal factors must also be acquired by the economist. The two classes of models are described below.

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[1] The nature of losses with respect to time are described in Foster and Trout [1995].

[2] The data collected should be of a short time period, such as weekly or monthly, in order to capture short-term cyclical or other business related effects.

A. Time Series Models. Time series models operate under the assumption that the value of a variable, such as monthly sales, is a function of the past behavior of the variable over time. There are two classes of these models, those that assume that there is a regular pattern of change over time, either linear or non-linear, and those that assume that there is some pattern in the error term over time.

The simplest extrapolation model is a *linear trend model*, described as:

$$S_t = c_1 + c_2 T$$

which says that each period's sales is a function of a simple time variable with values ranging from 1 to n, over n periods. The coefficient c_2 measures the absolute increase from one period to the next. One might also assume that each period has a growth with a constant percentage increase (or decrease), in which case an *exponential growth curve* might be appropriate, as shown below:

$$S_t = A e^{rt}$$

It is unlikely that this particular model would accurately depict historic and/or projected revenues for a firm over any significant time period.

There also exist a variety of *non-linear trend models* that are often useful in describing some historic pattern of sales. One of the most common is the semi-log or linear log model shown below:

$$S_t = c_1 + c_2 T + c_3 \ln T$$

which says that each period's sales is a function of a simple time variable with values ranging from 1 to n, over n periods, plus (or minus) the natural log of the time period. If the coefficient c_3 is negative, which is often the case, it shows a pattern of sales over time that have been increasing, but at a decreasing rate.

An alternative assumption is to assume that any period's sales value is equal to the past period's sales value, plus an error term that captures periodic fluctuations. Such a model can be expressed as:

$$S_t = c_1 + c_2 \; S_{t-1}$$

These models are referred to as *autoregressive trend models*. The basic assumption underlying this model is that the next period's value is equal to the last period, plus some random error. This type of model is often referred to as a "random walk."

The effect of some event on the sales of a business is usually captured by including an indicator variable in the equation that represents the onset of the event. A second indicator might be included to capture the long-run impact of the event on sales, as distinct from a short-run impact on sales.

B. Example–A Small Commercial Business: A business was affected by a flood which swept through the town and caused the business to be closed for most of a three month time period. The full effect of the flood lasted several months after the business had reopened and the neighborhood had been cleaned up. The sales data for the full time period of January 1990 through May 1996 is shown in Exhibit 1. The solid line depicts the actual monthly sales, while the dashed line depicts a forecast based on sales as a function of time, the natural log of time and an indicator variable for the month of March, which has abnormally large sales each year. Notice the large decline in January 1993 which was when the flood hit. The next two months also seriously affected the level of sales for the commercial business. The equation describing Exhibit 1 appears in Table 1. Of course, this equation does not include a variable to capture the effect of the flood.

Table 1

Dependent Variable: SALES
Method: Least Squares
Date: 04/18/02 Time: 23:26
Sample: 1990:01 1996:05
Included observations: 77

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	6170.517	1991.827	3.097919	0.0028
TIME	42.13090	38.44006	1.096015	0.2767
LN_TIME	2400.436	940.6864	2.551792	0.0128
MARCH	5102.335	1388.353	3.675099	0.0005

R-squared	0.521987	Mean dependent var	16334.18
Adjusted R-squared	0.502343	S.D. dependent var	4606.307
S.E. of regression	3249.511	Akaike info criterion	19.06095
Sum squared resid	7.71E+08	Schwarz criterion	19.18270
Log likelihood	-729.8465	F-statistic	26.57185
Durbin-Watson stat	1.795745	Prob(F-statistic)	0.000000

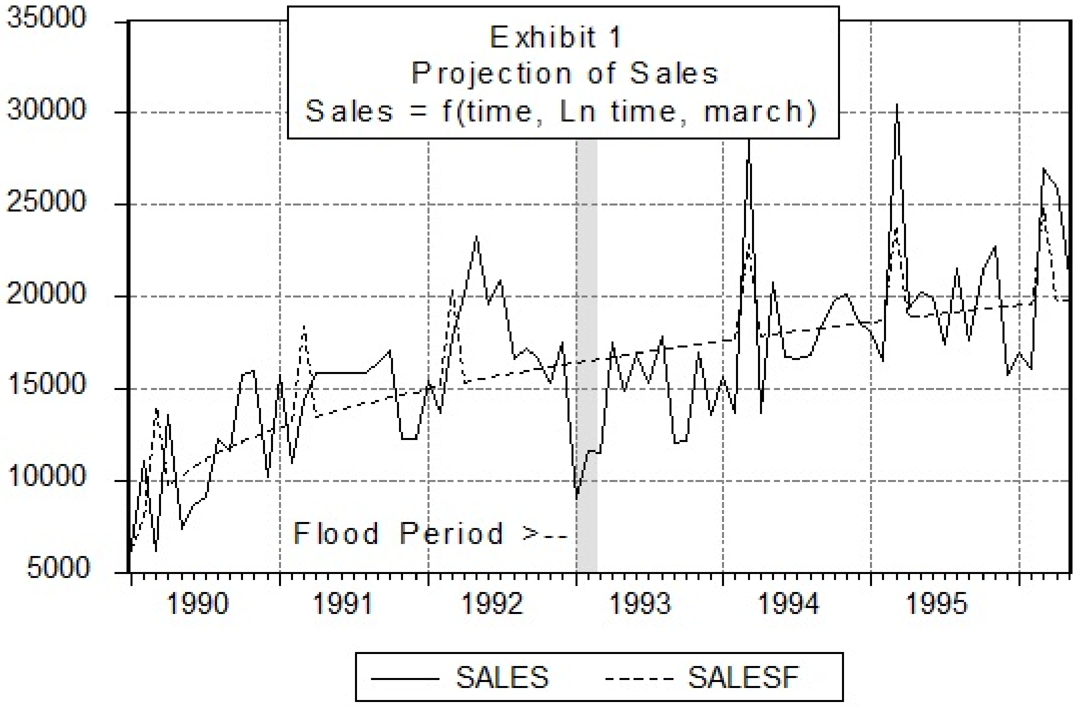

Table 2 shows the equation which captures the effect of the flood on monthly sales. The ST Flood variable (which has a value of 1 for the month of the flood and the two subsequent months) has a coefficient value of -8,050, indicating a relative decline in sales of $8,050 per month for those three months. The LT Flood variable has a coefficient value of -4,114, indicating a long run relative decline in sales of $4,114 per month. The forecast and the actual data are shown in Exhibit 2.

Table2

Method: Least Squares
Date: 04/18/02 Time: 22:37
Sample: 1990:01 1996:05
Included observations: 77

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	5642.280	1785.229	3.160536	0.0023
TIME	125.4815	49.64271	2.527692	0.0137
LN_TIME	2296.100	869.7807	2.639860	0.0102
ST_FLOOD	-8050.000	1854.221	-4.341446	0.0000
LT_FLOOD	-4114.019	1466.997	-2.804381	0.0065
MARCH	4775.912	1241.444	3.847061	0.0003

R-squared	0.629516	Mean dependent var	16334.18
Adjusted R-squared	0.603426	S.D. dependent var	4606.307
S.E. of regression	2900.782	Akaike info criterion	18.85807
Sum squared resid	5.97E+08	Schwarz criterion	19.04070
Log likelihood	-720.0356	F-statistic	24.12826
Durbin Watson Stat	2.139180	Prob(F-statistic)	0.000000

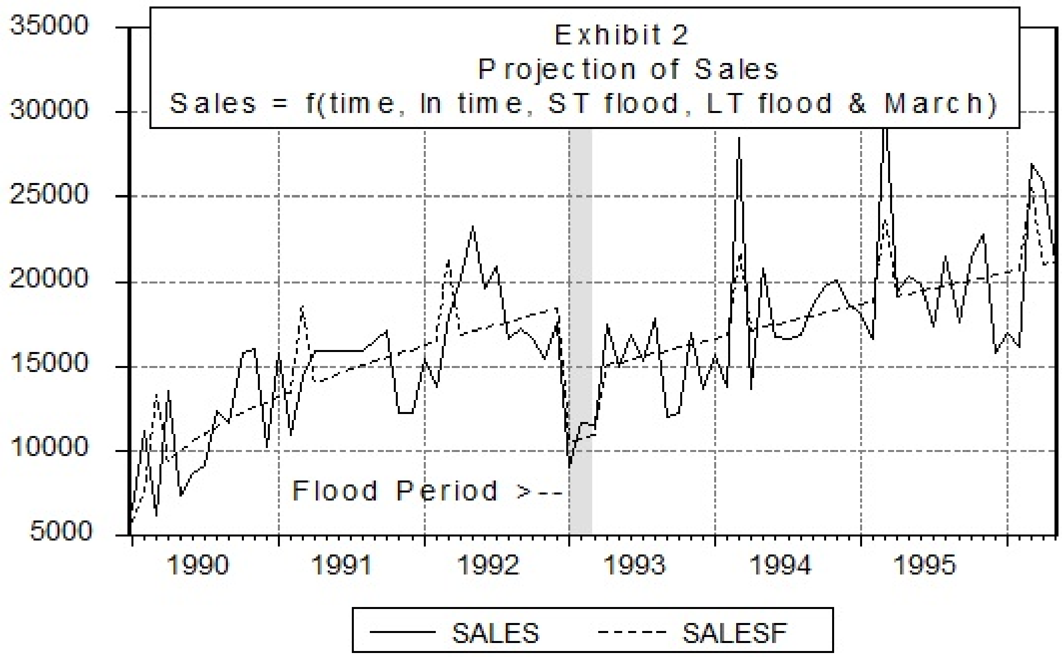

Exhibit 3 shows the actual monthly sales data depicted by the solid line, the forecast data using the equation in Table 2 as the shorter dashed line, and the projected sales for a no-flood situation as the longer dashed line. The economic losses can be computed by comparing the vertical distance between the longer dashed line (the projection) and the shorter dashed line (the forecast). Of course, we know from Table 2 that this difference is $8,050 for January 1993 through March 1993, and $4,114 thereafter.

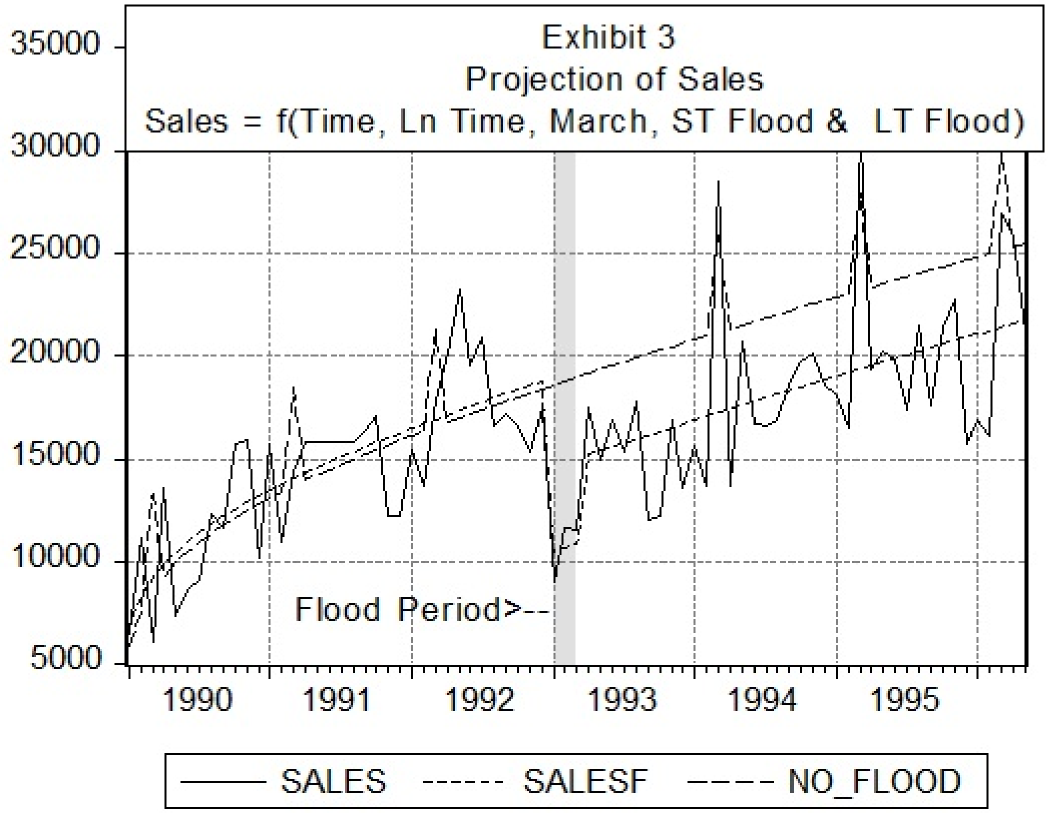

Exhibit 3
Projection of Sales
Sales = f(Time, Ln Time, March, ST Flood & LT Flood)
35000
30000
25000
20000
15000
10000
5000
Flood Period>--
1990
1991
1992
1993
1994
1995
SALES
SALESF
NO_FLOOD