Decision Makers' Ability to Identify Unusual Costs and Implications for Alternative Estimation Procedures

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Abstract

This paper reports the results of an experiment in which individuals visually fitted a cost function to data. The inclusion or omission of unusual data points within the data set was experimentally manipulated. The results indicate that individuals omit outliers from their visual fits, but do not omit influential points. Evidence also suggests that the weighting rule used by individuals is more robust that the weighting rule used in the ordinary least squares criterion.

Introduction

The cost prediction literature is nearly void of critical evaluations of the efficacy of various procedures for estimating cost relationships. The modern approaches to cost measurement and control need to focus clearly on the compatibility of alternative estimation techniques and the cost/benefit tradeoffs implicit in decision makers' actions. This paper reports the results of an experiment that evaluates decision makers' ability to identify unusual costs and discusses the implications of the observed loss functions.

Activity-based costing has forced management to focus more attention on the role of cost drivers in measuring and predicting costs. In an activity-based system, costs are first traced to activities, and then to products. This type of system typically uses a much larger number of cost drivers than a traditional volume-based system. The selection of cost drivers is subject to considerable judgment, as no set rules exist(Cooper, 1987). Generally, resources that constitute a large portion of a product's cost are identified and then evaluated for their correspondence to transaction-related drivers such as production runs, shipments, orders, and retooling. When it is not practicable to establish causality, as may likely occur in the case of a multiple driver setting, alternative procedures capable of estimation or tests for associative strength are necessary. In essence, activity based costing and the ease of spreadsheet based data analysis put added demands on management to analyze and understand data relationships prior to relying on the use of estimates.

Relationships among cost pools and potential drivers can be evaluated expediently using methods such as visual fitting or ordinary least squares(OLS). In the context of traditional volume-based product costing, various authors have commented on the uses for and limitations of OLS procedures. Benston(1966) provided a long-standing caution regarding the interpretation of model parameters, while Reimer(1987) suggested some alternative interpretations may be feasible. A necessary condition for a meaningful interpretation of the components of a relationship is the appropriateness of the estimated relationship. Fundamental to the efficacy of the derived relationship is the ability of decision makers to identify instances where the relationships among costs and drivers are unusual, either with or without the use of diagnostics. In addition, the correspondence of various estimators with loss functions that are implicit in decision makers' choices is important to the disposition of unusual costs. We define loss function to be the relative weight or importance assigned to cost prediction errors of different magnitudes[1]. More specifically, when a data stream includes combinations of values that are in some way different from the typical values, what weight, if any, should those values be given when developing cost functions? The answer depends on the decision maker's loss function.

Several strategies are available for considering unusual observations(Brook and Arnold, 1985). First, a computational method of identifying those points could be employed. Points identified as different could be eliminated from the analysis as deemed appropriate. This technique has been discussed by Tomczyk and Chatterjee(1986) in the context of cost modeling. The elimination of observations deemed different implies that management is operating under a loss rule consistent with the weighting used by the identification procedure. Second, a robust estimating procedure could be used to weight the observations in a manner consistent with management's loss function. There is then no need to eliminate certain points because they are somehow different.

Unusual Observations

Unusual observations are combinations of values that are different from the typical observation. For instance, an outlier is a data point where the value of the dependent variable is unusually large or small when compared to other values of the dependent variable given a specific range of the independent variable(s). Similarly, an influential point results from an unusual combination of independent variable values. Both types of unusual data values affect the analysis of a cost and driver relationship by influencing the computation of model parameters.

Existing cost measurement literature(Tomczyk and Chatterjee,1986) suggests that the method for dealing with unusual observations is to detect and omit these points from the estimation procedure when necessary. Using the OLS best-fit criterion, a rule for omitting outliers can be based on the standardized residual as follows(Neter, et al, 1989):

Rule 1:

OMIT WHEN: $\left| e_i / \sigma \right| > 4$;

WHERE: σ^2 = mean square error,

σ = standard error, and,

$e_i = Y_i - \hat{\beta}'\underline{X}$, such that $\hat{\beta} = (\underline{X}'\underline{X})^{-1}\underline{X}'\underline{Y}$

Similarly, influential observations can be omitted as follows(Neter, et al, 1989):

Rule 2:

OMIT WHEN: $h_{ii} > 2p/n$;

WHERE: the n x n matrix $\underline{h} = \underline{X}(\underline{X}'\underline{X})^{-1}\underline{X}'$, and

$E[h_{ii}] = p/n$, such that p=number of cost drivers, n=number of observations

Since the OLS procedure minimizes the sum of the ei's squared, the loss function weights an error of 2*e four times more than an error of 1*e. This weighting rule, or loss function, may result in the inclusion or exclusion of observations not consistent with management's desired loss function, consequently leading to decisions based on improper cost-benefit tradeoffs. Table 1 presents the diagnostics from a set of example data[2]. Column 6 represents the computation needed in Rule 1 above to identify outliers. Observation 15 has a standardized residual of -3.93, which as an absolute value, does not fit strictly the criterion for Rule 1, but is close to the omission value of 4. Column 7 presents the hii values used in Rule 2. According to that rule, the omission point would be approximately 0.083[3]. As such, observation 9 would be identified as being near this omission value. Accordingly, the cost analyst should consider the omission of one or both of these points from the estimation of the relationship.

Alternatively, all observations could be retained, and an estimation procedure that weights the errors differently could be used. These procedures are referred to as robust regression procedures. Some common robust procedures are mean absolute deviation(MAD) and median regression. The criterion for MAD regression is to minimize the absolute value of the errors, or more generally (Hogg, 1974):

MIN $T = \Sigma|\varepsilon_i|^p$, where $1<p<2$.

Median regression fits a line to the median observation of two extreme data partitions[4].

Hypotheses

To test the decision makers' ability to identify unusual observations we created a series of data plots in which the presence or absence of unusual observations was experimentally manipulated. The following hypotheses were tested:

H1: Individuals' visual fits omit outlying points.

H2: Individuals' visual fits omit influential points.

To test the consistency of an observed loss function with the available estimation procedures, we compared the visually fitted cost functions with functions derived from the following standard and robust procedures:

1) OLS estimator,
2) MAD estimator,
3) Median estimator.

Identification of the estimator most consistent with the observed loss function was made by comparing the subjects' change in estimated slope due to the omission of unusual observations and the slope changes provided by each of the numerical estimation procedures. Since OLS is widely used as an estimation criterion, the following hypothesis was tested:

H3: Individuals' loss functions are consistent with standard OLS estimators.

TABLE 1

OLS Diagnostic Computations: All Observations

OHCOST = 5.03*DLH + 16538

(1) MONTH	(2) OHCOST	(3) DLH	(4) PREDICTION	(5) RESIDUAL	(6) RESIDUAL/ Std. Error	(7) Hii
1	27600	2380	28509.4	909.4	0.7565723	0.000835
2	29200	2610	29666.3	466.3	0.3879367	0.037725
3	29800	2570	29465.1	-334.9	-0.278618	0.036577
4	26900	2240	27805.2	905.2	0.7530782	0.027787
5	29500	2490	29062.7	-437.3	-0.363810	0.034335
6	28700	2360	28408.8	-291.2	-0.242262	0.030844
7	28800	2600	29616	816	0.6788685	0.037436
8	32100	2970	31477.1	-622.9	-0.518219	0.048849
9	33600	3640	34847.2	1247.2	1.0376039	0.073375
10	32000	3150	32382.5	382.5	0.3182196	0.054950
11	31100	2980	31527.4	427.4	0.3555740	0.049179
12	30200	2810	30672.3	472.3	0.3929284	0.043728
13	31600	2900	31125	-475	-0.395174	0.046574
14	30500	2720	30219.6	-280.4	-0.233277	0.040972
15	35200	2770	30471.1	-4728.9	-3.934193	0.042492
16	29500	2640	29817.2	317.2	0.2638935	0.038597
17	31900	2920	31225.6	-674.4	-0.561064	0.047218
18	32900	3270	32986.1	86.1	0.0716306	0.059216
19	31800	2890	31074.7	-725.3	-0.603410	0.046253
20	29300	2710	30169.3	869.3	0.7232113	0.040671
21	31100	2800	30622	-478	-0.397670	0.043417
22	28900	2640	29817.2	917.2	0.7630615	0.038597
23	30000	2830	30772.9	772.9	0.6430116	0.044352
24	28900	2550	29364.5	464.5	0.3864392	0.036010

Experiment

The experiment involved subjects visually fitting[5] a line to a set of up to 24 data points. Exhibit 1 displays a plot of the full data set as presented to the subjects. We chose to use the data given by Tomczyk and Chatterjee(1986) because it was readily available and all of the related statistics are easily verifiable. Moreover, the unusual observations are marginally outlying and influential. Strict application of Rules 1 and 2 would allow those observations to remain in the data set. Since it is not clear whether these observations should remain in the data set, there is an element of judgment in evaluating the omission rules. The subjects were shown a series of eight plots, four were random plots, four were the experimental treatment effects. The presentation order was constant among subjects. Exhibit 2 lists the order of the four levels of treatment effects and the random plots. The slopes were determined by output of the screen coordinates of the endpoints of the fitted lines.

The subjects were eight faculty and fifty one senior accounting majors that had completed at least two courses in managerial accounting. All subjects were familiar with the limitations and interpretations of cost functions. Instructions and a brief description of the task were given to all subjects in advance. Subject surrogation is a debated research method and extreme caution must be used in justifying external validity. Abdel-Khalik(1974) questions the quality of subject surrogation and cautions against the use of students as surrogates. Further evidence provided by Abdolmohammadi and Wright(1987) indicates that students are not acceptable as surrogates when the task is unstructured or semi-structured, but that the decision making pattern in a structured task context would not show an experience effect. Amernic and Beechy(1984) summarize literature on personality types and conclude that accounting students and accounting professionals are predominantly the Conventional personality type, which is characterized as exhibiting preference for order and systematic data analysis. Inasmuch as the visual fit task is structured and systematic, and the surrogates are of similar personality type, we believe that the results are generalizable to real decision makers.

Results

Interactive visual fits were obtained from 59 subjects. The visual fit slopes presented in Table 2 are computed by averaging the individual observed slopes across subjects. Averages and significance are obtained from contrast estimates using a main effects ANOVA model[6]. Table 2 Panel A presents the OLS slopes reported by Tomczyk and Chatterjee(19-86), while Panel B presents the results of the visual fit experiment by treatment level[7]. The slopes in panel B indicate that

Exhibit 1

Plot of the Full Data Set

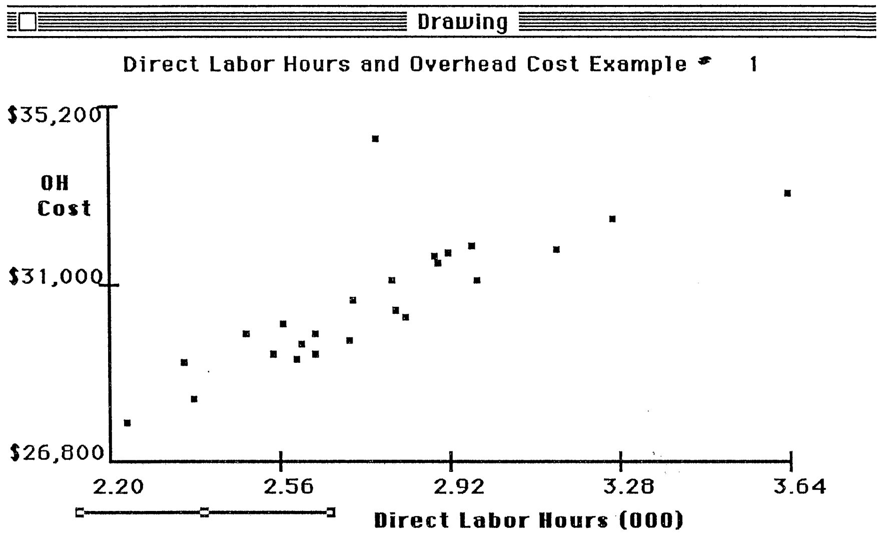

Exhibit 2

Presentation Order

Plot Number	Treatment
1	Full Data Set
2	Random
3	Random
4	Random
5	Random
6	Outlier Omitted
7	Both Outlier and Influential Point Omitted
8	Influential Point Omitted

the visual fits were somewhat steeper than the OLS slopes. The range of visual fit slopes is narrower than the OLS slopes, however. Significance tests suggest that the slopes obtained when the outlier is omitted are identical to two decimal places to the slopes obtained by visual fits to the full data set. Accordingly, hypothesis H1 cannot be rejected. Omission of the influential point results in a significantly steeper slope. Omission of both the outlier and influential point also results in a significantly steeper slope. The direction of the change is consistent with the results obtained from OLS fits, but with less magnitude. The change in slope leads to the rejection of H2. The results suggest that individuals were able to identify the outlier and did not consider that point in their visual fit. The results also suggest that the subjects did not omit the influential point from their estimates as evidenced by the significant increase in the slope parameter in treatments where the influential point was omitted. The observed slopes indicate that individuals use a different type of weighting scheme than the OLS procedure since the slopes are consistently steeper. The steep slopes may also result from some type of systematic judgment bias[8].

Table 3 presents the slope revisions from the full data set slope that occur when the unusual points are omitted. The largest revisions for both OLS and visual fits occur when the influential point is omitted. It should be noticed that the visual fit revisions are much smaller in magnitude than the OLS revisions. This leads to the rejection of H3 and suggests that the loss function used by the subjects was not the same as the OLS loss function. The slopes in Table 4 are computed using two robust regression procedures. Comparisons are made only for the omission of the influential point, since the visual fit was shown to be unaffected by the omission of the outlier. To two decimal places, the MAD procedure is not affected by the omission of the influential data point, while revision to the median regression estimator is less than the OLS and visual fit revisions. This observation implies that the subjects used a weighting rule more sensitive to influence than the robust procedures, but less sensitive than the OLS procedure.

TABLE 2

Estimated Slopes

PANEL A: OLS Slopes

Experimental Treatment	Slope
All Observations	5.03
Omit Outlier	5.03
Omit Influential	5.86
Omit Both	5.72

From: Tomczyk and Chatterjee(1986)

PANEL B: Observed Visual Fit Slopes

Experimental Treatment	Slope	P-Value*
All Observations	6.29	-
Omit Outlier	6.29	0.15
Omit Influential	6.63	0.002
Omit Both	6.40	0.15

*For test of hypothesis Ho: B(o)=B(a), where (o) denotes omission of observation and (a) denotes inclusion of all observations.

TABLE 3

Slope Revisions From Full Data Set

Type of Omission	OLS	Std. error of Slope	VISUAL	Std. error of Slope
Outlier	0	0.0483	0	0.1235
Influential	0.83	0.0912	0.34	0.105
Both	0.69	0.0457	0.11	0.0937

TABLE 4

Robust Slope Estimators

Procedure	Slope	Influence Omitted	Revision
MAD	5.56	5.56	0.00
Median	5.27	5.41	0.14

Conclusions & Limitations

The generalizability of these conclusions is limited by the consistency between the subjects' loss functions and the true loss functions of decision makers. Because the experiment involves a structured perceptual task, we feel that the results reasonably represent the outcome that would be obtained from actual decision makers.

Decision makers were shown to omit outliers from their estimation of cost functions. The reason for this may be due to the ease with which such observations are identifiable in a scatterplot. It was also shown that decision makers have difficulty identifying influential points. This may be due to a lack of clear conceptualization of relevant range, or the inability to perceptually distinguish high leverage data points. Better training on the role of influential points and relevant range in the development of cost functions is suggested. The evidence provided here supports the recommendation of Tomczyk and Chatterjee(1986), who stressed the use of diagnostic procedures.

We did find that decision makers' weightings were not consistent with OLS weightings. Subjects were found to be more robust in estimating cost functions than the OLS criterion. We believe that this finding warrants additional research on the consistency between decision makers' loss functions and numerical estimation procedures. Failure to adequately match the decision maker's loss function with the loss function implied in an estimation procedure will lead to the inclusion or omission of unusual costs not consistent with the appropriate cost/benefit tradeoff. The appropriateness of the estimated relationship to decision making is central to the success of activity-based costing. Cooper and Kaplan(1988, p. 103) point out that activity-based costing is designed to provide more accurate information to help managers make better decisions. It only follows that the estimation procedures used to identify and evaluate relationships between costs and drivers should be consistent with the loss function of the decision maker.

Endnotes

1. For example, if an error of $10 is assigned twice the weight of an error of $5, the individual is using a linear loss function where the weight is proportional to the ratio of the magnitudes.

2. The data are taken from Tomczyk and Chatterjee(1986).

3. Omission point = 2*p/n, or 2*1/24=0.083.

4. The data are ordered on the dependent variable scale and divided into three partitions of approximately equal dimension. The median coordinates from each of the two extreme partitions determine the slope of the median regression line.

5. The visual fit was accomplished in real time using a Macintosh based Pascal program. Subjects located the position and slope of the cost function in the X-Y plane using the mouse interface. The subjects were allowed to fit a function without time limitations. Infinite adjustments were allowed, but the subject could not return to the plot once they moved to subsequent plots.

6. The fitted model was: $\hat{\beta} = \mu + \alpha_i$;
where i designates the four levels of experimental treatment.

7. Analyses contrasting faculty and students showed no differences in the slope parameters between those groups.

8. It is possible that individuals anchor on the positive slope and consequently over-estimate steepness. We found some evidence of this as the subjects fit a positively sloped line(4.09) to data randomly generated to have a slope equal to zero.

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