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Monitoring Accounting Information via Control Charts

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INTRODUCTION

Currently, there is a lot of interest in supporting the continuous assurance of financial statements (Vasarhelyi, 2002). The current research suggests using control charts to assist decision-makers in the identification of patterns in the underlying processes that produce financial statements. Once interesting patterns are identified, decision-makers may focus on the processes that generated the patterns. The objective of continuous monitoring is detecting abnormalities as near as possible to the time of occurrence of the underlying event that generated the data. If an error or irregularity occurs, the situation can be corrected, and the effect mitigated. Overall, the purpose for monitoring financial information is to gain confidence that systems are operating as intended through the ability to identify and resolve of errors, irregularities, or inconsistencies.

CONTROL CHARTS

Manufacturing processes have been monitored through the use of control charts (Shirland, 1993). Viewing, metaphorically speaking, the creation of financial statements as a manufacturing process, control charts can be applied to determine whether the "financial statement creation process" is going "out of control." If a process is in control, the control chart will appear as if the variation in the line graph is randomly distributed between the control limits. If a process is out of control, the data will appear to have a pattern or some abnormality.

Through the application of the manufacturing metaphor, it is possible to potentially identify problem areas within the financial accounts using control charts. The accounts we investigate are based on suggestions by Mulford and Comiskey (2002) and Schilit (2002). The control charts may provide auditors with a method of monitoring information identified as "high risk" to the financial health of an organization.

METHODS

The data used do develop the control charts in this paper were collected from Compustat. The authors selected financial information relating to WorldCom, Inc., because of the scope and variety of accounting irregularities that have surfaced with the financial information they have reported over the past few years. For demonstration purposes, the authors extracted quarterly information for a ten year time period, providing forty data points for each graphic. In practice, an individual monitoring the accounts ideally should have access to the actual account values in a more continuous manner.

Several procedures were used to standardize the data extracted. For demonstration purposes, we only show the analysis with regards to the Cost of Goods account. Table 1 gives the first two years worth of values for the Cost of Goods and Net Sales accounts (see Actual Values in Table 1). First, following Schilit (2002), the data was "common sized" by dividing the selected accounts by the total sales, for the income statement accounts, or total assets, for the balance sheet accounts, for the same period. In this example, Cost of Goods Sold was divided by Net Sales (see Common Size Values in Table 1). Second, a moving average of four data periods (quarters) was used to provide the base line for the control chart. In this case, the first period in which a moving average was computable was for Dec-91 (see Moving Averages in Table 1). Third, we used a "z-transformation" of the data to set the base line to zero and standardize the periodic data. Next, we computed a moving standard deviation that in conjunction with the moving average could be used to compute a Z-score for each of the "4-period windows." An example of a control chart using ten years of data for the Cost of Goods sold account using this approach is shown in Figure 1.

A second approach is to common-size the accounts choosing a specific year's account values as the baseline and divide the other years' accounts by the baseline year's accounts' values (Schilit, 2002). Using this approach, we chose Mar-91 as the baseline period. In this case, we again used the Cost of Goods account (see Actual Values in Table 2). All other periods were divided by the Mar-91 value (see Common Size Values in Table 2). Once this transformation has been done, a moving average, a standard deviation, and z-transformation can be executed to create the values on which to base the control charts (see Moving averages, Moving Standard Deviations, and Z-Score Transformations, respectively, in Table 2). A control chart using this method for the Cost of Goods account is shown in Figure 2.

There are many different rules on which to base the control chart analysis. Currently, we are investigating the use of rules regarding runs in z-transformed account values to identify areas for additional investigation. For example, if the z-transformed value of a specific account has a set of seven positive (or negative) values above (or below) the moving average in seven consecutive time periods, there could be a problem with the underlying process. The probability of seven values in a row being above (or below) the mean is less than two percent. This is the so-called "rule-of-seven." In Figures 1 and 2, data points that fall under this rule are identified with an oval. Other rules that may be investigated include:

- If the values trend in the same direction (increasing or decreasing) for seven periods, then it is likely that the underlying process is out of control.
- If the values for two or more periods are greater than two standard deviations (Z = 2), but within the actual control limits, then it is likely that the underlying process is out of control.
- If the values for four or more periods are greater than one standard deviation (z = 1), but within the actual control limits, then it is likely that the underlying process is out of control.

Through the application of control charts to monitor the accounts, we believe that it is possible to potentially identify problem areas within the financial accounts, in a manner that it has been applied in manufacturing, before the accounts go "out of control."

CONCLUSION

In this research, we suggest that control charts may provide a way to continuously monitor business and financial processes. Control charts have been successfully used to monitor manufacturing processes and to identify processes when they become "out-of-control." We believe that they may also be beneficial when monitoring financial processes.

There are potential limitations in applying control charts to financial processes. Since this is a new domain for this application, the rules to interpret the charts and identify "out-of-control" systems may need to be modified. Alternatively, new rules may need to be developed. Consideration should be given to the frequency of reporting; are standard control charts as useful when monitoring accounting processes at all reporting frequencies, including continuous reporting.

REFERENCES

Mulford, Charles W. and Comiskey, Eugene E. (2002) *The Financial Numbers Game: Detecting Creative Accounting Practices*, John Wiley, New York.

Schilit, Howard (2002) *Financial Shenanigans: How to Detect Accounting Gimmicks & Fraud in Financial Reports*, 2nd Ed., McGraw-Hill, New York.

Shirland, Larry E. (1993) *Statistical Quality Control with Microcomputer Applications*, John Wiley, New York.

Vasarhelyi, Miklos A. (2002) Chapter 12: Concepts in Continuous Assurance, in Researching Accounting as an Information Systems Discipline, Vicky Arnold and Steve G. Sutton (Eds.), American Accounting Association, Information Systems Section, Sarasota, FL.

Table 1. Sample values

	Mar-91	Jun-91	Sep-91	Dec-91	Mar-92	Jun-92	Sep-92	Dec-92
Actual Values								
Net Sales	40.638	43.704	57.534	80.061	82.109	183.748	197.815	205.78
Cost of Goods Sold	22.097	25.074	33.763	48.63	49.622	105.252	112.311	116.821
Common Size Values								
Cost of Goods Sold	54.38%	57.37%	58.68%	60.74%	60.43%	57.28%	56.78%	56.77%
Moving Averages								
Cost of Goods Sold				57.79%	59.31%	59.28%	58.81%	57.82%
Moving Standard Deviations								
Cost of Goods Sold				0.03	0.02	0.02	0.02	0.02
Z-Score Transformations								
Cost of Goods Sold				1.105289	0.714374	-1.24137	-0.98211	-0.59309

Table 2. Baseline sample values

	Mar-91	Jun-91	Sep-91	Dec-91	Mar-92	Jun-92	Sep-92	Dec-92
Actual Values								
Cost of Goods Sold	22.097	25.074	33.763	48.63	49.622	105.252	112.311	116.821
Common Size Values								
Cost of Goods Sold	100.00%	107.54%	141.58%	197.01%	202.05%	452.16%	486.77%	506.37%
Moving Averages								
Cost of Goods Sold				136.53%	162.05%	248.20%	334.50%	411.84%
Moving Standard Deviations								
Cost of Goods Sold				0.44	0.46	1.39	1.57	1.42
Z-Score Transformations								
Cost of Goods Sold				1.368614	0.879116	1.470449	0.973004	0.667410

Figure 1. Control chart for the cost of goods sold account WorldCom quarterly data (March 1991-December 2000)

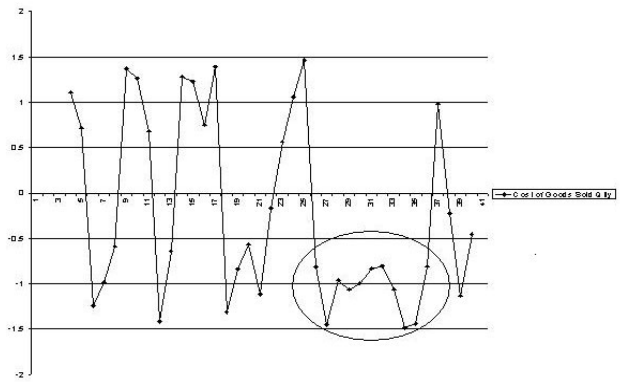
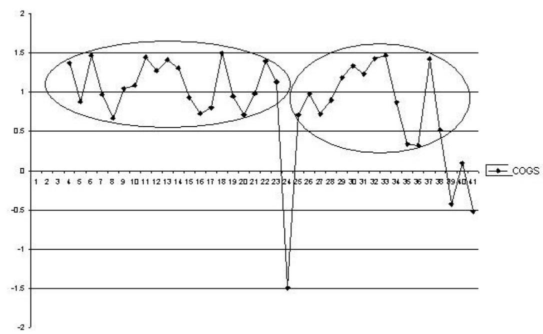


Figure 2. Baseline control chart for the cost of goods sold account WorldCom quarterly data (March 1991-December 2000)



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