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Auditing Symposium XI: Proceedings of the 1992 Deloitte & Touche/University of Kansas Symposium on Auditing Problems, pp. 141-169;

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7

Practical Experiences with Regression Analysis

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Abstract

Price Waterhouse has conducted a field experiment on the application of regression analysis, involving the launching of new software, micro-based training, and initial modeling for audit use. While the phases of the experiment included alpha and beta testing of the software as described herein, the core of the experiment involved field applications of regression analysis by engagement teams. Their experiences and reactions are described, as are the future plans of the firm. Experiences in prior field applications are likewise shared, to illustrate both the context in which regression analysis has been used and the nature of inferences drawn, as well as the statistical profile achieved in modeling. Insights are gained as to the tool's feasibility, time demands in its application, and perceptions of users.

Introduction

Over the years, a number of papers have appeared suggesting the benefits of using regression analysis as an analytical audit tool for risk identification and error detection. In some cases the authors have described individual applications of the technique. For example, Campbell and Rankin [1986] described the use of regression analysis to develop expectations of sales in a manufacturing company, Kask [1979] covered an application to identify out-of-line energy costs for a group of hospitals, and Akresh and Wallace [1981] discussed a public utility application. Others [Knechel, 1986 and Wilson and Colbert, 1989] have reported that regression analysis, compared with alternate analytical procedures, is a more accurate tool for identifying errors of varying sizes and patterns seeded into simulated data.

Despite these purported conceptual advantages from using regression analysis, Deloitte & Touche is the only major accounting firm that seems to have used it regularly, in sampling applications [Stringer, 1975 and Stringer and Stewart, 1986—referred to as STAR]. While Price Waterhouse has had field applications using regression analysis since 1979, the scope of application has not been pervasive throughout the World Firm, for a number of reasons detailed later in this paper. Overall, as has been reported by Daroca and Holder [1985] and Spires and Yardley [1989], the use of regression analysis and other advanced quantitative procedures by audit teams, across firms, has been rela-

tively rare. As usual, the marketplace is the ultimate proof of the pudding. Among the barriers have been the need for relatively powerful computing capability, the perceived complexity of the technique for non-statisticians, and uncertainty as to how to relate the results of a regression analysis application to an audit risk/satisfaction framework.

We have been involved in studying how and if these barriers could be overcome at Price Waterhouse. In this paper we report on our experiences to date.

The Interest

For a number of years the Price Waterhouse audit methodology has included an audit satisfaction hierarchy wherein alternate audit procedures are ranked based on their presumed efficiency [Walker and Pierce, 1988]. The actual procedures selected for the audit plan will depend on inherent risk assessments by assertion, assessed control risk, materiality, client expectations, and other factors. However, all things being equal (which is rarely the case), audit planners are encouraged to think first about relying on analytical procedures, then on internal controls, and to do detailed testing only when particular audit assertions cannot be satisfied in any more cost-effective way. This approach is consistent with evidence regarding the value of analytical procedures in risk assessment. Empirical studies in an external audit context, such as those by Kreutzfeldt and Wallace [1986] and Wright and Ashton [1988], have consistently shown that forty to fifty percent of errors detected were disclosed by analytical procedures. Coglitore and Berryman [1988] have shown how better use of analytical procedures might have prevented several well-publicized audit failures [also see Wallace, 1991]. Analytical procedures are clearly an important risk assessment tool.

Price Waterhouse believes that many advantages accrue from using analytical procedures in the audit. For example:

- Analytical procedures enhance the auditor's understanding of the dynamics of the client's business, which not only improves the quality of the audit but also makes the auditor better able to offer sound business advice to the client.
- Research confirms our own experience that analytical procedures can be very effective at finding errors. For example, Wallace and Kreutzfeldt [1986], Wright and Ashton [1988], and Knechel [1988a, 1988b] all present evidence along this line. However, Loebbecke and Steinbart [1987], Kinney [1987], and Blocher and Cooper [1988] show that trends and ratios are relatively ineffective, at least at the aggregate level at which they are conventionally used. Research suggests somewhat of a gulf between the effectiveness of trend and ratio procedures on the one hand and modeling procedures on the other.
- Analytical procedures are efficient because they usually provide evidence for several audit assertions simultaneously (in contrast to a detailed test which may address only one or two assertions).

At the same time as analytical procedures were receiving increased emphasis in the Price Waterhouse auditing methodology, professional pronouncements such as *Statement on Auditing Standards No. 56: Analytical Procedures* [AICPA, 1988] and *International Auditing Guideline 12* [IFAC, 1990] introduced new requirements for the use of analytical procedures in the planning and

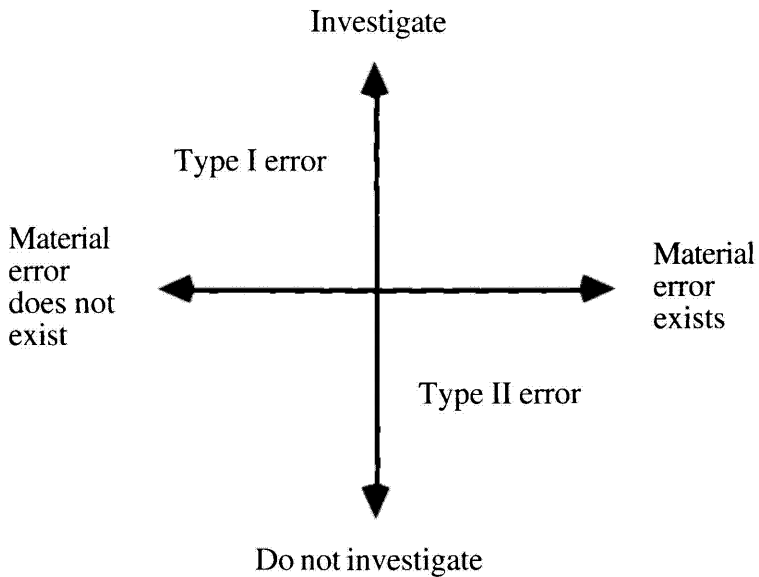
final review stages of audit examinations. In fact, the auditing standard setters were mandating what made common sense, and what, by and large, was already being done in practice.

The strategic emphasis by Price Waterhouse on analytical procedures stimulated an interest in regression analysis as a tool for the auditor. The potential advantages we saw from regression analysis were the following:

- In contrast to the judgmental predictive models embodied in the simpler analytical procedures such as ratio and trend analysis, regression analysis, through measures of precision and goodness of fit, would give a more objective assessment of the reliability of predictive audit models.
- Auditors generally have little difficulty assessing whether the direction of change in an accounting variable makes sense, but regression analysis could be a more effective tool for assessing the reasonableness of the *amount* of change.
- With regression analysis, auditors would be able to define unusual observations using objective mathematical probabilities rather than the subjective rules of thumb often associated with simpler analytical procedures. This should mean improved efficiency in detecting errors, a supposition borne out by empirical research. For example, Knechel [1986] concluded that “based on the analysis of Type I and Type II errors presented in this paper, the regression models were superior to the nonstatistical approaches in most cases.” This finding ties to the idea that the best analytical procedure is the one which alerts us when errors exist in the data, while minimizing the number of false alarms when the data is error-free. This concept is illustrated in Figure 1. The two alternate decisions are investigate or do not investigate. The two possible conditions of the accounting variable are that it is or is not materially in error. In the bottom left and top right quadrants, the risk assessor makes the correct decision. In the top left quadrant, the evaluator does an unnecessary investigation, referred to as a Type I error, in line with AICPA literature (note difficulties with this use of terms explored by Beck and Solomon [1985]). In the bottom right quadrant, the decision maker fails to investigate a situation which in fact warrants investigation, referred to as a Type II error. Wilson and Colbert [1989] reached a similar conclusion from their simulation tests that likewise focus on Type I and Type II considerations.
- Regression analysis may help to quantify important interrelationships in a client’s business which the auditor suspects exist, but cannot easily express mathematically. For example, one would be able to quantify the effect of categorical variables (like location) in addition to numerical variables.

For all of these reasons, Price Waterhouse decided in 1988 to invest in a research project related to regression analysis. The technique made sense conceptually, but the big unknown was the broadness of market acceptance within Price Waterhouse. Was it reasonable to expect audit partners and staff without real expertise in statistical concepts to try regression analysis with enthusiasm and confidence? Even if they were interested, would they conclude that the benefit from using regression analysis is large enough to justify the cost of developing the applications?

Figure 1. Considering Type I and Type II errors



The Software

Regression analysis had been used on audits done by the firm since about 1980. At that time the Firm developed its own regression analysis software which ran on a central mainframe accessible from the Firm's U.S. offices. Some early successes were reported by Wallace [1983]. Such examples are augmented by three actual case examples from field applications, reported in an Appendix to this paper. However, the mainframe computing instructions were complicated for those who did not use the software often. In addition, turn-around time for regression output was sometimes measured in terms of days rather than minutes or hours. The concept of regression analysis as an iterative model-building process was not well served by the mainframe. As a result, during the decade of the 1980's, regression was used only by a small band of devotees in several of the Firm's U.S. offices, and not at all outside the U.S.

One of the first imperatives was to secure user-friendly regression analysis software for a microcomputer. Price Waterhouse considered purchasing one of the available commercial micro-based regression analysis packages, but decided against that option. Some packages were replete with complex statistical jargon which we were sure would inhibit potential users. On the other hand, certain spreadsheet software packages offered regression analysis as an option, but these were overly simplistic modules which lacked the important statistical checks necessary for auditors to have confidence that their models were statistically valid. Also, none of the packages came with audit-relevant user help. A meeting of professionals who regularly used regression analysis in consulting and litigation support settings led to the decision to modify the mainframe soft-

ware to run on the microcomputers commonly used by Price Waterhouse partners and staff. The framework for approaching regression analysis appears in Figure 2, as do sample screens that provide an idea of the user-friendliness and documentary nature of the program. The user selects whether a time series or cross-sectional regression model is to be estimated and what confidence level is used.

Data to be modeled may be assembled in a wide variety of formats, but most commonly is collected in a common spreadsheet template. The software can accommodate up to fifteen variables and up to 1,000 observations per variable, subject to a maximum limitation of 5,000 data points. We have found that this is sufficient for all but cross-sectional applications on very large multi-location clients, such as major retailers with more than 1,000 stores. For such clients we suggest partitioning the locations into groups, each containing fewer than 1,000 units, with a separate model being created for each group. Figure 2 displays a sample input screen for the software. Once entered into the software, several analysis modules are designed to assess the data set prior to creating the regression equation. These modules provide the following information (see Wallace [1991] for elaboration on statistical terms):

- various measures of the distribution of each variable including the largest and smallest values; the sum of all values; mean, median, and quartile statistics; and measures of variation, skewness, and kurtosis.
- a matrix showing the degree of correlation between each variable and every other variable.
- a table of autocorrelation statistics with lags from one to twenty-four for each variable.

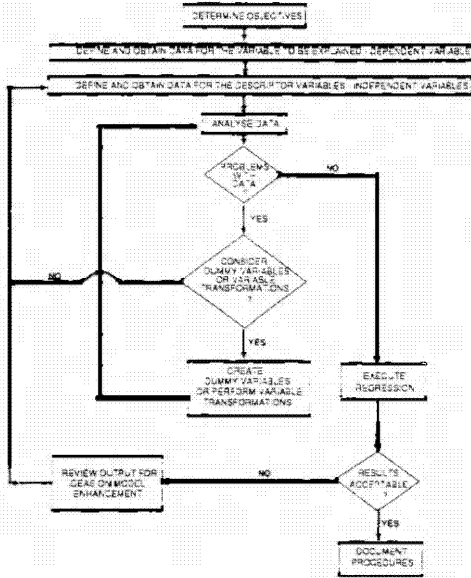
One purpose of the input analysis modules is to detect apparent data entry errors at an early stage of the process before the user's attention is drawn to outliers, precision intervals, etc. To illustrate, by examining the largest and smallest value for each variable, or by comparing the total for each variable to predetermined batch totals, one may expect to detect an incorrect value for a particular variable. A second objective is to detect an unusual distribution or pattern in the dependent variable. For example, it may prove to be skewed or to have kurtosis, or the autocorrelation test may show a seasonal or cyclical pattern. In such cases, the user is directed to the descriptor variables to see whether any reflect the same distribution or pattern. Generally this will prove to be the case, but if not, the user is asked to search for an additional descriptor variable to capture the attribute being exhibited by the dependent variable. A third purpose of input analysis is to study the correlation among the variables in the model, looking for relationships which in direction or magnitude are inconsistent with the auditor's expectations. Investigation of such surprises frequently leads to model improvements before the actual regression equation is produced.

Sometimes the analysis will lead the user to transform one or more of the variables. The software allows variables to be transformed into natural logs, reciprocals, and deflated values (i.e., to remove heteroscedasticity or size effects), and also facilitates the leading or lagging of variables. Figure 2 illustrates some of these choices in menu format. Those observations to be used in the base versus prediction phase are specified, alongside descriptive statistics. Transformations are facilitated, and help screens are available to provide the sort of graphics guidance depicted in Figure 2.

Once the user has responded to whatever conditions are revealed by the input analysis, he or she is ready to use the software to specify the regression equation. Unlike some other regression analysis products, the software does not use the stepwise technique for variable selection as the primary means of model creation, although stepwise is available as an option. We believe it is preferable

Figure 2. Overview of Software Design and Sample Screens

DESIGN OF MULTIPLE REGRESSION APPLICATION



TYPE OF REGRESSION ANALYSIS

Time Series
 Cross Sectional

OK Cancel

Confidence level for calculating achieved precision for base and/or prediction phase.

'99%' '80%'
 '95%' '70%'
 '90%' '60%'

OK Cancel

Enter observations per cycle

12

OK Cancel

Model Type	LR	LR dummy	LR	LR	LR	LR	LR
Dependent (Y) Variable	Independent (X) Variable	LR	LR	LR	LR	LR	LR
Variable Name (1-8 char)	LR	LR	LR	LR	LR	LR	LR
SALES	MARGIN	HOURS	SQ FEET	OWNER			
80	8325875	809876	9	90000			
111	76	8710753	818752	8	95000		
120	83	8720101	892546	12	88000		
121	93	8334058	871489	10	98000		
141	108	8982578	1108527	11	110000		
113	118	8882217	819910	8	98000		
133	120	7418240	1038189	9	97000		
136	138	8394320	836395	10	95000		
148	148	8015887	861133	9	89000		
181	150	8218567	710480	9	88000		
181	180	8326838	826772	9	87000		
211	170	8256067	832754	9	85000		
222	180	5508971	845172	12	75000		
241	88	8328827	867358	10	98000		

Variable	Mean	Standard Deviation	Coefficient of Variation	Largest Amount	Smallest Amount	Total Observations
(average)	(disparity)	(s.d. / mean)	(max)	(min)	(sum)	
SALES	809876	108400	0.12	8325875	76	281000000
MARGIN	818752	171521	0.21	1158200	2100	26745000
HOURS	9	1.71	0.19	14	6	45000
SQ FEET	9733	3166	0.32	114000	5800	4736000
OWNER						
1st						
2nd						
3rd						
Skewness (asymmetry)						
Kurtosis (peakedness)						
SALES	1.00	0.00	0.00	5.39	12.0	2231.315
MARGIN	1.00	0.00	0.00	8.36	3.0	70.000
HOURS	1.00	0.00	0.00	1.00	1.00	1.000
SQ FEET	1.00	0.00	0.00	48.000	58.000	58.000

REGRESSION OBSERVATIONS

11
 12
 13
 14
 15
 16
 17
 18
 19
 20

MAKE THIS VARIABLE SLIP

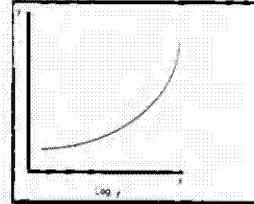
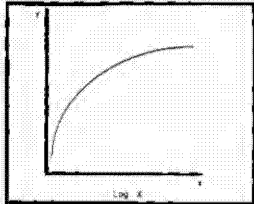
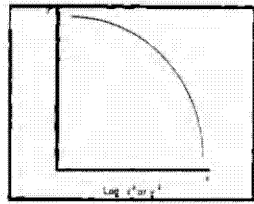
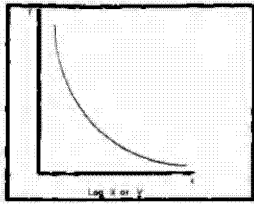
OK Cancel

Transformations
 Log
 Reciprocal
 Deflation

Enumerate
 Number Column B
 Order
 Reorder

Analysis
 Prediction
 Summ Stat
 Corr Matrix
 Autocorr Matrix
 All

Dummy
 Lintrend
 Seasonal
 Manual
 Relative
 Shift



MANUAL DUMMY

Type observation numbers individually separated by commas (e.g., 1,7,10) or if a range of observations, separated by colon (e.g., 7:12)

Name this variable:

RELATIVE SIZE DUMMY

Existing variable's name:

VALUE:

=

<=

<

>=

>

New variable name:

SHIFT DUMMY

Type observation numbers individually separated by commas (e.g., 1,7,10) or if a range of observations, separated by colon (e.g., 7:12)

Existing variable's name:

Observations to shift:

New variable name:

	A	B	C	D	E	F	G	H
17	DIAGNOSTIC TESTS							
18	Summary of tests performed on regression model:							
19	Consider Model							
20	Tests	Accepted	Description					
21	Autocorrelation	No	There are no significant systematic patterns in residuals of the regression equation. Most likely to occur in time series.					
22	Linearity	No	Relationship between dependent variable and independent variables with the model is a linear one. Most likely to occur in time series.					
23	Normality	No	This tests the assumption that residuals have a normal (i.e. bell-shaped and symmetrical) population distribution.					
24	Homoscedasticity	No	Residuals do not have constant variance in this regression model. It may be due to correlated observations across the data set.					
25	Collinearity	No	Tendency for a subset of observations to deviate from the regression line.					
26	Three regression statistics were not computed. Consider model revision if appropriate and include another variable that improves regression fit. Model results are displayed on the next slide.							
27	13. The data set may be more complex than the regression model used. Try the 24, 25, 26, 27, 28, 29, 30, 31, 32, 33, 34, 35, 36, 37, 38, 39, 40, 41, 42, 43, 44, 45, 46, 47, 48, 49, 50, 51, 52, 53, 54, 55, 56, 57, 58, 59, 60, 61, 62, 63, 64, 65, 66, 67, 68, 69, 70, 71, 72, 73, 74, 75, 76, 77, 78, 79, 80, 81, 82, 83, 84, 85, 86, 87, 88, 89, 90, 91, 92, 93, 94, 95, 96, 97, 98, 99, 100.							
28	14. The data set may be more complex than the regression model used. Try the 24, 25, 26, 27, 28, 29, 30, 31, 32, 33, 34, 35, 36, 37, 38, 39, 40, 41, 42, 43, 44, 45, 46, 47, 48, 49, 50, 51, 52, 53, 54, 55, 56, 57, 58, 59, 60, 61, 62, 63, 64, 65, 66, 67, 68, 69, 70, 71, 72, 73, 74, 75, 76, 77, 78, 79, 80, 81, 82, 83, 84, 85, 86, 87, 88, 89, 90, 91, 92, 93, 94, 95, 96, 97, 98, 99, 100.							
29	15. The data set may be more complex than the regression model used. Try the 24, 25, 26, 27, 28, 29, 30, 31, 32, 33, 34, 35, 36, 37, 38, 39, 40, 41, 42, 43, 44, 45, 46, 47, 48, 49, 50, 51, 52, 53, 54, 55, 56, 57, 58, 59, 60, 61, 62, 63, 64, 65, 66, 67, 68, 69, 70, 71, 72, 73, 74, 75, 76, 77, 78, 79, 80, 81, 82, 83, 84, 85, 86, 87, 88, 89, 90, 91, 92, 93, 94, 95, 96, 97, 98, 99, 100.							
30	16. The data set may be more complex than the regression model used. Try the 24, 25, 26, 27, 28, 29, 30, 31, 32, 33, 34, 35, 36, 37, 38, 39, 40, 41, 42, 43, 44, 45, 46, 47, 48, 49, 50, 51, 52, 53, 54, 55, 56, 57, 58, 59, 60, 61, 62, 63, 64, 65, 66, 67, 68, 69, 70, 71, 72, 73, 74, 75, 76, 77, 78, 79, 80, 81, 82, 83, 84, 85, 86, 87, 88, 89, 90, 91, 92, 93, 94, 95, 96, 97, 98, 99, 100.							
31	17. The data set may be more complex than the regression model used. Try the 24, 25, 26, 27, 28, 29, 30, 31, 32, 33, 34, 35, 36, 37, 38, 39, 40, 41, 42, 43, 44, 45, 46, 47, 48, 49, 50, 51, 52, 53, 54, 55, 56, 57, 58, 59, 60, 61, 62, 63, 64, 65, 66, 67, 68, 69, 70, 71, 72, 73, 74, 75, 76, 77, 78, 79, 80, 81, 82, 83, 84, 85, 86, 87, 88, 89, 90, 91, 92, 93, 94, 95, 96, 97, 98, 99, 100.							
32	18. The data set may be more complex than the regression model used. Try the 24, 25, 26, 27, 28, 29, 30, 31, 32, 33, 34, 35, 36, 37, 38, 39, 40, 41, 42, 43, 44, 45, 46, 47, 48, 49, 50, 51, 52, 53, 54, 55, 56, 57, 58, 59, 60, 61, 62, 63, 64, 65, 66, 67, 68, 69, 70, 71, 72, 73, 74, 75, 76, 77, 78, 79, 80, 81, 82, 83, 84, 85, 86, 87, 88, 89, 90, 91, 92, 93, 94, 95, 96, 97, 98, 99, 100.							

Prepared By: Audit Staff Client: Classical Book Example Period Ended: 12/31/90
Computer model run on: Mon Jan 21 17:12:54 1991

Autocorrelation - Supporting Details

	Actual Statistic	Threshold Significant @ Confidence Level			Significant?	
		90%	95%	99%		
Runs test:						
Number of Runs	408					
Observed	2014	-0.57	1.72	2.07	2.82	No
Expected	1824					
Ratio	1.10					

Comparison of the frequency of signs of residuals to a random distribution as expected under the regression assumption.

Chi square:

	Positive	Negative	Significant?
Positive at H	11	61	
Negative at H	1	1	

Chi square value: 1.56 2.71 3.84 6.63 No

The more disparate the values in the categories, the less independent the residuals are of one another and autocorrelation exists.

Jarque-Bera statistic:

	Positive	Negative	Significant?	
Positive	1.33	1.08	3.96	No
Negative	1.33	2.52	3.14	Yes

Measures the association between adjacent residuals. High autocorrelation exists if the statistic is close to 0 or 1.

Residual Autocorrelation

	Actual	90%	95%	99%	Significant?				
1-9	0.01	-0.02	-0.18	0.04	-0.15	-0.17	-0.11	-0.06	No
9-18	0.00	0.01	-0.05	-0.12	0.20	0.05	0.13	-0.07	No
17-22	0.21	-0.11	-0.13	-0.02	0.02	0.01			No

1-D and 2-D BLUE. Confidence intervals significance by statistics test.

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Computer model run on: Mon Feb 11 09:34:32 1991

Collinearity - Supporting Details

	Actual Statistic	Threshold Significant @ Confidence Level			Significant?
		90%	95%	99%	
Least 24	0.00	0.15	0.21	0.02	No
First 24	0.15	0.15	0.21	0.02	No

The above test for multicollinearity is a statistical test that determines whether or not the independent variables in the regression equation are correlated. Collinearity is a condition in which the independent variables are highly correlated and changes in the model coefficients are not likely to occur when the model is run.

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Computer model run on: Mon Jan 21 17:12:54 1991

Heteroscedasticity - Supporting Details

Descriptor Variable	Goldfeld-Smith Statistic	Threshold Significant @ Confidence Level			Significant?
		90%	95%	99%	
Intercept	2.03	0.50	2.18	1.25	No
CP	0.00	0.88	3.04	1.45	No
Scale of CP	0.00	0.53	3.04	1.45	No

Quantifies heteroscedasticity when the standard error of the estimate is not the same for all observations. Heteroscedasticity exists if the statistic is close to 0 or 1.

Descriptor Variable	Heteroscedasticity Statistic	Threshold Significant @ Confidence Level			Significant?
		90%	95%	99%	
Intercept	0.00	0.44	0.64	0.64	No
CP	0.00	0.11	0.44	0.64	No
Scale of CP	0.00	0.33	0.44	0.64	No

Statistical test that determines if the variance of the residuals is constant across the range of the independent variables. Heteroscedasticity exists if the statistic is close to 0 or 1.

Prepared By: Audit Staff Client: Classical Book Example Period Ended: 12/31/90
Computer model run on: Mon Jan 21 17:12:54 1991

Normality - Supporting Details

	Actual Statistic	Threshold Significant @ Confidence Level			Significant?
		90%	95%	99%	
Kolmogorov-Smirnov	0.14	0.08	0.23	0.31	No
Shapiro-Wilk	0.46	0.93	0.91	0.98	Yes

The above test for normality in the regression residuals.

Chi squared goodness of fit

	Actual	90%	95%	99%	Significant?
Chi squared	0.61	10.64	12.59	16.81	No

Compares the distribution of residuals to that of a normal distribution to see if it fits.

Misman check

	Statistic	Significant?
Shapiro-Wilk	0.46	No
Kolmogorov-Smirnov	0.14	No
Peaked Threshold	-1.16	Yes
Flat Threshold	-1.12	Yes

The actual Kolmogorov-Smirnov statistic should fall between the peaked/flat threshold statistic.

Note the assumption of normality is a robust assumption. This means that except for a very wide departure from normality, inferences that are made under the assumption (i.e. confidence and prediction intervals) are reasonably appropriate, with some exceptions, at these values.

Prepared By: Audit Staff Client: Classical Book Example Period Ended: 12/31/90
Computer model run on: Mon Jan 21 17:12:54 1991

Multicollinearity - Supporting Details

	Actual Statistic	Threshold Significant @ Confidence Level			Significant?
		90%	95%	99%	
Least 24	0.00	0.15	0.21	0.02	No
First 24	0.15	0.15	0.21	0.02	No

The above test for multicollinearity is a statistical test that determines whether or not the independent variables in the regression equation are correlated. Collinearity is a condition in which the independent variables are highly correlated and changes in the model coefficients are not likely to occur when the model is run.

Calculate
Protect Regression Sheet
Model Results
Statistical Checks
Autocorrelation
Heteroscedasticity
Normality
Multicollinearity
Continuity
Minimum Precision Estimate
Equiprobable Residuals
Summary
Unprotect Regression Sheet

A		B		C		D		E		F		G		H	
1	Reviewed By:	Audit Staff	Client:	Classical Book Store	Period:	Ended:	12/31/91								
2	Worksheet name: Model Results - Model on 11/23/91														
3	Regression Results				Number of Observations										
4	Time Series - Cross-Section				Base										
5	Variable to be explained: SALES				Predictor										
6					Regression										
7					Confidence										
8	Variable	Transform	Coefficient	Statistic	Level										
9	Constant		40583.48	0.97	0.66										
10	Margin		7.68	28.73	0.98										
11	Hours		-37267.96	-1.66	0.71										
12															
13	The t-ratio measures the statistical significance of an individual regression coefficient. Absolute, positive or absolute value of 2 or better.														
14															
15															
16															
17	The F-ratio measures the statistical significance of the whole model.														
18															
19	Minimum precision expected for any one estimate in the production phase.														
20															
21	Confidence: Minimum Precision Minimum Precision /														
22	Level	(t)	Mean												
23	95%	1.96	10%												
24	90%	1.64	15%												
25	85%	1.44	20%												
26	80%	1.28	25%												
27	75%	1.10	30%												
28	70%	0.96	35%												
29	65%	0.82	40%												
30															
31	Should you be prepared to accept a 10% risk of error?														
32	Should you be prepared to accept a 5% risk of error?														
33															
34	Minimum precision and accuracy for the regression model.														
35															
36															
37	Other Statistical Information:														
38	R-squared value: 0.98														
39	Adjusted R-squared value: 0.97														
40	F-ratio of 98.88 - confidence level: 0.00														
41	Df for error: 15														
42	Df for total: 16														
43	Df for regression: 1														
44															
45	The 2 parameters are the slope of the regression line and the intercept.														
46	The slope of the regression line is the change in the dependent variable for a one unit change in the independent variable.														
47	The intercept is the predicted value of the dependent variable when the independent variable is zero.														
48															
49															
50															
51															
52	The standard error of the estimate is the standard deviation of the residuals.														
53	The standard error of the estimate is the standard deviation of the residuals.														
54	The standard error of the estimate is the standard deviation of the residuals.														
55	The standard error of the estimate is the standard deviation of the residuals.														
56	The standard error of the estimate is the standard deviation of the residuals.														
57	The standard error of the estimate is the standard deviation of the residuals.														
58															
59															
60															

A		B		C		D		E		F		G		H		
CLIENT NAME																
Regression Results				Number of Observations												
Cross Section Levels				Base												
Variable to be explained: SALES				Predictor												
				Regression												
				Confidence												
1	Variable	Transform	Coefficient	Statistic	Level											
2	Constant		40583.48	0.97	0.66											
3	Margin		7.68	28.73	0.98											
4	Hours		-37267.96	-1.66	0.71											
5																
6	The t-ratio measures the statistical significance of an individual regression coefficient. Absolute, positive or absolute value of 2 or better.															
7																
8																
9																
10																

Obs	Actual	Regression Estimate	Residual	Residual Recorded	Interval Estimate						Observed Interval	Interval above	Interval below
					Lower Bound	Upper Bound	Lower Bound	Upper Bound	Lower Bound	Upper Bound			
1	2		3	1-2	4-3/1	5	6-5	7-6	8-7	9-7			
2	101944.00	101944.00	0.00	0.00	276361.84	1401340.16	2013518.08	2611085.92	3208653.76	3806241.60	0.00	347511.92	
3	245100.00	245100.00	0.00	-0.09	2478114.17	22149118.85	21623455.58				0.00	0.00	
4	3041000.00	3041000.00	0.00	0.04	2462657.80	24470813.86	31388929.70				0.00	0.00	
5	31217000.00	31217000.00	0.00	0.03	2466028.14	27961493.65	32386520.35				0.00	0.00	
6	4251000.00	4251000.00	0.00	0.07	2738416.16	16761077.16	41724554.36				0.00	366743.92	
7	2701000.00	2631000.00	-700.00	-0.15	2537467.64	127144660.55	2833794.58	52860.51			0.00		
8	1121000.00	1121000.00	0.00	0.00									
9	1121000.00	1121000.00	0.00	0.00									
10	1121000.00	1121000.00	0.00	0.00									

105 Aggregate Base Model Estimate for 98 Data Points in the Base Model:			
Confidence	Achieved	Precision (%)	Required Amount
100%	1244736.55	0.03	
95%	12144832.23	0.02	
90%	3405526.24	0.02	
85%	519085.84	0.04	
80%	520188.95	0.01	
75%	431679.70	0.01	
114 Aggregate Standard Error for Base Model:			519.9

Confidence	Minimum Precision	Minimum Precision
Legal	(α)	Minimum
95%	141668.38	0.75
93%	138833.85	0.13
90%	87456.18	0.16
80%	634762.94	0.13
70%	640944.95	0.10
60%	24096.70	0.08

Bank Order

Select rank ordering criteria for equiprobable residual analysis

Absolute Values
 DN.V Positive Values
 DN.V Negative Values

Number visible

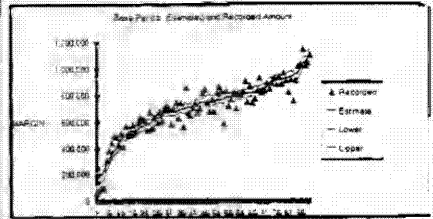
How many observations do you want displayed?

All
 Partial

Minimum number of partial observations is 5.

OK Cancel

Obs	A	B	C	D	E	F	G	H
1	CLIENT NAME							
2	Rank Order of Equiprobable Residuals							
3	1500176	3205731	1936371	444211	620413	186975	3956	
4	0.00	3127.48	1846.42	433.44	6327.54	1826.80	28.84	
5	0.00	0.00	3082.97	485.73	19203.46	3374.03	45.00	
6	0.00	0.00	0.00	506.18	7389.57	1802.18	33.85	
7	0.00	0.00	0.00	0.00	4371.34	1540.07	29.94	
8	0.00	0.00	0.00	0.00	0.00	1503.73	26.82	
9	0.00	0.00	0.00	0.00	0.00	0.00	26.67	
10	0.00	0.00	0.00	0.00	0.00	0.00	0.60	
11	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
12	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
13	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
14	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
15	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
16	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
17	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
18	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
19	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
20	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
21	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
22	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
23	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
24	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
25	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
26	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
27	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
28	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
29	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
30	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
31	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
32	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
33	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
34	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
35	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
36	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
37	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
38	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
39	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
40	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
41	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
42	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
43	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
44	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
45	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
46	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
47	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
48	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
49	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
50	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
51	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
52	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
53	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
54	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
55	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
56	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
57	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
58	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
59	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
60	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
61	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
62	0.00	0.00	0.00	0.00	0.00	0.00	0.00	



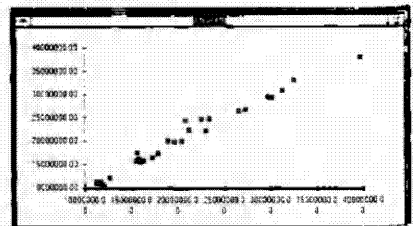
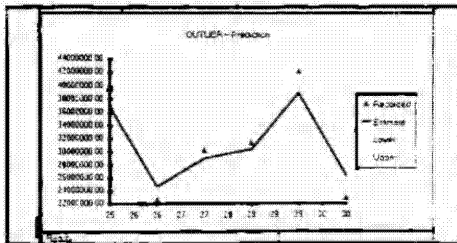
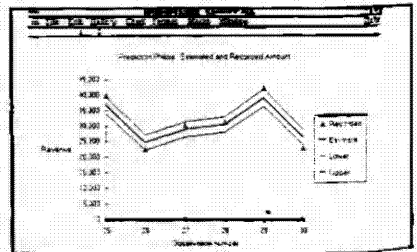
Confidence	Adjusted	Precision
95%	6848628.58	0.00
93%	6327154.93	0.63
90%	6227118.95	0.61
80%	4013684.84	0.62
70%	3240995.73	0.62
60%	2592829.21	0.61

Advanced

Cochrane Druett
 First Difference Levels
 Cochrane Druett Stepwise
 Cross Sectional Stepwise
 First Difference Stepwise
 Levels Stepwise
 Time Series Stepwise

Obs #	Amount	Level
30	926660.511	below
25	36743.92	above
25	242511.92	above

Obs #	Cum. Total
30	2585762.0
28	2118517.65
25	2012177.11
25	1183183.18
27	407185.52



for the user to specify the model based on his or her understanding of the client's business, and to think carefully about the regression coefficients to see whether they have the expected direction and magnitude. It is our judgment that in an audit context, the use of the stepwise technique runs the risk of turning the program into a "black box" which the user accepts without understanding. Moreover, statistical criteria are only one of the considerations of an auditor; indeed, descriptive power may be sacrificed intentionally in exchange for the greater evidential value provided by externally-generated independent variables, as prescribed in *Statement on Auditing Standards No. 31* [AICPA, 1980]. Nonetheless, an advanced module of the program is accessible that permits use of stepwise, and overrides certain automated decisions integrated with the core program (such as the time-series choice among levels, first-differences, and Cochrane-Orcutt models)—see the end of Figure 2 for a sample menu.

Table 1
Automatic Statistical Checks

Statistical Consideration	Tests Performed
AUTOCORRELATION	<ul style="list-style-type: none"> • Planning phase consideration of autocorrelation • Time-series model selection of first difference and Cochrane-Orcutt • Runs test • Chi-square test of contingency table • Durbin - Watson test • Autocorrelation of residuals for twenty-four lags
HETEROSCEDASTICITY	<ul style="list-style-type: none"> • Goldfeld Quandt • Non-parametric rank correlation <p>(These are performed for each independent variable.)</p>
NORMALITY	<ul style="list-style-type: none"> • Planning phase consideration of descriptive statistics. • Kolmogorov - Smirnov • Shapiro - Wilk • Chi squared goodness of fit. • Moment check for both skewness and kurtosis.
MULTICOLLINEARITY	<ul style="list-style-type: none"> • Planning phase consideration of correlation matrix • Haitovsky statistic.
CONTINUITY	<ul style="list-style-type: none"> • Chow test if forty-eight observations are available • Alternate dummy variable test if fewer than forty-eight observations are available

For each independent variable, the user is presented with a regression coefficient, a t-statistic, the confidence level associated with the t-statistic, and guidance on interpretation. For the model as a whole, the user is presented with various statistics, most notably R square, adjusted R square and the F statistic, again with guidance on their interpretation. A sample screen of such output is provided in Figure 2. At this stage, the user will decide whether to proceed or whether the model requires modification.

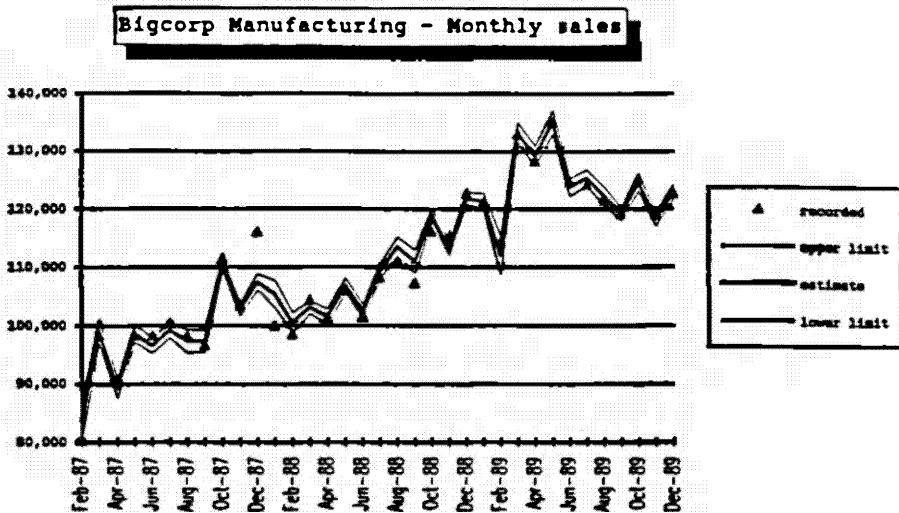
If the user proceeds, the next output module involves a series of statistical checks for autocorrelation of residuals, heteroscedasticity, multicollinearity, non-normality of residuals, and continuity. For most of these conditions, more than one test is performed. For example, the checks for autocorrelation of residuals include a runs test, a Chi-Square Test of a Contingency Table for residuals, the Durbin Watson statistic, and a test for autocorrelation in the residuals with lags from one to twenty-four. The users are not expected to know how the various statistics are calculated. More importantly from their perspective, heuristics built into the software warn them when the tests indicate that there is a problem with one or more of these conditions. If a problem is indicated, it is explained and the user is provided with on-screen guidance on how best to respond. Table 1 summarizes the automatic statistical checks performed. Figure 2 provides a sample screen for the summary of checks and illustrative detail-level screens. Test statistics are reported at ninety, ninety-five, and ninety-nine percent levels of confidence, to enable model builders to evaluate how severe the problem is, if detected.

Once the statistical checks have been reviewed, the next module compares the recorded value with the regression estimate for each observation in the data set. Confidence intervals are presented for each observation and for the data set as a whole. Over the years a variety of strategies have been presented for residual investigation—for example, by Kinney [1979], Kinney and Salamon [1982], and Knechel [1988a]. While recognizing that this is a topic on which more research is undoubtedly necessary, at present we are suggesting to users that aggregate precision for the reporting period should not exceed materiality, and that all but very small outliers should be investigated. This operationalizes the Kinney approach (extended to a multiple regression environment) of computing an aggregate standard error for the regression model in both the base and prediction phase, which can be compared with materiality. Related output appears in Figure 2. As evidenced in such illustrative screens, the focus is on precision, and the confidence level is derivative, rather than the other way around. A lower than desired level of confidence will suggest the need for additional audit procedures to be employed to achieve the desired level of audit satisfaction.

The outliers themselves are easily spotted through both tabular and graphical presentation, as illustrated in both Figures 2 and 3. To further assist the user in identifying anomalous observations requiring investigation, the last module presents a table of equiprobable residuals (and a related graphic) (again, extending work by Kinney) to complement the outliers in the previous module. Choices available for evaluating equiprobable residuals (reflective of one-tail and two-tail concerns) are shown in Figure 2, with screen output. A summary of the most unusual observations permits consideration of both evaluation tools: outliers and equiprobable residuals. Users are encouraged to consider both outliers and large equiprobable residuals when selecting items for investigation.

Some might feel that we are insufficiently prescriptive in our approach to

Figure 3. Graphic presentation of regression outliers



investigation of outliers. However, given the substantial amount of judgment which underlies the audit process (for example, materiality determination or inherent risk assessment), it seems natural to us that context-sensitive professional judgment should play a role in developing a strategy for residual investigation. Prediction phase screens analogous to base model screens, one of which is shown in Figure 2, are particularly useful in time-series applications.

Another issue raised in the literature is the linkage between regression analysis and statistical sampling. For example, Knechel [1988a, 1988b] shows how analytical procedures can reduce sample sizes. It is a logical conceptual link, because both forms of evidence lend themselves to mathematical expression—the playing out, as it were, of the multiplicative risk model. In practice, we do not expect that audit teams will often need to develop integrated strategies involving both regression analysis and sampling aimed at the same audit assertion. Sampling can be a very effective form of audit evidence when it is required, but it can be costly evidence to obtain and may not be required. For a variety of reasons, we would prefer audit planners to combine regression analysis and other analytical procedures with assessment of control risk below the maximum level where possible, including tests of the client's internal control structure. To provide perspective as to the statistical profile of past field applications, Table 2 describes a sample of models. Dependent and independent variables are described, comparisons can be made between standard deviation and standard errors achieved. The types of precision and incidence of outliers are

Table 2
Statistical Profiles of a Sample of Field Applications Using Regression Analysis

Application (Independent Variables are italicized)	Average Value of Dependent Variable (Standard Deviation)	Standard Error (95% Precision)	Prediction Phase Achieved, Precision Range 95%	Statistical Problems	R ² (Adjusted R ²)
Benefit Reserves Life Insurance	222,347 (11,604)	577 (1,117)	1,285 to 1,784 [no outliers]	Haitovsky Nonparametric Rank Correlation	.35 (.15)
<i>Number of policies, face amount in force, premiums, maturity benefits, interest component</i>					
Supplemental Contract Reserves	26,186 (5,436)	279 (566)	586 to 762 [3 outliers]	Durbin-Watson Goldfield & Quandt	.53 (.49)
<i>Number of contracts, premiums, benefits, statutory reserves, interest</i>					
Oil and Gas Production Revenue	64,529 (13,537)	1,486 (3,026)	2,849 to 3,859 [2 outliers] Achieved Precision in Aggregate for One Year: 12.892 or 4%	First Differences	.89 (.89)
<i>Volume, average price of daily crude futures, closings on the New York Mercantile Exchange for the prompt month, composite spot wellhead average prices (Natural Gas/Week)</i>					
Cost of Goods Sold: Chemicals	46,630,431 (2,056,448)	2,045,235 (4,254,088)	Residual/Recorded Value: 4% to 13% [no outliers]	Multicollinearity	.96 (.95)
<i>Natural gas, ethylene, chlorine, quarter, product line sales</i>					
Retailing Cross-Sectional	203,552 (78,613)	67,640 (137,986)	Residual/Recorded Value: 3% to 170%	Heteroscedasticity Normality Multicollinearity	.23 (.21)
<i>Square footage, economic area, age, type of store, median income, population, nature of neighborhood</i>					

Table 2 (Continued)

Application (Independent Variables are Italicized)	Average Value of Dependent Variable (Standard Deviation)	Standard Error (95% Precision)	Prediction Phase Achieved Precision Range 95%	Statistical Problems	R ² (Adjusted R ²)
Warranty Expense	1,687 (313)	264 (538)	[no outliers]	.Haitovsky	.47 (.28)
<i>Average labor cost, total sales, agged sales, months in service, direct labor, hours charged, part price, sales season: May and December, quarter end, linear trend</i>					
Gross Profit Retailing	100,736 (40,377)	2,550 (5,023)	259 to 80,835 Residual/Recorded Value: .01% to 11%	Heteroscedasticity .Normality .Multicollinearity	.99 (.99)
<i>Sales, square footage, economic area, nature of neighborhood</i>					
Accounts Receivable: Utility	17,646 (3,538)	2,162 (4,365)	[2 outliers] 3713 to 5311	.Heteroscedasticity .Autocorrelation	.25 (.24)
<i>Residential revenue, temperature bill fluctuation rate</i>					
Retail Advertising	14,563 (2,955)	886 (1,798)	Residual/Recorded Value: 1% to 11% [no outliers]	.Cochrane- Orcutt	.90 (.89)
<i>Linear trend, retail sales, number of weeks in a given month (measured as number of Sundays)</i>					
Classified Advertising	11,744 (1,683)	562 (1,142)	Residual/Recorded Value: .09% to 9.7% [2 outliers]	None	.90 (.89)
<i>Homeseal index, help-wanted index, number of weeks in month, seasonality in December, lineage</i>					

Table 2 (Continued)

Application (Independent Variables are italicized)	Average Value of Dependent Variable (Standard Deviation)	Standard Error (95% Precision)	Prediction Phase Achieved Precision Range 95%	Statistical Problems	R ² (Adjusted R ²)
Uncollectibles	14,178 (3,346)	534 (1,106)	1,269 to 1,584 (no outliers)	.Cochrane - Orcutt .Heteroscedasticity	.81 (.78)
<i>Disposable personal income, unemployment rate, cash collections</i>					
Retailing Sales Cross-Sectional	173,609 (94,407)	10,883 (21,435)	Residual/Recorded Value: .35% to 8.31% 1,439 to 6,514	Heteroscedasticity	.99 (.987)
<i>Cost of goods sold, payroll, square footage, age</i>					
Bakery Sales Cross-Sectional	13,475 (6,628)	2,706 (5,320)	136 to 1,628	.Autocorrelation .Normality	.84 (.83)
<i>Number of customers on a route, receivables, number of hours worked, number of employees on straight time, number of items shipped to thrift store</i>					
Retailing Deposit	2,848 (4,238)	2,120 (4,169)	99 to 1,092	.Model Shift	.894 (.892)
<i>Number of customers, hours worked, number of employees on straight time, total sales</i>					
Manufacturing Expenses	3,649 (570)	323 (656)	Residual/Recorded Value: 24% to 82% 779 to 1,340	.Heteroscedasticity .Autocorrelation .Cochrane - Orcutt .Hartovsky	.75 (.67)
<i>Average labor, unit price, total sales, handling charge, February, March, December, quarter end</i>					
Retail Advertising Revenue	1,069 (127)	30.3 (62.8)	20 to 48 [3 outliers]	.Autocorrelation .Hartovsky	.96 (.95)
<i>Weeks, U.S. retail sales, season, linkage, linear trend</i>					

Table 2 (Continued)

Application of Independent Variables are Italicized)	Average Value of Dependent Variable (Standard Deviation)	Standard Error (95% Precision)	Prediction Phase Achieved Precision Range 95%	Statistical Problems	R ² (Adjusted R ²)
Classified Revenue	585,108 (95,876)	16,284 (33,685)	Residual/Recorded Value: 2% to 11% [2 outliers]	.Cochrane-Orcutt	.99 (.982)
<i>Lineage, home index, help wanted index, weeks, season, auto sales index</i>					
Commodity Manufacturing Cost of Sales (Refinery)	37,951 (11,014)	2,471 (4,928)	3,230 to 3,397 Residual/Recorded Value: .15% to 5% [1 outlier]	.Normality	.90 (.89)
<i>Volume of refined weight shipped, monthly raw sugar price indices from U.S. Labor Department</i>					
Brewery Labor Costs	11,882 (1,198)	291 (590)	Residual/Recorded Value: 44% to 7.71% 646 to 791	.Haitovsky	.95 (.94)
<i>Sales price, material use, hourly base rate for workers, consumer price index -- all urban customers</i>					
Educational Revenue (Cross-Sectional)	2,096 (1,994)	133 (268)	Residual/Recorded Value: .001% to 33% 47 to 147	.Haitovsky	.996 (.995)
<i>Collections, attrition, advertising dollars, average course price, cumulative to date active students for nine months, student head count</i>					
Course Service Costs (Cross-Sectional)	1,233 (1,109)	239 (481)	91 to 462 Residual/Recorded Value: 3% to 51%	.Haitovsky	.96 (.95)
<i>Revenue, student head count, building rent, average number of instructors, average instructor's rate, cumulative to date active students</i>					

Table 2 (Continued)

Application (Independent Variables are Italicized)	Average Value of Dependent Variable (Standard Deviation)	Standard Error (95% Precision)	Prediction Phase Achieved Precision Range 95%	Statistical Problems	R ² (Adjusted R ²)
<i>Interior Design Magazine Revenue</i>	1,073 (453)	84.97 (172.50)	32 to 130 Residual/Recorded Value: 1% to 16%	.Heteroscedasticity	.97 (.96)
<i>Printing, postage, paper, 100s of lines, percentage of articles that are editorial</i>					
<i>Cable Television Subscription Revenue</i>	6,771 (389)	115 (299)	299 [outlier]	Cochrane-Orcutt Normality Hainovsky	.96 (.95)
<i>Basic units, pay units, other units subscription, variable expenses</i>					
<i>Dairy Cost of Goods Sold for Fluid Milk Product</i>	25,964,241 (11,620,268)	1,068,493 (2,192,366)	Residual/Recorded Value: 1% to 13%	.Continuity	.99 (.99)
<i>Sales volume, milk sales in points, milk prices (class I)</i>					
<i>Bread Sales Time Series</i>	152,461 (19,698)	379 (784)	840 to 897 Residual/Recorded Value: .03% to 2.37	None	.99 (.99)
<i>Number of products produced, white bread, CPI index, other breads</i>					

reported, alongside statistical problems and information on the descriptive power of the various analyses. This profile suggests that models typically have a limited number of independent variables, precision that ranges from under one to 237 percent on an individual observation basis, substantial descriptive power, and statistical flags that require separate attention.

Testing the Technique

The modified software was completed and alpha tested by the end of 1989. We believed that we had good, user friendly software, but the question remained: would auditors without any special mathematical training or bent want to use regression analysis on actual client engagements? We decided to use 1990 for limited beta testing of the software and the training material we had developed to support it.

Beta Testing and Field Experience in 1990

Our approach was to train the engagement teams for a small number of audits, with emphasis on large clients involved in retailing, financial services, and utilities. These industries were selected as starting points because we knew that existing audit strategies for clients in those industries often put significant emphasis on analytical procedures incorporating operating and external data, as well as accounting information. Eleven audit engagement teams were selected from the United States, the United Kingdom, Australia, and Canada and were trained in 1990. We referred to these teams as “new users”, because they were deliberately selected to comprise people with no prior experience using regression analysis in auditing. Based on limited direction, each team collected data for their regression application and brought it to the training program. This facilitated “hands on” instruction using data familiar to them in a client context with which they had experience.

The results of the 1990 tests were generally positive, although inevitably they revealed a number of areas where our software and supporting training could be improved. The regression applications by these 1990 teams included:

Industry	Model Type	Dependent variable	Descriptor variables
Retailer	Cross sectional	Inventory shrink	Sales, inventory levels, store security expense, store size, type of store, store insurance rating.
Retailer	Cross sectional	Store gross profit	Sales, markdowns, inventory, shrinkage, geographic location <i>vis à vis</i> competitors.
Utility	Time series	Revenue	Volume, rate, number of customers, degree days.
Utility	Time series	Revenue	Volume, rates, number of customers, degree days, dew point, precipitation.

In addition to course attendance time, the eight teams providing formal feedback reported that they had spent an average of seventy hours (with a high of 103 and a low of twenty-eight hours) developing their models, including conceiving the application, obtaining the relevant data, and creating, modifying, and interpreting their regression model. The teams recognized that a regression application would typically require a front-end investment in the first year, but that the time required to maintain the application should drop substantially in the second and subsequent years. Considering that the average number of annual audit hours on the eight jobs was 7,700 (with a range of 1,100 to 20,000), the teams did not seem to consider that the required time investment was large.

Teams were asked whether they had changed the nature and extent of their other audit procedures as a consequence of using regression analysis. One retail team which used regression analysis primarily as an attention directing planning tool reported that it had been able to select fewer stores than normal for investigation as a consequence of improved risk identification. This was possible because regression analysis indicated that stores which were not outliers were in line with expectations, as quantified by the model. A banking team reported a similar experience and estimated that 200-250 hours of investigatory work had been saved. Four teams using regression analysis primarily as a source of audit satisfaction intended to replace other audit procedures, either less effective analytics (three cases) or detailed tests of transactions (one case). Two teams did not alter their other planned audit work in the first year because they were uncertain what they would learn by using this new technique.

Teams were also asked whether using regression analysis resulted in them learning anything new about the client. Six of the eight teams believed something important had been learned, typically additional insights into the interrelationship among financial and operational variables. Given the fact that these were large clients on which considerable audit effort was already being expended, this result is noteworthy.

All teams but one reported a favorable reaction from the client to Price Waterhouse's adoption of this new technique. Two of the clients already made some use of regression analysis as part of their business planning activity. Another client asked to license the software for use by its internal audit group.

The most revealing question concerned the teams' intentions regarding the future use of regression analysis. Seven of the eight teams planned to continue to use the application they had developed, while six of the eight planned to develop additional applications for the client. Individuals were asked whether they would like to use the technique on other clients, and eighty percent responded in the affirmative. Based on the Firm's experience in pilot testing a variety of methodological and software tools over the years, these are high approval ratings.

All eight teams believed there were industry-specific regression applications which could be used on many audits in their client's industry. To facilitate this, a central data base of all regression applications has been created which can be accessed through the Firm's wide area network. Thus a team contemplating a banking application, for example, can easily determine what regression models have been previously developed for bank audits, and who to contact for a detailed description of each application.

Following the successful completion of the pilot program and some attendant

internal publicity, a number of other engagement teams volunteered for training, with the result that by the end of 1990, about fifty engagements were using the software. Some of these represented engagements with previous mainframe applications which have been converted to the microcomputer.

Experience in 1991

By the end of 1991, approximately eighty engagement teams had been trained and more than 100 applications had been designed. Early in 1992, Price Waterhouse decided to survey users to gain a better understanding of how the use of regression analysis had affected their audit engagements. Key results based on the twenty-six replies received to date are outlined in Table 3. The relatively low response rate is the result of our sending the survey request out at a very busy time of year for the audit practice. In addition, a number of planned applications are currently in process, and so the teams were unable to report complete results at the time of this writing.

Regression analysis is being used on audits in a wide variety of industries, but as we had initially expected, retailing, financial services, and utilities seem to present particularly promising opportunities because of the wealth of objective operating information upon which models can be built to predict financial performance. Oil and gas, publishing, commodities, and hotels have also yielded several interesting applications.

There are an almost equal number of time-series and cross-sectional applications. Nearly all of the time-series applications involve modeling monthly financial data, and from two to five years of monthly observations are used to build the base model. The cross-sectional applications are generally used to identify anomalous locations in a multiple location business (e.g., retailing) and have involved from about thirty to 1,400 locations.

Most teams have chosen a confidence level of either ninety or ninety-five percent because they have found that this yields sufficiently tight precision relative to audit planning materiality, while minimizing the number of outliers to be investigated. Most of the models built have excellent explanatory power. Of the twenty-four teams which reported the value of adjusted R-squared in their application, eighteen had achieved ninety percent or better. (Note that R-square must be viewed in tandem with precision and is typically lower for balance sheet accounts than income statement accounts due to lower variability in such accounts).

The first-year time cost to develop and execute a regression application has varied considerably from twenty-two hours to 212 hours, with a mean of seventy-four hours. We estimate that the cost to repeat the application in the second year will be less than half this amount because the costs of learning about the technique, designing the application, and obtaining data will be substantially reduced.

It is currently difficult to tell how much time elsewhere in an audit can be saved because of this time investment. We have noticed that most teams, being uncertain of the value of this new technique, have opted to retain their previously planned detailed tests of balances and transactions "just in case". With only a few exceptions, the only effect of regression was to replace similar but less sophisticated analytical procedures. A better measure of savings would come in the second year of use when teams will be planning their audits with a much

Table 3
Field Study Feedback (Twenty-Six Engagements)

General				
1. Industry in which the client operates				
Financial services	5			
Retailing	5	High	14,000	
Oil and gas	4	Low	150	
Publishing	3	Mean	2,900	
Utility	2			
Hotels	2			
Manufacturing	1			
Distribution	1			
Health Care	1			
Communications	1			
Personal services	1			
	26			
2. Approximate annual recurring audit hours:				
		High	14,000	
		Low	150	
		Mean	2,900	
3. Attitude of engagement partner towards the use of regression analysis (1-5, with 5 being very supportive):				
		Mean	3.92	
4. Knowledge level of engagement partner about the application (1-5, with 5 being very knowledgeable)				
		Mean	3.44	
Details of the application				
5. Time-series or cross-sectional:				
Time-series -	12			
Cross-sectional -	14			
	26			
6. Confidence level selected:				
95% -	19			
90% -	5			
80% -	2			
	26			
7. Adjusted R squared value achieved:				
95% or more	14			
90% to 95%	4			
80% to 90%	3			
Under 80%	3			
Did Not Respond	2			
	26			
8. Number of observations:				
Time-series applications				
Base Model		Prediction Phase		
High	60	12		
Low	24	6		
Cross-sectional applications				
High	1,400			
Low	33			
9. Method of data entry:				
Downloaded from client computer	7			
Manual entry by client staff	5			
Manual entry by audit	14			
	26			
10. Time invested in first year (hours):		High	Low	Mean
Learning about regression analysis		32	2	1
Developing the application		80	3	18
Obtaining the data		32	1	12
Analyzing the input		30	1	3
Analyzing the output		40	2	10
Following up outliers		25	0	7
Documentation		20	1	8
Reviewing		10	2	5
Total time spent (not additive)		212	22	74
- obtaining data for model building in an audit context is simplified by its past orientation, in contrast to forecasting applications.				
- follow up of outliers can involve detailed testing procedures, re-estimator of the model to see if additional descriptors explain the outliers, and other evidence-gathering procedures.				

Table 3 (Continued)**Impact of regression analysis on the audit**

11. Used as attention-directing tool during planning?

Yes	6
No	19
Did not respond	1
	26

12. If yes to 11, did the use during planning change the extent of the work during execution phase?

Yes	1
No	5
	6

13. Used to provide satisfaction during execution phase?

Yes	20
No	5
Did not respond	1
	26

- note that when management inquiry suggests an explanation for results differing from expectations, the regression model can be rerun to corroborate the reasonableness and sufficiency of management's explanations.

14. Did regression replace other procedures which would otherwise have been carried out?

Yes	10
No	16
	26

- generally regression analysis replaced less sophisticated analytical procedures.

- in a small number of cases regression analysis enabled a reduction in detailed testing at various locations of multi-location clients.

15. Did regression analysis improve audit effectiveness?

Yes	12
No	14
	26

- since past audits were viewed as effective, the "No" responses can merely suggest comparable effectiveness.

16. Did you learn anything new about your client's business as a result of using regression analysis?

Yes	16
No	10
	26

17. Does the client use regression analysis for internal management purposes?

Yes	4
No	22
	26

18. Client reaction to the auditor's use of regression analysis (1-5, where 5 is very supportive)

Mean	3.59
------	------

Future plans for using regression analysis

19. Will repeat this application?

Yes	23
No	2
Did not respond	1
	26

20. Will develop other applications on this client?

Yes	6
No	20
	26

better understanding of what they can expect from regression analysis.

The use of regression analysis has had a number of very positive results. One positive result was that sixteen of the twenty-six teams reported gaining new insights into their client's business as a consequence of the use of regression analysis. Most often, the learning involved an improved appreciation of how key financial variables respond to changes in different operating variables. Another positive result was the reaction of clients, very few of whom make use of regression analysis themselves. Most were very interested in and supportive of what the auditors were doing. However, there was some degree of polarization in the answers, because a small minority of the clients were somewhat skeptical of a technique with which they were not familiar.

The most revealing question concerned the teams' intentions regarding the future use of regression analysis. Nearly all teams intend to continue with the application which they had developed. However, somewhat surprisingly, only six teams indicated plans to develop other applications for the same client. Since cross-sectional applications often focus on a single model, this result could be skewed by the nature of respondents. Moreover, training tends to focus on the revenue stream, whereas multiple-year experience has led to diverse modeling of income and expense streams, as well as balance sheet accounts.

Conclusions

Our experiences to date with regression analysis have been generally positive:

- The software works well and teams find it easy to use.
- Once teams build an application, they nearly always maintain it.
- Auditors have been able to improve their understanding of clients' businesses through the use of this technique.
- Most clients react positively to the use of a technique which they consider to be thoughtful and innovative.

On the other hand, some sobering realities are apparent:

- A minimum of two days' training is required before auditors are reasonably self-sufficient.
- Building a regression application is time-consuming, particularly when the values of key operating variables are not immediately available (as is frequently the case). At the same time, it should be noted that a significant portion of the first-year time investment is non-recurring.
- The firm must maintain, as a centralized resource, people who possess an enhanced level of understanding of both theory and application issues regarding regression analysis.
- Even after implementing the technique on a significant number of engagements, it is not yet obvious that regression analysis will save more audit time than it costs.

While teams generally reported that the use of regression analysis improved the effectiveness of their audit, it is difficult to link the identification of specific adjusting journal entries to the sample under study. However, it would be wrong to conclude that regression analysis failed to find significant errors which existed. Most of the clients in this sample are large and well-controlled, and would not be expected to make significant errors in their financial statements. Our

experience to date does not lead us to challenge the results reported by researchers who have studied the performance of regression analysis in simulation experiments. Indeed, among the findings of past regression applications are:

- discovery of reporting errors by branch operations,
- a theft ring that accounted for a retailer's poor performance,
- recognition of a change in cost allocation techniques that had not been disclosed,
- identification of a \$300,000 transaction improperly placed in a suspense account which should have been in the share balance, and
- selection of five units to visit, three of which had just been discovered by management as having serious problems.

It is the intention of Price Waterhouse, for the balance of 1992, to continue to expand the use of the technique in a controlled manner, focusing on industries such as financial services and retailing where we have begun to accumulate a significant number of successful applications, with underlying concepts that can be easily replicated at other client settings.

We believe that for regression analysis to have a chance of success in auditing, auditors need software which is audit-oriented and easy to understand, yet statistically rigorous. They also need proper training and support, and an appropriate client situation in which to use the technique. Given all of these requirements, regression analysis can be a very useful tool. Its promise is at last being realized.

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Appendix

Field Applications

A Time-Series Illustration for Revenues

Bank audits are often highly reliant on analytical procedures. One reason is the availability of a pervasive, readily available, totally objective descriptor variable in the form of the bank prime rate of interest.

The audit team at a money center bank decided to build a regression model to predict the bank's interest income each month on the commercial loan portfolio. The bank was well-controlled and the team reasoned that if they satisfied themselves with the controls over the production of accounting information using an integrated test facility, and did quality analytical procedures on the aggregate commercial loan interest income, it would be possible to eliminate much time-consuming detailed testing of individual interest income calculations.

Often regression models are built by thinking of the price and quantity dimensions of the variable of interest. In this case, a quantity dimension was the average monthly loan portfolio, for which audit satisfaction had been derived in part from a test circularization of customers. However, the team first excluded non-performing loans from the portfolio since they were typically not generating any income. A second quantity dimension included in the model was time, since the number of days in a given month could vary from twenty-eight to thirty-one. The price dimension was provided by the average market rate of interest for each month. Some experimentation was done with both U.S. prime and the London interbank overnight rate (LIBOR) individually and in combination, before it was established that the inclusion of U.S. prime alone resulted in the model with the best predictive power.

The model was built to predict monthly recorded interest income. However,

the auditors recognized that monthly income was sometimes affected by certain non-routine transactions, of which the three most common examples were the following:

- Interest was sometimes received on non-performing loans and credited to income.
- When a loan was classified as non-performing, any unpaid interest accrued on that loan was reversed.
- On occasion, a non-performing loan was restored to the performing category, and previously reversed income was restored (usually because the customer had paid the arrears).

The audit team decided that it would wish to know of and examine non-routine transactions individually, and so they were extracted from the monthly recorded income figure used for the regression model.

Monthly data for the two years preceding the year subject to audit were obtained for average adjusted performing loans, average U.S. prime, number of days in the month, and adjusted interest income. The resulting regression model was able to predict about ninety-four percent of the month-to-month fluctuation in interest income during this base period, which the auditors regarded as satisfactory reliability. All of the descriptor variables had significant t-statistics, indicating that they were contributing meaningfully to the model. Statistical tests did not indicate any problems. Therefore, the model was used to predict monthly interest income for the year subject to audit.

The results were very satisfactory. The aggregate of the twelve months' recorded income was only thirteen percent different from the aggregate of the twelve months' regression predictions, a difference which the audit team did not consider to be significant. The aggregate precision of the estimates for the prediction period was +/- 2.1%, which was considered to be acceptably tight relative to the materiality for the engagement. In fact, this precision will very likely improve in the future as more months' data are added to the base model used to create the regression equation. Finally, none of the individual monthly recorded balances were statistically different (ninety-five percent confidence was used) from the corresponding regression estimates.

In this case the audit team believes that the use of regression analysis has helped to reduce substantially the time required by them to obtain audit satisfaction with respect to a substantial proportion of the client's interest income. At the same time, the auditors' awareness of the non-routine transactions was heightened by their need to identify them and exclude them from the recorded income figures used in the regression model. The audit effort is properly focused on ensuring that the accounting for these transactions is correct.

A Time-Series Illustration for Expenses

The auditors of a Fortune 500 company decided to use regression analysis software for their audit of payroll costs at a major division. Their objective was to assess the risk that recorded payroll costs might be misstated for any quarter.

They decided to use gross payroll costs as the dependent variable, after first excluding incentive compensation which they decided to test in detail. As explained above, many regression models have measures of price and quantity as descriptor variables. After considering various possibilities, the audit team selected the average monthly number of employees as the quantity variable, as

obtained from personnel department statistics, and the consumer price index as the price variable.

Actual data was obtained for the previous five years, or for twenty quarters in total. It was then realized that during the period, two special events had occurred which were not reflected in the model. During one quarter, the division had incurred a significant level of severance costs as part of a staff reduction program, while just before the end of another quarter a significant level of new hiring had taken place, affecting the headcount statistics significantly for that quarter, but having only a negligible effect upon the compensation costs. Additional variables were created to control for the effect of those two programs.

Based on the data for the twenty quarters, a regression model was created which was able to explain about ninety-five percent of the quarter-to-quarter fluctuation in payroll costs. However, six of the twenty quarters exhibited differences between actual and predicted payroll costs which were statistically significant at a confidence level of ninety-five percent. Of those six, two quarters had particularly large differences on the order of four to five percent of the recorded payroll costs. Further analysis was planned to understand better the causes of these fluctuations. If the causes, once understood, were reflected in the model, the model would become an even more effective prediction tool. In other payroll applications, descriptor variables have included vacation pay, sick pay, overtime, down-time, and part-time employee factors, as well as the influence of the mix of unionized and non-union personnel.

While possible refinements to the base model differences were being investigated, the audit team used the existing model to assess the risk of error in payroll costs for the first two quarters of the current year. The aggregate payroll cost for the six months exceeded the regression estimate by about two percent, and the auditors decided that no further detailed testing of payroll costs was required.

The benefit of this regression application was to direct the attention of the auditors to quarters where payroll costs were significantly different from expectation, and to minimize or even eliminate work on quarters which were closely aligned with expectations. It should be noted that the concept would apply equally to monthly payroll data, except that fewer than five years' history would suffice for model-building purposes.

A Cross-Sectional Illustration

A large food processor operates about forty plants producing the same baked goods product line for sale to food retailers in their local geographic area. Part of the audit strategy calls for field visits to a selected number of plants to assess internal controls and to test accounting balances and transactions. The auditors desired to develop a more sophisticated risk-based approach for deciding which plants they would visit.

Each plant is a profit center with its own balance sheet and income statement. The principal items on the balance sheet are receivables, inventories, and accounts payable. Two important income statement items are cost of ingredients and payroll costs. The auditors decided to build separate cross-sectional predictive models for each of these five accounting variables, using as independent variables other accounting information and operating statistics such as sales, pounds produced, and number of employees. The descriptor variables for each

model varied depending on what was considered to be most relevant. The models produced were all effective at predicting most of the plant-to-plant variability, ranging from about eighty-two percent of the fluctuations in payables to ninety-eight percent of the fluctuations in payroll costs.

The auditors judgmentally ranked the risk of material error for each of the five dependent variables as 3, 2 or 1 (3 being highest risk) based on the past history of errors and other factors. The regression models were run, and the residuals captured for each variable for each plant (the residual is the difference between the recorded amount and the regression estimate). The five residuals for each plant were first standardized to take into account differences in the size of the plants and the variables, then were weighted by the inherent risk factors, and finally were added together to produce a single overall risk score for each plant. The auditors intend to focus their location visits on the plants with the highest risk scores. In addition, unusual fluctuations for any of the variables for a location not visited are to be at least discussed with the plant controller to determine whether there is a plausible explanation.

The auditors believe they have developed a much more objective approach to selecting plants to visit. However, they recognize that their models are capable of continuous improvement as they gain an improved understanding of the business by investigating differences between actual and expected performance. These investigations have identified such relevant factors as the introduction of new product lines, unionization, intracompany purchases, economies of scale effects, private label arrangements, and the possibility of obsolete wrappers or similar disruptive factors influencing descriptor variables.