AN ALGORITHM FOR THE DETECTION OF REVENUE AND RETAINED EARNINGS MANIPULATION

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ABSTRACT

This paper presents a statistical analysis confirming the former empirical findings that positive differences between the growth rates of P-Score and Z-score appears in financial statement data of companies involved in major financial fraud. The paper examines firms that engaged in fraud in the late 1990's through early 2000's. The paper reports the results of regression analysis, using ratios, from financial statement data used in the calculations of P-Score and Z-Score. The results show that positive values of the difference between the growth rates of P-Score and Z-Score correlate with Net Income, Revenue, Retained Earnings and Total Equity ratios. Both ratios represent the financial statement areas where most identified fraud occurred. The findings imply that positive differences between the rates of growth suggest financial statement manipulation. The standard error of the estimate shows the early linear regression to be coarse. The final part of the paper optimizes the linear regression formula and discusses its limits. The paper shows the potential uses of Extensible Business Reporting Language (XLRB) for getting the necessary values for algorithm calculations.

JEL: M41, M42, M48

KEYWORDS: Financial statements, fraud, manipulation, Z-Score, P-Score, revenue, retained earnings, XBRL

INTRODUCTION

According to 2008 ACFE Report to the Nation (ACFE, 2008) over 41% of all material misstatements in financial reporting results from altering the accounting records connected to revenue generation. Investment brokers and investors make important investment decisions using these revenue figures. According to (Summers & Sweeney, 1998) the knowledge of such misstatements can become a basis for insider trading in any affected company. Many financial scandals, which took place at the turn of the 21st century, were the result of improper revenue recognition and altering existing revenue figures to prove that company had achieved its financial targets (Agrawal & Chadha, 2005).

Despite efforts to automate the discovery of financial statement manipulation, most discoveries of manipulation, which lead to fraud charges later in court, still come from non-accounting sources, such as internal tips and unrelated police work. According to (ACFE, 2008) around 60% of all fraud charges were not a result of audit or accounting work. Because of this, the use of the computerized means of manipulation prediction becomes important.

Recently, there were several notable efforts to create criteria of prediction of the financial state of the enterprise. Altman, created a Z-Score designed to predict bankruptcy (Altman, 1968) . Beneish, 1999 designed several ratios, which showed statistically different results for known manipulators with the financial statements as opposed to non-manipulators. Combining these ratios into one regression formula was largely unsuccessful and produced slightly over 50% success in detecting manipulators.

The AAER statements issued by Security Exchange Commission in the USA shows the character of financial statement manipulations differs from one infraction to the next. The character of infractions, committed be the companies are listed in Appendix. The study described in (Pustylnick, 2009) shows it is nearly impossible to create any statistical solution, which would be equally suitable for all statement manipulation techniques. Pustylnick (2009) created the complementary score named P-Score (Pustylnick, 2009). The study found that for the companies convicted of revenue manipulation ΔP > ΔZ when:

$\Delta P = \frac{P_t - P_{t-1}}{|P_{t-1}|}$, the rate of change of P-Score

$\Delta Z = \frac{Z_t - Z_{t-1}}{|Z_{t-1}|}$, the rate of change of Z-Score

This paper is organized as follows. After the introduction, the paper reviews the latest literature on financial statement manipulation and existing attempts to discover manipulations. In the next section, the paper introduces the main hypothesis. The following sections describe the method of research, the gained results and their optimization. The paper finishes with a discussion of the results and the place of XBRL in the proposed manipulation discovery.

LITERATURE REVIEW

Most journal articles on financial reporting fraud describe and classify existing cases of fraud. Rezaee, (2002) was the first large work following the financial scandals. It is the first comprehensive effort to itemize fraud cases. Rezaee, (2005) concentrated on recommendations of how to prevent the cases of fraud. James 2003) tries to connect the deterrence of fraud with internal financial controls (James, 2003). Other authors find similar fraudulent trends in Europe while exploring the financial practices of the Austrian government (Stalebrink & Sacco, 2007).

An older paper by (Lee, Ingram, & Howard, 1999) shows inconsistency existing between Earnings in the Income Statement and Cash Flow in the Statement of Cash flow is a potential indicator of manipulation. (Grazioli, Johnson, & Jamal, 2006) build a cognitive theory of successful fraud detection. They claim that setting up patterns of enterprise inner workings and managerial behaviour helps identify deviations from set patterns, which in turn lead to financial fraud. (Skousen & Wright, 2008) try to create a manipulation detection mechanism to detect tampering with financial statements. However, they use several variables, which are not publically available thus limiting the usefullness to internal audit. (Dechow, Ge, Larson, & Sloan, 2010) undertook a comprehensive research, which involved over 2000 AAER statements from SEC. The analysis used over 100 variables many of which may not be available to the general public.

The study by (Kirkos, Spathis, & Manopoulos, 2007) shows that use of data mining of financial information over a prolonged period can reveal patterns of manipulation. These findings echo the works of (Beneish, 2001). The ratios set ip in (Beneish, 1999) were observed over the period of two years. (Lenard & Alam, 2009) make a connection between corporate bankruptcy and financial statements, which in turn proves that Altman Z-Score (Altman, 1968) is suitable as a sign of financial statement manipulation. Detecting financial statement manipulation requires working with large amounts of financial data. (Debreceny & Gray, 2001) argue that XBRL provides a statement presentation mechanism. (Debreceny et. al., 2005) evaluate the practice of using XBRL in SEC EDGAR reporting. (Pinsker, 2003) offers a theory that XBRL can be a tool successfully used in auditing procedures. (Li & Pinsker, 2008) evaluate the effectiveness of the use of XBRL in distribution of financial data and imply that this low-cost method of assembling financial reports is useful for companies and shareholders alike.

The review of the literature suggests the following conclusions. There is theoretical support for the notion that researchers can discover financial statement manipulations by examining data from the same corporation over a period of time. XBRL rapidly becomes a standard of financial statement filing. The processing of the XBRL based statements is a viable option for extracting data, which becomes a base of manipulation detection algorithms.

METHODOLOGY

The data for this research exists in the SEC EDGAR database for the period of five consecutive years for each company (where it was available). The original data collecting effort is described in (Pustylnick, 2009). The sample included 29 companies charged with financial statement fraud. The data, collected for each company, exists in the public year-end financial statements of each company (10-K) for the five years preceding the fraud charges. For a number of companies, such as Enron, the data existed in fewer statements as the company did not operate for five full years preceding the charges.

We obtained three sets of results: (1) the result for the whole sample of 145 observations; (2) the sample of 59 positive values each greater than 0.1; (3) 63 "negative" scores each less than 0.1. We deleted the abnormal scores of +/- 5 or above as they represent the known aberrations which do not exist for a mature company in full operation.

Validation of the described data required a sample obtained from companies considered free from statement manipulations. The authors assume companies convicted of financial statement fraud underwent a thorough financial statement audit in the years preceding the charge. Examination of subsequent AAERs showed that auditors did not discover fraud in the years preceding the year of charges. Therefore, these years can comprise a so-called "clean pool". Due to this assumption, the authors divided data into two samples: (1) with values of $(\Delta P - \Delta Z) > 0.1$ for a pool with the potential for manipulation, (2) the rest of the data for the years when the authors considered the data free from manipulations.

The difference between P-Score and Z-Score calculations revealed four potential variables, which influenced the value of the difference between the rate of change of P-Score and the rate of change of Z-Score, namely: Net Income, Current Assets, Current Liability and Retained Earnings. Realizing that these variables differ from one company to another we created a set of the following ratios:

$$X1 = \frac{Current\ Assets}{Total\ Assets},$$

$$X2 = \frac{Net\ Income}{Revenue},$$

$$X3 = \frac{Current\ Liabilities}{Total\ Liabilities},$$

$$X4 = \frac{Retained\ Earnings}{Total\ Equity}$$

And constructed the following linear regression formula:

$$(\Delta P - \Delta Z) = \alpha + \beta_1 X1 + \beta_2 X2 + \beta_3 X3 + \beta_4 X4 \qquad (1)$$

The main hypothesis for the study became: There exists a solution for this regression line when $(\Delta P - \Delta Z)$ is positive. The statistically significant values of the coefficients β_i confirm the existence of the solution.

As the study was exploratory by nature and did not include a significanly large population we considered that all results have significance levels of 95%. According to (Pustylnik, 1968) this level of significance is enough to discover statistical trends. The study attempts to find the best possible regression line solution by using least squares method and the calculation of Pearson Correlation coefficients between the result and the variables involved in the analysis.

RESULTS

The results, gained in this study, belong to three categories: 1) The results for the full set of data, containing all values (145 in total), selected for the analysis 2) The results for the set of data, containing values of (ΔP-ΔZ) > 0.1 and 3) The results for the set of data, containing values of (ΔP-ΔZ) < 0.1

Table 1 shows the combined results for the full data set. The only variable with any significant statistical correlation is X2, which represents Net Income/Revenue. This means that Net Income and Revenue are the only two values which influence the final result slightly. The negative sign of the coefficient means that the result value increases when the ratio decreases. T-value used for n=120 is 1.98. This implies that for any T with absolute value of less than 1.98 we must accept the Null Hypothesis and infer that coefficients are not statistically significant. The only statistically significant coefficient is the one representing Net Income/Revenue Ratio.

Table 1: Combined Results for the Full Set of Data

	Panel A				Panel B	
	ΔP-ΔZ	X1	X2	X3	Coef. Value	T-value
X1	-0.099				-1.01	-0.85
X2	-0.359***	0.129			-3.66	-4.19***
X3	-0.064*	0.540***	0.155*		0.31	0.29
X4	-0.046**	0.314***	0.246***	0.183**	0.033	0.73
Const.					0.682	1.44

*This table shows the results gained for the full data set. Panel A shows Pearson correlation values for the variables used in Formula (1). Panel B shows regression estimates for the Formula (1). ***, ** and * shows significance at the 1, 5 and 10 percent levels respectively for correlation coefficients and T-values*

We note stronger negative correlation between the result value and Net Income/Revenue ratio. There is also a degree of correlation between the result value and the ratio of Retained Earnings/Total Equity The T-value used for n=60 is 2.00. This implies that for any T with absolute value of less than 2.00 we must accept the Null Hypothesis and infer that coefficients are not statistically significant. Based on the results, summarized in Table 2, coefficients for X2, X3 and X4 as well as the constant are statistically significant and the Null Hypothesis must be rejected for all values except for the value of coefficient related to X1. This allows us to cut out X1 as non-significant and to construct the regression equation for three remaining variables

$$\Delta P - \Delta Z = 0.426 - \ 2.84 * X2 + 0.598\ X3 - 0.233\ X4 \qquad (2)$$

All coefficients of the linear regression function are statistically significant with at least 95% probability and that Null Hypothesis can be successfully rejected for all of them. The linear regression formula can be accepted for the tested sample of (ΔP-ΔZ) > 0.1

The data presented in Table 3 clearly shows that there is no significant correlation between the negative values of ΔP-ΔZ and any of the four variables selected for this research. We also constructed a linear regression function for the sample with negative values of ΔP-ΔZ. The analysis had a sample of sixty. The T-value allowing rejection of the Null Hypothesis is 2.00. Based on this none of the coefficients in the regression formula are statistically significant. This implies that a statistically significant linear regression formula does not exist for this sample.

Table 2. Combined Results for the Set of Data with (ΔP-ΔZ) > 0.1

	Panel A				**Panel B**		**Panel C**	
	ΔP-ΔZ	X1	X2	X3	Coef. Value	T-value	Coef. Value	T-value
X1	-0.080				*-0.352*	*-0.90*		
X2	-0.566***	0.108			-2.80	-6.75***	-2.84	-6.89***
X3	-0.141	0.574***	0.100		0.743	2.58**	0.598	2.52**
X4	-0.282**	0.174	-0.207	0.080	-0.225	-4.24***	-0.233	-4.48***
Const.					0.454	3.63***	0.426	3.53***

This table shows the results gained for the set of data with (ΔP-ΔZ) *>0.1. Panel A shows Pearson correlation values for the variables used in Formula (1). Panel B shows regression estimates for the Formula (1). Panel C shows regression estimates for the formula* (ΔP-ΔZ) $=\alpha+\beta_1$X2+β_2X3+β_3X4. ****, ** and * shows significance at the 1, 5 and 10 percent levels respectively for correlation coefficients and T-values*

The analysis of the samples shows that linear regression formula (2) is the only fully statistically significant formula which can predict the value of ΔP-ΔZ. Since the sample of the positive values matches the values existing in years when the companies were charged with manipulation it is possible to reject a Null Hypothesis and accept the main hypothesis stated earlier**.** Formula (2) is the result of splitting the sample into two parts based on the criterion of ΔP-ΔZ > 0.1. The results presented in Table 2 (Panel C) allow to create a fully statistically significant regression equation. The results presented in Table 3 (Panel B) do not allow to create a statistically significant regression equation. Therefore based on the terminology from (Nalimov & Chernova, 1965), the first set of results represents the information part and the second represents the noize part of the sample. This also means that only one part of the sample (used to construct formula(2)) is statistically significant which proves the main hypothesis.

Table 3. Combined Results for the Set of Data with (ΔP-ΔZ) < 0.1

	Panel A				Panel B	
	ΔP-ΔZ	X1	X2	X3	Coef. Value	T-value
X1	-0.001				-16.58	-0.68
X2	-0.070	0.121			2.71	0.13
X3	-0.146	0.532***	0.321***		31.80	1.23
X4	-0.020	0.364***	0.342***	0.248**	0.0220	0.03
Const.					-13.32	-1.22

This table shows the results gained for the set of data with (ΔP-ΔZ) *>0.1 . Panel A shows Pearson correlation values for the variables used in Formula (1). Panel B shows regression estimates for the Formula (1). ***, ** and * shows significance at the 1, 5 and 10 percent levels respectively for correlation coefficients and T-values*

The linear regression formula (2) has a few drawbacks: (1) the standard error of estimate S = 0.39. Since many observed cases lie in the area of 0.1 – 0.5, it would be practically impossible to suggest the formula can predict positive ΔP-ΔZ for many cases. (2) $R^2 = 0.55$ shows that slightly over half the error is the result of the regression, making prediction using formula (2) practically impossible. Removal of the variable representing the asset ratio produces better statistical results. However, this approach is not acceptable from the fraud investigation perspective.

<u>Enhancements for Regression Equation for (ΔP-ΔZ)>0.1</u>

The following non-linear polynomial formula represents the improvements to the original regression formula (2).

$$Y = 1.93 - 0.654 * X1 + 1.22 * X2 - 6.33 * X3 - 16.4 * X4 + 1.46 * X2^2 + 6.47 * X3^2 - 3.97 * X4^2 - 2.94 * X1 * X2 - 2.75 * X2 * X4 + 67.4 * X3 * X4 - 57.1 * X3^2 * X4 - 4.12 * X2^3 \quad (3)$$

The values of the variables underwent normalization. The original values of the variables are:

$$X1_{Orig} = X1 * 0.756126$$
$$X2_{Orig} = X2 * 0.487894$$
$$X3_{Orig} = X3 * 0.972419$$
$$X4_{Orig} = X4 * 5.54826$$

The results are presented in Table 4. The following formula originates from the method, described in (Nalimov & Chernova, 1965), which prescribes the use of the new members representing original variables in square and cubic forms as well as the products of multiplication of the original variables. The formula (3) is the product of elimination of the members, the absence of which does not deteriorate R^2 and does not increase S. The goal of optimization is to obtain the regression equation, which has the minimal number of members. Formula (3) has S=0.23 and R^2=0.87, which is an improvement over the original. All coefficients in the final formula are 95% significant.

The study mentioned formula (3) for the scaled data. The values of each variable were divided by the highest value for this variable existing in the original sample. By using this scaling mechanism we can better estimate the influence of each formula member on the product of the equation as they all remain in the interval [0…1].

Table 4. Statistical Analysis of Regression Coefficients

Predictor	Coef. Value	T-value
Constant	1.93	7.87***
X1	0.654	-3.24***
X2	1.22	2.59**
X3	-6.33	-6.49***
X4	-16.4	-4.92***
$X2^2$	1.46	2.91***
$X3^2$	6.47	7.32***
$X4^2$	-3.97	-3.20***
X1*X2	-2.94	-3.89***
X2*X4	-2.75	-2.72***
X3*X4	67.4	5.25***
$X3^2$*X4	-57.1	-5.31***
$X2^3$	-4.12	-4.48***

This table shows the regression coefficients obtained for the set of data with (ΔP-ΔZ) *>0.1 . It presents regression estimates for the Formula (3). ***, ** and * show significance at the 1, 5 and 10 percent levels respectively for correlation coefficients and T-values*

DISCUSSION OF RESULTS

The main objective of the paper was to prove whether the observed phenomenon of positive ΔP-ΔZ is not a statistical fluctuation and it has a significant likelihood of reoccurrence. The results show that the positive values of the observed ΔP-ΔZ have a distinct negative correlation with the variable X2, which represents a ratio of net income to revenue. Decreases in this ratio do not always constitute manipulation. However, a few fraud cases involving energy trading companies OneOk, Reliant, Nicor, etc. involved profitless revenue (Maize, 2003), which is a result of round-trip trading. Financial statements, existing for the years the described fraud was committed, yield both low X2 and positive ΔP-ΔZ.

Decrease in the values of X4, which has noticeable negative correlation with the value of ΔP-ΔZ, also leads to increases in the value of the equation product. A few companies in the sample, such as Adelphia were carrying heavy losses, which resulted in negative retained earnings. This would increase the influence of X4 by reversing the equation sign. When X4 decreases, which means that retained earnings make up a small part of the total equity, the value of ΔP-ΔZ also grows. Inflated share prices may also inflate the goodwill noted as one of the manifestations of fraud by (Colloff, 2005).

Neither current liabilities nor current assets bear information used in the discovery of fraud cases. The studies of major fraud events (Hogan, Rezaee, Riley Jr., & Velury, 2008) confirm this. From the practical perspective, both current liabilities and current assets contain items with tangible information, which are also part of other sources: books, receipts, warehouse declarations, bank statements, etc.

The variables defined for this research contain values, which are part of the financial statements. (KPMG, 2004) gives a good explanation of how to place and locate these variables in the XBRL based reports. XBRL has become a standard for electronic financial reporting in some countries including the USA. The use of it can increase by providing XBRL outbound data streams in addition to the web based reports. This will allow financial analysts and researchers quick unobstructed access to financial data similar to that used in this study.

Although the XBRL standard has a clear and concise definition, it works best in collecting data. The authors of this paper investigated US-GAAP taxonomy, which is one of the oldest and most developed XBRL taxonomies. The concept (value) items, mentioned in the taxonomy roughly match the company General Ledger entries. Certain values, such as Net Income appear in XBRL, as concept items bearing values, others, such as total revenue require a computational arc around all potential revenue items, appearing in the inbound feed.

The authors envision two equally suitable ways of extracting the values necessary to comprise the outbound feed. The first solution would mandate the computation arcs for items used in variables X1-X4, such as Total Revenue, Total Assets, Total Liabilities, etc. If these arcs are in place at the time of filing, the information extractors can use them to produce necessary values. The second solution prescribes the creation of the outbound feed, using XSLT on the existing documents. This approach will allow government agencies to create and sell ready-made feed to the companies, which would look for potential manipulations.

The authors prefer the first approach to the second. XBRL concept items are not compulsory and do not exist in their entirety in all reports. In order to mark the borders of the revenue or AR areas the authors of the report will have to create definition arcs. Since the areas are already clearly marked, creation of the calculation arc should not be a significant burden on the reporting company. It will also allow the company preparing the XBRL statements to be in charge of any calculations required to produce the previously mentioned totals and ensure that they correspond to the business situation.

CONCLUSIONS, LIMITATIONS AND FUTURE RESEARCH

The authors conducted this study with the purpose of supporting or rebutting findings obtained in (Pustylnick, 2009). We confirm correlation between the decrease in the net income to revenue ratio and the increase of the target predictor. However, the high standard error of estimate, even in the best of regression formulae (0.24), places uncertainty over the number of observed cases.

At the beginning of the paper, the authors stated that the described mechanism is not relevant in cases of formal audit as the auditors have access to proprietary data, not available to external observers. In the view of the previously mentioned, we conclude that the usefulness of this method is limited to researchers with no access to internal data, such as financial analysts, investors and members of general public. These users do not need precise measurement of the degree of manipulation. They want to be aware of the manipulation potential of statements under review. In this case, any value of the predictor in excess of 0.5 should become a cause for a concern.

We also limit this study to cases where manipulations occur in the areas of general revenue and retained earnings. The literature describes a number of fraud cases which this algorithm cannot detect, such as embezzlement, false statements, etc. In some cases, such as the cases of Merck or HealthSouth, the authors noted difficulty in detecting manipulations. This happens when manipulations are on a smaller scale compared to total revenue and assets. The coarseness of the detection mechanism is one drawback of the proposed solution.

In the future, it is necessary to massage the variables so that we can reduce the standard error of estimate and increase the R-square 90%. The presented study carried exploratory task. The size of the sample is another limitation of this study. The authors gradually increased the size of the sample over the course of data collection when the knowledge of modern cases, such as GM came to life. However, the study would benefit from a containing over 100 positive values, matching known fraud cases.

In the discussion section of the paper, the authors touched on the number of the potential limitations of using XBRL. Now, companies use XBRL to create inbound reports used for viewing corporate data. The matching outbound feed, which contains the values, needed to execute the described algorithm, does not exist. Creation of this feed may require creating an alternative outbound feed taxonomy (schema). The financial values, serving as input for the algorithm must become the part of the future outbound schema.

APPENDIX

The list of the major cases used in the analysis

Company	Year of Charge	Detection Year	$\Delta P > \Delta Z$
Adelphia	2001	1999	X
American Electric	2002	1999	X
AOL	2001	1998	X
Brystol Myers Squibb	2001	-	-
Cendant	2000	1998	X
Coca-Cola	2002	2001	-
CMS	2002	2000	X
Computer Associates	2001	2001	X
Duke	2002	2000	X
Dynegy	2002	2002	X
Enron	2001	1998	-
ElPaso	2002	2000	X
Global Crossing	2001	1999	X
Halliburton	2002	1998	X
Health South	2002	1999	X
Kellogg	2002	2001	-
Kmart	2002	2000	X
Merck*	2002	2001	X
Microstrategy	2003	1999	X
Nicor	2002	2000	X
Oneok	2002	2000	X
Peregrine	2002	1999	X
Quest	2002	1998	X
Reliant	2002	1998	X
Tyco	2002	2000	-
Unify	2002	1999	X
Waste Management	1999	1995	X
WorldCom	2002	1997	X
Xerox	2001	1998	X

This table shows the list of the major cases of fraud, discovered and investigated in the late 1990s – early 2000s. Each company in this list carries financial statement fraud charges. The second column shows the year when the auditors discovered the fraud. The third column shows the year when the first year in the selected five when the indicator of manipulation (ΔP-ΔZ) was positive

Figure 1: American Electric P-Score and Z-Score

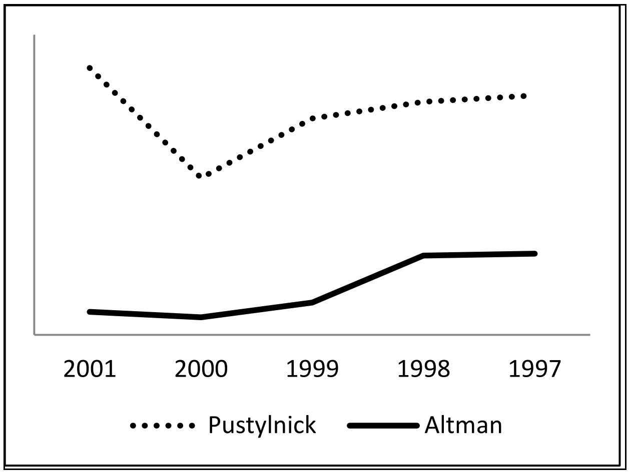
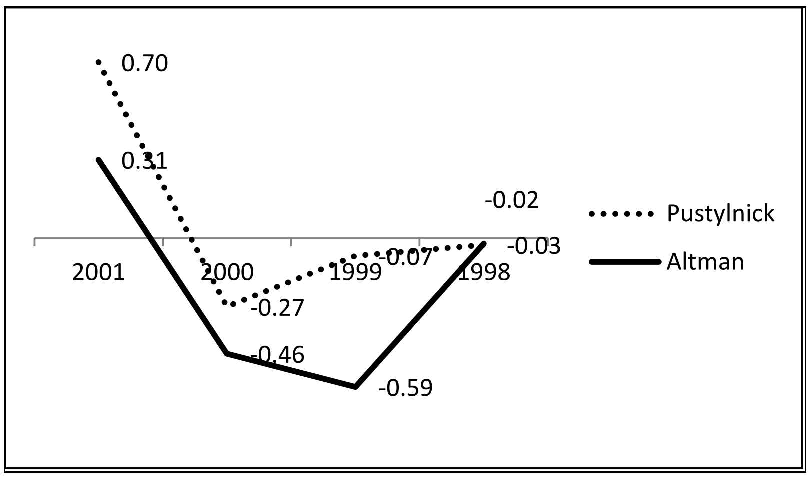


Figure 2: American Electric rates of growth for P-Score and Z-Score



REFERENCES

ACFE. (2008). *2008 Report to the Nation on Occupational Fraud and Abuse.* New York: ACFE.

Agrawal, A., & Chadha, S. (2005). Corporate Governance and Accounting Scandals. *Journal of Law and Economics*.

Altman, E. (1968). Financial Ratios, Discriminant Analysis and the Prediction of Corporate Bankruptcy. *Journal of Finance*.

Beneish, M. (1999). The Detection of Earnings Manipulation. *Working Paper Series, Kelley School of Business, Indiana University*.

Beneish, M. (2001). Earnings Management: A Perspective. *Managerial Finance*, 27(12), 3-17. doi:10.1108/03074350110767411

Colloff, M. (2005). The Role of the Trustee in Mitigating Fraud in Structured Financings. *The Journal of Structured Finance*, 10(4), 73-80. doi:10.3905/jsf.2005.470601

Debreceny, e. a. (2005). Financial Reporting in XBRL on the SEC's EDGAR System: A Critique and Evaluation. *Journal of Information Systems*, 19(2) 191-210.

Debreceny, R., & Gray, G. (2001). The production and use of semantically rich accounting reports on the Internet: XML and XBRL . *International Journal of Accounting Information Systems*, 2(1), 47-74.

Dechow, P. M., Ge, W., Larson, C. R., & Sloan, R. G. (2010, May 24). *Predicting Material Accounting Misstatements*. Retrieved March 30, 2011, from SSRN: http://papers.ssrn.com/sol3/papers.cfm?abstract_id=997483

Grazioli, S., Johnson, P., & Jamal, K. (2006, January 3). *A Cognitive Approach to Fraud Detection*. Retrieved April 25, 2011, from SSRN: http://papers.ssrn.com/sol3/papers.cfm?abstract_id=920222

Hogan, C., Rezaee, Z., Riley Jr., R., & Velury, U. (2008). Financial Statement Fraud: Insights from the Academic Literature. *AUDITING: A Journal of Practice & Theory*, 27(2), 231. doi:10.2308/aud.2008.27.2.231

James, K. (2003). The Effects of Internal Audit Structure on Perceived Financial Statement Fraud Prevention. *Accounting Horizons*, Vol. 17.

Kirkos, E., Spathis, C., & Manopoulos, Y. (2007). Data Mining techniques for the detection of fraudulent financial statements. *Expert Systems with Applications*, 32(4), 995-1003. doi:10.1016/j.eswa.2006.02.016

KPMG. (2004, April 03). *Welcome to XBRL Instance and Taxonomy Documents*. Retrieved May 05, 2011, from XBRL Learning Tutorials: http://www.us.kpmg.com/microsite/xbrl/train/86/86.htm

Lee, T., Ingram, R., & Howard, T. (1999). The Difference between Earnings and Operating Cash Flow as an Indicator of Financial Reporting Fraud. *Contemporary Accounting Research*, 16(4), 749-786. doi:10.1111/j.1911-3846.1999.tb00603.x

Lenard, M., & Alam, P. (2009). An Historical Perspective on Fraud Detection: From Bankruptcy Models to Most Effective Indicators of Fraud in Recent Incidents. *Journal of Forensic & Investigative Accounting*, Vol 1, Iss 1.

Li, S., & Pinsker, R. (2008). Costs and benefits of XBRL adoption: early evidence. *Communications of the ACM*, 15(3). doi:10.1145/1325555.1325565

Maize, K. (2003). Opening up energy trading. *Spectrum, IEEE*, 40(1), 54-58.
Nalimov, V., & Chernova, N. (1965). *Statistical Methods of Planning Extreme Experiments.* Moscow: Nauka Publishing.

Pinsker, R. (2003). XBRL awareness in auditing: a sleeping giant? *Managerial Audit Journal*, 18(9), 732-736. doi:10.1108/02686900310500497

Pustylnick, I. (2009, June 19). *Combined Algorithm for Detection of Manipulation in Financial Statements* . Retrieved March 30, 2011, from SSRN: http://papers.ssrn.com/sol3/papers.cfm?abstract_id=1422693

Pustylnik, E. (1968). *Statistical Methods for Analyzing and Processing of Observations.* Moscow: Nauka Publishing.

Rezaee, Z. (2002). *Financial Statement Fraud. Prevention and Detection.* Hoboken, NJ, USA: John Wiley and Sons.

Rezaee, Z. (2005). Causes, consequences, and deterence of financial statement fraud. *Critical Perspective on Accounting*, 16(3), 277-298. doi:10.1016/S1045-2354(03)00072-8

Skousen, C. J., & Wright, C. J. (2008, August 21). *Contemporaneous Risk Factors and the Prediction of Financial Statement Fraud*. Retrieved March 30, 2011, from SSRN: http://papers.ssrn.com/sol3/papers.cfm?abstract_id=938736

Stalebrink, O., & Sacco, J. (2007). Rationalization of financial statement fraud in government: An Austrian perspective. *Critical Perspectives on Accounting*, 18(4), 489-507. doi:10.1016/j.cpa.2006.01.009

Summers, S., & Sweeney, J. (1998). Fraudulently Misstated Financial Statements and Insider Trading: Empirical Analysis. *The Accounting Review*, 73(1), 131-146.

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