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Empirical Algorithm of Detection of Manipulation with Financial Statements

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This paper introduces a new approach to the detection of manipulations with the data in the financial statements. We observe the dynamics of Altman Z-Score over the period of 5 years and compare it with the dynamics of change of the complementary P-Score, formula for which is introduced in the paper. We find that in 82% of the cases the positive differential between the rate of change of P-Score and the rate of change of Z-Score coincides with the year when the company was charged with statement fraud. We think that this criteria can be effectively used for primary detection of manipulations with financial statements. The described algorithm uses data, which can be easily found in the financial statements of the companies using US GAAP

JEL Codes: M41, M42

1. Introduction

The report on fraud issued by Deloitte Forensic Center in 2008 (Deloitte 2008) states that during the period 2000-2007 Securities and Exchange Commission (SEC) issued 383 Accounting and Enforcement Releases (AAER) for US companies. Examining the trend we can see that after 2001, when the most glaring cases were discovered, there is no significant decrease in the number of the discovered cases. The same report states that average discovery time for the manipulations with financial statements is 4.7 years and the longest lasting fraud was perpetrated over the span of 18 years.2008 ACFE report on fraud (ACFE 2008)states that major sources of fraud discovery are still internal tips at 46% of all cases and accidental discovery at 20%.Therefore practically 2/3 of all cases are still being discovered by the non-computational means. The research upon which the ACFE report was built was conducted when both Statement of Auditing Standards No.99 (issued by AICPA) and Sarbanes-Oxley Act were already accepted and the majority of actions stipulated by these documents have already been implemented. While both documents were important instruments in combating and preventing fraud, the dynamics of fraud discovery has not changed dramatically after their issuance and acceptance.

The roots of fraud are often sought in the environmental factors surrounding particular cases. (Dunn 2004) associates the concentration of power with fraud in financial reporting. (Beasley 1996) attributes high fraud potential to board of director's composition. The research efforts of (Abbott, Park & Parker 2000) and (Abbott & Parker

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2001) show that there is a direct link between the independence of auditing committee and the abilities of auditors to discover fraud.

The annual Deloitte report(Deloitte 2008), connecting fraud and bankruptcy also shows that for the company on the verge of bankruptcy there is much higher probability to be engaged in the fraudulent activities. These findings link bankruptcy to the state of corporate health, established by (Altman 1968) in the form of corporate health score or Z-Score.(Beneish 1997)links possibility of manipulation in the financial statements with various variables of the corporate financial statements. He created series of indicators of manipulation in financial statements.(Beneish 1999) establishes a comprehensive probability manipulation function PROBM, which he uses to detect manipulations with financial statements. Further (Skousen & Wright 2008)establish a more comprehensive formula, which includes other factors, which contribute to the pressure of committing fraud. Any single manipulation criteria existing today would detect no more than 50-70% of all cases. There is also a possibility that any formula would be geared towards prediction of a certain type of fraud.

The volatile nature of business changes the ways in which manipulation with financial statements is committed. The goal of this paper is to give the auditing practitioner a set of tools, which would be able to raise the probability of detection of fraud to the maximum possible level. Previous research clearly indicates that it would not be possible to use one single tool for this detection. The main objective of this study is to use the set of financial tools for prediction of corporate health and manipulation with financial statements and to show that using combination of these tools will raise the possibility of detection.

The secondary objective of this study is to segregate the set of financial variables, which could be obtained in the financial statements of public companies. It is very important for the practicing auditor to have the set of tools, which is not only finite, but can be clearly identified. Therefore this study forgoes some of the new research in order to maintain simplicity and transparency of the set of variables. The remainder of the paper is structured as follows: we present a literature review followed by the introduction of the sample and the discussion of the observed results. The paper ends with conclusions and the recommendations for further research and the limitations of the present study.

2. Literature Review

Despite the abundance of journal articles on fraud in financial reporting, the majority of them describes and classifies the existing cases of fraud. (Rezaee 2002) was the first large work following the aforementioned financial scandals. It was the first attempt on comprehensive itemization of the fraud cases. It was followed by (Rezaee, 2005) where the author concentrated on recommendations on how to prevent the cases of fraud. (James 2003) attempts to conect deterrence of fraud with internal financial controls. (Stalebrink & Sacco 2007) find similar fraudulent trends in Europe while exploring the financial practices of the Austrian government.

The older paper by (Lee, Ingram & Howard 1999) shows the potential correlation between the discrepancy between Earnings value in the Income Statement and Cash Flow value in the Statement of Cash Flows as a potential indicator of manipulation. (Grazioli, Johnson & Jamal 2006) build a cognitive theory of successful fraud detection. They claim that establishing of patterns of inner workings of the enterprise and the managerial behaviour would help identifying the deviations from the established patterns, which in turn lead to the financial fraud. (Skousen & Wright 2008) attempt to create a manipulation detection mechanism, which would be able to detect financial statement manipulation. However, they use several variables, which are not publically available thus limiting the discovery mechanism to the internal audit, which would have access to the internal company data. (Dechow et al. 2010) undertook a very comprehensive research, which involved over 2000 AAER statements from SEC. The statistical analysis was based on over 100 variables many of which may not be available to the general public.

(Levi 2008)in his book points out the connection between financial fraud and bankruptcies. He states that companies commit fraud by having no intention of maintaining a normal mode of operation. The bankruptcies are often a logical extension of the on-going misappropriation and mismanagement of firm’s funds. Works of (Altman 1968)and (Altman, Haldeman & Narayanan 1977)on quantification of corporate financial health were the first step in the direction of determining of the true financial state of the company by using financial ratios as indicators of corporate financial health.(Nugent 2003) uses a modified Altman Discriminant Score in the following format:

$$Z = 1.2 * X1 + 1.4 * X2 + 3.3 * X3 + 0.6 * X4 + 1.0 * X5, where$$
$$X1 = \frac{Working\ Capital}{Total\ Assets},$$
$$X2 = \frac{Retained\ Earnings}{Total\ Assets},$$
$$X3 = \frac{EBIT}{Total\ Assets},$$
$$X4 = \frac{Market\ Value\ of\ Equity}{Book\ Value\ of\ Total\ Debt},$$
$$X5 = \frac{Net\ Sales}{Total\ Assets}$$

(Nugent 2008)further adjusts the weight assigned to X4 relative to declines in gross margin under the assumption that as gross margin declines, debt service becomes significantly more onerous. The figures, used in this modified Altman formula can be found in or derived from the balance sheet or the statement of income provided within the US 10-K submissions to SEC prepared in accordance with US GAAP. *Working Capital* is the difference between current assets and current liabilities. *Earnings before Income Taxes (EBIT)* can be found in the statement of income. This value is used as an indicator of pre-tax real earnings of the company as opposed to net income. *Market Value of Equity* is the value of all outstanding company’s shares at market value at the date of the issue of the financial statements. *Book Value of Total Debt* is the sum of all liabilities (not equities) as they are recorded in the balance sheet. *Net Sales* figure can also be found in the statement of income.

Altman's Discriminant Function shows the proportion of all non-liability elements to the total assets. (Altman 1968) predicted that the higher the weighted sum of these ratios, the better the company health is. The absolute number of Z-Score can be very telling if compared with the other companies in the industry. However, we consider that the best approach to using Altman's Modified Z-Score is to perform score comparison over the number of years.

Altman's method has also a number of drawbacks. It must be used with a degree of caution when applied to firms from different industries. Companies in different industries have different degrees of capitalization and different liquidity needs(Kaplan & Peterson 1998).It would be unreasonable to compare Z-Scores of the companies from software development industries, where capitalization is relatively low, according to(Nowak & Grantham 2000), with oil and gas industries, which have to capitalize all exploration and refinery equipment and operations(Lilien & Pastena 1982). Altman has developed several Z-Score formulas for different industries in order to mitigate this problem (Altman 1996). However, (Nugent 2008) finds another drawback of the Z-Score approach because the degree of entity asset wealth can mitigate Altman's time line. It means that Altman Z-Score may not show us the whole picture of the company's state, but only the numbers, included in the calculations. One must not make an assumption over the entity's performance based on Altman Z-Score alone. (Nugent 2008) recommends that for obtaining the full picture the Modified Z-Score should be used in conjunction with other tools.

Altman Z-Score is created to measure the corporate financial health. Therefore it uses two important net worth indicators, which are Net Sales (Net Income) and Working Capital, which clearly show the financial position of a firm in terms of its robustness and solvency. The study by (Kirkos, Spathis & Manopoulos 2007) establishes that the use of data mining of financial information over the prolonged period of time can reveal the pattern of manipulation. These findings echo the works of (Beneish, 2001) where the ratios established in (Beneish, 1999) were observed over the period of two years. (Harrington 2005) states, that Beneish ratios are a very good tool for initial detection of fraud in the financial statements. However, she also admits that the accuracy of detection of fraud by using PROBM is about 50%. It means that using financial ratios alone may not be sufficient for fraud detection. Perpetrators of fraud familiar with the work of Beneish can adjust the financial statements so that they "comply" with the ratio values.

(Lenard & Alam 2009) make a connection between corporate bankruptcy and financial statements, which in turn proves that the Altman Z-Score (Altman 1968) can be used as an indicator of the manipulation of financial statements.

3. Method and Hypothesis

As it was stated earlier in the paper, the existing methods of detection of the manipulations of the financial statements have the following problems:

- The methods, having a high detection rate, are using the variables, which are not available through the company's public statements.
- The methods based on the publicly available variables have very low detection rate (50-60%)

The initial goal of this study was to answer a research question: "Is it possible to improve the detection rate for manipulations of financial statements by using only publicly available variables?"

According to (Deloitte 2008) over 50% of the cases of manipulation are based on improperly recognized revenue or manipulation with non-current assets such as good will. We created a complementary formula based on Altman's Z-score equation. This new score, called P-Score, performs similar calculations to Z-Score using Revenue and Shareholders Equity instead of Net Income and Working Capital respectively. Calculation of the P-Score is performed in the following way.

$$P = 1.2 * X1 + 1.4 * X2 + 3.3 * X3 + 0.6 * X4 + 1.0 * X5, where$$

$$X1 = \frac{\boldsymbol{Shareholders\ Equity}}{Total\ Assets},$$

$$X2 = \frac{Retained\ Earnings}{Total\ Assets},$$

$$X3 = \frac{EBIT}{Total\ Assets},$$

$$X4 = \frac{Market\ Value\ of\ Equity}{Book\ Value\ of\ Total\ Debt},$$

$$X5 = \frac{\boldsymbol{Revenue}}{Total\ Assets}$$

The singular values obtained through calculations of P-Score and Z-Score yield very little new information. However, the observation of these values over the period of five years has shown that the graphs of P-Score and Z-Score had different slope angles (See graph in Appendix).

Practically all of the companies included in the sample are mature enterprises. For a mature enterprise with the established production cycle we expect the slopes of P-Score and Z-Score to be practically identical. Observing the significant difference has lead us to the conclusion that additional information can be obtained by comparing the rate of change of P and Z values at the periods when manipulations occurred. In order to quantify the results we introduce two new variables.

$\Delta P = \frac{P_t - P_{t-1}}{|P_{t-1}|}$, 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

During the initial observation it was noticed that at the periods preceding the charges of fraud for many companies the slope of P-Score was significantly steeper than the slope of Z-Score. As a result of these observations, we introduced the following hypothesis: *During the periods of the manipulations with the financial statements ΔP > ΔZ is true for all statements where manipulation occurred.*

4. Sample and Observations

The method introduced in the previous section requires collecting a number of variables from the financial statements, which are required to be present in accordance with US GAAP. The following table shows the list of the required variables and the statements they can be found in.

Table 1: Variables Used in Calculation

Variable	Statement
Total Assets	Balance Sheet
Total Liabilities	Balance Sheet
Retained Earnings/Accumulated Deficit	Balance Sheet
EBIT	Income Statement
Total value of shares	Balance Sheet
Operating Expenses	Income Statement
Current Liabilities	Balance Sheet
Total Receivables	Balance Sheet
Revenue	Income Statement
COGS	Income Statement
PP&E	Balance Sheet
Depreciation and Amortization	Cash Flow
Long Term Debt	Balance Sheet
Current Assets	Balance Sheet
Net Income/Loss	Income Statement

This table shows the main variables used the calculation of P-Score and Z-Score and points to the financial statements, where these variables must be stored according to US GAAP

In the selection of the sample we considered the companies, which were indicted with financial statement fraud by SEC. It is important to note that finding the alternative pool of ‘clean’ companies is not possible. According to (Deloitte 2008) the average fraud discovery time can be 5-6 years and the longest period between the commission and the discovery of fraud was 18 years. Therefore we argue that any company not yet indicted with fraud may be found guilty later when the new facts come to life.

Since the nature of this study was to discover the common elements in the known cases of fraud the sample of the companies (listed in Table 2) contained 29 companies with known history of fraud charges. In the process of observation we compared the occurrence of positive ΔP-ΔZ with the years when the charges were laid by SEC through issuing AAER statements.

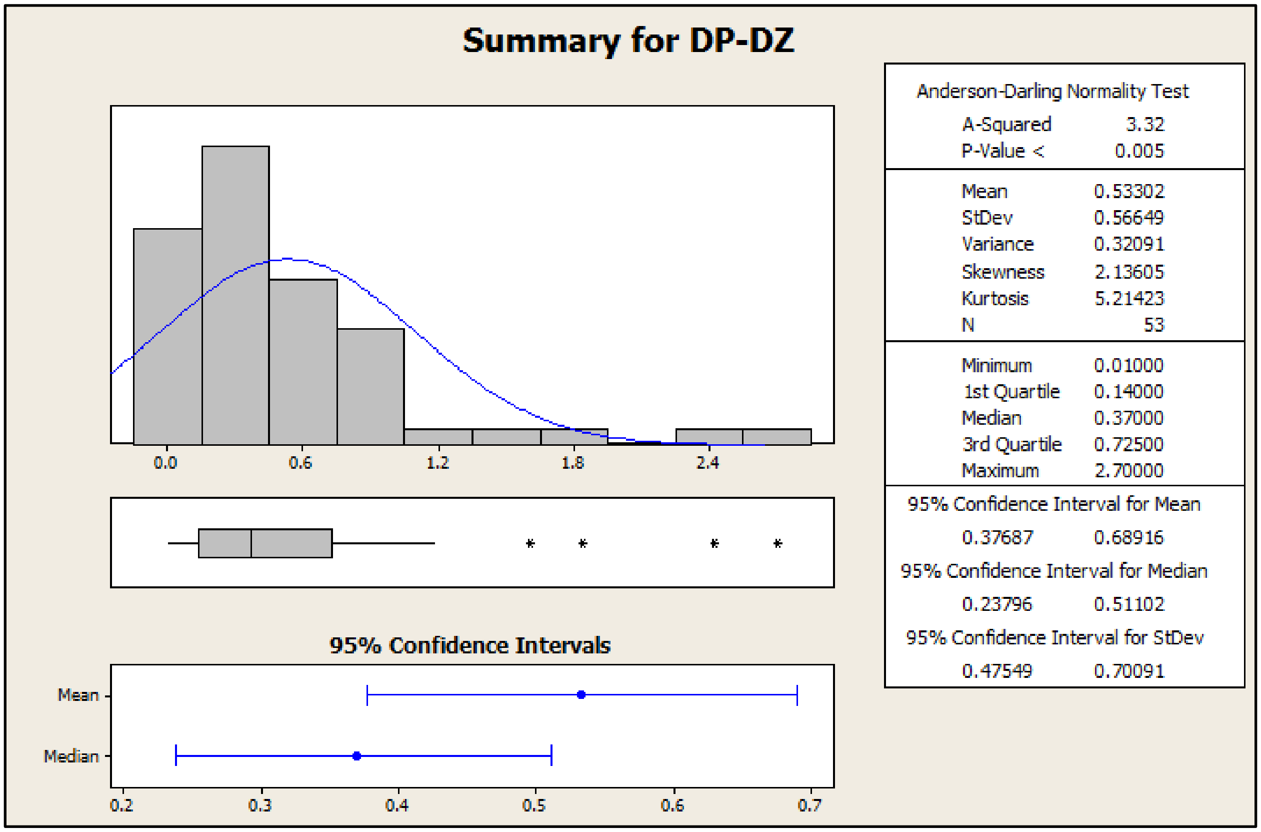
Table 2: Companies Charged with Fraud

Company	Year ofCharge	Detection Year	ΔP > ΔZ
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 lists the companies charged with fraud, the year of charge and the first year when the similar pattern was discovered.The X in the last column shows that the criteria stated in the hypothesis was met.

Based on the data, obtained for the following companies we conducted a simple statistical analysis, which is summarized in the Figure 1. The sample of data includes the values for the variables, listed in Table 1 over the period of 5 years. The sample was reduced for those companies where data was not available for all five years. The sample data and the sample graphs are provided in the Appendix.

Figure 1: Descriptive statistics for ΔP-ΔZ distribution



The analysis of the sample distribution shows that the majority of cases lie in 0.1 – 0.6 interval. The sample does not follow the normal distribution, which was expected before the observation occurred. However, the fact that median and mean are close to each other leads us to believe that the findings correlate with the initial predictions. The shape of the distribution also leads us to believe that by removing the most 'glaring' cases we can bring the sample to adhering to the normal distribution.

The observation of the sample and the number of positive cases confirm the main hypothesis of the paper that positive values ΔP-ΔZ indicate the presence of manipulations with the financial statements. We suggest that any result calculated for the arbitrary company, which produces a number higher than the median (0.37), indicates that the statements of the company were manipulated.

5. Discussion

Manipulations with the financial statements have become a common element of corporate financial life. The 2008 Deloitte report on fraud (Deloitte 2008)shows that fraud figures do not decrease despite all efforts put into fraud prevention by the companies, such as implementation of the recommendations of the Sarbanes-Oxley Act. The report shows that in 2007 SEC issued 45 new AAER statements. It also shows that average length of fraud detection had increased from 5.8 to 6.3 years. The techniques of uncovering fraud, presented in this paper have the potential to greatly reduce the amount of time, required to detect financial statement manipulations.

Decreasing the length of fraud discovery has a large socio-economical effect on our society in general. Unlike the internal fraud, such as asset misappropriation or kickbacks, the manipulations with financial statements are directed towards the deceit of the unsuspecting investors, both private and corporate. These investors often continue to invest into a “sinking ship” of an organization, such as the US Unify Corporation or a company, which thrived on lies and deception such as the US Enron Corporation. Stopping these companies from deceiving investors would have caused redirection of the investments into healthy organizations, which may not be as profitable but would have produced stable results.

(Deloitte 2008) also states that in the aftermath of fraud detection many companies suffer great financial hardship. Companies see decline in their stock prices and appear on the verge of bankruptcy. It is important to distinguish between the companies like Enron, which resorted to producing totally fraudulent statements, and the companies, which may have only erred once, such as Reliant or Xerox. Doling equal punishment to both kinds of companies can be detrimental for economy as a whole.

Auditors must also be able to distinguish fraudulent statements from the statements of the company which experiences rapid growth and/or rapid decline. At the beginning of the 21st century many organizations rushed to become public companies and issued IPO while still remaining in entrepreneurial stage of their development (Martens 2004). During this stage rapid growth is possible, which causes natural high increases in revenue (Quinn & Cameron 1983). These leaps of growth can be fraudulent in nature but can also be a result of natural growth activities.SEC and regulatory agencies in other countries can either exercise discretion towards these companies or deny IPO to the companies whose financial activity has not yet stabilized.

The mechanisms described in this work can become an effective tool, pointing auditors in potentially right direction by detecting manipulation in financial statements. However, the described method is probabilistic by nature. It can warn auditors that fraud is more likely in the statements of particular companies. The auditors still need to perform extra work in order to confirm the conditions detected by the described algorithm.

Fraud is a legal term and people and/or organizations can be charged with fraud only through the discovery and the presentation of the material evidence or a lack of thereof. It is important to note though, that a large number of fraud cases today are discovered via non-financial means, such as internal tips, police work on unrelated matters, hotline calls and so on. This mechanism if properly implemented may reduce the dependence of SEC and other regulatory agencies on chance and tips in initial discovery of fraud.

6. Conclusions and Limitations

SEC and Canadian Securities Administration (CSA) embrace Extended Business Reporting Language (XBRL) as new standard of automated financial reporting. At the present time the statements, submitted to SEC and CSA have very loose presentation format, which does not obligate submitting companies to calculate the numbers, for the parameters, used in this research. By mandating the use of XBRL both agencies are forcing companies to supply these parameters in the explicit manner. If the company has multiple elements, such as receivables from different sources, XBRL has the capability to group these elements so that the full amount of receivables can be calculated. The same principle can be applied to any of the financial parameters, used in this research.

The previous paragraph describes how the mechanism can be implemented based on the inbound XBRL stream, which agencies receive. At the same time SEC and other government agencies can form an outbound stream, which may be used by the participating companies (such as Investing or Brokerage houses) in order to receive the financial information to be used in their internal calculations. It should be possible for private mutual or equity funds to make their own decisions based on the same mechanism without waiting for the formal charges of fraud laid by the government agencies. These charges may take a long time to be confirmed by a formal audit. Independent decisions by the funds will allow them to protect their capital during the period of audit.

The mechanism of fraud detection presented in the paper has the following limitations, which must be considered during its implementation:

- The statements of the company examined by using this method must adhere to the rules similar to the US GAAP. The reporting rules in the different countries permit omissions of such important parameters as Cost of Goods Sold (Italy)and Accounts Receivable (India)
- Irregularities in the financial statements must be material. If the company with multi-billion revenue figures has several millions in unsubstantiated revenue, this mechanism would not be able to conclusively detect it. In order to obtain conclusive results this work used an established threshold, set by baseline calculations. It is possible for the users of the detection mechanism to lower the threshold and obtain better detection. However, the probabilistic nature of the described detection mechanism would preventthe results obtained in this manner to be considered conclusive.

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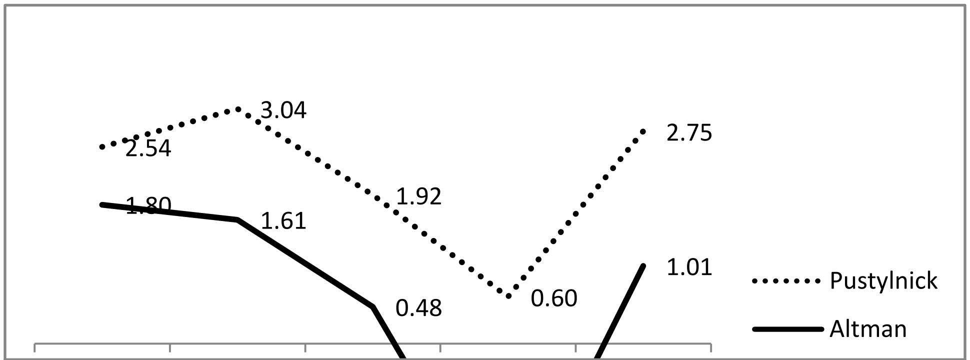
APPENDIX

Sample of data, obtained from SEC EDGAR Web Site for AOL

Fields	2000x1M	1999x1M	1998x1M	1997x1K	1996x1K
Total Assets	$10,673.00	$5,348.00	$2,214.00	$846,688.00	$958,754.00
Total Liabilities	$4,512.00	$2,315.00	$1,616.00	$718,654.00	$446,252.00
Retained Earnings	$1,346.00	$151.00	$451.00	$110,107.00	$511,575.00
EBIT	$2,014.00	$1,096.00	$92.00	-$449,347.00	$62,339.00
total_share_price	$ 4,815.00	$2,882.00	$2.00	$1,103.00	$927.00
Sales Op. Expenses	$5,488.00	$4,319.00	$522.00	2,190,874.00	$1,028,611.00
Current Liabilities	$2,395.00	$1,725.00	$894.00	$554,470.00	$289,906.00
AR	$ 532.00	$285.00	$196.00	$91,399.00	$72,613.00
Revenue	$4,400.00	$4,777.00	$2,600.00	$1,685,228.00	$1,093,854.00
COGS	$3,458.00	$2,657.00	$1,678.00	$1,040,762.00	$627,372.00
PP&E	$ 991.00	$657.00	$363.00	$233,126.00	$101,277.00
Depreciation	$287.00	$374.00	$132.00	$64,572.00	$33,366.00
Long Term Debt	$2,117.00	$590.00	$722.00	$164,184.00	$156,346.00
Current Assets	$4,428.00	$1,979.00	$930.00	$323,473.00	$270,529.00
Net Sales	$1,398.00	$458.00	$78.00	-$505,646.00	$65,243.00

Pustylnick

Graph of P-Score and Z-Score calculations over the given years



Graph of ΔP and ΔZ calculations over the given years