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Comparison of liquidity based and financial performance based indicators in financial analysis

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Keywords: *earnings management; financial statement fraud; revenue manipulations; M-Score; Z-Score*

Abstract
Research background: Since the turn of the 21st century financial statement manipulations became the center of attention for accountants, auditors and financial analysts. Since being classified by the regulators as fraudulent, earnings management has required a separate detection methodology. The majority of detection research is performed through the comparison of a large number of statements for the same company in order to find irregularities in earnings behavior. Shortening of the detection time and the amount of data becomes important.
Purpose of the article: The goal was to compare the characteristics of M-Score and ΔP-ΔR and to find their advantages and limitations. Applying both indicators to the different samples, the research attempted to determine the statistical connection between them and to set up the limits of their applicability. Since M-Score indicator is liquidity-based, this research attempted to determine to which extent M-Score and Z-Score are statistically related.
Methods: The research paper compares the behavior of both indicators using various samples of financial data: the sample of companies, charged with fraud, the sample with exceptional liquidity, the large random sample and the sample from the emerging market economy. Based on the original observations, two other subsamples (one based on poor Z-Score and one based on exceptional Z-Score) were extracted from the main sample. For all sam-

ples ΔP-ΔR, M-Score and Z-Score were statistically compared among and between themselves.
Findings & Value added: The research found the limitations of ΔP-ΔR and M-Score in the stable markets and was able to connect them in the emerging market by using linear regression model (also including Z-Score). The research confirmed that M-Score can mistake exceptional performance for manipulations, resulted in Type I errors. ΔP-ΔR appeared somewhat coarse and prone to Type II errors. The combined use of both in the emerging markets will provide the best approach.

Introduction

Traditionally, financial statement fraud remains a major concern of accountants and auditors. During the steady economic periods, the instances of financial statement fraud rarely present a major economic concern. However, in the periods of upward and downward economic turmoil the companies "play with" financial statements in order to catch up with the current marketing conditions (Fich & Shivdasani, 2007). The unstable conditions of the financial markets create higher demand for the accounting efforts, which are called "creative accounting" or "earnings management" (Cormier & Martinez, 2006).

The commonly used approach of determining the presence of earnings management in the financial statements was set by Healy (1985) and Jones (1991). The researchers looked at the financial statements of a single company compiled for a significant period of time and made an observation whether the company deviates from a linear accrual pattern. Any deviation was considered as a manifestation of deliberate earnings management resulting in appearance of so-called discretionary accruals.

The described approach produced tangible results, which are discussed in detail in the accounting research journals (Dechow *et al.*, 1995; Jansen *et al.*, 2012). From the practical perspective, such way of determining, whether earnings management is present in the financial statements of an organization, was not feasible. The investment analysts, financial analysts and auditors never possess the required volume of historical data, required to perform a proper analysis of the presence of earnings management in the financial statements.

A frequently cited survey by Bruns and Merchant (1990) illustrates the practitioners' view on the phenomenon of earnings management. The survey shows that the managers of the company consider using earnings management acceptable when the immediate conditions warrant such approach. The review of the earnings management criteria set by U.S. SEC, provided by Dechow and Skinner (2000), shows that the financial regulators view earnings management as an immediate action, which requires immediate consequences and, if required, a swift punishment.

One of the most significant efforts of shortening the amount of information, required for detection of the presence of earnings management, was presented by Beneish (1997). The cumulative indicator, called M-Score or PROBM has been used in many different research efforts to establish the presence of manipulations with financial statements, out of which earnings management is the likeliest one (Franceschetti & Koschtial, 2013; Tarjo, 2015).

From the practical perspective, the use of M-Score gives a lot of advantages because Beneish used the data from two adjacent years, rather than over 10 years as in the research of Jones, to create the set of financial indicators comprising M-Score equation. The goal of the research by Beneish was to determine whether extreme performance of the examined firms is due to their use of exceptional business practices or due to the extreme earnings management, which can be constituted as fraud.

The theory of earnings management distinguishes, according to McKee (2005), two different types, namely upward earnings management, designed to create exceptional earnings results by concealing or refactoring expenses, and downward earnings management, the goal of which is to decrease earnings results to minimize the tax burden (Dyreng *et al.*, 2010). It appears that the goal of the majority of the research efforts in the area of earnings management has been directed predominantly towards establishing the presence of upwards earnings management. However, the researchers and, especially the practitioners, often use the formulas like the one for M-Score without full understanding of their potential limitations. This type of use of the tool leads to a large number of Type I errors (the presence of earnings management is falsely undetected).

The research started in 2016 (Pustylnick, 2016) takes the same approach as the one used by Beneish. The data from two adjacent years was taken to create an indicator of earnings management ΔP-ΔR, which can work for both upward and downward earnings management. One of the goals of this paper was to compare M-Score with the new indicator and assess their compatibility and ability to interchange one with another.

In order to achieve this, the research examines the components of M-Score formula and applies statistical methods which are designed to determine the limitations of M-Score and the mentioned new indicator. The rest of the paper is structured in the following manner: it will present the methods used in this research and will discuss the results obtained based on these methods. The paper will provide the conclusions, which are based on the current research effort, and the directions in which the research may be continued or extended.

Research methodology

In this paper, we use the original Beneish formula as provided in (Beneish, 1997). Obviously, there are a number of variations which were created later in the research process, but they do not change the original intention of the author.

$$M = -4.84 + 0.920 * DSRI + 0.528 * GMI + 0.404 * AQI + 0.892 * SGI + 0.115 * DEPI - 0.172 * SGAI + 4.679 * TATAI - 0.327 * LEV \quad (1)$$

The indicator variables, included in the formula are the extensively used financial ratios, which are well known to the accountants and financial analysts: *DSRI* — days sales in receivables, indicating how much time it takes to convert the sales into cash, *GMI* — gross margin, representing a ratio of gross profit to revenue, *AQI* — asset quality ratio, showing the percent of non-capital assets in the total assets, *SGI* — sales for the current year, *TATAI* — working capital without depreciation in relation to assets, *DEPI* — ratio of depreciation to capital asset value, *SGAI* — ratio of operating expenses to revenue, *LEVI* — *t*otal debt to assets ratio.

The formula uses the ratios of variables in the adjacent years presented as X_T/X_{T-1}, where X is the variable and T represents the year for which the variable was calculated. Beneish set up the separation threshold for the companies, engaged in the high-performance fraud and the companies, performing in regular fashion as M-Score = -1.78. The companies having higher M-Score are, according to Beneish, more likely to be engaged in earnings manipulation fraud then the companies, which have M-Score below the threshold.

According to Beneish, the indicators must be close to one, or deviate from that figure slightly for all companies which exhibit normal (financially healthy) performance. If this is indeed the case, then the factors, influencing the final result the most, are Revenue(Sales), Working Capital and Gross margin. This observation leads to the conclusion that the companies with the extreme performance must have the highest possible liquidity, calculated via Z-Score defined by Altman (1968).

$$Z = 1.2 * X1 + 1.4 * X2 + 3.3 * X3 + 0.6 * X4 + 1.0 * X5 \qquad (2)$$

where:

$$X1 = \frac{Working\ Capital}{Total\ Assets},$$

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

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

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

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

According to Altman, the higher the Z-Score of the companies, the better the overall liquidity, which is based on the same accounting variables used by Beneish. Altman sets up Z-Score = 3 as the threshold of healthy performance and Z-Score = 1 as the threshold for proximity to bankruptcy. Since Beneish established M-Score equation for the companies with extreme performance, it is possible to formulate the following hypothesis:

H1: The companies with healthy liquidity Z > 3 have M-Score > -1.78 regardless of their involvement in financial fraud.

The procedure of rejection of the null hypothesis can be performed by using the method of series, described in (Pustylnik, 1968). Based on this method, any number of random occurrences of a certain event must stay within an interval, described by the formula 3.

$$\omega - u_{1-p/2}\sqrt{\frac{\omega(1-\omega)}{n}} \leq p \ \leq \omega + u_{1-p/2}\sqrt{\frac{\omega(1-\omega)}{n}} \qquad (3)$$

Here, u is a quantile of normal distribution with required significance p, ω is the estimated random frequency and n is the total number of observations. For the hypothesis H1, the event Z > 3 can be considered given and the frequency of M > -1.78 can be considered absolutely random, occurring with the probability 0.5.

Coincidental appearance of M-Score and Z-Score values in a certain range warrants exploring another indicator of earnings management ΔP-ΔR, which was defined in (Pustylnick, 2016) as a difference in the rates of change of Perceived Wealth, calculated as:

$$P = 0.367 * Y_1 + 0.980 * Y_2, \tag{4}$$

where:

$$Y_1 = \frac{Shareholders\ Equity}{Total\ Assets}, Y_2 = \frac{Revenue}{Total\ Assets}$$

and Real Liquidity, defined as:

$$R = 0.150 * X_1 + 0.924 * X_2, \tag{5}$$

$$X_1 = \frac{Working\ Capital}{Total\ Assets}, \quad X_2 = \frac{Operating\ Income}{Total\ Assets}$$

Here rates of change for P and R are calculated as:

$$\Delta P = \frac{P_t - P_{t-1}}{|P_{t-1}|} \tag{6}$$

$$\Delta R = \frac{R_t - R_{t-1}}{|R_{t-1}|} \tag{7}$$

for current year (t) and prior year (t-1).

The development of the indicator ΔP-ΔR was based on superimposition of two samples: one compiled of the companies, which were charged with the fraud in financial statements by the U.S. SEC, having low average Z-Score ≤ 1, and another sample of the companies, compiled in (Escalada, 2011) based on them having high average Z-Score > 3. Since the hypothesis H1 uses the same liquidity threshold, it is important to compare ΔP-ΔR and M-Score and determine how these indicators relate to each other.

Data samples

The research uses several data samples for the verification of effects of M-Score and ΔP-ΔR. One of the samples represents the set of financial data, obtained from the companies, charged with revenue manipulations by the U.S. SEC. There are 31 companies in the sample, which fit the desired criteria. For each company, the data was collected over a five-year span when the infractions occurred. In the public AAER, issued by U.S. SEC, the range of periods, in which manipulations occurred, are specified. The five-year span allowed for including all periods of infractions with high degree of certainty. The data was manually collected from the web presentation of Edgar database.

The second sample of data is the set of companies taken from the web page, provided by Escalada (2011). All companies of the sample have extremely high Z-Score > 3. The data for each company was collected using five-year period. The data was also collected from Edgar database. Few researchers, including San Miguel (1977), expressed reservations about the accurateness of COMPUSTAT database, commonly used for the financial research involving multi-year financials. Therefore, the data for this sample was also collected by hand. The sample contained observations for 10 companies with five years of observations for each of them.

The third sample is a large set of financial data from the companies, submitting data in XBRL format to the same Edgar database. The choice of XBRL over COMPUSTAT was made based on the previously mentioned concerns by San Miguel as well as more recent observations by Chychyla and Kogan (2013), who also state that the data, submitted in XBRL format differs from the data obtained from COMPUSTAT for the same company and the same year of observations. Since any manual extraction of the data would use the financial figures found in Edgar Database, XBRL data would be close to what average observer would see at U.S. SEC website.

In examining XBRL based data, there was also an effort made to eliminate the exceptions, which were created by the submission errors. The overly high and low numbers were eliminated. There was also a need to eliminate the financial statements, which lacked the data required for calculation of indicators, included in M-Score equation. The most notable exceptions include the lack of separation between operating expenses and cost of goods sold as well as omission of certain liabilities, such as current portion of debt, etc. Out of 3500 entries considered for the large sample only roughly 1200 were used in this research. Apart from using a large random sample, the subsets of this sample were also used to mimic the behavior of first two samples. These subsets were created by using Z-Score as a main criterion, examining the entries with Z-Score > 3 and Z-Score < 1.

Another sample which was used in this research is the sample of the financial data from a country with developing economy and emerging market system. Several research efforts published in the recent years used M-Score to determine the amount of fraud in the financial statements from the public companies registered in such jurisdictions (Das *et al*., 2016; Shette *et al*., 2016).

Results and discussion

Upon the examination of the mentioned samples, the results given in table 1 and 2 were obtained for M-Score.

All three samples appear to be different. The fraud sample, where the earnings based infractions occurred, exhibits the values of M-Score below — 1.78 threshold. The sample, which was deemed ‘clean’ of fraud exhibits the worst results compared to M-Score threshold. Simple comparison of the means of three samples shows that mean of the fraud sample is statistically different from the means of other samples at the significance level of 1% . The means of clean and random samples are different at the significance level of 1%.

Visually, the subsets of the random sample, based on Z-Score are very similar to fraud and clean samples. Statistically, for the means of the fraud and Z < 1 samples as well as for clean and Z > 3 samples, null hypothesis of their equality cannot be rejected. Based on this observation, it is also possible to suggest that the appearance of M-Score < -1.78 and Z-Score < 1 is not random. Similar suggestion can be made for the pairing of M-Score > -1.78 and Z-Score > 3.

In the large random sample, there are 199 (56%) joint occurrences of M < -1.78 and Z < 1 and 158 (68%) occurrences of M > -1.78 and Z > 3. Using the method of series, it is possible to determine that with the significance of 95%, the interval in which the frequency would be considered random for the first case is 0.46≤p≤55 and for the second case 0.43≤p≤57. In both cases, the obtained frequency lies outside of the interval of the values, which can appear due to chance. The frequency of the desired observations is higher than the upper end of the “random” interval. For the hypothesis H1 formulated earlier, the null hypothesis can be safely rejected for the case of M > -1.78 and Z>3 because such combination does not appear due to chance.

According to SAS 99, there must be a motivation to commit financial statement fraud (Marzcewski & Akers, 2005). The companies, which already exhibit good performance are less likely to be involved in financial statement fraud. Good performance is often related to an exceptional liquidity standings of the organization under review. Therefore, M-Score will indeed produce a relatively high number of Type I errors or false positives.

Similar results were obtained for ΔP-ΔR. The same samples are compared to each other (Table 3 and 4).

The "ideal" value of ΔP-ΔR is as close to 0 as possible. The indicator is based on the corporate performance and its values are fluctuating from one year to the next. It was empirically determined that absolute values of the indicator above 0.3 will constitute the presence of artificial altering of financial statements (Pustylnick, 2016). Similar to M-Score, the values of ΔP-ΔR are collected for the subsamples for Z > 3 and Z < 1.

The behavior of the subsamples is very similar to the behavior of the main random sample. Statistical comparison of the means of four main samples and the subsamples against each other reveals that it is not possible to reject the null hypothesis of the equality of two means of ΔP-ΔR for all of the pairings between different samples. This confirms the findings that the cases, pointing towards the signs of manipulations with financial statements are at the far edges of all samples.

Earnings management indicator ΔP-ΔR was created by superimposing the clean and the fraud sample and by performing the discriminant analysis of the variables involved in computing P and R. Taking into consideration that the companies of the clean sample were selected using Z-Score > 3 as a criterion, it is important to compare ΔP-ΔR and M-Score for the samples previously reviewed.

Results in Table 5 show that positive correlation between M-Score and Z-Score exists when the samples appear to have a large number of suspicious entries. When the samples are compiled at random, no correlation exists among three elements. The most prominent correlation can be noted between M-Score and two other indicators only for the emerging sample. The negative correlation between M-Score and ΔP-ΔR shows that when M-Score increases ΔP-ΔR is negative and decreases below the threshold for this indicator.

For emerging economy sample it can be possible to create a linear regression model since correlation appears to be significant.

$$M - Score = \alpha * (\Delta \mathrm{P} - \Delta \mathrm{R}) + \beta * (Z - Score) + \varepsilon \qquad (8)$$

Analysis of the coefficients based on the emerging sample shows the results compiled in Table 6.

The R-square value of the model is 43.3%, which means that it has a fairly good prediction quality for a linear regression model based on commonly unrelated values. The parameters of the model are statistically significant. The ability to create such model shows that there is a strong relation between the observed indicators for the emerging markets. For such markets, any of the indicators: M-Score or ΔP-ΔR can be successfully applied to determine the presence of signs of manipulations in the participating financial statements.

The obtained results show that as the indicator of earnings management ΔP-ΔR appears to be more comprehensive. It is created based on the values of Z-Score in the samples but it does not correlate with Z-Score values in any of the samples provided. On the other hand, one can notice that the values of M-Score follow Z-Score values and any attempt to create more liquidity can be mistaken for the fraudulent actions. Beneish M-Score indicator and ΔP-ΔR indicator appear to have more connection in the sample from the emerging markets. Such connection may be explained by the smaller size of the sample and by the volatility of the company financial reports in the adjacent years, which may indeed be a sign of fraud.

Conclusions

The review of the ΔP-ΔR and M-Score indicators offers an insight into the potential use of these indicators to assess the presence of earnings management in the financial statements of an organization or a group of organizations under review. The goal of this research was not to superimpose these indicators against each other, but rather to show the advantages and the limitations of each approach to the researchers and the practitioners in the field of accounting, auditing and financial analysis.

The examination of M-Score and the understanding of the nature of the research, which lead to its creation, prompt the conclusion that M-Score would increase any time when the overall liquidity of the organization increases. Since the increase of the liquidity, commonly expressed through Z-Score value, is one of the major goals of any organization, any such raise of liquidity would result in "abnormal" values of M-Score. This means that using M-Score can become a source of Type I errors, when perfectly law abiding companies will be flagged as having signs of fraud in their statements.

As an indicator of earnings management, ΔP-ΔR was created based on DuPont formula, which contains financial variables used in assessment of the corporate financial performance. By its nature, it guarantees that the change in the performance of the organization will be reflected in its value. It also guarantees that both upward and downward earnings management are reflected by its absolute value. However, based on a very coarse discriminant analysis, ΔP-ΔR is effective only outside of certain value thresholds, established presently as |ΔP-ΔR|>0.3. Such coarseness of the indicator allows to detect the cases of *material* earnings management, but will also have false negatives or Type II errors inside the threshold interval.

These observations offer interesting new directions for the research, which can be undertaken, based on the results, presented in this paper. Because of the dual nature of earnings management, it would be interesting to determine if M-Score can have an interval threshold rather than a single value threshold it has at the moment. It is especially interesting since M-Score can only somewhat detect upward earnings management and does not have a provision to recognize downwards earnings management.

ΔP-ΔR can be a potent indicator of upward and downward earnings management. It works very well when the manipulations with the financial statements are *material*. However, the large interval of potentially safe values leads to an equally large area of uncertainty, which includes the majority of the organizations filing their reports according to the observed statistics. Such ambiguity would warrant the replacement of some of the variables comprising ΔP-ΔR formulas with other ratios or variables.

The last part of the presented research shows that ΔP-ΔR and M-Score can complement each other. Created regression model shows decent coverage of the results and good predicting ability if applied to the financial results for the companies from the emerging economy markets. Since every emerging economy is slightly different, it would be interesting to replicate the obtained using another set of data from a different country.

The goal of this research was not to superimpose two indicators (M-Score and ΔP-ΔR), but rather find the common points and the directions where both indicators can complement each other. The shift of the research on fraud in the financial statements to the areas with less developed emerging economy gives a boost to the joint use of these indicators together with Z-Score in order to build a model which may predict fraud with a larger degree of certainty.

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Annex

Table 1. Comparison of M-Score for four announced samples

Sample	N	Mean	St. Dev.	Q1	Median	Q3
Fraud	98	-1.834	1.137	-2.461	-1.949	-1.132
Clean	32	-1.261	0.940	-1.870	-1.380	-0.579
Random	1082	-1.509	1.255	-2.369	-1.621	-0.803
Emerging	35	-1.439	2.178	-2.178	-1.009	-0.079

Table 2. Comparison with M-Score subsamples based on Z-Score

Sample	N	Mean	St. Dev.	Q1	Median	Q3
Fraud	98	-1.834	1.137	-2.461	-1.949	-1.132
Clean	32	-1.261	0.940	-1.870	-1.380	-0.579
Random	1082	-1.509	1.255	-2.369	-1.621	-0.803
Random with Z < 1	353	-1.784	1.526	-2.669	-2.024	-0.736
Random with Z > 3	234	-1.104	1.088	-1.928	-1.156	-0.426

Table 3. Comparison of ΔP-ΔR for Four Announced Samples

Sample	N	Mean	St. Dev.	Q1	Median	Q3
Fraud	96	0.078	0.844	-0.199	-0.045	0.280
Clean	32	-0.135	1.230	-0.204	-0.027	0.172
Random	1035	-0.001	0.469	-0.061	-0.001	0.054
Emerging	35	-0.066	0.906	-0.259	-0.067	0.246

Table 4. Comparison with ΔP-ΔR Subsamples Based on Z-Score

Sample	N	Mean	St. Dev.	Q1	Median	Q3
Fraud	96	0.078	0.844	-0.199	-0.045	0.280
Clean	32	-0.135	1.230	-0.204	-0.027	0.172
Random	1035	-0.001	0.469	-0.061	-0.001	0.054
Random with Z < 1	324	0.015	0.579	-0.084	0.002	0.084
Random with Z > 3	220	0.013	0.222	-0.045	0.000	0.034

Table 5. Correlation between Z-Score, M-Score and ΔP-ΔR

Correlation	Fraud	Clean	Random	Random Z < 1	Random Z > 3	Emerging
M to Z	0.401***	-0.280	0.083***	-0.218***	-0.008	0.688***
M to ΔP-ΔR	-0.128	-0.108	-0.031	-0.035	0.040	-0.381**
Z to ΔP-ΔR	-0.157	-0.031	-0.034	-0.067	-0.030	-0.209

Note: *** is 99% significance, ** is 95% significance, * is 90% significance

Table 6. Regression coefficients with statistic significance

Coefficient	Value	T-Value	P-Value
Constant	-2.260	-7.24	0.000
Alpha	0.385	4.36	0.000
Beta	-0.380	-1.65	0.108