ARE RETURNS CONDITIONAL UPON THE BENEISH M SCORE? A STUDY BASED ON TEN-YEAR DATA OF 500 LARGEST INDIAN COMPANIES

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ABSTRACT

In this paper we study the link between returns and the Beneish-M score, an index modeled on eight financial ratios. Outside India, this index has been shown to indicate whether a company is likely to have manipulated its profits. Our study using ten-year data of NSE500 Indian companies demonstrates that Indian companies with an M-score above the threshold value of -1.78 report lower returns, on an average, in the following year. This lends credence to the hypothesis that the market seems to penalize fiscal manipulation. Though our findings vary from one year to another, this study shows that the Beneish-M classification has a strong association with the rate of returns in the subsequent year, with the flagged companies reporting a lower market return on an average.

These findings can provide strong clues to investors to avoid stocks of companies based on a classification using the Beneish M-score.

Keywords: Beneish M, Earnings Manipulation, Earnings Management, Indian Companies, Market Returns.

INTRODUCTION

In financial reports to investors, board of governors and other stakeholders, earnings is the most important item (Jooste, 2017; Burgstahler and Dichev, 1997; Beaver, 1998). A company's health is judged from its reported financials which can thereby incentivise further investment. Consequently, there are strong incentives to manip- ulate these figures. Such manipulation is also not difficult considering the amount of latitude of interpretation in accounting provisions and methods set by the GAAP standards.

If the investors are aware of a manipulator, they would avoid the investment in such company. Once such a company falls from grace its stock will generate a lower or negative return. In order to identify a manipulator investors have to wait for an official statement from the market regulator. Many a times such announcements, if the company in question is large, meet with adverse reactions from market operators, such as in the cases of Enron, WorldQuest, Satyam Computers etc. Beneish 1999; Beneish et al. 2013 have developed a model using financial statement variables that aims to find companies that are manipulating their accounts. In this paper we expand this approach to see whether in the Indian context this model is able to predict the direction of future returns of these 'possible' manipulators.

Earnings management is a phenomenon where managers make accounting judge- ment that do not always reflect a firm's underlying financial performance (Jackson and Pitman 2011) and even if earnings management does not explicitly violate ac- counting rules it

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remains a questionable practice. Unless checked, it could lead to material misstatement in financial statements (Clikeman 2003).

Managers have strong incentives to avoid reporting losses, decline in earnings where earnings fall short of street expectation (Degeorge et al. 1999; Burgstahler and Dichev 1997; Das and Zhang 2003; Barghathi et al. 2017). Magrath and Weld 2002 found that inappropriate practices of revenue recognition caused one third of all voluntary or forced restatements of income by companies for the period of 1977 to 2000.

A report 'Panel on Audit Effectiveness' (2000) by the Public Company Accounting Oversight Board observes that "the term earnings management covers a wide variety of legitimate and illegitimate actions by management that affect an entity's earnings".

Academic researchers have primarily focused on two types of earnings manage- ment. Accruals earnings management which may alter the timings of reported earn- ings (Healy 1985; Dechow et al. 2010; Gao et al. 2017; Izadi et al. 2019). Real activities management which is harder to detect involves deviations from normal business ac- tivities including decisions on discretionary expenditures with a purpose of meeting certain earnings thresholds (Nuryaman et al. 2019; Roychowdhury 2006; Cohen et al. 2008). In recent years researchers have also focused on classification, shifting misclas- sifying of core expenses as a tool for earnings management (McVay 2006; Nagar and Sen 2016; Zalata and Roberts 2017).

Beneish 1999 defines earnings manipulation as improving a company's financial performance through illegal earning management schemes. These include violation of General Accepted Accounting Principles (GAAP) and of accounting standards. (Magrath and Weld 2002; Degeorge et al. 1999) observe that accounting policies are chosen to reduce losses and increase profits.

As discussed earlier, Beneish 1999; Beneish et al. 2013 developed a model aimed to find companies that are possibly manipulating their accounts through financial state- ment variables. Beneish used a probit regression model to compute a probability of manipulation. This model computes an M-score to distinguish between manipulators and non-manipulators. It has been extensively used in financial research to assess the quality of earnings and identification of financial frauds. Beneish et al. 2013 concluded that this model can be used to pick up non-manipulators for better equity return. Golden et al. 2006; Warshavsky 2012; Mantone 2013 also found the M-score model effective in identifying earnings manipulation.

Though there is extensive research on different facets of earnings management, little research has been done to explore this phenomenon from the point of view of market participants. Kwon et al. 2012 argue that accruals quality increases the predictability of future earnings. In other words, if the accruals ratio is high the future earnings of the company tend to be unpredictable.

Rajgopal and Venkatachalam 2010 found a strong linkage between idiosyncratic return volatility and financial reporting quality. Sun 2014 also confirms the notion that with more likely earnings management, asset returns will exhibit greater volatil- ity. Aboody et al. 2005 finds a negative relationship between firm level earnings management and firm's stock return. Beneish et al. 2013 found that Beneish 1999 model has the ability to both detect the fraud and predict direction of future earnings. We expand this approach to see whether in the Indian context this model is able to predict the direction of future returns. A possible manipulator should have less or negative return in comparison to the average return market will be able to manage.

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In the next section we describe the methodology that we have used, along with a brief description of the Beneish-M indicator. Following this, in Section 3 we discuss the aggregate results obtained for the data of NSE500 companies for 10 years, 2009-10 to 2018-19. In Section 4 we use modeling techniques to evaluate whether the forward returns of companies can be estimated using the Beneish framework. The results showa large variation across the years of our study, indicating a wide variation of ‘earnings management’ techniques depending upon temporal and possibly some other factorsas well.

METHODOLOGY

We conduct the present study on NSE500 companies which represent India’s largest 500 companies listed on National Stock Exchange of India. A total of eleven years’ data is extracted from Ace Equity database to conduct a ten-year period study for the period 2008-09 to 2017-18 (In India, most companies follow the April to March fiscal year). We removed the companies with incomplete records, companies follow- ing a different fiscal year and companies belonging to banking and financial services sector. Companies that did not have their price data available for the entire period for the construction of portfolio were omitted from the study. After making all these adjustments, we were left with our final sample of 3,021 company records.

To compute the returns, we look for 12 months ahead return of the portfolios created at the beginning of the fourth month after the fiscal year end. To create size adjusted portfolios and to compute return, we created decile wise portfolios, using the market capitalization as the reference point at the beginning of the fourth month following the fiscal year end to assign the companies their respective bucket.

Beneish-M: an Indicator of manipulation in Financial Records

Beneish 1999 relied on three sources for the eight explanatory variables from financial statement of the companies. These are (a) signals about future prospects that appear in literature, with poor future prospects providing possible impetus to earning manipulation, (b) variables based on cash flow and accruals, and (c) variables drawn from positive-theory research which hypothesizes contract-based incentives for earnings management.

There are eight ratios that are considered in Beneish’s model. Day’s sales in receivables (DSRI) are the ratio of days’ sales in receivables for two consecutive years to find if they are in balance. A disproportionate increase may indicate revenue inflation. Gross margin index (GMI) is the ratio of gross margin of two consecutive years. A ratio of more than 1 indicates the drop in gross margin resulting in not so good prospects for the company. Such company is more likely to engage in earnings manipulation. Asset quality index (AQI) is the ratio of non-current assets other than property, plant and equipment (PPE) to total assets. These assets indicate less certain future benefits. An AQI greater than 1 indicates the company’s likely engagement in cost deferral by capitalizing expenses. Sales growth index (SGI) measures the ratio of sales in current year to that in the previous year. Though the ratio does not necessarily indicate manipulation, growth companies are more likely to manipulate inorder to keep up their track record.

Depreciation index (DEPI) is the ratio of the rate of depreciation in consecutive years. A ratio of greater than one indicates the declining depreciation rate which increases the probability that the company is decreasing expenses thus boosting income either

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by changing the estimated useful life of assets or by changing the depreciation method. Sales, general, and administrative index (SGAI) is the ratio of sales, general and administrative expenses to sales in current year to previous year. It is assumed that an abnormal increase in this ratio indicates poor future prospects of company. The Accruals indicator captures if accounting profit is supported by cash profit. For manipulators, this indicator would be higher, indicating less cash. In an earlier ver- sion (Beneish, 1999) used a variable, TATA, defined as total assets to total accruals variable. This produced similar results. Leverage index (LVGI) is the ratio of total debt to total assets in current year relative to previous year. It captures the incentives in debt covenants to earnings manipulations. A ratio greater than one indicates more leverage thereby indicating a higher chance of earnings management.

Beneish introduced the following formula for an overall manipulation indicator:

$$Beneish-M = -4.954 + 0.789\ (DSRI) + 0.459\ (GMI) + 0.306(AQI) + 0.701\ (SGI) + 0.033\ (DEPI) - 0.006\ (SGAI) + 3.937\ (Accruals) - 0.264\ (LVGI)$$

According to Beneish 1999 a Beneish-M score of -1.78 or more would indicate possible financial manipulation. Beneish 1999 used a sample of 74 companies that manipulated earnings and 2332 non-manipulators. He arrived at the threshold of -1.78 for classifying possible financial manipulation. Scores higher than the threshold would indicate possible manipulation of earnings by the respective company.

Beneish 1999 proposed this cut off score of -1.78 by considering the costs of misclas- sification arising from both Type-I (misclassifying a manipulator) as well as Type-II (misclassifying a non-manipulator) errors. The ratio of cost of misclassification aris- ing from Type-I Error to that arising from Type-II Error was taken by Beneish to be 20:1 or 30:1. An M score greater than -1.78 is a possible indicator of financial statement manipulation. A cut off score of-2.22 is proposed by Mantone 2013, War- shavsky 2012 and many other researchers. At the ratio of costs of misclassification of 20:1 or 30:1 assumed by Beneish, the proposed cut-off of -1.78 misclassified 26% of manipulators and 13.8% of non-manipulators. At a cut-off of -1.89, which was also considered by Beneish, the corresponding misclassifications were 24% and 17.5%. Though the Type-I error reduced marginally, the increase in Type-II error, falsely implicating non-manipulators as manipulators, jumped from 13.8% to 17.5% - almost a 27% increase. In this paper, we stick to the cut-off value of -1.78 to flag a companyas a possible manipulator.

ANALYSIS OF RESULTS

We have data for 379 companies for the period 2009-10 to 2018-19. Of these, 76 companies have the incomplete data - data is available for less than ten years. Each of the 3021 company financial performance records is next classified with the Beneish-M indicator, which is set to 'Y' for records with a Beneish-M score of -1.78 or more - an indicator of possible fiscal manipulation - and 'N' otherwise.

Three tables depict the overall market returns in the forward year, conditional on the M-score, with the records classified in three different ways. Table 1 explores the year-wise returns for the companies which are not flagged, (Beneish-M score $<$ -1.78), as against the companies which are flagged (Beneish-M score $\geq$ -1.78). Table 2 depicts returns in the forward year. The companies are segregated into ten deciles by the current

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year's market capitalization. Here too, we depict the returns separately for flagged and non-flagged company records with the presumption that the forward returns would be lower for companies that are flagged, that is those which are likely to have manipulated their financial figures. Table 3 revisits the market returns con- ditional on the M-score, but in this case the company records are segregated by the accruals in the current year.

Year-Wise Market Returns based on the Beneish Classification

Table 1 depicts the returns for companies marked as possible manipulators and non-manipulators indicated by Beneish's model. For the full sample period possible manipulator companies recorded an average return of 16.4% whereas non-manipulators clocked returns of 28.4%., thus outperforming flagged companies by 12 percentage points. Spread between returns of possible manipulators and non-manipulators is positive in most of the years. Possible manipulators significantly underperform in four years viz. 2012-13, 2013-14, 2017-18 and 2018-19. In 2012-13 and 2013-14 the differ- ence in market cap returns is significantly higher for non-flagged company records.In terms of returns non-manipulating companies showed significantly stronger re- sults than manipulating companies. In 2010-11 non-manipulating companies reported a 5.9% delivered in returns, while manipulators reported a decrease of 1.5%. This pat- tern was reported with stronger results in 2012-13, where the return was 14.3% for possible non-manipulating companies while the possible manipulating companies re- ported a negative growth of 0.9%. Buoyed by the huge surge in stock price growth in 2013-14, we see that non-manipulators had an average increase in returns of a whopping 117.3%. The increase for manipulators was a far lower 78.8%. 2018-19 proved to be a dismal year and both non-manipulators and manipulators suffered a decrease in returns. Here too, the non-manipulating companies reported a reduction of 4.45% in market cap, while the manipulating companies reported a significantly higher reduction of 10.5%.

Table 1
YEAR-BY-YEAR MARKET RETURNS

		Not Flagged			Flagged			For Year	
Year	**N**	**%**	**Returns**	**Sig.**	**%**	**Returns**	**Sig.**	**Spread**	**Sig.**
2009-10	236	78.0	63.4		22.0	57.6		5.8	
2010-11	255	80.4	5.9		19.6	-1.5		7.4	
2011-12	275	45.1	-2.5		54.9	-4.0		1.5	
2012-13	282	69.9	14.3		30.1	-0.9	***	15.2	***
2013-14	291	73.9	117.3	*	26.1	78.8	***	38.5	***
2014-15	303	78.9	29.8		21.1	33.2		-3.4	
2015-16	309	83.2	12.0		16.8	7.6		4.4	
2016-17	335	74.3	30.9		25.7	31.3		-0.4	
2017-18	357	78.4	21.0		21.6	9.6	**	11.4	
2018-19	378	72.0	-4.4		28.0	-10.5	*	6.1	*
All	**3021**	**73.6**	**28.4**		**26.4**	**16.4**		**12.0**	*****

Size Adjusted Returns Conditional on the Beneish-M Classification

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To compute size adjusted returns, we divide the companies into ten quantiles based on their market capitalization on the reference date.

Table 2 depicts the decile-wise returns for the sample companies. Possible manipulators significantly under perform for the two smallest decile portfolios. However, for all the deciles, the returns are higher for non-manipulating companies.

Table 2
DECILE WISE RETURNS CONDITIONAL ON M-SCORE

	Full Sample		**Not Flagged**		**Flagged**		
Decile	**N**	**Returns**	**N**	**Returns**	**N**	**Returns**	**Diff***
1	303	77.1	222	89.2	81	43.9	***
2	302	53.7	236	59.2	66	34.3	**
3	302	42.9	212	47.6	90	31.9	
4	302	16.7	213	18.0	89	13.7	
5	302	12.3	232	13.5	70	8.1	
6	302	14.6	221	15.4	81	12.4	
7	302	11.8	220	13.2	82	7.9	
8	302	12.0	223	13.5	79	8.0	
9	302	7.6	218	9.6	84	2.5	
10	302	3.5	225	4.3	77	1.1	
All	**3021**	**25.2**	**2222**	**28.4**	**799**	**16.4**	

*Significance of difference in returns between flagged and non-flagged.

The small cap companies (lowest two deciles) have significantly lower returns for possible manipulators. Even for the third market cap decile, the average returns for possible manipulators are 15.7% lower.

Accrual Ratio-Wise Returns Conditional on the Beneish-M Classification

As already observed, researchers have paid attention to accrual portion of earnings to detect earnings management by companies. Considering the fact that cash portion of the earning is more persistent in future, investment in a company with higher ac- cruals should result in lower returns as the future earning prediction becomes difficult.

Beneish (2013) observed that out of eight variables of the model, three pertain to aggressive accounting and are linked with various facet of accruals namely – DSRI, DEPI and Accruals. Authors also observed that incremental power of the model over traditional accruals measurement adopted come from the other variables of the model.

To better understand the phenomenon, we test the joint ability of Beneish model and accruals. Following Healy 1985; Dechow et al. 2010 and Jones (1991) we find the accruals component from our set of companies. We create decile wise sets for companies where the first decile represents companies with the lowest accruals component. We further categorise the decile with companies classified as manipulator and non-manipulators and evaluate their forward returns. Results are shown in Table 3.

For the non-flagged companies, none of the decile groups show significantly different

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returns from the overall average of 28.4%. However, the flagged companies show significantly lower returns for seven out of the ten years. In all the deciles, possible manipulator companies recorded a lower growth than possible non-manipulators and in seven of the deciles, returns for possible manipulators are significantly lower. Spread is the maximum in the last decile; that with the companies having highest accruals.

Table 3
ACCRUAL RATIO-WISE RETURNS CONDITIONAL ON THE M-SCORE

Accrual	Full Sample		Not Flagged		Flagged			Spread	
Decile	N	Returns	N	Returns	N	Returns	Sig.	pps	Sig.
1	297	23.9	221	27.2	76	14.2	*	13.0	**
2	301	32.4	257	34.2	44	22.0		12.2	
3	303	24.6	261	26.9	42	10.4	**	16.4	**
4	301	21.7	241	24.8	60	9.5	**	15.2	**
5	302	23.2	247	25.7	55	11.9	**	13.9	**
6	302	26.9	243	30.4	59	12.6	**	17.8	**
7	304	24.5	223	28.0	81	15.0	*	13.0	**
8	300	26.0	199	26.7	101	24.5		2.2	
9	304	23.2	185	25.0	119	20.4		4.6	
10	307	26.0	145	37.8	162	15.4	***	22.4	*
All	3021	25.2	2222	28.4	799	16.4		12.1	***

Returns Modeling using the Beneish Framework

In this section we study the predictive ability of the Beneish-M score and develop models to test the hypothesis that possible manipulation of financial figures, as indicated by an M-Score above -1.78, is punished by investors and leads to company losing in terms of returns.

Depending upon various macro- economic factors and the sector a comany is in, its returns are seen to vary widely from one year to another. The spread of returns shows high variability across the years. For the NSE-500 Companies the average returns vary from -6.15% in 2018-19 to 107.22% in 2013-14. In 2018-19 the returns were very low, whereas 2013-14 witnessed very high overall returns. The most negative return deviation - that is the percentage deviation from the mean returns in that year, -231.18% is seen for a household appliances manufacturing company in the year 2010-The highest return deviation, 696.83%, is for a company in the real estate business in the year 2017-18.

Does the Beneish indicator provide significant indication of the returns of a company in the next year? An empirical study to test this hypothesis is fraught with limitations arising from (i) the overall macro-economic situation obtaining in each year and (ii) the specific sectoral swings that influence investor sentiment in that year. We attempt, in this section, to develop a predictive model solely based on certain financial figures reported by the companies. These financial ratios are di- rectly taken from Beneish's model. We also incorporate in the model the categorical Beneish-M indicator.

We examine if

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1. A general model, across the years under our study, provides significant empirical evidence for returns in the next year
2. Can we identify patterns from year-wise predictive models, and draw relevantconclusions

We test linear regression models for the following-year returns based on selected Beneish ratios.

Table 4
STAGE 1: PREDICTIVE MODELS FOR RETURNS

Model	Dependent	Independents	
1	Returns ~	all 8 Beneish ratios	
2	Returns ~	GMI + Accruals + LVGI	
3	Returns ~	Accruals + LVGI	

Table 5
STAGE 1: SIGNIFICANCE OF COMPARATIVE RETURNS MODELS

Model	Res.Df	RSS	Df	Sum of Sq	F	Sig
1	3012	14906230				
2	3017	14914888	-5	-8657.547	0.3498743	0.8825755
3	3018	14923782	-1	-8894.147	1.7971795	0.180155

Model 1 has a r-squared value of 0.1422. Of the eight regressors however, only accruals (p-value=1.23×10^{-5}), leverage (p-value=1.07×10^{-97}) and GMI (p-value=0.0917) are significant at the 10% level.

Model 2 which retains the three regressors GMI, leverage and accruals from the 8 beneish parameters is not significantly worse, neither is Model 3.

Model 3 is highly significant (1.86×10^{-100}) with both the model predictors, accruals and leverage significant, p-values= 1.01×10^{-5} and 6.69×10^{-98} respectively.

In the nest stage, we test nested linear models based only on the significant pre- dictors, in order to evaluate their stage-wise significance. In this exercise we also consider the interaction effect of the dichotomous Beneish-M classifier based on the cut-off value of -1.78 (**indic** in the models shown in Table 4).

The 2*nd* model, boosted by the interaction of the categorical Beneish indicator with leverage and accruals, appears to be the most significant.

Table 6
STAGE 2: PREDICTIVE MODELS FOR RETURNS

Model	Dependent	Independents			
1	Returns ~	Accruals + LVGI			
2	Returns ~	Accruals + LVGI + indic:Accruals + indic:LVGI			

Table 7
INCREMENTAL SIGNIFICANCE OF MODELS

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Model	Res.Df	RSS	Df	Sum of Sq		F	Sig
1	3018	14923782					
2	3015	14801078	3	122704.3		8.331681	1.62E-05

Of the eight Beneish-M parameters, only two, Accruals and Leverage are significant predictors for the following year's returns. An investigation of the eight factors used in the Beneish model shows that leverage and the accruals in a year have the most pronounced effect on returns in the following year. The inclusion of the Beneish-M indicator significantly improves the model, more so if its interaction terms with accruals and leverage are included.

The best linear model is shown in Table 8 below. The model is highly significant (2.32e-102), but is not uniformly applicable across the years as can be seen from thefact that the model r-squared is a poor 0.1482.

Yearwise Returns Modeling using the Beneish-M Classifier

In this section we develop yearwise regression models in an attempt to see whether and how strongly the financial results reported have influenced the returns.

We have seen that the pattern of forward year returns varies, depending largely upon accruals and leverage, from one year to another. It is also seen that, in India, the returns vary widely from one year to another, as also the manner in which the returns are dependent on accruals, leverage and the Beneish-M dichotomous classifier flag.

Table 8
PREDICTIVE MODEL FOR FORWARD YEAR RETURNS

	Estimate	Std. Error	t value	Sig
(Intercept)	0.391	1.942	0.201	8.40E-01
Accruals.x	-101.245	21.559	-4.696	2.80E-06
LVGI	26.045	1.179	22.093	0.00E+00
indicY	13.995	8.376	1.671	9.49E-02
LVGI:indicY	-25.227	7.742	-3.258	1.13E-03
Accruals. x:indicY	115.616	34.343	3.366	7.71E-04

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To study the interdependence of returns and the Beneish-M classifier, we categorise returns into two levels - (a) those with a value greater than the median returns for the year and (b) the companies with returns less than the median return value for the year. Table 6 shows the year-wise contingency tables of proportion of companies, non-flagged and flagged with returns greater or less than the year's median returns. In all the years, except 2011-12, 2014-15 and 2016-17, the non-flagged companies had a higher proportion than flagged companies with greater-than-median returns. However, the χ^2 test of association turns out to be significant only for 2013-14 (p-value: 0.0037). Considering the data for all the years, the χ^2 test is significant (p- value: 0.0349) Table 9.

Table 9
INTERDEPENDENCE OF RETURNS AND THE BENEISH CLASSIFIER

		Median			Chi Squire	
Year	**ind**	**Return**	**More**	**Less**	**Statistic**	**Sig.**
2009-10	N	47.18	78.81	21.19	0.10	0.7534
	Y		77.12	22.88		
2010-11	N	-0.96	83.46	16.54	1.52	0.2184
	Y		77.34	22.66		
2011-12	N	-9.60	43.07	56.93	0.45	0.5013
	Y		47.10	52.90		
2012-13	N	1.08	73.05	26.95	1.36	0.2428
	Y		66.67	33.33		
2013-14	N	85.45	81.38	18.62	8.42	0.0037***
	Y		66.44	33.56		
2014-15	N	18.60	76.82	23.18	0.76	0.3820
	Y		80.92	19.08		
2015-16	N	4.62	85.06	14.94	0.79	0.3752
	Y		81.29	18.71		
2016-17	N	21.35	74.25	25.75	0.00	0.9744
	Y		74.40	25.60		
2017-18	N	3.31	79.21	20.79	0.13	0.7201
	Y		77.65	22.35		
2018-19	N	-9.40	75.66	24.34	2.57	0.1089
	Y		68.25	31.75		
All Years	**N**	**15.84**	**51.04**	**48.96**	**4.45**	**0.0349****
	Y		**46.68**	**53.32**		

Table 10 depicts the essence of the year-wise regression models - the regression coefficients and the average values for leverage and accruals for the respective years and the two levels of the Beneish indicator. It may be noted that the mean leverage

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value is less for companies with the Beneish indicator 'Y' in 8 out of 10 years. In each of the ten years the value of accruals is larger and for companies with the Beneish indicator 'Y'. Except in two years the accruals for Beneish-M 'N' companies was negative.

Table 10
YEAR-WISE MODELS FOR RETURNS

		Regression Coefficients			Avergae		
Year	Ind	Intercept	LVGI	Accruals	LVGI	Accruals	% Returns
2009-10	N	98.26	-36.48	-135.10	1.0324	-0.0209	63.4
	Y	194.68	-132.15	-34.94	1.0235	0.0513	57.6
2010-11	N	33.77	-28.56	-46.85	0.9781	-0.0021	5.9
	Y	-63.92	59.61	77.89	0.9674	0.0615	-1.5
2011-12	N	-2.50	-0.50	-94.35	0.9121	-0.0053	-2.5
	Y	-7.64	1.07	40.07	0.9305	0.0649	-4.0
2012-13	N	-35.88	49.17	-17.48	1.0173	-0.0116	14.3
	Y	11.13	-7.78	-45.15	1.0460	0.0860	-0.9
2013-14	N	116.87	-1.68	-298.68	1.1755	-0.0079	117.3
	Y	98.14	-16.63	-29.01	0.9890	0.1002	78.8
2014-15	N	31.47	-2.13	-55.10	1.0124	-0.0090	29.8
	Y	56.71	-38.33	146.59	1.0126	0.1046	33.2
2015-16	N	9.51	2.61	-76.33	1.0073	0.0016	12.0
	Y	12.06	-4.81	-0.79	0.9191	0.0872	7.6
2016-17	N	30.92	-2.15	-181.92	1.1016	-0.0129	30.9
	Y	20.23	19.05	-73.70	0.9086	0.0842	31.3
2017-18	N	-43.09	56.04	-12.31	1.1421	-0.0085	21.0
	Y	16.88	-8.72	4.59	0.8832	0.0931	9.6
2018-19	N	-0.11	-4.21	4.23	1.0311	0.0019	-4.4
	Y	-44.43	34.04	6.08	0.9800	0.0878	-10.5

Table 11 below shows the year-wise models. It is clear that the fitted models are very different across the years. For all the years under study, accruals has a much lower - in fact, negative - impact on returns for non-flagged companies. In 2018-19 though, Accruals for flagged as well as non-flagged companies had a similar impact on returns.

Except for three years, 2012-13, 2013-14 and 2016-17, the model for forecasting future returns is highly significant. The interaction of leverage with the categorical Beneish indicator is significant in 5 out of the 10 years. For 3 of the 10 years, the interaction of accruals with the Beneish indicator is significant in predicting returns. It is only in two years, viz. 2011-12 and 2014-15 that the interactions are insignificant; in these two years the respective company accruals is significant in the predictive model.

Citation Information: Jain, G., & Bose, A. (2023). Are returns conditional upon the beneish m score? a study based on ten-year data of 500 largest indian companies. *Academy of Marketing Studies Journal, 27*(3), 1-13.

Table 11 YEAR-WISE SIGNIFICANCE OF PREDICTORS					
		Significance of model and regression coefficients			
				Leverage	Accrual
Year	Model	Leverage	Accruals	:Ind	:Ind
2009-10	0.004***	0.143	0.773	0.001***	0.964
2010-11	0***	0 ***	0.934	0.014 **	0.821
2011-12	0.004***	0.417	0 ***	0.453	0.127
2012-13	*0.457*	0.858	0.081 *	0.684	0.357
2013-14	*0.101*	0.096 *	0.672	0.229	0.031 **
2014-15	0.003***	0.46	0.014 **	0.791	0.119
2015-16	0.037**	0.168	0.647	0.024 **	0.765
2016-17	0.255	0.962	0.738	0.903	0.013 **
2017-18	0.001***	0.979	0.447	0 ***	0.084 *
2018-19	0.031**	0.052 *	0.045 **	0.066 *	0.334

CONCLUSION

In the Indian context the Beneish-M classifier does not provide an unequivocal commentary on the nature of earnings management resorted to by a company. This is evidenced from the varying differences in average returns for companies flagged and non-flagged. Rather, the prevalent economic situation, as well as the market capitalization of the company can provide decisive pointers, if used along with the leverage and the accruals of the company for the financial year. While small cap companies show a large variation in average returns between Beneish flagged and non-flagged companies, the differences become insignificant for medium to large cap companies. Market cap decile-wise though, the non-flagged companies have larger average returns compared to the flagged companies.

A general model for predicting returns based on the most significant Beneish indi- cators, leverage and accruals, along with the dichotomous Beneish classifier appears significant in spite of having poor predictive capability.

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Citation Information: Jain, G., & Bose, A. (2023). Are returns conditional upon the beneish m score? a study based on ten-year data of 500 largest indian companies. *Academy of Marketing Studies Journal, 27*(3), 1-13.

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Received: 28-Nov-2022, Manuscript No. AMSJ-22-12934; **Editor assigned:** 30-Nov-2022, PreQC No. AMSJ-22-12934(PQ); **Reviewed:** 24-Jan-2022, QC No. AMSJ-22-12934; **Revised:** 20-Feb-2022, Manuscript No. AMSJ-22-12934(R); **Published:** 06-Mar-2023