USING SENSITIVITY ANALYSIS TO EVALUATE MATERIALITY*

An Exploratory Approach

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ABSTRACT

A large body of the published research in financial accounting provides strong and persuasive evidence on the association between accounting numbers and stock prices but falls short of drawing any implications about accounting policies on measurements or on reporting. Attempting to go beyond association the author of this paper provides an application of a possible methodology for evaluating materiality of accounting measurements in a given decision situation. The methodology employs discriminant analysis in which the sensitivity of the discriminating model to the changes in mean earnings per share provides a decisions reaction scale and shows that a change in mean earnings per share equal to or less than 10% does not significantly affect the prediction. The validity of the results would depend on the correspondence between this model and the behavior of decision-makers. However, in situations such as the one chosen here, in which an investor's decision-making process cannot be normatively structured, appropriate statistical methods effectively can be utilized to describe the process.

INTRODUCTION

To some extent, judgments on materiality determine the level of aggregation and disclosure of financial data reported to external users. For this reason, official pronouncements in the form of opinions, standards, or regulations are qualified by limiting their applicability to material items. Furthermore, the importance of the concept stems from the practice of appealing to materiality in making a choice from among competing accounting alternatives and in permitting deviations from accepted accounting methods. Because such a practice pervades all aspects of accounting and because there is no coherent set of criteria determining materiality, the Financial Accounting Standards Board (FASB) issued a Discussion Memorandum on the subject [12], which provides an excellent review of the literature and suggests several issues of substance.1

* A summary of this paper was presented at the Southeast Regional meeting of the American Accounting Association which was held in Richmond on April 24-26, 1975. Helpful comments were provided by N. Doouch, C. L. Nelson, J. Schienex and an anonymous referee.

1 The discussion memorandum provides an excellent synthesis of the literature on materiality, but the nature of that synthesis suggests that the issue continues to be broad and that an attempt to narrow it down to a manageable set of criteria perhaps is not forthcoming.
In its conceptual formulation, materiality always has been defined by the expected impact on users' decisions. The Accounting Principles Board Statement No. 4 specifies that "Financial reporting is only concerned with information that is significant enough to affect evaluations or decisions [1, par. 128]." From this characterization it seems that judgments on materiality would be rendered by a direct measure of decision-effects. In reality, however, the management of a reporting firm and an accountant jointly determine the level of materiality, that is, senders always make judgments for users. The first problem, therefore, lies in measuring materiality in a way contrary to its concept. The problem was recognized in a recent article by O'Connor and Collins [21] who suggested that research on the predictive ability and the informational content of accounting data has direct implications to a user-oriented materiality. It is recognized, however, that the type of research referred to by the authors has concentrated on discrete events, e.g., earnings, announcements, switch in accounting methods, rather than on a continuous event whose impact can be assessed by its strength. At the same time, Boatsman and Robertson [7] emphasized the point and experimented with some decision rules.

In deciding to act for users in an unbiased manner, accountants find themselves devising some arbitrary rules that give the appearance of objectivity. A percentage of net income or of some other known object is usually relied upon in determining what could be considered material for users. For example, SEC regulations provide quantitative measures of materiality that vary from 3% to 10% of net income, depending on the requirement [12, pp. 27–30]. In other instances, a combination of measures is used. For example, the Accounting Series Release #147 [11] states that lease disclosure requirements need not be followed

if the present value of the minimum lease commitments is less than five percent of the sum of long-term debt, stockholders' equity and the present value of the minimum lease commitments, and if the impact on net income required to be disclosed under (vi) below is less than three percent of the average of net income for the most recent three years. [Italics were added by the author.]

With the exception of the studies mentioned above, research on the subject also has been channeled into finding a cutoff point for materiality which conveys objectivity. The studies by Hicks [16], Neumann [20], and Bernstein [5] suggest that practice follows a cutoff point in the range of five to ten percent of net income, while Frishkoff [13] suggests that a change in accounting methods is considered material in practice if it affects net income by twenty-five percent. These studies attempt to categorize what accountants consider to be the limits of materiality. The only studies

\[ \text{A discrete event also can have implications to materiality. Retiring long-term debt is an event that might generate gains or losses, but whether or not these gains or losses are material is another matter that requires identifying a threshold for significance. On the other hand, O'Connor and Collins suggest the substitution of "market reactions" for the mythical "average investor" on whose behavior all measurements depend.} \]
that explicitly consider decision effects are by Rose et al. [22], Dopuch and Watts [10], Boatsman and Robertson [7], and O'Conner and Collins [21]. Dopuch and Watts recommend the measurement of materiality by the effect of the changes in accounting methods on the parameters of a time series model of income generation, provided that the model can be estimated and accepted. Rose et al. found that a change in a stimuli by a certain percentage affects judgments of students in a laboratory experiment. In a field experiment, Boatsman and Robertson used discriminant analysis to evaluate the judgments of CPA's and of Financial Analysts. They found that 4% of the current year's net income would be considered material.

**THE PROBLEM**

There are two basic limitations in the way decisions presently are made regarding materiality. Most important is the fact that the potential impact on users' decisions is measured by an accountant's own perception of what is important to users rather than by a direct assessment of the effect of information on decisions. Furthermore, inferring decision-effects by applying a percentage rule to the reporting practice of management implies a symmetry between the judgments of an accountant (and of the management of a reporting firm) at one end and users' decision-effects at the other end although it never has been shown that such an implication is reasonable. This assumption, however, is reinforced by the reluctance of users and decision-makers to coherently specify their decision models. Thus, it is difficult to use their viewpoint to evaluate materiality.

**THE OBJECTIVE**

The goal of this paper is to explore the use of sensitizing decision models to assess users' oriented materiality. The paper develops a model which may be viewed as a surrogate for investors' decision rules for a given decision situation. The paper addresses the question of materiality on the basis of the estimated rule. Different levels of materiality are assessed by evaluating the costs (of making the wrong decision) to the investor which are associated with different levels of changes in financial accounting variables. The discussion assumes that changes in financial accounting variables can be the result of switching from an accepted accounting method to another, of waiving the adoption of an accepted accounting method for what an accountant judges to be a lack of "material" effect, or of committing measurement errors.

**THE DECISION SITUATION**

An investor's decision to discriminate between aggressive and defensive stocks is chosen for this study. Operationally, a stock is aggressive if its intrinsic volatility is higher than the volatility of the "average" stock. A stock is defensive if its intrinsic volatility is below that of the "average" stock. To the extent that an investor forms expectations about market behavior, he is necessarily interested in the volatility of the stock composing his portfolios. In general, investors are known to form strategies when the market is expected to go up that are different from those formed when the
market is expected to go down. In particular, investors are interested in the \textit{ex ante} volatility. Other than using \textit{ex post} beta of the market model as a surrogate measure for future volatility, measurements of \textit{ex ante} volatility are not defined beyond mere speculation. However, investors use several criteria in forming judgments about \textit{ex ante} volatility, and they rank order stocks on this basis.

In order to understand the criteria used in making these judgments, the author questioned five portfolio managers and investment counselors about the manner in which volatility is estimated. In general, they decided against using the market beta measure, mainly because of being unable to relate to it, and declined specifying any decision rule. They agreed that they measure volatility in some sense in order to reach some reasonable categorization of stocks by rank ordering their volatility. Two of them suggested occasional use of beta values. From the interviews, several financial factors emerged as possible determinants of volatility: size, profitability of the firm, performance of the stock, liquidity, managerial policies, and growth rates.

These factors are almost identical to those suggested by traditional security analysis and used in accounting research \cite{4} \cite{14} \cite{2} \cite{9} \cite{6}. The financial variables commonly suggested as indicators for each factor or dimension are shown in Table 1, in which growth is measured by trends over time. The commonality of the raw data used in measuring these variables would suggest some redundancy in their explanatory power, an issue which is addressed later in this paper.

\begin{table}[h]
\centering
\caption{Variables Suggested as Bases for Assessing Stocks' Volatility}
\begin{tabular}{|l|l|l|l|}
\hline
\multirow{2}{*}{Dimension} & \multicolumn{3}{c|}{Variables} \\
\cline{2-4}
 & Size & Profitability & Liquidity & Management \\
 & & & & Policies \\
\hline
\text{ex. intangibles} & 3. P/E ratio & 3. Cash flow/total & expenditures per \\
3. T. assets & 4. Return on common & debt & share \\
 & equity ex. intang. & 4. Current ratio & \\
 & 5. Return on invested & & \\
 & capital & & \\
\hline
\end{tabular}
\end{table}

\textbf{Surrogation for the Ex Ante Volatility:}

Historical or \textit{ex post} volatility of a stock is defined as the stock's systematic, non-diversifiable market risk and is estimated by the Beta coefficient of Sharpe's model,

\begin{equation}
R_{j,t} = a_j + \beta_j R_{m,t} + e_{j,t},
\end{equation}

where \( R_{j,t} \) is the return on stock \( j \) at time \( t \), \( R_{m,t} \) is the market return, \( a_j \) is the intercept, and \( \beta_j \) is the beta coefficient.
where

\[ R_{j,t} \] is the rate of return on investing in stock \( j \) at time \( t \);
\[ R_{m,t} \] is the market's rate of return at time \( t \);
\( a_j \) and \( \beta_j \) are parameter estimates, where

\[
\beta_j = \frac{\text{Cov}(R_{j,t}, R_{m,t})}{\text{Var} R_m};
\]

\( e_{j,t} \) is a stochastic error term with \( E(e_j) = 0 \);

\( E(e_j, R_m) = 0 \) and \( E(e_{j,t}, e_{j,t-s}) = 0 \) for \( s \) greater than zero.

A stock is said to be more volatile than the market if its beta is higher than unity, less volatile than the market if its beta is below unity, and as volatile as the market if its beta is unity. Accordingly,

\[
\begin{aligned}
\text{aggressive if } \beta_j > 1 \text{ (Population A);} \\
\text{neutral if } \beta_j = 1; \\
\text{defensive if } \beta_j < 1 \text{ (Population D).}
\end{aligned}
\]

When Beta (the historical measure of volatility) is used as a surrogate for an investor's judgment on \textit{ex ante}, volatility is perhaps a simplifying assumption whose accuracy could not be attested to because of the inability of estimating \textit{ex ante} beta.

Deriving the Decision and Materiality Rules

In order to simplify the situation and also because most of the stocks have a (market) beta different from one, an investor's rule will be derived only for aggressive stocks and defensive stocks. A discriminant function is estimated which will enable the classification of stocks in population A or in population D. The discriminant rule should use the most discriminating financial variables chosen from those presented earlier and should provide a classification of stocks' volatility better than random chance. The model is a multivariate discriminant analysis model which minimizes the

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3 For the purposes of this paper, neutral stocks were defined as stocks with true beta equal to one. However, since there is a measurement error in the estimation of \textit{ex-post} beta, various possible measurement errors were considered. As shown in Table 5, measurement errors were assumed to have affected the measurement of beta by an amount that varies from 0.20, to 0.30, 0.40, or 0.50. In the first case, for example, neutral stocks were defined to have beta between 0.90 and 1.10. Similarly, for the last case, neutral stocks were defined to have beta between 0.75 and 1.25. Defensive stocks were those stocks with beta below the lower limit of neutral stocks and aggressive stocks were those stocks with beta above the upper limit of neutral stocks. Discriminant functions were estimated for each of these cases in order to see whether the ability to discriminate was sensitive to the possible errors in estimating beta. The values of chi-square in Table 5 show that the discriminant function was not sensitive to the variation in the interval size from 0.20 to 0.50.
cost of incorrect classification. If \( X_j = (S_{1j}, S_{2j}, \ldots, S_{nj}) \) represents the vector of independent variables for the \( j^{th} \) stock \( (j = 1, \ldots, m) \), then the discriminant function which minimizes the cost of misclassification takes the form [8, pp. 243–257], [17, pp. 334–340], [19, pp. 156–165]:

\[
Z_j = a + X_j B',
\]

with the critical value of the \( Z \) score

\[
Z_c = \log \left( \frac{P_D}{c(D|A)/P_A \cdot c(A|D)} \right),
\]

where \( B' = (b_1, b_2, \ldots, b_n) \) is a column vector of the discriminant coefficients

\( P_D \) (or \( P_A \)) which is the a priori, unconditional probability that a stock with a given vector \( X \) is in \( D \) (or in \( A \)), and

\( c(D|A) \) (or \( c(A|D) \)), which is the cost of misclassifying an \( A \) stock in \( D \) (or a \( D \) stock in \( A \)).

Provided that the above model is a good surrogation for the model used by investors, the classification rule will be the following.

Classify the \( j^{th} \) stock in:

\[
\begin{cases} 
group A, \text{ if } Z_j > Z_c \\
group D, \text{ if } Z_j < Z_c. 
\end{cases}
\]

Materiality could then be measured by the extent to which a change in accounting policies or in measurements will induce a change in the independent variable \( S_{ij} \) (for example, earnings per share), such that the grouping of the \( j^{th} \) stock changes from correct to incorrect classification. If the new \( Z \) score is designated \( Z'_j \), it is easy to verify that the magnitude of a change in \( Z \) needed to incorrectly classify a stock is

\[
|\Delta Z_j| = |Z'_j - Z_j| \geq |Z_j - Z_c|. \text{ It also could be verified that}
\]

\[
Z_j = b_i \Delta S_{ij}.
\]

Accordingly, the change that would be considered material is equal to \( \Delta S_{ij} = \Delta Z_j/b_i \).

The relative (critical) change needed can then be computed as \( \Delta S_{ij}/S_{ij} \), providing a decision-effects percentage rule which is derived from a (hypothetical) investor’s model of classifying stocks according to their volatility. This derivation, however, assumes that all \( S_{ij} \) in \( X_j \) are independent and that a change in one variable will not induce a change in others. Multicollinearity is dealt with later in the paper.

The Sample and Data

Two samples, each containing 250 stocks, were selected from the industrials in Value Line stocks. The first sample was selected at random. The second sample—which was used for validation and prediction—was selected in such a way that both
samples would have similar industry representations. After eliminating neutral stocks and stocks with missing data, the two samples were reduced to 111 and 122 and were split between aggressive and defensive stocks as shown in Table 2.

**TABLE 2**

<table>
<thead>
<tr>
<th>Number of Observations in Each Sample</th>
<th>Defensive Stocks</th>
<th>Aggressive Stocks</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Estimating Sample</td>
<td>60</td>
<td>51</td>
<td>111</td>
</tr>
<tr>
<td>Validation Sample</td>
<td>64</td>
<td>58</td>
<td>122</td>
</tr>
</tbody>
</table>

The first sample was used for estimating the weights assigned to accounting measurements used in the decision rule. The second sample was used for cross validation and for testing the rule's predictive ability.

The data for estimating the rule were based on the variables contained in Table 1. Because analysts look at trends and variability of data, each of the fourteen components was represented by four information measures: the mean representing the magnitude, the standard deviation representing a measure of variability, the coefficient of variation representing a standardized measure of variation, and the time trend representing growth. The measures were computed for each stock over a period of nine years from 1962 through 1970. This period was used because the available data base contained information only for those years and because it encompassed the time base used for computing betas.

With four information measures for each of the fourteen variables, the data base consisted of fifty-six possible explanatory variables. However, a discriminant function estimating a decision rule with such a large number of variables would be meaningless because the suggested explanatory variables share common data sources, which renders them collinear as revealed by examination of the correlation matrix. Therefore, a step-wise discriminant analysis was employed in selecting the relevant variables and in estimating the weights. The lack of a theoretical underpinning made the use of this

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4 Ibid.
5 Because this is perhaps the first report of the use of step-wise discriminant analysis in accounting, an explanation is appropriate. With two groups, a 0-1 regression is equivalent to a discriminant function with unscaled coefficients. With population A given 1 and population D given 0, a step-wise regression was utilized to select the most discriminating variables from the set of accounting data available. The coefficients of the regression were scaled by using the equation

$$\Sigma^{-1}(\bar{X}_D - \bar{X}_A),$$

where $\Sigma^{-1}$ is the inverse of the variance-covariance matrix and $\bar{X}_D$ and $\bar{X}_A$ are the vectors of the means of the variables used in the step-wise regression.
technique valuable for observation and for selection of variables that would best
discriminate between the two populations. Variables entered the discriminant func-
tion in a descending order of their discriminating power and were terminated after
fourteen variables when the power of the function ceased to improve (as measured by
adjusted $R^2$) by at least 1%.

Applying the rule of retaining only significant discriminators and eliminating
highly collinear variables resulted in the function shown in Table 3. The correlation

### TABLE 3
The Discriminant Function Obtained From
The Estimating Sample

<table>
<thead>
<tr>
<th>Variable***</th>
<th>Coefficient</th>
</tr>
</thead>
<tbody>
<tr>
<td>A) Mean: Earnings per share</td>
<td>2.3225</td>
</tr>
<tr>
<td>B) CVAR: Total debt</td>
<td>-7.508</td>
</tr>
<tr>
<td>C) S.D: Funds flow per share</td>
<td>-4.187</td>
</tr>
<tr>
<td>D) CVAR: Funds flow per share</td>
<td>10.185</td>
</tr>
<tr>
<td>E) CVAR: Capital Expenditure per share</td>
<td>4.307</td>
</tr>
<tr>
<td>F) CVAR: Return on invested capital</td>
<td>-11.1525</td>
</tr>
<tr>
<td>G) Trend: Return on invested capital</td>
<td>0.912</td>
</tr>
<tr>
<td>H) Mean: Funds Flow/Total Debt</td>
<td>2.678</td>
</tr>
<tr>
<td>I) Trend: Funds Flow/Total Debt</td>
<td>-27.594</td>
</tr>
<tr>
<td>J) Mean: Payout ratio</td>
<td>0.021</td>
</tr>
<tr>
<td>K) Trend: Payout ratio</td>
<td>-0.0734</td>
</tr>
</tbody>
</table>

This function obtained the following classification.**

<table>
<thead>
<tr>
<th>Actual</th>
<th>Defensive</th>
<th>Aggressive</th>
</tr>
</thead>
<tbody>
<tr>
<td>Predicted</td>
<td>56</td>
<td>8</td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>44</td>
</tr>
</tbody>
</table>

* $X^2$ (with 11 d.f.) = 71.36, significant at below 0.01.
**Maximum chance of correct classification is 0.54, but the discriminant function classification obtained is 0.90.
***CVAR = coefficient of variation, S.D., = standard deviation, and funds flow is from operations.

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6 Almost all research (in accounting) using statistical analysis attempts to understand some phenomenon that cannot be normatively measured. Due to the nature of the problems studied, the lack of a strong theory is a problem underlying all empirical research in accounting. For this reason, the result obtained in this paper should be taken only as an approximation. Specifically, some of the discriminant variables are not normally distributed so that significance tests are approximate and are used as indicators.
matrix between the discriminating variables is reproduced in Table 4. The discriminant function estimated from the primary sample obtained a 90% correct classification. Furthermore, the discriminating power of the function was not affected by the width of the interval between measurements of betas of aggressive and defensive stocks. As shown in Table 5, the discriminating power of the discriminate function has not fallen below 90% with chi-square significant at below 0.01. The discriminating power of this function finally was tested by cross validation. The functions estimated for each interval between aggressive and defensive stocks were used, and the predictive power of the cross validation ranged from 72% to 74%, that is, the predictive power of discrimination was not affected by the relative strength of low and high volatility of stocks. Furthermore, a 74% cross validation prediction is considered high in view of the 0.53 maximum chance of correct classification.

### TABLE 4

<table>
<thead>
<tr>
<th>A</th>
<th>B</th>
<th>C</th>
<th>D</th>
<th>E</th>
<th>F</th>
<th>G</th>
<th>H</th>
<th>I</th>
<th>J</th>
<th>K</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>1.0</td>
<td>-0.09</td>
<td>0.53</td>
<td>-0.31</td>
<td>-0.18</td>
<td>-0.14</td>
<td>0.07</td>
<td>-0.06</td>
<td>0.05</td>
<td>0.12</td>
</tr>
<tr>
<td>B</td>
<td>1.0</td>
<td>0.11</td>
<td>0.22</td>
<td>0.35</td>
<td>0.0</td>
<td>0.01</td>
<td>0.10</td>
<td>-0.5</td>
<td>-0.08</td>
<td>-0.14</td>
</tr>
<tr>
<td>C</td>
<td>1.0</td>
<td>0.27</td>
<td>0.03</td>
<td>0.26</td>
<td>0.32</td>
<td>-0.16</td>
<td>0.01</td>
<td>0.13</td>
<td>-0.17</td>
<td></td>
</tr>
<tr>
<td>D</td>
<td>1.0</td>
<td>0.13</td>
<td>0.69</td>
<td>0.01</td>
<td>-0.15</td>
<td>-0.01</td>
<td>-0.12</td>
<td>-0.13</td>
<td></td>
<td></td>
</tr>
<tr>
<td>E</td>
<td>1.0</td>
<td>0.06</td>
<td>0.04</td>
<td>-0.01</td>
<td>-0.07</td>
<td>-0.01</td>
<td>0.0</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>F</td>
<td>1.0</td>
<td>-0.04</td>
<td>-0.13</td>
<td>-0.07</td>
<td>0.18</td>
<td>-0.14</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>G</td>
<td>1.0</td>
<td>-0.24</td>
<td>0.23</td>
<td>0.07</td>
<td>-0.17</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>H</td>
<td>1.0</td>
<td>-0.27</td>
<td>0.01</td>
<td>-0.03</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>I</td>
<td>1.0</td>
<td>-0.15</td>
<td>-0.08</td>
<td></td>
<td></td>
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<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>J</td>
<td>1.0</td>
<td>-0.09</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>K</td>
<td>1.0</td>
<td></td>
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<td></td>
</tr>
</tbody>
</table>

### TABLE 5

The Effect of the Interval Width Between Aggressive and Defensive Stocks on the Discriminating Power

<table>
<thead>
<tr>
<th>Interval Width [Beta Ag. - Beta D]</th>
<th># of stocks</th>
<th>% Correct Classification</th>
<th>Chi Square*</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.20</td>
<td>111</td>
<td>0.90</td>
<td>71.36</td>
</tr>
<tr>
<td>0.30</td>
<td>103</td>
<td>0.91</td>
<td>70.14</td>
</tr>
<tr>
<td>0.40</td>
<td>90</td>
<td>0.93</td>
<td>67.6</td>
</tr>
<tr>
<td>0.50</td>
<td>77</td>
<td>0.90</td>
<td>51.5</td>
</tr>
</tbody>
</table>

*With 11 degrees of freedom all are significant below 0.01.
TABLE 6

The Classification Matrix for the Cross Validation Sample

<table>
<thead>
<tr>
<th></th>
<th>Defensive</th>
<th>Aggressive</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Actual</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Def.</td>
<td>51</td>
<td>13</td>
<td>64</td>
</tr>
<tr>
<td>Total</td>
<td>72</td>
<td>50</td>
<td>122</td>
</tr>
</tbody>
</table>

The maximum chance of correct classification is 0.53.

The correct classification under the decision rule is $P = 0.72$. This ratio was not affected by the change in the width of the interval between aggressive and defensive stocks. The ratio of correct classification continued to be in the range of 0.72 to 0.74 as the interval width changed from 0.20 to 0.30, 0.40, and 0.50.

Using the Decision Rule and Measuring Materiality

With this discriminating power, the function is reasonably validated. The remaining step is to measure the extent to which changes in accounting measurements induce incorrect classification. $\Delta Z_j$ was obtained for seventeen stocks that were classified correctly only marginally. If the issue of collinearity between explanatory variables is temporarily ignored and if mean earnings per share is used as the common denominator for measuring materiality, then the measure $(\Delta Z_j/b_i)/S_i = C/\sqrt{EPS}$ provides the ratios of the change in earnings which would result in the misclassification of stock $j$ as to whether it belongs in the aggressive or in the defensive category of stocks. The

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7 The mean earnings per share was used as the benchmark for determining materiality for two basic reasons. First, it is meaningful to a user to relate materiality to earnings per share since this relationship is used as a common variable in almost all financial analysis. Second, the variable was highly significant in discriminating between the two groups of stocks. This significance was assessed by the $F$ values for the earnings per share variable when the variable was made to enter the discriminant function last. Comparing the $F$ values before and after the inclusion of earnings per share was equivalent to having two different discriminant functions. The values of the $F$ ratio for the variable to enter the discriminant function at the end [that is, the significance of earnings per share as the variable to enter] under different conditions was found to be highly significant. These values were as follows.

<table>
<thead>
<tr>
<th>$F(d.f., n/dn)$</th>
<th>Width of Beta Interval Between the Two Groups</th>
<th>Significance Level</th>
</tr>
</thead>
<tbody>
<tr>
<td>9.81 (10/100)</td>
<td>0.20</td>
<td>0.01</td>
</tr>
<tr>
<td>10.93 (10/92)</td>
<td>0.30</td>
<td>0.01</td>
</tr>
<tr>
<td>9.59 (10/79)</td>
<td>0.40</td>
<td>0.01</td>
</tr>
<tr>
<td>10.33 (10/66)</td>
<td>0.50</td>
<td>0.01</td>
</tr>
</tbody>
</table>

[The author is indebted to an anonymous referee for suggesting this test.]
measure is reported for various levels of change in Table 7, $b_1$ is the discriminant coefficient for the mean earnings per share, and its value is $+2.3225$; $C$ is the value by which mean earnings per share (the sign preserved) is expected to change before incorrectly classifying a stock; $1.75$ and $0.98$ are the values for the mean earnings per share for the two groups, defensive and aggressive, respectively. A change in mean earnings per share by $\pm 10\%$ would result in an incorrect classification of six stocks, and a change by $\pm 20\%$ would result in a significantly different data structure (i.e., chi-square would be significant at the $5\%$ level) which would render a change in earnings per share by $20\%$ significant. Nevertheless, a change by $10\%$ could be significant to an investor if the assumption of equal cost of misclassifying stocks in either group is not maintained. Any change below $10\%$ is not significant.

**TABLE 7**

<table>
<thead>
<tr>
<th>Group</th>
<th>$\Delta Z$</th>
<th>$-C = \Delta Z/b_1$ for D stocks</th>
<th>$-C/1.79$ for A stocks</th>
<th>$-C/1.134$ for A stocks</th>
</tr>
</thead>
<tbody>
<tr>
<td>D</td>
<td>$+0.07$</td>
<td>$-0.03$</td>
<td>$-0.017$</td>
<td></td>
</tr>
<tr>
<td></td>
<td>$+0.13$</td>
<td>$-0.055$</td>
<td>$-0.031$</td>
<td></td>
</tr>
<tr>
<td></td>
<td>$+0.13$</td>
<td>$-0.056$</td>
<td>$-0.031$</td>
<td></td>
</tr>
<tr>
<td></td>
<td>$+0.38$</td>
<td>$-0.163$</td>
<td>$-0.09$</td>
<td></td>
</tr>
<tr>
<td></td>
<td>$+0.71$</td>
<td>$-0.306$</td>
<td>$-0.17$</td>
<td></td>
</tr>
<tr>
<td></td>
<td>$+0.73$</td>
<td>$-0.31$</td>
<td>$-0.17$</td>
<td></td>
</tr>
<tr>
<td></td>
<td>$+0.76$</td>
<td>$-0.33$</td>
<td>$-0.18$</td>
<td></td>
</tr>
<tr>
<td></td>
<td>$+0.86$</td>
<td>$-0.37$</td>
<td>$-0.21$</td>
<td></td>
</tr>
<tr>
<td></td>
<td>$+0.88$</td>
<td>$-0.38$</td>
<td>$-0.21$</td>
<td></td>
</tr>
<tr>
<td>A</td>
<td>$-0.008$</td>
<td>$+0.003$</td>
<td>$+0.003$</td>
<td>$+0.015$</td>
</tr>
<tr>
<td></td>
<td>$-0.04$</td>
<td>$+0.017$</td>
<td>$+0.015$</td>
<td>$+0.15$</td>
</tr>
<tr>
<td></td>
<td>$-0.4$</td>
<td>$+0.17$</td>
<td>$+0.15$</td>
<td></td>
</tr>
<tr>
<td></td>
<td>$-0.808$</td>
<td>$+0.35$</td>
<td>$+0.308$</td>
<td>$+0.308$</td>
</tr>
<tr>
<td></td>
<td>$-0.83$</td>
<td>$+0.36$</td>
<td>$+0.308$</td>
<td>$+0.34$</td>
</tr>
<tr>
<td></td>
<td>$-0.925$</td>
<td>$+0.39$</td>
<td>$+0.34$</td>
<td></td>
</tr>
<tr>
<td></td>
<td>$-1.023$</td>
<td>$+0.44$</td>
<td>$+0.39$</td>
<td></td>
</tr>
<tr>
<td></td>
<td>$-1.185$</td>
<td>$+0.51$</td>
<td>$+0.45$</td>
<td></td>
</tr>
</tbody>
</table>

* $-C/1.79$ represents the ratio by which earnings per share should decrease to make $\Delta Z = 0$ and thus incorrectly classify the stock. Conversely, $-C/1.134$ is the ratio by which earnings per share should increase to make the value of $\Delta Z = 0$ and incorrectly classify the stock.
Checking the Results:

The materiality measure suggested above uses only the coefficient of mean earnings per share (\( \overline{EPS} \)) in obtaining the change that would alter a correct classification of stocks. However, like regression, this coefficient shows the marginal effect on the discriminant value, given that all other variables are held constant, i.e., \( \frac{\partial Z}{\partial \overline{EPS}} = b_1 \). This assumption, however, would not be valid if the collinearity between \( \overline{EPS} \) and each of the remaining twelve variables were high. In order to evaluate the extent to which collinearity could affect the results, the correlations between \( \overline{EPS} \) and other discriminating variables were examined. As shown in Table 4, correlation coefficients were between \(-0.18\) and \(0.53\). A possible way to evaluate the effect of this collinearity is to transform the discriminant function into one variable, \( \overline{EPS} \), by expressing each of the variables as a function of \( \overline{EPS} \). Thus, for any variable \( S_i, i=2,3, \ldots, 11 \),

\[
S_i = a_i + c_i \overline{EPS}.
\]  

The discriminant function can be re-written as

\[
Z_i = a + \sum_{i=2}^{11} a_i \overline{EPS} + \sum_{i=2}^{11} b_i (c_i \overline{EPS}) + \sum_{i=2}^{11} \overline{EPS} = a' + k \overline{EPS}.
\]

The significance of collinearity can be evaluated by comparing the values of \( k \) and \( b_1 \) because the measures derived would be altered if the value of \( k \) is significantly different from the value of \( b_1 \). The results show that \( k = 2.305 \), which is close to the value of \( b_1 = 2.3225 \). Thus, collinearity between the discriminating variables should have no impact on the measures of materiality obtained here, and the results reported in Table 6 are unaltered.

CONCLUSIONS AND LIMITATIONS

This paper suggests a methodology for estimating some behavioral decision-making rules whose sensitivity to changes in accounting numbers can be used to evaluate materiality from the standpoint of a decision maker. To demonstrate this methodology, a multivariate discriminant analysis was used to estimate a decision-making rule predicting the level of market volatility of common stocks. For this particular decision situation, the power of the discriminant rule was tested by projecting it onto another sample. The result was about 75% correct classification (prediction). In turn, the impact of changes in earnings per share on this level of correct classification was studied. The behavior of the discriminant value for a given change in mean earnings per share was observed, and thus, a measure of decision-related materiality was developed in conformity with the following operational definition. A change in
earnings per share would be considered material if, as a consequence, a number of the correctly classified (predicted) observations would become incorrectly classified in such a way that the classification (confusion) matrix would become significantly different. In other words, given this well-defined decision situation, materiality is measured directly by evaluating decision effects. This evaluation was based on the discriminating coefficients of the mean earnings per share and was found unaffected by the slight collinearity existing between the discriminating variables. The advantage of deriving measures of materiality in this manner is in operationalizing its definition by using potential decision effects as the basis of measuring materiality.

The analysis of the discriminant value of the stocks that were classified correctly on the margin showed that a change in mean earnings per share by 20% or higher would result in a significantly different classification (prediction) matrix, while a change by 10% or less would not have a noticeable effect. A change between 10% and 20% could conceivably be significant to some users, depending on the relative costs of misclassification of each stock to a particular user. Thus, for the decision rule estimated in this study, a change in mean earnings per share by 10% or less has no significant impact on predicting the level of volatility of stocks and, therefore, is not considered material. Mean earnings per share was used instead of a single period earnings per share because betas were not computed over a single period and because it was desirable to avoid the fluctuations associated with a single period measure. This particular measure has a strong implication for the results. Namely, a single change in earnings per share by higher than 10% would not affect the classification of stocks on the basis of their volatility unless this change were a direct result of some events which would be perceived by investors to change earnings per share by at least 10%.²

There are some limitations to the approach presented in this paper. First, the research is exploratory and descriptive. Second, the data used in generating trends, coefficients of variations, mean, and dispersion measures are based on observations from a nine year period from 1962 through 1970, and no analysis was done on a different time horizon. These limitations would tend to undermine the generalizability of the method. However, a generalizable conclusion relates to the feasibility of using the methodology in judging decision-relevant materiality and also to the determinants of stocks' volatility levels.

REFERENCES


²The realism of this discriminant function would be tested by a field experiment which would ascertain the correspondence between the model and the actual usage. This test would require requesting decision-makers to use the discriminating variables in classifying stocks according to the level of volatility, aggressive or defensive. An attempt to conduct this experiment has failed due to the impossibility of getting analysts to respond to this request.


