Running Title: On the non-linear relationship between disclosure and its determinants

On the non-linear relationship between disclosure and its determinants

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Abstract

A linear relationship exists between interim disclosures submitted to the Helsinki Exchanges and their determinants over the period 1985-1993. A non-linear model better explains the relationship. This finding has implications for the design of other disclosure index studies.

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Introduction

Disclosure indices have been investigated for many years. They are used to quantify qualitative information in wide variety of relationships. Linear models are commonly employed in the construction of these studies. This article argues that disclosure index researchers should consider the possibility of non-linearity in their investigations. The use of a non-linear model improves the understanding of the relationship of disclosure indices and interim disclosures submitted to the Helsinki Exchanges over the period 1985-1993. Perhaps non-linearity exists in other venues.

For over 30 years, accounting researchers have been investigating the determinants of the information disclosed in corporate financial reports (Schadewitz and Blevins, 1997c). Multiple linear regression (MLR) is a frequently applied technique. Recently, the linear relationship that serves as justification for the use of MLR is being questioned. However, Cooke (1998) applies several new transformations to disclosure data from Japan and Saudi Arabia and does not find any overwhelming superiority of non-linear models over linear ones.

One method not included by Cooke (1998) is the generalized method of moments (GMM) (Gourieroux and Monfort, 1995). This article adds to the literature by comparing linear MLR results with those obtained with the previously overlooked GMM non-linear model. GMM produces significantly different results from those obtained using MLR. Disclosure index researchers my find the use of non-linear models improve their understanding of the relationships they are attempting to discover.

Data

Independent variables

The literature lists several variables that might help determine the magnitude of interim disclosure. Cooke (1989) includes 224 variables. This is far too many to be of service in the development of a practical disclosure strategy. There is a call for parsimony (AICPA, 1994, p. 124). Accordingly, this study clusters 34 previously identified variables into each of nine classes of independent variable. These are: (1) governance--6 variables, (2) business risk--6 variables, (3) size--2 variables, (4) market risk--1 variable, (5) capital structure--2 variables, (6) stock price

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adjustment--2 variables, (7) growth--3 variables, (8) growth potential--4 variables and (9) market maturity--8 years. Data for each of these variables is obtained from the databases maintained by the Helsinki School of Economics and Business Administration and the University of Oulu.

Stock market data are available from the Helsinki Exchanges.

Dependent variable

A disclosure index is constructed for each of 28 qualitative characteristics. Each interim report submitted to the Helsinki Exchanges over the period 1985 through 1993. The finance and insurance sectors are excluded (Niskanen, 1990). Missing independent variable data and the existence of three outliers reduce the original set of 573 interim reports to 251 complete sets of observations available for the final sample. This research is able to avoid the perceptive bias pointed out by Lang and Lundholm (1993).

Results

Before an independent variable enters either model, it is checked for correlation with the other variables in that particular group (Rawlings, 1988). Five of the original variables are eliminated from the overall disclosure model. This leaves 29 variables to enter the MLR and GMM calculations. The comparative results of the significant variables are shown in table 1.

[Table 1 goes about here]

Linear Findings

Backward elimination is used (Draper and Smith, 1981). The final model is constructed such that at least one variable from each of the nine variable classes is included in the model (Parviainen, 1999). The results are not significantly influenced by multicollinearity.

Significance is found in seven of the original nine groups. When there is a hypothesized direction for a variable one-tailed t-test is applied, otherwise two-tailed tests are used. Significant groups are: (1) governance, *Firms* α =.041, (2) business risk, σ (% δ NS) α =.012, σ (δ FA/A) α =.000 (3) capital structure, δ E/EB δ E α =.097, (4) growth, % δ NS α =.018 (5) growth potential, *P/NS* α =.000, (6) size, *lnWorker* α =.000, and (7) market maturity, *CY*₈₅, ..., *CY*₉₂. A joint test,

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where the yearly dichotomy variables were added to the model, yielded F(7, 234)=3.59, α =.001, indicating that the yearly dichotomy variable is statistically highly significant. The signs of the coefficients for the market maturity variable are positive, indicating that a greater amount of regulation induces greater overall disclosure. The hypothesized relationships of: (1) market risk and (2) stock price adjustment are not evidenced: the coefficient for each of these variables is insignificant. Linear results from this data set are detailed elsewhere (Schadewitz, 1997; Schadewitz and Blevins, 1997a, 1997b, 1998a, 1998b, 1998c; Schadewitz et al. 1999, Forthcoming).

Non-linear Findings

GMM estimation is accomplished here with the regression analysis of time series Doan (1997). There are 34 iterations. Overall , the GMM results are more robust than are those obtained with MLR. For example, the standard deviation for estimated coefficients are markedly lower with GMM for all but one variable (*Firms*).

The normality tests applied are Kolmogorov-Smirnov (KS) (Siegel, 1956) and Jarque-Bera (JB) (Jarque and Bera, 1987). Two normality tests are employed because the KS test is rather rigid and may be somewhat less acccurate than is the JB test. According to the KS test, only the independent variable stock valuation, *PostCAR* passes the normality test. With JB test, none of the independent variables passes the normality test.

This article highlights four advantages of the use of the GMM methodology, three of these are illustrated empirically. There is one disadvantage of the use of GMM that is demonstrated by this research.

Benefit 1--Because a straight line is a special case of a curve, it is expected that significant MLR results will be confirmed by the GMM model. This is the case with four of the variables: (1) Governance: *Firms*; (2) Business Risk: $\sigma(\%\delta NS)$, $\sigma(\delta FA/A)$; (3) Growth: $\%\delta NS$; and (4) Size: InWorker. In each case, the coefficient is duplicated, indicating the existence of a linear relationship between that variable and the disclosure index, all else constant. In the last two cases, $\sigma(\delta FA/A)$ and InWorker, the MLR results are as highly significant as is currently measurable, each with an $\alpha = .001$. In these cases, the GMM duplicates both the coefficients and the levels of

significance.

Benefit 2--The governance variable, Firms, indicates another property of the use of a non-linear model to confirm results with a linear model. **The level of significance might be improved by allowing non-linearity**. This is the case with *Firms*. The coefficients are the same with the MLR and GMM models, but the level of significance improves from a low $\alpha = .041$ to the highest measurable in this study ($\alpha = .001$).

Benefit 3--A third property of the use of non-linear models is the identification of a curvilinear relationship that masks itself as a linear one. A second business risk measure $[\sigma(\%\delta NS)]$ illustrates this property. Under MLR the coefficient is .123 with very good $\alpha = .012$. In fact, a non-linear relationship, with a coefficient of .159 provides a better model of the relationship, with the most excellent $\alpha = .001$. The capital structure measure $\delta E/EB\delta E$ is another example. The linear relationship, with its $\alpha = .097$, is improved to $\alpha = .001$ when a curve is called upon to fit the data.

Benefit 4--A fourth property of the use of non-linear models is, perhaps the most obvious one: **a non-linear model may detect a non-linear relationship**. Such relationships are overlooked with linear models. This research has no example of this case.

Sacrifice--Each of the above cases is a reason the researcher might consider the use of GMM. The procedure, however, has a complication. The *P/NS* measure of growth potential is an example of such a complication. Applying MLR, the coefficient is *negative* (-.337), with the *highest* reported level of significance ($\alpha = .001$). With the curvilinear model, the GMM coefficient is *positive* (.107) and the level of significance is *reduced* to $\alpha = .016$. This finding illustrates the need for a final comment regarding the use of models: **results are mechanically driven**. The output of any model is the natural outcome of the manipulation of the numbers, using a predetermined set of assumptions.

Researchers often do not know the relationships that underlie the data. The search for that

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relationship is often precisely the reason for the study in the first place. Perhaps the use of nonlinear models will help discover relationships that are not evidenced in linear analyses of disclosure indices.

Summary and conclusions

Non-linear models can be used to detect the relationship between a disclosure index and its determinants. Although widely used in macroeconomic and aggregate finance applications, the GMM is not reported as a measurement device in disclosure index studies. This article presents such a study, *via* a comparison of GMM with MLR results. There are some revealing findings.

One, the level of significance found with a linear model might be improved by the use of a non-linear descriptor. Two, GMM can identify a relationship that appears to be linearly related but that is not related at all. Three, GMM can disclose a curvilinear relationship that masks itself as a linear one. Four, GMM may detect a non-linear relationship, which is missed when linear models are used.

Each of these four conclusions is a benefit from the use of GMM. There is, however, a complication. Due to the different assumptions that underpin the various models, conflicting results can be obtained. This research exposes such a result.

The conclusion is that the researcher should match the model with the characteristics of the data, if known. If the characteristics of the data are unknown, the researcher should clearly state the assumptions, so readers can make informed judgments about the appropriateness of the study.

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Independent Variables	MLR		<u>GMM</u>	
Class: Aconym	Coefficient	α = Level of Significance	Coefficient	α = Level of Significance
Governance:				
Firms	001	.041	001	≤.001
Business Risk:				
$\sigma(\%\delta NS)$.123	.012	.159	≤.001
$\sigma(\delta FA/A)$.003	≤.001	.003	≤.001
Capital Structure:				
$\delta E / EB \delta E$.026	.097	.041	≤.001
Growth:				
% SNS	049	.018	071	≤.001
Growth Potential:				
P/NS	337	≤.001	.107	.016
Size:				
lnWorker	.038	≤.001	.038	≤.001

Table 1. Regression results of interim reports submitted to the Helsinki Stock Exchange over the period 1985-1993

Where:

Firms	= percentage of corporate ownership,
$\sigma(\%\delta NS)$	= standard deviation of percentage change in net sales,
$\sigma(\delta FA/A)$	= standard deviation of net investments/total assets ratio,
δΕ/ΕΒδΕ	= ratio of change in equity/equity before the change,
%δNS	= percentage change in net sales,
P/NS	= profit/net sales ratio, and
lnWorker	= natural logarithm of the number of personnel.

Boldface (*italic boldface*) designates statistical significance at the $\alpha = .05$ (.001) level.

Neither the market risk measure, β ; nor the stock valuation variable, *PostCAR*, is significant, so they are not listed in the table.

The market maturity variables, CY_{85}, \dots, g_2 , are taken as a whole, so they are not listed in the table.