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Errors-in-Variables Problems in Financial Models

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1. Introduction

The errors-in-variables (EIV) problems in finance arise from using incorrectly measured variables or proxy variables in regression models. Errors in measuring the dependent variables are incorporated in the disturbance term and they cause no problems. However, when an independent variable is measured with error, this error appears in both the regressor variable and in the error term of the new regression model. This results in contemporaneous correlation between the regressor and the error term, and leads to a biased OLS (Ordinary Least Squares) estimator (even asymptotically) and inconsistent standard errors. The biases introduced by measurement errors can be significant and can lead to incorrect inferences. Further, when there are more than one regressor variable in the model the direction of the bias is unpredictable. The effect of measurement errors on OLS estimators is discussed extensively in several econometrics texts including Maddala (1992), and Greene (1993). A comprehensive discussion of errors-in-variables model is in Fuller (1987) and a discussion in the context of econometric models is in Griliches (1985), and Chamberlain and Goldberger (1990).

The errors in the regressor variable could be due to several causes. We can classify them into the following two groups: (1) measurement errors, and (2) use of proxy variables for unobservable theoretical concepts, constructs or latent variables. Measurement errors could be introduced by using estimated values in the regression model. Examples of this are the use of estimated betas as regressors in cross-sectional tests of the CAPM (Capital Asset Pricing Model), and two-pass tests of the APT (Arbitrage Pricing Theory) where estimated rather than actual factor loadings are used in the second pass tests. The second major source of errors arises from the use of proxy variables for unobservable or latent variables. An example of this in finance would be the testing of signaling models where the econometrician observes only a noisy signal of the underlying attribute that is being signaled. In this article we examine several alternative models and techniques employed in financial models to mitigate the errors-in-variables problems. Some areas in finance where errors-in-variables problems are encountered are described below:

I. *Testing asset pricing models*: There are several potential problems in these tests; these include measurement errors associated with the use of estimates for risk measures and the problem associated with the unobservability of the true market portfolio.

II. *Performance measurements*: Measuring the performance of managed portfolios (mutual funds, pension funds etc.) is an important exercise that provides information about the ability of managers to provide superior returns. However, any method used to measure performance must specify a benchmark, and an incorrect specification of the benchmark would introduce errors in the performance measures.

III. *Market response to corporate announcements*: Several articles analyze the response of the market to unexpected earnings, unexpected dividends, unexpected splits and other announcements. To obtain the unexpected component of the variable one needs to specify a model for the expected component. An incorrect specification of the expectation model or estimation errors can result in the unexpected component being measured with error.

IV. *Testing of signaling models*: In signaling models it is argued that managers with private information can employ indicators such as dividends, earnings, splits, capital structure etc. to signal their private information to the market. In testing these models one has to realize that the indicators are noisy measures of the underlying attribute that is signaled (investment opportunities, future cash flows etc.).

A researcher can employ several approaches to correct for the errors-in-variables problem, and to obtain consistent estimates and standard errors. We examine these approaches under the following eight classifications: (1) Grouping Methods, (2) Direct and Reverse Regressions, (3) Alternatives to Two Pass Methods, (4) MIMIC Models, and (5) Artificial Neural Networks (ANN) models. We also discuss other models where the errors-in-variables problems are relevant. These are examined under the categories: (6) Signal Extraction Models, (7) Qualitative Limited Dependent Variable Models, and (8) Factor Analysis with Measurement Errors.

2. Grouping methods

Grouping methods have been commonly used in finance as a solution to the errors-in-variables problem. See, for instance, Black, Jensen and Scholes (1972), Fama and MacBeth (1973) and Fama and French (1992) for a recent illustration. We will refer to these papers as BJS, FM and FF respectively in subsequent discussion. The basic approach involves a two-pass technique. In the first pass, time series data on each individual security are used to estimate betas for each security. In the second pass a cross-section regression (CSR) for the average returns on the securities is estimated using the betas obtained from the first pass as regressors. This introduces the errors-in-variables problem. Since grouping methods can be viewed as instrumental variable (IV) methods, grouping is used to solve this errors-in-variables problem. There are frequent references to Wald's classic paper in this literature but the simple grouping method used by Wald is not the one used in these papers.

Wald's method consists of ranking the observations, forming two groups and then passing a line between the means of the two groups. Later articles suggested that the efficiency of the estimator could be improved by dividing the data into three groups, discarding the observations in the middle group, and passing the line between the means of the upper and lower groups. Wald's procedure amounts to using rank as an instrumental variable, but since rank depends on the measurement error, this cannot produce a consistent estimator (a point noted by Wald himself). Pakes (1982) argues that contrary to the statements often made in several textbooks (including the text by Maddala, 1977, which has been corrected in *Introduction to Econometrics*, Second. Ed. 1992) the grouping estimator is not consistent. This problem has also been pointed out in the finance literature in a recent paper by Lys and Sabino (1992) although there is no reference in this paper to the work of Pakes (1982).

The grouping method used in FM and FF is not the simple grouping method used by Wald. The procedure is to estimate the betas with, say, monthly observations on the first 5 years and then rank the securities based on these estimated betas to form 20 groups (portfolios). Then the estimation sample (omitting the first 5 years of data) is used to estimate a cross-section regression of asset returns on the betas for the different groups.

2.1. *Cross-sectional tests*

In the cross-sectional tests of the CAPM, the average return on a cross-sectional sample of securities over some time period is regressed against each securities beta (β) with respect to a market portfolio. In the first stage, $\hat{\beta}_i$ is estimated from a time series regression of the return on a market index R_{Mt} on the individual stock returns R_{it}.

$$R_{it} = \alpha_i + \beta_i R_{Mt} + v_{it} \ . \tag{1}$$

In the second stage, a cross-sectional regression model of the average return on the individual security $\bar{R}_i$, is regressed on the estimate of beta.

$$\bar{R}_i = \gamma_0 + \gamma_1 \hat{\beta}_i + \epsilon_i \ . \tag{2}$$

Finally, the estimated coefficient $\hat{\gamma}_0$ is compared to the risk-free rate (R_f) in the period under examination and $\hat{\gamma}_1$ is compared to an estimate of the risk premium on the market ($\bar{R}_M - R_f$) estimated from the same estimation period. The first direct test based on cross-sectional regression was by Douglas (1969). In this test Douglas estimated a cross-sectional model of the average return on a large number of common stocks on the stock's own variance and on their covariance with a market index. The tests were inconsistent with the CAPM because the coefficient on the variance term was significant while the coefficient on the covariance term was not significant.

A detailed analysis of the econometric problems that arise from a cross-sectional test was first given by Miller and Scholes (1972). They concluded that measurement error in $\hat{\beta}_i$ was a significant source of bias that contributed toward the findings by Douglas. Fama and MacBeth (1973) use a portfolio approach to reduce the errors-in-variables problem. In particular, they estimate the following cross-sectional-time-series model.

$$R_{pt} = \gamma_{0t} + \gamma_{1t}\beta_{p,t-1} + \gamma_{2t}\bar{\beta}^2_{p,t-1} + \gamma_{3t}\bar{\sigma}_{p,t-1}(\epsilon) + \eta_{pt} \ , \tag{3}$$

where, β_p is the average of the betas for the individual stocks in a portfolio, $\bar{\beta}^2_p$ is the average of the squared betas and $\bar{\sigma}_p(\epsilon)$ is the average residual variance from a market model given by equation (1).

If $\hat{\beta}_i$ is estimated with an unbiased measurement error v_i then the regression estimate of γ for the model described by equation (2) is given by

$$p\lim \quad \hat{\gamma}_1 = \frac{\gamma_1}{1 + \dfrac{\mathrm{Var}\ (v_i)}{\mathrm{Var}\ (\beta_i)}} \tag{4}$$

where, $\mathrm{Var}(v_i)$ is the variance of the measurement errors, and $\mathrm{Var}(\beta_i)$ is the cross-sectional sample variance of the true risk measures β_i. Thus, even for large samples, as long as β_i's are measured with errors the estimated coefficient $\hat{\gamma}_1$ will be biased toward zero and $\hat{\gamma}_0$ will be biased away from its true value. The idea behind the grouping or portfolio technique is to minimize the $\mathrm{var}(v_i)$ through the portfolio diversification effect, and at the same time one would like to maximize the $\mathrm{Var}(\beta_i)$ by forming portfolios by ranking on β_i's.

2.2. Time series and multivariate tests

Black, Jensen and Scholes (1972) employ a time-series procedure to test the CAPM that avoids the errors-in-variables problem. They estimate the following model:

$$(R_{pt} - R_{Ft}) = \alpha_p + \beta_p(R_{Mt} - R_{Ft}) + \epsilon_{pt} \ , \tag{5}$$

where, R_{pt} is the return on a portfolio of stocks ranked by their betas estimated from a prior period, R_{Ft} is the risk free rate, and R_{Mt} is the return for the market portfolio. In this specification, the test is based on the hypothesis that $\alpha_p = 0$ if CAPM is valid.

Gibbons (1982) employs a multivariate regression framework in which the asset pricing models are cast as nonlinear parameter restrictions. The approach avoids the errors-in-variables problems introduced by the two pass cross-sectional tests. Gibbons uses the method to test the Black's (1972) version of the CAPM which specifies the following linear relationship between expected return on the security and risk.

$$\mathrm{E}(R_{it}) = \gamma + \beta_i[\mathrm{E}(R_{mt}) - \gamma] \ , \tag{6}$$

where, $\mathrm{E}(R_{it})$ is the expected return on security i for period t, $\mathrm{E}(R_{mt})$ is the expected return on the market portfolio for period t, γ is the expected return on a zero beta portfolio, and $\beta_i = \mathrm{cov}(R_{it}, R_{mt})/\mathrm{var}(R_{mt})$. In addition, if asset returns are stationary with a multivariate normal distribution, then they can be described by the "market model"

$$R_{it} = \alpha_i + \beta_i R_{mt} + \eta_{it}, \quad i = 1, \ldots, N \ , \quad t = 1, \ldots T \ . \tag{7}$$

In terms of equation (7), Black's model given by equation (6) implies the restrictions

$$\alpha_i = \gamma(1 - \beta_i) \quad \forall \quad i = 1, \ldots, N \ . \tag{8}$$

Thus, Black's version of the CAPM places nonlinear restrictions on a system of N regression equations. The errors-in-variables problems with the two-pass procedure are avoided by estimating γ and β's simultaneously. Gibbons employs a likelihood ratio statistic to test the restrictions implied by the CAPM.

One important point to note in the cross-sectional tests is that grouping to take care of errors in variable is not necessary. The problem here is not the one in the usual EIV models where the variance of the measurement error is not known. Note that the betas are estimated but their variance is known. This knowledge is used in Litzenberger and Ramaswamy (1979) (referred to later as L-R) to get bias corrected estimates. In the statistical literature this method is known as consistent adjusted least squares (CAL) method and has been discussed by Schneeweiss (1976), Fuller (1980) and Kapteyn and Wansbeek (1984), although the conditions under which the error variances are estimated are different in the statistical literature and the financial literature. The L-R method involves subtracting an appropriate expression from the cross-product matrix of the estimated beta vector to neutralize the impact of the measurement error. The modified estimator is consistent as the number of securities tends to infinity. However, in practice, this adjustment does not always yield a cross-product matrix that is positive definite. In fact, Shanken and Weinstein (1990) observe this in their work and argue that more work is needed on the properties of L-R method. Banz (1981) also mentions "serious problems in applying the Litzenberger-Ramaswamy estimator" in his analysis of the firm size effect.

Besides the L-R method, another promising alternative to the traditional grouping procedure for correcting the EIV bias, is the maximum likelihood method. Shanken (1992) discusses the relationship between the L-R method and the ML method.

In addition to the bias correction problem there is the problem of correcting the standard errors of the estimated coefficients. Shanken (1992) derives the correction factors for the standard errors in the presence of errors-in-variables.

2.3. Grouping in the presence of multiple proxies

The above discussion refers only to simple regression models with one regressor (estimated beta). However, there are models where several regressors are measured with error. Here, grouping by only one variable amount to using only one instrumental variable, and therefore cannot produce consistent estimates. An example of multiple proxies is the paper by Chen, Roll and Ross (1986) which uses the Fama-MacBeth procedure. We will refer to this paper as CRR. They consider five variables describing the economic conditions (monthly growth in industrial production, change in expected inflation, unexpected inflation, term structure, and risk premium measured as the difference between the return on low grade (Baa) bonds and long-term government bonds.) They use a two-pass procedure. In the first pass the returns on a sample of assets are regressed on the five economic state variables over some estimation period (previous five years). On the second pass the beta estimates from the first pass used as independent variables in 12 cross-sectional regressions, one for each of the next 12 months, with asset returns for the month being the dependent variable. Each coefficient in this regression provides an estimate of the risk premium associated with the corresponding state variable. The two-pass procedure is repeated for each year in the sample, yielding time-series estimates of the risk premia associated with the macro variables. The time series means are then tested by a t-test for significant difference from zero.

CRR argue (p. 394) that "to control the errors-in-variables problem that arises from step c of the beta estimates obtained in step b, and to reduce the noise in individual asset returns, the securities were grouped into portfolios." They use size (total market value at the beginning of each test period) as the variable for grouping. CRR further argue that the economic variables were significant in explaining stock returns and in addition these variables are "priced" (as revealed by significant coefficients in the second pass cross-sectional regression). Shanken and Weinstein (1990), however, argue that the CRR results are sensitive to the grouping method used and that the significance of the coefficients in the cross-sectional regression is altered if EIV adjustment is made to the standard errors.

There are two issues that arise in the CRR approach. First, when there are multiple proxies, does grouping by a single variable give consistent estimates? Since grouping by size is equivalent to the use of size as an instrumental variable, what CRR have done is used one instrumental variable (IV). The number of IV's used should be at least equivalent to the number of proxies, in the case of multiple proxies.

The second issue is that of alternatives to the grouping methods. One can use the adjusted least squares as in the L-R method discussed earlier, although there would be the problem of the resulting moment matrix being not positive definite. Shanken and Weinstein (1990) discuss adjusting the standard errors only but (we should be) making adjustments for both the coefficient bias and the standard errors.

3. Alternatives to the two-pass estimation method

In the estimation of the CAPM model, the errors-in-variables problem is created by using the estimated betas in the first stage as explanatory variables in a second stage cross-section regression. Similar problems arise in the two-pass tests of the arbitrage pricing theory (APT) developed by Roll and Ross (1960), Chen (1983), Connor and Korajczyk (1988), Lehmann and Modest (1988) among others.

While Gibbons' (1982) approach avoids the errors-in-variables problem introduced by a two-pass method, the methodology does not address the issue of the unobservability of the "true" market portfolio. As pointed out by Roll (1977), the test of the asset pricing model is essentially a test of whether the proxy used for the "market portfolio" is mean-variance efficient. Gibbons and Ferson (1985) argue that asset pricing models can be tested without observing the "true" market portfolio if the assumption of a constant risk premium is relaxed. This requires a model for conditional expected returns which is used to estimate ratios of betas without observing the market portfolio.

The problems due to the unobservability of the market portfolio and the errors-in-variables problems can be avoided by using one-step methods where the underlying factors are treated as unobservables. We discuss models with unobservables in Section 5, and factor analysis with measurement errors in Section 9.

Geweke and Zhou (1995) provide an alternative procedure for testing the APT without first estimating separately the factors or factor loadings. Their approach is Bayesian. The basic APT assumes that returns on a vector of N assets are related to k underlying factors by a factor model:

$$\begin{aligned} r_{it} &= \alpha_i + \beta_{i1} f_{1t} + \beta_{i2} f_{2t} + \ldots + \beta_{ik} f_{kt} + \epsilon_{it} \ , \\ i &= 1, \ldots, N \ , \quad t = 1, \ldots, T \ , \end{aligned} \tag{9}$$

where, $\alpha_i = \mathrm{E}(r_{it}), \beta_{ik}$ are the factor loadings, and ϵ_{it} are idiosyncratic errors for the i^{th} asset during period t. This model can be written compactly, in vector notation as

$$r_t = \alpha + \beta f_t + \epsilon_t \ , \tag{10}$$

where r_t is an N-vector of returns during period t, α and ϵ_t are $N \times 1$ vectors, f_t is a $k \times 1$ vector and β is a $N \times k$ matrix. The standard assumptions of the factor model are the following:

$$\begin{aligned} &\mathrm{E}(f_t) = 0 \ , \mathrm{E}(f_t f_t') = I \ , \ \mathrm{E}(\epsilon_t | f_t) = 0 \quad \text{and} \\ &\mathrm{E}(\epsilon_t \epsilon_t' | f_t) = \Sigma \ , \quad \text{where} \quad \Sigma = \mathrm{diag}[\sigma_1^2, \ldots, \sigma_N^2] \ . \end{aligned} \tag{11}$$

Also, ϵ_t and f_t are independent and follow multivariate normal distributions.

It has been shown that absence of riskless arbitrage opportunities imply an approximate linear relation between the expected returns and their risk exposure. That is

$$\alpha_i \simeq \lambda_0 + \lambda_1\beta_{1i} + \ldots + \lambda_k\beta_{ki} \qquad i = 1, \ldots, N \ , \tag{12}$$

as $N \to \infty$, where λ_0 is zero-beta rate and λ_k is the risk premium on the k^{th} factor. Shanken (1992) gives alternative approximate pricing relationships under weaker conditions. A much stronger assumption of competitive equilibrium gives the equilibrium version of the APT where the condition (12) is an equality. Existing studies based on the classical methods test only the equillibrium version. Geweke and Zhou (1995) argue that their approach measures the closeness of (12) directly by obtaining the posterior distribution of Q defined as

$$Q = \frac{1}{N}\sum_{i=1}^{N}(\alpha_i - \lambda_0 - \lambda_1\beta_{1i} \ldots - \lambda_k\beta_{ki})^2 \ . \tag{13}$$

For the equilibrium version of APT, $Q \equiv 0$. Geweke and Zhou argue that inference about Q in the classical framework is extremely complicated. They use the Bayesian approach to derive the posterior distribution of Q based on priors for α, β, λ and Σ. Since the Bayesian approach involves the integration of nuisance parameters from the joint posterior distribution and since analytical integration is not possible in this case, they outline a numerical integration procedure based on Gibbs sampling.

The most flexible two-pass approach is the one developed by Connor and Krajezyk (1986, 1988) which is a cross-section approach that can be applied to a large number of assets to extract the factors. By contrast the approach of Geweke and Zhou is a time-series approach and therefore has a restriction on the number of assets that can be considered ($N \leq T - k$). However, the former approach ignores the EIV problem but the latter does not.

Geweke and Zhou illustrate their methodology by using monthly portfolios returns grouped by industry and market capitalization. An important finding is that there is little improvement in reducing the pricing errors by including more factors beyond the first one. (See also the conclusions in Section 9 which argue in favor of fewer factors.)

4. Direct and reverse regression methods

In his 1921 paper in *Metroeconomica*, Gini stated that the slope of the coefficient of the error ridden variable lies between the probability limit of the OLS coefficient and the probability limit of the "reverse" regression estimate of the same coefficient. This result, which has also been derived in Frisch (1934), does not carry over to the multiple regression case in general. This generalization, due to Koopmans (1937), is discussed, with a new proof in Bekker et al. (1985). Apart from Koopmans' proof, later proofs have been given by Kalman (1982) and Klepper and Leamer (1984). It has also been extended to equation systems by Leamer (1987).

All these results require that the measurement errors be uncorrelated with the equation errors. This assumption is not valid in many applications. Erickson

(1993) derives the implications of placing upper and lower bounds on this correlation in a multiple regression model with exactly one mis-measured regressor. Some other extensions of the bounds literature is that by Krasker and Pratt (1986), who use a prior lower bound on the correlation between the proxy and the true regressor, and Bekker et al. (1987) who use as their prior input an upper bound on the covariance matrix of the errors. Iwata (1992) considers a different problem — the case where instrumental variables are correlated with errors. In this case, the instrumental variable method does not give consistent estimates but Iwata shows that tighter bounds can be found if one has prior information restricting the extent of the correlation between the instrumental variables and the regression equation errors.

In the financial literature the effect of correlated errors has been discussed in Booth and Smith (1985). They consider the case where the errors and the systematic parts of both y and x are correlated (all other error correlations are assumed to be zero). They also give arguments as to why allowing for these correlations is important. This analysis has been applied by Rahman, Fabozzi and Lee (1991) to judge performance measurement of mutual fund shares, which depends on the intercept term in the capital asset pricing model. They derive upper and lower bounds for the constant term using direct and reverse regressions. These results on performance measurement are based on the CAPM. There is, however, discussion in the financial literature of performance measurement based on the APT (arbitrage pricing theory) which is a multiple-index/factor model. See Connor and Korajczyk (1986, 1994). In this case, the bounds on performance measurement are difficult to derive. The results by Klepper and Leamer (1984) can be used but they will be based on the restrictive assumption that the errors and systematic parts are uncorrelated (an assumption relaxed in the paper by Booth and Smith). The relaxation of this assumption is important, as argued in Booth and Smith.

5. Latent variables / structural equation models with measurement errors and MIMIC models

5.1. Multiple indicator models

Many models in finance are formulated in terms of theoretical or hypothetical concepts or latent variables which are not directly observable or measurable. However, often several indicators or proxies are available for these unobserved variables. The indicator or proxy variables can be considered as measuring the unobservable variable with measurement errors. Therefore, the use of these indicator variables directly as a regressor variable in a regression model would lead to errors-in-variables problems. However, if a single unobservable (or latent) variable occurs in different equations as an explanatory variable (multiple indicators of a latent variable), then one can get (under some identifiability conditions) consistent estimates of the coefficients of the unobserved variable. These models are discussed in Zellner (1970), Goldberger (1972), Griliches (1974), Joreskog and Goldberger (1975), and popularized by the LISREL program of Joreskog and Sorbom (1989, 1993).[1] Although many problems in finance fall in this category, there are not many applications of these models in finance. Notable exceptions in corporate finance are the models estimated by Titman and Wessels (1990), Maddala, and Nimalendran (1995), and Desai, Nimalendran and Venkataraman (1995).

Titman and Wessels (TW) investigate the determinants of corporate capital structure in terms of unobserved attributes for which they have indicators or proxies which are measured with error. The model consists of two parts: a measurement model, and a structural model which are jointly estimated. In the measurement model, the errors in the proxy variables (e.g. accounting and market data) used for the unobservable attributes are explicitly modeled as follows:

$$X = \Lambda Z + \delta \ . \tag{14}$$

where, $X_{q\times 1}$ is a vector of proxy variables, Z_{mx1} is vector of unobservable attributes and $\Lambda_{q\times m}$ is a matrix of coefficients, and $\delta_{q\times 1}$ is a vector of errors. In the above measurement model, the observed proxy variables are expressed as a linear combination of one or more attributes and a random measurement error. The structural model consists of the relationship between different measures of capital structure (short term debt/equity, long term debt/equity etc.), $Y_{p\times 1}$, and the unobservable attributes Z. The model is specified as follows where ϵ is a vector of errors:

$$Y = \Gamma Z + \epsilon \ . \tag{15}$$

Equations (14) and (15) are estimated jointly using the maximum likelihood technique (estimation techniques are described later in this section). TW estimate the model for 15 proxy variables, 8 attributes and 3 different capital structure variables. In order to identify the model additional restrictions are placed. In particular, it is assumed that the errors are uncorrelated, and 105 of the elements of the coefficient matrix are constrained to be zero. The principal advantage of the above model over traditional regression models is that it explicitly models the errors in the proxy variables. Further, if the model is identified then it can be estimated by full information maximum likelihood (FIML) which gives consistent and asymptotically efficient estimates under certain regularity conditions.

Maddala and Nimalendran [MN] (1995) employ an unobserved components panel data model to estimate the effects of unexpected earnings on change in price, change in bid-ask spreads and change in trading volume. Traditionally, the unexpected earnings (actual-analysts forecast), ΔE, is employed as a regressor in a regression model to explain the changes in spreads (ΔS) or changes in volume

[1] These models have also been discussed extensively under the titles: linear structural models with measurement errors, analysis of covariance structures, path analysis, causal models and content variable models. Bentler and Bonett (1980) and Bollen (1989) provide excellent introductions to the subject.

(ΔV).[2] However, the unexpected earnings are error-ridden proxies for the true unexpected earnings. Therefore, the estimates and the standard errors suffer from all the problems associated with error in variables. MN employ an unobserved components model to obtain consistent estimates of the coefficients on the unobserved variable and the consistent standard errors. In the 3-equation model they consider, it is assumed that the absolute value of the change in price $|\Delta P|$, the change in spread ΔS, and the change in volume ΔV are three indicator variables of the unobserved absolute value of the unexpected true earnings $|\Delta \mathrm{E}^*|$. The specification of the model is,

$$\begin{aligned} |\Delta P| &= \alpha_0 + \alpha_1 |\Delta \mathrm{E}^*| + \epsilon_1 \\ \Delta S &= \beta_0 + \beta_1 |\Delta \mathrm{E}^*| + \epsilon_2 \\ \Delta V &= \gamma_0 + \gamma_1 |\Delta \mathrm{E}^*| + \epsilon_3 \ , \end{aligned} \tag{16}$$

where it is assumed that the errors, $\epsilon_i, I = 1, 2, 3$, are uncorrelated and they are also uncorrelated with the unobserved variable $|\Delta \mathrm{E}^*|$. Then the covariance matrix of the observed variables implied by the model is given by

$$\sum = \begin{pmatrix} \alpha_1^2\sigma_e^2 + \sigma_1^2 & \alpha_1\beta_1\sigma_e^2 + \sigma_{12} & \alpha_1\gamma_1\sigma_e^2 + \sigma_{13} \\ - & \beta_1^2\sigma_e^2 + \sigma_2^2 & \beta_1\gamma_1\sigma_e^2 + \sigma_{23} \\ - & - & \gamma_1^2\sigma_e^2 + \sigma_3^2 \end{pmatrix} , \tag{17}$$

where, $\sigma_{ij} = \mathrm{cov}(\epsilon_i, \epsilon_j), i, j = 1, 2, 3$ and $\sigma_\epsilon^2 = \mathrm{Var}(\Delta \mathrm{E}^*)$.

Since the sample estimates of the variance-covariance matrix are consistent estimates of the population parameters, one can estimate the parameters $\alpha_1, \beta_1, \gamma_1, \sigma_1^2, \sigma_3^2$, and σ_e^2, by setting the sample estimates equal to the population variance-covariance elements. However, there are seven unknown parameters and only six pieces of sample information. Therefore the system is under identified and only β_1/α_1 and γ_1/α_1 that are estimable. The parameters α_1, β_1, and γ_1 are not separately estimable. Among the variances $\sigma_1^2, \sigma_2^2, \sigma_3^2$ are estimable and so is $\alpha_1^2\sigma_e^2$. Let the variance-covariance matrix based on sample data be given by

$$S = \mathrm{Var}\begin{pmatrix} |\Delta P| \\ \Delta S \\ \Delta V \end{pmatrix} = \begin{pmatrix} s_{11} & s_{12} & s_{13} \\ - & s_{22} & s_{23} \\ - & - & s_{33} \end{pmatrix} . \tag{18}$$

Then consistent estimates for the parameters are given by:

[2] Morse and Ushman (1983) examined a sample of OTC (Over the Counter) firms and found no evidence of change in the spread around earnings announcements. Skinner (1991) using a sample of NASDAQ firms found only a weak evidence of an increase in spread prior to an earnings announcements. Skinner used change in price around the earnings announcement as a proxy for the forecast errors.

$$\frac{\hat{\beta}_1}{\hat{\alpha}_1}=\frac{s_{23}}{s_{13}},\quad \frac{\hat{\gamma}_1}{\hat{\alpha}_1}=\frac{s_{23}}{s_{12}},\quad \hat{\alpha}_1^2\hat{\sigma}_e^2=\frac{s_{12}}{\hat{\beta}_1/\hat{\alpha}_1},\ \hat{\sigma}_1^2=s_{11}-\hat{\alpha}_1^2\hat{\sigma}_e^2,$$
$$\hat{\sigma}_2^2=s_{22}-\hat{\beta}_1^2\hat{\alpha}_1^2\hat{\sigma}_e^2,\quad \text{and}\quad \hat{\sigma}_3^2=s_{33}-\hat{\gamma}_1^2\hat{\alpha}_1^2\hat{\sigma}_e^2 \tag{19}$$

It should also be noted that the model described by equations (16) can be written as:

$$\begin{aligned}
\Delta S &= \beta_0^* + \frac{\beta_1}{\alpha_1}|\Delta P| + \epsilon_2^*,\\
\Delta V &= \gamma_0^* + \frac{\gamma_1}{\alpha_1}|\Delta P| + \epsilon_3^*, \quad \text{where,}\\
\beta_0^* &= \beta_0 - \frac{\beta_1}{\alpha_1}\alpha_0 \quad \text{and} \quad \epsilon_2^* = \epsilon_2 - \frac{\beta_1}{\alpha_1}\epsilon_1 \ .
\end{aligned} \tag{20}$$

with γ_0^* and ϵ_3^* defined similarly. From equations (19) and (20), it is easy to see that $\hat{\beta}_1/\hat{\alpha}_1$ is the IV (instrumental variable) using ΔV as an instrumental variable, and $\hat{\gamma}_1/\hat{\alpha}_1$ is the IV estimator from using ΔS as an instrumental variable.

The above model shows that it is not necessary to observe the unobservable variable to estimate the parameters of the model. The sample moments contain sufficient information to identify the structural parameters. Also, since the above model is exactly identified, the method-of-moment estimators are also maximum likelihood estimates under normality assumption, with all its desirable properties. The above model gives estimates of the effects of unexpected earnings on the other variables that are free of the errors-in-variables bias involved in studies that use $|\Delta\mathrm{E}|$ or $|\Delta P|$ as a proxy for $|\Delta\mathrm{E}^*|$. MN find that errors-in-variables can result in *substantial* biases in OLS estimates leading to *incorrect inferences.*

Maddala and Nimalendran (1995) also estimate a 4-equation model in which the absolute value of the unexpected earnings ($|\Delta\mathrm{E}|$) is used as an additional proxy. When there are more than 3 indicator variables, the model is over identified (assuming that the errors are mutually uncorrelated and they are uncorrelated with the latent variable). That is there are more unique sample pieces of information than unknown parameters. If there are N indicators then there are $N(N+1)/2$ sample moments (variances and covariances) but there are only $2N$ unknown parameters. The additional information allows one to estimate additional parameters such as some of the covariances between error terms. More importantly, MN use the panel data structure (quarterly earnings for a cross-section of firms) to obtain within group and between group estimates that provide information about the short term and long term effects of earnings surprises on microstructure variables.

5.2. Testing signaling models

The study of the relationship between signals and markets' response to them is an important area of financial research. In these models it is argued that managers with private information employ indicators such as dividends, earnings, splits, capital structure etc. to convey their private information to the market. In testing these models one has to realize that the indicators are only "error ridden" proxies for the "true" underlying attribute being signaled. Therefore, the latent variable/structural equation models would be more suitable compared to the traditional regression models.

Israel, Ofer and Siegel (1990) discuss several studies that use changes in equity value as a measure of the information content of an event (earnings announcement, dividend announcement, etc.) and use this as an explanatory variable in other equations. See, for instance, Ofer and Siegel (1987). All these studies test the null hypothesis that there is no information content about earnings embodied in a given announcement, by testing for a zero coefficient on the change in equity value ΔP. Israel, et.al. assume that ΔP is a noisy measure of the true information content ΔP^*, and they investigate the power of standard tests of hypotheses by simulation for given values of the slope coefficient, and the ratio of the error variance to var(ΔP).

The information in dividend announcements above that in earnings data, and whether such announcements lead to subsequent changes in earnings estimates, have been studied *interalia* in Aharony and Swary (1980) and Ofer and Siegel (1987). Ofer and Siegel use change in equity value surrounding the dividend announcement as a proxy for the information content and use this as an explanatory variable in the dividend change equation. However, a more reasonable model to estimate, that is free of the errors-in-variables bias is to treat information content as an unobserved signal and use change in equity value, unexpected dividends, and change in expected earnings as functions of the unobserved signal. This is illustrated in the paper by Desai, Nimalendran and Venkataraman [DNV] (1995). DNV estimate a latent variable/structural equation model to examine the information conveyed by stock splits which are announced contemporaneously with dividends. They also examine whether dividends and stock splits convey a single piece of information or whether they provide information about more than a single attribute. Their analysis shows that dividends and splits convey information about two attributes, and more importantly the latent variable approach gives unbiased and asymptotically efficient estimators.

Several recent papers in the area of signaling have argued that management may use a combination of signals to reduce the cost of signaling. It is also possible that management can signal in a sequential manner using insider trading and cash dividends (see for example John and Mishra (1990) and the references in it). Many of the signals used by management are changes in dividends, stock splits, stock repurchases, investment and financial policies, insider trading and so on. In testing these models one has to measure the price reaction around the announcement date and also estimate the unexpected component of the signal used (such as unexpected component of dividend change). Generally simple models such as setting the expected dividend equal to past dividend is used. These naive models can lead to substantial errors.

5.3. MIMIC models

If there are multiple indicators and multiple causes, then these models are called MIMIC models (Joreskog and Goldberger (1975)). Note that the multiple indicators of a single or multiple latent variables model is a special case of the MIMIC model. The structural form is

$$\begin{aligned} Y &= \Lambda z^* + \epsilon \\ z^* &= X'\Delta + v \end{aligned} \tag{21}$$

where, $Y_{m\times 1}$ represents the vector of indicator variables, z^* is unobservable and is related to several causes given by the vector $X_{k\times 1}$, and $\Delta_{k\times 1}$ is a vector of parameters. A potential application of the above model in financial research involves the effects of trading mechanisms (or information disclosure) on liquidity and cost of trading. One function of a stock market is to provide liquidity. Several theoretical and empirical papers have addressed this issue (see for example Grossman and Miller (1988), Amihud and Mendelson (1986), Christie and Huang (1994)). The effect of market structure on liquidity is generally examined by analyzing the change in spreads (effective or quoted) associated with stocks that move from one market to another (as in Christie and Huang (1994). However, spread is only one of several proxies that measure liquidity (other proxies are volume of trade, market depth, number of trades, time between trades etc.) More important, there could be several causes driving a stock's liquidity that include: an optimum price, trading mechanism, frequency and type of information, type of investors, type of underlying assets or investment opportunities of the firm. Given multiple indicators and multiple causes, a MIMIC model is more suitable to evaluate effects of trading mechanism and market structure on liquidity.

5.4. Limitations with MIMIC / latent variable models

5.4.1. Problem of poor proxies and choice of proxies

There are several limitations of the latent variable or MIMIC models. Since the model formulation amounts to using the proxies as instrumental variables in the equations other than the one in which it occurs, the problem of poor proxies is related to the problem of poor instrumental variables, on which there is now considerable literature. Therefore the problems associated with the use of poor instruments suggests that caution should be exercised in employing too many indicators. For instance, Titman and Wessels (1988) use 15 indicators and impose 105 restrictions on the coefficient matrix. The problems arising from poor instruments are not likely to be revealed when one includes every conceivable indicator variable in the model.

Very often there are several proxy variables available for the same unobserved variable. For instance, Datar (1994) investigates the effect of 'liquidity' on equity returns. He considers two proxies for liquidity: volume of trading, and size (market value). Apart from the shortcoming that his analysis is based on size-based and volume-based grouping (which amounts to using the proxy variables as instrumental variables), he argues for the choice of volume as the preferred proxy for liquidity based on conventional t-statistics. The problem of choosing between different proxy varibales cannot be done within the framework of conventional analysis. A recent paper by Zabel (1994) analyzes this problem within the framework of likelihood ratio tests for non-nested hypotheses. However, instead of formulating the problem as a choice between different proxies, it would be advisable to investigate how best to use all the proxies to analyze the effect of say "liquidity" on stock returns. This can be accomplished by using the MIMIC model (or multiple indicator model) approach.

Standard asymptotic theory leads us to expect that a weak instrument will result in a large standard error, thus informing us that there is not much information in that variable. However, in small samples a weak instrument can produce a small standard error and a large t-statistic which can be spurious. Dufour(1994) argues that confidence intervals based on asymptotic theory have zero probability coverage in the weak instrument case. The question of how to detect weak instruments in the presence of several instruments is an unresolved issue. There are some studies like Hall, Rudenbusch and Wilcox (1994) that discuss this but this study also relies on an asymptotic test. Jeong (1994) suggests alternative criteria based on an exact distribution. Thus the issue of which indicators to use and which to discard in MIMIC models needs further investigation. It might often be the case that there are some strong theoretical reasons in favor of some indicators and these any how need to be included (as done in the study by DNV).

5.4.2. *Violation of assumptions*

The second important limitation arises from the assumption that the errors are uncorrelated with the systematic component and among themselves. In the multiple indicator models, some of the correlations among the errors or the errors and the systematic parts may be introduced only if the number of indicators is more than three. The third problem arises from possible non-normality of the errors. In this case the estimates are still consistent, but the standard errors and other test statistics are not valid. Browne(1984) suggests a weighted least squares (WLS) approach which is asymptotically efficient, and provides the correct standard errors and test statistic under general distributional assumption. Finally, there is the question of small sample performance for the different tests based on the latent varibale model and FIML.

5.5. *Estimation*

All the models described in this section can be estimated by FIML. See Aigner and Goldberger (1977), Aigner, Hsiao, Kapteyn, and Wansbeek (1984), and Bollen (1989). The FIML approach provides an estimator that is consistent, asymptotically efficient, scale invariant, and scale free. Further, through the Hessian matrix one can obtain standard errors for the parameter estimates. However, these standard errors are consistent only under the assumption that the observed variables are multivariate normal. If the observed variables have significant excess kurtosis, the asymptotic covariance matrix, standard errors, and the χ^2 statistic (for model evaluation) based on the estimator are incorrect (even though the estimator is still consistent). Under these conditions, the correct standard errors and test statistics can be obtained by using the asympotically distribution free WLS estimators suggested by Browne (1984). The FIML estimates for the model are obtained by maximizing the following likelihood function.

$$L(\theta) = \text{constant} - \left(\frac{N}{2}\right)\left[\log|\Sigma(\theta)| + \text{tr}[S\Sigma^{-1}(\theta)]\right] , \tag{22}$$

where S is the sample variance-covariance matrix for the observed variables, and $\Sigma(\theta)$ is the covariance matrix implied by the model. Several statistical packages including LISREL and SAS provide FIML estimates and their standard errors. LISREL also provides the asymtotically distribution free WLS estimates.

6. Artificial neural networks (ANN) as alternatives to MIMIC models

One other limitation of the models considered in the previous section is the assumption of linearity in the relationships. The artificial neural network (ANN) approach is similar in structure to the MIMIC models (apart from differences in terminology) but allows for unspecified forms of non-linearity. In the ANN terminology the input layer corresponds to the causes in the MIMIC models, and the middle or hidden layer corresponds to the unobservables. In principle, the model can consist of several hidden or middle layers but in practice there is only one hidden layer. The ANN models were proposed by cognitive scientists as flexible non-linear models inspired by certain features of the way the human brain processes information. These models have only recently received attention from statisticians and econometricians. Cheng and Titterington (1994) provide a statistical perspective and Kuan and White (1994) provide an econometrics perspective. An introduction to the computational aspects of these models can be found in Hertz et. al. (1991) and the relationship between neural networks and non-linear least squares in Angus (1989).

The ANN is just a kind of black box with very little said about the nature of the non-linear relationships. Because of their simplicity and flexibility and because they have been shown to have some success compared with linear models, they have been used in several financial applications for the purpose of forecasting. See Trippi and Turban (1993), Kuan and White (1994) and Hutchinson, Lo and Poggio (1994). Apart from the linear vs. nonlinear difference, another major difference is that the MIMIC models have a structural interpretation, but the ANN models do not. However, for forecasting purposes detailed specifications of the structure may not be important. There is considerable discussion about identification in the case of ANN, but the whole emphasis is on approximation and forecasting with a black box. Hornik, Stinchcombe and White (1990), for instance, show that single hidden layer multi-layer neural networks can approximate the derivatives of an arbitrary non-linear mapping arbitrarily well as the number of hidden units increases. Most of the papers on ANN appear in the journal *Neural Newtorks*. However, not much work has been done on comparing MIMIC models discussed in the previous section with ANN models (with the exception of Qi, 1995).

7. Signal extraction methods and tests for rationality

The signal extraction problem is that of predicting the true values for the error-ridden variables. In the statistical literature this problem has been investigated by Fuller (1990). In the finance literature the problem has been discussed by Orazem and Falk (1989). The set-up of the two models is, however, different.

This problem can be analyzed within the context of MIMIC models discussed in the previous section. Consider, for instance, the problem analyzed by Maddala and Nimalendran (1995). Suppose we now have a proxy ΔE for ΔE^* which can be described by the equation,

$$\Delta E = \Delta E^* + \epsilon_4 \ , \tag{23}$$

where, ΔE is unanticipated earnings from say the IBES survey. The estimation of the MIMIC model considered in the previous section gives us an estimate of Var (ΔE^*). The signal extraction approach gives us an estimate of ΔE^* as

$$\Delta\hat{E}^* = \gamma(\Delta E) \qquad \text{where} \qquad \gamma = \frac{\mathrm{Var}\,(\Delta E^*)}{\mathrm{Var}\,(\Delta E)} \ . \tag{24}$$

Thus, if we have a noisy measure of ΔE^*, then this, in conjuction with the other equations in which ΔE^* occurs as an explanatory variable, enables us to get estimates of γ and this can be accomplished if we have other variables where ΔE^* occurs as an explanatory variable. This method can also be used to test rationality of earnings forecasts (say those from the IBES survey). For an illustration of this approach see Jeong and Maddala (1991).

8. Qualitative and limited dependent variable models

Qualitative variable models and limited dependent variable models also fall in the category of unobserved variable models. However, in these cases there is partial observability (observed in a range or in a qualitative fashion). The unobserved variable models discussed in the previous section are of a different category. There is, however, a need to combine the two approaches in the analysis of event studies. For instance, in the signaling models, there are different categories of signals: dividends, stock splits, stock repurchases, etc. In connection with these models there are the two questions, of whether or not to signal, and how best to signal. When considering the information content of different announcements, (say dividend change or stock split) it is customary to consider only the firms that have made these signals. But given that signaling is an endogenous event (the firm has decided to signal), there is a selection bias problem in the computation of abnormal returns computed at the time of the announcement (during the period of the announcement window).

There are studies such as McNichols and Dravid (1990) that consider a matched sample and analyze the determinants of dividends and stock splits. However, the computation of abnormal returns does not make any allowance for the endogeneity of the signals. In addition, there are some conceptual problems involved with the "matched sample" method almost universally used in financial research of this kind. The problem here is the following. Suppose we are investigating the determinants of dividends. We have firms that pay dividends and we get a "matched sample" of firms that do not pay dividends. The match is based on some attribute X that is common to both. Usually the variable X is also used as an explanatory variable in a (logit) model to explain the determinants of dividends. If we have a perfect match, then we have the situation that one firm with the value of X has paid a dividend, and another with the same value of X has not. Obviously, X cannot explain the determinants of dividends. The determinants of dividend payments must be some other variables besides the ones that we use to get matched samples.

The LISREL program can deal with ordinal and censored variables besides continuous variables. However, combining MIMIC models with selection bias in the more relevant financial applications, as in the example of McNichols and Dravid (1990) is more complicated if we allow for endogeneity of the signals. It is, however, true that the self-selection model, has as its reduced form a censored regression model. Thus the LISREL program can be used to account for selection bias *in its reduced form*. But the estimation of MIMIC models with selection bias in the structural form needs further work.

9. Factor analysis with measurement errors

In the econometrics testing of the APT (arbitrage pricing theory) many investigators have suggested that the unobserved factors might be equated with observed macro economic variables. See *inter alia* Chen, Roll and Ross (1986); Chan, Chen and Hsieh (1985); and Conway and Reinganum (1988). The papers using observed variables to represent the factors treat these variables as accurate measures of a linear transformation of the underlying factors so that the regression coefficients are estimates of the factor loadings. However, these observed macro-economic variables are only proxies which at best measure the factors subject to errors of measurement.

Cragg and Donald (1992) develop a framework for testing the APT considering the fact that the factors are measured with error. They apply this technique to monthly returns over the period 1971–90 (inclusive) for 60 companies selected at random form the CRSP tape. They consider 18 macroeconomics variables but found that they represent only four or five factors. The method they used, as outlined in Cragg and Donald (1995) is based on the GLS approach to factor analysis, which is an extension of earlier work by Joreskög and Goldberger (1972) and Dahm and Fuller (1986). Cragg and Donald argue that there is no way of estimating the underlying factors in an APT model without measurement error. In particular this holds for macro-economic variables that are possible proxies. However, as argued in the previous sections, an alternative method to handle the measurement error problem is to use the unobserved components model where the macroeconomic variables (used as proxies) are treated as indicators of unobserved factors. The LISREL program can be used to estimate this model. Tests of the APT can be conducted within this framework as well, and it will be free of the errors-in-variables problem. The LISREL program handles both the GLS and ML estimation methods. However, the MIMIC models impose more structure than the Cragg-Donald approach. A comparison of the two approaches – the multiple indicator approach and the approach of factor analysis with measurement errors is a topic for further research.

10. Conclusion

This article surveys several problems in financial models caused by errors-in-variables and use of proxies. In addition, the article also examines alternative models and techniques that can be employed to mitigate the problems due to errors-in-variables. As noted in the different places, several important gaps exist in the financial literature.

First, many models in finance use grouping methods to mitigate error-in-variables problems. This approach can be viewed as the use of instrumental variable (IV) methods. Therefore, it is appropriate to make use of the recent econometrics literature on instrumental variables, which discusses the problem of poor instruments, judging instrument relevance, and choice among several instruments.

Second, since the use of proxy variables for unobservables is also very pervasive, use can be made of the vast econometrics literature on latent and unobservable variables. For instance, MIMIC models are not used as often as they should be. Also, the interrelationships and comparative performance of MIMIC models, ANN models and factor analytic models with measurement errors need to be studied.

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