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Investing in negative book equity stocks that do not default

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1. Background and Aims of Project

Recently, it has been shown that 'extreme' value stocks that are often omitted in value portfolios, such as those that have negative book value, can consistently enhance returns. However, such stocks are more prone to default. So, how can a fund manager who invests in negative book equity stock to enhance returns avoid defaulters? An accurate model of default is needed. We have developed a superior non-linear static methodology for estimating default risk. Marrying this static non-linear technology with a dynamic one that permits default risk to change as a function of time should result in superior default risk forecasting.

One method of value investing is based on Book-Equity (see Fama and French (1993)). A firm's book equity is a measure of the value held by a firm's ordinary shareholders. Increasingly, it is being reported as a negative number. Since the firm's limited liability structure means that shareholders' value cannot take negative values, negative book equity has no obvious interpretation. Consequently, both practitioners and academics typically omit such stocks.

These stocks represent a missed opportunity to invest. In prior work ((Brown, Lajbcygier & Li, 2008) and (Li, Lajbcygier, Guo and Chen, 2008)) we studied the relationship between these negative book equity stocks, returns, and default risk. We found that they do earn higher returns but carry higher default risks.

A fund manager may be wary of investing in stocks that have a high probability of default. Therefore, providing an accurate predictor of default is vital if investment, based on negative book-equity, is to be successful.

Default prediction is an area of research that has received extensive academic attention over the years. Beginning with the seminal work of Altman (1968), numerous researchers have developed default prediction models that rely on the use of accounting ratios. There is a good reason for this, as various accounting ratios have been shown to be reliable predictors of default.

An issue with default risk modelling, and any type of modelling in general, is to correctly ascertain the relationship between the explanatory variables and the variable of interest. In many cases, it is reasonable to expect a non-linear relationship between the explanatory variables and the variable of interest. In the past, a common technique employed to deal with this issue is to transform the accounting variable in order to linearize the relationship with default. However, if the relationship between an accounting variable and default risk is highly non-linear, then a parametric modelling framework will not capture the true underlying relationship with the variable, even after a transformation has been applied.

In our recent work, we (Chan, Faff, Gharghori, Koffman, Lajbcygier, 2008) proposed a new non-linear approach for modelling the relationship between accounting variables and default risk. The technique we employ utilises a logistic generalised additive model (GAM) (see The Static Model: The Logistic GAM in "Description and Approach"). Such models permit the independent variables to be estimated using non-linear/non-parametric regression. We compared the models we create with extant models of default using validation techniques that are novel to the default risk literature. We exploited a unique Australian accounting dataset and used a comprehensive sample drawn from the Australian equities market. We observed marked non-linearities between the accounting variables and default risk. Further, our prediction oriented validation tests showed that the non-linear models are superior to their linear counterparts.

Whilst this model represents an important innovation in the default risk literature, it does not include any information how the probability of default changes over time. Such models are known as survival or hazard models. We propose to incorporate survival analysis in our logistic generalised additive models. Such models should provide greater forecast accuracy of default risk (see The Dynamic Model: The Hazard Model in "Description and Approach").

2. Significance and Innovation

Precise bankruptcy forecasts are of great interest to academics, practitioners, and regulators. Regulators use forecasting models to monitor the financial health of banks, pension funds, and other institutions.

Practitioners use default forecasts in conjunction with models like that of Duffie and Singleton (1999) to price corporate debt. Academics use bankruptcy forecasts to test various conjectures like the hypothesis that bankruptcy risk is priced in stock returns (e.g., Suhmway). Given the broad interest in accurate forecasts, a superior forecasting technology is valuable.

We argue that a superior technology can be obtained by marrying our static non-linear logistic GAM technology with dynamic hazard model technology. Even our new model which incorporates non-linear dependence between the probability of default and the independent variables is mis-specified as it is a static model. A dynamic model is required that permits the probability of default to change over time.

This project is innovative in the sense that we propose to marry a model of time varying default risk with a model that can handle non-linearity in explanatory variables. We believe that this combination will result in a more accurate default probability forecast than either technology on its own. To the best of our knowledge, we will be the first to attempt to combine these technologies.

3. Description of Approach

The static model: Logistic Generalized Additive Models

The methodology used to estimate the default prediction models is logistic GAMs. GAMs can accommodate non-linear relationships in the explanatory variables. They are also useful where the relationship between the variables is expected to be complex (Hastie and Tibshirani, 1990) and not easily fitted by standard linear or non-linear models; there is no ***a priori*** reason for using a particular model; and, where we would like the data to suggest the appropriate functional form.

When modelling non-linear relationships, GAMs replace the coefficients found in parametric models with a smoother, which is a tool for summarising the trend of a response variable (Y) as a function of one or more predictors ($X_1, ..., X_p$). It produces a smooth estimate of the trend between X and Y. In equation 1, for each variable X_j, a unique, variable-specific smoothing function $f_j(.)$ is applied.

$$Y\left(\overset{\mathbf{v}}{X}\right) = a + \sum_{j=1}^{p} f_j\left(X_j\right) \qquad (1)$$

In the case of this study, Y is a dichotomous variable that takes the value of one if a firm defaults and zero otherwise, and X is the set of accounting variables useful for predicting default. We use a cubic regression spline to estimate $f_j()$.[1] This method provides a flexible inductive (i.e. data driven) way of modelling the relationship between default risk and the accounting variables.

The Dynamic Model: The Hazard Model

Hazard models resolve the problems of static models by explicitly accounting for time. The dependent variable in a hazard model is the time spent by a firm in the healthy group.

The hazard function can be estimated thus:

$$h(t) = h_0(t)\exp \boldsymbol{B}^{\boldsymbol{T}}\boldsymbol{x} \qquad (2)$$

where $h_0(t)$ is a baseline hazard function which is modified multiplicatively by covariates. Our aim will be to incorporate Equation (1) into the above Equation (2). For example, may use Equation (1) to estimate multi-period logit models (Pagano, Panetta, and Zingales (1998) and Denis, Denis, and Sarin (1997)).

To paraphrase Shumway (2001), in econometric terms, there are three reasons to prefer hazard or dynamic models to pure static models for forecasting bankruptcy:

I. Static models fail to control for each firm's period at risk. When sampling periods are long, it is important to control for the fact that some firms file for bankruptcy after many years of being at risk while other firms fail in their first year. Static models do not adjust for period at risk, but hazard models adjust for it automatically. The selection bias inherent in static bankruptcy models is a result of the failure to correct for period at risk.

II. Dynamic models incorporate time-varying covariates, or explanatory variables that change with time. If a firm deteriorates before bankruptcy, then allowing its financial data to reveal its changing health is important. Hazard models exploit each firm's time-series data by including annual observations as time-varying covariates. Unlike static models, they can incorporate macroeconomic variables that are the same for all firms at a given point of time. Hazard models can also account for potential duration dependence, or the possibility that firm age might be an important explanatory variable.

III. Dynamic models may produce more efficient out-of-sample forecasts by utilizing much more data. The hazard model can be thought of as a binary logit model that includes each firm year as a separate observation. Since firms in the sample have an average of 10 years of financial data, approximately 10 times more data is available to estimate the hazard model than is available to estimate corresponding static models. This data results in more precise parameter estimates and superior forecasts.

4. Data

Australian accounting data are obtained from two sources. Pre 1992, the data are hand collected from Australian Stock Exchange research reports. Post 1992, the data are obtained from the Aspect Huntley database. The data is collected on an annual basis from the final financial statements. Specifically, the accounting data we obtain are current assets, total assets, current liabilities, total liabilities, total equity, retained profits, trading revenue, profit before tax and abnormals, profit after tax but before abnormals, depreciation expense, amortisation expense and interest expense. Hand collected data from the ASX research reports is available for the period 1974 to 1992; the Aspect Huntley data is from 1992 to 2004. The first defaulted firm we identify is in 1977, so our sample period is 1977 to 2004. Market capitalisation data is sourced from the Australian Graduate School of Management (AGSM) database for the entire sample period.

[1] The advantage of cubic splines it that they are computationally efficient and it is possible to linearise the spline.

The US accounting data we plan to use will be from the COMPUSTAT database recently available at Monash University.

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