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Abstract

In this paper, we use option based measures of financial performance that utilize market information in a binary probit regression to examine their informational context and properties as distress indicators and to estimate default probabilities for listed firms. Then, we enrich them with fundamentals that utilize accounting information. The results suggest that by adding accounting information from financial statements to market information from equity prices we can improve both in sample fitting and out of sample predictability of defaults. Therefore, option theory does not generate sufficient statistics of the actual default frequency. Our main conclusion is that while market information can be extremely valuable, it is most useful when coupled with accounting information in assessing default risk of listed firms.

Keywords: option theory, fundamentals, default risk

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1 Introduction

Default risk refers to the uncertainty associated with a firm's ability to meet its required or contractual obligations. Over the last 3 decades, default risk measurement has developed in a significant body of research in Finance and Accounting. A large number of academic researchers have been dedicated to assessing default risk since the direct and indirect costs of failure are substantial to the whole environment of a firm, equityholders, debtholders, entrepreneurs, employees, clients, suppliers and auditors. Note that due to contagion-effects the direct and indirect costs of a firm failure in a large network of related companies may cause a negative spiral to the general economic environment. Furthermore, financial institutions need to manage their credit risk exposure, price loans and perform risk/return analysis of credit portfolios. Finally, the integration of financial markets and the three pillars of the Basel II Capital Accord have increased the demand for more sophisticated default risk models.

Two are the main categories of default risk models: credit scoring models and structural models. Credit scoring models build on the seminal works of Beaver (1966), Altman (1967,1975), Ohlson (1980) and Zmijewski (1984) and adopt the traditional approach. Accounting information and statistical techniques are used in this approach for assessing the default probability of a firm.[1]. Structural models build on the pioneering works of Black and Scholes (1973) and Merton (1974) and adopt the option approach. Market information and option pricing techniques are used in this branch for assessing the default probability of a firm.

The credit model initiated by Robert Merton (1974) in his seminal paper can be viewed as the starting point in the literature to assessing the default probability using option theory. Various empirical tests of the theoretical option (Merton type) approach have been repeated in Geske and Delianedis (1999), Charitou and Trigeorgis (2002), Huang and Huang (2002), Vassalou and Xing (2004), Charitou, Lambertides and Trigeorgis (2004). Geske and Delianedis (1999) find that the theoretical default probabilities generated from the option pricing approach have good predictive power over credit ratings and rating transitions. Charitou and Trigeorgis (2002) find that the primary option variables of the generated default theoretical probabilities can explain financial distress up to five years prior to bankruptcy filling. Furthermore , Huang and Huang (2002) argue that the above mentioned probabilities are consistent estimates of the observed credit spreads. Using similar measures Vassalou and Xing (2004), Charitou, Lambertidis and Trigeorgis (2004) examine the effect of default risk in equity returns and find that Famma and French factors (SMB, HML) do not capture default risk. Finally, KMV Corporation which has been recently acquired by Moodys, developed the most successful commercial variant of option theoretical approach to estimate non-parametric probabilities of firm failure in a number of different countries and over a range of forecasting horizons.

The main advantage of option pricing models over credit scoring models is that the generated theoretical default probabilities reflect market information from equity prices. However, these potential benefits are derived from extreme assumptions and unrealistic simplifications which serve to facilitate the mathematical representation of the models and can be considerable weakened. Thus, many researchers, have struggled to overcome the above limitations of the pure option

[1]Default and Failure are interchangeable terms in this paper

pricing models in the prediction of default probabilities and credit spreads by incorporating additional accounting information. As pointed out, by Sobehart and Keenan (2002), Hillegeist, Keating, Cram and Lundstedt (2004), Benos and Papanastasopoulos (2005), the power of the option implied default probability estimates can be improved by adding other accounting information publicly available in financial statements. Models that combine market information from the option approach and accounting information from financial statements are referred in the literature as hybrid models.

The purpose of this study is to explore and extend the usefulness of the two major default risk modelling approaches, the traditional approach and the classic option pricing approach. Our paper extends prior research by using market information from option motivated transformation of leverage ratio, profitability ratio and business risk to assessing default risk for listed firms. The above option based measures of financial performance are used in a binary probit regression to examine their informational context and properties as distress indicators and to estimate default probabilities for listed firms. We find that the default probabilities estimated from the above option based measures of financial performance have more explanatory power in assessing corporate failure than the distance to default rates generated from the same option pricing model. Then, we combine the two modelling approaches by enriching the option based measures with accounting based measures of financial performance. The results suggest that by adding accounting information from financial statements to market information from equity prices we can improve both in sample fitting and out of sample predictability of defaults. Therefore, option theory does not generate sufficient statistics of the actual default frequency. Our main conclusion is that while market information can be extremely valuable, it is most useful when coupled with accounting information in assessing default risk of listed firms.

The remainder of this paper is organized as follows: Sections 2 and 3 provide a detailed description of the two major default risk modelling approaches, the traditional and option approach. In Section 4 we discuss the theoretical foundations for their combination and development of hybrid models for default risk measurement. Section 5 presents our research design, while section 6 provides details about sample, variable estimation and data collection. In section 7 we discuss the estimation results and provide empirical tests. Section 8 summarizes and concludes the paper.

2 Traditional Approach in Default Risk Measurement

Credit scoring models that adopt the traditional approach, pre-identify which characteristics of financial performance such as size, liquidity, leverage , profitability, efficiency and cash flow adequacy are important in assessing the default probability of a firm. These models evaluate the significance of the above characteristics, mapping a reduced set of accounting based measures, mainly financial ratios, accounting variables and other information from financial statements into a quantitative score. In some cases, this score can be literally interpreted as a default probability while in other cases can be used as a system to classify firms into a failing group or a solvent group of firms with a certain degree of accuracy or misclassification rate.

The pioneering study of Beaver (1966) has introduced the traditional approach in default risk measurement with univariate discriminant analysis on a number of financial ratios. Beaver has applied a dichotomous classification tests to find which accounting based measures were the best in predicting corporate failure. In 1968 Altman has extended univariate discriminant analysis into a multivariate context and estimated a credit scoring model, called the "Z-Score model". Multivariate Linear Discriminant Analysis (MDA) is based on a linear combination of two ore more accounting based measures that will discriminate best between a priory defined groups : the group of defaulted and the group of solvent firms. An MDA model weights the accounting based measures and generates a single composite discriminant score applying the rule of the whole being more than the sum of the parts. This multivariate discriminant score gives an indication of the financial health of the firm. This is why an MDA model is called a continuous scoring system. A firm is classified into the group of defaulted firms if its score is less than the optimal cut of point and it is classified into the group of solvent firms if its score is greater or equal to the optimal cut off point. It is straightforward, that MDA has the advantage of considering an entire profile of financial characteristics of a firm, as well as the interaction of these properties. Moreover, the above characteristics are quantified with a set of coefficients. Furthermore, the major advantage of MDA is the reduction of the credit analysts space with the transformation of the above characteristics into a single discriminant score. However, an important drawback of MDA is the multivariate normality assumption for the accounting based measures which may result in bias to the tests of significance and the estimated error tests. Empirical studies have shown, that especially in the group of defaulted firms the normality assumption is violated. Another, disadvantage is that the variance-covariance matrices are assumed to be equal for every priory defined group. The violation of this assumption affects, the significance tests of differences in variables means between the two groups. A potential solution to this problem is the use of a quadratic MDA model. However, a quadratic MDA model outperforms a linear MDA model only in cases of large samples of firms, small number of independent variables and substantial differences in the variance-covariance matrices. Finally, possible multicollinearity among independent variables causes unstable discriminant coefficients and affects the accuracy of the classification results. Thus, many researchers avoid to include highly correlated independent variables in an MDA model.

After 1980's, MDA has been often used as a baseline method for comparative studies and replaced by the conditional binary probability models: the logit model and probit model. These models are based on certain assumptions concerning the probability distribution of error terms. The logit model assumes a logistic distribution while the probit model assumes a cumulative normal distribution function. The pioneering work of Ohlson (1980) has introduced logit analysis (LA) in default risk measurement, while the pioneering study of Zmijewski (1984) has introduced probit analysis (PA). The conditional probability models are based on a combination of two ore more independent variables (accounting based measures) that will discriminate best between a priory defined groups: the group of defaulted and the group of solvent firms. The models weight the independent variables and generate a multivariate probability score with a non-linear maximum likelihood estimation procedure . This score indicates the default probability of the firm and can be also used as classification system when compared to its optimal cut off value. The firm is classified into the group of defaulted firms if its score is greater than the optimal cut off point and it is classified into the group of solvent firms if its score is less or equal to the optimal cut off point. The conditional probability models concentrate the same advantages with the MDA models. Moreover, they do not require the normality assumption of the independent variables or the equality assumption of variance-covariance matrices. However, they are extremely sensitive to the problem of multicollinearity. Thus, the inclusion of highly correlated independent variables must be avoided.

The main benefit of credit scoring models is their simplicity since their implementation requires only statistical knowledge. However, these models are not flexible since they extract accounting information from financial statements that appear at annually or quarterly time intervals. Note also that quarterly financial statements are not always audited by an external firm. Thus, it is very difficult with these models to update default probabilities over the course of the fiscal year. Moreover, financial statements are formulated under the going concern principle which assumes that the firm will remain solvent. Another important deficiency of the credit scoring models is the reliability of accounting information. There is empirical evidence that financial statements are often subject to creative accounting practices. Firms, in general manage their earnings upwards and avoid reporting earning decreases especially when the time of default is very near. Thus, these upward manipulated earnings will cause profitability measures to be overstated and introduce bias in default risk measurement. To address the above issues, Merton (1974) in his seminal paper has proposed structural models that adopt option theory in assessing default risk. As we will see in a next section of the paper, we explore the usefulness of the traditional approach by estimating a new credit scoring model using probit analysis for default risk measurement of listed firms.

3 Option Approach in Default Risk Measurement

Structural models that option theory, consider equity as a call option on the assets of the firm. Equityholders, have the right but not the obligation to buy the firm's assets from debtholders by re-paying debt. To see this, consider the case of a simple firm with market value of assets $A = (A_t)_{t \geq 0}$, representing the expected discounted future cash flows and a capital structure with two classes of liabilities: equity with market value equal to $S = (S_t)_{t \geq 0}$ and zero coupon debt with face value D^T and maturity at time T. If at debt's maturity T the market value of assets A_T exceeds the face value of debt D^T, equityholders will exercise their option and repay debt obligations. In this case, debtholders will receive the promised payment D^T and equityholders will receive the residual claim $A_T - D^T$. However, if the market value of assets A_T does not exceed the face value of debt D^T, then equityholders will find it preferable to let their option expire, exercise their limited liability rights and default on the promised payment D^T (equity is then worthless). These payoffs imply that equity will be worth either $A_T - D^T$ or zero, whichever is best for equityholders (i.e. $S_T = max(A_t - D^T, 0)$). Therefore, the payoff of equityholders is equivalent to that of a European call position on the assets of the firm, with strike price equal to D^T (default boundary) and expiration at debt's maturity T.

It is straightforward from the above analysis that we need a number of assumptions regarding the firm value process and the risk free interest rate process to derive analytically the market value of equity and the default probability of a firm. Merton (1974) involves the Black-Scholes (1973) settings by assuming that the risk free interest rate is constant and identical to borrowing and lending and that the firm value follows a geometric Brownian motion with a constant drift equal to the risk free interest rate r and a constant diffusion rate equal to σ_A :

$$\frac{dA_t}{A_t} = r(A_t, t)dt + \sigma_A dW_t \tag{1}$$

where W_t is a standard Brownian motion.

Under the above assumptions on asset and risk free interest rate dynamics, and assuming also that dividends paid by the firm accrue to equityholders before debt's maturity T, the current market value of common equity S_0 is given by the Black-Scholes equilibrium pricing formula for European call options :

$$S_0 = A_0 e^{-\delta T} N(d1) - D^T e^{-rT} N(d2) + (1 - e^{-\delta T})A_0 \tag{2}$$

where $d1 = \frac{\ln(\frac{A_0}{D^T}) + (r - \delta + \frac{\sigma_A^2}{2})T}{\sigma_A \sqrt{T}}$ and $d2 = d1 - \sigma_A \sqrt{T}$, N notes the standard normal distribution function and δ is the continuous dividend rate.

The first term $A_0 e^{-\delta T}$ in the right hand side of the above formula is the risk neutral discounted expected value of the firm provided that it will remain solvent at debt's maturity T. Note that the term $e^{-\delta T}$ accounts for the reduction in the firm asset value A_0 since dividends are assumed to be distributed to equityholders before debt's maturity T. The second term $D^T e^{-rT} N(d2)$ equals the risk-neutral discounted expected value of riskless debt $(D^T e^{-rT})$ with face value D^T and maturity T times the risk neutral expected probability that the firm will remain solvent at debt's maturity $(N(d2))$. The third term in the formula $(1 - e^{\delta T})A_0$ accounts the addition of equityholders wealth due to the fact that the stream of dividends is assumed to be distributed to them before debt's maturity T. Finally, note that the term $e^{-\delta T}$ does not appear in the original Black-Scholes equilibrium formula for valuing European call options on dividend-paying stocks since in this case the stream of dividend payments does not accrue to optionholders.

Since the current market value of common equity S_0 is observable for listed firms from the stock market, one can apply the above formula to back out the current market value of the firm's assets A_0. However, the volatility of asset returns σ_A which captures the business risk is still an unknown parameter. In general, equity volatility which can be estimated for listed firms from historical data and asset volatility are related through the following equation:

$$\sigma_S = \sigma_A \frac{A_0}{S_0} N(d1)(e^{-\delta T}) \tag{3}$$

The latter equation is derived from Ito's lemma and provides the equity-implied asset volatility estimate. Equations (4) and (5) is a set of two nonlinear equations with two unknowns that can be solved with numerical recipes. Under this framework, the risk neutral expected default probability $RNEDP$ is simply the probability that the option to default will expire unexercised by equityholders :

$$RNEDP = N\left(-\frac{\ln(\frac{A_0}{D^T}) + (r - \delta - \frac{\sigma_A^2}{2})T}{\sigma_A \sqrt{T}}\right) \tag{4}$$

Therefore, the risk neutral expected default probability is a function of the distance between the current market value of the firm's assets and the face value of its debt $(\frac{A_0}{D^T})$ adjusted for the expected growth in asset values $(r - \delta - \frac{\sigma_A^2}{2})$ relative to asset volatility σ_A and debt's maturity T. This function is often termed in the literature as the risk neutral distance to default rate which measures the number of standard deviation that the firm asset value is away from the default point (D^T) :

$$RNDD = \frac{\ln(\frac{A_0}{D^T}) + (r - \delta - \frac{\sigma_A^2}{2})T}{\sigma_A \sqrt{T}} \tag{5}$$

However, the above risk neutral default probability is not the actual default probability since the underlying firm asset value is risky and does not drift to the risk free interest rate. In order to convert the risk neutral to the actual default probability the expected return on the firm asset value μ (market profitability ratio) must be substituted for the risk free interest rate r:

$$EDP = N(-\frac{\ln(\frac{A_0}{D^T}) + (\mu - \delta - \frac{\sigma_A^2}{2})T}{\sigma_A \sqrt{T}}) \tag{6}$$

Similarly, the distance to default rate under an objective probability measure equals to :

$$DD = \frac{\ln(\frac{A_0}{D^T}) + (\mu - \delta - \frac{\sigma_A^2}{2})T}{\sigma_A \sqrt{T}} \tag{7}$$

The difference between the risk neutral and the actual default probability reflects the risk premium required by investors on the risk associated with default. In general, default risk premium reflects risk aversion to both the risk of timing of default and the risk of the loss in the event of default (loss given default). Note also, that the risk neutral default probability serves as an upper bound of the actual default probability. Since the risk neutral distribution and the actual distribution of the firm asset value have the same diffusion rate and the actual distribution has a greater mean (due to investor's risk aversion), the risk neutral distribution with the smaller mean implies the higher default probability.

It is straightforward from the above analysis that in Merton's framework the default probability depends on the following variables :

- The current market value of firm's assets A_0.
- The face value of firm's debt (default boundary) D^T.
- The asset volatility σ_A.
- The expected return on the firm asset value (market profitability ratio) μ.
- The length of time horizon T.

To get a deeper understanding of the implications of the above option motivated variables as determinants of the default probability we need to conduct sensitivity analysis with default probability Greeks. These default probability Greeks can be calculated as the derivatives of the default probability w.r.t. on its parameters $(A_0, D^T, \sigma_A, \mu, T)$:

- The sensitivity of the default probability EDP with respect to a change in the market value of assets A_0 is given by :

$$\frac{\vartheta EDP}{\vartheta A_0} = -\eta(DD)\frac{1}{A_0\sigma_A\sqrt{T}} < 0 \tag{8}$$

where $\eta(DD) = \frac{1}{\sqrt{2\pi}}e^{-\frac{DD^2}{2}}$ and DD is the distance to default rate. The above inequality implies that the default probability of a firm EDP decreases with its market value of assets A_0.

- The sensitivity of the default probability EDP with respect to a change in firm's face value of debt (default boundary) D^T is given by :

$$\frac{\vartheta EDP}{\vartheta D^T} = -\eta(DD)\frac{D^T}{\sigma_A\sqrt{T}} > 0. \tag{9}$$

Intuitively, the default probability of a firm EDP increases with its face value of debt D^T. In addition, the default probability of a firm increases with its market leverage ratio $\frac{D^T}{A_0}$.

- The sensitivity of the default probability EDP with respect to a change in firm's asset volatility σ_A is given by :

$$\frac{\vartheta EDP}{\vartheta \sigma_A} = \eta(DD)(\frac{\ln\frac{A_0}{D^T} + (\mu - \delta + \frac{\sigma_A^2}{2})T}{\sigma_A^2\sqrt{T}}) > 0 \tag{10}$$

The above inequality implies that the default probability of a firm EDP increases with its asset volatility σ_A.

- The sensitivity of the default probability of a firm EDP with respect to a change in the expected return on assets μ is given by :

$$\frac{\vartheta EDP}{\vartheta \mu} = -\eta(DD)\frac{\sqrt{T}}{\sigma_A} < 0 \tag{11}$$

Intuitively, the default probability of a firm EDP decreases with its market profitability ratio μ.

- The sensitivity of the default probability of a firm EDP with respect to a change in the time of debt's maturity T is given by :

$$\frac{\vartheta EDP}{\vartheta T} = \eta(DD)(\frac{ln\frac{A_0}{D^T}}{2\sigma_A T^{\frac{3}{2}}} - \frac{\mu - \delta}{2\sigma_A\sqrt{T}} + \frac{\sigma_A}{4\sqrt{T}}) \tag{12}$$

According, to the above inequality the effect of debt's maturity T on the default probability EDP of a firm is ambiguous. The default probability of low levered firms decreases with debt maturity time. However, the default probability of highly levered firms increases and then decreases with debt maturity.

Default probability Greeks provide a theoretical framework to analyze the effects of several option motivated variables as determinants of corporate failure. Summarizing, the default probability EDP of a firm is an increasing function of its leverage ratio $\frac{A_0}{D^T}$ and its asset volatility σ_A, and a decreasing function of its expected return on assets μ. As we will see in a next section, our paper differs from the existing literature in that we implement the usefulness of the option pricing approach by using the above option based measures of financial performance in a binary probit regression to examine their informational content and properties as distress indicators and to estimate default probabilities of listed firms.

4 Hybrid Models of Default Risk Measurement

As we have already noted, the major benefit of the credit scoring models that utilize accounting information from financial statements in modelling default risk, is their simplicity since their implementation requires only statistical knowledge. Recall also, that the most important deficiency of these models is that the generated default probabilities may present an incomplete or distorted picture of the true economic condition of a firm due to the fact that financial statements are designed to measure past performance, formulated under the going concern principle and are subjective to creative accounting practices. This issue has been tackled by structural models that adopt option theory and utilize market information in assessing the default probability of a firm. However, these models are based on strict assumptions and unrealistic simplifications that serve to facilitate their mathematical representation and can be considerable weakend. First of all, structural models rely on assumptions about market efficiency, perfect liquidity and lack of arbitrage conditions. However, equity and debt markets do not seem to be perfectly informed as required by these models. Moreover, market uncertainty may create temporary distortions in equity prices which lead to bias in default prediction. In addition, even if the stock market summarizes all relevant and available information about the default risk of a firm, there is no guarantee that any option pricing model will capture that information accurately. Note, also that equity prices can not directly inform about the default probability of firms that experience severe liquidity problems, or inadequate management or both. Furthermore, in these models is inherent the assumption that refinancing and renegotiation of firm's debt obligations is not permitted. The borrowing capacity of the firm is completely exhausted at debt's maturity since the firm is forced to repay its obligations to debtholders. However, the ability of firms to refinance and adjust their liabilities, especially when they encounter difficulties, plays an important role in default risk measurement. Finally, the assumption that the firm asset value follows a lognormal distribution may not be appropriate since the likelihood of large adverse changes in the relationship of the asset value to the default point is critical to the determination of the actual default probability. Note also that, defaults are rare events and occur when the asset value of a firm substantially drops. Empirical evidence indicates that typical default returns are likely to follow fat-tailed distributions and therefore, the fatness of tails becomes central in default prediction. [2] Therefore, KMV first

[2]KMV, has demonstrated using historical instances of default that the actual default probability has fatter tails than the normal distribution.

generates the distance to default rate for each firm and then estimates non-parametric default probabilities using empirical distributions instead of the normal distribution. This methodology must be viewed with some scepticism since one cannot back out the unknown values of asset and asset volatility by assuming normality and using the Black-Scholes option pricing formula and the optimal hedge equation from Ito's lemma and then turn to argue that returns are not really normal and estimate the default probabilities from empirical distributions. In addition, empirical distributions require large historical default databases that are not often publicly available. The above limitations have been addressed with the introduction of hybrid default risk models that combine the default probabilities generated from option theory with additional accounting information publicly available in financial statements. As we will see in the next section, our paper extends prior research in that we estimate a hybrid model for default risk measurement of listed firms by combining the three primary option based measures of financial performance (market leverage ratio, market profitability ratio and business risk) that determine the option implied default probabilities with other accounting based measures of financial performance.

5 Research Design

As we have already said the purpose of this paper is to explore and extend the usefulness of the two major modelling approaches in default risk measurement, the traditional approach and the option approach. For this purpose, we use a sample of solvent and defaulted listed firms and apply ordinary probit regressions that include one firm year observation for each firm. In such a regression the dependent variable is binary and takes the value 0 for solvent firms and the value 1 for defaulted firms. The estimated default probability $Prob_{default}$ from a probit regression takes the following form, where x is a constant, X is the vector of the explanatory (independent) variables, β is the coefficient vector and N is the cumulative normal distribution function :

$$Prob_{default} = 1 - N(-(x + X_i\beta)) \tag{13}$$

We start our empirical analysis by estimating a traditional model with accounting based measures of financial performance. We refer this model as *Fundamentals Model (FM)*. In this way we evaluate their importance in default risk measurement. Moreover, we generate default probabilities that utilize accounting information from financial statements. To deduce which accounting based measures we include in the analysis we draw in previous empirical studies. Due to the large number of accounting based measures found to be significant, we evaluate a set of twenty-five accounting based measures that can be classified into seven categories according to the financial characteristic they capture (liquidity, cash flow adequacy, solvency, profitability, leverage, size and efficiency). The initial set with the 25 accounting based measures is listed in Table 1. It is obvious that an important aspect of estimating a traditional model is the selection of the final set of the independent variables from an initial set of accounting based measures. The procedure of reducing the initial set of accounting based measures to an acceptable number is an attempt to determine the relative importance within a given variable set. Several methods (e.g. simultaneous, stepwise) have been proposed in the literature to select from an initial set of distress indicators a final set but none has been accepted as a basis for a theoretical variable selection since they focus solely on the statistical grounds of the variables and ignore their economic importance. In order to derive the final set of accounting based measures we use the following procedures. Fist, we consider all possible combinations of our accounting based measures when taken five at a time. From, the above combinations we select those combinations with accounting based measures that have statistical significance at $p < 0,1$ confidence level and no intercorrelation between them. This means, that the correlation among the independent variables in those combinations is less than $0,7$ in absolute value. Then, we evaluate their economical significance by neglecting all combinations that assign a counter-intuitive sign for one or more coefficients. Finally, we arrive at the optimal set of accounting based measures by selecting the combination with the highest explanatory power Mc- Fadden (R-squared) ratio and the lowest information criteria (Akaike, Schwarz, Hannan-Quinn). Therefore, with the above iterative procedure we select from our initial 25 accounting based measures those five that are doing the best overall job together in default risk measurement.

In contrast with previous research, we estimate a binary probit model using the three primary determinants of the option implied default probabilities as explanatory variables. We refer this model as *Option Variables Model (OVM)*. In this way, we evaluate the informational context and the properties of these variables as leading indicators of corporate distress. Moreover, we generate default probabilities of listed firms that utilize market information from equity prices. These option motivated variables are :

- The market leverage ratio $\frac{D^T}{A_0}$.
- Asset volatility σ_A.
- The expected return on the firm asset value (market profitability ratio) μ.

The above option motivated variables capture several characteristics of financial performance that are important in assessing the default probability of a firm. The market leverage ratio captures leverage effects, asset volatility captures business risk effects and the expected return on assets captures profitability effects. Recall, that default probability is increasing with market leverage ratio and asset volatility and decreasing with the expected return on assets. Hence, using them as explanatory variables in a model we relate different default risk factors in an analytical way and allow non-linear effects among them. Furthermore, for benchmarking purposes we estimate a model with the distance to default rate DD as unique explanatory variable. We do not use the theoretical default probability EDP as explanatory variable since it is not consistent to use independent variables in the form of probabilities in a binary probit model (as well in a binary logit model). Note, that the distance to default rate DD is generated from the same option pricing model as the three primary option based measures of financial performance.

Recall, that although the structural models are theoretically appealing they rely on economic theories about market efficiency. However, equity and debt markets do not seem to be perfectly informed as required by these models. Moreover, market uncertainty may create temporary distortions in equity prices which lead to bias in default prediction. In addition, structural models do not inform directly about the default probability of firms with severe liquidity problems and inadequate management. Furthermore, they can not readily incorporate financial restructuring such as refinancing and renegotiating of debt contracts. Thus, questionable is whether accounting based measures of financial performance reflect information about the default probability of a firm beyond those contained in option based measures. In order to capture this possibility, we enrich the above option based measures that utilize market information with the selected accounting based measures that utilize financial statement information into a hybrid model of default risk measurement. By considering additional information about firm's fundamentals such as liquidity, cash flow adequacy, efficiency and size, we are able to overcome the above limitations of structural models, enhance the definition of default likelihood and increase accuracy in assessing corporate failure. We refer this model as *Hybrid Model (HM)*. Note, that this is the first study in the existing literature that uses the three primary determinants of the option implied default probabilities with other accounting based measures of financial performance as explanatory variables for the estimation of a hybrid default risk model. To select, the optimal profile of measures, we follow the procedure used for the estimation of the *Fundamentals Model (FM)*.

In the final part of our empirical analysis, we compare the explanatory and the classification power of the *Fundamentals Model (FM)* , the *Option Variables Model (OVM)* and the *Hybrid Model (HM)*. To compare the explanatory power of each of the above models we use relative information tests. Explanatory power is assessed by comparing the Mc-Fadden (R-squared) ratio and the information criteria (Akaike, Schwarz, Hannan-Quinn) for each default risk model and the model with the highest Fc-Fadden ratio and the lowest information criteria is deemed the best. In order, to compare their classification power we use prediction-oriented tests. These tests examine the prediction accuracy and error generated by each default probability estimate when discriminating firms as defaulters and non-defaulters. Two are the types of misclassification errors that can be generated : type I error and type II error. If a firm is misclassified as non-failing by the model a type I error is made. If a firm is misclassified as failing by the model then a type II error is made. Both types of errors have serious and different consequences. Type I error cost is the default risk cost (total amount lost, principal lost, interest lost) of lending to a financially weak firm which defaults. Type II error cost is the opportunity cost (profits on loans not approved) of not lending to a financially healthy firm which does not default. These tests, require the determination of an optimal cut off point or an optimal cut off default probability. The determination of an optimal probability threshold, at which we can safely classify firms as defaulters and non-defaulters amounts a trade off between the marginal cost of committing a type I error or a type II error. Several studies, have used arbitrary cut off points such as $0,5$. This view is supported by Hammer (1983), who assumed that a firm will be labelled as potential bankrupt if the probability of bankruptcy is greater than $0,5$. While this approach may have some intuitive appeal, it lacks any theoretical or empirical support. Moreover, Palepu (1986) and other researchers, estimate the optimal probability threshold by minimizing the total number of misclassifications. This approach is based on the assumption that the cost of type I error and type II error is equal and constant. However, this assumption is unrealistic since the loss from the misclassification of a defaulter as non-defaulter is significantly greater than the opportunity cost from the misclassification of a non-defaulter as defaulter. Therefore, our optimal cut off default probability selection criterion is based on maximizing the absolute value of accurate classifications of defaulters rather than on minimizing the absolute value of misclassifications. Following the approach of Powell (2001)[3] we divide firms by their estimated default probability into ten equal portfolios. The optimal cut off point, is then the first default probability in that portfolio that has the highest ratio of defaulters to the total number of firms in the portfolio (concentration ratio). Note that the above criterion recognizes that the cost of type I error is significantly larger than the cost of type II error.

However, the in-sample classification accuracy does not come as a surprise as each model is evaluated with the same data that we use to estimate them. Thus, we also examine the ability of each model to rank the population of firms accurately using the above optimal cut off thresholds and a different sample of failed firms and non-failed firms. Then, following Altman, Haldeman and Naraynan (1977) and Saretto (2004) we construct an index, called "Error Classification Cost Index" ($ECCI$) to evaluate the economic significance of their classification power :

$$ECCI = p_I P(II|I) c_I + p_{II} P(I|II) c_{II} \tag{14}$$

where p_I is the observed default probability of defaulted firms, p_{II} is the observed survival (non-default) probability of solvent firms, $P(II|I)$ is the probability of type I error, $P(I|II)$ is the probability of type II error, c_I is the cost of type I error (default risk cost) and c_{II} is the cost of type II error (opportunity cost). The "Error Classification Cost Index" ($ECCI$) measures the cost of incorrect classifications generated from each default risk model per 100$ loan. Thus the better the model is the lower $ECCI$ would be. The default risk cost c_I in this index is determined as the loss given default rate while the opportunity risk cost c_{II} as the spread between corporate and treasure bond rates. Many empirical studies such as Altman (1992), Franks and Torous (1994), and Elton, Gruber, Agrawal and Mann (2001) report that the average recovery rate (one minus loss given default rate) vary from 50% to 60% and that spread between BBB corporate and treasury bond rates vary from 1% to 1.5%. Following these studies we set $c_I = 40\%$ and $c_{II} = 1\%$ as conservatism estimates of the default risk cost and opportunity cost respectively. It is obvious, that using the $ECCI$ index we can evaluate the default prediction power of each model in terms of an economically sensible measure. As a final measure of the classification power of each model we plot their cumulative accuracy profiles (CAP curves). To plot cumulative accuracy profile for a given model we rank the firms by their estimated default probability into ten deciles from the riskiest to the safest (horizontal axis). Then, for a given percentage x% of the sample we calculate the percentage y% of the defaulters with estimated probability equal or lower than the one of x% (vertical axis). Thus, the better the model is in differentiating defaulters from non-defaulters the more bowed towards the upper left corner its cumulative accuracy curve would be. In other words the accuracy of a model is determined by the percentage of defaults that are classified in the highest deciles. The cumulative accuracy curve of the ideal model is a straight line capturing the 100% of defaulters, within a fraction of the population equal to the default rate of the sample. If the model is totally uninformative and estimates default probabilities randomly, then we would expect to capture a proportional fraction of x% of the defaulters within x% of the sample, generating a 45 degree curve.

[3]Powell (2001) has applied logit analysis to predict takeover target firms

6 Data & Variable Estimation

The sample used in this study covers industrial listed firms from U.S.A. and Canada during the period 2002-2003. Financial firms were not considered due to the differences between their financial statements than those of industrial firms. We use the loan-default as the definition of failure since it is more consistent with economic reality than the legal definition of bankruptcy. This definition of failure offers the great advantage that the time of loan default can be objectively dated. In contrast, the legal definition of bankruptcy suffers from the fact that there is a great time gap between the time of failure and the time of the declaration of bankruptcy. In addition, many defaulted firms may not bankrupt. Note also that many defaulted firms may reorganize or merge with another firm instead of declaring a bankruptcy. For solvent firms we require a corporate credit rating in order to ensure that the firm has not filed a bankruptcy. Accounting data that we need to measure accounting variables and financial ratios are derived from the annual financial statements at the end of the last fiscal year. Balance Sheets, Profit & Loss Accounts and Cash Flow Statements are collected from the Compustat database. Market data for capitalization and equity volatility that we need to estimate the current market value of assets and asset volatility are obtained from Datastream database. Moreover, data on defaults and ratings are obtained from the S&P annual reports on Ratings Performance. After meeting the above criteria and combining available data from all these sources we obtain a sample with 342 solvent and 68 defaulted firms. Then we use observations on year 2002 for our estimation procedures and observations on 2003 for our validation tests since for a default risk model to operate well as an early warning system not only good in sample forecasting ability is necessary but also accurate out of sample forecasting performance is essential as well. According to the above adjustments our estimation sample covers 270 solvent firms and 40 defaulted firms, and the validation sample covers 72 solvent firms and 28 defaulted firms. In our empirical tests we use the whole estimation sample described above and not a matched pair sample of solvent and defaulted firms. Matching, enables the researcher to control some characteristics such as size, age, industry that are believed to have some predictive power but are not included in the set of prediction variables. However, constructing the sample of the solvent firms on the basis of characteristics of defaulted firms may result in estimation bias on the tests of significance, cause unstable discriminant coefficients and affect the accuracy of the classification results. Furthermore, matched samples may lead to selection bias if the matching criteria link with the default probability. The size criterion for example, may lead to serious problems since it is an important factor in default risk measurement (smaller firms tend more often to default). In fact, as the explanatory power of the matching variable is eliminated, this lead to a restricted model of default risk measurement instead of a general model. Thus, in our analysis we decide to use the whole sample described above and include several measures (option-based, accounting-based) to allow for size effects. Finally, constant treasury bill rates are used as proxies for the risk free interest rates, and they are obtained from Datastream database.

To empirically implement the option pricing approach to assessing default risk of listed firms we need to estimate the current market value of assets A_0, asset volatility σ_A and the expected return on the firm asset value μ. since the value of these parameters are not directly observable. First, we solve simultaneously the Black-Scholes European call option pricing formula and the optimal hedge equation from Ito's lemma for the unknown parameters A_0 and σ_A with the Newton-Raphson iteration method. Market value of equity S_0 is set equal to the total market capitalization at the end of the last fiscal year. Equity volatility σ_S is estimated from the standard deviation of the continuously compounded (not annualized) equity returns during the past fiscal year trading days. Following Vassalou and Xing (2004), all of the firm's liabilities are assumed to be due in one year $T = 1$, and face value of firm's default boundary D^T is approximated as the face value of all short term liabilities plus half of the face value of all long term liabilities. Although, there is a certain arbitrariness in the above truncated method, we agree with the conclusion of Vassalou and Xing (2004) that the method behaves quite well within the model and generates reasonable results. The dividend rate δ is defined as the sum of last year's common and preferred dividends divided by the last fiscal year's book value of assets ($\frac{CD_{t-1}+PD_{t-1}}{BVA_{t-1}}$). The Newton-Raphson iterative process ends when the pair of values of the unknown parameters A_0 and σ_A solves the equation. Note, that the process took less than five iterations to converge. Furthermore, the expected return on assets μ is defined as the last fiscal year's annual net income NI_{t-1} divided by the current market value of assets A_0 that has been estimated in the previous step. Once, we derive the values of the unknown parameters A_0, σ_A and μ we use them to estimate the distance to default rate DD.[4]

7 Results

Our results are presented in four sections. Section 7.1 provides descriptive statistics of the sample that is used in our estimation and validation procedures. In section 7.2 we report the estimation results of the three models: the *Fundamentals Model(FM)*, the *Option Variables Model(OVM)*, and the *Hybrid Model(HM)*. Finally, in section 7.3 we present prediction oriented tests that are designed to investigate the in sample and out of sample classification power of the above three estimated models.

7.1 Descriptive Statistics

Table 2 presents the descriptive statistics (mean, median and standard deviation) for the accounting and option based measures of financial performance for the sample of defaulted and non-defaulted firms that is used in our estimation and validation procedures. * indicate the significance of the mean and median values at the 0.05 confidence level using parametric Paired t-tests (PtT) and non-parametric Wilcoxon tests (WT) respectively. The final two columns report the p-values from Paired t-tests (PtT) and Wilcoxon tests (WT) of significance of the mean and median differences between the two groups. For defaulted firms, we see that in most cases the mean and median values of the accounting and option based measures of financial performance are significant the 0.05 confidence level (Return on Equity, EBIT Margin, Debt to Equity Ratio and Equity Turnover Ratio are the exceptions). The same holds, for non-defaulted firms since only

[4]According to option pricing theory the expected return on assets μ cannot be negative. In those cases, to calculate the distance to default rates DD we set the expected return on the firm asset value μ equal to the risk free interest rate r.

Net Profit Margin and Return on Equity have mean values that are not significant. Moreover, consistent with prediction theories we show that the mean and median values of liquidity, cash flow, solvency, profitability, size and efficiency ratios of defaulted firms are lower than those of non-defaulted firms, while the mean and median values of leverage ratios are higher. In addition, the p-values from parametric Paired t-tests (PtT) and non-parametric Wilcoxon tests (WT) indicate that in most cases there are significant differences between their mean and median values for the two groups (Quick Ratio, Gross Profit Margin, Debt to Equity Ratio, Equity Turnover Ratio and Inventory Turnover Ratio are the exceptions). Furthermore, consistent with our expectations from option theory we find that the mean and median values of the distance to default rate (DD) and market profitability ratio (μ) of solvent firms are higher than those of distressed firms, while the mean and median values of the market leverage ratio ($\frac{D^T}{A_0}$) and asset volatility (σ_A) are lower. Note also that there are no differences in their mean and median values across the two groups. In summary, the results suggest that the majority of the above measures represent important sources of variation in the financial performance of defaulted and non-defaulted firms.

7.2 Estimation Results

In table (3) we provide the estimation results of the *Fundamentals Model (FM)* with the five accounting based measures of financial performance. The five explanatory variables are cash ratio, free cash flow margin, basic earnings power ratio, debt ratio and asset size. Hence, the model focuses on liquidity, cash flow adequacy, efficiency, leverage, profitability and asset size. In addition, the coefficients of all explanatory variables are significant at $0,01$ confidence level. Moreover, their signs are consistent with prediction theories. The signs of cash ratio, free cash flow margin, basic earnings power ratio and asset size are negative. Hence, the default probability is a decreasing function of those accounting based measures of financial performance. However, debt ratio that captures leverage effects has a positive coefficient. That means, default probability is increasing with debt ratio. Furthermore, according to the correlation tests which are reported to table (4), we see that the selected accounting based measures are not highly correlated. Note, that basic earnings power ratio was also significant in Altman's Z-Score (1968) and in Altman's ZETA Score (1977). Finally, asset size was also significant in Altman's ZETA Score (1977) and in Ohlson's O-Score (1980).

In table (5) we present the estimation results of the *Option Variables Model (OVM)* with the three option based measures of financial performance as explanatory variables. As discussed above, these option based measures of financial performance are the primary components of the distance to default rates (DD) and the option theoretical default probabilities (EDP). The market leverage ratio ($\frac{D^T}{A_0}$) and the expected return on assets (μ) are significant at the $0,01$ confidence level, while asset volatility (σ_A) is significant at the $0,1$ confidence level. Moreover, their signs are entirely in accordance with the theoretical considerations of the default probability Greeks. The market leverage ratio that captures leverage effects, and asset volatility that captures business risk effects have positive signs. However, the expected return on assets (market profitability ratio) that captures profitability effects have a negative sign. Therefore, the default probability of a firm is an increasing function of its market leverage ratio and its asset volatility, and a decreasing function of its expected return on assets. Furthermore, the correlation tests in table (6) indicate that the option based measures are not highly correlated. For benchmarking purposes we estimate a model using the distance to default rate as unique explanatory variable. The results of estimating this model is reported in table (7). Comparing the two models, we can see that the *Option Variables Models (OVM)* have the highest Mc Fadden (R-squared) ratio and the lowest information criteria (Akaike, Schwarz, Hannan-Quinn). Therefore, the results indicate that the three primary option based measures of financial performance have more explanatory power than the distance to default rates generated from the same option pricing model in assessing the default probability of listed firms.

Recall, that in order to estimate the *Hybrid Model (HM)* we consider all possible combination of the above option based measures and the selected five accounting based measures of financial performance when taken five at a time, and select the optimal. We convert also the estimated default probabilities from the option based measures and the accounting based measures of financial performance into scores using the inverse cumulative distribution function and find that their correlation is positive and low in magnitude (0.546). This low correlation, suggests that the two models capture different information about the default probability of a firm. Table (8) presents the estimation results of the *Hybrid Model (HM)*. The five explanatory variables are market leverage ratio ($\frac{D^T}{A_0}$), market profitability (μ), cash ratio, free cash flow margin and asset size. Hence, the model focuses on liquidity, cash flow adequacy and efficiency, leverage, profitability and size. In addition, the coefficients of market leverage ratio and asset size are significant at $0,01$ confidence level. In addition, the coefficients of market profitability ratio and free cash flow margin are significant at $0,05$ confidence level while the coefficient of cash ratio is significant at the $0,1$ confidence level. Furthermore, their signs are consistent with prediction theories and the foundations of default probability Greeks. The signs of cash ratio, free cash flow margin, market profitability ratio and asset size are negative, while the sign of market leverage ratio is positive. Finally, according to the correlation tests that are reported in table (9), we see that the selected option based measures and accounting of financial performance are not highly correlated. Therefore, we can argue that accounting based measures of financial performance capture additional information about the default probability of a listed firm beyond those reflected in the option based measures.

In table (10), we collect the in sample fitting measures of the three estimated models. First, we see that *Option Variables Model(OVM)* has higher Mc-Fadden (R-squared) ratio and lower information criteria (Akaike, Schwarz, Hannan-Quinn) than the *Fundamentals Model(FM)*. Therefore, researchers can increase the explanatory power of their tests in assessing default risk of listed firms by using option based measures of financial performance. This finding is not surprising since they utilize market information from equity prices. Recall, that they also have more explanatory power than the distance to defaults rates generated from the same option pricing model. Moreover, it is obvious from the listed fitting measures that the *Hybrid Model* outperforms the above models. Its superior performance indicates that the option pricing approach does not generate sufficient statistics of the actual default frequency. Furthermore, several assumptions of these models should be seen with scepticism. Finally, the results suggest that while market information can be extremely valuable, it is most useful when coupled with additional information about firm's fundamentals.

Note that we also estimate the above models, by alternatively eliminating one defaulter at a time. The aim of these robustness test is to check if a possible outlier drives the above fitting measures, We find that the results did not change substantially and therefore we discard this possibility.

7.3 Classification Power

At this point, we use prediction oriented tests to compare the classification power of the three estimated models. These tests, require the determination of an optimal cut off probability that is used to classify the population of firms as defaulters or non-defaulters. As discussed above, we follow the approach of Powell (2001) to determine the optimal cut off probability. Table (11) reports the within estimation sample discrimination ability and the optimal cut-off probability for each model . In the first four columns on the left side of the table we report the percentage of correct and incorrect classifications for default and non-default firms, in the fifth column the total accuracy ratios and in the rightmost column the optimal probability thresholds. We see that the *Option Variables Model (OVM)* and the *Fundamentals Model (FM)* show similar ability in discriminating defaulters and non-defaulters. Specifically, they predict accurately 67.5% of defaulted firms and 98.5% of solvent firms and have a total accuracy ratio of 94.5%. Furthermore, the *Hybrid Model (HM)* outperforms these two models since it predicts accurately 70% of defaulted firms and 99.3% of solvent firms and has a total accuracy ratio of 95.4%. Therefore, we can argue that accounting based measures of financial performance reflect information for classifying accurately firms as defaulters and non-defaulters beyond those contained in option based measures. Finally, we see that the optimal cut off probabilities are 54.6%, 65.4% and 69.8% for the *Fundamentals Model(FM)*, the *Option Variables Model (OVM)* and the *Hybrid Model (HM)* respectively. These values are 4.6%, 15.4% and 19.8% higher than the established threshold of 50% used in earlier studies.

However, the in sample classification accuracy does not come as a surprise since each model is evaluated with the same data that we use to estimate them. For a default risk model out of sample forecasting ability is essential as well. Thus, we examine the ability of each model to rank the population of firms accurately, using the above thresholds and a validation sample of failed and non-failed firms. Then we evaluate the economic significance of their prediction power using the "Error Correction Cost Index" ($ECCI$) that represents the cost of the generated incorrect classifications per 100$ loan. Thus the better the model is the lower $ECCI$ would be. Table (12) provides the results for each model respectively. In the first four columns on the left side of the table we report the percentage of correct and incorrect classifications for default and non-default firms, in the fifth column the total accuracy ratios and in the rightmost column the $ECCI$ rates. We see that the three estimated models, have similar power in type II classifications since they predict correctly 98.6% of non-defaulted firms. However the *Option Variables Model (OVM)* has higher total forecasting ability than *Fundamentals Model (FM)* since it classifies more accurately the population of distressed firms. In particular, the *Option Variables Model (OVM)* predicts accurately 75%, while the *Fundamentals Model (FM)* predicts accurately 71.4% of defaulted firms and their total accuracy ratio is 92% and 91% respectively. Moreover, we notice that the *Hybrid*

Model (HM) has the highest default prediction power since it discriminates accurately 82.1% of failed firms and the highest total classification power since it forecasts correctly 94% of failed and non-failed firms. The default prediction power of the *Hybrid Model (HM)* is 7% and 10.7% higher than that of the *Option Variables Model (OVM)* and the *Fundamentals Model (FM)* respectively. In addition, the total classification power of the *Hybrid Model (HM)* is 2% and 3% higher than that of the *Option Variables Model (OVM)* and the *Fundamentals Model (FM)* respectively. These findings, confirm again that the *Hybrid Model (HM)* outperforms the other two models. However, one can argue that the above differences are marginal. For this purpose we evaluate their economic significance using $ECCI$ and find that the cost of their incorrect classifications is 8.794\$, 8.273\$ and 6.47\$ per 100\$ loan for the *Fundamentals Model (FM)*, the *Option Variables Model (OVM)* and the *Hybrid Model(HM)* respectively. Thus, the *Hybrid Model (HM)* has the lowest $ECCI$, followed by the *Option Variables Model (OVM)* that has an additional cost of 1.803\$ per 100\$ loan. Note that the main source of this additional cost arises from type I incorrect classifications (default risk) since the two models have similar power in type II classifications. Furthermore, we see that the *Fundamentals Model (FM)* has an additional cost of 2.324\$ per 100\$ loan than the *Hybrid Model (HM)*. Therefore, using the $ECCI$ we see that the superior perfomance of the *Hybrid Model (HM)* has great economic significance. Note that if we have a more aggressive estimate for the default risk cost such as $c_I = 50\%$, the additional cost would rise to 2.254\$ and 2.906\$ per 100\$ loan for the *Option Variables Model (OVM)* and the *Fundamentals Model (FM)* respectively. Finally, we assess the prediction performance of each model by constructing their cumulative accuracy profiles (CAP curves). Recall, that the CAP curve for each model is generated by the cumulative fraction of defaults over the entire population of firms ordered by their estimated default probability. Thus, the better the model is in differentiating defaulters from non-defaulters the more bowed towards the upper left corner its CAP curve would be. Figure I, plots the cumulative accuracy profiles of the three models estimated in this paper. Observing, the three different curves, we notice again the superior performance of the *Hybrid Model* over the the *Option Variables Model (OVM)* and the *Fundamentals Model (FM)*. Summarizing, the results suggest that accounting information from financial statements can be incrementally informative to market information from equity prices in developing early warning systems of corporate distress.

8 Conclusion

This paper, explores and extends the usefulness of the two major default risk modelling approaches: the traditional approach and the classic option pricing approach. Specifically, option based measures of financial performance that utilize market information and accounting based measures of financial performance are used in binary probit regressions to examine their informational context and properties as leading indicators of corporate distress and to estimate default probabilities of listed firms. Our results, demonstrate that the estimated default probabilities from the above option based measures have more explanatory power in assessing default risk than those from the accounting based measures. However, the option pricing approach suffers from extreme assumptions and unrealistic simplifications and does not generate sufficient statistics of the actual default frequency. We find that by adding the above accounting based measures to the option based measures of financial performance into a hybrid model of default risk measurement, we can improve both in sample fitting and out of sample predicting accuracy. Hence, our main conclusion, is that while market information can be extremely valuable, it is most useful when coupled with accounting information in assessing default risk of listed firms.

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Tables and Figures

Table 1: List of Accounting Based Measures

In table 1 we provide the list of the accounting based measures that we use to estimate the *Fundamentals Models (FM)*.

List of Accounting Based Measures		
Type	**Name**	**Definition**
Liquidity	$Working\ Capital\ Ratio$	$\frac{Working\ Capital}{Total\ Assets}$
Liquidity	$Current\ Ratio$	$\frac{Current\ Assets}{Current\ Liabilities}$
Liquidity	$Quick\ Ratio$	$\frac{Quick\ Assets}{Current\ Liabilities}$
Liquidity	$Cash\ Ratio$	$\frac{Cash}{Current\ Liabilities}$
Cash Flow	$FCF\ Margin$	$\frac{Free\ Cash\ Flow}{Total\ Sales}$
Cash Flow	$CF\ Margin$	$\frac{Cash\ Flow}{Total\ Sales}$
Cash Flow	$FCF/CL\ Ratio$	$\frac{Free\ Cash\ Flow}{Current\ Liabilities}$
Cash Flow	$CF/CL\ Ratio$	$\frac{Cash\ Flow}{Current\ Liabilities}$
Solvency	$Interst\ Coverage\ Ratio$	$\frac{EBIT}{Interest\ Expense}$
Solvency	$CL\ Coverage\ Ratio$	$\frac{EBIT}{Current\ Liabilities}$
Profitability	$Return\ on\ Assets$	$\frac{Net\ Income}{Total\ Assets}$
Profitability	$Return\ on\ Equity$	$\frac{Net\ Income}{Total\ Equity}$
Profitability	$Internal\ Growth\ Rate$	$\frac{Retained\ Earnings}{Total\ Assets}$
Profitability	$Basic\ Earning\ Power$	$\frac{EBIT}{Total\ Assets}$
Profitability	$Gross\ Profit\ Margin$	$\frac{Gross\ Profit\ Margin}{Total\ Sales}$
Profitability	$EBIT\ Margin$	$\frac{EBIT\ Margin}{Total\ Sales}$
Profitability	$Net\ Profit\ Margin$	$\frac{Net\ Profit\ Margin}{Total\ Sales}$
Leverage	$Total\ Leverage\ Ratio$	$\frac{Total\ Liabilities}{Total\ Assets}$
Leverage	$Debt\ Ratio$	$\frac{Total\ Debt}{Total\ Assets}$
Leverage	$Debt\ to\ Equity\ Ratio$	$\frac{Total\ Debt}{Total\ Equity}$
Size	$Asset\ Size$	$\ln(Total\ Assets)$
Size	$Sales\ Size$	$\ln(Total\ Sales)$
Efficiency	$Asset\ Turnover\ Ratio$	$\frac{Total\ Sales}{Total\ Assets}$
Efficiency	$Equity\ Turnover\ Ratio$	$\frac{Total\ Sales}{Total\ Equity}$
Efficiency	$Inventory\ Turnover\ Ratio$	$\frac{Total\ Sales}{Total\ Inventories}$

Table 2: Descriptive Statistics

Table 2 present the descriptive statistics (mean, median and standard deviation) for the accounting and option based measures of financial performance for the sample of defaulted and non-defaulted firms that is used in our estimation and validation procedures. * indicate the significance of the mean and median values at the 0.05 confidence level using parametric Paired t-tests (PtT) and non-parametric Wilcoxon tests (WT)respectively. The final two columns report the p-values from Paired t-tests (PtT) and Wilcoxon tests (WT) of significance of the mean and median differences between the groups of defaulted and non-defaulted firms.

Descriptive Statistics								
Variable	**Mean**	**Median**	**Std**	**Mean**	**Median**	**Std**	**PtT**	**WT**
	Defaulted Firms			**Non-Defaulted Firms**				
Working Capital Ratio	−0.157*	-0.018	0.456	0.104*	0.071*	0.178	0.000	0.000
Current Ratio	1.068*	0.914*	0.787	1.561*	1.317*	0.979	0.000	0.000
Quick Ratio	0.717*	0.522*	0.646	0.908*	0.692*	0.784	0.059	0.000
Cash Ratio	0.113*	0.052*	0.548	0.378*	0.139*	0.687	0.000	0.000
FCF Margin	−0.624*	−0.064*	2.251	0.059*	0.064*	0.119	0.000	0.000
CF Margin	−0.704*	−0.175*	2.323	0.068*	0.075*	0.252	0.000	0.000
FCF/CL Ratio	−0.526*	−0.123*	0.964	0.118*	0.143*	0.421	0.000	0.000
CF/CL Ratio	−0.649*	−0.331*	1.073	0.347*	0.337*	0.579	0.000	0.000
Interst Coverage Ratio	−1.847*	−0.455*	6.437	6.755*	3.126*	13.076	0.000	0.000
CL Coverage Ratio	−0.311*	−0.058*	0.778	0.368*	0.331*	0.501	0.000	0.000
Return on Assets	−0.333*	−0.199*	0.381	0.021*	0.028*	0.097	0.000	0.000
Return on Equity	-0.362	-0.201	8.377	0.028	0.099*	1.691	0.000	0.000
Internal Growth Rate	−0.711*	−0.409*	1.119	0.155*	0.145*	0.301	0.000	0.000
Basic Earning Power	−0.086*	−0.031*	0.245	0.083*	0.079*	0.085	0.000	0.000
Gross Profit Margin	0.204*	0.254*	0.673	0.316*	0.283*	0.185	0.008	0.159
EBIT Margin	-0.488	-0.052	2.579	0.077*	0.078*	0.154	0.000	0.000
Net Profit Margin	−0.988*	−0.282*	3.011	0.001	0.027*	0.275	0.000	0.000
Total Leverage Ratio	1.129*	1.017*	0.627	0.674*	0.674*	0.187	0.000	0.000
Debt Ratio	0.807*	0.754*	0.585	0.348*	0.340*	0.174	0.000	0.000
Debt to Equity Ratio	3.217	1.222	41.004	1.972*	0.979*	8.565	0.610	0.845
Asset Size	6.884*	6.917*	1.342	8.584*	8.540*	1.367	0.000	0.000
Sales Size	6.336*	6.416*	1.473	8.497*	8.467*	1.342	0.000	0.000
Asset Turnover Ratio	0.858*	0.624*	0.776	1.141*	0.930*	0.792	0.007	0.000
Equity Turnover Ratio	1.655	0.454	32.714	6.235*	2.964*	30.433	0.094	0.127
Inventory Turnover Ratio	19.79*	8.458*	34.559	11.89*	7.634*	15.197	0.002	0.151
Market Leverage Ratio	1.344*	1.009*	1.560	0.421*	0.414*	0.228	0.000	0.000
Asset Volatility	0.366*	0.286*	0.405	0.289*	0.252*	0.164	0.000	0.000
Market Profitability Ratio	−0.576*	−0.337*	0.870	0.035*	0.023*	0.075	0.000	0.000
Distance to Default	0.247*	0.239*	1.012	3.875*	3.549*	2.178	0.000	0.000

Table 3: Estimation Results of the *Fundamentals Model (FM)*

This table presents the estimation results of the *Fundamentals Models (FM)*.

Fundamentals Model (FM)		
Independent Variables	**Coefficient**	**Prob**
Constant	0.906	0.407
Cash Ratio	- 1.825	0.004
Free Cash Flow (FCF) Margin	-2.355	0.006
Basic Earnings Power (BEP)	-9.633	0.000
Debt Ratio	2.720	0.000
Asset Size	-0.355	0.002
Fitting Measures	**Value**	
Mc Fadden (R-squared) Ratio	0.640	
Akaike info criterion	0.315	
Schwarz criterion	0.387	
Hannan-Quinn criterion	0.344	

Table 4: Correlation Matrix of the Selected Accounting Based Measures

This table presents the correlation matrix (p-values in parenthesis) of the selected accounting based measures.

Correlation Matrix of the Selected Accounting Based Measures					
Variables	**Cash Ratio**	**FCF Margin**	**BEP**	**Debt Ratio**	**Asset Size**
Cash Ratio	1	-0.196 (0.001)	-0.160 (0.005)	-0.054 (0.346)	-0.182 (0.001)
FCF Margin	-0.196 (0.001)	1	0.453 (0.000)	-0.266 (0.000)	0.155 (0.006)
BEP	-0.160 (0.005)	0.453 (0.000)	1	-0.326 (0.000)	0.215 (0.000)
Debt Ratio	-0.054 (0.346)	-0.266 (0.000)	-0.326 (0.000)	1	-0.387 (0.000)
Asset Size	-0.182 (0.001)	0.155 (0.006)	0.215 (0.000)	-0.387 (0.000)	1

Table 5: Estimation Results of the *Option Variables Model (OVM)*

This table presents the estimation results of the *Option Variables Model (OVM)*.

Option Variables Model (OVM)		
Independent Variables	**Coefficient**	**Prob**
Constant	-5.653	0.000
Market Leverage (ML) Ratio $\frac{D^T}{A_0}$	5.576	0.000
Asset Volatility σ_A	1.876	0.076
Market Profitability (MP) Ratio μ	-3.934	0.003
Fitting Measures	**Value**	
Mc Fadden (R-squared) Ratio	0.700	
Akaike info criterion	0.256	
Schwarz criterion	0.304	
Hannan-Quinn criterion	0.257	

Table 6: Correlation Matrix of the Option Based Measures

This table presents the correlation matrix (p-values in parenthesis) of the option besed measures.

Correlation Matrix of the Option Based Measures			
Variables	**ML Ratio**	**Asset Volatility**	**MP Ratio**
ML Ratio	1	0.256 (0.000)	-0.632 (0.000)
Asset Volatility	0.256 (0.000)	1	-0.386 (0.000)
MP Ratio	-0.632 (0.000)	-0.386 (0.000)	1

Table 7: Estimation Results of the *Distance to Default Model (DDM)*

This table presents the estimation results of the *Distance to Default Model (DDM)*.

Distance to Default Model (DDM)		
Independent Variables	**Coefficient**	**Prob**
Constant	1.007	0.000
Distance to Default Rate	-1.383	0.000
Fitting Measures	**Value**	
Mc Fadden (R-squared) Ratio	0.636	
Akaike info criterion	0.293	
Schwarz criterion	0.317	
Hannan-Quinn criterion	0.302	

Table 8: Estimation Results of the *Hybrid Model (HM)*

This table presents the estimation results of the *Hybrid Model (HM)*.

Hybrid Model (HM)		
Independent Variables	**Coefficient**	**Prob**
Constant	-1.739	0.211
Market Leverage (ML) Ratio $\frac{D^T}{A_0}$	4.472	0.000
Market Profitability (MP) Ratio μ	-4.414	0.011
Cash Ratio	-1.441	0.093
Free Cash Flow (FCF) Margin	-2.967	0.015
Asset Size	-0.325	0.006
Fitting Measures	**Value**	
Mc Fadden (R-squared) Ratio	0.779	
Akaike info criterion	0.209	
Schwarz criterion	0.281	
Hannan-Quinn criterion	0.238	

Table 9: Correlation Matrix of the Selected Option and Accounting Based Measures

This table presents the correlation matrix (p-values in parenthesis) of the selected option and accounting based measures.

Correlation Matrix of the Selected Option and Accounting Based Measures					
Variables	**ML Ratio**	**MP Ratio**	**Cash Ratio**	**FCF Margin**	**Asset Size**
ML Ratio	1	-0.632 (0.000)	-0.096 (0.092)	-0.189 (0.001)	-0.235 (0.000)
MP Ratio	-0.632 (0.000)	1	-0.090 (0.112)	0.343 (0.000)	0.297 (0.000)
Cash Ratio	-0.096 (0.092)	-0.090 (0.112)	1	-0.196 (0.001)	-0.182 (0.001)
FCF Margin	-0.189 (0.001)	0.343 (0.000)	-0.196 (0.001)	1	0.155 (0.006)
Asset Size	-0.235 (0.000)	0.297 (0.000)	-0.182 (0.001)	0.155 (0.006)	1

Table 10: Fitting Measures

This table presents a summary of the fitting measures of the *Fundamentals Model (FM)*, the *Option Variables Model (OVM)*, and the *Hybrid Model (HM)*.

Fitting Measures				
Models	**Mc Fadden**	**Akaike cr.**	**Schwarz cr.**	**H-Q cr.**
Fundamentals Model (FM)	0.640	0.315	0.387	0.344
Option Variables Model (OVM)	0.700	0.256	0.304	0.257
Hybrid Model (HM)	0.779	0.209	0.281	0.238

Table 11: In Sample Classification Power

This table presents the within estimation sample classification power and the optimal cut off probability (COP) for the *Fundamentals Model (FM)*, the *Option Variables Model (OVM)* and the *Hybrid Model (HM)*.

	Default		Non-Default		Total	
Model	**Correct**	**Incorrect**	**Correct**	**Incorrect**	**Correct**	**COP**
Fundamentals Model(FM)	67.5%	32.5%	98.5%	1.5%	94.5%	54.6%
Option Variables Model(OVM)	67.5%	32.5%	98.5%	1.5%	94.5%	65.4%
Hybrid Model(HM)	70%	30%	99.3%	0.7%	95.4%	69.8%

Table 12: Out of Sample Classification Power

This table presents the out-of sample classification power and the values of the "Error Classification Cost Index" ($ECCI$) for the *Fundamentals Model (FM)*, the *Option Variables Model (OVM)* and the *Hybrid Model (HM)*.

	Default		Non-Default		Total	
Model	**Correct**	**Incorrect**	**Correct**	**Incorrect**	**Correct**	**ECCI**
Fundamentals Model(FM)	71.4%	28.6%	98.6%	1.4%	91%	8.794
Option Variables Model(OVM)	75%	25%	98.6%	1.4%	92%	8.273
Hybrid Model(HM)	82.1%	18%	98.6%	1.4%	94%	6.47

Figure1: Cumulative Accuracy Profiles (Out of Sample)

Figure 1 plots the cumulative accuracy profiles (out of sample) of the *Fundamentals Model (FM)*, the *Option Variables Model (OVM)* and the *Hybrid Model (HM)*