OPTIMAL ACCOUNTING BASED DEFAULT PREDICTION MODEL FOR THE UK SMEs

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ABSTRACT

The discovery of most predictive model for firm's default would be beneficial for both lending banks and firms and would consecutively lead to more stable and prosperous economy. The study employs more than 30,000 UK SMEs covering the period from 2000 to 2008 to determine the most optimal accounting based ratio model for predicting the default event. To achieve this goal, two widely applied probabilistic models for firm's default - Altman's and Ohlson's - are tested in terms of reliability and prediction power using logistic regressions. The results indicate that, both models are more or less compatible with the original models while some inconsistencies were found in terms of variables reliability and validity. However, after implementing the out-of-sample performance tests, the efficiency of Altman's model over Ohlson's model was approved by indicating the lower level of both type I and type II errors in prediction.

This research also sheds lights on the concepts of industry and corporate governance effect on the UK SMEs default prediction. The study examines all 22 2-digit UK manufacturing industries and confirms that SMEs show differences with respect to predicted default across industries. Moreover, it is essential to consider the theme of credit risk separately in the private and public SMEs segments in the UK. In fact, the results of the study ascertain that controlling for industry and corporate governance effect significantly enhances the reliability and accuracy of the UK SMEs default models and it is absolutely useful in order to make the best financing decision for both banks and firms.

INTRODUCTION

According to the relevant literature such as Matlay and Westhead (2005), Smyrnios and Romano (1994) and Michaels et al., (1999), SMEs encompass the vast portion of global economy and economies' growth factors such as innovation, productivity and employment are significantly affected by SMEs. In fact SMEs play an important role in improving the political and socio-economical infrastructure of both developed and developing countries. Considering the crucial effect of these firms on any country's economy, finding an optimal structure for SMEs financing would lead to their successes and boost the economy as a whole. However, according to Jordan et al., (1998) most of the researches about the capital structure have used the large listed firms as a sample of the study and ignored SMEs by and large. As these firms are different in many aspects from their larger counterparts and showing different attitudes in terms of financing policies, this study aims to investigate the aspect of credit risk in UK SMEs to find of the most optimal model for predicting the default in these firms. It is worth to mention that in credit risk literature, two main concepts of default and bankruptcy are mostly being evaluated as a signs for assessing the firms' financial failure. Nevertheless, some researches such as Bei and Liu (2005) clearly pointed out that the theme of bankruptcy is not appropriate to efficiently represent the firm's financial failure. Bankruptcy might be happened for some reasons other than financial problems and also it has different definition in different economies. Thus, in this study also the concept of default would be considered as a sign to investigate the firms' financial failure.

According to the literature, SMEs are normally riskier than their larger counterparts but considering the tremendous numbers of SMEs in developed countries such as UK and US, allocating the necessary credit to these firms would be beneficial for the banks. Hence, there is an absolute need for the elaborate and optimal default prediction model specifically for SMEs to ease the process of crediting and also being more beneficial for the banks. Additionally, another reason that indicates the necessity for developing the particular models for SMEs default prediction lies in Basel II regulation. Based on the Basel II new regulations, banks are obliged to generate their internal procedure in order to assess the firms in terms of credit allocation. This regulation requires the banks to establish their own rating system and obtain the most effective formula to estimate the unexpected loss and capital requirement which needs the Probability of Default as a main input. Basel II suggests the different policy to be taken in the case of SMEs which brings the reduction in capital requirement proportional to SMEs size. Hence, it should be different method specifically related to SMEs in the case of default analysis. Moreover, by observing the recent financial crisis which hit world economy, the access of SMEs to finance becomes tougher than the past. This causes many smaller banks to restrict their credit which was granted to the SMEs before the recession. From the other point of view, the development of efficient default prediction model apart from being interesting for lenders and business investors, it can give the policy makers an insight into the reasons why UK SMEs goes to default and how it can be avoided.

According to the relevant literature, there are a huge number of studies for default prediction models which all intend to introduce the most effective model for predicting the firms' default. However, most of the studies in this case are widely based on the listed companies and there are only few studies in which the SMEs considered separately in the case of default prediction. Edmister (1972) and Altman and Sabato (2007) were used the different models to determine the optimal indicators for SMEs default event. Edmister (1972) have tested 19 financial ratios to choose the most efficient indicators and used the multivariate discriminant analysis to predict the firms' default. Altman and Sabato (2007) introduce the Logistic regression instead of MDA for their analysis and obtained the more accurate and promising results compared to the previous relevant studies. However, as these firms are not normally in a stock market, the management of these firms are usually not committed for disclosing the accurate information and lack of transparency problem in SMEs research is always a crucial case.

The fundamental goal of this research is to indicate the different attitudes of SMEs in the case of default and to prove that it is essential for the banks to model credit risk separately for these firms. The analysis would be carried out in this study by evaluating the two major accounting-based probabilistic default prediction models, Altman's and Ohlson's, which are widely applied in the relevant literature and to find the most optimal one for UK SMEs. The process of evaluating these models would be done by selecting the most predictive indicators of default for these firms in the UK economy. Thus, the objective of this study is not to test any specific theory and it is more or less pragmatic. Additionally, this study aims to look at the concept of SMEs credit risk by including the industry effects and corporate governance effects in the model to find the possible impacts of different industries and corporate governance structure on SMEs default prediction power and reliability.

Finally, to implement the research analysis, this study selected the number of 30000 UK SMEs for 15 to 36 Primary UK SIC 2003 codes from FAME database. The financial data needed for this research were obtained from profit and loss account, balance sheet and headings for 2000-2008 financial year and 2009 were selected as a hold-out sample to test the accuracy of the models subsequently. In addition, the pool logistic regression was employed in this study for both models which is the most appropriate model for probabilistic analysis of the event.

LITERATURE REVIEW

ACCOUNTING-BASED MODELS

One of the first major studies that have been done in credit risk was Beaver (1967) in which the univariate analysis has been used to predict the default and not-default firms. The downside for this approach was inconsistency problem. To avoid this problem, Altman (1968) used the possible predictive ratios by applying the Multivariate Discriminant Analysis (MDA) statistical method. He concluded that traditional ratio analysis is no longer a reliable approach and it should be replaced by MDA which is more sophisticated in terms of predicting the default. Altman's (1968) findings brought a noticeable success in terms of accuracy compared with the previous studies and become highly applied by the future research as Z score model. In his study, he chose 66 companies, 33 failed and 33 non-failed that had a bankruptcy petition in the specific period. For obtaining the best results, Altman at first found all the possible financial ratios which could be considered as predictive indicators of firms' default and classified them into five standard ratios category such as activity, solvency, leverage, liquidity and profitability. Finally, Altman selected 5 most predictive ratios out of that 5 main categories based on the best overall job they have shown in predicting the firm's default event.

After Altman study, vast number of researches used the MDA statistical method as a default prediction model for their analysis such as Blum (1974), Altman et al. (1977), Micha (1984), Lussier (1995) and Altman et al. (1995). However, according to the more recent studies, there are some critical problems related to MDA which lay doubts on the efficiency of the model. For instance, Karles and Prakash (1987) argued that the two major assumptions of the MDA are being severely violated through the research: 1) the independent variables of the model should be multivariate which are normally distributed. 2) variance-covariance matrices or the group dispersion matrices are equivalent across the non-failing and failing group. Karles and Prakash (1987) concluded that only if the normality conditions are met in MDA model, the results obtained are reliable and the Multiple Discriminant Analysis method is optimal.

Ohlson (1980) was one of the first corporate failure studies which challenged the Altman's (1968) model and aimed to mitigate the previous models problems through using the logistic statistical method and introduction of O-score. Moreover, his study was one of the first in the literature which used the probabilistic model for predicting the firm's failure. Ohlson (1980) claimed that his model outperforms Altman (1968) Z-score model and also removes the fundamental problems of MDA methods. Ohlson used 9 explanatory variables to generate the default prediction model but he did not represent any theoretical justification for the variables. In the next step of his research, he picked industrial firms from 1970 to 1976 which had at least 3 years trade background in US stock exchanges and found 2000 non-failed along with 105 failed firms. Ohlson estimated three different models : the first model was to predict the default within one year , the second was to predict the default within two years and the last one was to predict the default in one or two years. Finally, for predicting the probability of firm's default, he used the logistic regression in all three models. Ohlson (1980) pointed out that the previous studies oversold the predictive accuracy of the existed default models. Additionally, he asserted that the predictive powers of the default models are majorly rely on the choice of cut-off points and also the importance of each type of errors (Type I and Type II) for specific users. The study concluded that the time in which the information are available, determines the predictive power of the specific model. In addition, Ohlson (1980) suggested that choosing the larger sample of estimation and also adding more default indicators increases the predictive power of the study significantly. After introducing the Altman's and Ohlson's models which are the most widely applied accounting-based models in the literature, the accounting-based default prediction models particularly for SMEs would be reviewed in the next section.

SMEs DEFAULT LITERATURE

According to Berger (2004), after new Basel Accord regulations (Basel II) was widely implemented, some studies pay their attentions to the SMEs segment of the economy to analyse the effects of new rules on these types of firms. According to Kolari and Shin (2004) findings, normally the SMEs are more risky than their larger counterparts. But as they comprise the vast portion of the economy, they can be very beneficial for the banks in terms of crediting. However banks are being extremely meticulous about these firms and imposing the tough requirements in order to grant the necessity credit to small businesses. Recently many relevant studies just raise their objections against the illogical requirements of very high level of capital for SMEs credit allocation. They warned that the unavailability of credit for SMEs financing would result in credit crisis of the small firms and affect the economy negatively. Thus, there is a general consensus in relevant literature that banks should be following a unique credit risk model for SMEs to gain the best possible outcome. The relevant research indicates that nowadays many banks employ the specific model for SMEs credit risk but still there is a gap in the literature about this claim.

SMEs FINANCIAL FAILURE FORCAST MODEL

According to the literature, the studies related to the SMEs financial failure prediction are also quite diversified. Altman and Sabato (2007) prediction model can be named as one of the most important models which were generated specifically for US SMES. As this model is one of the model which is applied in this study and will be described elaborately , in this section we only point out some other SMEs studies and their contributions to the literature and leave the description of Altman's model for the Methodology section of the paper.

Pederzoli and Torricelli (2010) investigate the SMEs effective default prediction model for specific region in Italy and found out that the logistic model with four explanatory variables would be the most predictive model for Italian SMEs default. They carried out some performance measure methods such as associate Accuracy Ratio (AR) and Cumulative Accuracy Profile (CAP) to examine the ability of the model in predicting the non-defaulted and defaulted firms. The accuracy tests in this study indicate that the level of accuracy in the models to some extend depends on choosing the specific cut-off value. Increasing the cut of value clearly increases the type I error and cause the reduction in type II error level and vice versa. On the other hand, it was found that by fixing the cut off value at the level of sample default rate the average error rate is low. The results of the study show that parsimonious model with only four predictors are enough to predict the firms' default effectively. Surprisingly, the equity ratio on its own is a very good predictor of defaults. Thus, it can be concluded that regardless of unavailability of market data for SMEs, the idea underlying the Merton model regarding the relationship between equity, liabilities and assets is also compatible for small firms. Sohn and Kim (2006) developed the random effects logistic regression model to predict the default events in SMEs. The random effect model has the advantage of taking into account the uncertainty that is not possible to be explained by individual factors along with the individual characteristics of each SMEs. The results of the study signify that the random effects logistic regression model in terms of classification accuracy is more efficient than fixed effect model.

Lugovskaya (2009) attempted to figure out whether the statistical model is an appropriate model to predict Russian SMEs default and does it show the sufficient predictive accuracy for SMEs or not. The statistical model of the study is based on financial ratios while size and age variables are added into the model. According to the study findings, In the case of estimating the accuracy of the model, it is important to distinguish between type I and Type II errors. Lugovskaya (2009) mentioned that as the type I error is more severe than type II for lenders, the user might be more interested to reduce this type of error and therefore the model developed in this study is valuable. The study concluded that although there are a lot of drawbacks in using the accounting ratio based models in predicting the defaults; in the case of Russian SMEs the financial ratios derived from balance sheet and profit loss account are good predictors of default. Moreover, liquidity and Activity are the most crucial factors in predicting the Russian SMEs default and the positive effect of age and size variables on SMEs default prediction also was clarified in the study results.

METHODOLOGICAL ISSUES RELATED TO THE ESTIMATION OF SMEs FINANCIAL DISTRESS

In the case of SMEs credit risk also there are some specific limitations which hinder both firms and banks to implement an appropriate crediting process. The limitations which can be considered are presence of heterogeneity in the default models, adverse selection problem, asymmetric information, and lack of transparency and generalizability. Zambaldi et al. (2009) investigated the obstacles that are in the way for Brazilians' SMEs to receive their essential credit from the banks. The study concludes that as a consequence of asymmetric information and transaction cost, the Brazilians banks have sort of limitations to supply enough credit to SMEs. In this situation with availability of the positive public information regarding the borrowers, financial institutions would make considerable benefits out of it.

Adverse selection is another important problem existed in default prediction modelling of SMEs. Ryo and Hideaki (2010) studied the Japanese SMEs credit scoring system to create the model for maximizing the Japanese banks profit in terms of crediting. They concluded that finding the solutions for window dressing and adverse selection problems in SMEs default scenario is the most important way to increase the level of activity in Japanese banks lending system. Moreover, the lack of transparency in financial statements and also omitted variables bias are other important factors which affect the activity of banks crediting. They suggested that banks can handle these problems by concentrating more strictly on company visits and management interviews although it would be more costly for the banks.

DATA & METHODOLOGY

SAMPLE OF THE STUDY

The definition of SMEs for this study follows the BaselII definition of SMEs which contains the companies with sales less than $65 million. The dataset for this study contains the number of 30000 unbalanced panel data for UK SMEs during 2000 to 2008 period while financial year 2009 will be retained to use as a hold-out sample for testing the accuracy of the model. However, as the dataset is unbalanced and the number of firms is changes every year due to some reasons such as bankruptcy, merge &acquisition and etc. The total observations for 10 years (including the hold-out sample) dataset is 225000 while 5200 observations would be considered separately as 2009 hold-out sample for testing the accuracy of the models. Additionally, data is collected form Balance Sheets and Profit Loss accounts of 15 to 36 Primary UK SIC 2003 codes which are including in the UK manufacturing industries. The other necessary information about the inside of the firms and their characteristics would be obtained from the headers of the firms which is also available in FAME database package. The main logic behind using the manufacturing industry as a sample of the research is related to the nature of these industries. The UK manufacturing industries are more homogenous in terms of firms' characteristics and also they are involved in the same economical environment. Therefore, the results of the research can easily be generalized to all the firms in the industry. Moreover, Altman's model which is supposed to be considered in this study is also based on the manufacturing dataset and it helps the study to more effectively replicate this default prediction model in this research. Finally, it is worth to mention that all the information in the dataset was needed to be deflated to be used in the regression analysis. The deflating process was done by using an appropriate deflator for each year and for different SIC codes.

The hold-out sample also will be used in this study to test the accuracy of the model. This sample contains the information from 2009 financial year for SMEs with 15 to 36 Primary UK SIC 2003 codes. For generating the appropriate hold-out sample to assess the default prediction models' accuracy, firstly the possible numbers of defaulted firms is collected from population and then the number of non-defaulted firms is being collected on the basis of keeping the default rate on average default rate for UK SMEs in 2009 which is 5% (EIB Annual Report 2008). Due to the availability of the company status in FAME database, the defaulted and non-defaulted firms can be collected very easily. In this study the firms that are signed Active are considered as non-defaulted firms and the firms which are signed as In Liquidation, In Administration and In Receivership or Dissolved are considered as defaulted firms subsequently. These criteria for choosing the defaulted firms in this study were widely applied in the previous literature such as Altman and Sabato, (2007) and Altman et al. (2007).

METHODOLOGICAL REVIEWS AND DEFAULT MODELS

As it was explained in previous section, there are many different default prediction models in the literature such as accounting based models, market based models, hazard models and ANN models. The focus of this research is only on the accounting based models and the other alternatives for default prediction in SMEs would be studied in further research.

The main goal of this study is to compare the results of two widely applied models of default prediction, Altman's (1968) and Ohlson (1980), on the sample of UK SMEs to investigate the accuracy of the models in this case. Instead of using the Altman' (1968) MDA model which bears many deficiencies, the new generated model by Altman and Sabato (2007) for US SMEs which contains the logistic regression analysis would be employed in this study. On the other hand Ohlson (1980) was one of the first studies which used logistic regression O-score and since that time his model was vastly used in practical and academic fields to predict the firms' defaults. The Ohlson and Altman models used in this study are more or less similar to the original models. However this study aims to add Time factors to control for the possible effects of different time on SMEs default prediction and also to add Industry and Structural factors to the model in order to account for any possible internal and external effects on default prediction models in SMEs.

ALTMAN'S MODEL

Altman and Sabato (2007) used 5 major accounting ratios such as Activity, Liquidity, Leverage, Coverage and Profitability as a basis for the default prediction model variables and chose the most predictive ones by applying the different sort of tests. The variables definitions of the model are as below:

Profitability = Retain Earnings / Total Assets

Activity = Net Income / Turnover
Liquidity = Cash / Total Assets
Coverage = EBITDA / Interest Expenses
Leverage = Short-term Debt / Equity Book Value

It is worth to mention that Altman's model used two variables, Retained Earnings/Total Assets and EBITDA/Total Assets, as two major indicators of SMEs' default behaviour. However, this study found that as these two default indicators are very similar somehow, including both of them in the model leads to an unreliable regression results. Thus, EBITDA/Total Assets was replaced by Net Income/Sales in the model and caused more sensible and reliable results which approved this transformation in this study. Finally, the variables are collected directly from the FAME database information while in some cases calculation and replacements are carried out to obtain the variable.

In the case of dependent variable, Altman and Sabato (2007) pointed out that considering the default event and in order to have a positive intercept and slopes, KPG (probability of being good) is used in their study since the higher the final logit score, the lower the likelihood of the firm will be defaulted. Thus the dependent variable in this study is a probability of being good (KPG) in predicting the defaulted firms and will be indicated by using the binary approach (0= defaulted, 1= non-defaulted). Moreover, Altman and Sabato (2007) also suggested that the logarithmic transformation of the variables should be used to decrease the range of values by each variable. It also would compensate the lack of accuracy existed by excluding the qualitative data in the study. Considering the advantages mentioned by Altman and Sabato (2007) study in improving the accuracy of the model, and as logarithm transformation makes the variables distribution closer to normal and mitigate the effect of outliers on the estimation results, in this study form the first step the logarithm transformation of all 5 explanatory variables would be used for Altman's model.
The model of the analysis would be as below:

$$\mathbf{KPG_{it} = \alpha + \beta_1 (Leverage)_{it} + \beta_2 (Coverage)_{it} + \beta_3 (Liquidity)_{it} + \beta_4 (Activity)_{it} + \beta_5 (Profitability)_{it} + \varepsilon_{it},}$$

OHLSON'S MODEL

We used the same criteria for choosing the predictive variables as it was used by Ohlson (1980). He chose the variables by considering that how frequent they are being used in the literature. For the purpose of generating the default prediction model, Ohlson used 9 variables which are widely used in previous studies and indicated the highest level of accuracy in predicting the firms' default. The explanatory variables in Ohlson's model are as blow:

FFO/TL = Pre-tax income plus depreciation and amortization divided by total liabilities.
WC/TA = Working capital divided by total assets.
TL/TA = Total liabilities divided by total assets.

CL/CA = Current liabilities divided by current assets.
OENEG = an indicator variable equal to one if owners' equity is negative, and zero otherwise. (1 if total liabilities exceed total assets, 0 otherwise)
Size = The ln (Total Assets/GDP price level index).
INTWO = An indicator variable equal to one if cumulative net income over the previous two years is negative, and zero otherwise.
NI/TA = Net income divided by total assets.
CHIN = (NIt-NIt-1) / (|NIt|+|NIt-1|) is the scaled change in net income.

For Ohlson's model also some variables such as Working Capital, Sales, Current Liability, total Assets and etc. can be obtained directly from the FAME dataset while for the others, calculation or replacements are necessary. The logistic dependent variable of Ohlson (1980) model is the reverse of Altman and Sabato's (2007) model dependant variable as it represent the Probability of Default (PD) instead of Probability of Being Good (KPG). In Ohlson's (1980) model the dependant variable is Default Probability of the firm if the firm defaulted in 4-16 months following the fiscal year ends. Thus in this study the Ohlson 's dependent variable take the value of 1 if the firms defaulted in supposed 2009 and take the value of 0 otherwise. The probability of each firm goes defaulted in this year will be calculated by running the model and would be between 0 and 1.
The model of the analysis would be as follow:

$$\mathbf{PD_{it} = \alpha + \beta_1\,(FFO/TL)_{it} + \beta_2\,(WC/TA)_{it} + \beta_3\,(TL/TA\;) + \beta_4\,(CL/CA\,)_{it} + \beta_5\,(OENEG)_{it} + \beta 6\,(\,Size)_{it} + \beta_7\,(INTWO)_{it} + \beta_8\,(NI/TA)_{it} + \beta_9\,(CHIN) + \varepsilon_{it}}$$

Finally, it is worth to mention that the models introduced above are only theoretical models of the study which were originated from the relevant literature. However, the empirical models for testing the accuracy might be changed considering the compatibility of the variables and their prediction power for UK SMEs.

RESEARCH FINDINGS

At this stage of the study, both Altman's and Ohlson's models will separately be investigated and the results would be analysed by considering the level of significance and signs. This section of the study also can be summarised in 3 different parts to comply the objectives of the study. First, the simple logistic regression was implemented for each model and the results were scrutinized. Then, the time factors were added to the model as Time dummies for 9 years (2000 to 2008) to control for the possible effects of Time on SMEs defaults prediction behaviour. In the next step, industry effects would be considered by adding the 22 industry dummies for all UK Manufacturing Industries. Finally, the structural effects on UK SMEs default prediction would be investigated by including the dummy variables related to 4 different UK SMEs legal forms, Private, Public, Unlimited and others.

ALTMAN'S MODEL

To obtain the most predictive coefficients for the model, the logistic regression was done first as a pool logistic regression and then the results were compared with the Random Effects Logistic regression results. Although the results of the regression in terms of coefficient signs and expectations were compatible, the pool regression indicates the higher level of significance for the explanatory variables in the model. Since the relevant literature such as Altman and Sabato (2007) also employed the pool logistic regression for the analysis, this method was chosen to be used in this study. However, as the observations for this study were selected from 9 years financial statements, there must be the effects of time on the default prediction. To control for the effects of time the 9 time dummies were added to the model and the results indicate that all the time dummies are highly significant which shed a light on the time effects on SMEs default prediction models. The regression results of the model are as below:

Regression Results of Altman's Model Including Time Factor

KPG	Coef.	Std.Err.	z	P>z	[95 %Conf.	Interval]
Liquidity	0.004	0.004	1.060	0.289	-0.003	0.011
Coverage	0.233	0.005	45.930	0.000	0.223	0.242
Leverage	-0.260	0.011	-23.180	0.000	-0.282	-0.238
Profitability	0.196	0.027	7.300	0.000	0.144	0.249
Activity	0.030	0.018	1.680	0.093	-0.005	0.064
_cons	0.848	0.017	48.950	0.000	0.814	0.882

*Log likelihood = -63005.532
*Time dummies were not displayed in order to conserve the space

The results of the regression indicate that all the variables except Leverage is positively affecting the SMEs default prediction which is compatible with the relevant literature. Additionally, Leverage, Coverage and Profitability variables are highly significant at %1 level while Activity is barely significant at %10 and Liquidity is not significant. All the time dummy variables used in the model are highly significant which indicates the important effects of time factor on default prediction models. The results indicate that using the pool logistic regression for predicting the default based on data for 9 years without taking time effects into consideration does not lead to the reliable results. It also signifies the effects of firms' environment and situation in different years on predicting the SMEs default. Finally, the log likelihood for this logistic model is quite high which confirms the reliability of the model as a whole.

ALTMAN'S MODEL INDUSTRY AND CORPORATE GOVERNANCE EFFECTS

As it was mentioned before, this study also aimed to control for the industry effects in default prediction models. The database of the study contains the information from 22 different UK manufacturing industries and therefore the presence of industry effects on default prediction models seems probable. To investigate the industry effects, 22 industry dummies were included in the Altman's model and being regressed against the Probability of Default as dependent variable. The results significantly certify the effects of different industry on default prediction behaviour as most of the industry dummies are highly significant in the model. Moreover, the regression results for the main variables of the model are more promising than the model without industry effects. According to the Table of results below, the level of significance for all the explanatory variables changes considerably. The new regression results indicate that all the variables are significant at %5 except for Liquidity which is highly significant at %10 level. In addition, the signs of the coefficients stay the same and still are highly compatible with the relevant literature. These results unequivocally approve the effects of different industry characteristics on UK SMEs default prediction and indicate the importance of including them in the model.

Another external effect that is aimed to be investigated in this study is the effect of different corporate governance on UK SMEs default prediction models. To reach this goal, the number of four structural dummies was included in the model considering the legal form information available in FAME database. The structural dummies which were selected to control for SMEs corporate governance effects on firms' default prediction are Private, Public, Unlimited and Other. The results of the study indicate that all the structural dummies are highly significant and have an important impact on models prediction power and reliability. The public dummy would be dropped in the process of analysis to avoid the problem of collinearity and also to investigate the effects of Private SMEs on the basis of Public SMEs. The results indicate that Private UK SMEs which contain the biggest proportion of firms in SMEs category are more probably to go bankrupt as the coefficient of this dummy is negatively affecting KPG which is the probability of being good. The negative effect brings the lower level of KPG in Private sector and illustrates that these firms are more risky than Public SMEs. The results of the study was expected as Private SMEs are normally small and more vulnerable than Public SMEs which are bigger firms with stronger asset structure and firm financial structure. Finally, including the structural dummies along with industry dummies enhance the reliability of the model significantly and turn all the main explanatory variables to be highly significant at %5 and %1 level while the signs of coefficients stay the same. The results of the study after including industry effects and governance effects are as below:

Regression Results of Altman's Model Including Industry and Governance Effects

KPG	Coef.	Std.Err.	z	P>z	[95 %Conf.	Interval]
Liquidity	0.008	0.004	2.240	0.025	0.001	0.015
Coverage	0.231	0.005	44.980	0.000	0.220	0.241
Leverage	-0.250	0.011	-22.000	0.000	-0.272	-0.228
Profitability	0.217	0.027	8.000	0.000	0.164	0.270
Activity	0.045	0.018	2.490	0.013	0.010	0.081
private	-0.164	0.043	-3.790	0.000	-0.249	-0.079
Unlimited	-0.644	0.103	-6.240	0.000	-0.847	-0.442
Other	-0.731	0.061	-12.000	0.000	-0.851	-0.612
_cons	1.863	0.186	10.020	0.000	1.499	2.227

*Log likelihood = -62251.741
*Industry and Time dummies were not included in the model in order to conserve the space

OHLSON'S MODEL

In the case of Ohlson's model also the same process was carried out for the analysis of the model. At first the same variables in the original model were employed in the logistic regression in which Probability of Firms' Default was Dependant variable. Then the industry dummies were added to the regression to evaluate the possible effects of different industry characteristics on Ohlson's model. Finally, the relevant structural dummies were included in the model to control for the effects of corporate governance differences on UK SMEs Ohlson's default prediction model.

The results of the study are more or less consistent with the original Ohlson's model in terms of signs and significance level. The explanatory variables are those 9 indicators that Ohlson (1980) selected for his model to predict the firms' default. The dependent variable for Ohlson's model is Probability of Default rather than Probability of Being Good which has been used for Altman's model. In this case the firms with lower probability are considered as non-defaulted firms and vice versa. The regression results of the model including time factor is as below:

Regression Results of Ohlson's Model Including Time Factors

	PD					[95	Int
		Coef.	Std.Err.	z	P>z	%Conf.	erval]
	FF	-	0.00	-	0	0.0	0.0
OTL		0.000	0	0.240	.813	00	00
	W	-	0.00	-	0	-	-
CTA		0.017	8	2.230	.025	0.033	0.002
	TL	0.0	0.00	-	0	-	0.0
TA		01	0	2.510	.012	0.002	00
	CL	0.0	0.00	0.590	0	0.0	0.0
CA		00	0		.558	00	01
	Siz	-	0.00	-	0	-	-
e		0.206	3	66.520	.000	0.212	0.199
	NI	-	0.00	-	0	-	0.0

TA		0.000	0	0.750	.452	0.001	00
	OE	0.2	0.01	13.94	0	0.2	0.2
NEG		38	7	0	.000	04	71
	IN	0.3	0.01	19.61	0	0.3	0.3
TWO		56	8	0	.000	20	91
	C	0.1	0.01	8.210	0	0.1	0.1
HIN		31	6		.000	00	62
	_c	-	0.03	-	0	-	-
ons		2.259	0	75.360	.000	2.318	2.201

* Log likelihood = -68085.479
*Time dummies were not displayed in order to conserve the space
*FFOTL, CLCA and NITA coefficients are displayed zero as they have very small values but the actual values are different from zero and the relevant signs can be interpreted.

The results of this study for Ohlson's model indicate that except for FFOTL, CLCA and NITA which are not significant, all the other variables are highly significant at %1 level and while WCTA is significant at %10 level. Moreover, considering the Table of results of Ohlson's model for UK SMEs, all of the variables except CHIN and OENEG are compatible with original model in terms of signs. CHIN variable accounts for the scaled change in Net Income considering the previous year and it is expected to have the negative effect with Probability of firms' Default as higher growth in net income should usually bring the lower probability of default. On explanation for this contradiction is that SMEs are not normally debt oriented and they strictly following the Pecking Order theory. According to Michaelas et al.(1999) and Jordan et al.(1998), these firms are more willing to use their internal funds as the first source of financing. If their retain earnings were not enough to finance their capital, they would use external sources such as debt and equity subsequently. Thus, the firms with higher growth in their net income are the ones which are less willing to use debt for their financing and applying lower level of debt in SMEs capital decreases the chance of bankruptcy in these firms consequently. Considering the rationale described, it should be the positive relationship between the SMEs CHIN variable and Probability of firms' default which is observed in this study. OENEG is also a dummy variable which depends on the owner's equity. It means that OENEG gets the value of one when total liabilities exceed total assets and otherwise. Hence, it is reasonable that there should be a positive relationship between OENEG and Probability of Default as bigger differences between liabilities and assets especially in SMEs increase the chance of default event by making these firms more susceptible financially.

As it was explained before, this study employed 9 years of UK SMEs observation to analyse the best accounting-based model for predicting SMEs default event. However, the method of analysis used for both model in this study is pool logistic regression in which the time different characteristics are not being taken into account. Thus, to control for the possible effect of time on default prediction behaviour of UK SMEs the time dummies for 9 years were included in Ohlson's model. The results indicate that all the time dummies are highly significant at %1 level which approves the effects of different time on UK SMEs default prediction. Nevertheless, the results for the main variables in the model stay more or less the same in terms of significance and coefficients' signs. The only difference is after controlling for time factor in Ohlson's model the WCTA which was only significant at %10 level becomes significant at %5 level which confirms the increase in the level of reliability of the model after including time factor. Finally, the log likelihood for this logistic model is quite high which confirms the reliability of the model as a whole.

OHLSON'S MODEL INDUSTRY AND CORPORATE GOVERNANCE EFFECTS

The next step of the analysis is to add industry dummies to the model to investigate the possible effects of different industry characteristics on prediction power and reliability of Ohlson's model. The results of the regression with industry dummies approve the effects of different industry characteristics on SMEs default prediction in Ohlson's model as most of the industry dummies for 22 manufacturing industry are highly significant at %1 level. However, contrary to Altman's model, the main variables in terms of level of significance and coefficient signs stay more or less the same as they were before including the industry effects in the model.

Finally, the same as what was observed for Altman's model, corporate governance choice also has substantial effect on UK SMEs default prediction as all the structural dummy variables included in Ohlson's model were highly significant at %1 level. As it is always the case for any dummy variables regression, one variable should be dropped in the regression to avoid collinearity and also to investigate the other variables behaviour based on that variable. Hence, Public dummy variable was dropped for this analysis in the model and other variables were assessed on the basis of that variable. The positive sign of the Private coefficient in the model indicates that the Probability of default for Private UK SMEs is higher than Public firms which are compatible with the Altman's model findings and it was expected considering the characteristics of Private and Public SMEs. The results of the model including industry and corporate governance effects are as below:

Regression Results of Ohlson's Model Including Industry and Governance Effects

PD					[95	I
	Coef.	Std. Err.	z	P>z	% Conf.	nterval]
FF	-	0.	-	0.	0.0	0
OTL	0.000	000	0.230	819	00	.000

W	-	0.	-	0.	-	-
CTA	0.016	008	2.040	041	0.031	0.001
TL	0.0	0.	-	0.	-	0
TA	01	000	2.300	021	0.002	.000
CL	0.0	0.	0.5	0.	0.0	0
CA	00	000	40	588	00	.001
Siz	-	0.	-	0.	-	-
e	0.214	003	65.720	000	0.220	0.208
NI	-	0.	-	0.	-	0
TA	0.000	000	0.680	494	0.001	.000
OE	0.2	0.	13.	0.	0.2	0
NEG	37	017	710	000	03	.270
IN	0.3	0.	20.	0.	0.3	0
TWO	73	018	380	000	37	.409
C	0.1	0.	7.9	0.	0.0	0
HIN	28	016	80	000	97	.160
Pri	-	0.	-	0.	-	-
vate	0.253	044	5.700	000	0.339	0.166
Un	0.5	0.	5.6	0.	0.3	0
limited	90	105	00	000	83	.796
Ot	0.6	0.	10.	0.	0.5	0
her	50	064	150	000	25	.776
_c	-	0.	-	0.	-	-

ons	2.720	183	14.900	000	3.078	2.362

* Log likelihood = -67398.601
* Industry and Time dummies were not included in the model in order to conserve the space
*FFOTL, CLCA and NITA coefficients are displayed zero as they have very small values but the actual values are different from zero and the relevant signs can be interpreted.

ACCURACY TESTS OF THE MODELS

The last part of the analysis is to find the most optimal model by looking at their prediction power and accuracy. For implementing the out-of-sample performances of the model, the 2009 financial year was selected as a hold-out sample. This sample was selected from 2009 UK SMEs sample which contains around 5000 UK SMEs firms. In order to obtain the Hold-out sample the number of 950 Active SMEs was selected out of 2009 sample. Then 50 Defaulted SMEs were picked to keep the default rate of the sample the same as the one for UK SMEs (%5). In the next step, the same process of variable selection and calculation was carried out and the PD and KPG was estimated for all the firms in the Hold-out sample according to the coefficients obtained for both models in this study.

In order to calculate the accuracy of the model, it is essential to determine the cut-off ratio for both models to estimate the type I and type II errors of prediction. In the case of Altman's model the KPG was calculated for all the firms in the hold out sample and then 5% of the firms with least level of KPG were selected as defaulted firms. For Ohlson's model cut-off ratio was selected at %5 level (default rate of the sample) based on the information in the sample and also the characteristics of the UK SMEs which are more risky than listed companies analysed in the original model. The Active firms for Ohlson's model are basically the ones with PD less than 5% and Defaulted firms are the ones with more than this level probability of default. Finally, type I and type II errors were estimated for both models based on the different accuracy tests criteria for each model (cut-off ratio).

The results of the tests acknowledge the efficiency of Altman's model over the Ohlson's model by showing the lower type I and type II errors. Considering the results, Altman's model type II error rate is 21% and type I error rate is 12%. It is worth to mention that in the process of determining the cut-off ratio for both models, the first priority was to minimize the type I error which is more severe than the type II in lenders point of view. In Ohlson's model also the type II error rate of 36% and type I error rate of 20%. Finally, the average of each model's type I and type II error will indicate the accuracy ratio of the model which is %83.5 for Altman's model and 72% for Ohlson's model. It is important to be pointed out that by changing the cut-off ratio for each model the level of type I and type II errors would change consequently.

CONCLUSION

This study used the financial statements information for the number of 30000 UK SMEs from 2000 to 2008 financial year to examine the reliability of two widely applied models, Altman's and Ohlson's, for predicting the default and to introduce the most optimal accounting based model for UK SMEs. The results of the study shed lights on the efficiency of Altman model in compared with Ohlson's model by considering the predictive power of the variables and also type I and type II prediction errors for each model.

The results of the study for UK SMEs regarding the effects of default prediction indicators on dependant variables, KPG and PD, are more or less consistent with the original models while there were some inconsistencies observed especially for Ohlson's model. Three explanatory variables, FFOTL, CLCA and NITA in UK SMEs Ohlson's model were not significantly affecting the Probability of Default while OENEG and CHIN have shown the opposite relationship with PD. These inconsistencies are all stemmed from the specific characteristics of the SMEs which differ substantially from their larger counterparts. As it was observed in this study, Altman's models which were intrinsically built for SMEs consideration was highly compatible with UK SMEs default behaviour and indicated more prediction power and reliability in compared with Ohlson's model which was mainly created for listed companies.

This study also aimed to investigate the possible effects of different industry characteristics and corporate governance choices on SMEs default events. The results of the regression including the industry effects and structural effects indicates that UK SMEs default events are highly affected by the different industry traits and also firms' governance structure. For instance, in the case of Altman's model, including those effects in the model increased the reliability and validity of the model substantially. Moreover, the results for both Altman and Ohlson's model suggested that UK SMEs Private sectors are more risky than Public sector. This results sound reasonable as Private sector mostly comprises the small firms which are owned privately and therefore are more susceptible financially than Public sectors firms which normally have stronger asset and firm financial structure.

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