Default Risk of the UK Real Estate Companies: Is There a Macro-economy Effect?

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Abstract. This paper empirically identifies the factors which are important in explaining default risk of the UK real estate companies over the past 20 years. We estimate a pooled probit model where the probability of failure is expressed as a function of both macroeconomic variables and company financial ratios. We find that the most important determinants of bankruptcy of the UK real estate companies are company liquidity, profitability and debt coverage as well as financial market volatility, interest rates, current account and the economic cycle. The latter provides evidence that the macro-economy crucially affects the probability of default of these companies.

JEL Classification: C35, G33, L85.

Keywords: Default probability, Probit binary-response model, Real estate companies.

1. Introduction

Default risk of real estate investment companies has asymmetric properties across business cycles. In an upturn in the business cycle, credit is easily available; banks are willing to sanction property loans and to fund new developments, usually at very low interest rates, which boost economic activity. Confidence is high, the expected profitability of new developments improves and the probability of default of construction and development companies is kept at reasonable levels. In contrast, in a downturn there is oversupply of new developments (overbuilding) while simultaneously demand of new space levels off due to the contraction in economic activity. In this phase of the business cycle monetary authorities usually follow tighter monetary policy in order to decrease liquidity in the system and to combat potential inflationary pressures in the economy. This results to higher interest rates which increase the debt burden of real estate investment companies. At the same time they also find themselves unable to generate sufficient income to cover the interest payments on their loans due to the contraction in economic activity. Moreover, refinancing becomes more difficult because lenders alter their risk assessments, switch to conservatism/more cautious lending policy and become unwilling to provide property loans since capital values of real estate -used as collateral- have depressed. This is the so called “credit crunch” phenomenon. Consequently, the probability of default of the real estate investment companies increases dramatically as well as bankruptcies.

This is exactly what happened to the British real estate market when the worldwide recession in the early 1990s brought significant pressure to the UK economy. Things went worse due to the entrance of the British pound into the Exchange Rate Mechanism (ERM) of the European Monetary System (EMS) on 8th October 1990. The British pound entered ERM in a higher exchange rate than what the foreign exchange currency markets thought was, at the time, its equilibrium exchange rate. The British conservative government followed a restrictive monetary policy especially during 1992, to combat inflationary pressures and to defend the exchange rate (within the ERM narrow band) from the speculative attacks emerged in early 1990s. This naturally led to an increase in interest rates[2]. The increased interest rates in close relation to the fact that most of the UK companies’ debt is at floating interest rates[3] made a number of real estate companies unable to service their debts. As Davis (1995) points out the simultaneous i) fall in property rents by over 20% due to an increase in supply of retail and office stock in the early 1990s and ii) fall in commercial property prices by over 25% due to the general economic recession, led many property investment companies to insolvency. Given that around 10% of the total bank loans, at the time, were diverted to property companies (Ball et al., 1998), real estate defaults had a negative feedback effect to the whole economy; credit risk was transferred from the real estate companies to the whole economy through the banking system. Thus, the recession was deepened and unemployment rate increased. This led to wide spread concern among the British government, the Bank of England, banks and the real estate industry professionals. It was made obvious to the policy makers, commercial banks and investors that real estate company failures, banking crises and macroeconomic recessions were intertwined[4].

The need to introduce a failure prediction model for real estate companies in order to explain the factors that affect their probability of default has never been greater. The purpose of this paper is to build up an econometric model able to identify the factors that have a significant impact on the probability of default of the UK real estate companies. Kane et al. (1996) suggest that financial distress resulting in corporate failure can be dichotomised into two groups: 1) Macro-economic stress induced by a firm’s exposure to events such as a general recession, and 2) Micro-economic stress resulting from firm and industry specific causes. Along these lines we estimate a pooled probit model where the probability of failure is expressed as a function of both macroeconomic variables (inflation, interest rates etc.) and company financial ratios. The analysis is based on a unique panel data set collected from Thompson’s DataStream (total number of 139 companies) for the period 1980 to 2001. We find that the most important determinants of bankruptcy of the UK real estate companies are company liquidity, profitability and debt coverage as well as financial market volatility, interest rates, current account and the economic cycle. The latter provides evidence that the macro-economy crucially affects the probability of default of the real estate industry in the UK.

There are three basic reasons that lead us to believe that the results presented in this paper contribute to the existing literature on default risk. First, quantitative credit risk analysis of the real estate industry in the UK has not yet been developed. Patel and Vlamis (2006) were the first to look at this issue. Based on the Black and Scholes (1973) and Merton (1974) contingent claims model, they estimate the distance-to-default and the "risk neutral" default probabilities for a sample of 112 real estate companies over the period 1980 to 2001. They use a conceptual model[5] to predict the probability of default of the UK real estate companies. We extend this work by using an econometric model[6] instead, that is a Probit model, in order to identify the determinants of the probability of default of the UK real estate companies. Altman (1998) points out that developments and tests of Probit and Logit models have dominated the credit risk measurement literature in the scholarly journals. Nevertheless, we have not as yet seen an attempt of this kind in the literature for the UK real estate companies. One explanation for this lack of empirical work on the area is that very often real estate companies –together with companies in finance and insurance industry- are excluded from corporate financial distress studies because their financial accounts are not comparable to the rest of the companies. Second, the data set of the UK real estate companies employed represents one of the most extensive and detailed data sets in the study of real estate companies default. Third, one of the distinctive features of this study is to test the extent to which macroeconomic circumstances also contribute to real estate company failure. To the best of our knowledge none of the studies in this area provides systematic treatment of the state of the macro-economy as a contributory factor explaining real estate corporate failure. We think that this issue is an important empirical one, especially in the case of industries like construction and commercial real estate, which are prone to cyclical activity.

The rest of the paper is organized as follows. In section 2 a brief review of the literature is provided. In section 3 the Probit econometric model is outlined. Section 4 provides a description of the data collected. In Section 5 we present the explanatory variables used in our model. In Section 6 we discuss the Probit results and Section 7 concludes the paper.

2. Review of the Literature

Multivariate methods utilize two or more key accounting variables to explain failed and non-failed companies. The independent variables are combined and weighted in order to produce either a credit risk score or a measure of the probability of default. The three approaches to developing multivariate credit-scoring systems are the *Linear Probability Model*[7], the *Zeta Discriminant Model* and the *Probit/Logit model.* Altman (1968) is the first to apply statistical techniques, particularly the use of *Discriminant Analysis,* to identify bankruptcy risk of non-financial firms. This method divides borrowers into high or low default risk classes contingent on their observed characteristics. He maintains that there are several financial ratios that are of key importance to company failure. These ratios could act as an indicator of the company's propensity to fail. Later, Altman et al. (1977) produced a revised version of Altman's original equation, which is referred to as the *ZETA Discriminant Model*. This is based on the same philosophy but extends the number of independent variables employed (7-variable model). They apply their model in a sample of 53 bankrupt non-financial companies and a matched sample of 58 non-bankrupt entities in the USA, for the period 1969-1975. They follow an iterative process to end up with a model that gives the significant determinants of the probability of default; *return on assets, stability of earnings, debt service, cumulative profitability, liquidity, capitalization and company size*.

Martin (1977) is the first to apply Logit/Probit model to measure the soundness of the US commercial banking system. Martin's data set comprises the entire population of banks being members of the Federal Reserve System; approximately 5,700 with 58 of them having failed between 1970 and 1976. After running a number of regressions, he concludes that the Logit model, with 4 independent variables characterizing *profitability* (net income/total assets), *asset quality* (commercial loans/total loans), *capital adequacy* (gross capital to risky assets) and *expenses/operating revenues*, is the most satisfactory model. It also turns out that Logit model is superior to Discriminant Analysis when the criterion is solely the probability of default estimation. Heffernan (1996) employs an international database with 27 healthy and 12 failed banks to identify the causes of bank failure. He estimates conditional Logit model for the period between 1989 and 1992. His sample includes the following countries: Australia, Finland, France, Norway, Sweden and the United States. He finds that *net income/total assets* (profitability), *equity/total assets* (capital adequacy), the *growth rate of GDP*, the *nominal and real effective exchange rates*, *nominal and real interest rates* and *the rate of inflation* are variables that significantly explain bank failures.

Lennox (1999) evaluates the usefulness of the Probit, Logit and Discriminant Analysis by examining the causes of bankruptcy for a sample of 949 listed companies operating in various industry sectors in the UK; 90 of those companies failed between 1987 and 1994. He finds that the most important determinants of bankruptcy are *cash flow, leverage, company size, profitability and the economic cycle.* He also claims "that well specified logit and probit models can identify failing companies more accurately than the discriminant analysis". Kolari et al. (2002) estimate a Logit model to identify the factors that caused a surge of bank failures in the United States in the late 1980s and early 1990s. They collect and analyze a sample of 55 large failed banks and around 1,000 large non-failed banks for the period 1989-1992. Kolari et al. find that *net interest income/total assets, net income after taxes/total assets, total equity/total assets and net loan charge-offs/total assets* have a statistically significant effect on the probability of default of the USA large banks. Foreman (2003), in a recent study of bankruptcy of the US local telecommunications industry, estimates a Logit model using a cross section data set of 77 “Competitive Local Exchange Carriers” (14 bankrupt and 63 non-bankrupts) as of year-end 1999. He finds that the probability of default of the CLECs is crucially affected by traditional financial ratios such as, *the earnings per share, the retained earnings to assets, the return on assets and the working capital to sales.*

Our model has some similarities with Altman’s et al. (1977) in both the set up and the results (we will discuss this in section 6). However, the research methodologies employed and the data sizes (we will discuss this in section 4) are different. More specifically, Altman’s et al. Zeta Discriminant Analysis and our Probit default prediction model are not directly linked to a theoretical model; there is a lack of a theoretical basis for the selection of the financial ratios. As far as the research methodology employed is concerned, Altman et al. use Discriminant Analysis to divide borrowers/firms into high or low default risk classes contingent on their observed characteristics. This methodology has certain weaknesses (no allowance is made for *sampling bias)* that led researchers to use Probit and Logit models instead. The logistic and probit formulations are comparable and provide qualitatively similar results. In both Probit and Logit models the estimated range of default probabilities lies between 0 and 1. The only difference is that for the Logit model the assumed form of the probability function is the cumulative *logistic distribution function* while for the Probit model the assumed form of the probability function is the cumulative *normal distribution function.* Since Probit and Logit models have been extensively applied to previous accounting, finance and banking studies[8] and have been found to perform well, we have chosen to employ the binary response Probit model to analyze the determinants of the probability of default of the UK real estate companies.

3. Model Specification

Our econometric model is a discrete regression model in which the dependent variable Y_{it} is binary, where $i = (1, 2, 3.........\mathrm{N})$ refers to the firms and $t = (1, 2, 3.........\mathrm{T})$ refers to the year. We assume there is an underlying response variable Y_{it}^* defined by the regression relationship

$$Y_{it}^* = X_{it}\beta + \varepsilon_{it} \tag{1}$$

where X_{it} is the vector of the explanatory variables of the i[th] firm, ε is the error term (assumed to be standard normal with $\varepsilon_i \sim \mathrm{N}(0, \sigma^2)$ and β is a vector of coefficients to be estimated. In practice, Y_{it}^* is unobservable. What we observe is the dummy variable Y_{it} defined by

$$Y_{it} = 1 \quad \text{if } Y_{it}^* \geq 0$$

$$Y_{it} = 0 \quad \text{otherwise} \tag{2}$$

At each year t, Y_i takes the value 1 if a firm has defaulted during the time period $[t-1, t]$

and 0 if the company is "alive". The log-Likelihood Function is given by

$$\ln(L) = \sum_{i}^{N} \left[(1 - Y_{it}) \ln\left(1 - F\left(X_{it}\beta\right)\right) + Y_{it} \ln\left(F\left(X_{it}\beta\right)\right) \right] \tag{3}$$

Because $F(\bullet)$ is strictly between zero and one for probit, $\ln(L)$ is well defined for all values of β. A non-linear maximum-likelihood estimation procedure is used to obtain parameter estimates for the Probit specification. Econometric theory implies that the maximum-likelihood estimator is consistent, asymptotically normal and asymptotically efficient for random samples.

4. Data

Our analysis is based on a pooled unbalanced panel data set, collected from Thompson's DataStream and the financial press[9], over the period 1980 to 2001. It includes company accounts (Balance Sheets and Profit and Loss Accounts) for the whole population of the de-listed (16 defaulted, 54 taken-over and 19 management buy-outs[10]) and the listed (50 non-failed) commercial real estate companies, on the London Stock Exchange, as was their standing on the on 3rd of April 2000. This amounts to over 1,300 observations from company accounts and 139 companies.

We acknowledge the fact that our data size is relatively small compared to other empirical work done ((see Altman, Haldeman and Narayanan (1977), Martin (1977), Lawrence, Smith and Rhoades (1992), Lennox (1999), Kolari et al. (2002) and Foreman (2003)). If one limits the study to one country and furthermore focuses on one industry, like we do, the sample inevitably will not be large enough. It has though a number of distinctive features when compared with other empirical work done in the field. We do not follow a "matched pairing"[11] sampling technique, as Altman et al. (1977) and others did, and thus we avoid the weaknesses and problems of this technique. Moreover, if we had followed a matched pairing technique we would have ended up with 32 real estate companies (16 failed and 16 non-failed); a sample being too small to identify certain effects on the dependent variable.

From the population of the listed and de-listed UK real estate companies[13] (total of 139 companies) over the period 1980 to 2001, we have only included those with complete data in our model with regards to the selected explanatory variables i.e. financial ratios and macroeconomic time series. Exclusion of companies might lead to a sampling bias. However, as only a very small part of the whole population of companies (only seven companies; Canary Wharf Group, Development Securities, Grainger Trust, Great Portland Estates, Hammerson, Tops Estates and Unite Group) listed to the London Stock Exchange, as of 2000, is excluded due to incomplete data, this bias should not have a significant influence on the estimates of the Probit model parameters. Eichoholtz et al. (2004, p. 7 footnote 2) make a similar argument.

The period of analysis varies among the fifty non-failed companies according to data availability. Financial data covers up to 20 reporting periods (unbalanced panel data set). There are sixteen companies in the sample that defaulted during the period 1980-2001. For each failed company, financial data from 2 to 10 reporting periods prior to failure has been collected. For the purpose of our econometric model, failed companies are treated as non-failures for all periods up until the period in which they failed. Thompson's DataStream considers the companies that are de-listed from the London Stock Exchange as "failed". This is not accurate. Companies might get de-listed due to other reasons i.e. because they decide to go private, they are subject to a takeover or a management-buy-out bid. A company is deemed to have defaulted, in the legal sense, if it has entered liquidation, receivership or administration. For the purpose of our econometric analysis, we consider a company as failed when it publishes its last company report as an ongoing concern. Failed companies included up to the last report preceding their failure; none of the failing companies have published accounts after filing for bankruptcy. There is a time lag effect between when a company gets under supervision/administration or files for bankruptcy, and when it is finally de-listed from the stock exchange. This is consistent with Peel et al. (1986, p. 8) who find that for the UK corporate sector, "the mean time lag from the date of the last account's financial year end to the first notification of failure (comprised the suspension of the firm's listing by the Stock Exchange) is 14 months".

There are forty-nine companies in the sample that were subject to a takeover bid and five companies that merged with other companies, during the period 1980 - 2001. Financial data from 2 to 20 reporting periods, prior to the takeover or merger, was collected. Since these companies were subject to a takeover bid due to their relatively healthy financial condition[13], we are treating them here as non-failures for all periods including the period in which they were taken-over or merged. There are also thirteen companies in the sample that were subject to a management-buy-out (MBO) bid and six companies that went private during the period 1980 - 2001. Financial data from 4 to 19 reporting periods, prior to the MBO bid or the decision to go private, was collected. For the purpose of our econometric model, these companies are treated as non-failures for all periods including the period in which the MBO bid was recommended or the company went private

Table 1 shows the frequency of failed and non-failed companies in the pooled panel data set. The frequency of the defaulted companies is 1.20 percent (16 observations out of total 1,335) while that of non-failed companies is 98.80 percent (1,319 observations out of total 1,335). Survivorship bias might arise from the fact that default is a rare event; the observations of the non-failed companies might dominate those of the failed companies. We expect though that as soon as the sample frequency of failure is close to the population frequency, survivorship bias will not be a problem. We believe that the sample frequency of failure in our sample is not much different from the population frequency of failure (given that only seven companies have been excluded from the whole population of the UK real estate companies due to incomplete data). Possibly this is the reason why this kind of sample bias has not attracted any attention in the relevant literature. Survivorship bias is not acknowledged as a problem in recently published work in the area ((see Heffernan (1995), Lennox (1999) and Foreman (2003)).

Table 1. Frequency of Failed and Non-Failed Companies in the Panel Data Set

Companies	Frequency	Percent
Non-Failed	1319	98.80
Failed	16	1.20
Total	1335	100.00

Table 2 shows the distribution of the observations for the failed and non-failed commercial real estate companies over the period 1980 - 2001. It is evident that there is a clustering of defaults of real estate companies around the periods that recession hit the UK economy. Particularly, after the stock exchange crash in 1987 until the British pound exited the Exchange Rate Mechanism of the European Monetary System in September 1992, there were eight incidents of defaults. Also, six more companies defaulted during the late 1990s economic slump in the UK. The real estate sector in the UK and in many other mature economies experienced a pronounced construction and investment cycle in the late 1980s and early 1990s. Anderson and Sunderesan (2000) point out that default of diverse firms are likely to be correlated to and coincide with cyclical downturn.

Table 2. Distribution of the observations for the failed and non-Failed Commercial Real Estate Companies

Year	Non-Failed	Failed	Year	Non-Failed	Failed
1980	27	-	1991	63	2
1981	33	-	1992	62	-
1982	47	-	1993	60	-
1983	56	-	1994	71	-
1984	57	1	1995	74	-
1985	60	-	1996	83	-
1986	64	1	1997	89	-
1987	61	2	1998	87	-
1988	63	1	1999	81	2
1989	59	2	2000	62	4
1990	58	1	2001	2	-

5. Financial Ratios and Macroeconomic Variables as Explaining Factors of Real Estate Company Failure

As Plat and Plat (1991) correctly put it " …in the case of bankruptcy, there is not a widely accepted theory that might be used to guide model specification". The decision to include an additional variable in a model specification is not based on theoretical considerations. The choice between different explanatory variables and regression equations is rather an empirical issue.

We compiled a large number of individual company financial ratios from financial data obtained from companies' annual reports. All data is at fiscal year end. We use a stepwise regression procedure where variables were added to, or dropped from the model, one at a time, based on their statistical significance. From the total of 22 variables[144] (11 financial ratios constructed and 11 accounting variables extracted from companies' reports) we end up including a rather limited number of key financial ratios and accounting variables (four) in order to capture company specific effects. Other studies in accounting, finance and banking literature have included numerous financial ratios to capture the same effects. We believe that beyond a certain point, calculating a greater number of financial ratios adds little additional information. Each new ratio is essentially a variation of other ratios already used in the analysis. Also, we have not selected a number of financial ratios that were found significant in other empirical studies in the corporate failure literature. For example, we do not include "cash" (or other cash related financial ratios) as an explanatory variable in our model because as far as we are aware Thompson's DataStream does not provide Cash Flow Statements for the UK real estate firms. Moreover, we do not provide information about the loan structure (fixed vs. floating) for the UK real estate companies. This distinction though is not of prime importance for the UK firms where most of the debt (household and company) is at floating rate (see note 3).

Variables capturing profitability, liquidity, debt coverage and company size are shown in Table 3. Total assets are used as a measure of company size. Company's net income (in millions) taken from the profit and loss accounts is used as a measure of profitability. Earnings before interest and taxes (EBIT) divided by the interest payments is used as a measure of debt service. This measure is of particular interest to lenders who are concerned about a company's ability to repay them for issued loans. Lastly, current assets/total assets ratio is used as a measure of company's liquidity. In addition, from Thompson's DataStream we collected key macroeconomic variables for the UK economy such as inflation, interest rates, current account surplus, growth of GDP and the stock market volatility. The former four variables, which capture business cycle effects and the latter, which captures financial market uncertainty, are summarized in Table 3. The inclusion of macroeconomic variables marks a departure from most previous studies of company bankruptcy. In most studies, authors have restricted themselves to various company financial ratios in their attempts to identify problem or failed companies and their characteristics. One study for banking failure by Heffernan (1996) is an exception of this generalization. Both financial ratios and macroeconomic variables included in the study are in percentage terms. The column "Relation to Failure" in Table 3 shows the expected relationship (positive or negative) between the independent variables listed in the table and the state of default.

Table 3. Summary of the Explanatory Variables Used in the Probit Model

Variables	Abbreviation	Definition	Relation to Failure
Financial Ratios			
Size of company	Size	Natural Logarithm of the Total Assets (in millions) as a measure of company size	(-)
Net Income (Profitability)	Income	Company's Net Income (in millions) taken from the PNL Accounts	(-)
CATA ratio (Liquidity)	CATA	[Current assets/Total assets] x 100%	(+)
Interest Coverage ratio (Debt Service)	Coverage	Earnings Before Interest and Taxes (EBIT) divided by Interest Payments	(-)
Macroeconomic Variables			
Short-term Nominal Interest Rate	Sti	3-month Treasury-Bill rate	(+)
Inflation Rate	Inflt	Measured as the rate of change of the UK Consumer Price Index	(+)
Stock Market Volatility	Ftlsh	Measured as the annualized standard deviation of the FT All Share Price Index	(+)
Current Account Surplus	Current-s	Natural Logarithm of Exports minus Imports	(-)
Growth of GDP	Growthgd	Measured as the rate of change of the Gross Domestic	(-)

		Product	
Period Dummy for Recession and Slowdown	Sldown	Dummy takes the value 1 for the periods 1988-1992 and 1999-2001, 0 otherwise	(+)

Table 4 and Table 5 present a summary of descriptive statistics for the financial ratios in our model. Numbers for Income are in thousand pounds and for the rest of the independent variables are in percentages. Failing companies compared to non-failing companies, are smaller in size, have poor profitability (the average net income being nearly 1/3 of that of the non-failed companies), find it more difficult to pay their debts (the average coverage ratio being seven times smaller than that of the non-failed companies) and lastly have less flexibility to generate cash flows sufficient enough to cover their cash outflows (the average CATA ratio for failed companies is nearly twice as big as of that of the non-failed companies). These results are consistent with previous empirical studies of company bankruptcy (see for example Altman, 1977). The average inflation rate, interest rate, stock market volatility and growth rate of GDP, in the UK, for the period 1980 - 2001, were 5.46 percent, 9.58 percent, 11.55 percent and 2.3 percent, respectively. Please note the very high average equity volatility and the quite high average short-term interest rate for the period.

Table 4. Summary Statistics for the Failed Companies (16)

Variables	Mean	Standard Deviation	Min	Max
Size	10.81	1.30	8.35	12.67
Income	8466.63	15201.88	-6485.00	52545.00
Coverage	2.30	2.70	-3.08	7.03
CATA	0.45	0.32	0.003	0.94

Table 5. Summary Statistics for the Non-Failed Companies (123)

Variables	Mean	Standard Deviation	Min	Max
Size	11.47	1.65	6.50	15.87
Income	27465.46	74111.45	-120000.00	1195000.00
Coverage	15.62	96.45	-61.44	1843.00
CATA	0.28	0.29	0.0006	1.05

It would indeed have been very useful in such an analysis of credit risk of the UK real estate companies to consider how the different types (retail, office, residential and industrial) and the geographical region of property investment (South, North, East and West) could have potentially affected the probability of default of these companies[155]. Thompson's DataStream and other sources that we checked (Financial Times, London Stock Exchange, Property Week and The Estates Gazette Information Research Centre) do not archive details about UK property investment by asset type and geographical region. It is the data limitations, which precludes us from looking deeper into this issue.

6. A Probit Model for the UK Real Estate Companies: Empirical Results

We estimate a Probit model using a pooled panel data set for the public UK real estate companies. The estimation results for the Probit specification are presented in Table 6. Specifically, the Table reports the estimated coefficients, the marginal effects, corrected (robust) standard errors for both heteroscedasticity and dependence of observations within firms as well as the t-statistic for each of the explanatory variables.

Company size is found to have a negative effect on the probability of default. This is the so called "too big-to-fail" argument; the larger the company, the lower the probability of failure. It is the case where large mature companies have usually an established reputation as good bank customers and would be viewed by banks as safer risks. Thus, it might be easier for larger companies to find external financing, in more favourable terms compared to smaller companies, during periods that they experience temporary cash flow problems. Although correctly signed, the size coefficient is not statistically significant. We also find that interest coverage has a negative and significantly different from zero effect on the probability of default. This is in line with the economic theory; the higher the EBIT to interest payments the more comfortable the firm will serve its debt and thus less the risk of company default. Another accounting variable, the net income, is found to be negative and significantly different from zero. This is a very standard result in the literature; the higher the net profits for a company the more loose capital is available to finance new investment projects and to reduce debt burden. Our results confirm prior expectations ((see Ward (1994) and Lincoln (1984)) that illiquidity is positively related to financial distress. Companies with long-term assets have greater flexibility to generate cash-flows sufficient to cover their cash outflows during sudden decreases in cash flow.

With respect to the macroeconomic variables in our model, we know by intuition that the higher the current account surplus for an economy the less likely it is that the government increase the interest rates in order to finance possible trade imbalances and therefore, the lower the probability of default for domestic companies. The negative sign of the coefficient for the current account surplus verifies prior theoretical assumptions.

Table 6. Probit Estimation Results

Explanatory Variables	Coefficients	Marginal Effects (dF/dx)	Robust Standard Error	t-statistic
Size	-0.06	-0.00004	0.00009	-0.65
Income	-5.79e-06	-4.11e-09	5.56e-09	**-2.26****
Coverage	-0.03	-0.00002	0.00002	**-2.94***
CATA	1.18	0.00084	0.00098	**2.30****
Inflt_1	-0.14	-0.00010	0.00010	-0.78
Ftlsh_1	3.12	0.00222	0.00289	**2.68***
Sti_1	39.30	0.02793	0.03011	**2.41****
Current-s	-0.00006	-4.16e-08	4.69e-08	**-2.91***
Growthgd	12.01	0.00854	0.01240	1.59
Sldown	1.10	0.00474	0.00445	**3.18***
Constant	-6.51	-	1.78410	**-3.65***
Observations	= 1331			
Log likelihood	= -54.76453			
Pseudo R^2	= 0.3679			

Notes: One asterisk denotes significance at the 1% level and two asterisks denote significance at the 5% level.

In contrast, the short-term interest rate lagged one period, is found to be significantly different from zero and positive. When interest rates increase, the interest obligations and payments of the borrowers increase as well. Inability to meet the higher debt obligations is a precipitating factor in a firm's demise. In countries like the UK where most debt contracts are at floating interest rates, the relationship between the short-term interest rate and the probability of default is even stronger. This relationship might hold for any company in any industry but it is particularly strong in the real estate industry because real estate companies are highly leveraged companies ((see Ball et al. (1998) and Harvey (2004)) and risks are high ((see FDIC (1997), Ball et al. (1998) and Lennox (1999)). The standard deviation of the stock market index lagged one period is also found to be significantly different from zero and positive. That implies that the stock market volatility has a positive effect at the probability of default, with one period lag. If uncertainty prevails in the stock market, for example due to uncertainty about the economic growth prospects of an economy etc. it will naturally increase the volatility of the stock market. In this case, companies might find it difficult to raise new money from the issuance of new shares and it is likely that they will have to rely on the more expensive debt-financing alternative. Lastly, the period Dummy for economic recession (1988 - 1992) and slowdown (1999 - 2001) in the UK is found to be significantly different from zero and positive. Periods of economic slowdown or recession are expected to be associated with higher company defaults. As we show in Table 2 above, there is a clustering of defaults of real estate companies around the periods that recession hit the UK economy.

Pseudo-R^2 stands in one-to-one relation with the Chi-squared statistic for testing the hypothesis that the coefficients on all variables (overall significance) apart from the constant are jointly zero (Dhrymes, 1986). Pseudo-R^2 is admittedly quite low but Wooldridge (2006) argues that in binary response models “goodness-of-fit is not as important as statistical significance and economical significance of the explanatory variables”. Moreover, it is very common in empirical work in the bankruptcy literature to get very low magnitude for the Pseudo-R^2 ((Lawrence, Smith and Rhoades (1992) get 0.29 and Lennox (1999) gets 0.2169)).

Lastly, pseudo R^2 does not have the usual interpretation of explained variation/total variation because the binary response Probit model is a non-linear regression model. In most applications of binary response models one of the goals is to explain the effects of changes in any of the explanatory variables X_i on the response probability Pr (Y_{it}=1). It is important to know that the magnitudes of the coefficient estimates of the Probit model, like in any other non-linear regression model, are not especially useful and this is because they do not represent “marginal effects”. Marginal effects give the partial effect of a roughly continuous variable on the response probability. This is obtained from the partial derivative $\vartheta Pr(Y_{it}=1)/\vartheta X_{it}$. Marginal effects depend upon the point at which the probabilities are evaluated, and this point is conventionally chosen as the vector of sample means. The magnitude of the marginal effects in our model is very low. It is very common though for empirical work that includes financial ratios (measured in percentages) as explanatory variables to get very low magnitude for the regression coefficients. Other authors in the bankruptcy literature ((see Lennox (1999) and Foreman (2003)) also get very low marginal effects.

7. Conclusion

Although the Probit and Logit models have dominated the credit risk literature, this is the first attempt ever to apply quantitative credit risk models to a UK real estate data set. Our data set, compiled by means of using information from Thompson’s DataStream and the financial press, is unique. It includes company accounts for (nearly) the whole population of the de-listed (16 defaulted, 54 taken-over and 19 management buy-outs) and the listed (50 non-failed) commercial real estate companies, over the period 1980 to 2001. We pool the data of the total number of the UK real estate companies and run a Probit regression for the period 1980-2001.

In our model we include a number of financial ratios because the risk position of a company varies with the state of the balance sheet and profit and loss accounts. We find that *profitability*, the *debt service* and company's *liquidity* are statistically significant determinants of the probability of default of real estate companies in the UK. The distinctive feature of this study is that it tests the extent to which macroeconomic/financial circumstances also contribute to real estate company failure. We include a number of key macroeconomic and financial variables because default risk for all borrowers depends on the state of the financial and economic cycle. As we show in Table 2 there is a clustering of defaults of real estate companies around the periods that recession/slowdown (1988-1992 and 1999-2001) hit the UK economy. In general, default risk of companies has asymmetric properties across business cycles. This is especially the case in industries like construction and commercial real estate, which are prone to cyclical activity. Business cycle fluctuations are the main cause of defaults of the real estate investment companies in the UK, which occur mostly during or immediately after recessions. This pattern is – evidently- a sign of post cyclicality.

We find that variables such as *interest rates, current account surplus, stock market volatility* and the period *Dummy* for recession (1988-1992) and slowdown (1999-2001) significantly affect the probability of default of real estate companies in the UK. Should and can anything be done in order to prevent a repetition of the property market collapse and banking crises of the early 90's in the UK and their negative repercussion effects to the whole economy? Our econometric model for the UK real estate companies reveals interesting insights about the determinants of company failure. This information might be useful for the industry professionals, policy makers and the real estate lenders. They need to seriously pay attention to macroeconomic changes (changes in the interest rates and the current account) and financial environment changes (uncertainty in the financial market) because these changes might lead to an unforeseen deterioration in the credit standing of bank's counter-parties (for example commercial real estate investment companies). This might induce financial fragility which can, in turn, cause a non-performing loans crisis, bank failures and consequently a general economic crisis.

We believe that the results presented in this paper contribute to the existing literature on default risk. They suggest an early warning system that takes into account the state of the macro-economy as a contributory factor explaining real estate corporate failure is an attainable goal. Ultimately, the real issue is how well the models work and to what extent their use contributes to improved financial performance of a company. A conceptual model for the UK real estate companies (like the contingent claims approach employed by Patel and Vlamis, 2006) that performs well in terms of classification accuracy, has an advantage over a statistical model (like the Probit binary response model that we use here), which does not, and vice versa. To the best of our knowledge there are no published comparisons of these different research methodologies for the UK real estate companies. A comparative analysis of credit risk models for the UK real estate industry is next in our research agenda.

Notes

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2. Interest rates increased from 8.3 percent in 1988 to 12.6 percent in 1989, to 14.5 percent in 1990, to 13.4 percent in 1991 and to 15 percent immediately after the speculative attack to the British pound on Wednesday the 16th of September 1992 (the so called "Black Wednesday").
3. Most of the household and company debt is in floating rate in the UK. Particularly, the vast majority of loans to firms (around 90 percent of gross loans) are at variable interest rates. Also, a very high proportion of mortgage loans to households (around 90 percent of the stock of mortgages) have variable interest rates ((see Rowlatt (1993) and Miles (1994)).
4. See Browne and Case (1992), FDIC (1997), Hilbers et al. (2001), Collyns and Senhadji (2002).
5. A conceptual approach tells us which variables should be important and how they should be combined mathematically.
6. An econometric approach identifies important factors based on experience.
7. Although straightforward, the LPM method faces serious econometrics problems and is rather out of date. That's why we do not analyse it here. For the problems (non-normality of the disturbances, heteroscedastic variances of the variances, questionable value of R^2 as a measure of goodness of fit etc.) in estimation of LPM see Gujarati (2003).
8. See Beaver (1966), Altman (1968), Martin (1977), Peel et al. (1986), Peel and

Peel (1988), Platt and Plat (1991), Lawrence, Smith and Rhoades (1992), Morris R. (1997), Heffernan (1996), Lennox (1999), Kolari et al (2002) and Foreman (2003).

9. Information collected form *Financial Times,* the *Estates Gazette* Information Research Centre and the practitioners' journal *Property Week*.

10. The purchase of a business by part or all of its existing management with the help of a group of financial backers, such as, specialist divisions of commercial banks or investment banks and venture capital funds.

11. This involves state (choice) based samples with equal numbers of failed and non-failed firms, each group typically also "matched" to size and industrial classification. The matched pairing procedure produces an experimental sample of companies, which is not representative of the population of the non-failed companies. The matched pairing approach assumes that there is an equal 50:50 percent probability of any firm selected from the wider population of companies being a potential failure. In that respect a sampling bias is introduced. For more on the matched pairing procedure and its problems see Morris (1997).

12. A description of all 139 companies employed in this study as well as market capitalisation data and the period of analysis for each of the failed and non-failed companies are available from the author upon request.

13. Mergers and acquisitions add value only if they generate additional economic rents; providing a further competitive edge that is not easily reproduced. Motives for mergers and acquisitions include the following: synergies, revenue enhancement, cost reductions, ability to swap unused tax shields and use of surplus funds and economies of scope (combining complementary resources).

14. These variables are: book value of common equity, total capital employed, current assets, current liabilities, capitalization rate (proxy for capital adequacy), working capital ratio (proxy for capital liquidity), total assets (proxy for company size), total liabilities, market value of equity, equity/liabilities, total liabilities/ total assets (proxy for capital liquidity), return on assets, coverage (proxy for debt service), retentions (proxy for profitability), property revenue, profits, current liabilities/ total liabilities, trading profit margin, return on capital, current assets/total assets, income gearing and borrowing ratio.

15. For example, we expect that real estate companies investing in the office market (purchase of existing assets) or developing office space (create new fixed assets) face lower risks (thus, lower probability of default) lower than companies investing in industrial factories and warehouses. As a result, offices' yields tend to be less than those of industrial and residential properties. This is the case because prime offices can often be let to a single tenant providing an excellent covenant. Also, industrial premises tend to be less popular as investments due to the high risks involved. For example "many factories are built for a special purpose and if they have to be re-let difficulty may be experienced in finding a similar tenant, or, alternatively, expense is incurred in adaptation" (Harvey, 2004).

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