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**Citation:** Lux, N. & Tsolacos, S. (2021). Loan Characteristics as Predictors of Default in Commercial Mortgage Portfolios. *International Journal of Economics and Financial Research*, 7(71), pp. 1-4. doi: 10.32861/ijefr.71.1.4

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**Link to published version:** <https://doi.org/10.32861/ijefr.71.1.4>

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## Loan Characteristics as Predictors of Default in Commercial Mortgage Portfolios

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### Article History

Received: January 5, 2021

Revised: February 3, 2021

Accepted: February 14, 2021

Published: February 17, 2021

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### Abstract

This paper examines the role of loan characteristics in mortgage default probability for different mortgage lenders in the UK. The accuracy of default prediction is tested with two statistical methods, a probit model and linear discriminant analysis, using a unique dataset of defaulted commercial loan portfolios provided by sixty-six financial institutions. Both models establish that the attributes of the underlying real estate asset and the lender are significant factors in determining default probability for commercial mortgages. In addition to traditional risk factors such as loan-to-value and debt servicing coverage ratio lenders and regulators should consider loan characteristics to assess more accurately probabilities of default.

**Keywords:** Commercial mortgages; Probability of default; Loan characteristics; Probit regression; linear discriminant analysis.

## 1. Introduction

Probability of default is a crucial parameter in the calculation of economic or regulatory capital under Basel II for banking institutions. The present study focuses on the role of loan characteristics in commercial real estate mortgage portfolio defaults, a largely un-researched topic despite its significance. It is of particular importance again in view of the forthcoming new distressed asset cycle due to the Covid-19 crisis.

The present paper is analysing the probability of loan defaults observed for different types of lenders and lender portfolios in the UK covering the full credit cycle 2007 – 2017. The UK commercial mortgage market is characterized by the presence of a wide range of players such as global insurers, banks and global multi asset managers each with different business models and risk profiles.

There is a dearth of empirical research on the role of loan and lender characteristics on commercial real estate loan defaults. A common feature in existing research primarily in the US is the focus on analysing the impact of LTV (loan-to-value) and DSCR (debt service coverage ratio) on loan default. Most of recent studies though on the topic have emphasized the need for updated underwriting methods. Many distressed loans passed traditional underwriting standards suggesting that, in addition to LTV and DSCRs, other characteristics should be taken into consideration including loan size, controls for geographic location, property type and originator. The failure of two UK banks, Northern Rock and Bradford & Bingley in 2008/2009 testifies to this contention.

Cho *et al.* (2013), find that larger lenders and borrowers have lower default risk than smaller lenders and borrowers. Ambrose and Sanders (2003) highlights differences in the underwriting process between banks and non-banks. Black *et al.* (2012), examine data on US commercial mortgages securitized into CMBS since 1999, and find significant differences in the propensity to become delinquent depending upon whether a loan was originated by a commercial bank, investment bank, insurance company, finance company, conduit lender, or foreign-owned entity. The dataset used in this study consists of loan portfolio level information such as geography, asset types and loan size that allows us to further test these propositions in the literature. It also enables the testing of risk factors in the study of commercial mortgage defaults. Given the large number of diverse lenders in the UK market our analysis puts specific emphasis on examining the impact of lenders' business models (lender type) as a categorical variable on loan default risk.

## 2. Methodology and Data

We investigate the impact of lender business type, and loan characteristics such as geography and asset type on expected loan default risk. Loan default risk is defined as the proportion of loans in default by value of total loan book value. The dependent variable is of binary type that takes the value one when a lender has experienced an increased risk of default above a certain average threshold level and zero to indicate a default risk below the

benchmark. As a benchmark we take the observed 10-year average default risk of 11%. The sample period spans eleven years, from 2007 to 2017 representing a full loan default cycle (185 observations). In order to test the robustness of our results we apply two statistical models: a probit model and the linear discriminant function.

Both are multivariate models. They include the main credit risk indicators of a lender's loan portfolio attributing a weight to each of them that reflects its relative importance in determining whether the lender is expected to experience a risk of default that is higher or lower than the average level (benchmark).

For the probit regression model the response variable  $y_i$  equals one if a high risk of default occurs (with probability  $p_i$ ) and zero if the default risk is low (with probability  $(1 - p_i)$ ).

$$P(\text{default}_i = 1 | x_i) = P\left(\frac{\varepsilon_i}{\sigma} > \frac{s - x_i\beta}{\sigma}\right) = 1 - F\left(\frac{s - x_i\beta}{\sigma}\right)$$

$$P(\text{default}_i = 0 | x_i) = P\left(\frac{\varepsilon_i}{\sigma} < \frac{s - x_i\beta}{\sigma}\right) = F\left(\frac{s - x_i\beta}{\sigma}\right)$$

The credit risk indicators are:

- (i) Lender  $i$  business models. This factor is captured by dummy variables for the following categories: investment bank (*IB*), regional bank (*RB*), commercial bank (*CB*), mortgage bank (*MB*), insurer (*IN*), fund (*Fund*).
- (ii) Lender  $i$  loan turnover as proportion of total loan book (*Turnover*), £ millions.
- (iii) Max Loan size (*Max Loan*), £ millions.
- (iv) Lender portfolio  $i$  exposure to development loans (*Dev*)
- (v) Lender portfolio  $i$  exposure to alternative assets (*Alt*). The alternative assets are primarily health, student housing and hotels.
- (vi) Lender portfolio  $i$  exposure to standard commercial (*Com*). The standard assets are office, retail and industrial/logistics.
- (vii) Lender portfolio  $i$  exposure to UK regions (*Reg*).
- (viii) Lender portfolio  $i$  exposure to Central London (*CL*).

Variables iv – viii are measured as a percentage to lenders' total real estate loan book.

The second model is the linear discriminant analysis (LDA) framework. Fisher (1936), approached linear discriminant analysis by seeking the linear combination of the discriminating variables that provides maximal separation between the groups. The purpose of the linear discriminant analysis is to find the so-called discriminant function and to classify objects into one, two or more groups based on a set of features that describe the objects. The differences are measured by means of the discriminant variable –  $z$  score. In our case the LDA uses the same binary dependent variable to create two distinct groups - above and low default risk. The group of independent variables is identical to the probit model. Maximal separation of groups is determined by an eigenvalue analysis. For a given lender portfolio  $i$ , we calculate the score as follows:

$$z_i = \sum_{j=1}^n \gamma_j x_{j,i}$$

where  $x$  denotes a given risk feature  $j$  of the portfolio,  $\gamma_j$  is its coefficient in the estimated model and  $n$  is the number of indicators.

The availability of private debt data is generally limited restricting relevant research. The UK benefits from the existence of the Property Lending Survey of Cass Business School a survey that has been compiling information on lending portfolios from individual lenders since 1998. This investigation uses this unique database. The dataset contains aggregated portfolio information for each lender.

### 3. Discussion of Results

Starting with the probit model, the results after eliminating all non-significant variables, are presented in Table 1. All but one of the significant variables take a positive sign denoting a source of greater risk for loan defaults. The only significant variable that tends to lessen overall default risk is loan turnover. Hence a bank's or a lender's ability to increase loan turnover mitigates the risk of loan defaults.

Table-1. Probit regression results

Risk Factor	Coef.	Robust Std. Error	$z$	$P > z$
<i>IB</i>	1.25	0.51	2.45	0.01
<i>RB</i>	1.04	0.38	2.78	0.01
<i>CB</i>	0.85	0.28	2.99	0.00
<i>Turnover</i>	-3.68	0.73	-5.06	0.00
<i>Dev</i>	4.39	1.07	4.11	0.00
<i>Alt</i>	4.29	1.29	3.33	0.00
<i>Com</i>	2.53	0.96	2.63	0.01
<i>cons</i>	-3.59	0.85	-4.25	0.00

The Likelihood Ratio (LR) Chi-Square test confirms the significance of this group of variables in determining loan default risk.

Table 2 reports the marginal effect of each variable. Marginal effects show the change in the probability in default risk that will be produced by a 1-unit change in our predictor variables. For instance a unit increase of commercial exposure (*Com*) will increase default risk by 0.67. Exposure to development and exposure to alternative asset classes has the greatest impact on loan default rates. Further, loans originating in investment banks carry the highest default risk compared with regional and commercial banks.

Table-2. Marginal effects – probit model

Risk Factor	Marginal effect (dy/dx)	Std. error	z	P > z
<i>IB</i>	0.33	0.14	2.41	0.02
<i>RB</i>	0.28	0.10	2.70	0.01
<i>CB</i>	0.23	0.08	2.90	0.00
<i>Turnover</i>	-0.98	0.19	-5.23	0.00
<i>Dev</i>	1.17	0.29	4.01	0.00
<i>Alt</i>	1.14	0.34	3.34	0.00
<i>Com</i>	0.67	0.26	2.60	0.01

The explanatory power of our discriminant function is measured by the canonical correlation of 0.43 (Table 3) denoting a significant function.

Table-3. Significance of discriminant function

Function	Canonical Correlation	Eigenvalue	Variance Proportion	Variance Cumulative	Likelihood Ratio	F	df1	df2	Prob > F
1.00	0.43	0.23	1.00	1.00	0.81	5.44	7.00	165.00	0.00

The canonical discriminant function coefficients or unstandardized loadings along with the standardized coefficient obtained using the pooled within-group covariance matrix are given in table 4.

Table-4. Canonical discriminant function coefficients

	Unstandardised	Standardised
<i>IB</i>	-1.50	-0.32
<i>CB</i>	-1.16	-0.58
<i>RB</i>	-1.42	-0.58
<i>Dev</i>	-4.49	-1.08
<i>Alt</i>	-4.70	-0.65
<i>Com</i>	-1.98	-0.50
<i>turnover</i>	3.66	0.81
<i>Constant</i>	2.73	

Because we only have two groups, there is only one discriminant function. When analyzing the classification functions (table 6) loan turnover is the most important factor discriminating between the two groups. Lenders with low turnover show an increased risk of default as well as lenders with higher development exposure. This confirms findings of the probit regression model.

Table-5. Classification of model predictions

	Actual	Correctly Predicted	
		Probit	LDA
High risk	45	16 (36%)	10 (22%)
Low risk	128	115 (90%)	123 (96%)
Total	173	131 (76%)	133 (77%)

Both models classify 76-77% of portfolios correctly (Table 5). The probit model performs better at predicting high risk portfolios classifying 16 out of 45 high risk portfolio correctly, while the LDA model only classifies 10 cases correctly. When it comes to predicting low default risk the probit model classifies 115 out of 128 cases correctly compared to the LDA model which classifies 123 cases correctly.

Having obtained generally similar results from the two models, we now illustrate loan default predictions from both. For example following our classification functions, we can assume a hypothetical portfolio of a commercial bank with 30% turnover, 15% development exposure, 70% commercial investment loans and 10% alternative assets (Assumption I). Comparing the default risk prediction by both models the LDA model is more conservative as shown in table 6, by predicting with a 61% probably that the lender portfolio shows a low default risk.

Table-6. Case assumptions

	LDA	Probit
<i>Assumption I</i>		
High default risk	39%	15%
Low default risk	61%	85%
<i>Assumption II</i>		
High default risk	93%	93%
Low default risk	7%	7%
Number of predictors	4	4

Assumption II we assume a hypothetical portfolio of a commercial bank with 5% turnover, 60% development exposure, 40% commercial assets, and 20% alternative assets. The results from both models are similar, associating the lender portfolio with 93% probability falling into the high default risk category.

## 4. Conclusion

Using a unique commercial property portfolio loan database the present study quantifies the effects both of loan and lender characteristics on estimating the risk of commercial mortgage defaults. The study benefits from the composition of the database that includes a range of lenders. The key finding is that loan and lender attributes are important in the assessment of commercial mortgage portfolio default. For robustness purposes the analysis obtained results from two methodologies.

Development exposure increases the default risk in a lender's portfolio. De Jonghe (2010) and Brunnermeier *et al.* (2016) documented that non-interest generating activities (which includes development loans) increase bank system instability. A similar effect is found for loans to specialized assets such as hotel and health care. Diversification into these lines of business aggravates risks as management lacks the expertise and experience (Stiroh, 2006) and increase the risk of bank insolvency (Rossi *et al.*, 2009). Factors, which have led to the failure of Northern Rock and Bradford & Bingley.

Further, regional banks and investment banks appear to have built higher risk portfolios. Aside from portfolio concentrations in specific asset types, the reason for IB's is the increased warehousing risk—that is, the risk that the originator will be forced to hold a loan if it becomes delinquent prior to securitization or if the loan cannot be securitized.

The study highlights loan turnover as a variable mitigating default risk. We rationalize this finding by arguing that lenders with a high volume of loan book turnover constantly replace old loans with new originations. Newly originated loans are less likely to default immediately. It also shows that these lenders have been able to generate new business and successfully solved workout positions. Finally, there is no evidence of significant effects from the geographical distribution of loans and loan size.

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