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Exploring the performance of Small and Medium Sized Enterprises through the Credit Crunch

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Abstract

Small and Medium sized Enterprises (SMEs) make a major contribution to most western economies. They are often supported by government policies and in UK the government encourages banks to lend to them. It is generally believed that the credit crunch will have had an impact on performance of SMEs. This study looks at the impact of the crunch using large samples from 2007 through to 2010. It looks at performance by Region, Age and Industrial sector (SIC code). It then proceeds to explore the modelling of default over the years and especially focusing on young businesses. It is found that there is a degree of stability within the models, though, the level of default varies across years. Young businesses, as has been found before, are shown to be more vulnerable.

Keywords: credit scoring; small business; risk; banking, predictive modelling, credit crisis.

Introduction

The centrality of Small and Medium Sized Enterprises (SME) to western economies is attested to by the willingness of governments and regulators to provide special conditions associated with lending to them. Under Basel II and Basel III (BCBS, 2006, 2010) there have been special provision for SMEs. UK Government has just introduced the National Loan

Guarantee Scheme in order to increase lending to SME, (HM Treasury, 2011). They create innovation, provide jobs and contribute to Gross Domestic Product (Ma and Lin, 2010). Hence they are seen as an important part of the economy of most countries. They are, though, thought to be more vulnerable to the periods of economic downturn, (Howes, 2008). The recent 'credit crunch' and the subsequent global financial crisis has had an impact on the viability of many SMEs (Wilson, 2009).

There are several reasons for their vulnerability. Some authors have stressed the impact of late payment and cash flow on the SMEs (Howes, 2008). For some the vulnerability is related to Industrial sector the SME is associated with. For example, many thought both construction and hospitality suffered particularly from the recent crisis (Ma, 2011). Changes in discretionary spending has had impacts that are specific to certain sectors, e.g. Retail, construction, tourism, hospitality, new cars, new kitchen… This is driven from a lack of consumer confidence meaning people are reluctant to borrow or spend on credit cards.

Lack of credit is often quoted as a concern, but there is some evidence that SMEs have not taken up the credit that is available. A survey by SME Finance Monitor in UK found that in a sample of 5000 SME only 15% had applied for new credit. (ref?) There may be a range of reasons for this; SMEs unwilling to take on more lending. Many SMEs have a conservative strategy during a recessionary period desiring to reduce debt rather than take on more. Reduction in business confidence makes businesses more reluctant to invest and hence lower propensities to borrow. Other SMEs will not be in a position to take on credit since they do not have further collateral to support borrowing. Some business will have already borrowed up to their credit limit.

Banks have throughout the period been willing to lend to SMEs and have been encouraged to do so by governments. A market research by BDRC Continental in UK found 75% of SME had over drafts approved whilst 59% were successful in applying for loans (ref?). Project

Merlin was an agreement between banks and the government which set targets for bank lending to businesses as well as a target for SME lending. It is, however, the case that governments have already required banks to lend prudently. The increase in capital requirements under Basel III (BCBS, 2010) and Vickers Report (Independent Commission on Banking, 2011) has had and will have an impact on abilities of banks to lend. The availability to banks of money, until the recent initiative by the UK government (HM Treasury, 2011), though, the impact may only reduce the commercial lending rate by 1%. .

Given the need for prudent lending, in light of Basel Accords, there has to be a focus on modelling the probability of default (PD) and hence its impact on credit lending. Whilst Basel doesn't necessarily dictate prudent lending, greater unknowns around levels of conservatism required to ensure PD models are measuring a long run average PD will increase capital requirements. That is, a better understanding of how PD models work through the economic cycle could reduce the capital required to provide against bad debts and free more capital up for lending.

Obviously it becomes of interest to consider whether there has been a change in the models predicting default over the period of the crisis. Hence in this study the aim is to consider changes in terms of variables comprising the models and in terms of predictive accuracy of the models during this period of downturn. The current research is based on a large anonymised database supplied by Experian covering the 4 years: 2007, 2008, 2009 and 2010. The results reported are initial findings of exploratory analysis being carried out within the Centre for Credit Research at Edinburgh.

The structure of the paper is as follows. The data and preliminary data will be discussed in the next section. This will be followed by a description of the methodology. The results will be subsequently provided. The final section will be conclusion and description of further work.

Data and Preliminary Analysis

The dataset is described in Table 1. For each record there are 92 variables covering summary data, director data, payment and public record including searches, derogatory data, financial data, trend data, Experian data (CAIS and Delphi) and performance data. Two measures are used for performance, one indicating impairment but not necessarily default, and a measure closer to actual default. One of the key differences between the two measures is that the Definition 2 under-measures the default rates for businesses under £150k of total assets. Thus for assessment of the SME performance Definition 1 or closure is more helpful and is used in this study (see Table 1).

As shown in Table 1, 2009 is seen as the worst year for performance for both definitions. The change for Definition 1 is greater than Definition 2, and this is to be expected since impairment is more likely to be affected than actual default. Figure 1 provides regional variation in performance by Definition 1. The differences between regions may be due to date onset of downturn in a region or may be related to Industrial sectors present in a region. Figure 2 indicates changes over Industrial sectors. It is clear that the Services have suffered most during the initial stages of the 'credit crunch' with considerably higher rate in 2009 for Service sectors.

There is considerable evidence that 'young' SMEs are more vulnerable than older SMEs (Beresford and Saunders, 2005; Altman et al., 2009) and hence it is worth investigating differences. There are, though, issues surrounding very early casualties. Some SMEs are designed as a special financial vehicle for a single time limited event or may be a SME created but never active as a business. Additionally, many of the companies that are dissolved without ever filing accounts have never actually traded. These are difficult to pick out from the more genuine failures. To avoid this problem we have decided to divide the age scale into

3 sections: less than or equal to 36 months, greater than 36 months but less than or equal to 60 months and those greater than 60 months. Figure 3 highlights the observation about better performance by older SMEs. It can be argued that the very young and young businesses show closer performance in a downturn (especially in 2009) as compared to older companies. Hence it was felt appropriate to base the subsequent model-building on all the data, less than or equal to 60 months (Start-Ups) and greater than 60 months (Non-Start-Ups).

Methodology

The first step in considering the impact of 'credit crunch' on SMEs during period 2007 to 2010 is to look at whether there have been changes in associations between SMEs perfomace and their other characteristics that can be used to predict the performance/default. A random training sample of 10% was drawn from each of the 4 separate years, as a snap-shot of SMEs that existed in April of the corresponding year. The performance was assessed the following April. Twelve months is the usual observation time considered in credit scoring for the purpose of default modelling (Thomas et al., 2002). The firms conforming to Definition 1 within 12-month period have been classed as 'Bad' for this period, the remaining ones have been considered 'Good'. A list of some of the variables that have been included in the analysis is given in Appendix A, for commercial confidentiality unfortunately the whole set of variables cannot be released.

Training samples have been used to develop a number of models predicting probability of default, p_i, where i=2007, 2008, 2009 and 2010. Logistic Regression was used to model the relationship between probability of default and set of potential predictor variables, X_j, where j=1,2 … J, in the form:

$$\mathrm{Ln}\{ p_i /(1- p_i)\} = \alpha_i + \Sigma\, \beta_{ji} X_{ji} \qquad (1)$$

where i = 2007, 2008, 2009, 2010 and j=1,2 … J.

Following Lin et al., 2011 the predictor variables were coarse classified and transformed using the weights of evidence:

$$\mathrm{WoE} = \ln\, (g_i B \,/\, b_i G) \qquad (2)$$

where b_i (g_i) are respective number of Bads (Goods) within category i

B (G) are total numbers of Bads (Goods) in the sample.

The use of weights of evidence is common within credit scoring and Lin et al., 2011 demonstrated the benefits in using the approach for modelling SMEs.

A common problem in credit risk modelling is intercorrelation between predictor variables. In order to gain insights into the interdependence structure of predictors used in this analysis an Oblique PCA has been performed. This method is an extension of traditional Principal Component Analysis (PCA) that consists in rotating the orthogonal principal components and at the same time relaxing the condition of their independence. The procedure results in groups (clusters) of variables that ere linear combinations of the first principal component of a particular cluster. In predictive modelling this enhances interpretability of the solution, since each variable is assigned to one group, and judgements can be made on the variables that are mostly correlated with each other. More on Oblique PCA is gven in Harris and Kaiser (1964).A stepwise approach was employed using SPSS software, inclusion or removal based on 5% level of significance for variable under consideration, to obtain the linear combination. Clearly given the size of the data many variables might have been selected. To ensure a parsimonious model it was decided to consider the change in Cox and Snell or

Nagelkerke Psuedo R^2 Statistic (Cox and Snell, 1989; Nagelkerke, 1991). Variable selection was then terminated when the change in the Psuedo R^2 Statistic fell below 1% for the first time. Obviously it was possible that this would potentially terminate selection too early in the process. To avoid this problem the Psuedo R^2 Statistic for allowing the stepwise model to go to completion so no new variables where selected or removed with criterion above was also considered. In no cases was there found a large rise in the Statistic beyond the termination point. The Psuedo R^2 Statistics are reported in subsequent section.

Logistic Regression models were fitted to the to the training samples for each year, for all the companies, and separately for the Start-Ups (SU) and for Non-Start-Ups (Non SU). (Start-Ups were companies up to and including 60 months, and Non-Start-Ups were the remaining businesses.) This allowed comparison of the 3 models for each year and comparison across years. One aspect of comparison are variables that enter in each model, and therefore, are significant predictors of default. The assessment of model fit can be judged by Pseudo R^2. In credit scoring it is also important to consider the predictive accuracy of the models, which is measured via Area Under the ROC Curve (AUROC) (Thomas et al., 2002; Lin et al., 2011).

One more aspect of interest would be to examine the stability of the prediction over time. To explore this aspect it was decided to explore whether the models constructed for 2007 could provide reasonable prediction for subsequent years. Hence the model for 2007 was used to predict the outcome for the other years using the full datasets with over 2 million data points. Changes in predictive accuracy were compared using AUROC again as the assessment measure.

Results

In the preliminary analysis the impact of Region, Industrial sector and Age was seen on a univariate base. Appendix A lists the 26 variables that have been selected across the years and the data subsets for inclusion in the Logistic Default Model. It is notable that only 4 variables appear across all the models. These are Legal Form, Time since last derogatory data items (months), Lateness of Accounts and Time Since Last Annual Return. There is, however, more commonality within years and subsets of data (All data, Start-Ups and Non-StarUps).

For 2007 the commonality of variables consists additionally of Industrial sector, Total Value of Judgements in Last 12 Months and Total Assets. 2008 has additionally Total Value of Judgements in Last 12 Months. The models for 2009 have considerably more variables appearing with variables Number of Appointments in the last 12 Months as a percentage of the current board, Number of Directors Holding Shares, Total Assets and Full CAIS Delphi score. 2010 is more akin to 2007 with variable Total Value of Judgements in Last 12 Months added. Part of the explanation of this arises from the number of Bads being seen in each year. 2009 with more Bads has the largest number of common variables. When considering the subsets of data All data set has several additional variables in common with Number of Appointments in the last 12 Months as a percentage of the current board, Number of Directors Holding Shares, Total Value of Judgements in Last 12 Months, Total Assets, but both Start-Ups and Non-Start-Ups have limited number of extra common variables with Number of Appointments in the last 12 Months as a percentage of the current board and Full CAIS Delphi score for Start-Ups and Total Fixed Assets as a percentage of Total Assets for Non-Start-Ups.

Obviously this prompts the need to consider whether other commonalities are present in terms of associated variables. To study this Oblique Principal Component Analysis was employed using all 90 predictor variables, which was carried out for each of the years separately. Table 6 presents a summary of the clusters of the variables that are found. In terms of the variables used within the model Table 7 presents the oblique PCA cluster membership. The results for 2007 and 2008 are the same whilst they are different in 2009 and 2010. For the variables that are common across all models only Lateness of Accounts remains within same cluster throughout. If one assumes that members of the same clusters are commutable then the only distinct variables in the models that only appear occasionally, are Region, Number of appointments in the last 12 months as a percentage of the current board, Worst status in last 3 months on accounts opened 12 months ago and Full CAIS Delphi score. It is notable that Region appears in the early models whilst Worst status in last 3 months on accounts opened 12 months ago and Full CAIS Delphi score later models. An argument could be advanced that Region was significant in early models because of a differential initial effect of the credit crunch. The other two variables become more significant as the impact of credit crunch becomes more significant.

Model fit statistics (Cox and Snell, Nagelkerke Pseudo-R^2) are given in Table 3. It is notable that both measures improve from 2007 to 2009 on all subsets. After peaking in 2009, they come down in 2010. This is in line with the changes in the proportion of defaults, the model fit becomes better as the number of defaults grows, and vice versa. In a downturn, bad companies fail. In other trading circumstances, bad companies may limp on and survive. This supports a common wisdom that downtowns are beneficial for modelling – there is a silver lining in every cloud.

Yet it has been mentioned before that the focus of credit scoring is on predictive accuracy, and these results are reported in Table 4. AUROC shows the same tendency as with measures of model fit – predictive accuracy improves during the crisis. It should be mentioned that Table 4 presents in-sample measures, i.e. AUROC are calculated on the corresponding training samples. This normally leads to slightly optimistic results. Nevertheless, in the context of this study it is believed to be an acceptable limitation, since the focus is on comparison across the years and subsets and such comparison is not distorted by looking at in-sample results.

Table 5 demonstrates what would happen if one would continue using 2007 models through the crisis without re-developing them. A general dynamics is similar to results discussed above, and so it is possible to conclude that the models perform well in the downturn in terms of predictive accuracy. The column 'In Sample' is repeated form Table 4 and gives the benchmark of the performance of the most up-to-date model or the situation when the models are re-developed every year. The majority of subsets show the advantage of 'In Sample' models, which is to be expected. Yet this advantage is marginal, with maximum difference being 0.019. Therefore, one can conclude that predictive power of scoring models is y resilient.

There are several subsets (2007 SU, 2009 Non-SU, 2010 Non-SU) that show better performance of 2007 models. This is counter-intuitive, but can be explained by varying number of predictors selected into each model.

Conclusion and Further Work

It is obvious that the 'Credit Crunch' has had an impact on SME performance. 2009 exhibits the worst performance during this initial period of the 'credit crunch'. Of the enterprises those which are younger are more affected than older companies as are companies in the service sector more affected than others. There does not immediately seem to be a regional impact.

The initial interpretation of analysis may suggest that the models for the years are very different with only 4 variables appearing throughout all models: Legal Form, Time since last derogatory data items (months), Lateness of Accounts and Time Since Last Annual Return. Also regional and industrial sectors indicators do not appear across all models. It is, though, clear that there is stability across the years based on the evidence of the capability of the 2007 models to predict well performance in the other years. One possibility is that the difference in models is due to interdependence between the variables considered.

Given the stability found within the models it may be of interest to develop a resilient generic model across the four years. This would be based on the results found from the Oblique PCA analysis.

This paper represents the initial analysis of a longer study. Certain aspects that have proved significant in the current work need to be further researched. The issue of dependency within in the data set has not been fully explored. There is some evidence as shown in Figure X that region do respond on slightly different time scales. It may also be that regions employed could be refined. Whilst only a slight impact is seen in terms of Industrial sector there is evidence that especially in 2009 service related sector performs worst to the downturn. The classification of Industrial sector also needs refinement which is plausible given the data set. There may also be questions whether further structural modelling will provide insight to dependencies within the data.

As indicated age of the SME was found to be a significant aspect within the preliminary analysis. This aspects needs further to be explored within the data. It may be that certain businesses which are young are less vulnerable than others. This may aid business lending to newly established SMEs and help policy makers devise future strategy.

Finally the snapshots have been treated as separate data sets. Since there are available unique identifiers within the datasets it will be possible to track the behaviour over time. A subset of the data can be treated as panel data and hence be more fully investigated for time effects. With only 4 points of time currently we do not perceive, however, that it is possible to include macro-economic factors into the analysis.

Table 1: Dataset description and performance measure by Definition 1 and 2.

	Number of SMEs	**Definition 1 (%)**	**Definition 2 (%)**
2007	2,117,278	6.9	0.75
2008	2,227,610	11.81	0.97
2009	2,204,474	16.06	.0.95
2010	2,159,156	11.87	0.87

Figure 1: Poor Performance by Region.

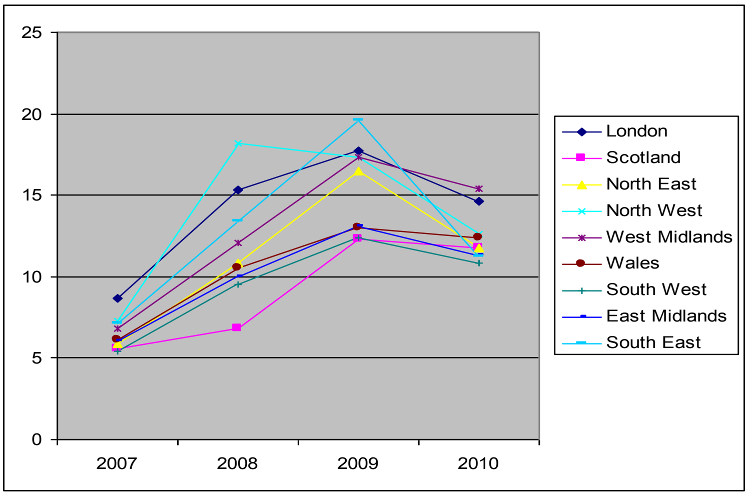

Figure 2: Industrial sectors displaying 1 digit level of SIC code

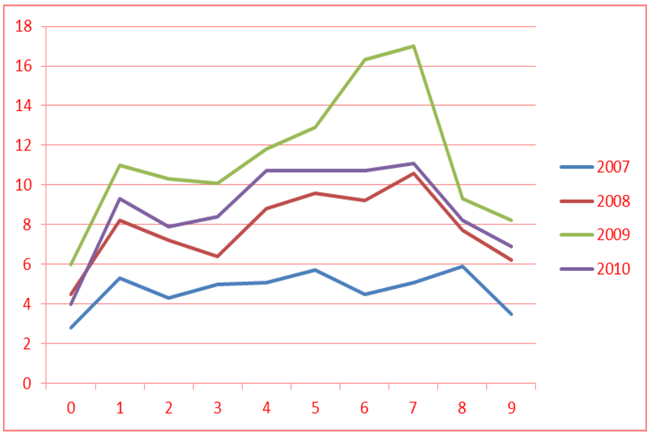

Figure 3: Poor Performance by Age in Months

Table 2: Variables included in the models (Variable list is given in Appendix A)

		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26
	A																										
2007	S																										
	N																										
	A																										
2008	S																										
	N																										
	A																										
2009	S																										
	N																										
	A																										
2010	S												x														
	N																										

Table 3: Pseudo R2 Statistics: Cox and Snell (CS), and Nagelkerke (N) for the models used in Table 2

		CS	N
2007	All	0.120	0.300
	Start-Up	0.149	0.324
	Non SU	0.052	0.196
2008	All	0.207	0.390
	Start-Up	0.235	0.390
	Non SU	0.126	0.336
2009	All	0.308	0.517
	Start-Up	0.329	0.500
	Non SU	0.205	0.427
210	All	0.211	0.401
	Start-Up	0.238	0.393
	Non SU	0.148	0.372

Table 4: Area Under the Curve (AUROC) with 95% Confidence Interval for AUROC (CI)

		AUROC	CI	
2007	All	0.820	0.816	0.824
	Start-Up	0.817	0.813	0.822
	Non SU	0.795	0.786	0.804
2008	All	0.852	0.849	0.854
	Start-Up	0.840	0.837	0.844
	Non SU	0.843	0.837	0.850
2009	All	0.886	0.884	0.888
	Start-Up	0.868	0.865	0.870
	Non SU	0.870	0.865	0.874
2010	All	0.851	0.849	0.854
	Start-Up	0.830	0.826	0.833
	Non SU	0.850	0.845	0.856

Table 5: Comparison of AUROC in Sample and Applying 2007 model across all years on full dataset

		In Sample	2007	Difference
2007	All	0.820	0.820	0.000
	Start-Up	0.817	0.820	-0.003
	Non SU	0.795	0.793	0.002
2008	All	0.852	0.841	0.011
	Start-Up	0.840	0.826	0.014
	Non SU	0.843	0.837	0.006
2009	All	0.886	0.876	0.010
	Start-Up	0.868	0.853	0.015
	Non SU	0.870	0.889	-0.019
2010	All	0.851	0.840	0.011
	Start-Up	0.830	0.811	0.019
	Non SU	0.850	0.851	-0.001

Table 6: Summary Table of Oblique PCA Results across the 4 Years

Year	Number of Cluster	Proportion of Variation Explained	Max Cluster size	Min Cluster size
2007	18	0.7895	24	1
2008	18	0.7852	24	1
2009	18	0.7712	14	1
2010	18	0.7891	10	2

Table 7: Oblique PCA Cluster membership of variables used in models

Variable	2007	2008	2009	2010
1	B	B	B	N
2	A	A	A	A
3	C	C	C	N
4	B	B	B	B
5	D	D	D	D
6	E	E	E	E
7	B	B	B	B
8	F	F	F	F
9	G	G	G	G
10	H	H	H	H
11	H	H	H	H
12	I	I	I	I
13	I	I	L	I
14	B	B	B	B
15	A	A	A	A
16	A	A	L	A
17	A	A	M	M
18	A	A	M	M
19	A	A	M	M
20	A	A	A	A
21	A	A	A	A
22	A	A	A	A
23	E	E	E	E
24	E	E	E	E
25	J	J	J	J
26	K	K	K	K

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Appendix A

Table of Variable Included in Models

Number	Variable Name
1	Legal Form
2	1992 SIC Code
3	Region
4	No of Current Directors
5	Number of Appointments in the last 12 Months as a percentage of the current board
6	Oldest Age of Current Directors/Proprietors supplied (Years)
7	Number of Directors Holding Shares
8	PP Worst DBT in the last 12 Months
9	Total Value of Judgements in Last 12 Months
10	Number of Previous Searches (last 6m)
11	Number of Previous Searches (last 12m)
12	Last derogatory item
13	Time since last degrogatory item (months)
14	Lateness of Accounts
15	Consolidated Accounts
16	Time Since Last Annual Return
17	Capital Employed
18	Retained Earnings
19	Total Assets
20	Issues Capital (Financial)
21	Current Liabilities
22	Total Fixed Assets as a percentage of Total Assets
23	Percentage Change in Shareholders Funds
24	Percentage Change in Total Assets
25	Worst status in last 3 months on accounts opened 12 months ago
26	Full CAIS Delphi score