Empirical Failure Prediction of UK Construction Industry Developers and Contractors

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INTRODUCTION

Since Beaver's 1966 study pioneering failure prediction modelling techniques using financial ratios, business failure prediction has developed into a major research area within corporate finance. In 2015, 252,000 of 2.67m active UK businesses across the economy failed, a rate of 9.4%. The UK construction industry experienced a failure rate of 9.3% - 31,000 failures

The economic importance of the construction industry in the UK is evident in it's contribution of £103 billion in GVA (6.5%) to the economy 2014, employing approximately 2.1 million people (6.2% of total UK employment) in 2015 (ONS).

DATA SOURCE AND FORMATION OF SAMPLE

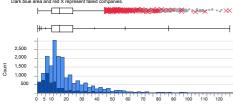
The Financial Analysis Made Easy (FAME) source was used to identify some 20,685 UK construction industry firms. To avoid sample selection biases, every firm-year for which data are available is sampled separately. Please refer to UK Construction Industry Business Models - Empirical failure prediction of Developers and Contractors with use of financial accounts BSc Disseration for full sample selection and cleaning methods.

SAMPLE CHARACTERISTICS

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Table 1 - Size & age for Sic codes									
	Size (count)					Age (years)			
SIC Code	Large	Medium	Small	Micro	Total	Mean	Median	Std Dev	
41100	93	628	1,292	1,207	3,220	18	14	15	
41 (excl. 41100)	233	773	1,166	1,866	4,038	20	15	17	
42 (all codes)	97	359	298	367	1,121	22	17	16	
43 (all codes)	288	1,434	2,049	6,690	10,461	17	13	13	
64203	39	96	27	0	162	16	10	18	
Total:	750	3,290	4,832	10,130	19,002				
% of All:	3.9%	17.3%	25.4%	53.3%	100.0%	1			

Graph 1 - Age Distribution



MODELLING TECHNIQUES

Lasso (Least Absolute Shrinkage and Selection Operator) regression analysis methods are applied to select predictor variables. During the computation of a Lasso regression, a penalty is applied to the regression coefficients given by the following equation: ∇^{P}

 $s^{so} = \operatorname{argmin}_{\beta} \left\{ \begin{array}{l} \sum_{i=1}^{N} -LogLikelihood(\beta \cdot y_i) + \lambda \sum_{i=1}^{N} |\beta_i| & \text{is the penalty, } \lambda \\ \sum_{i=1}^{N} -LogLikelihood(\beta \cdot y_i) + \lambda \sum_{i=1}^{N} |\beta_i| & \text{is the tuning parameter, N is the number of rows; and p is the number of variables.} \end{array} \right.$

Lasso penalties apply to strongly correlated variables where the less available variables are penalised more and subsequently removed. Lasso methods are forms of machine learning processes, replacing the need for manual and more subjective factor analyses procedures, commonly used to determine what combinations of variables lead to models that are both powerful and parsimonious.

Logistical Regression. Predicting a binary outcome (failed or non-failed) requires the application of logistical regression models. The general form requires the application of logistical regression..... of a logistic regression equation: $\ln\left(\frac{\rho}{1-\rho}\right) = \beta_0 + \beta_1 + \dots + \beta_n \\ e^{\beta_0 + \beta_1 + \dots + \beta_n}$

where the equation for calculating probability is: $\rho = \frac{e^{r_v + 1}}{e^{\beta_v + \beta_1 + \dots + \beta_n} + 1}$

Interpretability. Lasso regression and Logistic regression model outputs are not comparable and may only be analysed in isolation in terms of their magnitude, direction and statistical significance. Odds ratios are used for comparison of individual effects, with values over 1 suggesting an increased likelihood of failure with unit increases of the predictor.

LIMITATIONS

 Annual accounts data and biases:
 Lack of data coverage for micro and small firms result in under-sampling bias towards medium and large firms. Different types of financial information is subject to publication under the Companies Act, 2006, depending on in order to specify prediction models which are more applicable to micro and small firms and account for their

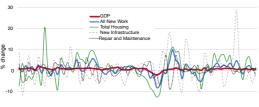
failure process.

Classification of business models: Classification of business models: The application of 2 digit SIC codes is an imperfect method for classifying business models. Further study is required to classify firms in groups according to their business models based on other measures, through clustering oncepts on important concentral continuums such as mark // conceptual continuums such as: make / buy ratios, e.g. turnover to number of employees, cost of sales to remuneration; ratios related to receivables and payables; ratios identifying the financial structures; and more detailed 3-5 digit SIC code classifications

classifications: • Missing data: Further work on data cleaning and missing data imputation is required in order to improve the predictive power of models (Ooghe and Balcaen, 2002). These approaches are most applicable where data can be considered as *missing at random*.

DEFINITION OF FAILURE

"Situations in which a company cannot pay lenders, preferred stockholders, suppliers, etc. or a bill is overdrawn, or the company is bankrupt according to law". (Ahn et al., 2000, p. 65) Graph 2 - GDP Change v CI Output Change [Seasonally adjusted]



CATEGORIES OF UK CONSTRUCTION FIRMS

• Main contractors (SIC 41 - buildings, 42 - civil engineering) - Tier 1 contractors, who respond to demand to construct buildings and linear contractors, who respond to demand to construct buildings and linear infrastructure. Volatile demand reduces their ability to maintain capacity or market share. Main contractors often act as the project and construction manager, subcontracting most of the works, as a means to protect against market volatility. Tier 1 firms tend to own only limited plant and equipment (forms of fixed asset) as most is leased, and directly employ small number of manual workers relative to turnover (Ball et al., 2000). • Specialist contractors (SIC 43 - sub-contractors, Tier 2, 3 and lower level of supply chain) - these are *direct specialist contractors* (Ive and Gruneberg, 2000) who undertake work on numerous projects simultaneously, and thus achieve diversification across markets. Sub-contractors key role is to work for the main contractors in the capacity of the *installe* of materials/loalt/equipment often providing the labour.

 Developers (SIC 41100) - these are the customers of contractors output, commissioning the construction of buildings (such as residential, retail and industrial) and infrastructure. Developers' main role is to buy land and develop the site (Ive and Gruneberg, 2000).

Defining characteristics of construction contractors:

Overoptimism about revenues arising from often applied percentage-of-completion method to forecast revenues on construction projects.

 completion method to forecast revenues on construction projects.
 High inventory ratio as contractors typically process large volumes of materials and supplies in comparison to other industries.
 Low level of fixed assets, in comparison to other firms which possesses land (such as developers), factories, equipment (including construction plant hire firms) or other durable assets, main contractors tend to have a larger portion of assets as current assets - trade debt and stock & WIP.
 High reliance on current liabilities arising from contractors use of short-term loans (Abidali and Harris, 1995) and business-to-business credit (Ive and Murray 2013) to make navments for material equipment and labour. and Murray, 2013) to make payments for material, equipment, and labour

DEVELOPERS

All models are of high reliability with minimum generalised R² of 71.4%. In years 2012 and 2014 the odds ratios for interest cover ratio (C5) are 0.765 and 0.885 respectively, indicating (with strong statistical significance) that a unit increase in interest cover ratio would reduce chances of failure by 76.5% and 88.5% respectively. In other words, the chances of failure by 76.5% and 88.5% respectively. In other words, the more profit a firm generates to pay interest, the lower are the chances of insolvency (Barkham, 1997). Developers have significantly lower interest cover ratios (C3) than other types of firms, resulting from more intensive use of debt to finance the purchase and long term ownership of land. A developer takes much longer to turnover over thier assets when compared to a contractor, often taking many years from purchase of land, through development and to final sale, so long term finance is essential. • From the odds ratios for equity multiplier (L1.3) for year 2009 it is evident that the new asceta rea financed to the procession. From the odds ratios for equity multiplier (LL3) for year 2009 it is evident that the more assets are financed by shareholders funds, the less likely such a firm was to fail (Arditi et al., 2000). The importance of shareholders funds as a source of finance is further supported when looking at return on shareholders funds (P4). In 2009, profitability helped finance operations and reduced likelihood of failure by around 25%.
 It is seen from 2012 and 2014 models, the older a firm is, the less likely it is to fail. This supports that with age a firm becomes more experienced in managing its finances. There is also an important auto correation here that with age of firm comes crowth and hence size, the larger a firm is.

that with age of firm, comes growth and hence size - the larger a firm is the more likely it is to survive.

Tab	ole 4	- Su	mm	ary	of P	-val	ues	of V	aria	bles	for	Mod	leis
	P-values (Statistical Significance) of Coefficients for Logit Fit Models												
	Developers			Main Contractors			Sub-contractors			Civil Engineering			
	2009	2012	2014	2009	2012	2014	2009	2012	2014	2011	2012	2014	Court
LI	•	•	•	•	•	•	0.00	0.04	•	0.77	•		3
L2	•	•	•	0.06	•	•	•	0.01	0.01	•	•	0.00	4
L3	•	0.01	•	0.01	٠	٠	•	0.43	•	•	•	•	3
L4	•	0.10	•	0.10	•	•	•	•	0.00	•	0.54	•	4
L5	•		0.03	0.18	•	0.07	0.00	0.05		•	0.06	0.00	7
L6	0.01	0.01	•	•	0.00	0.00	•	•	•	•	•	•	4
CI	•	•	•	0.03	•	•	0.03	•	0.00	•	•	•	3
C2	•	•	0.00	•	0.01	0.00	0.01	•	•	•	•	•	4
C3	0.00	0.01	0.00	•	•	0.01	0.07	•	0.00	0.03	•	0.05	8
C4	•	•	•	0.23	•	•	•	0.83	•	•	•	•	2
C5	•	0.04	0.01	0.36	•	•	0.00	•	0.00	•	•	•	5
C6	•	0.02	•	•	•	•	•	•	•	•	•	0.23	2
C7	•	0.07	•	0.05	•	•	•	•	0.10	•	•	•	3
C8	0.09	0.16	•	0.49	0.01	0.05	0.04	0.18	0.83	0.05	0.59	•	10
C9	•	0.00	0.40	0.28	•	•	•	0.49	•	0.00	•	0.05	6
CIO	•	0.02	•	•	٠	0.21	•	0.03	•	•	•	0.02	4
CLI	•	0.01	•	•	0.00	0.00	•	0.21	•	0.00	0.00	0.03	7
EI	•	0.06	•	0.01	•	•	0.26	0.51	•	•	•	0.27	5
E2	•	0.04	•	0.01	0.12	•	0.00	0.11	•	0.01	•	•	6
E3	•	•	•	0.00	•	•	0.00	0.03	0.00	•	•	•	4
E4	•	•	0.10	0.13	0.11	•	0.11	•	•	•	•	0.01	5
E5	•	0.23	•	0.02	•	0.00	0.12	0.70	0.00	· ·	•	•	6
LLI	•	•	•	0.04	0.12	•	0.08	•	•	•	•	•	3
LL2	•	0.01	•	•	•	٠	0.01	0.01	0.00	0.00	•	•	5
LL3	0.01	•	•	•	0.12	•	0.08	0.76	•	•	0.41	•	5
LL4	0.07	0.15	0.40	0.18	0.93	0.45	0.22	0.10	0.06	•	•	•	9
LL5	0.07	0.15	•	0.18	•	•	0.22	0.09	0.06	0.16	0.00	•	8
ΡI	•	0.01	•	0.01	•	0.00	0.01	0.11	0.00	•	•	•	6
P2	0.03	0.01	•	0.34	•	•	•	•	0.00	•	•	•	4
P3	•	0.01	•	0.01	0.00	•	0.00	•	0.04	•	0.54	•	6
P4	0.00	0.01	•	•	•	0.06	•	•	•	•	•	0.14	4
P5	•	•	•	•	•	•	•	•	•	0.67	•	0.12	2
P6	•	0.00	•	•	0.00	0.49	•	0.41	0.02	•	0.06	•	6
Age	•	0.00	0.01	0.42	0.00	0.13	•	0.05	•	0.00	0.00	•	8
Cours	8	23	8	22	12	13	19	20	16	10	9	11	

FACTORS AND VARIABLES

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Selection of factors has commonly been dependent upon the following criteria: popularity, priority, cash-flow concept, relevancy and independence (Altman, 1968; Beaver, 1966; Sun et al., 2014). Table 2 - Quantitative factors and variables



is the short-term financial position, covering and employees. This indicates to what exter quid assets (Horta et al. 2012; Horta & Camar relatively high liquidity is required for const on (Alaka et al. 2016). Although liquidity fa map. 1980) there are afficient for the second secon ating non-liquid as olvency A relativ

- Working Capital to Total Assets Ratio+, where Working Capital = Cur linuid Assets to Total Assets Ratio+

- ables to Current Assets Ratio ne success of a construction erefore to be more solvent ore solvent, a rea
- to dependents is necessary to acted outern having a negative cash flowal relative outer having a Cash Row Roto ⊂ posting Cash Row[™] + C () carnet Liquid Roto = 365 × ((Cruret Liquid) () cash Roto = 365 × (Cruret Liquid) () cash Roto Roto and Roto is the Roto)) netrest Cover Roto = Profit before Interest and C) Precosal Roto Coperaing Cash Row Ratio)) Working Capital Needs to Working Capital Roto)) Networks Capital Needs to Working Capital Roto

- oles to Payables Ratio
- Days' Receivables⁺ = 365 × Rec D) Days' Payables⁺ = 365 × Payab

als to Current Liabilities Ratio+ expand in cycle with the jab market and c down overheads can contribute to insolve firm's assets into cash (Ng et al. 2011), whi briding CapitalTurnover* = Turnover** + Wou tal Assets Turnover* = Turnover** + Total Ass ment Assets Turnover* = Turnover** + Fixed As

Assets timores — summers — NetAssets* Exerging ratios indicate long term solvency and therefore may be used as early warning signs (Horta et a 2012). As construction works are paid for only when completed, contractors are exposed to high det (Reverge) as they may be required to pay there sub-contractors and supplicits before they there is the solution from some relievel to fail (Ardit et al., 2000).

- (LL2) Debt Ratio⁺ = Total Liabilities ÷ Total Assets
 (LL3) Equity Multiplier⁺ = Total Assets[#] ÷ Sharehi
- (LL4) LongTerm Liabilities to Capital Employed Ratio
- (LL5) Shareholders Funds to Capital Employed Ratio

Iding (pricing), based on far from accurate estimates and th struction projects The bigher the profitability of a firm is th

- MORE Service
 Profit Margin = Profit before Interest and IAA
 Popt Margin = Profit before Interest and IAA
 Popt Margin = Operating Profit * Turnover**
 (Return on Shoreholders Funds (ROSP) = Profit before Interest and TAA
 (Marchine Capital = Profit before Interes

MAIN BUILDING CONTRACTORS

Overall, all three models are highly reliable with minimum generalised R^2 of 68.0% in the year 2009. From odds ratios, for years 2012 and 2014 - an increased value for current liquid ratio (C2), indicating an increased likelihood of failure. This may be explained by considering the case when operating rash flow is reduced (leading to higher current liquid ratio). operating cash flow is reduced (leading to higher current liquid ratio)

operating cash flow is reduced (leading to higher current liquid ratio) suggesting a weaker financial ability to cover liabilities. • Models suggest that an increase in receivables to payables ratio (C8) would reduce risk of insolvency. Increases in receivables or a decrease in payables indicate lower risk of insolvency, resulting from increases in working capital (current assets - current liabilities) suggesting a better ability to finance the firm operations (Kenley, 2003). • The more efficiently a firm can generate turnover from total assets (E2), the less likely it was to fail. With odds ratios of 0.942 in 2009 and 0.982 in 2013 this currichle has a table of fect, but was not related by the Jases

2012, this variable has a stable effect, but was not selected by the Lasso for the year 2014. Instead, in 2014 net assets turnover (E5) was selected, indicating with strong statistical significance that a unit increase in net assets turnover would increase risk on insolvency by a factor of 1.120 (a 12% increase in risk of insolvency). Increases in turnover alongside reductions in total assets can make it more difficult for firm to secure debt without adequate collateral.

 In years 2009 and 2012, the low odds ratios for profit margin is witnessed. with strong statistical significance (p-values of 0.008 and 0.000) indicating that increased profitability would greatly decrease insolvency risk.

CONCLUSIONS

Through analysis of 12 models (1 for each 4 types of firms within their sub-

Inrough analysis of 12 models (1 for each 4 types of tirms within their sub-industries over 3 time periods) the following conclusions are reached: • **Time dimension of failure:** Different variables are prioritised by the Lasso technique for predicting failures at different periods, potentially reflecting market conditions. A unified model applied over the business cycle without regard to time dependent effects of failure (including unique events such as the GFC) will lead to sub-optimal predictions as echoed by (Balcaen and Ooghe, 2006). It should be noted that some predictors (C3, E2, C8, LL4, P3) were selectedby the Lasso technique more often than others, contributing consistently to the power of models in varing neriods. changes in exogenous factors such as the competitive nature of the market, sectoral changes in the use of technology and the different phases of the business cycle clearly influence which variables are best able to predict failure (Wood and Piesse, 1987). • Specific business model characteristics: There is noticable consistency in the range of variables selected by the Lasso technique for

consistency in the range of variables selected by the Lasso technique for predicting failures within the different business model types. This suggests the underlying differences in the economic characteristics between business models are reflected in the prediction models (Chava and Jarrow, 2004; Kaplinski, 2008). For example, profitability related variables were infrequently selected for civil engineering contractors. Other factors seem more important for their businesses, for example the proportion of accruals within their current liabilities (C11). The age variable was selected for all 3 models for main contractors indicating the importance of managerial and operational strategy experience within the *buy* business model, where work is sub-contracted and managed rather than completed *in-house*. The overarching finding concerns success in identifying common factors of failure through the application of artificial intelligence methods of predictor

The overarching mutual concerns success in identifying common factors of failure through the application of artificial intelligence methods of predictor selection, particularly Lasso approaches. This method proved particularly valuable when considering the predictive capability of large numbers of financial ratios. More specifically, a key finding concerns the notable variance in predictor selection through time, as well as observing their relevance change as much within sub-industries as between them.

Table 4 - Si any of P-values of Variables for M

Table 3 - Summary of Odds Ratios for Models

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 small firms and account for their specific credit risks.
 Binary classification of failure: Although this study attempted to provide an objective definition of failure defined, different stages of failure have not been taken into consideration. The use of a linear classification rule (binary eutopmer, folded a new folded). outcome: failed or non-failed) does not truly reflect the complex nature of the

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