Do non-bank SME lenders require alternative stress testing methodologies?

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Outline

- In the years after the last financial crisis, bank lending to SMEs decreased significantly due to banks' capital constrains.
- New non-bank lenders have since flourished and have helped to fill the lending gap.
- We investigate what are the characteristics of SMEs that choose to borrow from an alternative lender. What is their risk level and their financial profile?
- We compare the characteristics of borrowers of an alternative lender to a generic sample of UK SMEs.
- We then propose several ways how to augment the existing sample in order to investigate SMEs behaviour long term and compare different augmented samples.
- We discuss the initial results of augmentation and further research which will include survival analysis for stress-testing.

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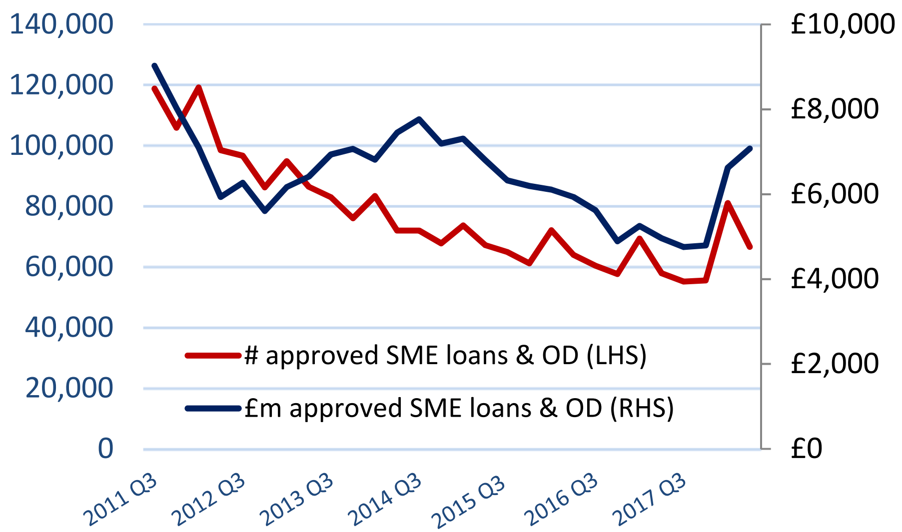
Bank lending to SMEs

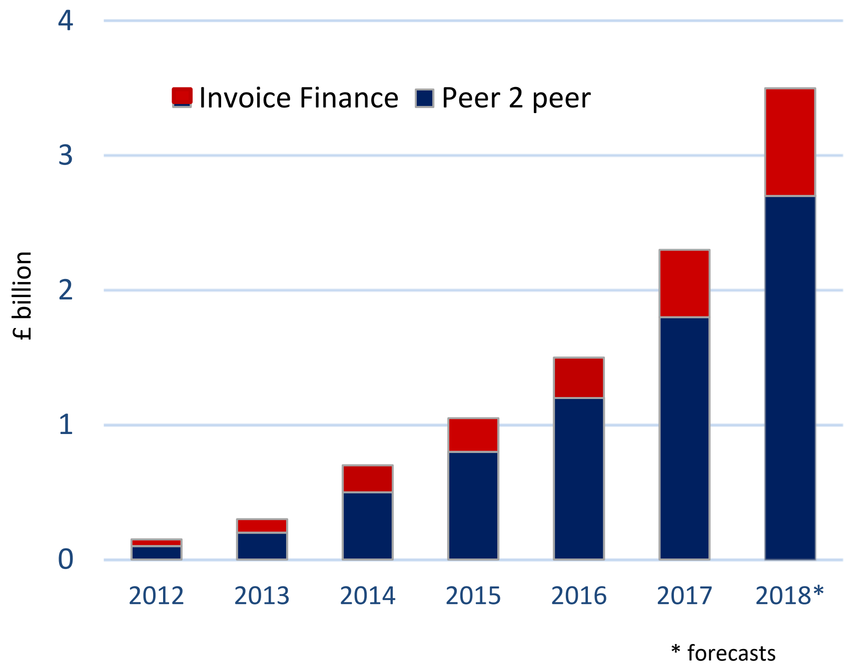


Are UK banks becoming less interested in the SME lending market?

Source: UK Finance, SME Finance Update Q2 2018

Banks approved almost 70,000 loans to SMEs in Q2 2018 and success rates remain high, with eight out of 10 applications getting the green light. Demand for finance amongst SMEs has increased, particularly among production and manufacturing industries.

Growth in UK peer2peer business lending and non-bank invoice finance



Are alternative lenders becoming the preferred choice?

Source: Brismo -AltFi Data and Author compilation, non-bank SME lending Q3 2018

Non-bank lenders' values continue to grow. According to Brismo Data, total lending in 2017 exceeded £5bn, an increase of 45% on 2016. This brings the total to £13.4bn since started recording data in 2011.

Previous research

- Bankruptcy/default prediction models for corporates has been used extensively since the pioneering work by Altman (1968).
- However, it was shown that SMEs are different from large corporates in many aspects, including the credit risk, and need to be assessed with separate models (Altman and Sabato, 2005).
- Altman and Sabato 2007; Altman *et al* 2010 have shown that the original Altman Z-Score models can be developed for SMEs and improved upon by transforming several of the key variables of that model and by adding non-financial and macroeconomic information.

The SME Z-Score

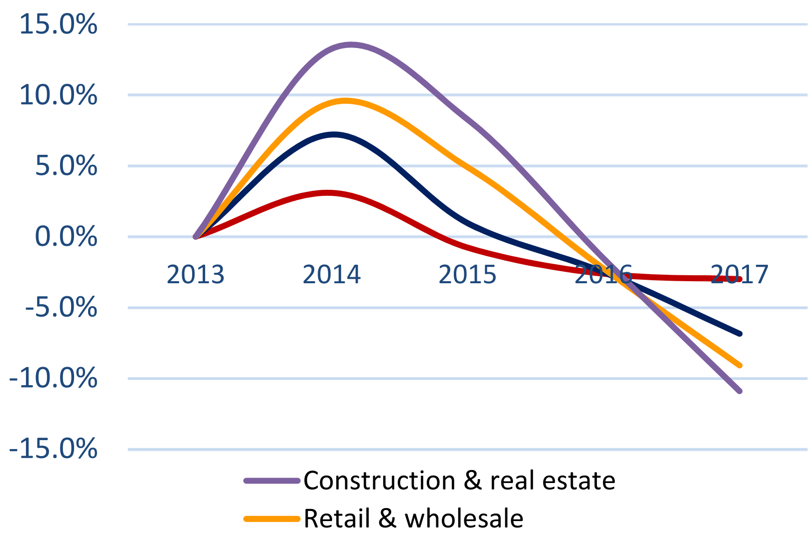
Replicate the human behavior to increase accuracy, stability and credibility

Financials
How is the business doing?

Corporate governance
Who is managing it?

Macroeconomics
What is the context?

SME Z-Score trends



wiserfunding

SME credit risk profile is worsening across all sectors

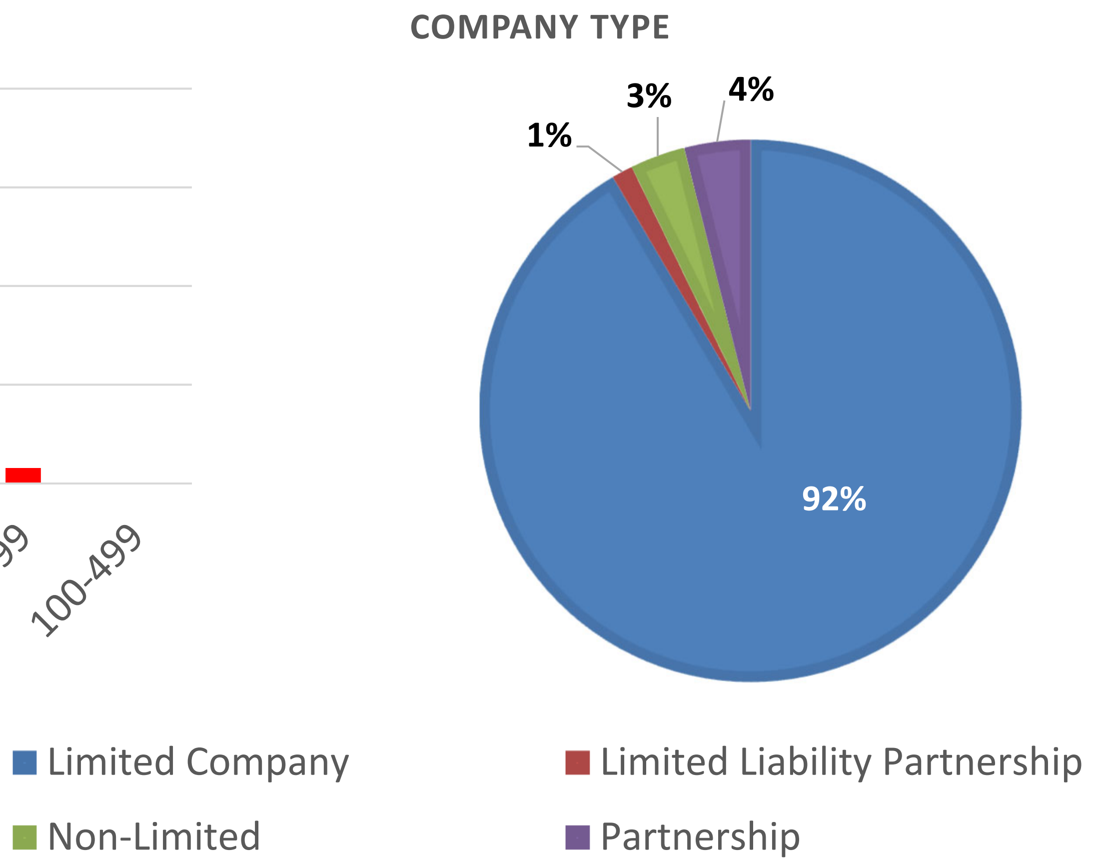
Source: Wiserfunding, SME Finance Review, Q3 2018

We run our models on more than 3 million active SMEs in the UK and we have consistently observed similar trends across regions and sectors with worsening credit risk profile and increasing amount of debt.

Borrowers of an alternative P2P lender

- The dataset of loans from one of the UK P2P alternative lender
- 3897 unsecured loans funded between 2015 and 2018, cross-sectional application data with some subsequent perfromance
- Maturity ranges between 6 to 60 months
- Loan amounts range from £5,000 to £515,000
- Interest rates range from 4% to 23.9%

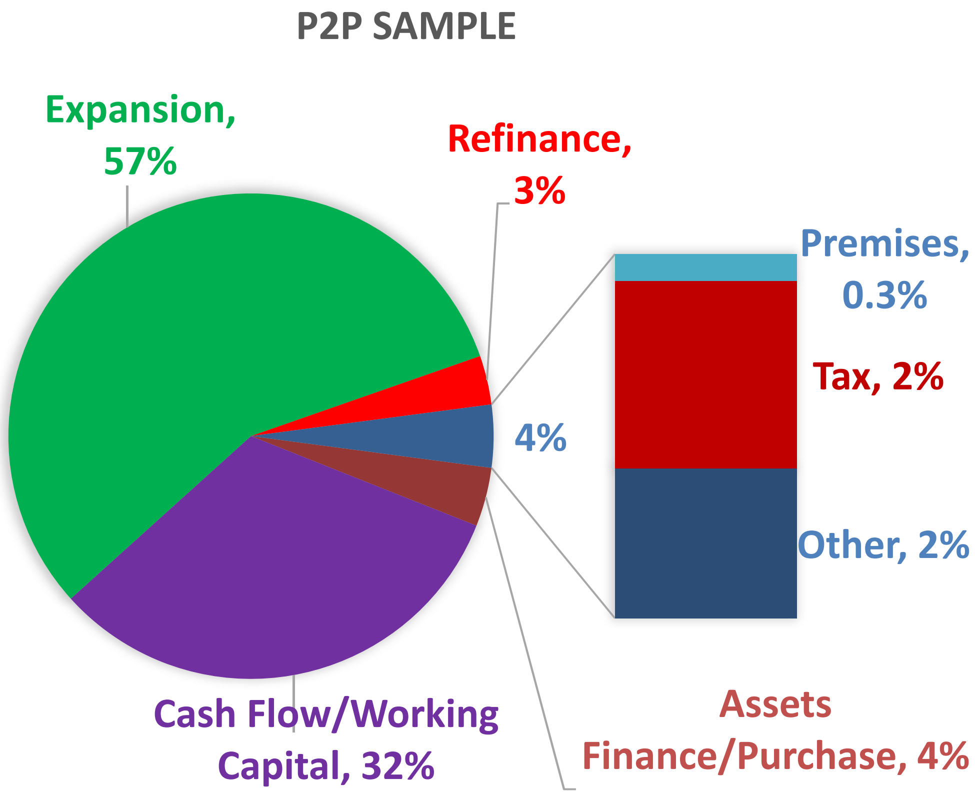
Some demographics



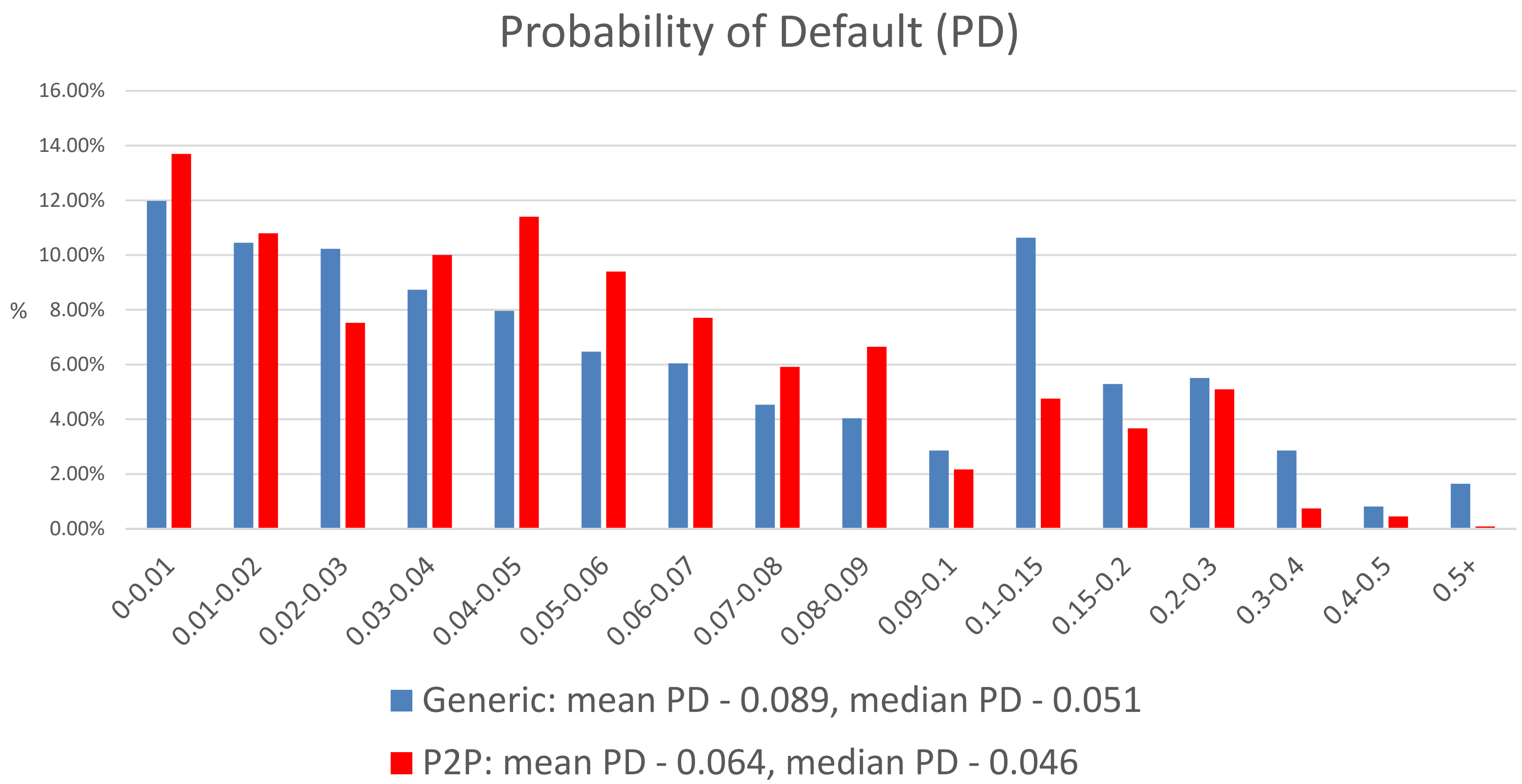
Comparison to the British Business Bank survey – loan purpose

- According to Business Finance Survey (BBB,2019) the main reason for seeking finance for the UK SMEs was for working capital (**40%**) or purchasing fixed assets (**33%**)
- **9%** of SMEs sought external finance for expansion in 2018, compared to **5%** in 2017

In contrast, in our P2P sample 57% borrowed for expansion.



Comparison to the generic sample – risk



The generic sample is a representative sample of the businesses in manufacturing and services. PD is based on SME Z-score estimated for both samples.

Comparison to the generic sample – age and financials

Logistic regression is used to estimate the probability of borrowing from an alternative lender on generic and P2P samples. The alternative lender clients are more likely to be younger with higher levels of debt but also higher returns.

Parameter	Estimate	Standard Error	P -value
Intercept	-1.9012	0.1444	<.0001
Age	-0.0617	0.00336	<.0001
Current Ratio = Current Assets/ Current Liabilities	-0.3056	0.0329	<.0001
Debt Ratio = Total Liabilities/ Total Assets	1.4405	0.1413	<.0001
Long Term Debt Ratio = Non-Current Liabilities/ Total Assets	0.8629	0.1645	<.0001
Asset Turnover Ratio = Turnover/ Total Assets	0.3615	0.0229	<.0001
ROE = Profit after Tax/ Shareholder Funds	0.0455	0.00671	<.0001
ROA = Profit after Tax/ Total Assets	5.3393	0.2143	<.0001

Research Question

- It seems that clients of the alternative lender are more financially savvy, they tend to borrow more, but use the funds efficiently.
- Still how would they perform long-term and especially in the downturn?
- But there are only 38 defaults, 70 late payments and 4 years of cross-sectional data…
- Is it possible to find firms similar to our alternative sample, but with more data?

Matching methodology

- Used FAME (BvD) and Companies House, around 5mln active SMEs
- Searched for companies with similar profiles using:
  - Collaborative filtering (point-to-point matching)
  - Clustering + collaborative filtering (centroid/medoid-to-point matching)
  - Probabilistic matching with machine-learning (work in progress).

Collaborative filtering

- A family of algorithms widely used in recommender systems, e.g. Amazon or Netflix
- Based of the similarity between past and new users to make recommendations to new users given the behaviour of the previous ones
- We used extended Gower's distance (Kaufman and Rousseeuw, 1990) as the similarity measure between the i^{th} and j^{th} observations, with p variables :

$$d\ (i,j) = \frac{\sum_{f=1}^{p} \delta_{i,j}^{(f)} d_{i,j}^{(f)}}{\sum_{f=1}^{p} \delta_{i,j}^{(f)}}$$

- For categorical variables, the distance $d_{i,j}^{(f)}$ equals 0 if x_i^p=x_j^p and 1 otherwise; for numeric variables, the distance $d_{i,j}^{(f)}$ equals the Manhattan distance; $\delta_{i,j}^{(f)}$ = 1 unless the value of the variable is missing.

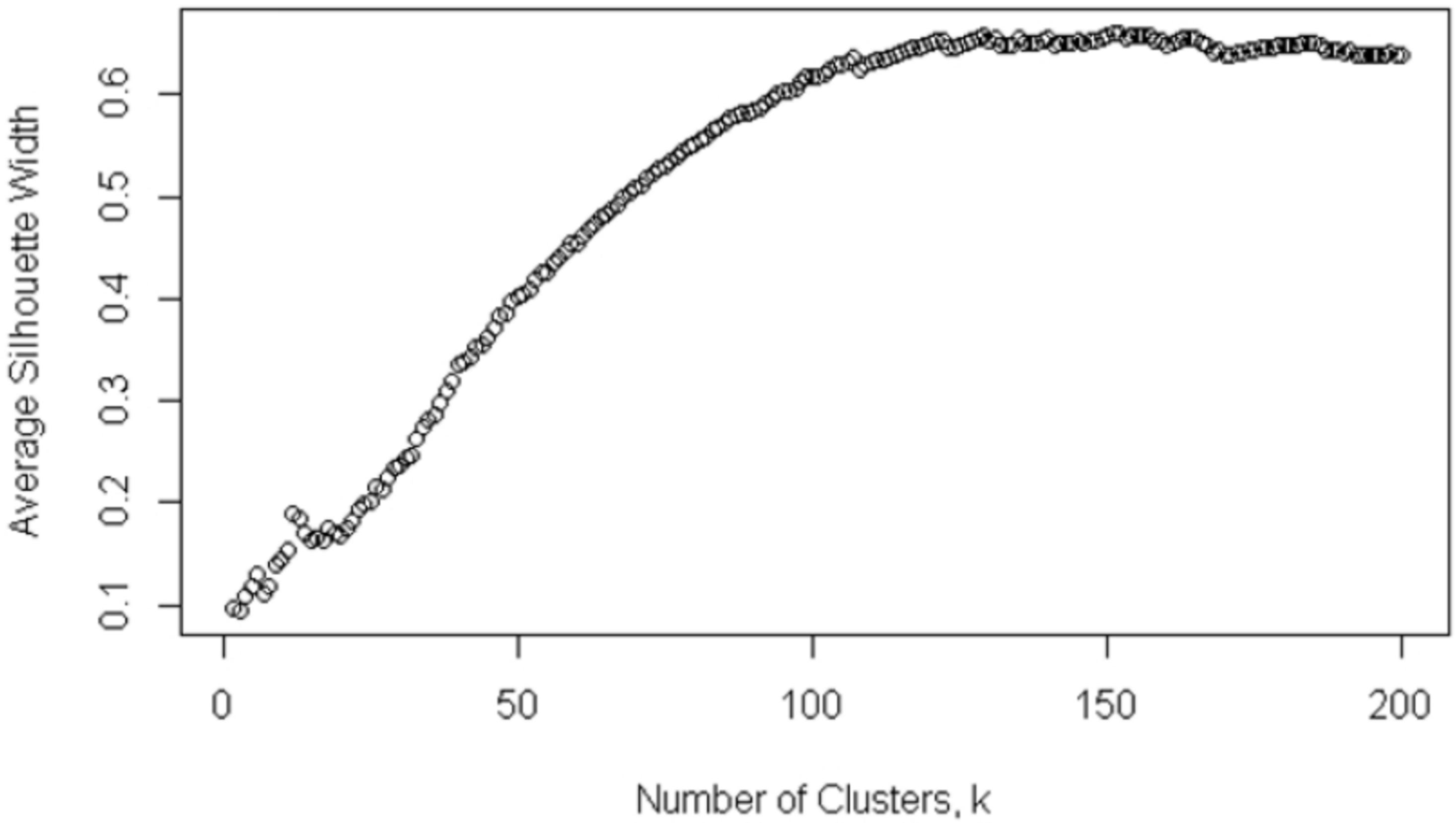
Clustering

- Cluster analysis splits the data into homogeneous groups
- We attempted to reduce the noise and computational burden by clustering the data before filtering/matching
- We used k-medoids (Kaufman and Rousseeuw, 1990; Arora et al., 2016)
- The number of cluster is determined based on the Silhouette width (Rousseeuw, 1987):

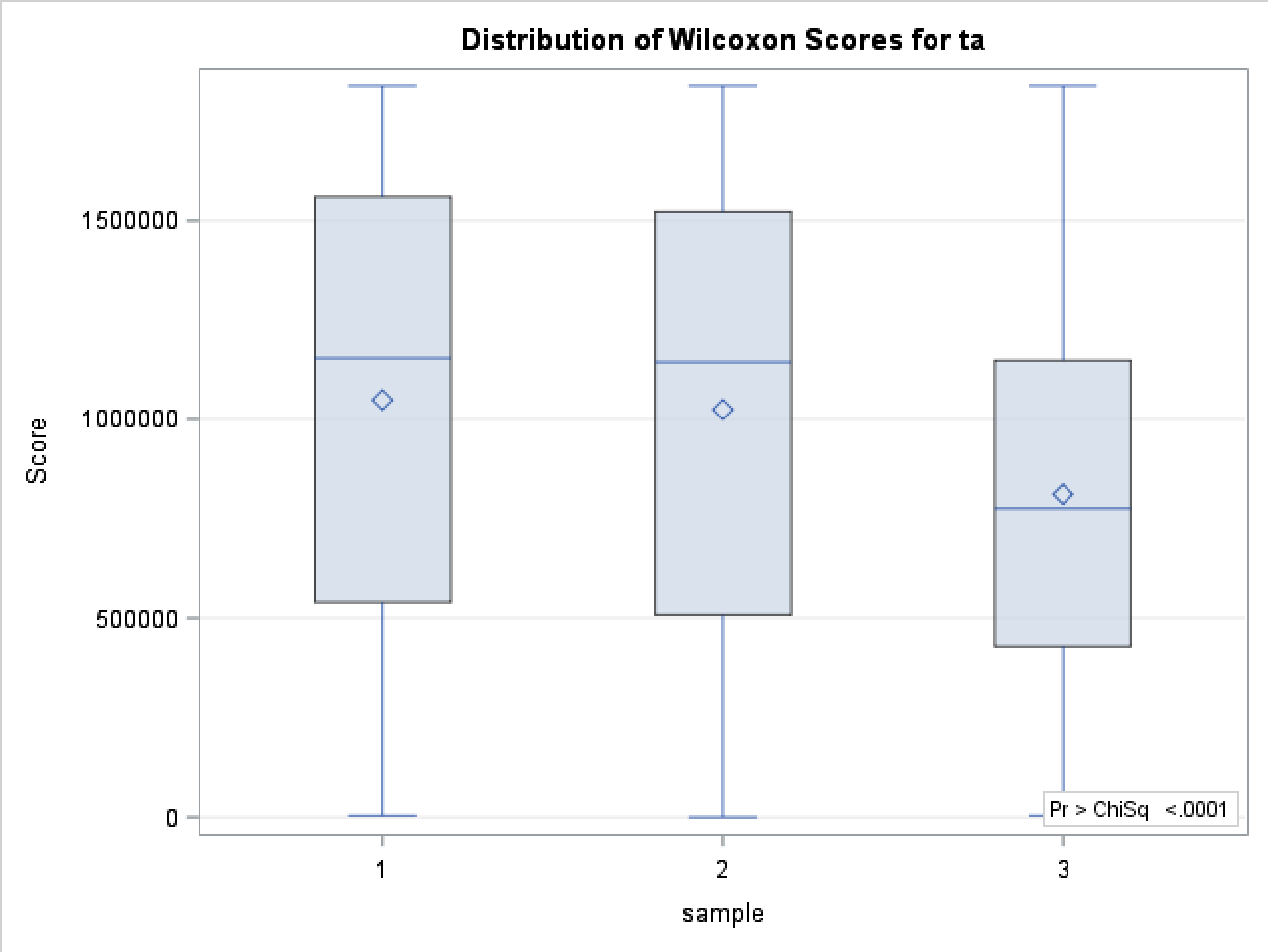
$$s(i)=\begin{cases} 1 - a(i)/b(i), & if\ a(i) < b(i) \\ 0, & if\ a(i) = b(i) \\ b(i)/a(i) - 1, & if\ a(i) > b(i) \end{cases}$$

Where $a(i)$ is the average dissimilarity (distance) between i and the other observations in its cluster C_i; $b(i)$ is the smallest average dissimilarity between i and other k-1 clusters. Higher values mean better homogeneity.

Used k = 150


Average Silhouette Width
0.1
0.2
0.3
0.4
0.5
0.6
0
50
100
150
200
Number of Clusters, k

Comparison – Total Assets



Test for : 1 - P2P sample; 2 – CF sample; 3 – Cluster + CF sample

Comparison – Short-term debt

Comparison - comments

- Collaborative filtering shows closer match to the original P2P sample.
- Clustering reduces the variability (as expected), but underestimates means and medians for most variables.
- As a next step, Cox proportional regression will be built on the extended samples with macro-economic variables.

Discussion and further work

- We have explored the profile of the borrowers of one the UK alternative P2P lenders.
- In contrast to the majority of the UK SMEs, their main reason for borrowing is expansion.
- In terms of risk, they are lower risks as compared to a generic UK sample. They have higher levels of debt and better return ratios.
- To investigate how they will perform long-term, we have explored different data augmentation methods, with collaborative filtering showing promising results (the distributions are close to the original sample).

Discussion and further work

- Further work will include:
  - Machine-learning matching;
  - Exploration of different survival analysis models for stress-testing;
  - Investigation of different scenarios of down-turn conditions and stress-testing the survival models.
- This research forms the foundation of a prototype Financial Health Check system, where lenders, regulators and SMEs themselves can compare their performance to a customised benchmark.
- The methodology can be applied in many other situations (e.g., when ids are not available for privacy reasons).

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