

## Quinton Vaughn Aguilera - Bank of England Technical Assessment

Analyst, Data Science, ARTIS (Req ID: 010242)

Thank you for the invitation to take part in the technical assessment stage of the application process. This document will be used to present the rationale and findings for tasks 1-3. All of the code used to complete the assessment can be found [here](#).

### **Contents (TASK 1):**

- 1) Exploratory Data Analysis & Data Cleaning
- 2) SCR Coverage Ratio Inspection
  - a) Failing to Meet Requirements
  - b) Using T-Tests to understand the differences between small and large firms.
- 3) Outliers & Changing Business Profiles
- 4) Presentation of Recommendations

### **Annex:**

- a1) K-Means Clustering & PCA for Further Outlier Detection (TASK 2)
- a2) Cloud Tools Considerations (TASK 3)
- a3) Other Examples of Mine (Python & R), Unrelated to the Assessment

### **Section 1: Exploratory Data Analysis & Data Cleaning**

Two tables of data were provided, each with 8 fields across five years (2016-2020). In total there were 16 fields with data for the past five years. Dataset 1 had 325 records, while dataset 2 had 456 records. For the purpose of being able to demonstrate data science concepts across both datasets, I chose to use only the 325 firms present in both datasets. The remaining 131 firms I would add to the list of firms requiring supervisory personnel to contact them and get more data for the first dataset.

The second stage was to do some further cleaning by finding out which records presented extremely unusual results compared to their peers in the industry. For this stage, I looked at each column, flagging any record that was nine standard deviations from its peers (nine SD was chosen quasi-randomly to represent a large number of standard deviations). In doing so, I was able to a) identify records that may have been input incorrectly and, b) even if data was correctly input, these firms are clearly operating at a scale that is highly unusual and ought to be put on the watchlist. By counting the number of times values exceeded nine standard deviations, it is possible to prioritise which firms to investigate. The results of this stage were as follows:

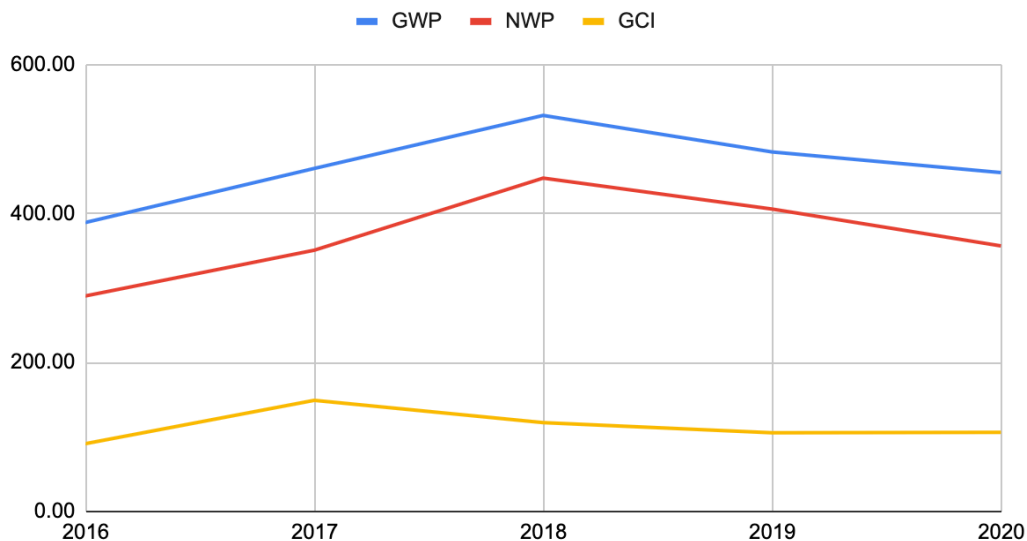
Dataset 1		Dataset 2	
Firm	No. Records > 9SD	Firm	No. Records > 9SD
4	13	28	6
210	9	188	6
105	8	216	6
311	5	99	3
127	2	105	3
10	1	166	3
26	1	284	3
66	1	112	2
131	1	161	2
216	1	228	2
247	1	17	1
320	1	70	1
		270	1

*Table 1*

In database 1, Firm 4 was the worst offender, with most other firms identified having only one instance of a value outside nine standard deviations. In dataset 2, repeat offences were more common. It is worth reiterating whether the data was misreported or not, all these firms should be added to the watchlist as even if data is correct, they are clearly operating at a scale significantly different to the industry average.

Finally, I sought to generate an industry snapshot using firms that were not already put onto the watchlist, looking at the development of five key variables over the five year period, with the results across two charts as follows:

### GWP, NWP and GCI Industry Average 2016-2020



*Chart 1*

## SCR and NCR Industry Average 2016-2020

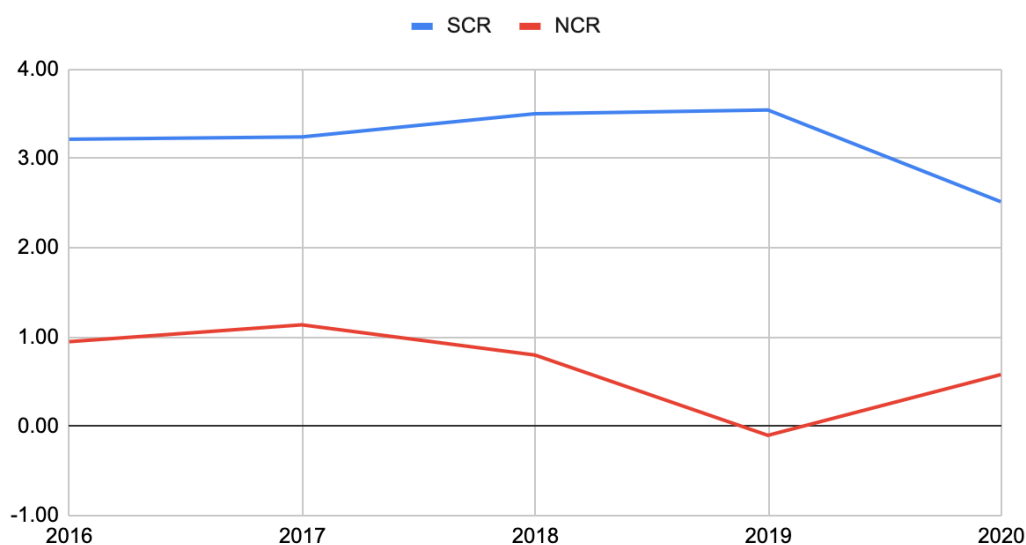


Chart 2

In chart 1, NWP and GWP clearly peaked in 2018, with the average size of firm's revenue decreasing since then. In 2020 there was a noticeable drop in SCR coverage ratio, combined with an increase in NCR, indicating firms struggled more than the preceding year. This observation also coincides with declining GWP and NWP. The negative reading of NCR in 2019 seems to be particularly unusual and potentially a point for further investigation at another time.

	GWP	NWP	SCR	GCI	NCR
2016	387.42	288.81	3.21	90.28	0.94
2017	459.98	350.28	3.24	148.46	1.13
2018	531.18	447.04	3.50	118.52	0.79
2019	482.17	405.46	3.54	104.94	-0.11
2020	454.42	356.04	2.51	105.51	0.57

Table 2

Table 2 is the raw data used in charts 1 & 2. SCR and NCR are clearly on a very different scale as seen in the table, resulting in the separate chart (2).

### 2) SCR Coverage Ratio

Firms thus far added to the watchlist have been identified on unusual reporting practices and missing data. Now we can proceed with analysing the data working on the assumption it is functionally accurate.

#### **2a) Failing to Meet Requirements**

All firms are required to have an SCR Coverage ratio of at least 100%, and failing to do so will result in supervisory intervention. This stage was simply counting the number of times firms failed to meet their requirements over the last five years. As seen in table 3,

just 56 firms did not breach the SCR minimum over the five years, suggesting that in general, this is an area of improvement for the industry. Any firm breaching SCR two times or more was added to the watch list - perhaps it should be only once, this is a question for regulators.

No. SCR Breaches	No. Firms
0	56
1	92
2	64
3	44
4	28
5	28

*Table 3*

## 2b) Using T-Tests to Understand the Differences Between Small and Large Firms

This large number of firms not meeting requirements demands some further analysis. I decided to split the industry into thirds based on GWP, on the premise that GWP is a good measure of the size of a firm. I then looked at the mean of each group's SCR Coverage ratio over the last five years and performed two-sample t-tests to see if there were statistical differences between the mean SCR of firms in each category. N.B. that t-test presuppose that samples are normally distributed, and due to time constraints, this was not verified. The technique was included anyway to demonstrate a use of a statistical test.

P-Values	Bottom 3rd	Middle 3rd	Top 3rd
Bottom 3rd			
Middle 3rd	0.1263		
Top 3rd	0.0011	0.0033	

	Average SCR
Bottom 3rd	1.9158
Middle 3rd	2.2623
Top 3rd	5.4147

*Tables 4 & 5*

Table 5 shows the average SCR for each of the firm sizes, and while they do increase on average, the top third seems to be substantially higher than the bottom and middle thirds. Indeed, conducting t-tests between each category show that the mean of the top third's SCR ratio is statistically higher than that of the other two categories at the 95% confidence interval. Meanwhile, the p-value for the test between the bottom and middle thirds is greater than 0.05, meaning that there is not a statistical difference between the means of these groups.

In aggregate, this shows us that the smaller GWP firms struggle to achieve the higher SCR ratios than the large firms, and that there are statistically significant differences between the average SCR ratios firms are able to achieve.

### 3) Outliers & Changing Business Profiles

This section looks at Gross Claims Incurred, Pure Net Claims Ratio and Excess Assets in percentage change terms over the five year period to understand how each of the firms have been evolving. Percentage change was chosen so as to account for the different sizes of the firms. For each of the variables, bar charts were created, but given the large number of firms there, they can be difficult to read per individual firm, and instead are used to find unusual developments in the industry.

Gross Claims Incurred per Firm per Year

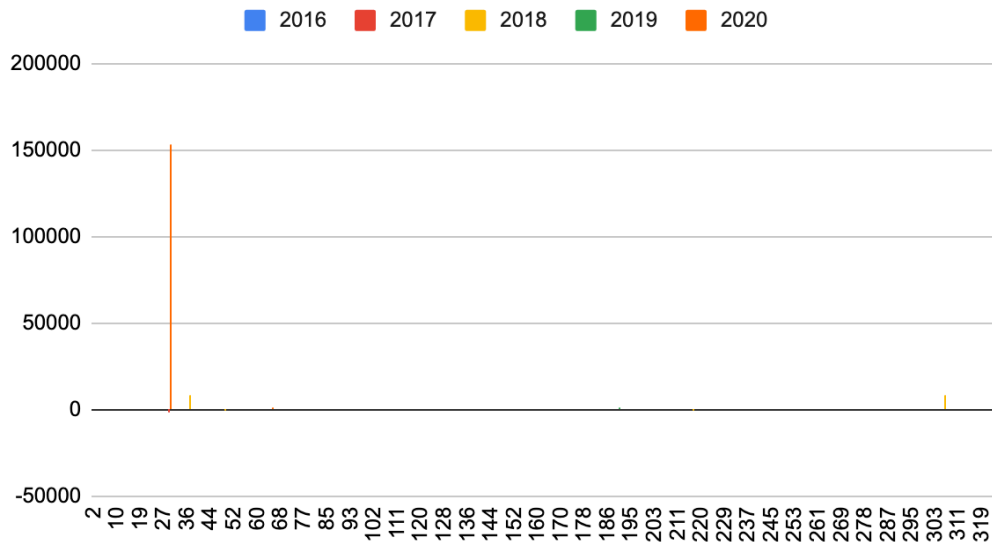


Chart 3

In chart 3 we can see two firms with highly unusual behaviour. Firm 27 had an increase of over 150,000% in GCI from 2019 to 2020, and firm 37 had an increase of over 8000% in 2018 (smaller yellow line). Both of these firms are added to the watchlist.

Excess Assets per Firm per Year

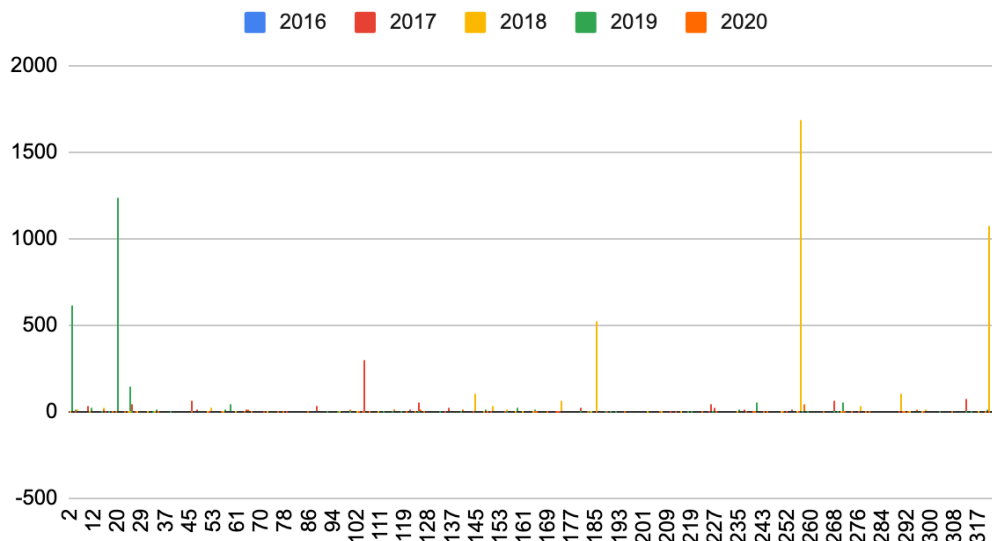


Chart 4

Chart 4 shows there to be an even higher number of suspicious-looking developments, occurring mainly in 2018 and 2019. Each of the firms in the six prominent peaks were added to the watchlist. These are firms 2, 19, 106, 185, 256 & 321.

Pure Net Claims Ratio per Firm per Year

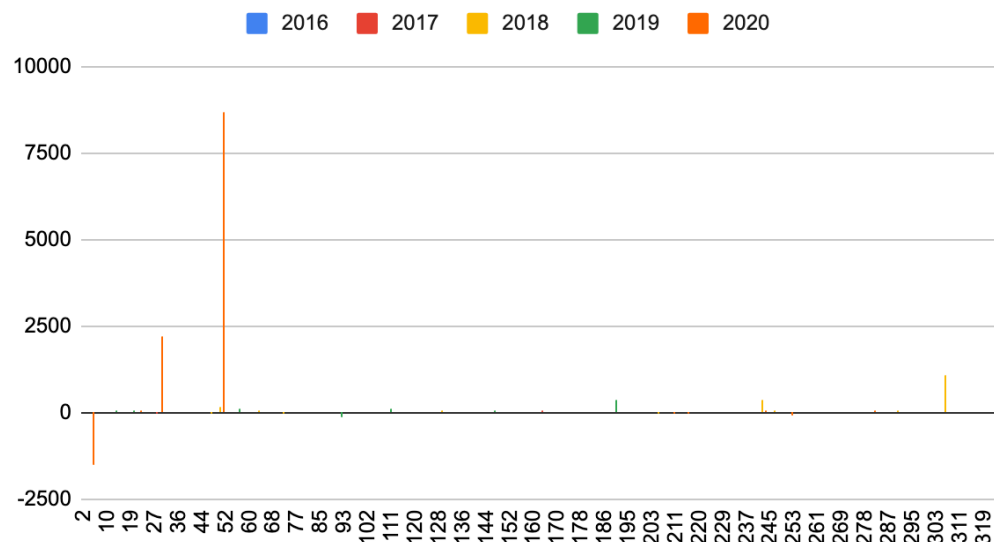


Chart 5

Unusual measures in chart 5 appear to be mainly in 2020. Each of the four largest developments here were added to the watchlist as firms 4, 29, 50 and 306.

In general, it seems like reporting was less outlier-prone in 2016 and 2017. A total of 12 firms were added to the watchlist in this stage.

#### 4) Presentation of Recommendations

After three rounds of analysis over 200 firms were added to the watchlist based on a variety of criteria. In section 1, firms with large swathes of missing data were added - these firms likely only need to be contacted for data. An additional 25 firms were added due to their data being on at least one occasion nine standard deviations away from the industry mean. They can be prioritised based on the number of times they had such records (see table 1).

In section 2, we reviewed the rampant SCR coverage ratio breaches, adding over 100 firms to the watchlist based on their inability to stay above 100% twice or more. We also proved the statistical differences between the average SCR coverage ratio between the upper third and lower two thirds.

Finally in section three we generated some charts to look at the development of various key statistics and added 12 more firms to the watchlist on account of their unpredictable developments.

There is more that could be done, but this represents a good start in choosing where to allocate resources.

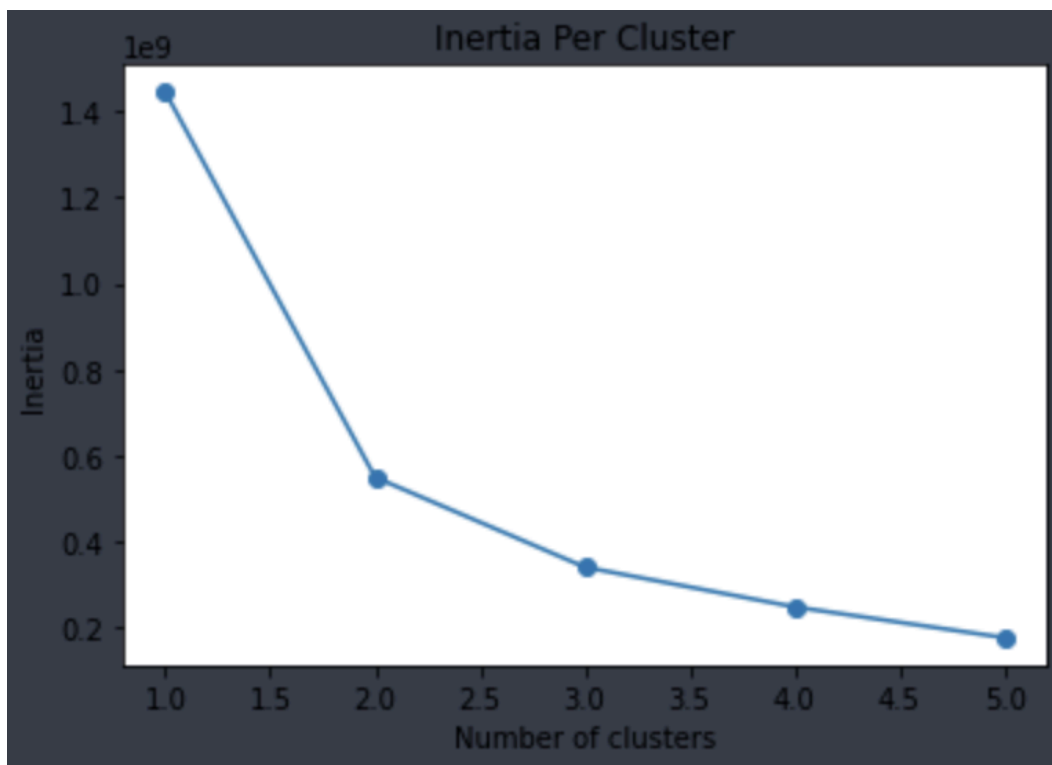
## Annex:

### a1) K-Means Clustering & PCA for Further Outlier Detection (TASK 2)

In terms of using some machine learning techniques, K-means clustering is an unsupervised learning algorithm that can be used to group firms into clusters. This may help uncover other relationships between firm types, and continue to help look for outliers.

In this step, the plan was to use K-means clustering to put the data into groups, and then principal component analysis is used to reduce the dimensionality of the data so it can be presented on a 2-D axis and visualised. The number of clusters was chosen based on the inertia readings at various trialled numbers of clusters.

There was not enough time to go through with the rest of the analysis, but four or five would have been selected as the number of clusters based on the decreasing marginal change in inertia as more groups are added.



### a2) Cloud Tools Considerations (TASK 3)

Using cloud tools will allow for the scripts to be run automatically, having access to this and any other data required. For further analysis. Services like Azure Cost Management can be used to identify cost saving opportunities as well.

In general the process would consists of using Azure Data Factory, process with Databricks, and could be used with something like powerBI for a summary of statistics, if a written report is not necessary, or simply for insights at a glance.

### a3) Other Examples of Mine (Python & R), Unrelated to the Assessment

Please also feel free to view [this](#) repo (unrelated to assessment) that has some other examples of topics I am familiar with such as the Black-Scholes model, the ARMA family of models, etc.