all figured out

Devising a Resilience Rating System For Charities & The Non-Profit Sector

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Purpose

The non-profit sector forms a vital part of both the UK economy and the provision of essential services. The question we raise in this research is whether funding decisions, especially where public funding is involved, could be improved if both funders and delivery organisations had access to better data on the financial health of both sectors and organisations.

Furthermore, if we aggregate data on the financial position of whole sectors or review the resilience of non-profit ecosystems in given geographies, to what extent could we spot issues of resilience and fragility that have thus far been overlooked?

This would then inform policy, funding and investment priorities at an earlier stage than if the warning signs are only addressed when organisations start to fail more visibly.

'A new statistical framework is needed to measure comprehensively the output and productivity of the charitable sector, taking account of social as well as private value-added...

The case should be considered for creating a benchmarking platform for charities as a means of boosting self-awareness & self-improvement across the sector.'

Andy Haldane
Chief Economist to the Bank of England and Co-Founder of Pro Bono Economics

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Executive Summary

One of the sectoral issues that COVID has shone a light on is that whilst social investors, grant funders and sector support organisations acquire detailed data about the activities they have commissioned individually, they do not have access to a similar level of data about the wider sectors in which they are operating. The aggregation of that information across multiple funders, and the bridging of analysis from restricted income project funding into a perspective on a whole organisation, are both difficult tasks. This limits the extent to which insight can be aggregated up into a summary carrying sufficient weight at Treasury level to unlock the necessary funds to support the sector through the pandemic.

Rating systems that track risk and performance are common in the commercial world and are widely used by banks, investors and supply chains. These rating systems mean that expert analysis, research and sector experience are channelled into the decisions made about which companies to invest in and develop versus those where it is preferable to reduce a portfolio liability by divestment of stocks or a non-renewal of contracts in a supply chain.

There is no equivalent in the non-profit world despite the fact that thousands of decisions to spend and invest many millions of pounds are made throughout the year by grant funders, banks, social investors and local authorities. These decisions influence the success and failure of hundreds of thousands of organisations whose services underpin the UK's ability to ensure that education, health care, the social contract, culture & leisure are provided to the whole population at all levels of society.

Whilst the use of financial data only as a means of assessing organisational resilience would lack the nuance of a qualitative analysis and would not take account of the people, place or passion that are so critical to success, the resilience rating which MyCake is developing can be deployed nationally across all sectors and geographies. Initially, it will not include social impact data either so, whilst not the only tool needed to report on a sector, place or organisation, we suggest that this work will nevertheless fill some critical gaps. It will enable the non-profit sector to provide evidence of both benefit and need to government, as well as supporting decision-making around allocation of funds, contracts and investment.

We have made rapid progress in four weeks to demonstrate the potential. We have proved that we can produce a functional tool with sufficient accuracy to make a useful contribution to decision making processes. We will be refining the algorithm further in the next phase of work.

1. Introduction

Rating and ranking systems are used widely across society – credit ratings, stock prices and similar are all mechanisms whereby data from the past is used to indicate the future reliability of an organisation and the degree to which trust can be placed in it by clients, suppliers, lenders etc. These risk/trust rating systems are common place in the commercial world.

There is however no rating system for the non-profit sector. There are a number of reasons for this which include:

- Very low borrowing levels and limited ability to repay debt - no credit rating
- Share ownership limited to Community Benefit Societies, Registered Societies and Community Interest Companies limited by share. These comprise the minority of the non-profit ecosystem. No public trading of these – no stock price
- Short term restricted income grant funding decisions often based on qualitative analysis of proposed activity and only require sufficient underlying financial resilience to ensure that marginal cost of delivery is achievable and that the organisation will outlive the delivery period - longer term resilience is not a key factor in decision making

Whilst data informed decision making is not ubiquitous neither is it entirely absent across the sector. Some grant funders have built strong data teams and capabilities. Social investors and capital grant funding programmes do undertake more rigorous financial due diligence. These rely on the experience of the investment managers in evaluating not just the on-paper risk but the quality of the team and the myriad other factors which influence whether an organisation is a sound investment prospect or not. This is similar to the early days of the development of the venture capital market in that there was insufficient track record in most sectors to evaluate risk with a strong set of quantitative tools.

Return on investment in the grant funding arena is achieved through the delivery of social impact. Return on the investment in the social investment market is tracked as the extent to which losses are limited. Given that the organisations delivering goods and services in the third sector are by definition operating in areas of market failure and in areas where the inability to turn a profit has driven out commercial organisations, this absence of a fiscal return on investment is to be expected. However the side effect is that there is relatively little focus on the development of data tools which could improve either the due diligence process through improved evaluation of risk or which offer data driven systems to risk management at portfolio level.

In summary whilst we could use data to inform grant and investment decision making to a greater degree as a sector we have not done so, as the processes in place have been sufficiently fit for purpose that the failure rate of non-profits has not negatively impacted either grant funders' ability to achieve impact from their grant programmes nor from social investors' ability to limit their loss levels.

One impact of COVID-19 on the decision making structures for the awarding of grants or provision of debt to non-profits is that economic environment has changed so rapidly and its future is so unknown that the markers of sufficient resilience to maintain operations for the term of a grant or a debt repayment are no longer enough to enable programme or investment managers to make decisions with confidence. Past successes are no longer a sufficient indicator of likelihood to maintain operations over the medium term future.

2. Goals

We do not anticipate being able to boil down all the factors which influence resilience against future shocks into a single numerical rating. There is also no marketplace in which multiple evaluations of risk are exchanged through the medium of share price changes.

The proposition therefore is to build a series of algorithms with which to evaluate the key elements of risk in a non-profit business model. The importance of each element can then be up or downgraded by a funder, investor or other sector expert so as to match their funding priorities, capacity for risk and timeframe over which they wish to achieve impact.

In the first two phases of development we intend to built a dashboard of metrics which look at:

- Turnover level
- Sector of primary operation
- Age of organisation
- Ratio of trading : grant income
- Types of trading income and ratios between them
- Salary spend levels
- Overhead levels
- Fixed : current assets ratios
- Working capital as a proportion of turnover

Our existing non-profit financial benchmark systems, structures and databases already contains detailed financial information on over 2,000 organisations for multiple years with granularity on income and expenditure which covers over 40 types of income and 40 types of cost. This data structure will form the basis of Algorithm II development in phase 2. Algorithm I takes a more limited dataset which uses only total income, total expenditure, reserves contributions and sector for organisations reporting to the Charity Commission.

Algorithm II development will also draw on a combination of the expertise in reviewing financial resilience already present in the MyCake team and combine it with the expertise of grant programme managers, social investment portfolio managers, sector development specialists. We will also leverage existing work in metrics development which is ongoing with grant funders such as Power to Change and social investors such as KeyFund.

In order to make use of this non-profit finance dataset we need to ensure that we run a set of managed samples by sector and turnover band which are representative of the wider third sector. This is not currently the case. We also need to understand the underlying propensity for financial failure in the third sector and the ways in which this varies by sector, age of organisation and turnover band.

3. What sorts of questions will these algorithms help to address?

Our start point in terms of questions about financial resilience and risk where a set of data tools can be expected to add value to decision making processes is as follows:

The algorithm I establishes an understanding of the underlying level of risk of failure by sector. Whilst it is based on analysis of large volumes of specific organisations it is not yet sufficiently sophisticated to be an accurate predictor of risk in a single organisation. This is because it is reflecting a set of broad trends rather than looking at the details of a single organisation. This level of risk rating is useful for looking at whole sectors. We also expect to be able to use it to compare the underlying risk of a portfolio of organisations versus the sectors in which they operate to look at whether a portfolio is holding more or less risk than the wider sectors. It is not yet sufficiently sophisticated as to be able to be used for an individual organisation as a summary of the risk of the business model and current position. We cannot yet indicate the time or level of investment required to intervene with a failing organisation and improve it’s financial resilience. This is a goal for the next phase.

The algorithm II will be more nuanced in that it will use a greater number of individual organisation reference points. In this phase we expect to produce a risk rating for a single organisation that indicates whether there are specific concerns about this organisation and what the root causes of fiscal fragility are.

4. Preparatory Work – A definition of 'non-profit' and a combined set of data sources

Whilst the MyCake benchmark contains data on a wide range of non-profit organisations across multiple sectors, turnover bands, geographic areas etc etc we do not run samples which are designed to be representative of any one sector, city or the national picture.

Our definition of what constitutes a non-profit is designed to mirror the variety of legal forms found in the portfolios of grant funders and investors and thus includes organisations who report to the Mutuals Register (Registered Societies and Community Benefit Societies) as well as organisations who report to Companies House without also reporting to the Charity Commission (Community Interest Companies limited by share or by guarantee).

Like NCVO[1] we tend to exclude independent schools, places of worship and government controlled bodies.

The implication of this wider definition is that we need to draw on data from Companies House and the Mutuals Register as well as from the Charity Commission. This presents a series of challenges in that the machine readable data from these sources lacks the financial detail found in the Charity Commission alpha feed and we cannot therefore immediately import turnover and expenditure data for multiple years from these sources at no cost. Nor can we easily match the SIC codes for Companies House organisations to the ICNPO definitions. There is no sector coding in the Mutuals Register data in a machine readable format.

Through other work we are addressing some of these issues either by buying in data at commercial rates or by filling in the data gaps for given cohorts of organisations when a project need arises.

Furthermore even where data can be obtained the fact that organisations which report to Companies House do not have to publish a P&L account if they are below a threshold of £10m turnover or 50 employees means that data from this source is only ever partial. Across the Companies House dataset approximately 10% of organisations below this threshold report a P&L even when not legally obliged to do so by Companies House or their Charity Commission reporting requirements. The rate of reporting is slightly higher in the non-profit legal forms.

The upshot is that whilst we can identify every non-profit organisation we may not have access to even the minimum financial information of total revenue and total expenditure on which our first algorithm is built. This places limitations on the extent to which we can make claims about the representativeness of any sample group. Nevertheless prior work has demonstrated the benefit and utility of being able to identify all non-profits in a given geographic area and combine the financial data available across the Charity Commission, Mutuals Register and Companies House.

[1] https://data.ncvo.org.uk/about/definitions/#income

In addition to these data sources we have also imported the 360 Giving dataset so that we can create cohorts by grant funder as well as by sector, geographic area, turnover band etc. Prior work means that we have already brought in deal data published by Big Society Capital[2] and have worked with the Community Shares unit. Whilst such datasets are not automatically updated the work of the Social Economy Data Lab should provide a live view on these sources of finance to the non-profit economy as well as a common data standard.

These datasets are valuable for their ability to shed light on specific types of capital and revenue income and the related long term liabilities.

The resulting dataset which combines these data sources is structured so that any one organisation could login securely to see their individual data benchmarked against a series of comparison cohorts of their choosing[3]. The data access structures also allow any portfolio manager to view the contents of their portfolio individually or in aggregate vs. a series of comparison groups. These views are in addition to a more generic results querying & download interface. An API is in the works. Results dashboarding improvements are ongoing.

Whilst we had already been acquiring data from a number of these sources the developments in the last four weeks have grown the data held from a series of partial views to one which gives us as complete a picture as can be acquired from public data sources without purchasing commercial data additions (on Companies House data) and with the structures necessary to update these sources regularly.

This will allow us to contextualise the full financial benchmark data already held and work out where further detailed data is required to build representative samples by sector of activity. Where the ICNPO structure offers insufficient detail (in particular for codes 4100 and 6100) we intend to add to our existing specific data cohorts.

We already hold complete datasets of either full benchmark data or 'lite'[4] benchmark data for all community shops, community pubs and community energy thanks to our work with Power to Change & the Plunkett Foundation.

In simply achieving the above we have already dealt with a series of substantial data cleaning and hosting challenges regarding the inconsistency of use of the legal names of organisations in the datasets of clients held by grant funders and social investors and the lack of use of the company or charity number as a unique reference number (URN). These are considerable hygiene factors in the ability to import data from multiple public and private sources. Datasets can now be matched and de-duped with good accuracy levels in a time efficient manner.

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[2] https://bigsocietycapital.com/latest/investments-social-enterprises-and-charities-december-2018/

[3] Organisations can also integrate a data feed from their book-keeping system (limited to Kashflow and Xero) should they wish to automate the process of importing their own data. Appropriate data security, confidentiality and GDPR compliance is in place to protect this data and withhold results where queries would generate too small a cohort from which individual organisations could be identified.

[4] Total income and expenditure for all years going back to 2014

In successfully combining the public data sources of Charity Commission, 360 Giving and Companies House with the private data sources of several funders, social investors and membership organisations we are able to contextualise the risk held in any given portfolio against the underlying risk by sector and turnover band nationally. Where data is private this is maintained in the data reporting structures and user viewing rights.

Where data has been shared with us via a prior project eg. a membership list, we cannot assume any ongoing rights to its use without a separate agreement.

This provides a strong set of foundations upon which to build a more sophisticated suite of tools which evaluate risk according to key financial metrics and to do so in a manner which enables grant funders, social investors and others to set their own definitions of acceptable risk, resilience and capacity for innovation.

MyCake is listed as both a data controller and data processor with the ICO, maintains GDPR compliant systems and all data access is via secure websites. MyCake data systems also integrate with live financial data sources such as SAAS book-keeping services such as Kashflow and Xero and continue to meet their data standards.

5. Preparatory Work – Underlying risk of financial failure of non-profits in England & Wales

In order to develop managed samples with which to test the elements of a resilience rating we need to better understand the national picture. In particular we need to understand the underlying risk of failure and the factors which influence it.

Algorithm I calculates the underlying risk profile for organisations which report to the Charity Commission. It takes account of the income, expenditure & contribution to reserves patterns, primary sector of operation and size of each organisation via the following steps.

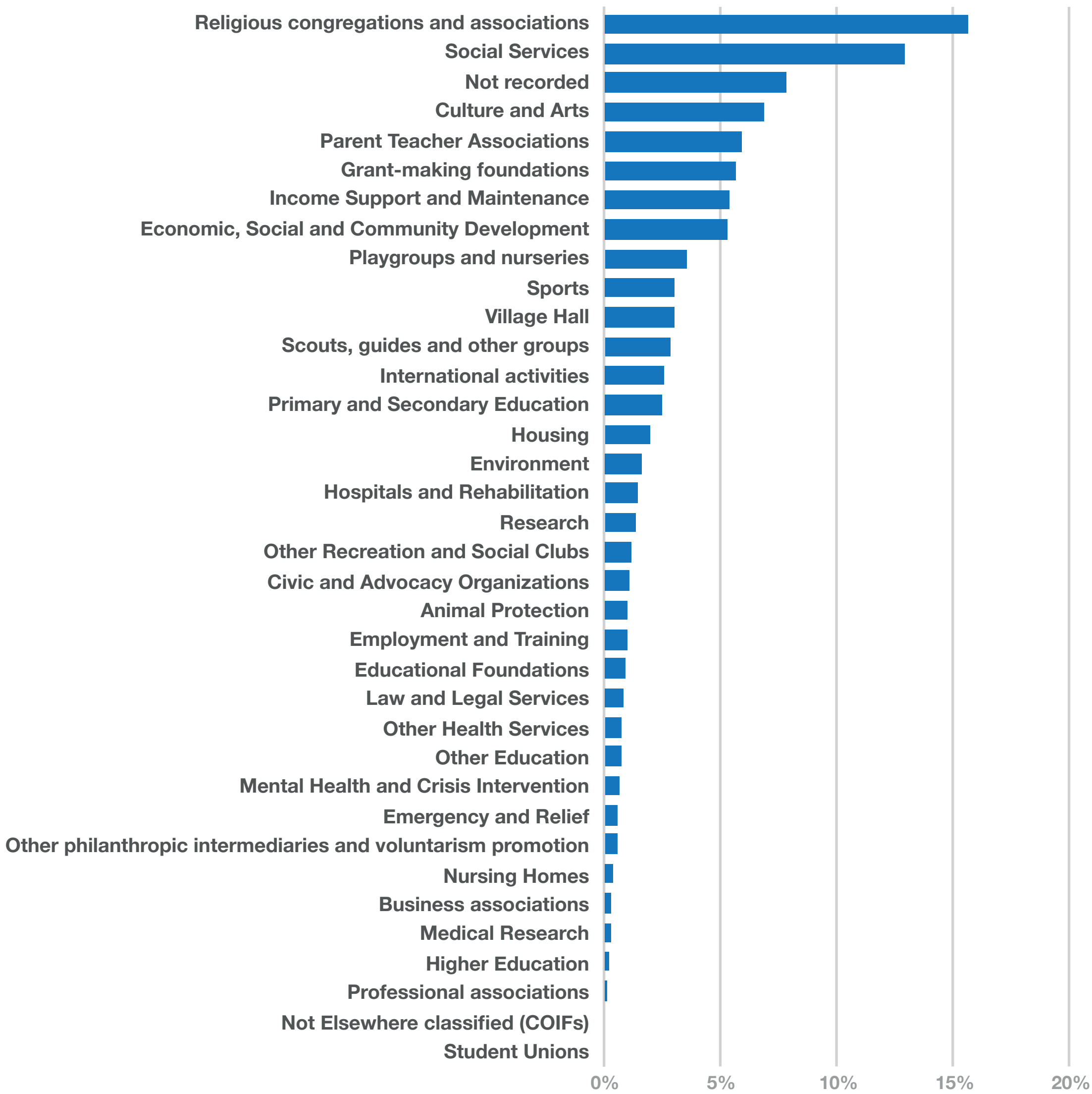
5.1. Step 1 – a mutually exclusive typology

NCVO and David Kane have already applied the ICNPO sector typology to the Charity Commission dataset so that every organisation is allocated to a one sector from the typology. This is a mutually exclusive set of allocations[5].

Fig1 shows the sorted list of the count of organisations represented in the data from 2009 to 2020. This is a total of 217,156 organisations.

[5] By contrast the Charity Commission data approach allows organisations to pick multiple activities from a list. As this structure is not mutually exclusive and very limited we cannot use it directly as a sector typology.

Figure 1: Charity Commission Organisations 2009_20



We are adding to this dataset over time by bringing in data from Companies House (COH) and the Mutuals Register (MR) in so far as it is made public by each organisation. Recent additions include data cohorts covering:

- Community Energy
- Community Shops
- Community Pubs
- Organisations who have undertaken a community shares offer
- Organisations who have successfully achieved social investment

Over time we will add in the COH and MR reporting organisations which are in receipt of grant funding from funders who report to 360 Giving. Where we already undertake work for a specific funder we are already maintaining up to date additions to the dataset.

5.2. Step 2 – Delivery-oriented Voluntary & Community Organisations

Our focus is the financial resilience of delivery-oriented voluntary and community sector (VCS) organisations as these are key to a functioning society and provide services in sectors such as education, healthcare, culture, housing and social care.

We have excluded some of the sectors above from subsequent work either because they are not directly involved in delivery e.g. grant-making foundations and organisations focussed on delivering international activities or because the primary funding route is a direct link from national and local government e.g. schools, universities, hospitals and similar. These latter types are not reliant on either trading activities or the winning of grants and contracts to ensure survival. Their resilience is thus underpinned directly by national and local government funding and to include them would be to skew the result.

5.3. Step 3 – Consideration of outliers

Very small organisations - The Charity Commission dataset contains a large volume of very small organisations. The financial models for these entities will, by necessity, be reliant on voluntary labour and other resources which are made available at below market costs (often free). In this sense resilience is achieved by needing little income to cover ongoing costs. Such financial models are not usually scalable and therefore cannot inform our thinking about resilience in entities with a larger set of fixed costs.

We have therefore excluded all organisations with an income in 2016-17 of less than £10,000.

Organisations with very large turnover changes in a two year period - As the Charity Commission data on income and expenditure quite commonly includes capital income and does not separate it out from the revenue income we have also excluded organisations whose surplus was outside a range of +/- 100% of turnover in 2016-17. Large injections of capital income tends to be achieved very rarely for any one organisation and its inclusion in a revenue model would skew the dataset very substantially. There is no guarantee that all organisations whose data displays this degree of income volatility have received capital funds but we expect it to be the most common cause. In some smaller organisations where the accountants have not amortised grants over multiple years and instead have shown the full grant in a single year the data would also appear as if there was a high degree of income and expenditure volatility. This first algorithm does not contain the granularity of data to separate out such reporting variations and thus it is safest to exclude such data outliers.

Young organisations - The first iteration of the algorithm draws on all organisations which have supplied non-zero data to the Charity Commission and are considered to be 'live' years from any year 2013 onwards. To be included in the analysis they organisation must be live in 2016-17. Failure rates of all businesses are much higher in the first few years of operation and for this reason future iterations of the algorithm will look at the need to exclude young organisations on the basis that their financials are not expected to be indicative of long term resilience.

This set of exclusions results in a dataset of approximately 65,000 organisations for which we have financial data during the period from 2013-2019. This is the cohort on which the first algorithm of underlying rates of financial failure is based.

In particular we have compared those who ceased trading in 2017-18 to those which have not failed financially in this period.

Fig2 shows the results of this algorithm as a set of underlying failure rates by sector. The blue line represents the all sector mean – 3.1% based on 2017-18 data.

5.4. Methods Summary

In order to create a risk rating we looked at the factors that were significant in explaining the difference between the organisations that ceased trading in 2017-18 compared to those that did not.

We used a binomial logistic regression analysis in order to estimate the probability of any one organisation failing, based on the presence (or absence) of the statistically significant risk factors.

These risk factors included the sector (which could increase or decrease the relative risk), the size (in terms of turnover) and a measure that we computed based on the change to the surplus over the last few years.

We carried out an in depth exploratory data analysis in order to identify likely candidates for variables that might explain financial failure. We tested alternative equations using the R statistical engine in order to find best fit.

This generated a set of estimates (coefficients) which we are then able to apply to any live organisation that has the relevant data, predominantly a financial history. As and when we are able to add further data we expect to refine and develop this algorithm.

Another way of expressing this is that we have identified those unique combinations of factors that increase risk by studying the failure rates, initially, in 2017-18. We then apply those estimates (co-efficients) to the data for any live organisation to create an individual risk score (probability of failure/resilience). These scores can be combined at a sector, portfolio or geographical level to create an aggregated risk score. These aggregated risk scorescan then be compared across portfolios or to a national score.

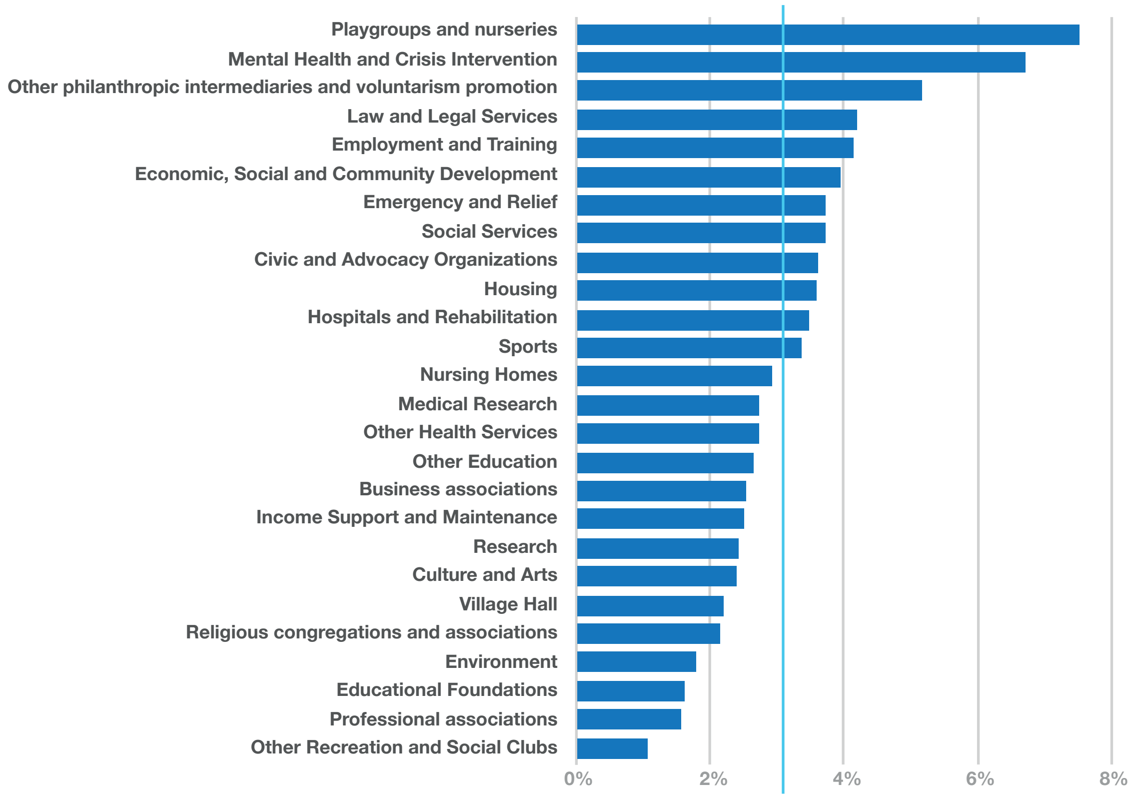
We are referring to the outputs of this work as algorithm I.

6. Results

The following results give us a baseline data set. We will be adding to this with data from Companies House and the Mutuals Register over the coming weeks.

6.1. Underlying Financial Failure by Sector

Figure 2: Percentage Ceased Trading in 2017_18



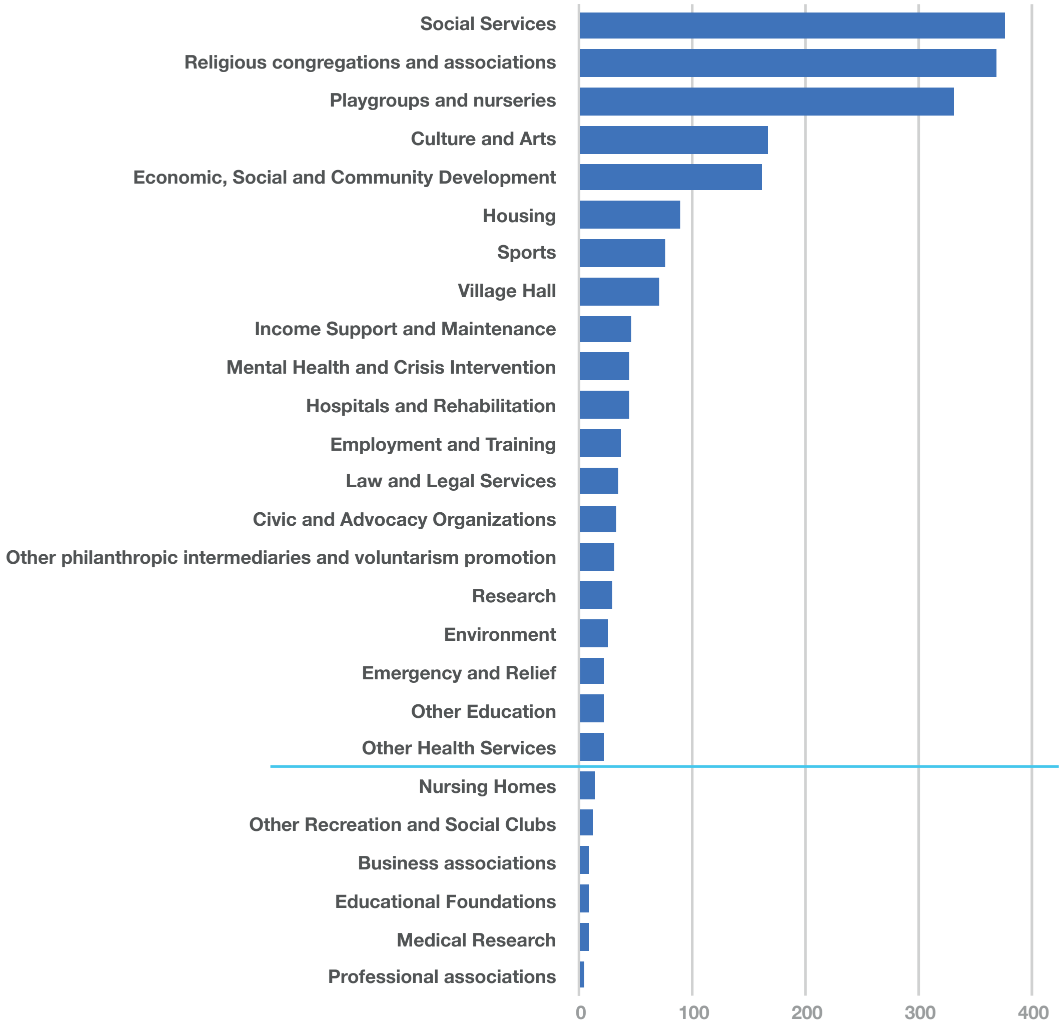
This chart shows the percentage of organisations that report to the Charity Commission which have ceased trading[6] in 2017-18 and the differences by sector.

This clearly demonstrates that some sectors of activity e.g. Playgroups and Nurseries are more prone to financial failure than others e.g. Village Halls.

It is important to note that not all sectors contain an equal volume of organisations. In order to avoid calculating an underlying failure rate on sectors with too little data for the result to be robust Fig 2 excludes the sectors with a count of less than 20. In Fig3 this means everything from Nursing Homes and below.

[2] Either formally closed or so late in their data submission for it to be reasonable for us to presume that they have ceased trading.

Figure 3: Number that ceased trading in 2017_18

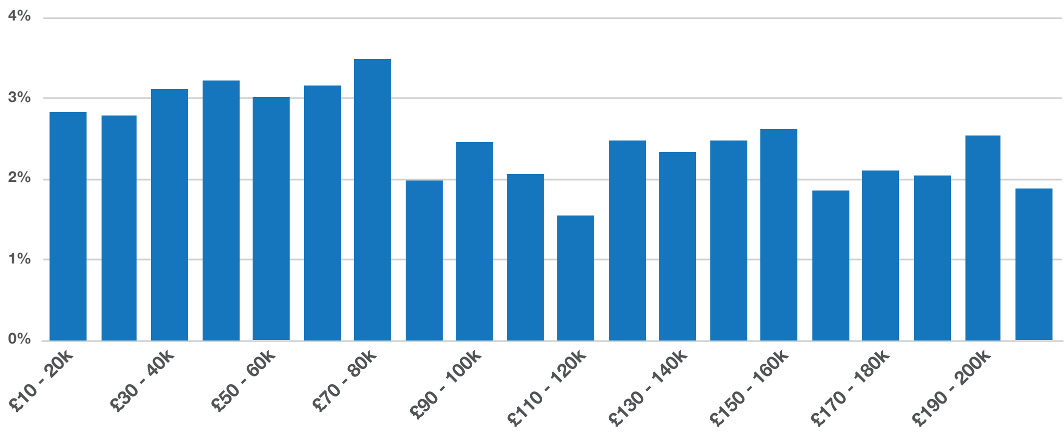


6.2. Underlying Financial Failure by Turnover

Failure of organisations is not evenly spread across all turnover bands. The rate of failure drops as turnover increases.

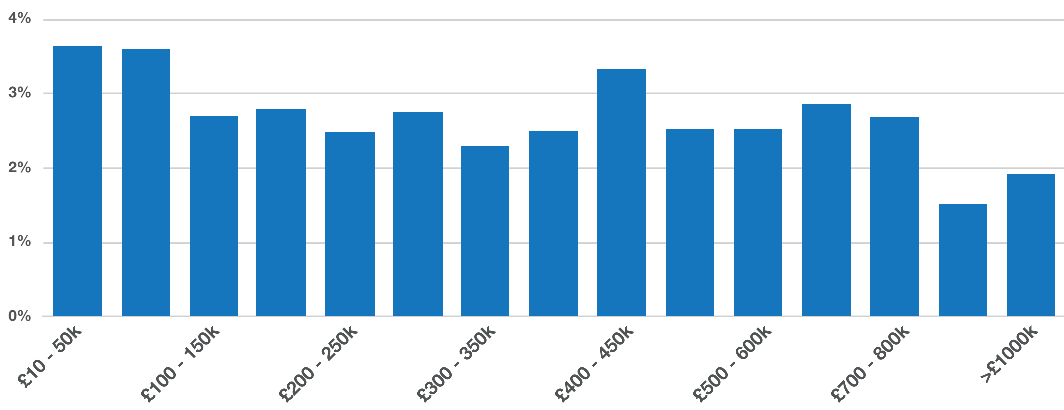
There is also a distinct shift in failure rates at the £80-90k turnover level i.e. higher risk for organisations with turnover below this level and as step change to lower risk as turnover exceeds £80k per annum. One possibility is that once organisations pass the VAT threshold (circa £90k) they are now required to submit quarterly VAT and tax data via an approved book-keeping system. This represents and inherent increase in financial management skills which may not exist in smaller organisations. However VAT only applies to trading income and not grants so this would not perfectly explain the phenomenon. We will explore this further in the next phase.

Figure 4: Percentage Ceased Trading in 2017_18 (lower incomes)



The rate of failure continues to reduce as turnover increases into the millions per annum.

Figure 5: Percentage Ceased Trading in 2017_18 (higher incomes)

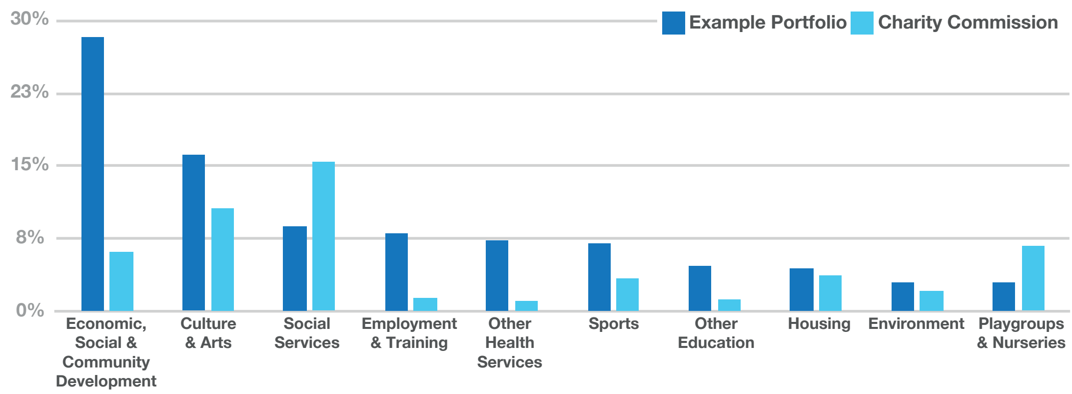


6.3. A Portfolio View

Up to this point all the charts do is show facts about failure rates of organisations in the Charity Commission dataset. Any data presented in blue is merely an expression of either failure rates or in the case of fig 6 the proportions of organisations in a portfolio by sector (no algorithm to see here).

Fig 6 shows the spread of organisations by sector in a portfolio vs. the national spread of all non-profits (as listed with the Charity Commission) by sector[7].

Figure 6: Sector Profile of Organisations in a Example Portfolio Compared to the National Distribution



We are presenting Fig6 in order to show that any given portfolio will be different from the national balance of non-profits by sector. It is a reference point for the analysis that follows.

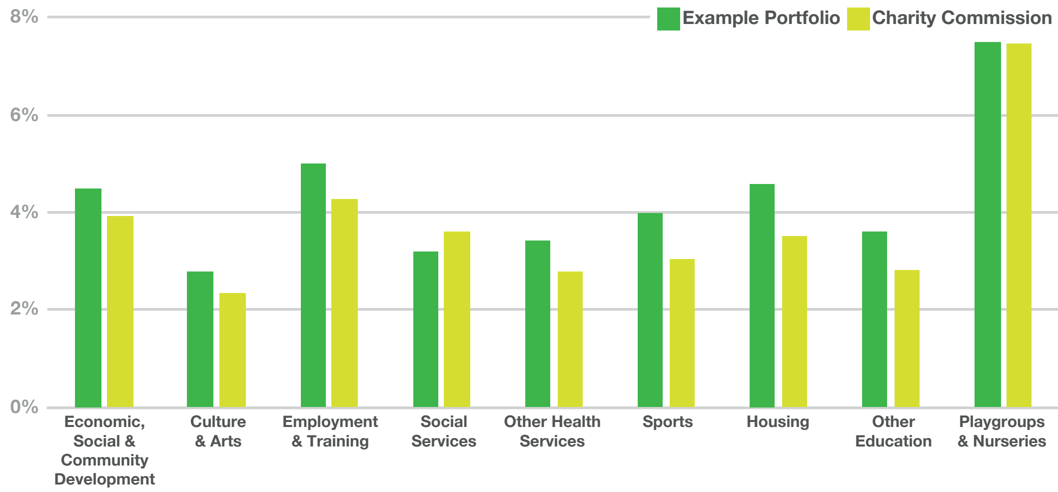
Algorithm I can be applied to a portfolio. The purpose of doing so is to identify the hotspots for risk of financial failure.

In particular when the perspective in Fig 6 on the dominance of some sectors over others in a portfolio is combined with the underlying risk score a picture starts to emerge of where the greatest challenges lie.

[7] It should be noted that no one portfolio (of grantees or investees) is likely to cover all the sectors found in the Charity Commission. For example this portfolio contains very few religious organisations or village halls which between them make up over 30% of all organisations registered with the Charity Commission.

Fig 7 shows the average risk score by sector and contrasts the national picture to a fictional example portfolio. You'll see that we've changed colour in order to denote the difference between facts (blue) and risk score (green).

Figure 7: Difference in Predicted Risk Score by Sector



This graph shows that the Example Portfolio has a group of organisations with a higher average risk score than the national picture. For each sector, with the exception of Social Services, the portfolio organisations are, according to the risk score, more vulnerable. The reason that they are more risky/less resilient is a reflection of their financial history. we are comparing the same sectors (nationally and portfolio) the variation in risk due to their sector does not apply.

If we were looking at a grant funder's portfolio we might expect to see concentrations by sector (not all sectors are included figs 6 & 7). This would influence the balance of risk across the portfolio as a whole. We might also expect to see concentrations by turnover band if a funder focusses either on capital funding (likely to exclude the very smallest organisations). Thirdly we might expect to see concentrations of risk if they are focussed on particular elements of a business model such as e.g. growth in trading, funding of innovation etc.

If we were looking at a social investor's portfolio we might expect that it would contain a greater degree of risk than the national picture given that the organisations are taking on debt either to buy them time to fix a business model which is no longer fit for purpose or in order to take the risks inherent in developing new income streams or maximising an opportunity to exploit a gap in the market.

An additional view point of this balance of low to higher risk organisations in a portfolio can perhaps be seen more easily when we simply look at a set of bands of risk rather than take a sector view of the data:

Figure 8: Comparative Risk of Portfolio to National Picture

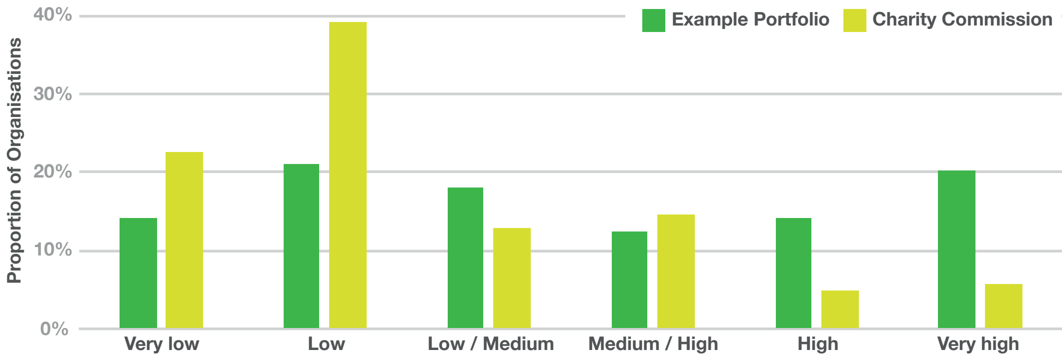


Fig 8 takes the portfolio and, ignoring sectors, looks at the range of low to high risk organisations. It compares the portfolio to the national balance of risk (in the Charity Commission). We are implying that we can identify individual organisations and their associated risk score. In reality, at the moment, we have further work to do to test and refine the accuracy of our analytical work and algorithm I which is based upon it.

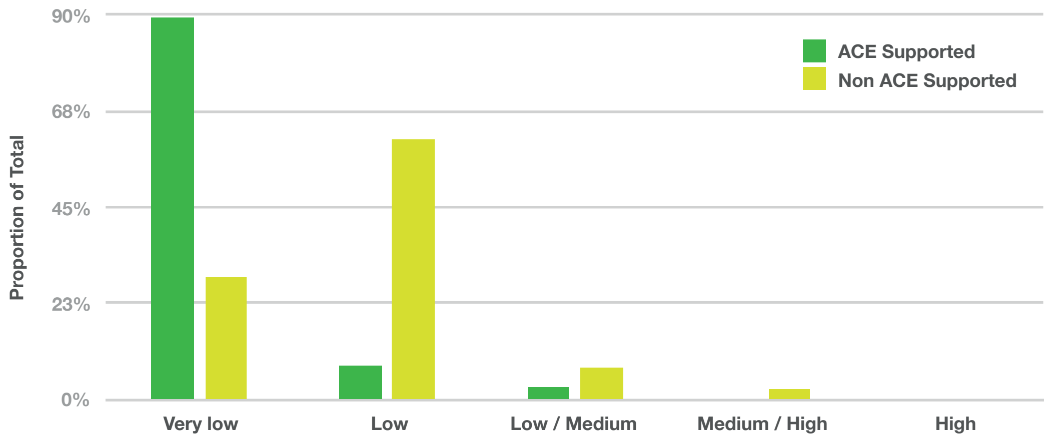
Figures 7 & 8 enable us to explore spread of risk across a portfolio, focus attention on potential at risk organisations. We can also explore portfolio balance versus the intentions of the portfolio manager.

It is worth noting that within a single grant funder or investor there will be a number of different funds. We expect that the mix of capital, delivery and innovation goals in a grant funder's programme will translate into variations in the risk and resilience of successful grantees. For social investors funds have a different capacity for risk which is reflected in the extent to which the fund can afford to absorb losses versus a requirement deliver a financially positive return.

We have not yet included this level of granularity in our analysis.

It should also be noted that whilst we can ascribe a risk rating by sector to all organisations the ability to encompass the influence of absolute turnover, relative changes in turnover, and contributions to/from reserves requires income and expenditure data. The gaps in Companies House data will therefore need to be filled by data supplied in confidence to a grant funder or investor.

Figure 9: Relative Risk of Culture and Arts Sector



In addition to looking at a portfolio as a whole we can focus on the risk scores for the organisations in a portfolio one sector at a time.

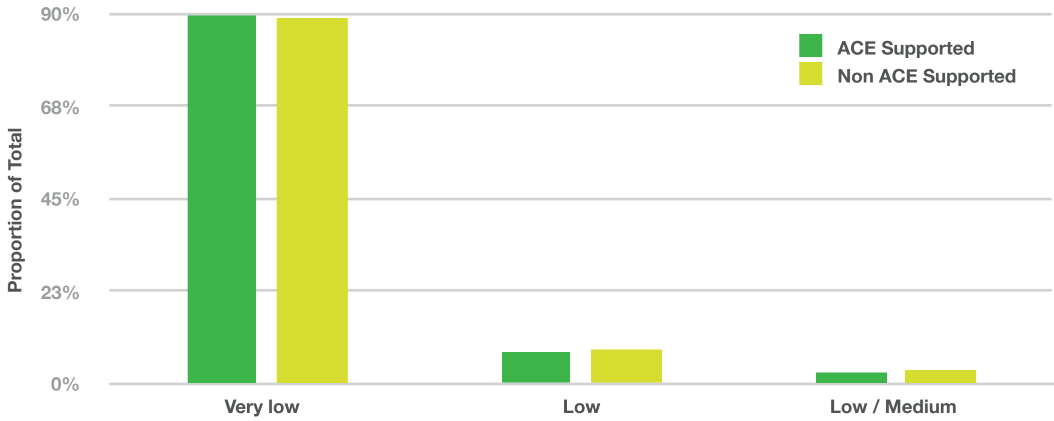
As an example we've taken a subset of the Arts Council England national portfolio (those who submit data to the Charity Commission) and mapped their risk ratings against the wider arts & culture sector data from the Charity Commission.

Once we exclude the smallest organisations from the first slice (contrast Fig 9 to Fig 10) we see that the risk in the portfolio roughly matches the risk in the wider sector. Our work with Cause4[8] on an arts and culture benchmark and with The Audience Agency on resilience[9] however would suggest that once we start breaking this down by art form, geographic region and turnover band we will start to see interesting variations in risk and resilience.

[8] https://artsfundraising.org.uk/benchmarking

[9] https://www.artscouncil.org.uk/publication/what-resilience-anyway-review

Figure 10: Relative Risk of Culture and Arts Sector, excluding smaller organisations



Algorithm I allows us to make a simple report on the portfolio balance of a grant funder or social investor.

It allows us to look at the extent to which a portfolio is taking more or less risk than is found nationally. It also allows us to show roughly where this risk sits by sector. We expect to be able to add slices which look at risk by turnover band shortly.

This level of algorithm is not sufficient to report accurately on risk for a single organisation.

To do that we would need a detailed P&L account and balance sheet, ideally for multiple years so that we can track the trends in key ratios such as trading : grant levels, working capital etc.

This is planned for phase 2.

7. Progress Summary

The key achievements in the past four weeks have been:

- The establishing of a regular and wide reaching set of data feeds - the myriad definitions of time periods, sectors, the variances in company names, need to identify duplicates and remove organisations which have closed but where their data has not be removed from the feed along with errors in the data. These were previously known to us but nonetheless have generated additional challenges when addressed at scale.

- The connection of a highly detailed financial benchmark with a set of feeds containing summary information – error rates and mismatches even within the same original datasource.

- Our analytical work (deploying a binomial logistic regression model to the Charity Commission data) has enabled us to identify those patterns in the financial history of an organisation, as well as other key explanatory factors (such as sector), that can be demonstrated to have a measurable impact on the underlying resilience (or not) of an organisation. It allows us to estimate the probability of an organisation surviving into the next year and, by judicious combination with other known information, enables portfolio managers to focus their attention rapidly on areas of greatest vulnerability.

- Exploring the algorithm in more detail, gives us further insight. For example it shows that risk is statistically significantly higher when turnover is below £80k and statistically significantly lower when over £1m and even allows us to estimate how much the probability of failure is increased, or decreased

When we apply this resilience rating to live organisations and view it in aggregate across a portfolio it generates a picture which meets our general expectations of the location and levels of risk based on our prior experience of a sector or cohort.

For example it shows us that smaller organisations are more risky than large organisations and it shows us that portfolios known to contain higher levels of debt finance than the national baseline also carry more risk. There is work ongoing to look at portfolio views matched to grant funder inputs and geographic areas. The checking is by no means complete; further improvements to the algorithm can be expected.

We are satisfied that the first iteration of this algorithm enables us to establish an underlying risk rating for all sectors. We consider it valid to use patterns in organisational failure in the Charity Commission dataset as a predictor of risk in live organisations. We consider it valid to apply this as a rating of an individual organisation if we limit the viewing of risk to the level of a portfolio i.e. with a degree of aggregation which purposefully counterbalances the lack of detail in the data we are using to drive the algorithm.

It should be noted that the crudeness of the financial data (total income, total cost, contribution to/from reserves) is such that to enable this resilience rating cannot be used as an accurate indicator of risk for a single organisation.

In order to achieve the goal of a resilience rating for individual organisations we will require the level of financial detail held in a set of annual accounts i.e. as found in the main MyCake benchmark dataset.

Other work streams are already developing the ability connect the benchmark data into dashboards of the types of key financial metrics used by social investors to analyse, track and monitor their portfolio. What we do not yet know is the relative weighting to apply to each key metric in order to harness this data into a more nuanced resilience rating system.

It is clear however we need to harness the long experience of managing risk and return found in investment and grantee portfolio managers. Whilst there is not a formal marketplace in which opinions on risk and return are tested in the battleground of stock prices the relative merits of an organisation are expressed in their ongoing ability to trade, their success in winning grants, their ability to secure debt finance and their backing by the community through share offers and volunteering.

In order not to bite off more than we can chew nor to make requests of a sector already flat out with providing emergency responses to the financial impact of COVID we will limit our goals for the next phase to two key activities:

- Testing the utility of the first algorithm via collaborations with grant funders, social investors and policy makers
- Developing a second algorithm which draws on more detailed financial data through a series of key metrics

Whilst the full list of metrics is yet to be agreed we expect it to include:

- trading : grant ratio
- salary spend as a proportion of turnover
- working capital

We also hope to explore the extent to which investment from multiple funders, investors and shareholders increases overall resilience.