



Title	Profiling Not-For-Profit Organisations with Machine Learning: The Role of Tax, Compensation, Acquisitions and Other Characteristics
Authors(s)	Matikonis, Karolis, Graham, Byron
Publication date	2023-06-23
Publication information	Matikonis, Karolis, and Byron Graham. "Profiling Not-For-Profit Organisations with Machine Learning: The Role of Tax, Compensation, Acquisitions and Other Characteristics," June 23, 2023
Conference details	The 14TH EIASM Workshop on the Challenges of Managing the Third Sector, Aberdeen, United Kingdom, 22-23 June 2023
Item record/more information	http://hdl.handle.net/10197/25873

Downloaded 2026-05-01 23:44:45

The UCD community has made this article openly available. Please share how this access benefits you. Your story matters! (@ucd_oa)



© Some rights reserved. For more information

**Profiling Not-For-Profit Organisations with Machine Learning:
*The Role of Tax, Compensation, Acquisitions and Other Characteristics***

ABSTRACT

Not-for-profit organisations (NPOs) are provided with support through tax reliefs and further funding in exchange for creating social benefit. They are, however, often accused of abusing and misallocating resources. Informed by configurational approaches, we apply a visual, non-parametric machine learning methodology to some of the largest UK annual financial micro-level datasets. The study profiles UK NPOs by establishing how their sectorial, growth and employment configurations differ from other organisations. The findings show that NPOs are more stable and more likely to become high growth firms. They have higher average employment than other organisations and most spend significantly more on employment-related costs and acquisitions than comparable organisations. The findings also show the interrelationships between lower tax paid and higher employment costs. The findings raise questions on the targeting and oversight of tax reductions, which are likely to be at least partly distributed through the inflated expenditure of larger NPOs.

Keywords: not for profit, charity, tax, compensation, acquisitions, United Kingdom

The UK has complicated not-for-profit organisation (NPO) taxation policies, but many NPOs may receive support through tax reliefs, mainly provided to those that are recognised by HM Revenue and Customs (HMRC) as charities. They do not have to pay tax on most types of income as long as they use the money for charitable purposes. These reliefs are accompanied by further funding. For instance, in response to Covid-19, the Chancellor announced £750 million for frontline charities in addition to an initial £330 billion of guarantees and £30 billion in support schemes available for all businesses (BEIS 2020).

It is expected that NPOs qualify for this support in exchange for creating social benefit. The fundamental principle for NPOs is that any surplus revenues should not benefit those with an interest in the organisation, but rather public interest. NPOs have long been associated with philanthropic rewards (Dempsey and Sanders 2010). Employees have been found to donate their labour by accepting submarket wages (Rose-Ackerman 1996) or extra workload (Knutsen and Chan 2014).

Having said that, management across all organisations is increasingly homogenous (Bromley and Meyer 2017). All sectors, including NPOs, are changing in similar ways and becoming more analogous, driven by the same practices and science underlying managerial practices (Leatherwood and O'Neal's 1996; Froelich 1999). NPOs and for-profit organisations now share a common pool of staff (Kim and Lee 2007; Ng et al. 2016) who are likely to be decision-makers shaping the organisation and, thus, in the power of distributing any tax savings or donations through above-market expenditure.

NPOs have been accused of abusing and misallocating resources. In some cases, trustees have been found to set their own salary without oversight and spending donations without appropriate

record-keeping (e.g., reported by The Charity Commission 2020). Owing to many scandals, the preferential treatment of NPOs has been extensively questioned by the media (Craig 2015).

This article aims to uncover NPO profiles by comparing configurations of key factors that distinguish organisations with an NPO status from other organisations to reveal whether the not-for-profit sector suffers from the misallocation of resources. It applies a data-driven strategy to some of the largest UK annual financial datasets, some of them capturing over 99% of annual business activity between 2000 and 2018. It also adds to the emerging literature on machine learning in policy research by supplementing the more standard descriptive and inferential statistics with supervised machine learning that enables to account for the nonlinearity and complementarity of NPO performance that, as Kolk's (2022) review suggests, have been lacking in research of NPOs for the past 20 years.

Contrary to expectations (Ruhm and Borkoski 2003; Johnston and Johnston 2021), we find that most UK NPOs have higher employment costs than comparable organisations. We identify the interrelationships between lower tax paid and higher employment costs. This is also the case with acquisitions. On average, NPOs also employ more staff, survive longer and are more likely to experience high growth than other organisations. The findings signal that the savings from the preferential tax treatment and other support may be distributed through acquisitions and inflated compensation practices.

The paper proceeds as follows. Section 2 discusses the background and forms research questions. Section 3 introduces the data that was used in the analysis, before discussing the variable choices and estimation methods. Section 4 presents the results of the study, including the profiles of factors that distinguish NPOs from other organisations. Section 5 discusses the findings, before offering conclusions in section 6.

BACKGROUND AND LITERATURE

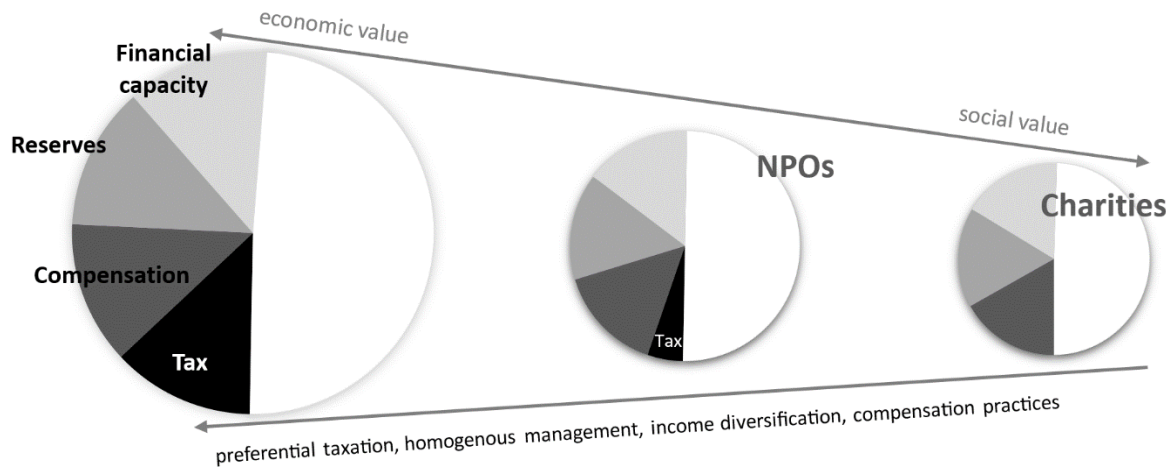
A not-for-profit, non-governmental organisation is a broad term for all independent organisations whose purpose is something other than to make a private profit for directors, members or shareholders. England and Wales is a common law, non-federal jurisdiction with five primary forms of NPOs: companies limited by guarantee, unincorporated associations, trusts, registered societies and charitable incorporated organisations. The organisations jointly own a non-distribution constraint on economics surplus, but the taxation regime for UK NPOs differs from for-profit organisations. Most notably, they receive discretionary reliefs from non-domestic property tax¹ as well as exemptions from VAT² for supplies of sporting, education and cultural services. The extent of these reductions is highly dependent on the company, its activities and its circumstances.

We draw on the literature to understand how this preferential tax regime interrelates with such factors as increasingly homogenous management across sectors, NPO income diversification and generous compensation practices. Our theoretical reasoning is illustrated in Figure 1. The changes in the NPO sector could potentially drive them away from social value creation. NPOs then would grow and distribute gains from the preferential tax treatment through excessive compensation, acquisitions and reserves.

¹ UK's tax system largely based on property. The commercial property tax reliefs were rising at unprecedented pace over the past decade (Gobey and Matikonis 2021 and Matikonis 2020).

² A value-added tax (VAT), known as a tax on consumer expenditure.

Figure 1 Theoretical Reasoning



The figure is only for illustrative purposes. The pie charts show how tax savings could potentially be absorbed by other than social activities. Arrows refer to the movement from social value to economic value creation and the main factors driving that.

NPO Characteristics

Although NPOs are highly heterogeneous and offer various services, management across all organisations is increasingly homogenous (Bromley and Meyer 2017). All sectors, including NPOs, are changing in similar ways and becoming more and more analogous, driven by the same practices and science underlying managerial practices. Larger NPOs now often operate as hybrid organisations (Hustinx et al. 2014) and diversify their income streams by adding business units similar to those of for-profit organisations (Froelich 1999; Easterly and Miesing, 2009).

Diversification of incomes has been found to increase efficiency (Ecer et al. 2017), financial independence (Pfeffer and Salancik 2003; Shon et al. 2019) and reduce financial vulnerability (Carroll and Stater 2008) by reducing the dependence on traditional funders.

Diversification has made it even more difficult to find an appropriate metric to measure NPO performance. Scales could focus on particular sector (Sabatier 2012; Moldavanova and Wright

2020), perception (Nederland 2020), subjective satisfaction ratings, third party evaluator metrics (Grant and Potoski 2015), grant funding (Faulk et al. 2017) or could rely on social impact, but these are rarely uniform or comparable. Thus, some researchers have resorted to assessing the growth in number of NPOs (Clifford 2016), expenditure (Van der Heijden 2013), revenue (Minaker 2021), board functions (Cornforth, 2001) and financial capacity (Bowman 2011; Chikoto and Neely 2014; Yan and Sloan 2016; Hodgkinson and Hughes 2019), which is broadly defined as the ability for an organisation to adapt to unforeseen pressures and seize opportunities (Bowman 2011). This study joins Chikoto and Neely (2014) who have used organisation size to assess the financial capacity. Focusing on size rather than social impact provides a more effective way of assessing and comparing the performance of NPOs, particularly when combined with measures of increased diversification (Dees 2003; Arya and Mittendorf 2015).

Alter's (2007) spectrum and subsequent studies (Laasch 2018) places social value creation in the opposite direction to economic value creation. NPOs could be moving further from social sustainability to financial sustainability and possibly reshaping their mission and stakeholders owing to the changing environment (Kuruppu and Lodhia 2019). However, the distinct requirement of NPOs states that they need to reinvest any profit back to the organisation (Hansmann 1980), allowing for an above-average expenditure on either social programmes or operational costs.

Compensation and Reserves amongst NPOs

More specifically, NPOs may accumulate³ tax savings and donations rather than allocate them directly, pound-for-pound, to their social objectives. The main motive for NPOs to save money is to prepare for potential revenue shortfalls (Jones et al. 2013) and associated revenue volatility (Fisman and Hubbard 2003 and 2005). Accumulation of reserves may also be driven by the need to smooth income, comply with terms of gifts, independence from questionable contracts and social status (Chang and Tuckman 1990 and Tuckman and Chang 1992).

On the other hand, there have been several calls for some NPOs to separate and report their spending on administrative costs, as these have been associated with inefficiency (Callen et al. 2003), deviation from social objectives (Bowman 2006; Lecy and Searing 2014) and reduction in donor confidence (Jacobs and Marudas 2009; Tinkelman and Mankaney 2007). Most notably, we may see the retained surpluses employed to support inflated compensation policies. This may seem counterintuitive as NPOs have been associated with lower than market wages, more philanthropic rewards (Dempsey and Sanders 2010; Bastos et al. 2014) and longer work hours (Feeney and Bozeman 2009). Employees have been found to donate their labour by accepting submarket wages (Rose-Ackerman 1996; Ruhm and Borkoski 2003; Johnston and Johnston 2021) or extra workload (Knutsen and Chan 2014) but had higher job satisfaction (Becchetti et al. 2014).

Having said that, compensation practices for managerial and professional staff could outweigh these lower than market wages as NPOs and for-profit organisations share a common pool of

³ Note that Morris et al. (2018) find that this is not the case for most of US NPOs with approximately half of them having less than one month of operating reserves. These low operating reserves are more likely to be found in smaller NPOs.

staff (Kim and Lee 2007; Ng et al. 2016) who are likely to be decision-makers shaping the organisation and, thus, in the power of distributing any tax savings or donations through above-market compensation. The shift towards economic value creation encouraged appointing board from non-social economic background (Bruneel et al. 2020). Private sector experience amongst senior managers was found to have a negative effect on their commitment to public organisations (Andrews et al. 2019). Wage increases associated with promotions were similar amongst NPOs and for-profit organisations but less likely to be based on merit or job performance (Devaro and Brookshire 2007) and in fact, 45% of US NPOs paid bonuses (Balsam and Harris 2018) and 24% provided perquisites (Balsam et al. 2020) to their executives that were found to use this to even influence election campaigns (Cox 2020). In general, corporate performance was found to have only weak connection to pay awards (O'Reilly and Main 2010).

High compensation packages in the not-for-profit sector were also found to be associated with larger firms (Balsam and Harris 2018 and Balsam et al. 2020), especially for NPOs involved in diversification (Moulick et al. 2019). Moulick et al. (2019) show that although US NPOs with lower involvement in for-profit activities still have lower compensation, those with more involvement in for-profit activities experienced a significant increase in compensation. This is likely to be due to differing income streams (Shon et al. 2019). Reliance on a sole type of income restricts spending on compensation, but diversification provides greater flexibility for organisations to allocate their resources.

Charities

We would expect even more substantial tax savings from NPOs recognised by HMRC as charities. Charities are not required to pay tax on most types of income as long as they use the money for charitable purposes. Their donations and profits from trading, rental or investment

income, selling an asset or purchase property are tax-free. They still, however, have to pay tax on other profits and purchases and contribute to non-domestic property taxation with an 80% discount⁴.

Having said that, unlike other NPOs, charities are required to prepare a set of accounts, an annual return and a Trustees' Annual Report. These reports are aimed at assuring their community that tax exemptions and support have been put to good use. Accountability is often studied through stakeholder theory, recognising the need to account for multiple stakeholders whilst including an ethical dimension (Ebrahim 2003), implying that charities could also determine the contribution of their social benefit. However, the empirical findings (Dhanani and Connolly 2012; Hyndman and McConville 2015; Dick and Coule, 2020) show that UK charities were found to be motivated by a more positive model of stakeholder theory. They used reporting to legitimise their activities rather than ethically showing their performance.

Configurational Approaches

To improve our understanding of the heterogeneity of these organisations, we draw on complexity theory to develop profiles that distinguish NPOs from other types of organisations. The complexity theory rejects a 'one size fits all' approach to studying organisations, enabling us to untangle the pathways of configurations that distinguish the different organisational forms. We build profiles by comparing NPOs and non-NPOs, and by comparing NPOs with charities. The profiles are based on configurations of key organisational characteristics, including tax, compensation, acquisitions, size, age, and employment costs.

⁴ Or even 100% when accompanied by discretionary relief.

The complexity theory extends to configuration approaches that are based on analysing the multidimensional constellation of conceptually distinct characteristics that commonly occur together (Meyer et al., 1993). This approach recognises the heterogeneity of organisations as a combination of factors that are particular to them. The relationships among these factors are non-linear, and two or more configurations may be equifinal in affecting the outcome variable (Meyer et al., 1993). This conceptualisation enables us to depart from strictly linear relationships and recognises that variables found to be positively related in one configuration may be unrelated or even inversely related in another (Meyer et al., 1993). Configurational approaches typically draw on set theoretic methods (Fiss 2007), or on machine learning methods which segment observations based on particular features (Graham & Bonner 2022). The latter approach has also been utilised in past work to develop organisational profiles (Duchessi and Lauría 2013).

Thus, we extend our discussion, summarised in Figure 1, by incorporating insights from configurational approaches in our research questions:

- Do NPO profiles include greater financial capacity? (R1)
- Do NPO profiles include greater expenditure on compensation and reserves, compared with other firms? (R2)
- Do charity profiles have higher levels of compensation and reserves compared with other NPOs? (R3)

RESEARCH DESIGN

Data

Three datasets are used to address the research questions, with each used to address one research question as shown in Table 1. To answer our first research question, the first dataset is obtained from the UK Office of National Statistics (ONS) Business Structure Database (BSD). The BSD is estimated to cover 99% of business activity, across a limited range of variables to provide a general description of the differences in characteristics between charities, NPOs and non-NPOs . We use annual reporting unit level data, including all single and multiple-unit enterprises that were active that year. The BSD variable names and descriptions are presented in Table 2. Refer to Appendix 1 for more detailed steps in data validation and matching of ARDx data. The dependent variable used to address R1 from the BSD data is a dummy taking a value of 1 when an organisation is classified as an NPO and 0 otherwise.

Table 1 Summary of Final Datasets for Analysis

	Dataset 1	Dataset 2	Dataset 3
Question	R1	R2	R3
Dependent Variable	NPO or non-NPO	NPO or non-NPO	NPO or Charity
Initial Dataset	BSD	ARDx	ARDx
Dataset for analysis	Full dataset	1-1 matching of NPOs to other firms	1-1 matching of charities to NPOs
Final sample size	849,614	3,927	972

Refer to Appendix 1 for more detailed steps in data validation and matching of ARDx data.

Table 2 BSD Variable Description

Variable	Description
NPO dummy*	A dummy taking the value of 1 when an organisation is classified as an NPO and 0 otherwise.
Charity dummy*	A dummy taking the value of 1 when an organisation is classified as a charity and 0 otherwise.
Employment	Number of employees
Turnover	Income that a firm generates through trading its goods and services in thousand £
Age*	Age in years
Labour productivity*	Income that a firm generates through trading its goods and services in thousand £ per employee
Size at birth*	According to the EU Commission Recommendation (2003), a micro firm does not have more than 10 employees and turnover higher than £1.8m. A small firm not more than 50 employees and turnover higher than £9m and a medium-sized firm not more than 250 employees and turnover greater than £45m. Thus, a dummy variable has been created: 1=micro, 2=small, 3=medium, 4=large.
High growth firm (HGF)*	A dummy taking the value of 1 in the years it meets the Eurostat-OECD (2007) definition, namely average annualised growth in employment (or turnover) greater than 20% per annum, over a three-year period with initial employment not lower than ten.
Foreign ownership*	A dummy taking the value of 1 when ownership is outside of UK.
Region	Wales, Scotland, North East, North West, Yorkshire and Humberside, East of England, East Midlands, West Midlands, London, South East and South West
Sector	Wholesale, catering, construction, production, property, retail and other services

* denotes derived variables. The variables were used to answer R1 and for matching to answer R2 and R3. Note that for matching, motor trade sector was also used. It is not available in BSD. For consistency, all values in € are converted to £ as of 5 June 2020 09:14 UTC.

To address research questions two and three, we apply a quasi-natural experiment design⁵ which enables us to better capture the change in organisations and also reduces endogeneity bias by eliminating firms that do not have common characteristics. A case-control approach is used to create the datasets for these questions. The data for both is derived from the full ARDx dataset, which combines two existing surveys, the Annual Business Inquiry (1998-2008) and the subsequent Annual Business Survey (2009-14). Representatives of organisations are legally required to complete this survey, producing high response rates. The sample frame for the full ARDx dataset is constructed using administrative data on employment and turnover from PAYE⁶ and VAT registered firms. It is a census of firms with 250 plus employees, with smaller firms sampled by stratifying population across size, sector and region.

Corsened Exact Matching (CEM)⁷ is used to generate the matched samples for the second and third datasets. The broad mechanism behind CEM is to group each variable by recoding so that appropriate similar values are assigned the same value. To generate the second dataset from the full ARDx data, each NPO was matched to an equivalent non-NPO organisation. Organisations were matched based on employment, turnover, labour productivity, region, and sector. Firms were matched on their first year appearing in the dataset, or for youthful firms their first observable year. This resulted in a final dataset for analysis consisting of 38,048 organisations,

⁵ Another alternative is within transformation based on an assumption that all relationships are population-level or fixed, which is unlikely to hold in reality owing to differences between businesses. Also, instrumental variable approaches are often applied, but they require strong instruments influencing some variables but not others.

⁶ Pay As You Earn, is the taxation withholding mechanism whereby employers deduct taxation from employee income on behalf of the tax authorities.

⁷ CEM does not use the random pruning applied in Propensity Score Matching, commonly applied in the field, e.g. in Wamser (2014), which is shown to increase the level of imbalance (King et al. 2019).

made up of 19,024 NPOs and 19,034 non-NPOs. The dependent variable used to address R2 is a dummy taking a value of 1 when an organisation is classified as a NPO and 0 otherwise.

To generate the third dataset from the full ARDx data, each organisation with an HMRC charity legal status was matched to an equivalent NPO. As in the generation of the second dataset, matching was based on employment, turnover, labour productivity, region, and sector. Firms were again also matched on their first year appearing in the dataset, or for youthful firms their first observable year. This resulted in a final dataset for analysis consisting of 972 organisations, made up of 486 charities and 486 NPOs without a charity status. The dependent variable in this dataset is a dummy taking a value of 1 when an organisation is classified as a charity and 0 otherwise.

The variable descriptions for the second and third datasets are presented in Table 3 below.

Table 3 ARDx Variable Description

Variable	Description
NPO dummy	A dummy taking the value of 1 when an organisation is classified as an NPO and 0 otherwise.
Charity dummy	A dummy taking the value of 1 when an organisation is classified as a charity and 0 otherwise.
Employment costs	Employment costs include gross wages and salaries, redundancy and severance payments to employees, employers national insurance contributions and contributions to pension funds
Purchases	Total purchases of goods, materials and services
Acquisitions	Acquisitions include acquisitions of land, existing buildings and any other acquisitions
Disposals	All disposals
Tax	Total rates, duties, levies and taxes

These variables were used to answer R2 and R3.

Analysis Approach

The analysis approach draws on machine learning to examine configurations and profiles, alongside more traditional inferential statistical techniques. Machine learning approaches were adopted to address all three research questions, and inferential statistics were used to supplement the analysis for research questions two and three. This is driven partly by the nature of the data, in which R1 relies on population data, whereas R2 and R3 draw on sample data. The use of inferential techniques is beneficial in enabling generalisations from the sample to the population.

Machine learning techniques have become increasingly popular in the social sciences for both theory testing and generation, complementing existing inferential statistical approaches (Shrestha et al. 2021; Tidhar & Eisenhardt 2020). These approaches have also been adopted in policy research (e.g. Brunori and Neidhofer 2021 and Kukk et al. 2022). As Bertomeu (2020) and Kleinberg et al. (2015) show, some policy issues can be solved better with ML built on predictions of a dependent variable from independent variables instead of focusing on causality. Millainathan and Spiess (2017) explain that scholars of economics often rely on one-point coefficients, β , estimated by comparing the variance in dependent, y , and independent, x , variables. These estimates can often be inconsistent,⁸ especially when we take an algorithm built for \hat{y} and presume that their coefficients, $\hat{\beta}$, will be associated with estimation output. The ML tools solve this issue, but they capture \hat{y} and not more typical $\hat{\beta}$. Thus, they cannot answer all policy questions, but are superior at answering others (Kleinberg et al. 2015).

⁸ See Basu (2020) for the discussion of inclusion of variables in OLS.

ML can uncover generalisable, multi-dimensional patterns from very extensive datasets and incorporate all possible functional forms (Bertomeu 2020). We expect to see many outliers in large datasets that are addressed by isolating those groups in the tree. We also expect to see non-linear relationships across very heterogeneous organisations under a not-for-profit umbrella. These heterogeneous firms may differ across regions and sectors. The ML enables us to control for this when comparing their characteristics and expenditure to other organisations. On the other hand, ML approaches are often susceptible to overfitting (Cook and Goldman 1984) and instability (Briand et al. 2009) which are addressed in Appendix 2.

To profile the features and expenditure of not for profit organisations in the UK, we use the recursive partitioning algorithm (Thereneau and Atkinson 2015). The algorithm recursively segments the data into increasingly homogenous groups based on the dependent variable, in effect classifying observations into groups based on the dependent variable. In our case, a completely homogenous group would consist of one that has all of the same type of organisation (NPO or non-NPO). The algorithm first searches across the variables to identify the variable, and the point within that variable, that results in the most homogenous groups if it is used to split the data. For each sub group, the procedure is repeated, further splitting the data into increasingly homogenous child nodes. This process is repeated until a stopping criterion is reached. By doing so, it incorporates all possible functional forms where their inclusion decreases error. There have been several literature reviews conducted on the development of decision trees (Loh 2014), so refer to them for more detail.

Modelling

The classification tree algorithm does not require the definition of additive or multiplicative relationships with legal status and can be expressed as;

$$\gamma_{it} = \gamma_{it}^* = f(.) = f(t_{it}, g_{it}, \rho_{it}, a_{it}, r_{it}, s_{it}, t_{it}, l_{it}, ID_i, FO_{it}) ,$$
$$i = 1, \dots, I \quad t = 1, \dots, \quad (1)$$

To answer R1, the dependent variable is γ_{it} , which is a dummy taking the value of one when an organisation i in period t is reporting its legal status as not for profit and zero otherwise. To answer R3, the dependent variable becomes γ_{it}^* which is a dummy taking the value of one when an organisation i in period t is recognised by HMRC as a charity and zero otherwise.

Other variables in equation (1) are aimed at defining the characteristics of firms required to answer R1. They are limited by BSD coverage. To capture the current size, we firstly focus on turnover, t_{it} and employment, l_{it} , to identify the key trends. To capture the relationship between these two, we also estimate revenue per employee, $tl_{it} = \frac{t_{it}}{l_{it}}$, which we define as labour productivity. We also use these values to estimate size at birth (ρ_{it}), which we define according to the EU definition (Commission Recommendation 2003). All firms above these thresholds are considered to be large. To differentiate between firms that are growing quickly, we include a variable, g , which is a dummy taking the value of 1 in the years in which it meets the Eurostat-OECD (2007) definition, implying that an average annualised growth in employment or turnover should be greater than 20% per annum over a three-year period with initial employment no lower than ten. Finally, we capture stability with the variable for age (a).

To at least partly control for random effects⁹, we also include a unique dummy variable for each firm, ID_i and year, t_t . We also control for the broad sectors (s) of wholesale, catering, construction, production, property, retail and other services: regions and nations (r) of Wales, Scotland, North East, North West, Yorkshire and Humberside, East of England, East Midlands, West Midlands, London, South East and South West; a foreign ownership dummy variable FO that takes one for firms with a foreign majority owner.

To answer for R2 and R3, we used matched ARDx data. Therefore, we now exclude all the other variables that were used for matching. We answer whether NPOs spend more on compensation and/or acquire more in reserves than comparable non-NPOs with the most aggregate variables to summarise their accounts: ec_{it} is total employment costs, gm_{it} is purchases of goods, materials and services as well as acquisitions, ac_{it} , and disposals, di_{it} . Our final tree, then, becomes:

$$\gamma_{it} = \gamma_{it}^* = h(ec_{it}, gm_{it}, ac_{it}, di_{it}, ID_t, t_i) \quad (2)$$

RESULTS

Do NPO profiles include greater financial capacity?

Table 4 presents the descriptive statistics for the BSD dataset, showing the key characteristics of NPOs and other organisations between 2000 and 2018. This provides insight into financial capacity, as well as describing the variables used for matching. Table 4 indicates substantial differences in employment and age between NPOs and non-NPOs, which we further explore

⁹ Note that several tree-based algorithms are capable of controlling for random effects, but they cannot handle a lot of missing data or require more computational power than available in the Secure Lab.

over time in Figure 2. NPOs have twice the employment level of non-NPOs, and the difference is even greater post-recession. By looking at the age, we uncover that NPOs tend to either survive much longer than other organisations or experience fewer entries and exits from the market. We also see that they are ten times more likely to have experienced substantial growth, exceeding 20% in either employment or turnover in the three previous periods, either pre or post-recession, but the proportion is still marginal. Only about 1% of annual observations from NPOs experienced high growth.

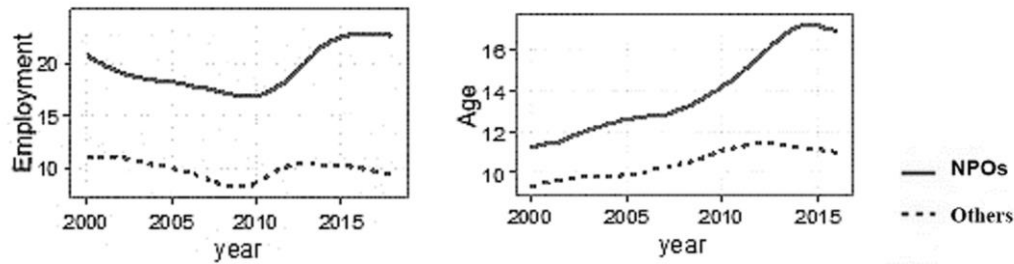
Only a small proportion of NPOs are foreign-owned. NPOs also have lower turnover, but have a much higher labour productivity, indicating a high proportion of non-employing NPOs. Their initial size also tends to be slightly larger than that of other firms, but the recent trend is downwards towards smaller firms for all organisations.

Table 4 Descriptive Statistics of BSD data.

Variable	NPOs		Non-NPOs	
	Mean	St. Dev	Mean	St. Dev.
Employment	19.5	187.3	9.8	347.6
Turnover in £'000	1000.3	30353.3	1538.2	144364.2
Age	14.1	10.7	10.5	9.6
Labour productivity	181.8	18640.5	79.3	6289.8
Size at birth	1.1	0.4	1.1	0.3
High growth firm	1%	1%	<0.01%	10%
Foreign ownership	<0.01%	2%	0.2%	4%

The table excludes region and sector and its values are after cleaning. Variable descriptions are in Table 2. The figures are based on BSD data and were estimated with the R programming language.

Figure 2 Average Employment and Age over Time



Variable descriptions are in Table 2. The figures are based on BSD data and the graphs were prepared with R.

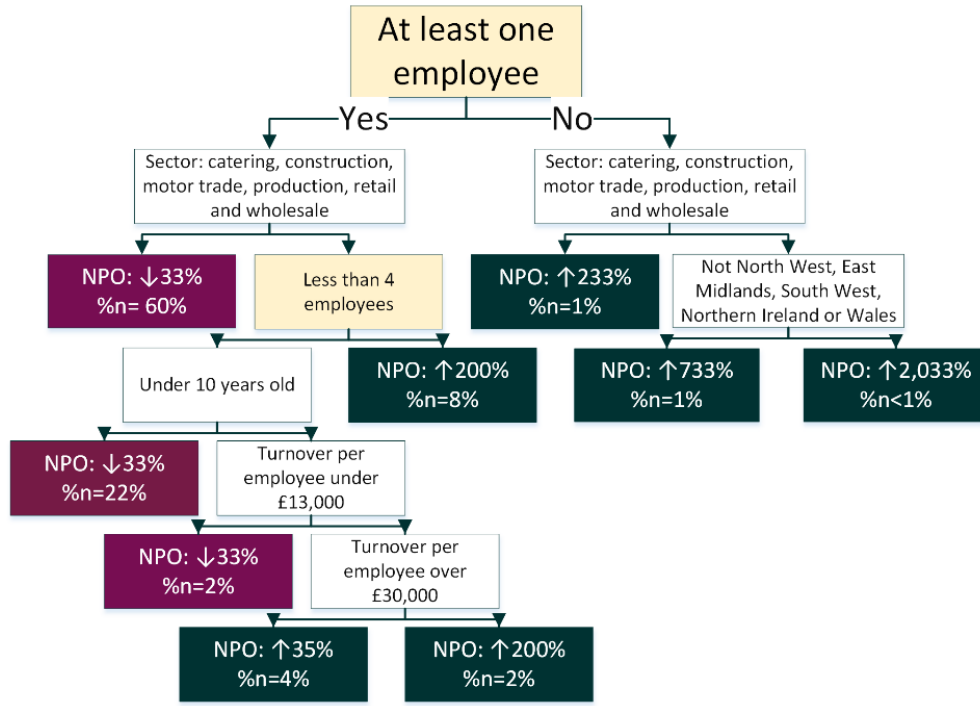
To address our first research question, we apply the decision tree algorithm to model the complex and non-linear patterns in these variables, enabling us to profile the organisations. The algorithm works by recursively splitting the data into purer segments of firms that are either NPOs or non-NPOs. The terminal nodes in the tree show the likelihood of being classified as an NPO based on the independent variables. The splits are not strictly hierarchical, as variables can enter a branch more than once but with different sub-values for points at which the data is split.

The tree structure is presented in Figure 3 and shows the dynamics related to employment, age and sector. The tree first splits on employment, indicating that this is the variable that best separates firms into NPOs and non-NPOs. We first move left of the principal split and follow firms employing at least one person, which include most of the observations (98% of all observations). This was further split into sectors. Only 1 in 50 organisations (a decrease of 33% from the average) operating in wholesale, catering, construction, production, property, retail sectors were NPOs, but 1 in 25 (an increase of 33% from the average) were in other service sectors. The latter segment of firms was further split based on employment. 1 out of 10 (an increase of 200% from the average) firms employing more than three people were operating as NPOs. For micro-firms employing between one and three people, we have further splits on age

and then labour productivity. Older firms and more productive (with higher revenue per employee ratio) firms were more likely to be NPOs than others. Those older than nine years with a labour productivity of at least £13,000 have a 4% likelihood of being classified as NPOs (an increase of 35% from the average), while more than doubling the revenue threshold to at least £30,000 increases the likelihood to 9% (an increase of 200% from the average) for the same firms. We do not see any further significant splits from other variables affecting organisations with at least one employee.

For non-employing organisations, the likelihood of being classed as an NPO increases more than fivefold. Furthermore, this likelihood is also affected by the region in which organisations are located. Following the principal split to the right, the probability of being an NPO increases fivefold for firms with no employees, but these account for only slightly over 2% of the whole population. We again observe that NPOs are less prevalent in wholesale, catering, construction, production, property, retail sectors, but now the likelihood of them being classed as NPOs is more than double (an increase of 233% from the average) even in those sectors without any employees. For a small number of organisations in other sectors, the likelihood of being classified as an NPO is extremely high (over 10 times the average). Out of these, 64% (an increase of 2,033% from the average) which are situated in North West, East Midlands, South West, Northern Ireland, Wales are NPOs, and 24% (an increase of 733% above average) in other regions.

Figure 3 BSD Tree (in colour)



The tree-like model of decisions and their possible consequences identified two broad groups of firms that have an increasingly homogeneous variation of the likelihood of being classified as an NPO. The first grouping is on the employment costs on which the tree splits into two branches. Those to the left are firms employing at least one person (98% of the total population). Those to the right are non-employing businesses. Figures in the final nodes are revised to aid interpretability. On average, 3% of firms were NPOs. Thus, the probabilities are accordingly converted to aid comparability. In the final nodes, the upper figures relate to increases (in green) or decreases (in burgundy) in the probability of being classified as an NPO in %, and the lower figure (%n) refers to the proportion of the sample in the terminal node. Figures are in £'000 after matching on variables in Equation 2. Variable descriptions are in Table 2. The figures are based on BSD data, calculated by using the R programming language and redesigned with Microsoft Visio.

Do NPO profiles include greater expenditure on compensation and reserves, compared with other firms?

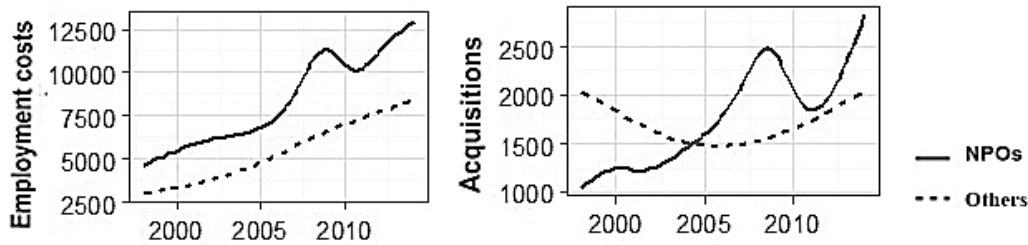
Table 5 shows the firm-level summary statistics of key variables measuring spending for NPOs and other organisations using the comprehensive ARDx dataset. We account for the previously described differences and focus on the matched NPO and non-NPO dataset, which is used to address R2. This dataset consists of 38,048 organisations from the wider ARDx dataset. As expected, NPOs pay 78% less in tax and have 62% lower purchases and 4% lower disposals. However, in support of the positive relationship in R2, we find that, on average, NPOs tend to spend more on employment and acquisitions than comparable organisations. NPOs have 54% higher employment costs and 3% higher acquisitions. Figure 4 shows the trend over time for these variables. Although an upward trend, similar to other organisations is evident, NPOs' employment costs and acquisitions rose steadily, especially during the recession. The ARDx database, unlike BSD, does not provide data on all organisations. Thus, we use the inferential statistics, namely t-statistic in Table 5, which allows us to reject the null hypothesis that the expenditure of NPOs is similar to non-NPOs for purchases, tax and employment costs.

Table 5 Descriptive and Inferential Statistics with ARDx Data

Variable	NPOs		Non-NPOs		T-test
	Mean	St. Dev.	Mean	St. Dev.	
Employment costs	8239.01	26154	5345.53	23282.86	15.88***
Purchases	5268.11	17748.46	13996.01	514286	-3.15***
Acquisitions	1751.74	8093.03	1702.02	24176.8	0.36
Disposals	282.39	2593.3	294.68	5092.85	-0.4
Tax	59.38	268.29	265.32	3670.27	-10.38***

Figures are in £'000 after matching on variables in Equation 2. They are based on ARDx data and were estimated with the R programming language. Variable descriptions are in Table 3.

Figure 4 Average Employment Costs and Acquisitions over Time (in £000's)



Variable descriptions are in Table 3. The figures are based on ARDx data, and the graphs were prepared with R.

Furthermore, we look at these trends by controlling for multiple interactions with the classification tree presented in Figure 5. Instead of the recession effect, the tree identifies the tax¹⁰ effect. The principal, and most influential variable differentiating NPOs from other organisations is still the employment costs. Higher costs are associated with NPOs, but now we also see significant thresholds and groupings. The likelihood of being classified as an NPO for an organisation increases by 35% when an organisation spends over £1.26m on employment costs. This accounts for almost one-third of observations in the sample.

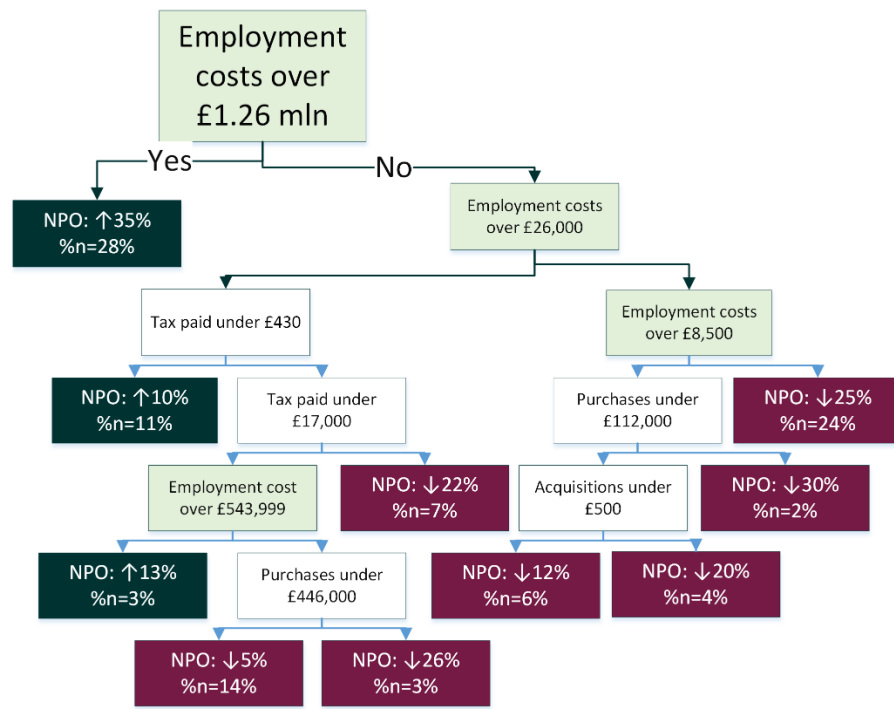
The tree further shows the interrelationship between tax paid and employment costs for firms with employment costs of over £26,000 but under £1.26m. We see that higher tax reductions are associated with higher employment costs. For instance, the likelihood of being an NPO increases by 10% if a firm pays very little in tax (under £430 annual expense) but has employment costs between £26,000 and £1.26m. If the tax paid is over £430 but under £17,000, we again see that

¹⁰ We also produce an alternative tree by excluding tax as a variable, as tax paid will be different for NPOs because of the reductions. The principle split in the alternative tree is the same and the subsequent relationships are very similar to those described below, but the alternative tree also splits on the recession years (namely 2008 and 2010). The same overall trends are observed, and the effect is likely to be captured by the tax variable as during the recession, tax paid was lower also for FPOs. The alternative tree is available upon request.

those organisations that spent over £543,999 on employment costs are 13% more likely to be NPOs. On the other hand, firms that had a more substantial tax bill (over £17,000) are not split on other variables and are 22% less likely to be classified as NPOs. Similarly, on the left of the tree, we observe that the observations for organisations which spent less than £26,000 on the total employment costs had a 12% decrease in the probability of being an NPO. Those with a very low spend (\leq £8,500) on employment costs are less likely to be NPOs than organisations that spent £8,500-£26,000.

The tree also explains the initial inferential and descriptive statistics indicating that NPOs have higher expenditure on acquisitions and lower expenditure on purchases. The tree shows that organisations that paid less than £17,000 in tax and had employment costs between £26,000 and £446,000 are further split on purchases, with NPOs more likely to have purchases less than £446,000. Similarly, NPOs with employment costs of £8,500-26,000 are further split on purchases and acquisitions. Organisations with lower spending on purchases of less than £122,000 and acquisitions of less than £500 are less likely to be classified as NPOs (a decrease of 12% from the average) but is still higher than when exceeding those thresholds (a decrease of 20% from the average).

Figure 5 NPO Tree with Matched ARDx Data (in colour)



The tree presents three distinct groups that have an increasingly homogeneous variation of likelihood of being classified as an NPO, to show which expenditures are associated with NPOs. Those to the left are firms spending over £1.26mln on employment-related costs (28% of the sample). Those in the centre are that spent between £26,000 and £1.26mln (37% of the sample) and to the right under £26,000 (35% of the sample). Figures in the final nodes are revised to aid interpretability. In final nodes, the upper figures relate to increases (in green) or decreases (in burgundy) in probability to be classified as an NPO in % and the lower figure (%n) refers to the proportion of the sample in the terminal node. Figures are in £'000 after matching on variables in Equation 2. Variable descriptions are in Table 3. The figures are based on ARDx data, calculated using the R programming language and redesigned with Microsoft Visio.

Do charity profiles have higher levels of compensation and reserves compared with other NPOs?

Table 6 compares charities to other organisations to identify whether the previously identified trends relating to NPOs are also applicable to charities. The BSD data indicates that charities had greater employment costs and acquisitions, possibly owing to their greater tax exemptions. They employ four times as many people as non-NPOs. The probability of being a high growth firm stays ten times greater. They are more stable than comparable non-NPOs as indicated by a

greater age. Once charities are matched to comparable non-charity NPOs, we find that their employment costs are 28% greater and acquisitions are 2% greater. Traditional inferential statistics are used to supplement the decision tree analysis, namely t-statistics. The results of this analysis reject the null hypothesis that charities are similar to other NPOs for variables relating to employment costs and tax.

Table 6 Descriptive and Inferential Statistics of Selected Variables from BSD and ARDx Comparing Charities with Other Organisations

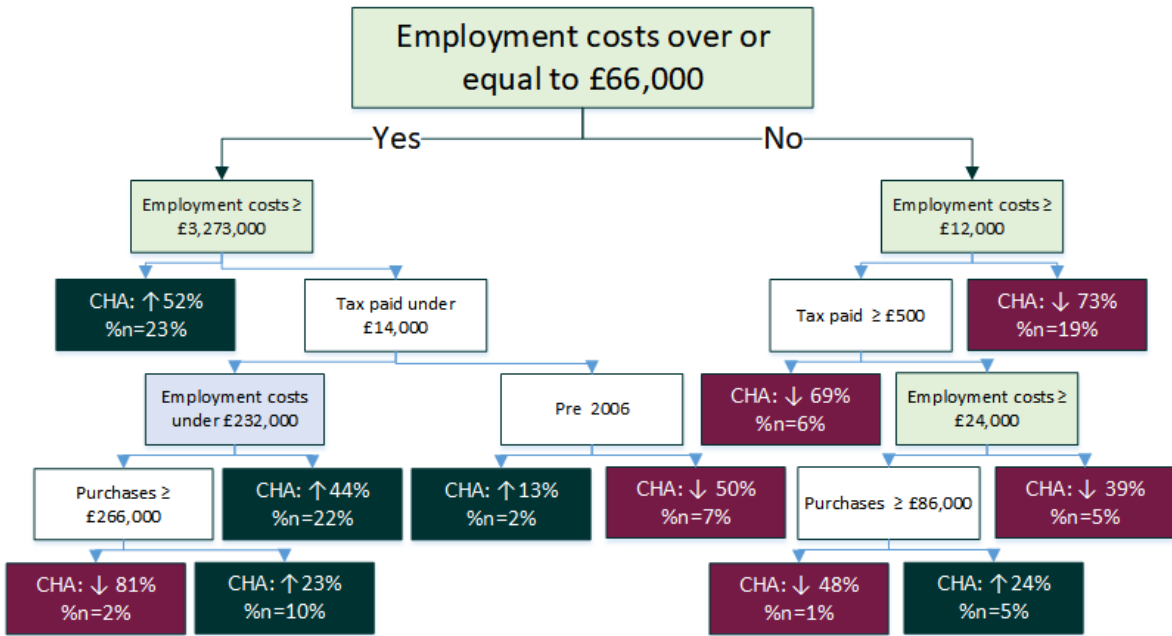
Dataset	Variable	Charities		Non-NPOs (for BSD) or NPOs (for ARDx)		T-test (DF=3,889)
		Mean	St. Dev.	Mean	St. Dev.	
BSD	Employment	41.28	242.42	9.8	347.6	
	Turnover in £'000	1,196.23	5,261.05	1,538.2	144,364.2	
	Age	12.95	7.52	10.5	9.6	
	High growth firm	1%	8%	<0.01%	10%	
ARDx	Employment costs in £'000	9,001.90	12,726.45	7,054.44	13,299.36	4.67***
	Acquisitions in £'000	1,176.89	4,750.21	1,152.24	4,701.66	0.16

Comparison from BSD data includes all firms, and from ARDx data includes only matched sample. The figures were estimated with the R programming language. Variable descriptions are in Tables 2 and 3.

We also present the charities tree in Figure 6. The tree structure is broadly consistent with the NPO tree structure presented in Figure 5, but the charity tree further profiles charities as leaning towards higher compensation than other NPOs. Those to the left in Figure 6 are firms spending over £3.273m on employment-related costs (23% of the sample). They have 52% higher likelihood of being charity than NPOs. Those in the centre that spent between £66,000 and £3.27m (42% of the sample) have interactions with tax paid and purchases, but still, charities are profiled as leaning towards higher compensation. Finally, for those to the right with the lowest

compensation, we notice a trend towards reducing the probability of being a charity, despite the further notable splits on tax liability and purchases.

Figure 6 Charity Tree with Matched ARDx Data (in colour)



The tree presents three distinct groups that have an increasingly homogeneous variation of likelihood of being classified as a charity to show which expenditures are associated with charities. Figures in the final nodes are revised to aid interpretability. The upper figures relate to increases (in green) or decreases (in burgundy) in probability to be classified as a charity in % and the lower figure (%n) refers to the proportion of the sample in the terminal node. Figures are in £'000 after matching on variables in Equation 2. Variable descriptions are in Table 3. The figures are based on ARDx data, calculated by using the R programming language and redesigned with Microsoft Visio.

DISCUSSION

We drew on complexity theory to develop profiles that distinguish NPOs from other types of organisations. We show that NPOs tend to have greater financial capacity than comparable organisations, but they are also much more likely not to have any employees. When accounting

for this factor and other characteristics with matching, larger NPOs spend substantially more on employment than other comparable organisations. We would expect to find the contrary, lowering expenditure and lesser employment, primarily because of the existing evidence related to the worsening employment conditions resulting from the UK government's austerity policies (Cunningham 2015; Baines and Cunningham 2020).

The tree classifying NPOs from non-NPOs shown in Figure 5 uncovered complex significant interrelationships between lower tax bills (or exemptions from paying taxes) and higher employment expenses for companies spending between £1.26m and £26,000 on employment-related costs. This suggests that diversification (Moulick et al. 2020), and increasingly uniform hiring practices with the for-profit sector (Kim and Lee 2007; Ng et al. 2016), among other factors, may have triggered the distribution of tax savings through above-market compensation for larger firms. Furthermore, in line with the positive model of stakeholder theory (Ebrahim 2003) and previous empirical findings (Dhanani and Connolly 2012; Hyndman and McConville 2015), we also find that the expenditure on compensation of larger NPOs recognised by HMRC as charities is even more extreme than that of other NPOs, suggesting that the current, more extensive reporting, may be ineffective.

The findings are alarming given that greater spending on overheads was often associated with inefficiency (Callen et al. 2003), deviation from social objectives (Bowman 2006; Lecy and Searing 2014) and reduction in donor confidence (Tinkelman and Mankaney ,2007; Jacobs and Marudas 2009). More broadly, Alter's (2007) spectrum and subsequent studies (Laasch 2018) place social value creation in the opposite direction of economic value creation. Larger NPOs might be keener to invest in the latter than the former, possibly resulting in greater stability and

size than comparable organisations due to more friendly operating environments with lower taxation and no returns to shareholders.

Many larger NPOs not only spend more on compensation, but also acquire more in assets than comparable non-NPOs. The relationships in Figure 5 do not necessarily indicate that one variable, employment costs,¹¹ is solely responsible for the main differences in probabilities. The differences in acquisitions in Figure 4 could have been captured by other variables, most likely employment costs. This is also confirmed by the moderate correlation between employment costs and acquisitions reported in Appendix 2 and broadly similar trends over time in Figure 4. This implies that many organisations would have both higher compensation and higher acquisitions.

NPOs were also associated with a higher probability of becoming high growth firms.¹² This is unexpected given that the objectives of NPOs are not based on growth aspirations but on furthering a specific social cause or advocating for a shared point of view. Having said that, the need for services from NPOs may have increased because of the Government's austerity policies, resulting in the expansion of the NPOs, as per Social Origins Theory (Salamon and Anheier 1998).

¹¹ In the same vein, although NPOs tend to have consistently lower turnover on average, we do not identify that it is substantially different from other organisations with similar characteristics. The tree in Figure 3 does not split on turnover, implying that the organisations differ more substantially with regards to employment, revenue per employee, region, sector and age. This also supports ideas (e.g. in Bromley and Meyer 2014) that NPOs are analogous to other organisations driven by the same practices and science underlying those practices.

¹² These firms are defined by their greater than 20% average annualised growth in either turnover or employment over a three-year period. They were found to be substantial contributors to the economy (Birch 1987). Anyadike-Danes et al. (2015) show that around 6% of HGF added about 40% of net jobs by 15-year survivors in the UK.

CONCLUSIONS

Profiling NPOs enabled us to contribute to the wider NPO literature (Ghosh Moulick et al., 2019; Kolk 2022; Kim and Lee 2007; Ng et al, 2016) by showing that they are less prone to enter or exit the market, employ more people and are more likely to become high growth firms. We also show, contrary to expectations in the academic literature (Cunningham 2015; Baines and Cunningham 2020), that larger NPOs spend significantly more on employment-related costs and acquisitions than comparable organisations with even higher expenditure by charities that receive further tax reliefs. The study thus raises questions on the lack of accountability in the not-for-profit sector as well as targeting and oversight of tax reductions, which are likely to be at least partly distributed through the inflated expenditure for larger NPOs.

The study also contributes to the NPO literature by offering solutions to the methodological shortcomings of previous research on NPOs (Kolk 2022). We show how configuration approaches, centring on non-linearity and equifinality, can be modelled with machine learning to avoid unrealistic regression-based assumptions, such as lack of multicollinearity, the distribution of errors and independence of observations (Douglas et al. 2020).

Limitations and Future Research

It is worth noting that the results related to expenditure are primarily about larger NPOs because of the stratification processes in ARDx, so they do not apply for very small NPOs. In Figure 3, we see that the tree algorithm separates organisations that do not have any employees. About half of the NPOs do not employ any people. For these micro organisations, we only observe some differences across sectors and regions. They are more likely to operate in other service sectors than wholesale, catering, construction, production, property, retail, and be situated in more deprived regions.

This study discussed how and which NPOs differ from other organisations with regard to their characteristics and expenditure, but it was limited by the available data. A more detailed investigation is required to identify whether the above-average employment costs are caused by disproportionate executive pay as well as whether acquisitions are related to social objectives. If this greater expenditure in the not-for-profit sector is not associated with social objectives, reform in the current NPO support practices should be required. The targeting should be improved so that smaller NPOs in more deprived areas could provide services to their communities rather than granting tax reductions to high performing organisations that could distribute surplus with above-average compensation and acquisitions. More efficient combination of mechanisms, as proposed by Hyndman and McConville (2018), including the further application of Easrery and Miesing's (2009) model, should be encouraged.

REFERENCES

- Alter, Kim. 2007. Social Enterprise Typology. Virtue Ventures, LLC.
- Andrews, Rhys, Jesper Rosenberg Hansen, and Katy Huxley. 2019. Senior Public Managers' Organizational Commitment: Do Private Sector Experience and Tenure Make a Difference? *International Public Management Journal* 0(0):1–32. doi: 10.1080/10967494.2019.1580231.
- Anyadike-Danes, Michael, Hart, Mark, and Du, Jun. 2015. Firm dynamics and job creation in the United Kingdom: 1998-2013. *International Small Business Journal*, <https://doi.org/10.1177/0266242614552334>
- Arya, Anil and Mittendorf, Brian. 2015. Career concerns and accounting performance measures in nonprofit organizations. *Accounting, Organizations and Society*, <https://doi.org/10.1016/j.aos.2014.10.002>
- Athey, Susan, Imbens, Guido W. 2019. Machine Learning Methods That Economists Should Know. *Annual Review of Economics*, <https://doi.org/10.1146/annurev-economics-080217-053433>
- Baines, Donna and Cunningham, Ian. 2020. 'How could management let this happen?' Gender, unpaid work and industrial relations in the nonprofit social services sector. *Economic and Industrial Democracy*, <https://doi.org/10.1177/0143831x17715768>
- Balsam, Steven and Harris, Erica E. 2018. Nonprofit executive incentive pay. *Review of Accounting Studies*, <https://doi.org/10.1007/s11142-018-9473-z>
- Balsam, Steven, Harris, Erica E. and Saxton, Gregory D. 2020. The use and consequences of prerequisite types in non-profit organizations. *Journal of Accounting and Public Policy*,

- <https://doi.org/10.1016/j.jaccpubpol.2020.106737>
- Bastos, Paulo, Natália P. Monteiro, and Odd Rune Straumez. 2014. The Effect of Private versus Public Ownership on Labour Earnings. *Oxford Economic Papers*, doi: 10.1093/oep/gpu017.
- Basu, Deepankar. 2020. Bias of OLS Estimators Due to Exclusion of Relevant Variables and Inclusion of Irrelevant Variables. *Oxford Bulletin of Economics and Statistics* 82(1):209–34. doi: 10.1111/obes.12322.
- Becchetti, Leonardo, Stefano Castriota, and Sara Depedriz. 2014. Working in the For-Profit versus Not-for-Profit Sector: What Difference Does It Make? An Inquiry on Preferences of Voluntary and Involuntary Movers. *Industrial and Corporate Change* 23(4):1087–1120. doi: 10.1093/icc/dtt044.
- Bertomeu, Jeremy. 2020. Machine learning improves accounting: discussion, implementation and research opportunities. *Review of Accounting Studies*, <https://doi.org/10.1007/s11142-020-09554-9>
- Birch, David. 1987. *Job Creation in America: How Our Smallest Companies Put the Most People to Work*. Free Press.
- Bowman, Woods. 2006. Should donors care about overhead costs? Do they care? *Nonprofit and Voluntary Sector Quarterly*, <https://doi.org/10.1177/0899764006287219>
- Bowman, Woods. 2011. Financial capacity and sustainability of ordinary nonprofit. *Nonprofit Management and Leadership*, <https://doi.org/10.1002/nml.20039>
- Breiman, Leo. 2001. Random forest. *Machine Learning*, <https://doi.org/10.1023/A:1010933404324>
- Briand, Bénédicte, Ducharme, Gilles R., Parache, Vanessa and Mercat-Rommens, Catherine. 2009. A similarity measure to assess the stability of classification trees. *Computational Statistics and Data Analysis*, <https://doi.org/https://doi.org/10.1016/j.csda.2008.10.033>
- Bromley, Patricia and Meyer, John W. 2017. ‘They Are All Organizations’: The Cultural Roots of Blurring Between the Nonprofit, Business, and Government Sectors. *Administration and Society*, <https://doi.org/10.1177/0095399714548268>
- Bruneel, Johan, Bart Clarysse, Matthias Staessens, and Stephan Weemaes. 2020. ‘Breaking with the Past: The Need for Innovation in the Governance of Nonprofit Social Enterprises.’ *Academy of Management Perspectives*, doi: 10.5465/amp.2017.0176
- Brunori, Paolo, and Neidhöfer, Guido. 2021. The evolution of inequality of opportunity in germany: a machine learning approach. *Review of Income and Wealth*, <https://doi.org/10.1111/roiw.12502>
- Callen, Jeffrey L., Klein, April and Tinkelman, Daniel. 2003. Board composition, committees, and organizational efficiency: the case of nonprofits. *Nonprofit and Voluntary Sector Quarterly*, <https://doi.org/10.1177/0899764003257462>
- Carroll, Deborah A., and Stater, Keely Jones. 2008. Revenue diversification in nonprofit organizations: Does it lead to financial stability. *Journal of Public Administration Research and Theory*, <https://doi.org/10.1093/jopart/mun025>
- Chang, Cyril F., and Tuckman, Howard P. 1990. Why do nonprofit managers accumulate surpluses, and how much do they accumulate? *Nonprofit Management and Leadership*, <https://doi.org/10.1002/nml.4130010204>
- Chikoto, Grace L. and Neely, Daniel Gordon. 2014. Building Nonprofit Financial Capacity: The Impact of Revenue Concentration and Overhead Costs. *Nonprofit and Voluntary Sector Quarterly*, <https://doi.org/10.1177/0899764012474120>

- Clifford, David. 2016. 'International Charitable Connections: The Growth in Number, and the Countries of Operation, of English and Welsh Charities Working Overseas.' *Journal of Social Policy* 45(3): 453–86.
- Cook, E. Francis and Goldman, Lee. 1984. Empiric comparison of multivariate analytic techniques: advantages and disadvantages of recursive partitioning analysis. *Journal of Chronic Diseases*, [https://doi.org/10.1016/0021-9681\(84\)90041-9](https://doi.org/10.1016/0021-9681(84)90041-9)
- Cordes, Joseph J, and Burton A Weisbrod. 1998. Taxation of Commercialization of Nonprofit Abstract. *Journal of Policy Analysis and Management* 17(2): 195–214.
- Core, John E., Guay, Wayne R. and Verdi, Rodrigo S. 2003. Agency problems of excess endowment holdings in not-for-profit firms. *Journal of Accounting and Economics*, <https://doi.org/10.1016/j.jacceco.2006.02.001>
- Cornforth, Chris. 2001. "What Makes Boards Effective? An Examination of the Relationships between Board Inputs, Structures, Processes and Effectiveness in Non-Profit Organisations." *Corporate Governance: An International Review* 9(3):217–27. doi: 10.1111/1467-8683.00249.
- Cox, Christian. 2020. Campaign Contributions by Non-Profit Executives and Government Grants. *Oxford Bulletin of Economics and Statistics*, 82(4):916–33. doi: 10.1111/obes.12341.
- Craig, David. 2015. *The Great Charity Scandal: What Really Happens to the Billions We Give to Good Causes?* The Original Book Company
- Cunningham, Ian. 2015. Austerity, personalization and the degradation of voluntary sector employment conditions. *Competition and Change*, <https://doi.org/10.1177/1024529415580261>
- Dees, J. Gregory. 2003. Social Entrepreneurship is about Innovation and Impact, Not Income. Center for the Advancement of Social Entrepreneurship Fuqua School of Business, Duke University. https://centers.fuqua.duke.edu/case/wp-content/uploads/sites/7/2015/03/Article_Deess_MeaningofSocialEntrepreneurship_2001.pdf. Accessed 13 April 2021.
- Dempsey, Sarah E. and Sanders, Matthew L. 2010. Meaningful work? Nonprofit marketization and work/life imbalance in popular autobiographies of social entrepreneurship. *Organization*, <https://doi.org/10.1177/1350508410364198>
- Department for Business, Energy and Industrial Strategy (BEIS). 2020. COVID-19: support for businesses (version as at 24 March 2020). <https://www.gov.uk/government/publications/guidance-to-employers-and-businesses-about-covid-19/covid-19-support-for-businesses>. Accessed 24 March 2021.
- DeVaro, Jed, and Dana Brookshire. 2007. 'Promotions and Incentives in Nonprofit and For-Profit Organizations.' *ILR Review* 60(3):311–39. doi: 10.1177/001979390706000301.
- Dick, Penny, and Tracey Coule. 2020. 'Nonconformance With Regulatory Codes in the Nonprofit Sector: Accountability and the Discursive Coupling of Means and Ends.' *Business & Society* 59(4): 749-786.
- Douglas, Evan J., Dean A. Shepherd, and Catherine Prentice. 2020. Using Fuzzy-Set Qualitative Comparative Analysis for a Finer-Grained Understanding of Entrepreneurship. *Journal of Business Venturing* 35(1), 105970. <https://doi.org/10.1016/j.jbusvent.2019.105970>.
- Duchessi, Peter, and Eitel J.M. Lauría. 2013. Decision Tree Models for Profiling Ski Resorts' Promotional and Advertising Strategies and the Impact on Sales. *Expert Systems with Applications* 40(15): 5822–29. <https://doi.org/10.1016/j.eswa.2013.05.017>.

- Easterly, Lisa, and Paul Miesing. 2009. 'NGOs, Social Venturing, and Community Citizenship Behavior.' *Business & Society* 48(4): 538–64.
- Ebrahim, Alnoor. 2003. Accountability in practice: Mechanisms for NGOs. *World Development*, [https://doi.org/10.1016/S0305-750X\(03\)00014-7](https://doi.org/10.1016/S0305-750X(03)00014-7)
- Ecer, Sencer, Magro, Mark and Sarpaça, Sinan. 2017. The Relationship Between Nonprofits' Revenue Composition and Their Economic-Financial Efficiency. *Nonprofit and Voluntary Sector Quarterly*, <https://doi.org/10.1177/0899764016649693>
- Efron, Bradley and Hastie, Trevor. 2016. *Computer Age Statistical Inference*. Cambridge Univ. Press.
- European Commission Recommendation of 6 May 2003 Concerning the Definition of Micro, Small and Medium-sized Firms. <http://data.europa.eu/ELI/RECO/2003/361/OJ>. Accessed 13 April 2021.
- Eurostat-OECD. 2007. Eurostat-OECD manual on business demography statistics. European Commission.
- Faulk, Lewis, Jasmine McGinnis Johnson, and Jesse D. Lecy. 2017. 'Competitive Advantage in Nonprofit Grant Markets: Implications of Network Embeddedness and Status.' *International Public Management Journal* 20(2):261–93. doi: 10.1080/10967494.2016.1141811.
- Feeney, Mary K., and Barry Bozeman. 2009. "Staying Late." *The American Review of Public Administration* 39 (5): 459–77. <https://doi.org/10.1177/0275074008327293>.
- Fisman, Raymond, and Hubbard, R. Glenn, 2003. The role of nonprofit endowments. In E. Glaeser (Ed.), *The governance of not-for-profit organizations*. (pp. 217-234). University of Chicago Press.
- Fisman, Raymond. and Hubbard, R. Glenn. 2005. Precautionary savings and the governance of nonprofit organizations. *Journal of Public Economics*, <https://doi.org/10.1016/j.jpubeco.2004.10.005>
- Fiss, Peer C. 2007. A set-theoretic approach to organizational configurations. *Academy of Management Review* 32(4): 1180–98.
- Froelich, Karen A. 1999. Diversification of revenue strategies: Evolving resource dependence in nonprofit organizations. *Nonprofit and Voluntary Sector Quarterly*, <https://doi.org/10.1177/0899764099283002>
- Galaskiewicz, Joseph and Bielefeld, Wolfgang. 2003 *The Behavior of Organizations*. In: Anheier H.K., Ben-Ner A. (eds) *The Study of the Nonprofit Enterprise*. *Nonprofit and Civil Society Studies (An International Multidisciplinary Series)*., Boston: Springer, https://doi.org/10.1007/978-1-4615-0131-2_13
- Ghosh Moulick, Abhisekh, Alexiou, Kostas, Dowin Kennedy, Elena and Parris, Denise Linda, 2020. A total eclipse of the heart: compensation strategies in entrepreneurial nonprofits. *Journal of Business Venturing*, <https://doi.org/10.1016/j.jbusvent.2019.105950>
- Gobey, Matthew and Matikonis, Karolis. 2021. Small business property tax reductions and job growth. *Small Business Economics*, <https://doi.org/10.1007/s11187-019-00219-9>
- Graham, Byron, and Karen Bonner. 2022. One Size Fits All? Using Machine Learning to Study Heterogeneity and Dominance in the Determinants of Early-Stage Entrepreneurship. *Journal of Business Research* 152: 42–59. <https://doi.org/10.1016/j.jbusres.2022.07.043>.
- Grant, Laura E., and Matthew Potoski. 2015. 'Collective Reputations Affect Donations to Nonprofit.' *Journal of Policy Analysis and Management* 34(4): 835–852.
- Hansmann, Henry B. 1980. The role of nonprofit enterprise. *The Yale Law Journal*, <https://doi.org/10.2307/796089>

- Hodgkinson, Ian R., and Paul Hughes. 2019. 'Public Service Performance: Exploring the Effects of Strategy Configurations Among Ownership Types.' *International Public Management Journal* 22(5):775–96. doi: 10.1080/10967494.2018.1461151.
- Hustinx, Lesley, Bram Verschuere, and Joris De Corte. 2014. 'Organisational Hybridity in a Post-Corporatist Welfare Mix: The Case of the Third Sector in Belgium.' *Journal of Social Policy* 43(2): 391–411.
- Hyndman, Noel and McConville, Danielle. 2018. Trust and accountability in UK charities: Exploring the virtuous circle. *The British Accounting Review*, <https://doi.org/10.1016/j.bar.2017.09.004>
- Hyndman, Noel, and McMahon, Danielle. 2010. The evolution of the UK charity Statement of Recommended Practice: The influence of key stakeholders. *European Management Journal*, <https://doi.org/10.1016/j.emj.2010.06.004>
- Jacobs, Fred A. and Marudas, Nicholas P. 2009. The combined effect of donation price and administrative inefficiency on donations to U.S. nonprofit organizations. *Financial Accountability and Management*, <https://doi.org/10.1111/j.1468-0408.2008.00464.x>
- James, Gareth, Witten, Daniela, Hastie, Trevor, and Tibshirani, Robert. 2021. *An introduction to statistical learning with applications in R*. 2nd ed. Springer.
- Johnston, Andrew C. and Johnston, Carla. 2021. Is Compassion a Good Career Move? Nonprofit Earnings Differentials from Job Changes. *The Journal of Human Resources* 56(4): 1226–1253.
- Jones, Christopher L., Kitching, Karen A., Roberts, Andrea Alston, and Smith, Pamela C. 2013. The spend-save decision: An analysis of how charities respond to revenue changes. *Accounting Horizons*, <https://doi.org/10.2308/acch-50285>
- Kim, Seok Eun and Lee, Jung Wook. 2007. Is mission attachment an effective management tool for employee retention? An empirical analysis of a nonprofit human services agency. *Review of Public Personnel Administration*, <https://doi.org/10.1177/0734371X06295791>
- King, Gary and Nielsen, Richard. 2019. Why Propensity Scores Should Not Be Used for Matching. *Political Analysis*, <https://doi.org/10.1017/pan.2019.11>
- Kleinberg, Jon, Ludwig, Jens, Mullainathan, Sendhil and Obermeyer, Ziad. 2015. Prediction policy problems. *American Economic Review*, <https://doi.org/10.1257/aer.p20151023>
- Knutsen, Wenjue Lu and Chan, Yolande. 2014. The phenomenon of staff volunteering: how far can you stretch the psychological contract in a nonprofit organization? *International Journal of Voluntary and Nonprofit Organizations*, <https://doi.org/10.1007/s11266-014-9476-8>
- Kolk, Berend van der. 2022. Performance Measurement in the Public Sector: Mapping 20 Years of Survey Research. *Financial Accountability and Management* 38(4): 703–29. <https://doi.org/10.1111/faam.12345>.
- Kukk, Merike, Merikull, Jaanika, and Room, Tairi. 2022. The gender wealth gap in Europe: application of machine learning to predict individual-level wealth. *Review of Income and Wealth*, <https://doi.org/10.1111/roiw.12596>
- Kuruppu, Sanjaya Chinthana and Lodhia, Sumit. 2019. Disruption and transformation: The organisational evolution of an NGO. *The British Accounting Review*, <https://doi.org/10.1016/j.bar.2019.03.003>
- Laasch, Oliver. 2018. Beyond the purely commercial business model: Organizational value logics and the heterogeneity of sustainability business models. *Long Range Planning*, <https://doi.org/10.1016/j.lrp.2017.09.002>

- Leatherwood, Marya L., and Don O’Neal. 1996. “The Transformation of Boards in Corporate and Not-for-Profit Sectors: Diminishing Differences and Converging Contexts.” *Corporate Governance: An International Review* 4(3):180–92. doi: <https://doi.org/10.1111/j.1467-8683.1996.tb00146.x>.
- Lecy, Jesse D. and Searing, Elizabeth A. M. 2014. Anatomy of the nonprofit starvation cycle: an analysis of falling overhead ratios in the nonprofit sector. *Nonprofit and Voluntary Sector Quarterly*, <https://doi.org/10.1177/0899764014527175>
- Lecy, Jesse D., Van Slyke, David M. 2013. Nonprofit sector growth and density: Testing theories of government support. *Journal of Public Administration Research and Theory*, 23, 189–214. <https://doi.org/10.1093/jopart/mus010>
- Loh, Wei-Yin. 2014. Fifty Years of Classification and Regression Trees. *International Statistical Review*, <https://doi.org/10.1111/insr.12016>
- Matikonis, Karolis. 2020. Unintended Recipients of Rising UK Non-domestic Property Tax Reliefs. *British Tax Review*, 2, 143-150.
- Meyer, Alan, Tsui, Anne and Hinings, C. 1993. Configurational Approaches to Organizational Analysis. *Academy of Management Stable URL* : <http://www.jstor.org/stable/256809>
Academy of Management Journal, 36(6): 1175–1195.
- Minaker, Bradley (2021) How Effective Are Charity Managers? Evidence from a Panel of Charities. *The Journal of Human Resources* 56(2): 632-654.
- Moldavanova, Alisa V., and Nathaniel S. Wright. 2020. “How Nonprofit Arts Organizations Sustain Communities: Examining the Relationship Between Organizational Strategy and Engagement in Community Sustainability.” *American Review of Public Administration* 50 (3): 244–59. <https://doi.org/10.1177/0275074019884316>.
- Morris, George, Roberts, Dylan, MacIntosh, John, and Bordone, Adrian. 2018. The Financial Health of the United States Nonprofit Sector. Oliver Wyman, <https://learn.guidestar.org/hubfs/Docs/The%20Financial%20Health%20of%20the%20US%20Nonprofit%20Sector.pdf>. Accessed 24 March 2021.
- Mullainathan, Sendhil and Spiess, Jann. 2017. Machine learning: An applied econometric approach. *Journal of Economic Perspectives*, <https://doi.org/10.1257/jep.31.2.87>
- Nederhand, José. 2020. Evaluating the Role of Government Collaboration in the Perceived Performance of Community-Based Nonprofits: Three Propositions. *Journal of Public Administration Research and Theory*, <https://doi.org/10.1093/jopart/muaa059>
- Newton, Ashley N. 2015. Executive compensation, organizational performance, and governance quality in the absence of owners. *Journal of Corporate Finance*, <https://doi.org/10.1016/j.jcorpfin.2014.12.016>
- Ng, Eddy S., Gossett, Charles. W. and Winter, Richard. 2016. Millennials and public service renewal: Introduction on Millennials and public service motivation. *Public Administration Quarterly*, 40(3), 1-16.
- O’Reilly, Charles A., and Brian G. M. Main. 2010. ‘Economic and Psychological Perspectives on CEO Compensation: A Review and Synthesis.’ *Industrial and Corporate Change* 19(3):675–712. doi: 10.1093/icc/dtp050.
- Office for National Statistics. 2019. Business Structure Database, 1997-2018. Secure Access. [data collection]. 10th Edition. UK Data Service. SN: 6697, <http://doi.org/10.5255/UKDA-SN-6697-10>
- Office for National Statistics. Virtual Microdata Laboratory (VML), University of the West of England, Bristol. 2019. Annual Respondents Database X, 1998-2015. Secure Access. [data

- collection]. 4th Edition. Office for National Statistics. UK Data Service. SN: 7989.
<http://doi.org/10.5255/UKDA-SN-7989-4>
- Pfeffer, Jeffrey and Salancik, Gerald R. 2003. The external control of organizations: A resource dependence perspective. Harper and Row.
- Philipp, Michel, Rusch, Thomas, Hornik, Kurt and Strobl, Carolin (2018) Measuring the Stability of Results From Supervised Statistical Learning. *Journal of Computational and Graphical Statistics*, 27(4), 685–700.
- Rabinowicz, Assaf and Rosset, Saharon (2020) Cross-Validation for Correlated Data. *Journal of the American Statistical Association*, DOI: 10.1080/01621459.2020.1801451
- Rose-Ackerman, Susan. 1996. Altruism, nonprofits, and economic theory. *Journal of Economic Literature*, 34(2), 701–728.
- Ruhm, Christopher J. and Borkoski, Carey (2003) Compensation in the Nonprofit Sector. *The Journal of Human Resources* XXXVIII(4): 992-1021
- Sabatier, Mareva. 2012. Does Productivity Decline After Promotion? The Case of French Academia. *Oxford Bulletin of Economics and Statistics*, 74(6):886–902. doi: 10.1111/j.1468-0084.2011.00681.x.
- Salamon, Lester M. and Anheier, Helmut. K. 1998. Social Origins of Civil Society: Explaining the Nonprofit Sector Cross-Nationally. *VOLUNTAS: International Journal of Voluntary and Nonprofit Organizations*, <https://doi.org/10.1023/A:1022058200985>
- Shon, Jongmin, Hamidullah, Madinah F. and McDougle, Lindsey M. 2019. Revenue Structure and Spending Behavior in Nonprofit Organizations. *American Review of Public Administration*, <https://doi.org/10.1177/0275074018804562>
- Shrestha, Yash Raj, Vivianna Fang He, Phanish Puranam, and Georg von Krogh. 2022. Algorithm Supported Induction for Building Theory: How Can We Use Prediction Models to Theorize? *Organization Science* 32(3): 856–80. <https://doi.org/10.1287/orsc.2020.1382>.
- Sloan, Frank A. 1998. ‘PART TWO : INDUSTRY STUDIES Commercialism in Nonprofit Hospitals.’ *Policy Analysis and Management* 17(2): 234–52.
- The Charity Commission. 2020. Trustee operated without oversight at ‘inadequately run’ charity finds Commission. <https://www.gov.uk/government/news/trustee-operated-without-oversight-at-inadequately-run-charity-finds-commission>. Accessed 24 March 2021.
- Thereneau, T. M., and E. J. Atkinson. 2015. An Introduction to Recursive Partitioning Using the RPART Routines. Mayo Foundation.
- Tidhar, Ron, and Kathleen M. Eisenhardt. 2020. Get Rich or Die Trying... Finding Revenue Model Fit Using Machine Learning and Multiple Cases. *Strategic Management Journal* 41(7): 1245–73. <https://doi.org/10.1002/smj.3142>.
- Tinkelman, Daniel, and Mankaney, Kamini. 2007. When is administrative efficiency associated with charitable donations? *Nonprofit and Voluntary Sector Quarterly*, <https://doi.org/10.1177/0899764006293176>
- Tuckman, Howard P., and Chang, Cyril F. 1992. Nonprofit equity: A behavioral model and its policy implications. *Journal of Policy Analysis and Management*, <https://doi.org/10.2307/3325133>
- UK Data Service. 2021. Data access policy. <https://www.ukdataservice.ac.uk/get-data/data-access-policy/controlled-data.aspx>. Accessed 24 March 2021.
- Van der Heijden, Hans. 2013. Small is beautiful? Financial efficiency of small fundraising charities. *The British Accounting Review*, <https://doi.org/10.1016/j.bar.2012.12.004>.
- Wamser, Georg. 2014. The Impact of Thin-Capitalization Rules on External Debt Usage - A

- Propensity Score Matching Approach. *Oxford Bulletin of Economics and Statistics*, 76(5):764–81. doi: 10.1111/obes.12040.
- Weisbrod, Burton A. 1997. The Future of the Nonprofit Sector: Its Entwining with Private Enterprise and Government. *Journal of Policy Analysis and Management* 16(4): 541–55.
- Yan, Wenli, and Margaret F. Sloan. 2016. The Impact of Employee Compensation and Financial Performance on Nonprofit Organization Donations. *The American Review of Public Administration* 46 (2): 243–58. <https://doi.org/10.1177/0275074014554000>.

APPENDICES

Appendix 1: Table 7 Steps in Data Validation and Matching of ARDx Data.

Step	Observations	Unique Organisations
Raw data	863,755	531,957
Incomplete data and missing cases removed	849,614	528,584
Matching for NPOs	73,817	38,048
Matching for Charities	3,927	972

Appendix 2: Model Diagnostics

The primary criticism of CART is related to overfitting (Cook and Goldman 1984), implying that the algorithm may follow errors, or noise, too carefully. The overfitted trees are often slower, less accurate and more difficult to interpret. To overcome this issue, we follow James et al. (2021) and impose a minimum number of observations in each final node, namely 1000 and 100 for models (2) and (3), respectively. This strategy was preferred instead of alternatives¹³ because of the disclosure controls imposed by the data owners limiting the minimum number of observations in outputs (UK Data Service 2020). Other options include building a model by using a training dataset and then estimating mean squared error with the hold-out data and cross-complexity pruning, estimating complexity factor to evaluate predictive capacity (James et al., 2013). We also report a correlation table with ARDx data in Table 8.

¹³ Other options include cross validation requiring to build a model by using a training dataset and then estimate mean squared error with the hold-out data and cross-complexity pruning estimating complexity factor with similar procedures as applied below to evaluate predictive capacity (James et al. 2021).

Table 8 Correlation Table with Unmatched ARDx Data

	Employment costs	Purchases	Acquisitions	Disposals	Tax	Employment	Turnover	Labour productivity
Employment costs	1.00							
Purchases	0.35	1.00						
Acquisitions	0.59	0.24	1.00					
Disposals	0.32	0.13	0.32	1.00				
Tax	0.09	0.16	0.07	0.03	1.00			
Employment	0.91	0.32	0.51	0.30	0.01	1.00		
Turnover	0.43	0.94	0.30	0.16	0.03	0.38	1.00	
Labour productivity	0.00	0.25	0.01	0.00	0.01	0.00	0.27	1.00

This table reports correlation coefficients based on full unmatched data with 528,584 unique organisations. The figures are based on ARDx data and were estimated with the R programming language.

Although not the main area of interest, we also test the predictive capacity of the primary model in Equation 3. We use 10 fold validation, in which we compare the predictive capacity of our trees to other candidate algorithms. We base our strategy on Robinowicz and Rosset's (2020) assumptions that should be met for the cross validation with longitudinal data to be affective. We produce ten random subsamples, where the same respondent firms are in both samples but at different times to preserve the distributional relation between the testing set to the training set. For each subsample, we train the algorithms with 80% train set and then use the remaining 20% to test the accuracy of predictions. The goal is to compare the accuracy of predictions of observations of the subjects, sampled at a random time-point from the same distribution. For the comparison, we use both Root Mean Squared Error (RMSE) and more reliable Mean Absolute Error (MAE). The results of the k-fold validation method are reported in table 9. The trees achieved a relatively high accuracy when compared to alternative

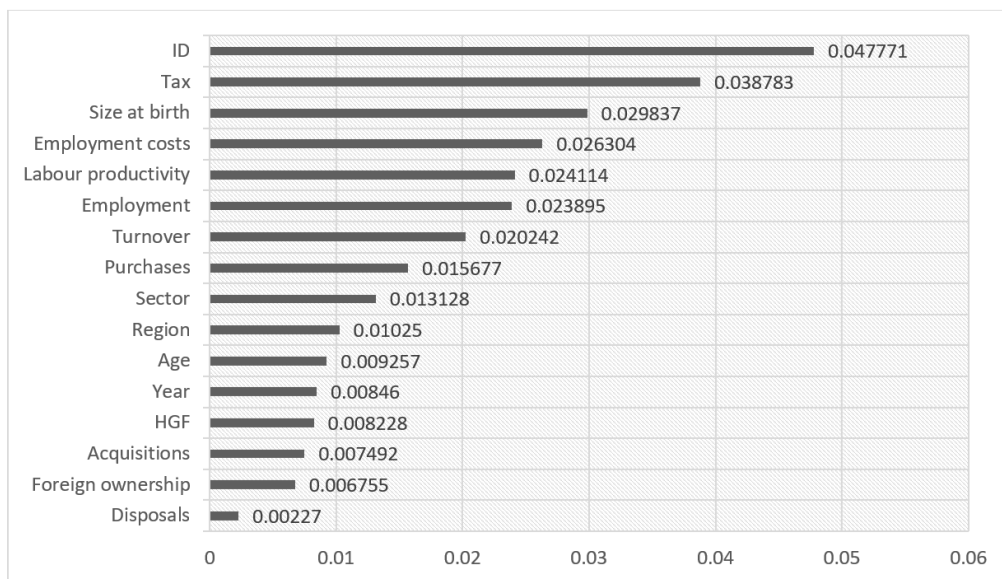
methods. Based on both RMSE and MAE, random forests slightly outperformed trees but the accuracy was much higher than with logistic regression or mixed model.

Table 9 Accuracy Tests

	RMSE	MAE
random forest	0.3	0.23
tree	0.44	0.4
logistic regression	8.5	2.49
mixed model	10.04	3.57

We also find broadly consistent results from the impurity-based feature importance estimated with random forest algorithm reported in Figure 7.

Figure 7 Random Forests - Importance Scores



To further assure the matching quality, the matched sample was manually examined. An equal number of observations were found in all sectors, regions and within size thresholds established according to the EU definition (Commission Recommendation 2003). We also explore substantial reduction in \mathcal{L}_1 statistic that includes imbalance with respect to joint

distribution and all interactions between recipients and non-recipients Iacus et al. (2009). The continuous variables were also examined with t-tests and no statistically significant results were found.

Table 10 Sensitivity Analysis with Logistic Regression

	Dependent variable: Nonprofit status				Dependent variable: Charity status	
	Full ARDx Data		Matched Sample		Matched Sample	
	(NPO1)	(NPO2)	(NPO5)	(NPO6)	(CHA1)	(CHA2)
Employment	0.010***	0.026***	0.030***	0.031***	-0.004	0.048***
Costs	(0.0003)	(0.0004)	(0.001)	(0.001)	(0.006)	(0.005)
Purchases	-0.006***	-0.017***	-0.007***	-0.011***	-0.011	-0.039***
	(0.0003)	(0.0004)	(0.001)	(0.001)	(0.008)	(0.008)
Acquisitions	0.009***	0.010***	0.018***	0.021***	-0.004	-0.011
	(0.0005)	(0.0005)	(0.002)	(0.002)	(0.008)	(0.008)
Disposals	-0.013***	-0.011***	-0.006*	-0.010***	0.008	-0.003
	(0.001)	(0.001)	(0.003)	(0.003)	(0.026)	(0.026)
Tax	-1.468***	-1.343***	-1.597***	-1.832***	-3.213***	-2.913***
	(0.039)	(0.031)	(0.062)	(0.062)	(0.604)	(0.563)
Age	0.075***		0.027***		0.040***	
	(0.002)		(0.002)		(0.010)	
Labour	0.0001***		0.0001***		-11.025***	
Productivity	(0.00001)		(0.00002)		(1.750)	
	-0.630***		-0.439***		1.180***	
HGF dummy	(0.040)		(0.028)		(0.121)	
FO dummy	-0.092***		-0.017		0.812***	
	(0.013)		(0.020)		(0.097)	
Constant	-3.213***	-2.830***	-0.334***	0.117***	-0.855	0.144***
	(0.061)	(0.005)	(0.100)	(0.008)	(1.236)	(0.039)
Observations	846,431	850,509	73,642	73,658	3,891	3,891
AIC	254,578.400	336,935.300	97,231.720	98,875.580	4,764.546	5,233.504

***p<0.01

This table reports sensitivity analysis that used more standard logistic regression to examine changes in the probability to be classified as an NPO (NPO1-NPO6) and charity (CHA1 and CHA2). NPO1 and NPO2 consist of full unmatched data with 528,584 unique organisations. NPO3 and NPO4 consist of the matched sample with 38,048 organisations. CHA1 and CHA2 consist of the matched sample with 972 organisations. NPO2, NPO4 and CHA2 include variables that were used with the classification tree in Equation 3. NPO1, NPO3 and CHA1 also include variables in Equation 2 as controls. Given the high correlations reported in appendix 2, turnover and employment were grouped according to the thresholds in the EU definition (Commission Recommendation 2003). Other controls that are not reported but were included are region dummies, sector dummies, as well as size at birth and current size based on turnover and employment. To aid interpretability, employment costs, purchases, acquisitions, disposals and tax were converted to millions. The figures are based on ARDx data and were estimated with the R programming language.

We also report sensitivity analyses with more standard logistic regression in Table 10. Logistic regression was chosen instead of mixed effects because it outperformed mixed effects in the previous assessment. Logistic regressions with and without controls uniformly showed a significantly positive relationship between the probability of being NPO and both employment costs and acquisitions, and negative coefficients were estimated for purchases, disposals and tax. The ratios were, as expected, nuanced with varying coefficients across models, supporting the need for more nuanced modelling with decision trees, especially once the dependent variable was replaced by the probability of being a charity.