The London School of Economics and Political Science

Data for Good?

Data Practices and Justification in the UK Non-profit Sector

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Declaration

I certify that the thesis I have presented for examination for the MPhil/PhD degree of the London School of Economics and Political Science is solely my own work other than where I have clearly indicated that it is the work of others (in which case the extent of any work carried out jointly by me and any other person is clearly identified in it).

I declare that my thesis consists of 90.600 words, including footnotes but excluding bibliography and appendices.

Abstract

The thesis analyses the politics and practices of data in the UK non-profit sector. It approaches the topic through scholarship in the Critical Data Studies field, which combines ideas from science and technology studies, sociology, and communications. The thesis focuses on the attempts to introduce new digital and quantitative measurement practices to the UK non-profit sector.

The thesis develops a novel conceptual framework to analyse politics and practices of data. The conceptual framework combines John Law's ideas on methods assemblages with a pragmatic sociology of value drawing upon Luc Boltanski and Laurent Thévenot. The central research question is "How are data practices used to demonstrate value in the UK non-profit sector?" To answer the question, the thesis uses Data for Good initiatives and interviews with non-profit data professionals as its empirical entry-point to non-profit sector data practices. The empirical analysis focuses on interviews with 35 non-profit sector data professionals, which are complemented with participation in Data for Good-themed events and public online information.

Data practices are shown to be used to demonstrate value in two ways: demonstrate value by either serving as proof in epistemic disputes or by enacting versions of reality that help to demonstrate value in other situations of dispute. The analysis suggests that the increasing use of data is shaping the way non-profits seek to demonstrate the value of their work. Furthermore, it suggests that use of data can create contradictions that undermine the ideals increased use of data is meant to serve. The interviewees were found to be aware of these contradictions, but they are shown to push for *better* quantitative and digital data practices rather than for alternative ways of understanding epistemic value. Conceptualising quantitative data practices through my interpretation of the concept of epistemic value allows me to highlight the difference between local data practices, which are always partial and fallible, and the general logic of perceiving quantitative and digital data practices as a way of demonstrating greater epistemic value.

The thesis contributes to research debates on non-profit sector data practices by arguing that data practices are linked to multiple different strategies to justify the value of non-profit work, which makes the politics of data relational and contingent. Moreover, the findings suggest that data science has found only limited use in the UK non-profit sector despite attempts to promote it. The thesis contributes to the Critical Data Studies field by developing and operationalising a new conceptual strategy. The approach of the thesis complements earlier literature on the politics of data practices by emphasising the connection between data practices and demonstrations of value and by using an inductive and symmetric approach to politics and normativity.

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Chapter 1:

Introduction

1.1. Politics and practices of data

This thesis explores the politics and practices of data in the United Kingdom (UK) non-profit sector. What I mean by politics of data is that questions pertaining to collection, analysis, and use of data have normative ramifications and social implications. This definition comes from the emerging Critical Data Studies field, which is a multi-disciplinary research programme that focuses on the social and political aspects of data and digital technology (Dalton et al., 2016; Iliadis & Russo, 2016; Kitchin & Lauriault, 2014). The concepts and frameworks in Critical Data Studies draw from sociology, science and technology studies (STS), and communications among other disciplines, and the thesis is situated in these fields of social science research.

In this thesis I use the concept of *data practices* to denote the way non-profits use data. The data practices concept is widely used in Critical Data Studies and STS to guide bottom-up analysis of how data is constructed by sociotechnical processes and used in relational contexts that shape, and are shaped by, the use of data. The concept is closely connected with the politics of data because studies of data practices recognise the way data practices are connected to knowledge regimes, institutional relations, and normative assumptions that guide data practices (Ruppert & Scheel, 2021). Yet individual studies conceptualise data practices with different analytical foci. Data practices have been analysed both with an emphasis on the situated and sociotechnical nature of data (e.g. Cruz, 2023; Fotopoulou, 2021; Garnett, 2016, 2017) and from a normative perspective of data practice shaping political relationships (e.g. Beraldo & Milan, 2019; Crooks & Currie, 2021; Milan, 2018). In this thesis I follow the definition of data practices offered by Scheel, Ruppert, and Ustek-Spilda, who define data practices as active social engagement with technological tools of quantification, emphasising their role as "activities performed by humans in relation to materials, technologies and shared understandings and occur within specific fields" (Scheel, Ruppert, & Ustek-Spilda 2019, pp. 7). I discuss my conceptualisation of data practices more closely in Chapter 2.

I analyse the politics and practices of data in the UK non-profit sector in the context of a surge in the public interest in digital data that occurred during the 2010s. Initially, this public interest unfolded under the banner of "Big Data" and later developed into a wider interest in computational technologies and data science (Kitchin, 2014b). The increased interest in data is also present in the non-profit sector where new data collection and analysis techniques are promised to make a major contribution to how non-profits tackle social problems (e.g. McCosker et al., 2022). Indeed, those who promote the use of new computational technologies often highlight that the ethical use of the new techniques should include the goal of using them for good purposes (Floridi et al., 2020). Proponents of the new computational technologies suggest that innovations in digital data collection and analysis by private companies can be harnessed in the service of social causes (Mann & Sahuguet, 2018; Tomašev et al., 2020).

Critical Data Studies offers a valuable vantage point on the politics and practices of data in the UK non-profit sector because it rejects two ideas that are common among those who are enthusiastic about the potential of data. First, the Critical Data Studies tradition rejects the idea that data is objective, technical, and neutral. It does so by highlighting that all data is sociotechnical and therefore linked to social and political processes that shape its construction. In Critical Data Studies data is not a static object, but something to be studied through the practices of its collection, analysis, and use. Second, research in the Critical Data Studies tradition is sceptical of the idea that computational technologies developed in the private sector can in themselves solve social problems when transplanted to the non-profit sector. Researchers in the field call such ideals technological solutionism, which refers to the idea that complex social problems can be reduced to technical problems that are possible to solve with technical solutions (e.g. Morozov, 2011). Research in the Critical Data Studies field is therefore valuable in analysing the processes that make data relevant for non-profit organisations in the UK and the practices that non-profits engage in when they use data.

1.2. Theoretical foundations and the argument of the thesis

The theoretical premise of the thesis is that new data practices associated with the development of quantitative and digital data analysis in the 2010s have a close reciprocal relationship with the strategies non-profit organisations use to justify their work. I explore the argument that changes in the quantitative and digital data practices used by non-profit organisations reflect changes in the way non-profit organisations justify the value of their work. To make this argument, I combine ideas from sociology and STS and apply them in the conceptual context of Critical Data Studies and in the empirical context of the UK non-profit sector.

What I mean by justification is inspired by the ideas of Boltanski and Thévenot (2006) and their expansion in the Valuation Studies field (Doganova et al., 2014; Helgesson & Muniesa, 2013; Kjellberg & Mallard, 2013). According to Boltanski and Thévenot, the need to justify value stems from the necessity of ordering competing normative claims through tests, and that these tests take different forms depending on what normative qualities must be demonstrated and ordered. They suggest there are multiple competing normative frameworks that cannot be reduced to each other, have their own ideals, and follow different conventions of demonstrating worthiness. These systems of assessing value have important differences in whether and how quantitative measurement techniques are used to demonstrate one's worthiness. The implications of these differences, especially the way measurement practices shape the demonstrations and standards of value, have become central to the field of Valuation Studies. For example, Emily Barman's (2016) analysis of different strategies to combine the measurement of economic and social value shows that different measurement techniques create their own metrics of value that serve different audiences and purposes. The choice of this approach is supported by earlier studies suggesting that one of the primary reasons non-profits adopt quantitative measurement practices is to try to defend themselves against doubt and criticism of how well non-profits are doing their job (Barman, 2007; Connolly & Hyndman, 2004).

In this thesis I build a novel interpretation of Boltanski's and Thévenot's arguments by combining their ideas with John Law's (2004) arguments on methods assemblages and his work on data practices in collaboration with Evelyn Ruppert and Mike Savage (Law, Ruppert, and Savage, 2011; Ruppert, Law, and Savage, 2013). Law and his colleagues suggest that data should be studied through methods assemblages that have their own proponents, that are nested in specific relational contexts, and that form the foundations for organisations in perceiving themselves in relation to their environment (Law et al., 2011). Here it suffices to say that the ideas of Boltanski and Thévenot can be used to deepen the analysis of normative ramifications of methods assemblages, and this combination is supported by earlier theoretical literature hinting at connections between the two (e.g. Blok, 2013; Guggenheim & Potthast, 2012). The combination of these theories allows me to build a conceptual framework to study politics and practices of data through the way non-profits justify their use of data for themselves, and how they use data to demonstrate the value of non-profit work. I explore the theoretical foundations of this combination in Chapter 2 of the thesis, and the combination is operationalised in the empirical analysis in Chapters 6, 7, and 8.

The central argument I propose in this thesis is that the changing uses of data are linked to changing practices and standards in demonstrating *epistemic value*. In other words, there is value in numbers themselves as a strategy of justification. Furthermore, I suggest that changes in demonstrating epistemic value have implications for the justification of many other forms of worthiness that rely on empirical evidence in attributing value. In this thesis I focus on how changing practices and standards of epistemic value influence the way non-profit organisations justify their worth when applying for grants and assessing the social value of their work. In both cases the data practices do not just provide epistemic value to the claims made by non-profits but actively shape what it means to be worthy of funding or contribute to social change. The study therefore introduces a new theoretical lens on how non-profit organisations are pushed to conform their work to what can be measured quantitatively. I build on Law's ideas on the performativity of methods assemblages to suggest that quantitative data practices do not just allow non-profits to claim credibility but to *render their claims as one version of reality*. Nevertheless, these enacted realities are always partial and uncertain, which makes them susceptible to criticism by alternative evidence if it is available.

Based on the study, people working with digital and quantitative data practices in the UK non-profit sector are shown to be aware of partiality and shortcomings in quantitative measurement, but this awareness tends to lead to calls for more data and better data, rather than to a more fundamental rethinking of quantification. I show that such critical discussion is common both in the context of grant-making and internal non-profit discussions on social value. Nevertheless, such critical awareness among quantitative data practice experts does not necessarily change their overall appreciation of the epistemic value of quantitative data practices. Instead, in the thesis I show that many non-profit data professionals wish "bad" measurement practices to be replaced with "better" ones. Conceptualising quantitative data practices through this approach to epistemic value allows me to highlight the difference between local data practices, which are always partial and fallible, and the general logic of perceiving data as a way of demonstrating epistemic value.

1.3. Empirical design and the 'Data for Good' initiatives

The empirical design of the study uses the expert interview method (Bogner and Menz, 2009) with a focus on people who have specialist professional knowledge of data practices in the non-profit sector. This method does not require recruitment of a representative sample of all the people working in the non-profit sector, and it focuses on accessing a narrower sub-group of people with an expected unique positionality in working closely with data in the non-profit sector. In the context of this thesis, I call this target group for interview recruitment *non-profit data professionals.* A thorough discussion of the characteristics and limitations of this group as a sample of interviewees can be found in Chapter 4 on methodology.

In the thesis I access my target group of interviewees through the loose promotional coalition of new data practices in the non-profit sector, which goes by the name of 'Data for Good.' I discuss the methodological aspects of this strategy in Chapter 4, whereas an empirical analysis of the Data for Good initiatives as an entry-point to data practices in the UK non-profit sector can be found in Chapter 5.

Various Data for Good initiatives have emerged in the Western world in the past decade to promote new data practices in humanitarian, non-profit sector, and public policy context, with the argument that novel computational technologies can make a positive contribution to society (Aula & Bowles, 2023). The work of these networks has invited critical research scrutiny. Moore (2019) and Green (2019) argue, for example, that the normative commitments of Data for Good initiatives are too vague to constitute a coherent political mission, which locates these initiatives as akin to a branding strategy for new computational techniques. Critical analyses suggest that use of technology promoted in such initiatives can compound existing problems and create new problems without delivering on their promises of social betterment (Madianou, 2021; Magalhães & Couldry, 2021). They can be seen as being misguided in reducing complex social problems to technical problems to be solved with more data collection (Espinoza & Aronczyk, 2021; Holzmeyer, 2021). This evidence complements earlier studies on using Big Data in humanitarian contexts which suggests that a focus on data is reductive and imposes a need for data collection and analysis that might displace broader humanitarian goals (Taylor & Broeders, 2015). However, no study at the time of writing has explored Data for Good initiatives in the UK non-profit sector. By using these initiatives as an entry-point to non-profit sector data practices, the study is intended to complement earlier empirical research into the dynamics of data practices and politics, and the focus of the study is not on the Data for Good initiatives themselves.

1.4. UK non-profit sector as an empirical context

In this thesis data practices are analysed in the empirical context of the UK domestic charity and non-profit sector. Specifically, the study focuses on non-profit organisations working in the social and health sector. In the UK, the non-profit organisations play a central role in the provision of social and health services by both providing services independently and acting as a contractor for public services. In the financial year 2019/2020 the total revenue of the UK non-profit sector was £58.7 billion, it had paid workforce of 951,611 employees, and had millions of UK citizens engaged in either formal or informal volunteering (National Council for Voluntary Organisations, 2022). Half of this revenue came from donations and one quarter from governmental grants and public service contracts.

Past research on the UK non-profit sector data practices highlights the influence of New Public Management (NPM) and Evidence-based Policymaking, which both have contributed to claims about the importance of quantitative measurement in guiding non-profit work. In the UK, NPM has led to increases in outsourcing of public services to non-profits, coordination of services with managerial measurement techniques that emphasise the efficiency, effectiveness, and monetary savings as measures of success, and a marketisation of public services (B. Evans et al., 2005; Hood, 1991; Smith, 2011). The effects of Evidence-based Policymaking are said to be felt more in the way non-profits are expected to measure the effectiveness of their work in terms of measurable change as an outcome of the services provided by a non-profit, which pushes non-profits to use quantitative and experimental methodologies to measure the impact of their work (Arvidson, 2014; Boaz et al., 2019). The UK non-profit sector has also been influenced by the austerity policies of the Cameron Government in the early 2010s, which saw cuts to both direct funding to non-profit sector and social policy budgets that indirectly influenced the money available for outsourced services (Alcock, 2016; Clifford, 2017).

As a result of austerity policies, the UK non-profit sector has come to shoulder an increasing burden of work in the social and health sectors while public spending on the non-profit sector has decreased. The idea that data can help non-profit organisation better succeed in their goals of social betterment thus falls on fertile ground of the non-profits in the UK as they are faced with growing inequality and decreased resources. The new ideas and practices regarding data and data science created a new push for quantification that extends and complements the existing legacies of NPM and Evidence-based Policymaking.

I want to highlight that the UK domestic non-profit sector differs in important ways as a context for politics and practices of data in comparison to the contexts examined in the global scholarship on the politics and practices of data. These differences are important in framing of my empirical case.

My focus on the UK non-profit sector differentiates the study from those that focus on politics and practices of data within the government. While the UK non-profit sector is closely linked to public service delivery, the use of data by non-profits has been shown to have a very different focus than government statistics, which were studied by Ruppert and Scheel (2021). While non-profit organisations are considered members of civil society, they treated as distinct from activist groups and interest-based associations because they tend to focus on service provision (Smith, 2011). This means that my case is has some important differences in comparison to the studies of activist data practices that have been explored in earlier literature (Beraldo & Milan, 2019; Crooks & Currie, 2021; Milan, 2018; Milan & van der Velden, 2016). However, the UK non-profit sector does share many qualities with the U.S. non-profit sector which has been deeply influenced by neoliberal ideology, an audit culture, and an emphasis on quantitative measurement (Hall, 2014; Hall et al., 2015).

Critical literature on the politics and practices of data often focuses on the humanitarian and development context. Madianou (2019, 2021) has argued that digital technologies in the humanitarian context can lead to exploitative colonial relations given the power asymmetries between the providers of the technology and the targets of the intervention (see also Irani et al., 2010). Power asymmetries also influence donor relations, as projects are developed with an eye on the interests and preferences of Western donor organisations rather than on local needs in beneficiary countries (Jenkins, 2010; Krause, 2014). Technology companies have become active players in the global philanthropic landscape and push for technology-centric strategies in alleviating social problems despite criticism of their misguided techno-solutionism and corporate exploitation (Haven & Boyd, 2020; Magalhães & Couldry, 2021) Studies have also critiqued the damage, wasted resources, and perverse incentives associated with humanitarian funding when it adheres to rationalist and quantitative ideals of measuring development and social change (Rottenburg et al., 2015). I suggest that only some of these observations are applicable in the *domestic* UK non-profit sector. Power asymmetry between donors and applicants for money, as well as the dominance of neoliberal thinking and quantitative measurement, influence data practices in the UK non-profit sector. Yet the donors and recipients of money *within* the UK are not directly representative of the colonial dynamics that are present in UK-based non-profit organisations engaging in humanitarian and development aid projects overseas. Furthermore, in previous research there is few, if any, signs of the presence of global corporations, Big Tech companies, or tech-executives-turned-philanthropists playing a significant role in the domestic UK non-profit sector. This stands in contrast to the major role played by philanthropists and Big Tech companies as funders and partners of humanitarian and development projects. The similarities and differences mean that the distinctive qualities of the case must be considered when assessing the contribution of this thesis in relation to research on politics of data in the humanitarian context. The historical, political, and technological context of the UK non-profit sector case is discussed in Chapter 3.

1.5. Research question

Having established the theoretical context and the empirical context of the study, I proceed to formulate the research question. My central research question combines insights from Critical Data Studies with its focus on data practices and methods assemblages and frames them in reference to Boltanski's and Thévenot's arguments on value and justification. The research question is:

- **How are data practices used to demonstrate value in the UK non-profit sector?**

I answer the research question by using Data for Good initiatives in the UK non-profit sector as an entry point to examine data practices and justification. To do so I build a conceptual framework for the analysis of data practices and justification, which I then operationalise empirically. Answering this question offers insight into the theoretical and empirical debates on the politics of data and advances empirical research on non-profit sector data practices. The rest of the thesis is organised as follows.

1.6. Outline of the thesis

The thesis is divided into nine chapters. Three of these chapter build the conceptual and methodological foundations of the study, whereas four chapters are dedicated to the empirical analysis.

Chapter 2 focuses on the theoretical foundations of the thesis. It positions my thesis within Critical Data Studies and related discussions in sociology, STS, and communications. In the chapter I offer my interpretation of the methods assemblage concept developed by John Law as an offshoot of Actor Network Theory (ANT) and explain why it is relevant in exploring politics of data practices. I then introduce Boltanski's and Thévenot's arguments on justification and value and discuss their shared origins with ANT. Finally, I combine these theoretical foundations to formulate the conceptual framework and present the research sub-questions that I explore in the empirical chapters.

Chapter 3 turns attention to earlier empirical evidence on non-profit sector data practices with a focus on the UK context. I review the historical background of the politics of quantification and assess recent trends. I discuss the influence of NPM and Evidence-based Policymaking in the UK, and the influence of Big Data boom on renewed interest in data. I finish the chapter by positioning my approach in the earlier literature on quantification and data practices in the non-profit sector.

Chapter 4 outlines the methodology of the thesis. In the chapter I first discuss the methodological implications that follow from my conceptual framework and how they can be operationalised in empirical inquiry. I then explain why expert interviews are chosen as the data collection strategy for the study, which I complement with minor elements of ethnographic fieldwork and supplementary online data collection. The sampling strategy of the interviews and its limitations are discussed as is the analysis process.

Chapter 5 is the first empirical chapter which employs elements of my conceptual framework. It examines Data for Good initiatives as an entry point to non-profit sector data practices in the UK and introduces a general picture of how my interviewees approached data practices. It identifies two anchors for data practices offered by my interview sample and positions them in the wider context of quantitative measurement in the non-profit sector.

Chapter 6 is the conceptual and empirical heart of the thesis, and it focuses on how the non-profit data professionals I interviewed appeared to value data. In the chapter I offer empirical evidence on how the interviewees were found to believe that quantitative and digital data practices can help them to better defend their claims. In doing so, it introduces my concepts of epistemic disputes and epistemic value. I show how all data practices are riddled with loopholes and shortcomings that undermine the idea that data could provide a stable epistemic foundation that non-profits can rely upon. The analysis provides a basis for proposing that epistemic value in the non-profit sector is always relational and that it supports some other, more substantive claim of value depending on what is in dispute. In other words, epistemic value is rarely the primary locus of interest for non-profit organisations, although non-profit data experts nevertheless are highly engaged with it. I also discuss non-profit data practices in the light of power asymmetries and a lack of resources in the sector and show how these factors place limitations on the potential of data science in the non-profit sector.

Chapter 7 applies my conceptual framework to a typical situation of dispute where non-profits must justify the value of their work: in applying for grants. The chapter shows that data plays three distinct roles in justifying why a non-profit should receive a grant. On the one hand, the use of data can demonstrate the accountability of non-profit organisations, providing a "proof" that they are worthy of funding despite concerns about possible misconduct. On the other hand, uses of data can demonstrate the impact of non-profit organisations even in the face of concerns about their ineffectiveness. Finally, data itself is shown to enact needs in the society, demonstrating that the work of a non-profit is necessary to tackle problems that deserve attention. I also show that non-profit data professionals worry about increased use of data and that this can lead to overclaiming and inconsistencies. These challenges may lead to increased distrust which the use of data was initially expected to counter.

Chapter 8 turns attention to another dispute non-profits often face: the measurement of needs and how it is connected to social value. The chapter discusses two distinct types of 'proof' that non-profits use to defend their choices in disputes about social value. On the one hand, they are shown to enact collective needs that inform what issues the non-profits should try to tackle and where to direct their work. On the other hand, they are found to enact and respond to individual needs, which guides the way non-profit work is managed. Importantly, many non-profit data professionals appear to believe that non-profits should be constantly improving their work based on what activities provide the most social value. Based on my analysis, this suggests that internal management of social value is particularly consequential because it tends to reshape non-profit goals towards achieving better alignment with what they can measure with data. The chapter also discusses examples of data science in measuring needs and improving non-profit work.

Chapter 9 provides a concluding discussion of the findings of the thesis, recapitulating my answers to the primary research question and the research sub-questions. The conclusion chapter also discusses the limitations of the study.

Chapter 2:

Data, methods assemblages, and justification

2.1. Introduction

In this chapter I review the theories and concepts that inform my analysis of the politics and practices of data. I open the chapter by discussing recent literature in the Critical Data Studies field which emphasises the political aspects of new computational technologies. Within Critical Data Studies, I build on arguments made by Ruppert, Law, and Savage (2013) on the need to analyse new developments in the uses and interpretations of data through politics of methods assemblages and what they enact. This approach differs from approaches that are informed by a strong normative position, such as is often present in the Data Activism and Data Justice literatures. Having situated the thesis in Critical Data Studies, I turn to the theories that inform a methods-centred approach to data and politics. I work with the concept of *methods assemblage* developed by John Law and Annemarie Mol as the key concept to inform my analysis of Data for Good initiatives. I discuss the roots of the concept in Science and Technology Studies (STS) and Actor Network Theory (ANT), especially the role of enactment and performativity. I then discuss the way politics and normativity are understood by John Law, Annemarie Mol, and Noortje Marres, all of whom have made contributions to a new way of incorporating politics into ANT. I suggest that while they successfully introduced normativity as an *empirical* topic to be analysed, several ambiguities remain in how politics and normativity is best identified in empirical inquiry.

To address these ambiguities in my interpretation of methods assemblages and ANT, I propose that these approaches can be complemented by drawing insight from pragmatic sociological approaches to value. I introduce ideas proposed by Boltanski and Thévenot and discuss their development in the Valuation Studies field. I highlight that this field shares a theoretical foundation with ANT which is helpful in elaborating on the normative and politics aspects of methods assemblages. Crucially, they provide a fruitful way of complementing an inductive approach to the study of data assemblages with an inductive approach to studying normativity. Thus, I propose that the normativity of methods assemblages can be studied by focusing on how they are used in *situations of dispute.* Furthermore, I suggest that resources used in *demonstrations of value* can be understood as being enacted through methods assemblages. The versions of reality enacted with methods assemblages therefore are suggested to offer a 'proof' of value in situations where value is in dispute or needs to be tested.

In the final section I outline the conceptual framework that informs the analysis in the thesis. I break the central research question, which was introduced in Chapter 1, into three sub-questions, which guide my empirical analysis.

2.2 Critical Data Studies

In this thesis I approach Data for Good initiatives and non-profit sector data practices through literature in the Critical Data Studies field. Critical Data Studies is a research programme that emerged in the early 2010s as a critical response to scholarly and popular claims about the "Big Data". The programmatic origin of Critical Data Studies can be found in a series of journal articles outlining the need to explore the social, political, ethical, and economic consequences of Big Data, and the need to counter technology-centred, positivist, and technologically deterministic arguments about digital data (boyd & Crawford, 2012; Crawford et al., 2014; Dalton et al., 2016; Iliadis & Russo, 2016; Kitchin, 2014a; Kitchin & Lauriault, 2014).

I have two primary reasons for framing my analysis of Data for Good initiatives in the UK non-profit sector through Critical Data Studies. First, the arguments presented in Data for Good initiatives align closely with the subject matter explored in Critical Data Studies, making it a *relevant empirical research debate*. For example, a review of the literature shows that proponents of Data for Good initiatives, which serve as my empirical entry point as discussed in the Introduction, routinely argue that the use of data and new computational tools is an opportunity to improve how non-profit organisations operate, and that the technological opportunities of data can be harnessed to serve the common good (Aula & Bowles, 2023). Because the focus of the thesis is to critically interrogate such claims and provide a nuanced analysis of the politics involved in the initiatives, Critical Data Studies offers a fruitful starting point.

Second, Critical Data Studies is a *thriving arena for theoretical debate* on how data and computational technologies should be studied. Critical Data Studies serves as an arena to debate the opportunities and shortcomings of the different conceptual tools that can be used to study the political ramifications of increasing interest in data (Hepp et al., 2022). By situating the thesis in Critical Data Studies, my aim is to advance theoretical approaches to the political ramifications of data. I next survey some of the key ideas and conceptual tools in Critical Data Studies. Although digital data in online environments or as collected by new sensory devices served as an initial focus of Critical Data Studies, the empirical focus has evolved to include the use of data and quantification in a variety of settings (e.g. Iliadis and Russo, 2016). Some of the initial themes such as algorithms, platforms, and datafication, have matured to become new 'fields' of study. However, fragmentation within the field means that there is considerable diversity in the conceptual tools and empirical insights (for an overview, see Hepp et al., 2022). For example, Zakharova (2022) proposes that the Critical Data Studies literature can be segmented by whether it focuses on data infrastructures, data representations, or datafied regimes, and that there is further diversity in the conceptual tools used to study these phenomena. Moreover, Critical Data Studies itself has embraced different conceptual and empirical interests that open up separate research debates, such as on Data Activism (Milan & van der Velden, 2016) or Data Justice (Dencik et al., 2016, 2019; Taylor, 2017). Some streams of research that explore the political ramifications of data and computational technologies do not explicitly frame themselves as part of the Critical Data Studies field, but serve as interlocutors in similar debates (Ruppert et al., 2017). Indeed, many of the theories used in Critical Data Studies can be traced to earlier arguments in STS, sociology, and communications studies, and this blurs the conceptual and empirical boundaries of the Critical Data Studies field. Despite diverse empirical foci and theoretical approaches, there are shared conceptual elements. These elements help to provide a focus for this thesis. The shared elements identified here are not exhaustive but serve as an anchor for my engagement with Critical Data Studies in this thesis.

A key shared element is that most approaches in Critical Data Studies work with the assumption that data should be understood as part of *sociotechnical assemblages* that also have political ramifications (Iliadis & Russo, 2016; Kitchin, 2014a, 2014c; Ruppert et al., 2013). The emphasis is on the *socio*-technical nature of assemblages, which underscores the social aspects of technical tools and infrastructures. Indeed, stressing the social element of data-related assemblages opens up an avenue for analysing the politics of data through the social relations embodied in technical systems. Although the social and material character of data has always been a key theme in STS, in Critical Data Studies it provides a poignant critique of the idea that data should primarily be understood as information or that data can be a neutral reflection of reality. This idea is best captured in the maxim "data is never raw," a catchphrase made famous by Geoffrey Bowker (2000, 2005) and Lisa Gitelman (2013). The concept of assemblages is used in Critical Data Studies to expand the empirical scope of analysis from a focus on data itself to the wider context of infrastructures, institutions, practices, interests, and values that shape why and what kind of data is generated in the first place. In this thesis I advance this focus on sociotechnical assemblages by building on ideas of Ruppert, Law, and Mol on methods assemblages and combining them with studies of the pragmatic sociology of value inspired by the work of Boltanski and Thévenot.

A second key element is a focus on data practices. Scholars working in the Critical Data Studies typically use the *data practices* concept to underscore the social, situated, and active nature of engaging with data as a sociotechnical assemblage. Discussing data practices emphasises that data is not a static technology, but something that is constantly engaged with and utilised for purposes defined by its users in a specific sociopolitical context. For example, recent Critical Data Studies analyses of activist and civil society uses of data have emphasised a data practice perspective to highlight that data can serve multiple political purposes depending on how the use of data is related to the political and institutional context (Beraldo & Milan, 2019; Cruz, 2024; Fotopoulou 2022). Data practices can also be studied on the micro-level of how data is made through classification, quantification, technological configuration, meaning-making, and collective sensemaking (e.g. Garnett, 2016; 2017), which connects the concept of data practice? back to the study of sociotechnical assemblages as discussed above.

In this thesis I follow the definition of data practices made by Scheel, Ruppert, and Ustek-Spilda (2019), who define data practices through the work of John Law (2004) and Annemarie Mol (2002), which also informs the theoretical foundations of this thesis. They define data practices as active social engagement with technological tools to enact realities, emphasising their role as "activities performed by humans in relation to materials, technologies and shared understandings and occur within specific fields" (Scheel, Ruppert, & Ustek-Spilda 2019, pp. 7). Furthermore, they emphasise that "practices always involve a *doing* and put sociotechnical arrangements to use that only come to matter by being used in practice" (*ibid.* pp. 7). Elsewhere, Ruppert and Scheel (2021, pp. 34–36) emphasise the connection between data practices, values, and beliefs that are situated in a particular context. This aspect, which emphasises the social element of socio-technicality, is relevant for my thesis because it foregrounds the importance of what is valued by people working with data and why. Such social aspects of valuation are necessarily embedded in the broader relational position of the practitioners, which influences the values and beliefs that guide the politics and practices of data. As suggested by Ruppert and Scheel (2021, pp. 34, emphasis added), the study of data practices must "*consider the discourses, knowledge regimes, legal norms, materialities, and technical affordances that shape and inform these practices.*" By following this definition, I emphasise the social, that is, what people do with data in given relational contexts, rather than a technical emphasis on the material operations of constructing data sets. This analytical choice is relevant to the connection I make between the analysis of methods assemblages and justification later in this chapter.

In addition to a focus on assemblages and data practices, many contributors in Critical Data Studies are attentive to normative considerations regarding the conduct of research inquiry itself and adopt a deliberately normative position to what would be desirable in the context of data practices. The initial formulations of Critical Data Studies embedded normative positions by highlighting the social, economic, and political asymmetries associated with the use of data (Andrejevic, 2014; boyd & Crawford, 2012; Dalton et al., 2016). However, certain arguments in Critical Data Studies are informed by specific normative goals, such as overcoming injustices and empowering citizens (Couldry & Powell, 2014; Dencik et al., 2019; Luka & Millette, 2018; Milan & Treré, 2019) or the formation of individual and collective rights regarding data (Isin & Ruppert, 2020; Ruppert et al., 2017). Furthermore, analysis in this tradition typically requires some empirical engagement with normative and political claims made by actors involved with the use or the promotion of data use (Richterich, 2018). In Critical Data Studies, normativity is therefore not only a stance taken by the researchers, but something to be analysed empirically.

In this thesis my contribution to the above developments in Critical Data Studies is to expand on arguments proposed by Evelyn Ruppert, John Law, and Mike Savage (2013; see also Law, Ruppert, & Savage, 2011) who offer one version of combining the analysis of data assemblages and normative considerations. Ruppert, Law, and Savage propose an approach that focuses on methods assemblages and how data *enacts* specific forms of sociality and political relations. This approach also emphasises the role of social practices in how methods assemblages enact realities, as I have discussed above when defining data practices (e.g. Scheel, Ruppert & Ustek-Spilda 2019). A central part of their argument is that our understanding of social and political relations is shaped by sets of social science methods that enact specific ways of understanding social and political phenomena. They propose that our understanding of the world is *already* shaped and saturated with data from surveys, statistics, censuses, accounts, registers, records, and ledgers. New forms of data generated with digital devices can enact new objects and relations, but such uses come in addition to the existing ways of enacting objects and relations. They propose that researchers should "*explore fields of devices as relational spaces where some devices survive and dominate in particular locations while others are eclipsed*" (Ruppert, Law & Savage*,* 2013, pp. 40, emphasis added). Ruppert, Law, and Savage therefore argue that new developments associated with the proliferation of digital data should *not* be understood as an epochal shift, but as an emergence of new methods assemblages that should be compared with existing assemblages that generate data and enact empirical objects. Furthermore, their argument implies that politics, normativity, and power are integral to any assemblage and should therefore be studied *relationally* by closely attending to how data is made and what is done with data in specific situations.

The approach I have chosen contrasts with some other strategies in Critical Data Studies. To highlight the distinctiveness of my approach, I compare it with work on Data Activism and Data Justice, which are empirically connected to research on civil society and are therefore relevant to my analysis of Data for Good in the UK non-profit sector. Research on Data Activism typically analyses the way the use of data shapes the practices of civil society organisations. Crucially, Data Activism research attends closely to the opportunities data provides for political action. Milan and van der Velden (Milan & van der Velden, 2016) argue, for example, that activism relating to digital data can be divided into activism to resist specific data practices and activism that uses data to advance collective causes (see also Beraldo & Milan, 2019). The Data Activism tradition has been used to study a variety of ways that data is used as a tool of activism or how the use of data and digital technology shapes the strategies used by social movements

(Baack, 2015; Currie et al., 2019; Ermoshina, 2018; Gray & Bounegru, 2019; Horgan & Dourish, 2018). In these works, knowledge about society provided by data uses is understood to lend credibility enabling activists to assert the validity of their claims and challenge the validity of other claims. Yet Lehtiniemi and Ruckenstein (2019) show that an activist ethos does not guarantee that the political mission of a movement is coherent or without contradictions. Cinnamon (2019) has pointed out that activists sometimes rely on what Neff and Nagy (2015) have called "imagined affordances", which means capacities for action and politics that are projected into data by its users with an optimistic vision of its impact. Indeed, pioneer groups operating as activists can promote systems that are in line with the normative goals of the group but also produce political problems or exacerbate inequalities (Hepp 2020). Arguments and findings similar to those in the Data Activism literature can be found in research on Data Justice (Dencik et al., 2016, 2019; Taylor, 2017), which explores how new data practices should be analysed through how they compound or tackle broader injustices in the society. Studies in the Data Justice tradition often take one step further in explicating the political commitments of researchers, focusing on whether and how new uses of data intersect with inequalities and power asymmetries identified in broader social science inquiry. For example, Dencik et al. (2016) suggest that increasing the use of data in development policies and humanitarianism can establish new varieties of surveillance and discrimination, which causes new injustices for the people who were supposed to benefit from the introduction of data-driven strategies. The normative viewpoint of the calls for Data Justice can vary within the broader goals of emancipation and social betterment, and examples include human rights and Amartya Sen's capabilities approach (Taylor, 2017) and anti-surveillance activism and the promotion of social justice (Dencik et al. (2016). Crucially, the approach towards politics in Data Justice approach often assumes the existence of structural inequalities between citizens and governments and citizens and corporations, which a focus on justice seeks to overturn. Data Activism research points towards some of the arguments made by Ruppert, Law, and Savage, but differs from it. Much of the Data Activism literature aligns with my work by pointing to how political debates are increasingly unfolding *through* data. However, the Data Activism literature differs from it insofar as it is generally motivated the aim of studying how civil society organisations can offer their own perspectives on social phenomena and therefore resist corporate or governmental power. It typically operates with political and normative commitments to align with activists and emancipatory goals. Likewise, a focus on Data Justice may take for granted specific social and political injustices, the manifestation or amelioration of which researchers seek to analyse. Nevertheless, strong political commitments sit uneasily with the idea of Ruppert, Law, and Savage that politics and social relations need to be studied relationally. From their perspective, the claims of activists and civil society organisations are not necessarily more legitimate or desirable than those of, for example, governments. The approach taken by Ruppert, Law, and Savage distances itself from taking some notions of social structures as *a priori* to the analysis of data. This stance suggests scepticism about some of the assumptions that inform many contributions to the Data Justice literature. This point is particularly important in analysing Data for Good initiatives in the non-profit sector, which have explicit goals for the betterment of society and social amelioration.

Many contributors to the Data Activism literature start their analysis with the assumption that the political and normative commitments of social sector civil society organisations are themselves desirable. Indeed, when activists use data with the goal of emancipating underprivileged groups, the desirability of this goal is rarely in question. Yet as Dencik et al. (2016) propose, civil society organisations and non-profits often face a quandary when they rely on corporate technological platforms such as social media in their activist work, despite knowing that this can implicate them in the harmful practices of the platforms. Research on Data Activism also suggests that reliance on data might *transform* political goals and organisational practices of the activists (Currie et al., 2019). Data in service of activist goals is therefore not free of the politics involved with use of data, but deeper engagement with the tensions and contradictions in the use of data can be difficult if premises vacillate between ideals of liberation *with* data and protection *from* data (Gray, 2018). This has led to some researchers to adopt nuanced approaches to the interplay between data and politics within the wider focus on justice, and to emphasise the importance of critical literacy and skills in making use of data (Crooks & Currie, 2021; Fotopoulou, 2021; Gray et al., 2018; McCosker et al., 2022). The approach in this thesis is close to some of these studies, but it retains a distance from the normative commitments that inform much of the activist literature.

Other arguments in Critical Data Studies traditions start from the assumption that reliance on data as a tool of social change might compound existing injustices, as in the Data Justice literature. Indeed, reliance on data in planning social interventions can lead to systematic differences in which groups receive help and which are left without it, even if the effects of the interventions themselves are positive (Heeks, 2018; Heeks & Shekhar, 2019). Following the Data Justice rubric, the dynamic effects of relying on new computational technologies, even if for good causes, can contribute to, rather than tackle, the sources of injustice and discrimination (Taylor, 2017). Following a strong *a priori* normative framework, I suggest, might therefore inform at least critiques, and in some cases, a rejection of data, as well as calls for alternative ways of understanding and tackling social problems.

While my analysis is intended to provide insight into a phenomenon that is closely aligned with the interests of much Data Activism and Data Justice research, my approach to normative and political considerations differs. I suggest that it is necessary to maintain a critical distance from strong normative commitments and prior assumptions about how politics will, or should, manifest in Data for Good initiatives in the UK non-profit sector. What I take from the Critical Data Studies tradition in this thesis is not so much whether Data for Good initiatives serve the goals of activism, justice, and emancipation. It is rather the ways that "goodness" is understood in Data for Good initiatives and how data is thought to contribute to it. I do not compare this to external normative standards but instead explore how normativity and the value of data in the non-profit sector is understood by the participants of Data for Good initiatives. It is the political and normative considerations found in Data for Good initiatives that are of central empirical interest in this thesis, as proposed in Chapter 1. My approach is an extension of the analytical position developed by Ruppert, Law, and Savage (2013), and I develop this further as a framework to address both the methods assemblages *and* normativity of data. [1]

In the next section I elaborate on the methods assemblage concept that informs my analysis and then propose a strategy to incorporate a symmetric analysis of normative arguments into analysis of methods assemblages. This strategy is intended to allow me to distance myself from prior normative commitments and to focus on understanding the vernacular notions of politics and normativity that are revealed in my analysis of Data for Good initiatives.

2.3. Methods assemblages and enactment

To expand on the approach proposed by Ruppert, Law, and Savage I focus on how I utilise their arguments about methods and politics. In doing so, I focus on the theoretical opportunities provided by ANT and especially on the arguments of John Law about how methods assemblages enact version of reality. In this subsection I discuss how I use the methods assemblage concept to specify the more general data practices concept outlined above. My conceptualisation of methods assemblages is in line with the above discussion on the conceptualisation of data practices, that is, I draw from similar theoretical foundations but argue for a slightly different conceptual focus.

ANT scholars argue that the way science produces knowledge cannot be reduced to social practices and relations alone and must, instead, be understood as a combination of practices, technologies, and relations with material objects that together produce versions of reality (e.g. Latour, 1987; Latour & Woolgar, 1986; Law,

[1] I recognize that my positionality as a researcher, my own normative commitments, and choices throughout the empirical data collection shape the way specific form of politics and normativity can be identified in the study. I discuss these predilections further in Chapter 4.

1986). Crucially, ANT scholars argue that debates about empirical reality are not settled though recourse to a reality that is thought to pre-exist the methods of learning about it. Instead, debates are settled by producing a version of reality, enrolling support for it, and producing networks of circulation where that version of reality can be stabilised through repeated remaking (Latour, 1987; Latour & Woolgar, 1986). As was evident in my discussion on the relationship between my ANT-inspired approach and Data Activism and Data Justice, this strategy represents a break from sociological notions of politics and power by focusing on the relations and networks that create the effects of politics and power (Latour, 1991; Law, 1986, 1987, 1991). In ANT scholarship this argument about the use of relational networks to make a version of reality has been applied to other practices beyond science, such as management (Law, 1994) and medical practice (Mol, 2002). It has also been explored in the context of, for example, social research (Law & Urry, 2004; Ruppert et al., 2013), focus groups (Lezaun, 2007), population census (Ruppert, 2011), digitalisation of statistics (Ruppert & Scheel, 2019; Scheel et al., 2019), and algorithmic tools (Bucher, 2018).

Law (2004) proposed the concept of methods assemblages to expand ANT work on the power of scientific methods to enact and establish notions of empirical reality. The way data is conceptualised in Ruppert, Law, and Savage (2013) is indebted to this work. The concept of assemblages is borrowed from Deleuze and Guattari (2013 [1980]) to denote an active collection of practices, knowledge, technologies, and relations that is bundled together to some purpose (Law, 2004, pp. 40–41), with the underlying ideas aligning with the arguments in the ANT literature.[2] A methods assemblage is defined as a set of practices and technologies that renders a phenomenon "out-there" in the

[2] The way Law uses the concept of assemblages, which is a translation from French word *agencemen*t, can be elusive because Law uses the concept as an open-ended empirical guideline for analysis rather than as a closely defined theoretical concept. For example, Law has defined assemblages as "episteme plus technologies" (Law, 2004, p. 41), which evokes the vocabulary of Michael Foucault, but, throughout the same book, the concept is used interchangeably with the ANT understanding of associations. Later the assemblage is equated with Foucault's understanding of the *dispositif* (Ruppert et al., 2013) or titled a "methodological complex" (Law et al., 2011, p. 3).

world to be found (Law, 2004, pp. 84–85). For Law, methods assemblages enact a particular version of empirical reality, “crafting and enacting necessary boundaries between presence, manifest absence, and Otherness” (Law, 2004, p. 144 italics in original). In this framework presence means the at-hand representations of reality enacted with methods assemblages, while manifest absences refer to the factors that are not allowed into the narrative of how a version of reality has been produced (e.g. human practices, serendipity, manipulation, political interests, contextual factors), and Otherness refers to the aspects of empirical reality that are not admitted into the representation created by the method assemblage (i.e. what is not present in the representations).

This approach to ANT emphasises the performativity of methods assemblages: the sustained coordination and deployment of methods assemblages actively creates and re-creates whatever it is meant to portray (Law, 2004, 2008; Law & Urry, 2004). According to Law (2008), performativity is a central tenet of ANT because it emphasises the need for active coordination of material and semiotic resources for any network or for their effects to continue existing. Quoting Law, performativity of methods assemblages means that “that *realities* (including objects and subjects) and *representations* of those realities are being enacted or performed simultaneously” (2008, p. 635 italics and parentheses in original). In ANT, this strategy is used to depart from “construction” as a keyword in STS research and to reorient analysis towards the *doing* of realities.

Law’s understanding of methods assemblages drew extensively on the work of Annemarie Mol (1999, 2002), who called for a reorientation of ANT analysis towards how conflicting notions of empirical reality are enacted by different methods. Mol suggests that “*ontology* is not given in the order of things, but that, instead, *ontologies* are brought into being, sustained and allowed to wither away in common, day-to-day, sociomaterial practices” (Mol, 2002, p. 6, italics in original). In other words, methods assemblages are understood to enact a particular version of reality, one that is never exhaustive, ever partial and that can be contrasted with others. Furthermore, the definition stresses that mundane professional and everyday practices enact versions of reality. Mol calls the negotiation between different versions of reality “ontological politics” (1999), a label which has been adopted in subsequent works by Law (e.g. 2004), and can be seen to influence the way Ruppert, Law, and Savage understand the relationship between different forms of sociality enacted in data.

Methods assemblages, however, do not refer only to methods in the traditional sense of scientific, quantitative, or computational methods. In fact, a key goal in Law’s work has been to expand the notion of methods beyond science and technology to consider other ways of enacting versions of reality. Law (2004) as well as Mol (2002) consider it important that we understand as methods assemblages the practices that are displaced when supposedly more rigorous and scientific methods are introduced. For example, Law (2004) emphasises that reality is too messy to be captured by what are commonly understood as scientific methods and, therefore, we also need to consider narrative, professional, and indigenous practices as methods assemblages that render reality knowable and actionable. Likewise, Mol’s studies of medicine emphasise the need to consider the enactment of diseases, physiological conditions, and patients beyond medical sciences by also considering practices of care (Mol, 2002, 2008). What is rendered absent through scientific methods assemblages can be present in enactments of other methods.

A further conceptual element I want to emphasise about Law’s and Mol’s understanding of methods assemblages is *enactment.* While in the approach proposed by Ruppert, Law, and Savage (2013) to study data emphasises the devices and practices that make up methods assemblages, Law’s and Mol’s conceptual work on methods assemblages emphasises their active role in enacting versions of reality (e.g. Law 2004; Law and Mol 2002; Mol, 2002). The emphasis they put on activity in the making of empirical phenomena draws from broader work on performativity in STS and sociology, which took forward the vocabulary of social constructionism to study how some current phenomena have been constructed and how the enactment of realities is an active effort where they are constantly made and remade (Law 2004; 2017).

The emphasis Law puts on enactment of realities works as a close corollary of his notion of ontology and ontological politics as a topic of empirical inquiry. If a methods assemblage is a collection of technologies and practices, enactment is the active work of methods assemblages in producing a version of reality to be grasped through the method. Law calls this the performativity of methods (Law 2004; 2017) and the theme of performativity has been picked up by other ANT scholars such as Callon (2006). My description of methods assemblages above is therefore a description of the social and technological character of enactment, and I use the methods assemblage concept whenever I address these elements. At the same time, addressing this same process from the perspective of action, process, and doing evokes the vocabulary of enactment. Enactment is also a useful concept for emphasising *what* versions of reality are made with methods assemblages, because it is always some*thing*, some object, or some phenomenon that is enacted with methods assemblages. [3]

Mol (1999) emphasises that a focus on enactment contrasts both with a focus on perspective and a focus on the construction of reality. In comparison with theories suggesting there is a single indivisible reality that is only described or *seen* from different perspective, a focus on enactments looks at how versions of that reality are performed. The metaphor of "seeing" has been popular in studies of measurement, data, and statistics although it has been used as a component of various theoretical frameworks, including ANT (Beer, 2019; Fourcade & Healy, 2017; Jasanoff, 2017; Law, 2009b; Scott, 1998). My approach aims to take multiplicity to a deeper level to explore ontological

[3] Law uses the concepts "performativity" and "enactment" interchangeably in many of his works, but individual published works might emphasise one or the other. In this thesis I prefer using the concept enactment to avoid confusion with other social science theories addressing performativity. In this thesis I favour the vocabulary of enactment due to the emphasis put on it in Law's After Method (2004) and Mol's use of the concept in Body Multiple (2002), which are both fundamental to my conceptualisation of methods assemblages.

politics. My approach differs from the social construction of technology tradition, which emphasises the socially and historically contingent shaping of technologies, documenting the process and choices of their emergence (e.g. Bijker et al., 1987; Pinch & Bijker, 1984). By comparison, a focus on enactments puts greater emphasis on the active doing and re-doing of technologies and versions of reality in the present.[4]

The idea that phenomena, especially social phenomena, are enacted by methods is not exclusive to ANT. The performative power of classification, for example, has been explored by other STS scholars (Bowker, 2005; Bowker & Star, 1999). Performativity and enactment have also been popularised discussion on the "ontological turn" in STS (Woolgar et al., 2008; Woolgar & Lezaun, 2013, 2015). Arguments on the performativity of statistics and quantitative methods can be found in the early works in historical studies of quantification, such as Hacking (Hacking, 1975, 1991) Desrosières (Desrosières, 1998), Porter (1986, 1995), and Gigerenzer et al. (1989). A 'looping effect' between methods and sociality has been explored especially by Hacking (1982, 1983, 1992, 1999a, 1999b) but is succinctly captured by Porter: "the quantitative technologies used to investigate social and economic life work best if the world they aim to describe can be remade in their image" (Porter, 1995, p. 43). Desrosières' pragmatic sociological approach to statistics greatly influenced research in this areas, especially in France (Desrosières, 1998; Diaz-Bone, 2016; Diaz-Bone & Didier, 2016; Didier, 2016). Work drawing on Desrosières' ideas has explored the political aspects of negotiating different performances of reality, such as by interest groups, civil society, and government actors who conduct political struggles through choice and promotion of specific methods (Bruno et al., 2014; Desrosières, 2014; Thévenot, 2019). The performativity of methods is central to the study of economic instruments (Callon, 2006, 2010; MacKenzie, 2006; Mackenzie & Millo, 2003). These works highlight the opportunities afforded by the

[4] Earlier arguments in the ANT tradition often discuss social constructionism or appeared in conversation with social constructivist arguments (Latour & Woolgar, 1986; Law, 1987), but development of the ANT in the 1990s and especially the arguments of Law and Mol distanced the approach from these debates (for overview, see Law & Hassard, 1999).

concept in various branches of the social sciences, although they are not always central to the conceptual debates in Critical Data Studies or this thesis.

Returning to the theoretical framing of this thesis, what use is there in thinking about non-profit data practices as methods assemblages that enact versions of reality? The first answer is that this allows me to conceptualise and analyse different types of computational and quantitative methods in the non-profit sector within an integrated theoretical framework. Surveys, statistics, impact measurement, managerial measurement, service data, and external data sources can be analysed as methods assemblages that enact specific objects of interest and build on different foundations. Furthermore, non-quantitative ways of knowing can also be incorporated in the framework rather than treating them as a fundamentally different strategy of enactment. This also helps to step back from the idea that data or computational technologies are particularly important in the non-profit sector. Keeping this critical distance is crucial to avoid taking the claims of Data for Good movement and proponents of digital data for granted.

The second reason I use methods assemblages and enactment as key concept is that this emphasises the enactment of competing and alternative versions of reality. I apply the concepts to analyse how specific versions of reality are enacted to serve political and normative goals. Thus, I use the methods assemblage concept to focus on the purposes of enacting specific versions of reality and what is done with those enactments rather than to trace the nuances of their crafting. While this latter issue is important and by no means neglected in the thesis, my exploration of Data for Good initiatives in the UK non-profit sector focuses on questions about “which realities” and “how they serve a specific notion of goodness” rather than on the microlevel dynamics and choices of specific practices relating to data collection.

I want to emphasise one further element in why the ANT-notion of methods assemblages is particularly relevant for this study: this is for whom a particular version of reality is enacted. Methods assemblages to enact versions of reality enable people to intervene with them, but they can also be enacted so that their existence and form can be proven or demonstrated to others. Since any enactment is relational, it follows that certain enactments are present only for those people who participate in their crafting or in the circulation of the proofs of those enactments (see Latour, 1987, 1996, 2005). In the context of science this means circulating scientific findings as broadly as possible and replicating the material conditions that enable them (Latour 1987). In the context of an organisation this can mean extending the reach of managerial practices (Law, 1994) or medical procedures and the diagnoses of illness they produce and act upon (Mol, 2002). In terms of digital technologies and data, this means extending the assemblages that make possible the enactment of a particular object, such as by making the use of those assemblages more widespread, increasing their intensity, or convincing others of the importance of what they are enacting (Law et al., 2011; Ruppert et al., 2013). The ontological politics of comparing and deciding between multiple versions of reality follow from the attempts to square the circle of competing enactments. The ontological politics involved in negotiating specific enactments often follow the fault lines between organisations, institutions, and groups of people who are invested in a particular set of methods assemblages and the versions of reality they enact. The reason I emphasise this perspective is that I argue it is crucial to gain an understanding of the situations in which the actively political with regard to data is taking place. In the case of the non-profit sector, this emphasises the relationships between individual non-profits, government institutions, philanthropic foundations, citizen donors, local communities, and various networks of collaboration.[5]

[5] Law and other ANT scholars are not alone in emphasizing this decentered analysis of how specific enactments take hold. Their importance is implicit in several classic works on quantification, such as Porter's (1995, pp. viii, 81-82) argument on quantification as a tool of communication that only acquires its validity when supported by necessary institutions across the society. They are also present in Espeland and Sauder's (2007) argument that it is impossible to understand quantitative rankings without considering how they are consumed by various internal and external audiences of those who are being ranked.

2.4. Theoretical origins within ANT

Before going deeper into how I further develop Law's and Mol's ideas, I want to situate my approach in the broader development of ANT as an approach within STS. I follow Law's (2009a) argument that the history of ANT can be divided between what he called "Actor Network Theory 1990" and later developments that see key authors going in different directions with regard to the central premises of ANT.

Key empirical works informing the early ANT debate were made by Bruno Latour (Latour, 1987, 1988), John Law (1986, 1987, 1992), and Michel Callon (1984). In these works, we find many of the ideas that would become the staple of ANT thinking: treatment of *any* object or a relationship as an outcome of a process rather than a stable entity in its own right and extending analytical symmetry to material agency and networks. These ideas contrasted with the wave of science studies that had emerged in the 1970s to analyse science through a sociological framing that did not grant unique status to science (Bloor, 1976; Collins, 1974, 1975). Latour, Callon, and Law disagreed with the emphasis on sociology and instead claimed that research on scientific practices should necessarily consider the materiality of tools, devices, and research objects. Instead of privileging sociological explanations they emphasised the material networks of tools, institutions, documents, and journals that are required to make scientific claims and to stabilize them. This material aspect of ANT, which has been theorised as 'generalised symmetry,' has become one of the foundational themes of ANT in social theory and has been expanded in analysis of technology and materiality more widely in the society.

Furthermore, proponents of ANT were dissatisfied with the laboratory or any other single site being the privileged location of empirical work and wanted to research sites of interest far beyond any single location. ANT scholarship prompted researchers to 'follow the actors' beyond what were taken as standard objects of interest in STS, mobilising ANT, not only as a critique of scientific and technological practices, but as the methodology used by other STS scholars. This expansive strategy is evident especially Latour's oeuvre (1987, 1988; Latour & Woolgar, 1986), which drew from anthropology and ethnography empirical methods to analyse science. However, Law (2009a) has argued that the idea of network-connections in ANT was also inspired by semiotic and post-structuralist social science which positioned network connections as open-ended and emergent in empirical research. This is important for the interpretation of ANT in this thesis, because my interpretation of ANT emphasises its semiotic elements rather than the material elements and informs my coupling of ANT with the pragmatic sociology of value tradition.

The 1990s saw ANT become prominent beyond science studies. However, this period also saw ANT scholars take different analytical directions, exemplified in the book "Actor Network Theory and After" (Law & Hassard, 1999). Gad and Jensen (2010) call this a shift to a 'post-ANT' stage that saw ANT theories diversify and integrate with other social science theories. Commenting on this development, Law (2009a, p. 142) elaborates that ANT became 'diasporic' in the 2000s rather than remaining a unified theory. Law has used the concept of post-ANT and after-ANT in his own work, but other key theorists like Latour and Callon did not recognise such a movement (c.f. Callon & Law, 2005; Latour, 2005).

Post-ANT can be conceptualised as an attempt to bridge ANT with its sociological and feminist critics. Susan Leigh Star (1991) criticised early ANT for its almost managerial approach to understanding networks, emphasising dominant and victorious scientific endeavours at the cost of alternative and marginalised efforts. She also criticised ANT for not seeing how people can adopt multiple identities that interact differently with their surroundings. ANT was criticised by scholars of Feminist Technoscience more widely, with Donna Haraway (Haraway, 1990, 1997) arguing that those applying ANT were unaware of their own politics, which can lead to naivete in terms of power and not being able to recognise power structures. Law's attempts to integrate this critique into ANT can be found in his discussion on power in the same volume as Star's critique (Law, 1991), in the emphasis on social order in 'Organizing Modernity' (Law, 1994), and his collaborations with Annemarie Mol (e.g. Law & Mol, 1995). [6]

The new approach that Mol and Law outlined came to wider attention with the publication of Mol's 'Body Multiple'(2002) and Law's 'After Method' (2004), which saw ANT's material-semiotic repertoire merged with overt post-structuralist themes of analysing presences, absences, and their production. They also had a normative message that had not been present in the early ANT. For Mol, the moral goal was to understand medical practices from the perspective of patients and caring instead of medical instrumentalism or economic choice (Mol, 2002, 2008). For Law, the moral goal was often to reflect on the implications of social science's methods of knowing (Law, 2004; Law & Mol, 2002). The emphasis on enactment and multiplicity has been applied in several contexts. Vicky Singleton has worked on topics such as agriculture (Singleton, 2012), and feminist theory (Singleton, 1996), and collaborated with Law on questions of policy (Law & Singleton, 2014) and health (Law & Singleton, 2005).

2.5. Normativity in methods assemblages

In this section I discuss how John Law, Annemarie Mol, and Noortje Marres propose that normative considerations can be studied as part of analysing methods assemblages. I also point to some shortcoming in these framings, suggesting that further conceptual elaboration is needed to fully incorporate empirical analysis of normative considerations into my framework.

Normative and political considerations play a significant role in the conceptual tools proposed by Law and Mol. Yet the idea that ANT provides the necessary tools to

[6] The history told here is a simplification, and Neyland (2006) rightly points out that Law himself has tried to assert ANT as a clear strategy just to later turn around and identify such solidification as a source of problems. Similar vacillation can be found in Latour's work, which was originally reluctant to adopt the ANT moniker in the early 1990s, lamented its solidification in 1999, but later re-doubled on ANT by writing perhaps the most seminal introduction to its use.

understand normative and political considerations has been critiqued by many, especially scholars of feminist technoscience as discussed in the previous section. Within these debates, the concepts of methods assemblages and ontological politics developed by Law and Mol stand out for developing explicit tools to incorporate normativity into the analysis.

Law and Mol propose that methods assemblages and enactments are never *only* about truth, but other political and normative goods as well. Crucial for their argument is Mol's (1999, 2002) notion of ontological politics: when different enactments are compared, there can be various positions that inform the preference for specific versions. This creates the need to decide which version of the "real" is considered more desirable than others when truth alone cannot solve the problem. Mol (2003, pp. 172 – 177) therefore argues that analysing the enactments and multiplicity of objects should be complemented with an analysis of different types of what goodness might entail. In her own work Mol uses an inductive and situated strategy of identifying these types of goodness, such as the tension between choice and care in medicine (Mol, 2008), norms ingrained in dietary advice (Mol, 2013), and the overall importance of an ethics of care as an approach to understand norms (Mol et al., 2010).

Law offers another take on normativity and ontological politics, asserting that "*truth is a good"* but that "truth is no longer the only arbiter" in assessing the use of scientific or other methods assemblages (2004, pp. 148, italics in original). What this quote suggests is that versions of reality are not enacted purely out of fidelity to truth, but to pursue a variety of normative goals that might or might not consider truth important. Law then introduces different versions of goodness to illustrate those differences, such as aesthetics, spirituality, and justice (*ibid*, pp 149 - 151). In this line of thinking, methods might enact versions of reality to satisfy normative goals such as beauty, revelation, and righteousness. This is important because the relevance of truth might be secondary if the motivation behind an enactment is to follow specific aesthetic standards, expectations of spiritual experience, or give service to specific political values. Furthermore, Law proposes that often the goal of enacting versions of reality is to satisfy normative commitments other than a commitment to truth, but that it is inadequate to consider these commitments only as politics. To borrow from Latour (2004, 2005), reduction of material-semiotic relationships mainly to relationships of power can obscure the way practitioners themselves understand the context, goals, effects, and commitments of their practices. Law's approach to normativity therefore invites us to consider the normative commitments of methods assemblages beyond those of truth and politics.

The foregoing opening of normative concerns established a new empirical terrain for analysis of methods assemblages: the normative considerations involved in choice of methods and enactments. However, I suggest that the opening provided by Law and Mol was not accompanied by clear strategies for how those commitments should be studied. Various normative resources might be embodied in practices, but Law is not always clear about how such commitments should be identified. In fact, Law's published works give few guidelines about how these commitments should be analysed beyond respect for situatedness and the need to consider the normativity of enactments beyond truth and falsity. In some studies, the normative considerations slowly emerge from ethnographic analysis of the situations under consideration (e.g. Law, 1994; Law & Singleton, 2005). In other cases, the focus is on crafting alternatives to current commitments and ways of knowing (Law, 2015). Indeed, a recurring normative argument made by Law is the need to look beyond standard Western scientific epistemologies to consider other ways of knowing, which Law identifies either through recourse to anthropological literature or ethnographic analysis (Law & Joks, 2018; Law & Lien, 2013; Law & Ruppert, 2016). Likewise, Mol's strategies for identifying normative considerations are situated mostly in normative debates in healthcare research, as in the analysis of choice and care in medicine (Mol, 2008) or in anthropological analysis as in the identification of ontological norms (Mol 2013). Mol's strategy has also been characterised as "empirical philosophy" to highlight the way normative considerations enter analysis mostly through philosophical reflection. Law and Mol therefore introduce normativity as a key consideration in the analysis of the methods assemblages, but the conceptual tools to analyse normativity remain ambiguous.

Politics and normativity are granted a more active role in the extension of ANT by Noortje Marres. Critiquing Latour's early work on ANT and Law's and Mol's notion of ontological politics, Marres (Marres, 2012; Marres & Lezaun, 2011) argues that many ANT notions of politics are too latent to capture the actively and deliberately political uses of technology or methods. This argument is closely tied to the subject matter of Marres' studies: normativity enters the picture in the new actors and new forms of public sphere, participation, and environmentalism (Marres, 2011, 2012, 2013; Marres & Lezaun, 2011). In her work, technologies and material objects are to be granted active normative and political capacities to conceptualise in new ways the link between citizens and politics.

Where Marres goes beyond earlier studies in ANT regarding normativity is the recognition that use of environmental technologies plays a role in valorising citizen's action as a *proof* of their environmental credentials. For example, the methods assemblages used in carbon counting are said to generate evidence on how environmentally considerate one is, the goal being to maximise environmentalism by minimising carbon emissions with the outputs of carbon counting serving as the proof of contributing to this normative goal (Marres, 2012). When compared to the idea of normativity of methods assemblages in the works of Law and Mol, Marres introduces a new element: evidence and proof of normative value. The argument Marres makes is not only that carbon counting is normative and enacts a version of reality where it is *possible* to count and *desirable* to reduce emissions, but that doing so provides a resource to say something about how committed someone is to the environment. Marres therefore opens the possibility that, not only can we use the analytical strategies of ANT to study the normativity of methods assemblages and enactments, but also to study how these enactments can *assess and demonstrate* some normative quality. Carbon counting in Marres' studies does not only enact carbon emissions and environmental effects as versions of reality but serves as a resource to judge whether something is environmentally friendly. Marres' notion of political capacity therefore extends the ideas of Law and Mol to consider the normative capacities of the objects enacted with methods assemblages and the outputs of the techniques producing this version of reality.

I suggest that theoretically separating the idea of *normativity is embodied in methods assemblages* from the idea that *data practices can demonstrate normative value* offers a fruitful way of studying the politics and normativity of data and complementing earlier theoretical work. When methods assemblages are used to generate data that is then reused for some other purposes, it is necessary to go beyond the analysis of the normative choices that go into generating data with specific methods assemblages. After data has been generated, it can be used as a proof of qualities in different situations with new normative considerations. In this interpretation the normative ramifications of data cannot be reduced to the normativity of methods assemblages alone because the use of data can link up with networks and relations beyond what brought the data into being. Data can be repurposed and reused to do things beyond what was originally done with the methods assemblages that generated it. In other words, data might be used to enact different versions of reality and perform different normative commitments than those that were originally thought of by the practitioners who generated the data. Following my interpretation of Marres' arguments allows my analysis to consider how data can serve as a resource and proof of contributing to specific normative goals.

Nevertheless, this valuable extension of analysing normativity leaves some questions unanswered. Crucially, it provides few clues about how normative and political capacities can be identified and compared in empirical analysis. Marres' extension provides a vocabulary for analysing how rearranging of social, material, and semiotic elements in actor networks can produce new political effects. However, there are ambiguities about how different normative commitments might be identified in empirical analysis, how to identify possible different normative commitments in similar methods assemblages, and how different methods assemblages can be identified to share a similar normative commitment. Yet such considerations are crucial in making sense of something like the Data for Good initiatives in the non-profit sector. In the next section I propose a way forward that takes its inspiration from Marres' arguments about data as proof and demonstration of normative value but links it to the literature on valuation.

2.6. A pragmatic sociology of methods and valuation

In this thesis I suggest that taking methods assemblages as a conceptual tool benefits from being complemented by ideas within two closely linked research programmes: the pragmatic sociology of worth developed by Luc Boltanski and Laurent Thévenot (Boltanski, 2011; Boltanski & Thévenot, 1999, 2000, 2006 [1991]; Thévenot, 2001, 2002) and Valuation Studies (Doganova et al., 2014; Helgesson & Muniesa, 2013; Kjellberg & Mallard, 2013). The conceptual tools to study the practices and performances of *value* offer a way of empirically analysing normative claims made with reference to data. I suggest that the strategies developed to tackle the question "how good," can be used to overcome some limitations when trying to identify and assess normative claims as part of analysing methods assemblages. I propose complementing the symmetric approach to truth and falsity in ANT with a symmetric and empirical approach to normativity as formulated in conceptual debates about valuation and worth.

Steps towards combining these theories have been taken in the past. Indeed, arguments have been made about how a combination of ANT and pragmatic sociology can benefit analysis of both methods and normativity (Blok, 2013; Guggenheim & Potthast, 2012). Boltanski's and Thévenot's pioneering work on justification explicitly notes their indebtedness to ANT (2006, pp. 20). Michel Callon, who is credited as one of the founders of ANT, is also a central figure in the emergence of valuation studies through his work on the performativity of economics (Callon, 1998, 1999, 2010; Muniesa et al., 2007). Furthermore, Law and Mol (2002) offer a sympathetic reading of Boltanski's and Thévenot's work, highlighting that a multiplicity of normative frameworks and multiple versions of reality are best treated as different sides of the same analytical sensibility. The volume, titled *Complexities* (Mol & Law, 2002), includes chapters by both Thévenot (2002) and Callon (2002), which underscores the exchange of ideas between them. Elsewhere, Mol (Heuts & Mol, 2013; Mol, 2013) similarly attends to a plurality of norms and notions of good, and how an object can be made to better match the standards of what is desirable. Elaborating on the concept of methods assemblages and normativity through the arguments made on worth and valuation is therefore warranted in theoretical terms.

Doganova et al. define valuation as a "social practice where the value or values of something are established, assessed, negotiated, provoked, maintained, constructed and/or contested" (2014, pp. 87). Analysis of valuation focuses on both the systems that define value and the means to assess it, analysing them as part of the social world and practices within it. In this research strategy, measurement and valuation are positioned as being co-constitutive of each other, and different ways of understanding value can be found in various areas of social, economic, and political life (Boltanski & Esquerre, 2015; Kjellberg & Mallard, 2013; Muniesa et al., 2007). The approach avoids predefined normative starting points and, instead, focuses on how normativity is implicated in different forms of valuing objects and actions.

The interaction between conceptualisations of value and quantitative methods of expressing value is central to this research programme for two reasons. On the one hand, many studies focus on economic value and the performativity of markets with a quantitative focus due to their subject matter (Mackenzie et al., 2020; Muniesa et al., 2007). On the other hand, quantitative operations are also found to be central in transforming different types of value into economic metrics as in green and environmental economy (Dalsgaard, 2016), social impact measurement (Caselli, 2020; Chiapello & Godefroy, 2017; Hellman, 2020; Williams, 2023b, 2023a), and, more generally, the idea of a "good" economy (Asdal et al., 2023). In all these cases there is an interplay between distinct types of value and the measurements used to determine what is more and less value.

A precursor to my focus on quantitative measurement and value in the non-profit sector can be found in Barman's (2016) pioneering work on the role of measurement techniques in combining economic and social forms of value. In this thesis I take up Barman's (2007) work in suggesting that measurement techniques are autonomous from conceptions of value, and that there is no unified notion of social value embodied in either a specific set of measurement tools or the non-profit sector. According to Barman, measurement techniques must be understood relationally and, while they do create assessments of value, these values are not as such embedded in the techniques themselves. Barman suggests that neither the non-profit sector nor the capitalist marketplace has a single unified set of values that all their participants follow. Instead, Barman suggests that researchers should look more closely into the role of measurement techniques in the judgement of worth across different means of valuation, and not only into the tension between specific moral logics such as those of the market and solidarity. This view aligns with my interpretation of Law, Mol, and Ruppert: slight differences in methods assemblages lead to different enactments of reality, and both the versions of reality and their normative ramifications are assembled in specific relational situations where realities must be enacted and choices justified.

The analytical interest in studying value empirically extends far beyond economic value that was central to the emergence of valuation studies. This approach to value means that economic as well as *any* other form of value is a result of social practices which, in many cases, are supported by technologies of measuring value. Indeed, there is a considerable plurality of values that can inform justifications, but only some of them make use of quantification (Boltanski & Thévenot, 2006). In studies of economic valuation, it is appropriate to focus on the performance of value through quantitative tools. However, in other contexts, quantification can be incompatible with the way value is understood and demonstrated. Boltanski and Thévenot (2006) identify a variety of normative systems that inform the justification and denunciation of value without recourse to quantification, such as inspired, civic, and domestic worth.[7]

2.7. Situations, tests, and demonstrations of value

In this thesis I make use of two insights from pragmatic sociological approaches to valuation. First, I propose identifying *situations of dispute* as the preferred empirical strategy for tackling normative considerations. Second, I suggest that conceptual insights on the *demonstration of value* with empirical proofs provides a helpful extension of the way Law, Mol, and Marres discuss the normativity in methods assemblages. My analysis of Data for Good initiatives will attend both to the role of data in enacting versions of reality and to use of data as a measure and demonstration of some notions of goodness or value.

I begin by addressing the role of situations of dispute in identifying and analysing valuation. Boltanski and Thévenot argue that frameworks of value manifest in everyday life through disputes over value and are settled through tests that attribute value (pp. 40-42, 130-138). It is through these situations and tests that the social practice of valuation emerges as something that can be studied *empirically.* A situation is the empirical site where the strength or weakness of justifications is tested to determine a position in a normative hierarchy, thereby revealing what is valued and how value is demonstrated. I suggest that a focus on situations of dispute and tests to demonstrate value provides helpful conceptual tools to address the ambiguities of identifying

[7] It is good to remember that Law (2004) also identifies a variety of normative ideals that might inform our use of methods assemblages, such as aesthetic, spiritual, and sociopolitical good (Law 2004, pp. 148-150).

normative considerations in the works of Law, Mol, and Marres. The relative value of different methods assemblages and their enacted objects can be analysed empirically by focusing on situations where value is attributed and when methods assemblages are granted a role in providing evidence of value. The role of methods assemblages in disputes about value is that the objects and versions of reality they enact also serve as proof of some variety of value.

Here I elaborate on the operationalisation of situations of dispute as an analytical concept. In some cases, disputes are matters of controversy. For example, there can be competing views of what should demonstrate value or what kind of value should be cared about. In other cases, disputes unfold seamlessly with value attributed to people and objects as a routine that has been naturalised. A situation of dispute is therefore not necessarily contentious. Participants may agree on the practices and metrics for determining value. In such cases the test of value can unfold in an amicable fashion and might be accepted by the participants even if the result is unfavourable to them. Yet in other cases tests of value can descend into altercation because there is disagreement about the correct practices, proofs, and metrics of value.

The theoretical foundation for this can be found in the original texts of the two theoretical approaches. Boltanski and Thévenot argue that "proofs [of worth] must be based on objects that are external to persons, objects that will serve in some sense as instruments or devices for determining worth" (2006, pp. 130). They add that "with the help of *objects* [--] people can succeed in establishing states of worth" (*ibid*, pp. 131, italics in original) and that "Objects substantiate worth, but at the same they impose constraints on tests by calling for valorisation" (*ibid*, pp. 131). In these quotes objects play a crucial part in demonstrating value. Considering those objects as either methods assemblages or as objects enacted with methods assemblages can be used to provide a connection to what normative capacities methods assemblages might entail.

The existence of this connection can be confirmed by elaborating on the arguments made by Law, Mol, and Marres. Both Law (2004) and Mol (Mol, 2002) argue that analysing the enactments of objects must go hand in hand with the normative commitments they might entail. Marres (2012) goes further by directly noting the role that carbon counting can have in providing proof of commitment to environmentalism and the environmental qualities of objects. When considering what these arguments mean in situations of disputes and tests of value, the normative and political aspects of methods assemblages that come to the fore are those that are under dispute and, therefore, in need of demonstration. In such situations some of the normative and political aspects of methods assemblages can be expected to take an explicit form in the claims of value, worthiness, and desirability that the methods assemblages are meant to enact and measure.

The second way I make use of valuation studies and Boltanski's and Thévenot's arguments elaborates on the role of proofs in demonstrating value. Specifically, I elaborate on their notion of "reality tests" and the role given to the "real" in demonstrating value (Boltanski & Thévenot 2006, pp. 40-42; 2001; Thévenot, 2001; Thévenot 2002). According to these authors, successful demonstrations of value rely both on establishing a legitimate state of reality that serves as a proof and on the normative and political meaning of that reality. As argued by Thévenot, 'the good' and 'the real' are linked together in a variety of different ways" (2002, pp. 76). Assessment and comparison of empirical proofs endow participants in a dispute with a 'real' position in normative hierarchies. The validity of any claim of justification is therefore based on succeeding in tests of value by using various resources that establish a position as something that is *real and just* rather than a mere claim.

In other words, debates over value are understood as being conducted through what is taken to be real. This extension is crucial, I suggest, because acknowledging a recourse to reality as the basis for normative settlement means that analysis of disputes cannot be limited to their linguistic, philosophical, or social elements. Because assessment of value is now connected to what is taken to be real, it follows that the arguments of Law and Mol on the enactment of different versions of reality can be seen in a different light. With this extension the debates regarding versions of reality become relevant in a new way: the enacting versions of reality and convincing others of their "reality" can be used to offer proofs that determine assessments of what is the real *value* of something. Following the symmetric approach of Boltanski and Thévenot, the enactment of proofs about the "real" state of affairs can be used both to substantiate or denounce a claim of value.

The idea that normative value is assessed through empirical demonstrations that can support it makes a strong connection to Law's and Mol's arguments about ontological politics: the versions of reality enacted with methods assemblages are not only about truth but also about other normative ideals. However, whereas Law and Mol sought to introduce the element of normativity into the enactment of the versions of reality, move in the other direction. Above I proposed that a focus on situations of dispute and test provides a way to locate normativity in the analysis of methods assemblages. What I propose here is the mirror image of this argument: I suggest that a focus on methods assemblages provides a way to identify how disputes about value are settled by enacting versions of reality that demonstrate value. In other words, I suggest that enactments can be used to assess and prove value. This move was hinted at in the previous section on the extension made by Marres to the political and normative capacities of data to serve as a proof of value. By linking the concept of methods assemblages with the idea of demonstrations of value, I aim to incorporate an appreciation of the normative and political role of methods assemblages and data in my study.

Some of Boltanski's and Thévenot's arguments in *On Justification* align with my approach to enactment of proofs and objects, bolstering the likely viability of the approach. For example, they argue that the use of tests and proofs includes "distinguishing between facts that can legitimately be invoked in a proof [--] and contingent circumstances, which are irrelevant," (2006; pp 135). In this quote a distinction is made between "facts" that have been constructed with agreed-upon standards, and “contingent circumstances” in determining a given state of reality. The argument seems analogous to the process of purification in ANT: the power to determine facts is gained by excluding the contingent elements of the process and delegating the demonstrative power to the agreed-upon standardised parts of it (e.g. Law 2004; Latour, 1987; Latour & Woolgar, 1986). Or, as in Law’s definition of methods assemblages as tools of “crafting and enacting necessary boundaries between presence, manifest absence, and Otherness” (2004, pp, 144), which proposes that methods assemblages make present only the “facts” whereas contingencies of the process are rendered absent. A further move towards appreciation of enactment can be found in Boltanski’s (2011) call for sociologists to interrogate the “whatness of what is” taken to be real regarding both a social phenomenon and the normative postulates that can be used to defend or critique it. This formulation bears a striking similarity to Mol’s (2002, pp. 172–177) call to explore the “politics of what” and ontological politics. My proposal to analyse proof in normative disputes through methods assemblages therefore would seem to align well with arguments made by key theorists who serve as its inspiration.

Some caveats are necessary. By focusing on situations of dispute as they are discussed by Boltanski and Thévenot, I do not suggest that the analysis of normativity and politics should follow their broader arguments about the “polity model” of justifications, or their strategy of using situations to derive a small set of universalistic notions of the common good. I do *not* use their framework of orders of worth but instead appreciate the way the framework has been further developed in Valuation Studies. This means that my study does not seek a prescribed set of values in Data for Good initiatives. I seek, instead, to use an inductive empirical strategy to identify forms of value that are demonstrated with the use of data.

Furthermore, I do *not* suggest that situations of dispute can reveal *all* the normative and political ramifications of methods assemblages. Nor do I suggest that it is irrelevant to consider politics beyond the notions of value that can be identified in situations of dispute over value. What I suggest is that such situations provide an empirical anchor to analyse *some* of the normative and political work done with methods assemblages. I argue that this provides a fruitful way of analysing what the connection between data and "goodness" in Data for Good initiatives can reveal about the initiatives themselves and the practices of using data in the non-profit sector more broadly.

Social or political critique is not explicitly part my analysis and arguments, which differentiates my approach from Boltanski's broader theoretical goals.[8] This does not mean that critical reflection is dismantled in favour of flat relativism. Indeed, thorough analysis in the Valuation Studies tradition requires recognition of the political implications of studied practices and reflection on values, beyond those that are immediately present in an analysis (Doganova et al., 2014). Similar to Pols (2015), my empirical strategy accepts that normativity "cannot be *prescribed*, but they may be *questioned*, for example by *comparing* them" (2015, pp. 83, italics in original). Indeed, Valuation Studies has been urged to shift attention from practices of valuation to the problematisation of valuation, implying that critical reflection constitutes a key part of the analysis (Board of Editors, 2020). Taking a step back to analyse normative claims symmetrically is not intended in this thesis as a strategy of political acquiescence.

My analytical focus is on situations in professional contexts of data and non-profit work rather than on everyday contexts of dispute and test. The role of professional and managerial contexts in *shaping* the way professionals engage with their

[8]The larger goal of Boltanski's work on justification has been to build a sociology of critique that explores the different repertoires and resources that make critique possible (Boltanski, 2011; Boltanski & Chiapello, 2018 [2005]; Boltanski & Thévenot, 2006). Doing so does not mean letting go of normative arguments but taking seriously why critique so often fails and how it can be revived (Boltanski & Chiapello, 2018). Boltanski (2011) argues, on the one hand, that sociology describes social reality with an aura of objectivity but that sociological descriptions of social reality never reach full correspondence with the lived experience of people living in the world. On the other hand, he argues that sociology is always partly a critique of society and politics, which requires researchers to discuss the problems with existing ways of determining social facts and search for new ways to re-invigorate sociological critique. In this thesis the aim is not to pursue this line of argument but to employ the framework as an empirical strategy for analysing normative claims and justifications.

work and versions of reality is emphasised by Law (1994). Thévenot (2002) also emphasises the influence that managerial and professional practice has on the way people engage with justifications, recognising this as a regime of planned action that differs from other ways of relating to the social and natural world. This differs from the generic approach used by Boltanski and Thévenot (2006) to identify any kind of dispute that might emerge in social life. The focus in my analysis also aligns with the analytical interests of STS and Valuation Studies which put empirical and conceptual emphasis on professional contexts.

2.8. Conceptual framework

In this chapter I have defined three concepts that I use to analyse the politics and practices of data: methods assemblage, situations of dispute, and demonstrations of value. With the theoretical foundations outlined, I present my approach to data practices and normativity which understands methods assemblages as enacting versions of reality that demonstrate value in situations of dispute.

What does this conceptual framework mean for the analysis of data practices in the non-profit sector? I defined data practices as active social engagement with technological tools of quantification, emphasising their role as "activities performed by humans in relation to materials, technologies and shared understandings and occur within specific fields" (Scheel, Ruppert, & Ustek-Spilda 2019, pp. 7). This definition builds on Law's theoretical work on methods assemblages. I acknowledge that there are likely to be methods assemblages that have nothing to do with quantitative or digital data, but their role will be examined only insofar as they relate to my analysis of the justifications and critiques of data. I approach normativity and politics of data practices through situations of dispute about value and demonstrations of value in them. This highlights that there are multiple forms of value that have their own systems of assessing higher or lower worthiness. I acknowledge that data might play a role only in some disputes and that my analysis cannot be exhaustive of all types of normativity.

In my conceptual framework, I take a symmetric approach to the treatment of what is taken to be more or less "true" about reality, and regarding different forms of value that might be found to be being tested. This approach allows me to analyse the politics and practices of data by attending in equal measure to data practice and to what form of value non-profits try to justify with it. Furthermore, it allows me to analyse non-profit data practices through Data for Good initiatives without making assumptions about whether some data practices are better or worse in comparison to other method assemblages as understood by the participants of the study, or that any specific notion normative system of value might *a priori* be more justifiable than another.

My conceptualisation of methods assemblages, situations of dispute, and demonstrations of value foregrounds the analysis of social practices rather than the material associations involved with specific devices associated with non-profit data practices. The way I combine analysis of methods assemblages with disputes about value aims to emphasise the analysis of the implications of what is enacted with methods assemblages, rather than emphasising the material associations that make up the assemblages. This strategy is in line with Law's (2002, 2004) emphasis on the semiotic and pragmatic aspect of material-semiotic analysis in ANT, and aligns with Mol's (2002) discussion on employing "empirical philosophy".

Although the conceptual framework consists of three concepts that are equally important in this study, their analytical vocabulary will vary in the empirical analysis due to differences in the analytical tradition of applying them. Situations of dispute and demonstrations of value provide my primary analytical vocabulary. This terminology will be used because it is helpful in structuring my data analysis and presentation of findings. The analytical themes related to methods assemblages will be addressed primarily by using the vocabulary of *enactment.* This follows Law (2002; 2004) and Mol (2002) in using the concept of enactments when analysing empirical materials to highlight the focus on doing versions of reality and acting on them. The methods assemblage concept, nevertheless, is fundamental to this understanding and will be used when discussing technologies and practices relating to data.

In the introduction of the thesis, I presented a research question:

- **How are data practices used to demonstrate value in the UK non-profit sector?**

My conceptual framework points to three sub-questions that guide my empirical analysis:

1. **What new quantitative or digital methods assemblages are promoted in the UK non-profit sector?**
2. **In what situations of dispute do data practices justify value?**
3. **How is the demonstration of value entangled with methods assemblages in these disputes?**

With the theoretical foundations of the thesis now outlined, in the next chapter I move to the empirical context of the UK non-profit sector.

Chapter 3

Quantitative measurement in the UK non-profit sector

3.1. Introduction

To understand how data practices and justification of value are entangled in the non-profit sector, it is important to consider the broader context of the politics of quantification. The current push by Data for Good initiatives towards more quantification, data collection, and data analysis is part of a historical continuum whereby society and charitable work have been shaped by quantitative measurement. In this chapter I review the historical and political antecedents of current data practices in the non-profit sector, as well as recent trends that are shaping the quantification of social good.

The first section focuses on the history of the politics involved with quantification which forms the historical backdrop for Data for Good initiatives. I then examine recent trends that are shaping data practice in the UK non-profit sector, such as New Public Management (NPM), Evidence-based Policymaking, and Big Data. I finish the chapter by discussing how my focus on methods assemblages and justification contributes to ongoing debates about the roles of data and data practice, situating the thesis in recent arguments about the politics of data in the non-profit sector.

3.2. The historical background of quantification and politics

Quantitative techniques have played a central role in shaping the historical relationship between state, society, and the economy. Although states and private companies have kept records for centuries, it was only in the early 19th century that the idea of quantifying social and economic phenomena led to a new understanding of them as objects of knowledge and intervention (Hacking, 1982, 1990). These developments were closely associated with the emergence of nation states with centralised professional administration in Europe and aimed both at establishing a standardised system of administration across the realm and equipping the government with the latest practical and scientific tools to steer its direction (Desrosières, 1998; Porter, 1995). After early development in the governmental context, the period starting from late 19th century saw probabilistic statistics and the collection of data by statistical authorities developed further and adopted in various fields of science. Their expansion can be found in the disciplinary histories of psychology, medicine, public health, and sociology (Gigerenzer, 1989), which have all contributed to the shape of the social and economic sphere in the present day.

Changing times have meant changes in the relevance of quantification for the civil society in various times. Porter's (1995), Hacking's (1990) and Desrosieres' (1998) historical analyses show how quantitative reasoning contributed to the emergence of a science-based approach to social problems and design policies to mitigate poverty and improve public health. The ideological backdrop for this new approach to society originates in Enlightenment philosophy which elevated rationalist knowledge as a standard of public discourse and framed it as a tool of social and political progress (Foucault, 2006, 2010). The early efforts in quantitative measurement slowly spread to state, private, and charitable institutions in the late 19th and early 20th century, ultimately leading to the emergence of government-led social policies and to civil society action for social betterment (Desrosières, 1998; Porter, 1995). The roots of present day charitable and humanitarian action can be found in this era, which saw social reformers combine moral aspirations for social progress with new quantitative techniques to understand social problems (Calhoun, 2008; Fitzpatrick, 2003). In the UK non-profit sector its effects were felt already in the first decades of the 20th century in a shift from individualised charity towards a community-based understanding of social problems, made possible with the use of surveys and statistics (Barman, 2007).

According to Boltanski and Thévenot (2005), new ideas and measurement techniques emerging in the 19th century led to a new understanding of social value that combined a collective notion of the common interest with a rationalist notion of how social phenomena can be known and measured. The new ways of enacting social problems with quantitative tools not only describe society but enact new social realities that are used to justify or denounce social interventions. In this new era governments resorted to the new technologies of government to manage the population as argued by Foucault (Burchell et al., 1991), and social phenomena became constantly re-enacted through a network of technologies, institutions, and experts, as argued by Latour (2005).

Statistics is not the only quantitative practice that has a long history. Business accounting and managerial quantification have a long history independent of social statistics. They have existed since the early modern era and underscore the ability of accounting techniques to generate a single space for the comparison of diverse commercial operations, one that is in no way natural, but that creates a particular version of commerce (Miller, 2001). Desrosières (2001) argues that business accounting, and the aggregation of data into national accounts especially from the 1950s onwards, is a particular form of a metrological pragmatism that establishes its objects to make them manageable and to establish trust between participants in economic governance. Furthermore, for well over a century, industry managers and policymakers have collected data and performed calculations with a view to optimising efficiency and to assessing the financial viability of their ventures, often drawing from engineering sensibilities rather than the social physics that inspired statisticians (Porter, 1995). Beyond optimising industrial performance, businesses have tried to understand their customers through personal accounts and credit cards for well over a hundred years, (Lauer, 2020). These quantitative ways of knowing business and financial operations were essential for the emergence of markets as an economic sphere that could be treated by researchers, policymakers, and businessmen as an independent and self-governing area of society. They also led transformed the way organisational processes were being optimised for industrial productivity and economic cost-efficiency. According to Barman (2007), an economic focus on the efficiency and effectiveness of charity started to take a hold in the UK non-profit sector after the Second World War, when it began to complement the importance of social statistics and supported accusations of inefficiency and profligacy in the non-profit sector.

The key takeaway of this early history of quantitative practices, society, and social good is that contemporary quantitative data practices are part of this longer continuum in the politics of quantification. Ever since the 19th century, the debates on society, social problems, social value, social interventions have been influenced by the statistical understanding of society as well as by rationalist techniques of measuring industrial efficiency. In this context, new data practices can be understood to enact new versions of society and social value, leading to changing notions of what is valuable and how worthiness can be assessed.

In todays' world quantitative data practices have acquired a special place because their epistemic rigour is associated with the democratic rule by public reason (Ezrahi, 1990; Rose, 1991). However, as noted by Mennicken and Salais (2022), numbers have a patchy record in achieving the utopian ideals of public reason because judgement based on numbers can lead to distrust of institutions whose work is difficult to capture with numbers, and persistent uncertainties with publicly used indicators create mistrust in the numbers that are supposed to bring certainty. Yet the ideals of objective and rigorous knowledge have a special place in today's public discourse which pushes organisations to follow the standards of quantitative measurement to withstand public pressure when it bears down upon them. This public pressure finds its way to the non-profit sector as a pervasive cultural and political pressure to use quantitative evidence in public affairs, but also through new institutional relations that use quantitative measurement as a tool of accountability and governance.

The present-day scholarly debate on quantitative practices associates them closely with forms of neoliberal governance. The link between quantitative practices and a new decentralised form of governance through self-regulation of individuals was recognised already by Foucault (Burchell et al., 1991) in his arguments on the technologies of government and this link became central to a neoliberal form of governing. However, later works on neoliberalism and quantification have come to associate the connection with the extension of market logic into new terrains of society, self-governance of markets and societies through the discipline of quantitative indicators, and the increased role of non-governmental and private organisations in governing social issues (Rottenburg et al., 2015). The quantitative element of neoliberal governance has been tackled by Espeland and Sauder (2007) and Desrosières (2003), who suggest that performance measurement and quantitative benchmarks and indices create feedback loops that intervene with and shape their targets. Desrosières emphasises that competition-inducing tools associated with neoliberalism have a distinct political and epistemological ethos in comparison to the statistical measurement activities of governments, which are not expected to have an immediate effect on the people, organisations, and phenomena they seek to enumerate (Desrosières, 1998, 2015). Because of this, quantitative tools of measuring market value and inducing market-like thinking to society also promote a particular notion of market morality (Fourcade & Healy, 2007), which is imposed on citizens through interactions with economic institutions and their use of quantitative measurement (Fourcade & Healy, 2013).

The effects of neoliberalism in the non-profit sector have been felt through increasing competition between charities for resources and the use of market- and business-like metrics to measure the success of non-profit work (B. Evans et al., 2005).

According to Krause (2014), managerialism and marketisation in the international humanitarian field has led non-profits to rethink their work as commodity-like products intervening with designated populations in need, together constituting a product that is "sold" to donors. Indeed, Clarke and Parsell (2022) draw from Latour's and Foucault's ideas to propose that a neoliberal form of charity constantly reproduces a society where benevolent donors affirm their own virtuosity by helping the poor without addressing the causes of poverty, and charities exist as enablers of this performance and as the rational managers of social services.

Yet this does not mean that there is a single quantitative logic to the marketising tendencies of neoliberalism. Davies (2015) argues that quantification under neoliberalism contains multiple moral orders depending on whether measurement aims at inducing market competition or competition in pursuit of well-being, both of which are contained in contemporary ideals of national competition. The neoliberal combining of the logic of the market and the logic of solidarity is also central to the recent surge of interest in social enterprises and social impact investing which has the explicit goal of uniting profit with socially-beneficial causes through new strategies of quantitative measurement (Barman, 2015, 2016; Williams, 2023b).

The combined effect of the long history of quantification and the more recent neoliberal turn in measurement practices is that the non-quantitative moral notion of solidary and caring, which predates the above developments, has come under enormous pressure. The older notions of solidarity, whether understood in the form of religious charity, virtuosity of volunteering, community action, or humanitarian benevolence, are increasingly critiqued according to the quantified metrics of social and market value. When interpreted from the perspective of changing logics and practices of justifying value (Boltanski and Thévenot, 2006), it becomes increasingly difficult to justify activities relating to social betterment without some form of quantitative evidence presented as a proof of its worthiness. What is important for this thesis is that quantification and value are understood to be entangled in multiple ways that go beyond recent debates on the marketisation of the non-profit sector and social betterment.

Having presented the broad history and context of the politics of quantification, I assess specific empirical developments that currently influence the UK non-profit sector. I discuss NPM, Evidence-based Policymaking, and Big Data as empirical trends influencing the practical work done in the UK non-profit sector. Each of these developments embodies a particular combination of the statistical, managerial, market-like, and neoliberal tendencies of quantification. They translate the ideals and techniques of quantification into practical reform programmes that inform and have been implemented in the UK.

3.3. New Public Management in the UK non-profit sector

NPM is a set of ideas and practices that has shaped the UK non-profit sector since the 1980s. The reforms of the 1980s and 1990s changed the relationship between the public sector, business, and charity, decreasing the role of the government in welfare service provision through cuts to funding, outsourcing of services, and privatisation. NPM is closely associated with neoliberalism and has led to increased marketisation of non-profit work and adoption of business-like practices (B. Evans et al., 2005). A corollary of this development is that normative criteria that used to be reserved only for private business are now used to assess public and non-profit services as well. New quantitative measurement practices were a key component of these reforms insofar as adoption of private sector managerial measurement and accounting practices were believed by many to be an opportunity for the public sector to improve its efficiency through closer management by numbers and managing of outsourced services through quantitative reporting practices (Hood, 1991). According to the proponents of NPM, it was desirable for UK government to do more “steering” than “rowing” as famously put by Osborne (1992), which meant that service provision was delegated to private and non-profit organisations funded by the UK government through competitive contracts.

From the perspective of quantification, the hallmark of the above developments was the reliance on performance measurement as the preferred way of coordinating work within and between the state, the market, and the non-profits, which, it is argued, pushed non-profits to embrace quantitative data collection and analysis (Hood, 1991; Pollitt & Bouckaert, 2011).

The push for contracts and reporting is related to what Power (1999) calls the "audit explosion" in the UK, referring to increased scrutiny of financial and operational accountability across society, and the process of administering accountability through standardised, external audits. As part of this broader phenomenon, non-profits adopted practices and standards that comply with the logic of audit and evaluation techniques, some of which include quantitative performance measurement (Hall, 2014).

While NPM was originally developed in the UK by the Conservative Party led by Margaret Thatcher in the 1980s, it also exercised substantial influence on Labour Party policies after their 1997 electoral victory. The New Labour policies under Blair pursued more integration between government and non-profits which manifested in increased funding, but also yet more management techniques to coordinate the non-profit sector, which by now was seen as a key player in delivering outsourced public services (Alcock, 2016). As a result, quantitative managerial measurement and contract-based outsourcing monitored with elaborate reporting schemes informed the UK government approach to the non-profit sector during Labour Party rule between 1997 and 2010.

According to Alcock (2016), the Conservative governments in the 2010s cut spending on non-profits, renamed the Labour-era "Office for Third Sector" as "Office for Civil Society", and emphasised a preference for more private financing of welfare and social services. The austerity policies in the UK following the 2008 financial crisis meant major reductions to government funding on social and health services, which reflected on funding to non-profits as one of the key providers of outsourced services (Clifford, 2017). Non-profit organisations in the UK have been pushed to increase their fundraising from private sources and to follow the priorities set by private philanthropic foundations. This trend continued all the way through to the data collection period for the thesis in 2019 and 2020. Developments relating to the implications of the COVID-19 pandemic were not part of the study since primary data collection ended in the first few months of the pandemic when its implications for non-profit work were still unknown.

Performance measurement is one of the most visible examples of the new quantitative methods assemblages promoted as part of NPM. Performance measurement is a loose family of methods that is interested in outputs and outcomes of charitable work, and its goal is to use this information to determine whether activities contribute to desired goals (Cordery & Sinclair, 2013; Lynch-Cerullo & Cooney, 2011). Prior research has found that non-profits adopt measurement techniques because of external pressure, but also because of internal pressure from managers and staff (Barman & MacIndoe, 2012; MacIndoe & Barman, 2012). In fact, Hall, Millo and Barman (2015) suggest that the introduction of reporting and measurement techniques is closely connected to stakeholders of non-profits rather than to internal development. Evidence from the UK suggests that non-profits mainly use performance measurement to satisfy their donors and funders rather than to improve their own work (Moxham, 2010). Combining evidence on stakeholder-driven measurement systems (Barman, 2007; Hall et al., 2015; Moxham, 2010) with evidence on the proliferation of audit and governing at a distance (Power, 1999, 2000; Rose & Miller, 1992, 2008), suggests that much measurement is meant to make non-profits comparable for organisations awarding funding. Performance measurement can be inconclusive in generating deeper insights into the performance of non-profit work, let alone aspects of charity that are not meant to serve instrumental normative goals (Cordery & Sinclair, 2013; Moxham, 2010). While there is a considerable body of research outlining the potential benefits, both recent and older work calls into question whether performance measurement can actually deliver the goals that are used to legitimise them (de Waal et al., 2011; Kanter & Summers, 1994; Milbourne & Cushman, 2015; Moxham, 2010). Indeed, quantitative measurement practices are by far not the only tools deployed to evaluate compliance and performance, and non-profits use various other strategies to assess their work (Hall, 2014)

Another set of quantitative practices that was pushed by NPM of the 1990s and after is the increased use of public indicators, metrics, and quantified rankings to compare organisations and judge their performance against each other. The role of public organisational rankings has been studied by Espeland and Stevens (2008b), who argue that they exercise substantial influence over organisations despite awareness of their simplistic and reductionist nature. Indices and rankings present complex issues through simple metrics and both the measured organisations and the consumers of such information may adjust their behaviour even if they doubt the veracity of the metrics (Espeland & Stevens, 1998). Such tools have emerged to rank non-profit organisations, to review how effective their internal administration is or what a pound in invested in them might generate in tangible outputs. These are easy to measure using available numeric evidence, but might not be good indicators of the difference that a charity actually makes (Cochrane & Thornton, 2016). Producing comparable measurements of non-profit work is sometimes undertaken by third-party organisations producing rankings and ratings of non-profits. The goal of rankings is to build a *marketplace* of recipients of donations and encourage them to *compete* against each other in being effective (Mitchell, 2014).

Rankings are a tool of marketisation that use quantification to constitute comparable environments of competition (Kurunmäki et al., 2016). To build large-scale rankings, third-party organisations use simple metrics that are publicly available and comparable across all non-profits regardless of their goals or context. This leads to ranking primarily using simple monetary cost-effectiveness measures, output measures, and ratios of the administrative cost and benefit of service delivery. These metrics, however, might not be good indicators for non-profit working in challenging environments with structural barriers, or for non-profits whose effectiveness is difficult to measure due to a variety of intervening factors, lags in effects, and difficulty in discriminating between causes and outcomes of change (Cochrane & Thornton, 2016). Furthermore, research on rankings suggests that they influence the behaviour of those being ranked regardless of the accuracy of the rankings, forcing them to rethink their work or measurement systems even if no positive change is expected to follow (Espeland & Sauder, 2007; Espeland & Stevens, 2008a).

From the perspective of justification and methods assemblages, NPM-inspired data practices suggest two implications for the non-profit sector that are important for the thesis. First, NPM pushes non-profits to adopt a new understanding of their value and to adopt new strategies of justifying their worthiness. NPM pushes non-profits to value their work according to the metrics of business-like efficiency. While the history of non-profit work and social policies is shaped by the rationalisation and quantification of care, the business-like measurement practices promoted by NPM brought in a new logic for the understanding of its value. According to Boltanski and Thévenot (2006), proponents of different orders of worth that follow different logics of justification might criticise each other or make a compromise. NPM has prompted the UK non-profit sector to do both. On the one hand, the business-like efficiency and marketisation of non-profit work has been extensively criticised as something that undermines the foundations of charity and solidarity by subjecting it to illegitimate standards. On the other hand, NPM has been embraced to make a compromise between solidarity and business-like marketisation with the new measurement practices providing evidence that is intended to justify value according to the new ideals. In the UK non-profits have had little choice in making this compromise, because asymmetric funding-relations have forced them to adopt the new metrics of value as a condition of receiving funding.

Second, the managerial techniques that enable NPM-inspired outsourcing and arms-length control can be seen as methods assemblages that enact non-profit work through the numbers they generate. They enact a partial version of the reality through the numbers that are generated as part of reporting and measurement schemes. This partiality is not unique to the new methods assemblages; according to Law and Mol all methods assemblages enact a partial version of reality. As a strategy of justification, they are constantly challenged by criticism that draws on other ways of understanding social good and sources of evidence that demonstrate these other understandings. Yet the proliferation of quantitative managerial measurement practices means that the particular type of realities they enact become more prevalent in the non-profit sector. In other words, it becomes more common for non-profit organisations to assess themselves through business-like and market-like forms of value. As I have argued above, non-profits often have little choice because their funding is increasingly tied to success according to these new forms of measuring value. NPM therefore entrenches its understanding of value through the methods assemblages it forces non-profits to adopt so that they can demonstrate their value.

3.4. Evidence-based Policymaking on the UK non-profit sector

Evidence-based Policymaking is another set of ideas that has influenced the way social and health policies are understood in the UK government and non-profit sector. Evidence-based Policymaking (EBP) refers to the idea that policies should be based on scientific knowledge and rigorous assessment of their effectiveness, and that policymakers should follow the expert advice of researchers and scientists (Boaz et al., 2008, 2019). The UK's version of the EBP movement originated in the UK and is supported by a network of research and policymaking institutions, but similar initiatives also emerged independently in the United States. The approach puts special emphasis on statistical evidence on impact and prescribes academic standards in assessing evidence; and it is internationally known for its promotion of Randomized Control Trials (RCTs) (e.g. Boaz et al., 2019). EBP has received widespread criticism. Critics have focused especially on its embrace of rationalist assumptions regarding policymaking as well as its narrow understanding of evidence (Botterill & Hindmoor, 2012; Cairney, 2016; French, 2019; Hammersley, 2005). Following extensive scholarly and public debate, the EBP program in the UK has relaxed some of its early emphasis on RCTs and promotes a wider set of research-based empirical evidence as the preferred source of evidence for policy (Head, 2016).

While the focus of the EBP movement in the UK has been on government policymaking, it influences the way the government allocates funding to the non-profit sector as well as the public expectations about how non-profits should use evidence. As a result, EBP ideals make it desirable for non-profit organisations to gather more rigorous evidence to justify their work, which often means giving more emphasis to quantitative measurement (Arvidson, 2014). At the most fundamental level, it pushes non-profits to value evidence in their decision-making rather than focusing on the charitable and moral aspects of helping those in need. In this way, the EBP movement extends the historical development of quantification and social policy in the 19th century, which I reviewed above. Promotion of EBP comes with its signature quantitative methods assemblages to produce the evidence. Proponents of EBP often emphasise the application of statistical techniques to assess the strength of evidence, which often retains the Randomised Control-Trials (RCTs) the “gold standard” of evidence in EBP and subsequently has led to active promotion of experimental designs and statistical analysis. Such techniques have been increasingly adopted in the non-profit sector, pushing them to invest in new methods assemblages to comply with new standards of evidence (e.g. Donovan, 2018; Williams, 2023). However, non-profit organisations face considerable challenges in trying to adopt such techniques because they lack the expertise, culture, and resources that are available to governments when designing evidence-informed policies (Bach-Mortensen et al., 2018).

A recent trend in the UK related to EBP, but partly distinct from it, is the promotion of social impact measurement with a focus on the economic aspect of impact. The Conservative Cameron Government in office from 2010 to 2016 was a vocal supporter of mobilising private capital in social and health services with Social Impact Bonds and promoted the use of economic modelling of social impact within the government and non-profit sector (Alcock, 2016; Dowling, 2017). This development is part of a wider global development of combining measurement of social and financial value to increase the role of the private sector in solving social problems (Barman, 2016, 2020; Williams, 2023b). During the Cameron Government interest in social impact investing coincided with severe cuts to social and welfare spending. The rationale for social impact bonds is that capital for social interventions is raised from private investors who receive profitable returns on their investment when the interventions funded by them create savings and positive impact as measured using econometric models. The way social impact is measured in such projects takes the ideals of EBP a step further by not only adopting RCTs as a way of determining the outcomes of interventions, but also by using economic modelling to assess the monetary value of interventions as a basis for rewarding investors. Critics of Social Impact Bonds in the UK propose that they have unintended consequences such as perverse incentives and mission drift towards activities that are easier to measure with RCTs (McHugh et al., 2013).

While EBP and the economic modelling of social value are present among policymakers and experts, there are related trends in the UK that have a resemblance with collective movements that influence public debate. One such trend is the effective altruism movement. Effective altruism is a loose network of organisations and individuals who promote charitable giving and believe allocation of donations should follow strict utilitarian ideals and rationalist quantitative metrics of impact (for an overview, see Greaves & Pummer, 2019). The movement was popularised by William MacAskill (2016) in the book *Doing Good Better* and is relevant because it has some overlap with the ideals behind Data for Good and AI for Good movements due to its promotion of a data-driven approach to social good. Members of the effective altruism movement emphasise the importance of doing good for society through philanthropic work, but approach this through idealised models of maximising social and economic utility as measured through quantitative data collection. Crucially, effective altruists are rarely influenced by mainstream sociological or economic theories to understand social problems as was the case with EBP. Their thinking is rather influenced by applied analytical philosophy popularised by MacAskill and basic data analysis is used as a justification for actions. The movement has led to controversy among civil society organisations and activists who criticise it for having a narrow view of social change, failing to address systematic injustices, and diverting attention away from community-based activism (Adams et al., 2023). The effective altruism movement is relevant for my study insofar it parallels Data for Good initiatives in the UK non-profit sector and shares the public space with aspirations for data-driven improvement of charitable work.

Economic ideas of measuring social value are embodied in the new quantitative methods assemblages promoted in the non-profit sector. Simple measurements of effectiveness and cost have been expanded into Social Return of Investment (SROI) models that take their inspiration from financial modelling. The goal of SROI is to estimate the amount of social impact that is achieved through monetary investment in a charity, producing an assessment of how much money would be saved or generated thanks to an intervention (Arvidson et al., 2013; Arvidson & Lyon, 2014). Impact investing is another instance where modelling is used to estimate the amount of social impact produced by a financial investment (Bourgeron, 2020; Hellman, 2020). While impact investment is not exclusively interested in non-profit work, it plays a key role in conceptualising charitable work as an investment that is expected to deliver dynamic financial benefits that outweigh the amount of invested money (Chiapello & Godefroy, 2017). SROI models and impact investing have gained traction especially among major private donors that try to use business strategy to guide their philanthropic work, a phenomenon that is sometimes coined “philanthrocapitalism” (Jenkins, 2011).

Because of the difficulties relating to validity and reliability of measures, critics suggest that it is more important to follow the conventions of speculative economic calculation and rhetoric about impact rather than reflect on social impact more deeply (Barman, 2016, 2020). In fact, Arvidson and Lyon (2014) found that non-profits decouple SROI metrics from their actual work, reserving one variety of quantification for the public and using other techniques to guide their own work. Sophisticated modelling is therefore prone to differentiation between the internal and external audiences of non-profits just as is the compliance-driven performance measurement discussed above. EBP and economic social impact measurement promote specific ways of understanding and justifying the value of non-profit work. In my conceptual framework, they are understood to promote different methods assemblages to generate proofs of value, and neither can be reduced to the methods assemblages promoted in NPM. EBP is best understood as a new iteration in the long history of rationalising social value using statistical methods, which I have reviewed earlier. What is new with EBP is the strict adherence to a statistical understanding of effectiveness, which can be seen as a particularly narrow conceptualisation of what it means to prove social value. The economics-inspired Social Impact Bonds and the Social Return of Investment calculations marry the older ideas of rationalising social value with an econometric reframing of its monetary value. They share with NPM-inspired techniques the compromise between social and economic value but justifies this with different methods assemblages than the managerial measurement techniques and business-like data collection promoted as part of NPM. Indeed, the methods promoted in NPM and EBP enact different versions of what social value is or how it should be measured. Non-profits therefore must reflect on whether to adopt new quantitative measurement practices, and on which ones to prioritise when they enact their versions of reality and justify conclusions about the social value of their non-profit work.

3.5 Big Data in the UK non-profit sector

While NPM and EBP are trends in quantitative measurement in non-profit work that originate in the UK, there are more universal trends that are shaping the UK non-profit sector. The most important wider trend in the context of this thesis is the idea that digitalisation and "Big Data" provide an opportunity rethink non-profit work and social betterment. Digitalisation gained pace in the 1990 and early 2000s as non-profit organisations started investing in digital technology, software, and online applications (Schneider, 2003). The proliferation of digital systems has given rise to the ideas of Big

Data and datafication, suggesting that new sources of transactional and sensory data from digital and online systems would mark a step-change in the accumulation of knowledge (Kitchin, 2014b). Van Dijck (2014) proposes that Big Data popularised "dataism" as a system of thinking, that is, a belief in the objectivity of digital data collected with online tools or digital devices, and trust in the institutions that collect and analyse such data. In addition to the increase in digital data, Big Data (sets) was also a powerful narrative that influenced public debate on the value of data (Beer, 2016; boyd & Crawford, 2012). Indeed, a key idea promoted as part of debate over Big Data was that data is valuable in its own right and that organisations should collect as much data as possible even if its utility is unclear at first (Mayer-Schönberger & Cukier, 2013).

The focus on digital technologies and Big Data had an impact on the data practices of the UK non-profit sector. With the proliferation of digital technologies, data management and databases emerged as an area of interest in the non-profit sector. Non-profits manage data internally to guide fundraising, donor communication, volunteer coordination, and marketing, which are done in addition to any performance management and compliance-driven needs (Mayer and Fischer, 2023). Non-profits face growing pressure to be innovative and imitate digital businesses in adopting novel tools even if their benefits are unclear (Scott-Smith, 2016). However, the cost and burden of maintaining databases can be substantial, making their upkeep as much a challenge as it is an asset (Voida et al., 2011). When incompatible internal and external needs require maintenance of multiple types of data, this can lead to fragmentation of non-profit work and drift in its goals (Bopp et al., 2017). The situation is not better in the case of empirical evidence on the use of digital technology in development sector non-profits, which suggests that digital innovation faces long-standing and substantial obstacles that call their value into question (Schelenz & Pawelec, 2021; Taylor & Broeders, 2015).

A belief in the positive value of digital data is an important issue in this thesis. Not only does it suggest that there is something intrinsically valuable in collecting as much data as possible or that data can be an objective source of knowledge, but also that transaction data generated by digital infrastructures can complement or even supersede quantitative data collected with more traditional statistical, managerial, and social scientific techniques. In other words, the surging interest in Big Data presented digital systems as a new methods assemblage to enact people and social phenomena as objects of intervention.

The social and political implications of digital data as a tool for understanding people and society have been extensively analysed. As suggested by Mau (2019), digitalisation has enhanced the role of markets and states as drivers of quantified notions of society and social value. Critical research has debated, for example, the role of data analytics in making sense of data sources as a tool of governing (Amoore & Piotukh, 2015), expansion of social media platforms and their understanding and monetisation of human sociality through digital transactions (e.g. Van Dijck, Poell, & De Waal, 2018), government and corporate online surveillance capacities (Roderick, 2014; van Dijck, 2014; Zuboff, 2015)), and the use of algorithmic and AI tools in online environments and decision-making (e.g. Cheney-Lippold, 2011; O'Neil, 2016). These sources of data give rise to new methodologies for researching social, political, and economic phenomena, changing how social science themselves operate (Borgman, 2016; Marres, 2017). A key topic in these debates is the prevalence of a false belief in the neutrality and objectivity of digital transaction data which is challenged by the opacity of its origins, its uncertain generalisability and representativeness, the implications of platform design for what data is generated and about whom, and problems of missing, biased, and incomplete data.

The first implication of digital data for my study is that whether we are discussing online sources of data, sensory devices, repurposing of digital databases, or some other aspects of datafication and Big Data, they comprise relatively new tools for how non-profits might use quantitative data to rethink their work. Law, Ruppert, and Savage have argued that digital technologies play a particularly important material role in how the new computational ways of knowing enact their objects, and that digital data should be understood as a change in the methods of enacting social phenomena (Law, Ruppert, & Savage, 2011b; Ruppert et al., 2013a). Furthermore, they argue that digital systems constitute a diverse set of methods assemblages, with small differences in the configuration of digital infrastructures leading to different data and enactments.

The second implication is that the digital data methods assemblages are coming from outside the traditional remit of the non-profit sector and the quantification of social phenomena. To tap into Big Data and datafication, non-profits are encouraged to invest into new digital systems which might come from commercial vendors whose systems were developed for very different purposes than non-profit work. Furthermore, the experts in digital data and data science often have a training in computer science and computational methods (Dorschel, 2021), which is different from the social science education that has informed debates on the quantification of social value. As a result, the digital data sources give rise, not only to a new technological configuration of non-profit methods assemblages, but their use might introduce new values, beliefs, and professional identities as a result of new types of professionals working in the non-profit sector.

Finally, the recent surge of interest in digital data and data science is accompanied by the presence of technological solutionism in tackling social problems. Technological solutionism, or techno-solutionism, refers to the idea that social problems can be effectively tackled by technological solutions, and that investment in technological innovation can contribute to solving social problems (Haven & Boyd, 2020; Milan, 2020). Techno-solutionism as a concept was popularised by Morozov (2013) as part of his critique of large technology corporations offering apps and online tools as solutions to social problems. While technological determinism refers to the wider idea that social change is driven by technological change, techno-solutionism operates on the level of how social problems are understood and tackled. Techno-solutionism can be linked to the promotion of any technology, but it often overlaps with promotion of digital data collection and analysis since many of the technological innovations of the

2010s focused on digital technologies. In such scenarios techno-solutionism can take a form that assumes that digital data collection itself is a solution to social problems, or that increased digital data collection and analysis can be of significant help in tackling social problems.

The ideas behind techno-solutionism are not tied to the concept and has emerged independently in different scholarly fields, especially in development studies and communication. The MIT-led One Laptop Per Child project as a strategy of tackling inequality is a prominent example of techno-solutionism in the development context (Ames, 2019). Data for Good initiatives and AI for Good initiatives in the development context are likewise are examples of how investment in technology has been seen by the United Nations, Non-governmental Organisations, and their corporate partners as a way to tackle global challenges despite doubts about the effectiveness and asymmetric power-relations (Aula & Bowles, 2023; Madianou, 2021; Magalhães & Couldry, 2021). In the development policy context criticism is connected to the concept of "philanthrocapitalism", which denotes the growing power of billionaire philanthropists with backgrounds in technology businesses bringing to the non-profit sector their ideals of entrepreneurship, managerial measurement, and technical innovation (Jenkins, 2010). Techno-solutionism has not been discussed less in the context of the domestic UK non-profit sector, and past research shows that the ideas of data-driven and technological optimisation are common in UK civil society as well (e.g. Powell, 2021).

3.6. Contribution of my approach

I expand on the studies reviewed above by focusing on the entanglement of quantitative measurement and value, using the Data for Good initiatives as an entry point to explore new data practices. My study elaborates on findings on the social and political element of quantitative measurement but does this from a bottom-up perspective that explores the diversity of old and new quantitative methods assemblages and the way they present themselves to the practitioners using them. My conceptual framework focuses on the relationality of both methods assemblages and situations of dispute which means that my analysis aims to be sensitive to multiplicities, tensions, and discrepancies in the use of quantitative measurement in the non-profit sector. Because I assume that value and versions of reality are achieved as an outcome of practices, my approach puts quantitative techniques, their situatedness, and their relationality front and centre in the analysis.

This approach was expected to offer insight into the debate on neoliberal developments and marketisation in the UK non-profit sector. The aim is to contribute to the research gap identified by Rottenburg et al. (2015, pp. 21-22) regarding the need for social scientific bottom-up studies of quantification and politics, in contrast to studies focusing on macro-level dynamics and domination. The *empirical* developments I have discussed regarding increased competition, the proliferation of quantitative techniques borrowed from the private sector, changing notions of value, and a diminishing role of the state are relevant, but my conceptual framework means that I aim to understand these changes not through analysis of the structural transformation of the non-profit sector or its colonisation by market logic. In my analysis neoliberalism is not positioned as a self-sustaining force that drives changes in the non-profit sector, but as relations that are sustained and constantly re-enacted through the way non-profits justify their work and use quantitative measurement techniques to assess its value. The sociotechnical approach of my study is intended to highlight not only the micro-level social elements of how such dynamics present themselves to practitioners, but how they are put into practice in the relational use of quantitative measurement techniques.

The study elaborates on the arguments of Mennicken and Salais (2022) that the politics of calculative and quantitative techniques are determined neither by technologies themselves nor by the macro-level context of their use. In the study I assume that measurement has variable political capacities that lend themselves to domination and resistance, bureaucracy and activism, utopia and dystopia. My analysis in subsequent chapters complements their analysis by going deeper into the entanglement of enactment and valuation, focusing especially on how quantitative measurement techniques themselves are changing and non-profit organisations are presented with multiple alternative ways of quantifying and valuing their work.

I acknowledge the Foucauldian arguments of Rose and Miller (1991; 1992, 2008) on the importance of quantitative techniques in new modes of governing. However, my focus on relationality and blending of different forms of justification means that their arguments about the epochal shift of a unified neoliberal moral or political logic penetrating the entire UK non-profit sector is not my starting point. I do not assume that the UK non-profit sector or current historical era are neoliberal *per se*. Instead, the application of my conceptual framework enables me to assume that the developments and logics associated with neoliberalism will emerge from an analysis of the relational position of which techniques non-profits use to demonstrate their value and what role they are given in the institutional landscape of the sector.

This approach also builds on Porter, Hacking, and Desrosieres' work on the role of quantification in historical changes of politics and institutions, which pioneered the analysis of politics of quantification. My focus differs in being synchronic and relational, rather than historical or focused on temporal change. Though situated in a specific time and place, I follow Ruppert, Law, and Savage (2011; 2013) in focusing on the role of methods assemblages in producing contemporary forms of value and non-profit work rather than analysing them as part of epochal shifts.

Barman's (2016) conceptual strategy and findings which revealed how economic and social value can be combined and enacted in immensely diverse ways depending on what measurement techniques are used to capture them is also drawn upon. However, my empirical focus is on new forms of data practices, not new forms of marketisation or the conflation of financial and social measurement.

My conceptual framework also builds on Krause's (2014) work on how beneficiaries and their needs are quantified by non-profits so that they can be presented to funders. However, my interest is not the market dynamic of the initiatives I am studying, but the role of methods assemblages in justifying value given the proliferation of digital data and data science. My study provides an opportunity to detect the myriad ways that UK non-profit organisations use methods assemblages to enact their beneficiaries, and how these practices are under pressure given the emergence of new waves of data practices.

As I said above, the study contributes to themes explored by Rottenburg et al. (2015) by highlighting the sociotechnical micro-foundations of quantification and power, but my focus on the UK domestic non-profit sector means that the study is based in a different institutional and political context than the context of the global field of humanitarian and development policy which forms the backdrop to Rottenburg et al.'s work

Finally, I want to emphasise that a primary benefit of my approach is that it does not anchor quantitative techniques to any specific reform movement such as NPM, EBP, or Big Data. While each has a programmatic goal of promoting specific measurement techniques and technologies, methods assemblages both transcend such promotional coalitions and are more specific than their generalised promotion can lead us to believe. Multiple groups can promote the adoption of the same quantitative measurement techniques, and the politics of technique are not tied to any specific movement. In my framework, the relationality of methods assemblages and justification means that the politics of quantitative measurement operate locally and not only on level of the programmatic ideals driving their promotion. In my empirical analysis I illustrate this by examining how Data for Good initiatives in the UK non-profit sector provide an entry point to understanding the relational politics of quantitative data practices and the assemblages associated with Big Data and data science.

Chapter 4:

Methodology

4.1. Introduction

The goal of this thesis is to explore the politics of data practices in the UK non-profit sector with Data for Good initiatives serving as the entry-point. In Chapter 2 I proposed methods assemblages, situations of dispute, and demonstrations of value as key concepts in my conceptual framework. In this chapter I discuss my methodology, the way I operationalise my key concepts, and how I collected and analysed empirical materials to answer the research questions. My methodology is guided by studies in the ANT and sociological pragmatism and employs interviews as the primary way of collecting empirical materials. The chapter is divided into seven sections. First, I outline my methodology and discuss how the theories discussed in the previous chapter influence the research design. I then discuss my use of interviews as the primary research material and how these were complemented with auxiliary data collected from organisations participating in Data for Good initiatives. The discussion then turns to the operationalisation of concepts and how this guided the data collection. Finally, I present how the materials were analysed, including interview coding strategies. The chapter finishes with a reflection on research ethics and my positionality as a researcher.

4.2. Methodological foundations

My conceptualisation of data practices follows the work of Evelyn Ruppert (Ruppert, Law, and Savage, 2011; Ruppert & Scheel, 2021; Scheel, Ruppert, and Ustek-Spilda (2019) and draws from the ideas of Law (2004) and Mol (2002), which I enrich by combining them with arguments in pragmatic sociology of value (Boltanski & Thévenot, 2006). The approach combines analysis of the social and material aspects of data practices. In this section I outline the methodological foundations of this approach by first reviewing past methodological discussions on ANT and pragmatic sociology of value and then laying out how they inform my study. As suggested in my theory chapter (Chapter 2), my analysis prioritises the social aspects of data practices and puts less emphasis on the analysis of materiality. This emphasis also guides my research design and methods, which uses interviews as the primary method and complements it with additional data collection from public and online sources to elicit insights on the materiality of data sets and methods assemblages discussed in interviews.

ANT starts from the analysis of associations, i.e., the idea that objects of study should be understood as members in a network of relationships rather than as singular objects (e.g. Law & Mol, 1995). This strategy emphasises the associative and relational constitution of what is studied empirically. The strategy is sometimes called material-semiotics, because it understands objects as relational entities that change when their position in relation to other objects is changed, just as in semiotics the meaning of words and symbols changes when their discursive positions are adjusted (Law, 2009a, p. 149; Law & Mol, 1995). In this chapter I primarily refer to the approach as material-semiotic analysis to emphasise this methodological tradition. Researchers following the material-semiotic approach analyse how certain objects come to hold particular positions in a network, and how those positions displace and redistribute other actors. Callon (1984) calls such changes translations, because they change what is deemed social, natural, or technical in specific circumstances, and how they are granted the ability to affect future relationships.

Because a material-semiotic research strategy is open to a variety of associations and things that can be associated, the approach is permissive in terms of empirical data collection techniques. Many projects draw methods from ethnography and anthropology in the tradition of science studies (e.g. Latour & Woolgar, 1986; Law, 1994; Mol, 2002). Others employ historical analysis (Law, 1987) or are based on public events and document analyses (Law & Moser, 2012). Interviews have gained standing as a data collection method and have been used in ethnographic studies using ANT (Demant & Ravn, 2020). Because of this diversity, the research strategies used in material-semiotic analysis are informed more by the research interest, questions, and subject matter. As Law (2017) suggests, material-semiotic analysis is focused on practices and case-studies, with the methods, theories, and empirical work 'folded' into each other. Therefore, a variety of empirical materials can be used to examine methods assemblages, situations of dispute, and proofs of value in Data for Good initiatives.

Pragmatic approaches to valuation and worth share the methodological diversity of ANT and are not unified by any specific data collection strategy. However, studies of valuation emphasise the social character of their research subject: normativity and politics are positioned as markedly social phenomena and interviews, ethnographies, multi-modal fieldwork, and case-studies are common in studies on valuation. Crucially, even studies that focus on the role of tools and quantification in valuation rely on social research methods to analyse where the tools come from, how they are used, and what their implications are. Studies of valuation are often designed as case-studies: the researchers are interested in a particular tool of valuation or particular types of valuation that can be found in a specific case or situation (Balsiger & Jammet, 2022; Barman, 2015; Langford, 2022). Empirical material may consist of interviews, participation in events, document analysis, analysis of media products and of scholarly publications. What ties these materials together is the attempt to build a comprehensive description of the context where valuation happens and of the tools used to attribute value. The number of empirical strategies available in pragmatic studies of value and worth is therefore expansive and transdisciplinary (Doganova et al., 2018).

Some key differences can, however, be found in pragmatic studies of value. The sociological work of Boltanski on orders of worth is focused on analysing common public strategies of justification that can be employed regardless of context, with the number of such orders of worth being limited to those identified by Boltanski and Thévenot (2006) with some additions (Boltanski & Chiapello 2018; Blok, 2013). Studies following this strategy focus on elaborating on and comparing the use, compromises, and critiques among the orders of worth across time and place (Ylä-Anttila & Luhtakallio, 2016). Another empirical strategy is found in performative studies of economics, which focus on the material constitution of markets, measurements, financial practices (Callon & Muniesa, 2005; Mackenzie & Millo, 2003; Muniesa et al., 2007). In contrast to the studies of justification across different spheres of normativity, they focus on the constitution and attribution of economic phenomena and value. Studies on the performativity of markets are akin to material-semiotic analysis and sociological pragmatism in their use of diverse methods, such as interviews ethnographies, case-studies, and analysis of scholarly texts. The empirical strategies used to study quantification and valuation employ a variety of social research strategies that yield information on the use and implications of quantitative tools of valuation or discourses around them.

What then are the shared methodological foundations that I use to inform my empirical analysis that combines ideas from ANT and valuation studies? I emphasise three principles. First, I emphasise the importance of studying how people engage with methods assemblages and situations. Second, the analysis is focused on situations of dispute, which I understand as sets of social and material relations that can be reproduced in different contexts and locations. Third, I undertake an inductive analysis that is informed by my theory and aims to develop insights into comparable practices.

In this thesis I emphasise the study of human informants. Studies in ANT and valuation studies give high importance to studying the practices and understandings of experts. Indeed, the analysis of value and normativity involves a focus on the social and political aspects of practices and engagement with interviewees who can offer insight. I explore how data practices demonstrate value through an analysis of the understandings of the people participating in Data for Good initiatives and those who work with data in the non-profit sector. The material-semiotic relationship between technologies and people in methods assemblages is understood as a network of associations where neither can exist without the other, but empirical analysis of methods assemblages can foreground different aspects of such associations depending on the focus of the study. I draw upon the concept of methods assemblages and enactments as understood by Law and Mol, which grounds them in the professional environment and situations of people *using* digital devise and trying to *do* things with them.

A focus on people and practices is also common in valuation studies, where the use of specific tools of valuation is often studied in specific professional environments. In such cases the use of valuation tools cannot be separated from the goals of experts in trying to assess the financial value of a social intervention (Barman, 2015; Hellman, 2020; Williams, 2023b), negotiating the value of the bioeconomy (Asdal et al., 2023) or pricing and valuing environment and land (Foale et al., 2016; Langford, 2022). The corollary of this position is that I enter the field of Data for Good and non-profit data through people who are experts in non-profit data, and who use the tools and techniques that have come to be associated with attention to data in the non-profit sector. My analysis of methods assemblages then expands on the insights provided by human informants.

Both material-semiotics and the pragmatic sociology of valuation emphasise situated analysis. The goal of analysis is to locate the relevant practices, techniques, and people within specific instances of when digital tools and data practices are deployed. In the analytical traditions that I draw upon, situation is understood to be more than just a unique temporal instance in a spatial location. Indeed, what is meant by situations in the spirit of material-semiotic analysis and pragmatic sociology of value is a situation of relations that reoccurs whenever networks and association are arranged in a way that reproduces it. A situation of a market valuation of an object, such as the valuation and exchange of strawberries (Garcia-Parpet, 2007), is produced, for example, whenever people come together to determine the price of the object following a similar set of techniques. Similarly, a situation of determining a specific medical diagnosis, such as atherosclerosis (Mol, 2002), is produced whenever a patient enters the medical system with a set of symptoms recognised by the doctors who initiate the procedures and devices for generating evidence on the possible presence of an illness. In these cases, there can be various locations where such situations occur, but the situation is produced through specific social and material arrangements that are similar across localities. Both cases can also be understood as situations of dispute insofar as they include the assessment of value. In the case of strawberry market this means determining the economic market value of strawberries whereas in the case of medical diagnosis patients are valued according to their experiences of health and welfare.

The orientation towards empirical evidence in both ANT and a pragmatic sociology of value is *inductive:* analysis is developed through close engagement with empirical materials, producing detailed accounts of practices. However, the approach is also theory-driven insofar as it operationalises key concepts in material-semiotic analysis, which in my study are situations of dispute, methods assemblages, and demonstrations of value. These concepts are used to focus the analysis to relevant aspects of the interviews, which then are analysed and coded inductively. The goal of inductive analysis is not necessarily generalisation, but capturing a specific effect, its implications, relationships, dynamics, or process that may be of broader relevance in comparable situations. This means that I do not seek to reject or confirm theory or hypotheses but to elicit insight into the entanglement of data practices and demonstrations of value." The contribution of the findings derives from identifying relationships, effects, and processes that can be shown to be relevant in comparable uses of methods assemblages or comparable situations in the non-profit sector.

Finally, I reiterate that my methodological approach is grounded on the assumption that it is possible to operationalise ANT with interviews as a primary research method as illustrated by John Law's work and in the pragmatic sociology of valuation tradition. My combination of ANT with pragmatic sociology of value already shifts analytical attention towards the social element of justifications and the role of methods assemblages in situations of dispute. Given this approach, social research methods as the primary tools of empirical inquiry are legitimate methods as well as putting less emphasis on the direct observation of the materiality of data practices. Although generalised symmetry in terms of social and material objects is often the core component of ANT research, scholarship has expanded to include other methodologies. Mol's work is an example because it operationalises ANT ideas as an analytical register that has been characterised as empirical philosophy (Mol, 2002). My combination of ANT with the pragmatic sociology of value follows this analytical track by enriching the material-semiotics of ANT with the more philosophical focus of Boltanski and Thévenot.

This combination, however, limits how generalised symmetry and the analysis of materiality are operationalised. In the thesis I combine interviewee descriptions of their data practices with information from public data sources to build a more comprehensive picture of data practices and methods assemblages. Even if interviews do not offer the same possibility for analysis of material artefacts as ethnography, they do invite interviewees to discuss the data practices and technologies they use. Insights from the interviews can then be complemented with analysis of empirical data from public and online sources. In this thesis I use this strategy to structure the analysis around findings from interviews and complement interviewee discussions on data practices with additional data collection that seeks to verify details from the interviews and allow the analysis of the materiality of specific data practices when needed. For example, when an interviewee in my study discussed their use of the London Data Store, interview insights are supplemented by other sources after the interview (see Chapter 7, pages 199-200). Likewise, when an interviewee in the study discussed how they developed an algorithmic system to use data from a foodbank to predict foodbank dependence, the interview insights could be complemented with detailed discussions on that the algorithm and the data it used that was provided in public blogs and reports about the case (See Chapter 8, pages 227-231). I acknowledge that public information is not available on all data practices discussed by the interviewees, and in the thesis, I limit detailed analysis of materiality only to those data practices and methods assemblages where such material is available.

4.3. Operationalisation of research questions and concepts

In Chapter 2 I identified the concepts and central research question that guide my empirical analysis and outlined three research sub-questions. In this section I discuss how I use empirical analysis to answer them.

The first research sub-question was “What new quantitative or digital methods assemblages are promoted in the UK non-profit sector?” The key concept here is methods assemblages. Answering the research question requires first understanding what kinds of data practices are promoted in Data for Good initiatives and then identifying specific methods assemblages. To learn about Data for Good initiatives, I combine interviews with supplemental materials. I use interviews with human informants to ask questions about their quantitative and digital data collection and analysis practices. This took different forms depending on what type of organisations the interviewees represented, which I discuss below in the section on data collection. In the interviews the use of methods assemblages is explored with a focus on the social aspects of socio-material assemblages. This is done by asking the interviewees to describe what kind of data they collected as part of their work, what kind of analysis techniques they used, who was data collected for, and what did they try to achieve with their data collection and analysis. If the interviewees worked for organisations that did not themselves use data but rather facilitated the use of data by others, then questions were asked about typical client projects and data collection and analysis techniques they found particularly relevant in the non-profit sector. Given that interviews as a method emphasise the social aspect of methods assemblages, information provided by interviewees was then elaborated by exploring public documentation and public available information on the practices, or examining the public data sources that were discussed by the interviewees to understand the material side of these assemblages. Information on the methods assemblages promoted in Data for Good initiatives was also collected by participating in relevant public events. This combination of methods helps attending both to the social and material aspects of sociomaterial practices and operationalising both the material and semiotic aspects of the material-semiotic analysis.

The second research sub-question was "In what situations of dispute do data practices justify value?" To answer this question, I identify and analyse situations of dispute with interviews. Following Boltanski and Thévenot, situations of dispute are understood as a relationship between at least two actors where there is a need to determine the relative value of objects, people, or courses of action. In these situations, the participants engage in implicit or explicit tests of which evidence needs to be enrolled to demonstrate value. Crucially, the way I understand situations is not a unique spatio-temporal event, but as relationships that can repeat and manifest in different instances. Situations of dispute can be identified in interviews by exploring what the interviewee try to do with data in relation to attempts to claim worthiness, deflect criticism, or assess the relative value of alternative courses of action. Because situations of dispute are by definition social, they can be identified and analysed with interview data. Unlike the analysis of data practices, identification of situations of dispute does not require the analysis of materiality, although situations can be underpinned by specific material relationships that are implicated in the circulation of data between different actors in the non-profit sector.

The third research sub-question was "how is the demonstration of value entangled with methods assemblages in these disputes?" Operationalising this question involves a corollary of the previous two. Once methods assemblages and situations of dispute have been identified, analysing the demonstrations of value appears at their intersection: a demonstration of value is any object that is enacted with methods assemblages and taken as a resource for legitimate judgement within a dispute of value. In this thesis I focus on the social and socio-material entanglements, which I analyse through interviews and additional data collection from public data source. Interviews provide information on these entanglements insofar as they include interviewees describing how specific methods assemblages are used within specific situations of dispute, which can be supported by asking interviewees questions that specifically address the data sets and analysis techniques used to conduct some specific piece of analysis. The materiality of these methods assemblages can then be further explored in the same way outlined in answering the first sub-question, i.e. seeking further information on the data practices from public sources to complement the information given in the interviews. If a situation of dispute has multiple participants, it is possible to combine insights from interviewees on different sides of the dispute to understand their perspectives to the issue. Answering the third sub-question also provides a way to approach the second. When a methods assemblage has been identified, it is also possible to examine the situations, tests, and judgements that are used in, and the forms of value it is taken to demonstrate.

4.4. Expert interviews as a qualitative method

The approach in this thesis is qualitative, which means my interest is in practices, their meaning, their construction, and their implications (for an overview, see Hammersley, 2013). It can be characterised as a naturalistic form of inquiry insofar as it tries to get as close as possible to how people participating in Data for Good initiatives or people using data in the non-profit sector *themselves* understand and make sense of their practices (de Vries & Beuving, 2015). However, as discussed above, I focus on how the material and social aspects of specific practices and technologies come together. This means that while I am interested in the people participating in Data for Good initiatives and using data in the non-profit sector, I am primarily interested in the material-semiotic practices relating to them rather than their purely social aspects.

Interviews are the primary research method used in the study. Interviews are an interactive social event where knowledge is produced through a reciprocal process of questions, answers, and comments between an interviewer and an interviewee (Warren, 2012). The interview techniques relevant for my research are in-depth interviews, semi-structured interviews, or thematic interviews that emphasise mutual interaction, exchange, and exploration of how themes are approached (Roulston & Choi, 2014). Interviews provide an opportunity for interviewees to reflect on their work, therefore offering insights into different facets of how they understand the practices they engage in.

Interview methods are common in material semiotic analysis and pragmatic sociology, and they are widely used in Critical Data Studies. They are used to gather insights, especially on expert knowledge, practices, and tools, and are common in research on science, technology, quantification, and digital tools. Interviews are often positioned within multi-modal case studies or in fieldwork involving interviews, participant observation, document analysis, online information search, and other empirical materials that are relevant for a study. In this thesis interviews as the primary method of data collection are complemented with additional data collection through participant observation, analysis of information from public sources, and analysis of public data sets discussed in the interviews.

I use an expert interview method. Expert interviews are a special method within the wider family of interview methodologies (Bogner et al., 2009). They differ from other interviewing strategies in recruitment, interview design, and analysis. Expert interviewees are recruited based on their distinguishing professional characteristics rather than for their representativeness of a social group or category.

The expert interview method I use is what Bogner and Menz (2009) call the "systematising expert interview" and "theory-generating expert interview". According to Bogner and Menz, systematising expert interviews "means that the expert is treated here primarily as a guide who possesses certain valid pieces of knowledge and information, as someone with a specific kind of specialised knowledge that is not available to the researcher" (2009; pp. 47). The goal of the interaction between the interviewer and the interviewee is then to gain access to this knowledge, which is considered important because it provides insights into the work of the expert, sequences of events, social situations, and their personal reflection and interpretation of them (Bogner & Menz, 2009, pp. 47). I use this approach to interviews in constructing a picture of Data for Good initiatives and uses of data in the non-profit sector. However, I also go deeper than the surface evidence provided by the interviewees and engage in what Bogner and Menz call the theory-generating interview. This type of expert interview is interested not only in the technical and processual knowledge held by the expert by also in the interpretative facet of meaning-making, routines, and assumptions about their practices. Here the goal is the "communicative opening up and analytic reconstruction of the subjective dimension of expert knowledge" (Bogner & Menz, 2009 pp. 48). This interpretative aspect is crucial in elaborating the normative and political aspects of practices relating to data in the non-profit sector. It constitutes a vantage point in reconstructing what it *means* to use data in specific situations.

My conceptual framework also emphasises the role of materiality and material tools. This begs a question: how can materiality be analysed through interviews? Three answers can be given in addition to the rationale given in section 3.2. on methodological foundations.

First, my analytical focus is informed by concepts of methods assemblages, situations of dispute, and demonstrations of value. Of these concepts, materiality plays an important role only in methods assemblages. As argued in Chapter 2, my analytical focus on studying methods assemblages is in their role in enacting versions of reality to demonstrate value within disputes and tests. This analytical focus prioritises the social element of methods assemblages and their situatedness in specific relational contexts where value is to be demonstrated, which makes interviews a valid way of answering my research questions. My approach gives less emphasis to the material aspects of methods assemblages than would be present in classical applications of material-semiotic analysis, such as studies focusing on the construction of specific data sets.

Second, the way material elements of assemblages, disputes, and proofs are understood in this thesis is *not* exclusively tied to ethnographic analysis that is often used as a tool in approaching materiality in material-semiotic analysis. Indeed, many studies using material-semiotic analysis consider materiality without resorting to ethnography or direct engagement with material artefacts (e.g. Law, 1987, 2002). In this study the descriptions of practices, processes, and events offered by interviewees are assumed, nevertheless, to give an indication of material aspects. For example, materiality may be implicated in discussions about the circulation of data within and between organisations or in describing the strategies of data collection used by an organisation.

Lastly, I complement interviews with supplementary materials collected before and after the interviews to substantiate claims and access the material aspects of their work. The supplementary materials used in the study included document analysis, online information gathering, participation in events, information on key organisations, and examination of public data sets mentioned in the interviews. Supplementary materials were also important in deepening my understanding of publicly celebrated use cases of data science in the non-profit sector which were often mentioned by participants of Data for Good initiatives in their online communication and public events. Supplementary materials were used to substantiate details that are difficult to ascertain in interviews, such as technical details, practical examples, and organisational arrangements. Auxiliary research materials provided supporting evidence on details learned in the interviews and offered an opportunity for triangulation. However, the interviews were used as the primary empirical material and constitute the backbone of the empirical analysis.

4.5. Data collection and sampling

The sampling strategy in my study follows the expert interview method, where interviewees are chosen based on their specialist knowledge professional position, and they are not representative of the entire population of possible interviewees in a given organisation, network, or a field (Bogner and Menz, (2009). In this thesis criterion for selection was focused on people who are experts in use and analysis of data in the non-profit sector. I accessed this group of experts through Data for Good initiatives, using participation of organisations and individuals as an entry point to the world of professionals who dedicate their professional work to questions about the use of digital and quantitative data in the non-profit sector.

In this thesis the category of experts sampled for interviews is called *non-profit data professionals;* a sub-group of professionals working in the non-profit sector. The interviewees selected are best understood as experts in data analysis and not as a sample of non-profit sector managers, subject-matter experts, project managers, or front-line workers. Each interviewee is not assumed to be an expert in data in the same way. The interviewees came from diverse professional roles with different levels of quantitative or computational skills, but they were unified by their work focusing on data in the non-profit sector. The job descriptions, skills, and background of the interviewees is discussed more closely below.

Non-profit data professionals can be conceptualised as an extreme case of people working in the non-profit sector (e.g. Chen, 2015). Because of this, my analysis of data practices in justifying the value of non-profit work is not intended for generalisation to the whole of the UK non-profit sector. My sample constitutes an extreme case of non-profit sector workers who are professionally involved in justifying the value of data for non-profit sector and using data to justify the value of non-profit work.

The recruitment of interviewees focused on finding informants who were expected to be familiar with more advanced and innovative uses of data since this was consistent with my focus of Data for Good initiatives. This meant that the sampled interviewees were more likely to be enthusiastic about novel data practices than an average employee in the non-profit sector. This choice was consistent with my focus on new use of data science and digital data which had been shown Chapters 1 and 3 to underpin the emergence of Data for Good and AI for Good initiatives globally and has been a scholarly focus in the Critical Data Studies field.

Interviewees were selected based on purposive and snow-ball sampling. In purposive sampling interviewees are selected based on unique characteristics that make them relevant beyond their representativeness of some larger population (Tongco, 2007). Sampling began by targeting participation in Data for Good initiatives or those with links with these initiatives as an entry point to analysis of data practices in the non-profit sector. I sought interviews with people from organisations that were active in Data for Good initiatives and had participated in public events to promote the use of data. Potential interviewees were first identified based on their public presence in promoting Data for Good. This led to the interviewee sample with an emphasis on those working in organisations that were visible participants in Data for Good initiatives. Furthermore, it became apparent that most of their work focused on social and health sectors, and the sampling strategy means that findings are relevant mainly to social and health sector non-profits.

Descriptive information on the interviewees is presented in Table 1 and more detailed information on each interviewee is provided in Table 3. Altogether 37 interviews were conducted during the study. The number of unique individuals interviewed for the study is 35. The difference is explained by five interviewees being interviewed twice and two interview sessions having more than one participating individual. The average length of interviews was 61 minutes. The total running time of recorded interviews was 36 hours, 45 minutes. All interviews were recorded and transcribed verbatim. The gender-split of the interviewees was almost even, although this was not a factor in recruitment.

The interviewee backgrounds can be divided into three distinct groups of non-profit data professionals, which define the characteristics and limitations of the sample. These groups are facilitators, service providers, and funders. This classification is also used throughout the empirical analysis. The majority of the interviewees were from facilitator organisations (N=24, 68%). Interviewees from funding organisations tallied to seven interviews (20%) and interviewees from service-providing non-profits amounted to four (11%).

Table 1. Description of interview sample

Total interviews	37
Total unique persons interviewed	35
Male interviewee	18 (51%)
Female interviewee	17 (49%)
Interviewees in facilitator organisations	24 (68%)
Interviewees in service-providing organisations	4 (11%)
Interviewees in funding organisations	7 (20%)
Total recorded interview minutes	2205 min

Interviewees in facilitator organisations means that the interviewee worked for an organisation whose services were geared towards non-profit organisations rather than directed at some group of beneficiaries. For example, an important facilitator organisation in the sample was DataKind UK, which was a prominent leader of the Data for Good network and offered volunteer data science services for other non-profits. Another example is Data Orchard, which was a founding member of Data for Good networks in the UK and offered data-related consulting services for non-profit organisations. Facilitator organisations relied on publicity to attract attention and potential clients, and they could be fee-taking or charitable organisations themselves.

The majority of interviewees in the facilitator category had more than five years of relevant experience in the non-profit sector, but some had up to twenty years of experience. The backgrounds of these interviewees were almost exclusively in the non-profit sector, and they had often worked in analyst, project delivery, and managerial roles in service-providing and grant-giving organisations before moving to providing expert advice in data skills and analysis. Only some of the interviewees had worked exclusively in analysis and research roles, whereas the majority had held varying types of positions before ending-up in data-related roles. Interviewees with exclusive backgrounds in analysis and research roles tended to be proficient in quantitative data analysis and had university-level training in statistics, social sciences, or programming, but in their current day to day work, training, facilitation, and project delivery was likely to be more important than data analysis. For interviewees in the facilitator category and had long careers in the non-profit sector, their roles tended to be more varied and could include work outside the non-profit sector. Long careers and experience in facilitative and consultative work enabled these interviewees to discuss the use of data from various perspectives drawing examples from their earlier careers and clients, giving the interviews depth and breadth.

Second, interviewees were recruited from funders, i.e. non-profit organisations that specialised in awarding grants and funding. Interviewees from the funding organisations included staff who were involved with analysis and evaluations of applicants. Only a few of these organisations were directly involved with Data for Good initiatives but were referred by other interviewees. Not surprisingly, the focus of these interviews was on how data was used to assess grant applications, which provided insights into one of the key situations that data was used to demonstrate value. Seven interviewees belonged to this group, and they were on average more experienced than other interviewees, with some having more than twenty years of experience in the non-profit sector. Questions were asked, for example, about how they use data, how they collect data, do they use external sources, why they use data, and what they try to achieve with data.

Third, interviewees were recruited from non-profits that offer services in the social sector. These interviewees were recruited especially through snowball-sampling with recommendations from interviewees in facilitator organisations. Overall, the focus was on organisations thought likely to be in some ways advanced or innovative in their use of data because this was expected to yield further insights into the supposedly new and innovative ways of using data that were promoted in Data for Good initiatives. Three interviewees in this group had leading roles in their organisations regarding data collection and data analysis, and their work was focused on providing insights on the services the organisations was providing. Interviews with study participants from service-delivering non-profits focused on how they used data in their own work. This allowed me to deepen my understanding of cross-cutting themes that were identified by interviewees from facilitator organisations and to build richer case-studies of how individual organisations collected, analysed, and used data.

Detailed information on the classifications, job titles, and backgrounds of each interviewee is available on Table 2. In the empirical analysis I use the pseudonym, job title, level of experience, and interviewee category with each quote to illuminate their backgrounds. Most job titles listed in Table 2 are the job titles of the interviewees at the time of the interviews, but some have been modified to protect interviewee anonymity while signalling the level of seniority and professional specialisation. Changes are made when a title is unique and would immediately identify the interviewee, or when the title, together with other background information, would present a risk to anonymity. In the table I also list the length of relevant experience that each interviewee has had in working in the non-profit sector. Background information was collected as part of the interviews, and further details were collected from the online biographies of the interviewees on their organisational websites and public information posted on online professional networking sites.

The sampling strategy limits the generalisability of the findings. The most obvious limitation is that the sample skews strongly towards people who are committed to advancing the use of data or whose professional work focuses on data. Not included in my sample are non-profit sector employees whose primary work is not about data or whose organisations are not known as leaders in the use of data. Groups of non-profit employees not interviewed include front-line workers, service managers, volunteers, and trustees. These groups would likely provide different insights on the value of data and data practices in the non-profit sector. The sample also is skewed towards facilitator organisations. These organisations were relevant for the understanding of Data for Good initiatives and could comment on data practices in various non-profit organisations, but their insights are likely to be different from those involved in the day-to-day management of non-profit work and the use of data as part of this.

Table 2. Interviewee background information

Interviewee pseudonym	Job Title	Type of experience in the non-profit sector	Relevant experience	Category	Gender
Interviewee 1	Civil Society Data Officer	Community engagement	4 years	Facilitator	Female
Interviewee 2	Manager	Director of an organisation supporting digital and data skills	15+ years	Facilitator	Female
Interviewee 3	Digital Adviser	Digital and data skills training in the non-profit sector	5+ years	Facilitator	Female
Interviewee 4	Director of Services	Frontline work, trainings, and non-profit service management	15+ years	Service-provider	Female
Interviewee 5	Product Lead	Research, analysis, and data science in the non-profit sector	10+ years	Facilitator	Male
Interviewee 6	Support & Engagement Manager	Database skills expert and trainer	10+ years	Facilitator	Female
Interviewee 7	Data Scientist	Data science volunteer, background in natural sciences	2 years	Facilitator	Male
Interviewee 8	Data & Research Lead	Research and analysis in the non-profit sector	1 year	Facilitator	Female
Interviewee 9	Grants Manager	Charity grant management	20+ years	Funder	Male
Interviewee 10	Senior Commissioning Officer	Local council procurement in social and housing sectors	20+ years	Funder	Male
Interviewee 11	Community Engagement Manager	Community engagement	5+ years	Facilitator	Female
Interviewee 12	Head of Community Investment	Grant management and project management	25+ years	Funder	Female

Interviewee 13	Data Manager	Data analyst and database manager	5+ years	Facilitator	Male
Interviewee 14	Entrepreneur and activist	Database management and data analysis	5+ years	Facilitator	Male
Interviewee 15	Entrepreneur and activist	Volunteer in digital innovation	1 year	Facilitator	Male
Interviewee 16	Data & Research Lead	Research, analysis, and data science in the non-profit sector	5+ years	Facilitator	Female
Interviewee 17	Entrepreneur	Volunteer in data analysis	2 years	Funder	Male
Interviewee 18	Entrepreneur	Consulting and training for digital technology and impact in the non-profit sector	20+ years	Facilitator	Male
Interviewee 19	Senior manager	Research, analysis, and data science in the non-profit sector	5+ years	Facilitator	Female
Interviewee 20	Head of Data and Analytics	Research, analysis, and data science in the social and health sectors	5+ years	Service-provider	Male
Interviewee 21	Data Science manager	Research, analysis, and data science in the non-profit sector	10+ years	Facilitator	Female
Interviewee 22	Senior manager	Consultant and facilitator in digital social innovation	10+ years	Funder	Female
Interviewee 23	Chief Economist	Analysis, research, and evaluation	2 years	Facilitator	Male
Interviewee 24	Data Lead	Research, analysis, and data science in the non-profit sector. Facilitation and consulting.	5+ years	Facilitator	Male
Interviewee 25	Principal consultant - digital innovation	Grant management, non-profit consulting, data science	10+ years	Facilitator	Male
Interviewee 26	Member Engagement Manager	Community engagement	5+ years	Facilitator	Female
Interviewee 27	Senior manager	Research, analysis, and data science in the non-profit sector. Consulting and facilitation of skills.	15+ years	Facilitator	Female
Interviewee 28	Senior manager	Research, digital innovation, and management in the non-profit sector. Consulting and facilitation of data analysis skills	20+ years	Facilitator	Female
Interviewee 29	Senior manager	Digital technology, marketing, management, data analysis in the social sector	15+ years	Facilitator	Male
Interviewee 30	Director of Impact and Innovation	Digital technology, digital innovation, data analysis, charity management.	5+ years	Service-provider	Female
Interviewee 31	Senior manager, data science	Data science, database management, management	5+ years	Service-provider	Male
Interviewee 32	Product & Programmes manager	Data analysis, database management, data skills facilitation	5+ years	Facilitator	Female
Interviewee 33	Programme Director	Data analysis, data skills facilitation	5+ years	Facilitator	Male
Interviewee 34	Evaluation and Learning Lead	Project management, grant management, grant evaluation and monitoring.	15+ years	Funder	Male
Interviewee 35	Transparency and reporting lead	Data analysis and grant management	2 years	Funder	Male

More interviewees from beneficiary-serving non-profit organisations would have yielded more detailed and situated insights into the realistic situations of non-profit sector data practices. They would have been likely to provide insight into the methods assemblages beyond quantitative data collection and analysis as a result of their client interactions and community engagement. Furthermore, three of the four interviewees from service-providing organisations can classified as large non-profits with a dedicated data team, and interviewees were recruited through referrals from other interviewees who recommended particularly advanced cases of data science in the non-profit sector. Indeed, the three organisations provided some of the most detailed and situated accounts of the novel data science techniques in non-profit work, and the sample in this category skews towards advanced skills and enthusiasm for data. Interviewees with those from other service-providing organisations might have offered a more critical take on quantification and data practices. However, since there was no lack of critical reflection or explicit critique of quantification and data practices even among the interviewees whose job was to promote the use of data, this sample limitation was not deemed problematic for my study.

The primary focus in collecting empirical materials changed during the study, reflecting my developing understanding of politics of non-profit data. Data collection can be divided into two parts.

The study began in October 2019 with a focus on the politics of data science in the UK non-profit sector and followed a classical fieldwork strategy. In this stage the focus was particularly on the political aspects of how novel data science tools are used to address socially and politically important questions, with a special interest in hackathon-type events with participants who had a background in data science.

The first interviews were conducted around an event to facilitate the use of data in the non-profit sector. This event was used as an anchor to identify and access event participants both before and after the event. During the event I conducted participant observation on how individuals worked with data sets, what they tried to achieve with them, and what concerns they had. Altogether 17 interviews were conducted around the event, including five people who were interviewed both before and after the event. These interviews followed the strategies of ethnographic interviewing, trying to get as close as possible to the work, concerns, and uses of data in the non-profits that participated in the event or, alternatively, to the work to facilitate the use of data in the non-profit sector. Interviews in the first stage began in November 2019 and ended in February 2020.

A semi-structured interview guide was used in these interviews, but with alterations to reflect individuals' backgrounds. (for full interview schedule, see Appendix 1). Before the event, interviews with few key organisers were conducted to discuss their goals for data skills facilitation, the design and context of the event, and their expectation on the use of data in the event. During the event I conducted participant observation with detailed fieldnotes. After the event, the first interviewees were re-interviewed to reflect on how the event went and how they see the use and facilitation of data use in the non-profit sector more broadly. Further interviewees were recruited in and after the event, with the interview schedule focusing on their past use of data, experience of the event, and broader context of using and facilitating the use of data in the non-profit sector.

Already in the first interviews I started to learn about the loose network of organisations that collaborate in promoting the use of data in the non-profit sector. This led to a realisation that the event I was using as my access point was just one of the various events and trainings organised by the network. Crucially, many of the organisations in the network professed working on "Data for Good." After finishing the first wave of interviews a decision was made to refocus the study around Data for Good initiatives, since many of the interviews had already explored them.

With the new focus on Data for Good initiatives, a new interview guide reflecting my interest in politics of non-profit data and Data for Good initiatives was drawn up (Appendix 2). Further interviewees were recruited by approaching organisations that were found to be active participants in Data for Good initiatives, which was determined through online searches and discussions with interviewees. Because of this focus, many of the new interviewees came from facilitator organisations and consultancies, which were the most active promoters of Data for Good initiatives. To complement interviews with facilitators and consultants, interviewees were also sought from organisations that were identified by other interviewees to be particularly innovative or forward-looking in their use of data. These interviews, which were categorised either as service-provider organisations or funding bodies, were crucial in elaborating on data practices used in the non-profit sector.

In contrast to the first stage of interviews, the second stage focused more on the data practices and past experiences in the use of data by the organisations represented by the interviewees, as well as their experience from the work done Data for Good initiatives and networks. Following the semi-structured interview strategy, questions could be asked in different orders depending on the information given by the interviewee and follow-up questions were used to expand on information already given. In the follow-up questions the focus was on getting the interviewees discuss as close as possible what kind of data they collected and how it was used. This meant that the conversation in the interview could be very specific to the practices of a certain organisation and the personal experiences of the interviewees on what difference data made in the work of their organisation or in the non-profit sector more broadly. The semi-structured strategy allowed me to understand the data practices used by the interviewees and situations they were used in, as well as contextualise their use in the broader dynamics of the non-profit sector.

The focus of this second stage of the study emphasised interviews partly for reasons beyond the control of the research design. Initially the plan was to continue the fieldwork with the new focus, because events held under the Data for Good banner were deemed a relevant source of information on the initiatives and their understanding of data in the non-profit sector. However, the fieldwork was interrupted with the onset of the COVID-19 pandemic in early 2020. As of March 2020, the UK was in full lockdown and all potentially relevant events were cancelled. This made continuation of fieldwork untenable. However, the new focus proved to be a viable empirical strategy because interviews could be conducted remotely. A total of 19 interviews were conducted in the second stage with 21 unique participants. Interviews with a special focus on Data for Good initiatives constitute 51% of all interviews and 60% of unique interviewees. No follow-up interviews were conducted in the second stage. Starting from March 2020, all subsequent interviews were conducted online. The last interview was conducted in June 2020.

Interviews were conducted using various media. Variations in interview medium were due to the onset of the COVID-19 pandemic around half-way through the interviews which prevented in-person meetings with interviewees. Video-interviews were conducted using Zoom or Teams software provided by the university. Of all the interviews, in-person interviews amounted to 19 (51%), phone interviews to three (8%), and remote videoconferencing interviews to 15 (41%). Written consent to participate was obtained from all interviewees, save for interviews conducted online whose consent was recorded by voice.

Additional data collection within the limits of the COVID-19 pandemic ensued during the second stage of interviewing. Information was gathered on potential interviewees and key organisations. Online information searches were conducted to confirm details learned in the interviews and to study specific public data sets discussed in the interviews. Further ethnographic observation and participation was conducted only on one occasion in 2021 when the key organisations studied in the project organised a major online event titled "Data4Good Fest". This was a follow-up to an event by the same name held in 2018, which was the first occasion many of the interviewees had been involved with Data for Good initiatives. During the online event, I observed panels, speeches, and presentations primarily by people I had already interviewed, which allowed me to deepen my understanding of their work with data. These materials are used in this thesis primarily to offer illustrations of specific ways that the use of data was promoted in Data for Good initiatives, and to provide empirical details on particularly relevant empirical cases of using data. When materials from the supplementary materials or the observation in the “Data4Good Fest” are used in this thesis, the source is marked in footnotes and interpreted in ways appropriate for the type of materials.

Table 3. Technical details of interviewees

Pseudonym	Interview stage	Date	Length (minutes)	Interview medium
Interviewee 1	First stage	6.11.2019 and 9.1.2020	63 and 89	In-person
Interviewee 2	First stage	21.11.2019 and 18.12.2019	65 (individual) and 78 (with interviewee 3)	In-person
Interviewee 3	First stage	18.11.2019	78	In-person
Interviewee 4	First stage	15.11.2019 and 5.12.2019	50 and 34	Phone
Interviewee 5	First stage	20.11.2019 and 13.12.2019	61 and 73	In-person
Interviewee 6	First stage	12.12.2019	77	In-person
Interviewee 7	First stage	21.11.2019 and 6.2.2020	65 and 52	In-person
Interviewee 8	First stage	12.12.2019	67	In-person
Interviewee 9	First stage	17.12.2019	78	In-person
Interviewee 10	First stage	18.12.2019	66	In-person
Interviewee 11	First stage	10.1.2020	55	In-person
Interviewee 12	First stage	29.1.2020	34	Phone
Interviewee 13	First stage	12.2.2020	60	In-person
Interviewee 14	First stage	13.2.2020		In-person
Interviewee 15	Second stage	14.1.2020	73	In-person
Interviewee 16	Second stage	20.2.2020	52	In-person
Interviewee 17	Second stage	27.2.2020	55	In-person
Interviewee 18	Second stage	27.2.2020	75	Video
Interviewee 19	Second stage	12.3.2020	38	Video
Interviewee 20	Second stage	12.3.2020	49	Video
Interviewee 21	Second stage	17.3.2020	75	Video
Interviewee 22	Second stage	16.4.2020	33	Video
Interviewee 23	Second stage	30.3.2020	59	Video
Interviewee 24	Second stage	24.3.2020	67	Video
Interviewee 25	Second stage	24.3.2020	58	Video
Interviewee 26	Second stage	15.4.2020	59	Video
Interviewee 27	Second stage	6.4.2020	62 (with interviewees 28 and 29)	Video

Interviewee 28	Second stage	6.4.2020	62 (with interviewees 27 and 29)	Video
Interviewee 29	Second stage	6.4.2020	62 (with interviewees 27 and 28)	Video
Interviewee 30	Second stage	16.4.2020	61	Video
Interviewee 31	Second stage	22.4.2020	54	Video
Interviewee 32	Second stage	21.4.2020	75	Video
Interviewee 33	Second stage	28.5.2020	65	Video
Interviewee 34	Second stage	8.6.2020	74	Video
Interviewee 35	Second stage	1.6.2020	54	Video

4.6. Data Analysis

Interview transcripts were coded using the qualitative analysis software NVIVO. The analysis of the interviews proceeded iteratively, using both inductive coding of the interview content and theory-driven coding to operationalise my key concepts.

The first round of coding was inductive and thematic, identifying ways of using data, data practices, specific forms of data, understandings of "goodness" in Data for Good, and what difference data makes in non-profit work. Information on Data for Good initiatives and the role of specific organisations was also coded at this stage. This stage of coding yielded an understanding that the practical concerns that drove the use of data and were focused only on a relatively small set of issues and suggested that the way to understand politics of data was tied to these issues. This insight led to situations of dispute becoming one of the key concepts in the thesis.

The second round of coding employed theory-driven coding. Using the concept of situations of dispute, I re-coded the inductively coded materials according to the situations where data was used or required as part of demonstrating some normative quality. This round of coding was informed by the earlier analysis, and it explored salient themes by approaching them through situations of dispute. Situations of dispute were identified through analysis of interviewee discussions on what normative qualities they tried to prove, and how interviewees discussed how data might make things "better", "improve" something, or help non-profits go "forward".[9] Organisational relationships and discussions on the circulation of data were also relevant for identification of situations of dispute because they were expected to reveal for whom data was collected and for what purposes, or what data some organisation or part of an organisation wanted to help in answering some question that requires normative assessment. For example, the relationship between grant-givers and grant-applicants was discussed in various terms in the interviews, and the relationship that requires demonstration of value was found to be never far from these considerations. Furthermore, situations and tests could also be inferred from discussions on the benefits and shortcomings of data in the non-profit sector: by analysing interviewee assessments of how the use of data might change their work or where it might fall short of what non-profits want to do, it was possible to work towards the situations and normative hierarchies from the vantage point of proofs, rather than first identifying situations. In all these instances, I sought evidence of a meaningful difference being made between better or worse options, which I treated as indications of a normative assessment.

As a result of the second round of coding, four different situations of dispute were identified. After the analysis, a decision was made that evidence on the details of the situations, methods assemblages, and proofs was sufficient for deeper analysis in three situations of dispute. The identified situations are discussed in Chapter 5 on Data for Good initiatives as an entry point and the three subsequent empirical chapters each focus on one of the situations: Situation of better knowledge, situation of improving delivery of social value, and situation of demonstrating worthiness of funding.

A further round of inductive coding was conducted to elaborate on the methods assemblages and proofs of value within specific situations of dispute. Evidence of different types of proofs and different types of data was analysed to understand how

[9] It is important to remember that a situation of dispute is not necessarily contentious. Normative assessment might have become naturalised in the way interviewees think and in the situations they face (See Chapter 2).

they were used as demonstrations of value in the situations of dispute. Furthermore, special attention was given to identifying the use of data science that had been found to be one of the key ideas and practices promoted in Data for Good initiatives.

4.7. Positionality and ethics

Conducting research with interviews and fieldwork locates me as part of the methods assemblage that produces my results. My positionality and personal relationship with the topic and interviewees therefore influenced how the study was conducted, especially regarding the identification of normative considerations.

My personal background is that I grew up, studied, and worked professionally in Finland before starting this PhD project. I had never visited the UK before coming to pursue postgraduate studies in the country in 2017. At the beginning of the study, I had no connections to either the Data for Good initiatives or the UK non-profit sector. As a foreigner who had lived in the UK only two years at the start of the fieldwork, my initial position was that of a cultural outsider although there are some similarities between the Finnish and UK cultures. My sociocultural and ethnic background was broadly similar to the majority of the interviewees who tended to be white and highly educated, which reduced the social and cultural distance between me and the interviewees. In fact, some of the interviewees had themselves been students at the LSE or we had similar career backgrounds working for governments or in consulting. Furthermore, I had experience of being a board member in various civil society organisations in Finland which helped me relate to the work of UK non-profits. Being affiliated with a prestigious university meant that my interest in the interviewees might also have been considered flattering and interviewees were happy to talk with me. In fact, almost all the people I contacted agreed to be interviewed with very few refusing or not responding.

In the interviews, three factors stemming from my positionality may have influenced interviewee responses. First, as an outsider from an academic institution the interviewees may have felt pushed to offer a positive and defensive narrative on the way they used data and of the work in Data for Good initiatives. Since I was interested in a topic that was exciting for the participants, it is possible that this led to an optimistic tone towards data practices among the interviewees. In my interpretation of the interviews, I emphasised critical reflection on how the interviewees presented their work and thoughts about data practices.

Second, my interest in data practices was likely to lead the snowball-sampling towards organisations that were particularly well-regarded for their successful use of data. This may have increased the risks of overly optimistic views being expressed by the interviewees. The focus on novelty and innovation might also have led interviewees to not discuss ways of knowing beyond their engagements with data, which might have presented an obstacle to comparing different methods assemblages.

Third, in the interviews I followed the expert interview strategy to avoid positioning myself as a sceptic or a critic to minimise the risk that interviewees would hesitate to share their thoughts, be defensive, and avoid mentioning any critical reflections (Bogner & Menz, 2009). I tried to position myself as someone who cares about non-profit work and wanted to know more about whether and how data might help non-profits. To facilitate genuine interaction, I tried to leverage any signs of shared professional or educational background or past experiences since in expert interviews this can help to build trust to share views “among experts” rather than explaining things to an outsider. This strategy was meant to elicit critical reflection from interviewees which might not have occurred if directly critical questions had been asked.

The risks of skewing towards optimism were partly dispelled insofar as the interviewee data contains numerous instances of critical reflection, negative opinions, and frustrated retellings of past event. Interviewees might themselves be optimistic about the use of data, but critical of whether non-profit organisations were, had been, or could be in a position to take full advantage of the opportunities.

Analysing the political aspects of data practices is necessarily influenced by my own political positionality. As a researcher trained in STS I am inclined towards scepticism about the political potential of new technologies. With an educational background in political science, I am also inclined towards scepticism regarding claims about something representing vague normative ideals like “goodness.” This sceptical attitude was helpful in balancing out the potential skewedness towards optimism in the interview sample. However, as a researcher using a symmetric approach to data and normativity, my approach to the subject matter in this thesis is not critical in sense understood in Critical Theory or Critical Sociology. My motivations did not include the goal of criticising as such the use of data in the non-profit sector or fundamentally questioning the desirability of using quantitative data. My personal scepticism towards politics and technological innovation therefore does not extend to the uses of quantification or statistics as such. This view also reflects my positionality as a person who has grown up in a Western country and was educated in a Western scientific tradition. Similarly, my analysis was not influenced by a goal of criticising current economic structures of either the UK non-profit sector or social sector, but neither did I have a goal of defending them.

Chapter 5:

Data for Good initiatives as an entry-point to UK non-profit sector data practices

5.1. Introduction

The goal of this chapter is to offer an empirically grounded analysis of Data for Good initiatives in the UK non-profit sector and their possible use of new data practices. I discuss the origins and characteristics of the initiatives as the backdrop for more detailed analysis of methods assemblages, situations of dispute, and demonstrations of value in the later chapters. The analysis underscores the importance of taking a relational approach to data practices used by non-profit data professionals.

The chapter begins by discussing the origins and composition of Data for Good initiatives in the UK through the eyes of my interviewees. I identify two entry-points to non-profit sector data practices within the initiatives: one with a focus on the new opportunities of data science in the non-profit sector, and another with a broad-based focus on promoting diverse forms of quantification in the UK non-profit sector. I then examine these entry-points in closer detail and describe the data practices and methods assemblages they promote. The findings suggest that the entry-point to data science in the UK non-profit sector can be regarded as a new area of data practices. Yet most of the data practices discussed by the interviewees are mundane and familiar from earlier research. The chapter finishes by discussing how the findings arising from taking Data for Good as an entry-point are situated in what is known about the UK non-profit sector.

5.2. Origins of Data for Good and the importance of focusing on data practices

Although quantification and measurement have a long history in the UK non-profit sector, the emergence of Data for Good initiatives is located in a specific time period. Data for Good initiatives in the UK non-profit sector are linked to surging interest in Big Data and data science in the early 2010s, as I indicated in Chapter 3. Understanding their specificity and situatedness in the UK non-profit sector is necessary because it helps to clarify the kind of an entry-point they are to non-profit sector data practices more widely. In Chapter 4 (methodology), I explained that the study initially focused on data practices in the non-profit sector. When it was discovered that many of the organisations promoting the use of data in the non-profit sector were interconnected and used the Data for Good to characterise their work, the emphasis shifted to these initiatives. In this section I discuss how my interviewees understood Data for Good as a loose network of organisations, which I use in this thesis as my entry point to non-profit sector data practices.

Because interest in quantitative and digital data in the UK non-profit sector is linked to several historical trajectories, it is no surprise that the interviewees saw the boundaries of the emerging Data for Good network as fluid and ambiguous. In the following quote an interviewee who had been a founding member a key organisation promoting the use of data in the non-profit sector reflects on the origins of Data for Good as a loose network of people working to facilitate the use of data in the non-profit sector. Having worked in the UK non-profit sector prior to their involvement in Data for

Good and with a background in technology-related civil society organisations, they were well-positioned to reflect on the emergence of the network.

> *When I started, most of those organizations didn't exist. Data Kind UK didn't exist, 360Giving didn't exist, Data Orchard was just forming but I think we, over the years had all worked in different ways, quite closely together on different projects. I would say the learning that we shared amongst those organizations, were purely from personal relationships. It's just like grabbing a cup of coffee with someone. There was never any formal grouping of us. I suppose Data Orchard set up a conference. That was the first time that we brought it all together, which is great. I'd say it was like a loose friendliness. (Interviewee 19, Senior manager, Facilitator organisation, Female, 5+ years of relevant experience).*

I want to underline two things in the quote. On the one hand, the interviewee lists several organisations that they recognise as being central to the Data for Good initiatives at the time of the interviews. These organisations are DataKind UK, Data Orchard, and 360 Giving, and I return to them later in the chapter. By identifying these organisations as key players in what comes to be known as Data for Good the interviewee acknowledges the role, they have played in bringing together a network focused on non-profit data. The interviewee also emphasises how loose the relationship between these organisations has been, and how key organisations have not had formal relationships or collaborations with each other. The interviewee mentions that the organisations first came formally together in a conference organised by Data Orchard, the 2018 Data4Good Festival that brought together people working in data-related roles across the UK non-profit sector. I suggest that the interviewee's comments stress that the Data for Good network in the UK non-profit sector does have central organisations but that it is united more by its interest in new data practices in the non-profit sector than by formal coordination.

The simultaneous broadness of affiliations and specificity of interest in novel data practices was repeated in many other interviews. For example, the following quote is a good example of how the interviewee saw Data for Good initiatives as a wide coalition with diverse participants, but with key element of novel data practices. The interviewee worked for an organisation promoting the use of data in the non-profit sector and themselves used the Data for Good concept and collaborated actively with other organisations in facilitating the use of data. The interviewee had worked in the sector for more than ten years, and they had special expertise in database technologies and provision of data-related training.

> *"In a way, we're sort of one actor in [Data for Good] and then the Data for Good really is quite broad in terms of coalition because it goes all the way from data scientists or data products, looking to provide services to the charity sector or not-for-profit things, all the way down to charities who are exploring how to use data for themselves and sort of interested." (Interviewee 6, Support & Engagement Manager, Facilitator organisation, Female, 10+ years of relevant experience)*

In this quote Data for Good is discussed as being a "*quite broad in terms of a coalition*." Data for Good is said to include both organisations that try to provide data-related services to non-profit organisations and people working in non-profit organisations in data-related roles. The quote itself is circumspect regarding the data practices relating to Data for Good, but the interviewee identifies data scientists as one group of people involved in the initiatives. The mention of data scientists is important because it again links Data for Good to something new emerging in the 2010s rather than portraying it in reference to the established practices of quantitative measurement promoted by New Public Management (NPM) and Evidence-based Policymaking (EBP).

Another perspective on Data for Good as a loose network comes from an interviewee working for a facilitator organisation interested in helping non-profit using more data. The interviewee was relatively new to the non-profit sector, and had a background in community engagement, which had led them to their current role in helping non-profits get interested and started in using data. The description of Data for Good initiatives provided by the interviewee offers another take on the diversity and ambiguity of the network.

> *"When I talk about Data for Good it's probably organizations who support charities to develop their own data capacity, but then that term*

> *also includes organizations who use data for social purpose and social action and data scientists who use certain data to make health apps. [--]. I think it's like a catch-all term and when I use it, I probably mean paid people like DataKind or Data Orchid who are making data more accessible for charity sector" (Interviewee 1, Civil Society Data Officer, Facilitator organisation, Female, 4 years of relevant experience)*

According to this interviewee, Data for Good is a "*catch-all term*" that can be used both by organisations facilitating the use of data and the organisations that do charitable work. This distinction is important, because the snow-ball-sampling techniques I used to identify new interviewees (see Chapter 4) skewed the sample towards organisations facilitating the use of data. The above quote suggests that this is one of the key groups of people participating in Data for Good initiatives. However, the interviewee also claims these initiatives can include "*data scientists who use certain data to make health apps*." Based on the passage, it seems that Data for Good can tie different types of organisations beyond the non-profit sector, although it is notable that the connecting element is "data scientists" which links these initiatives to novel computational data practices accompanying the Big Data boom. Yet the interviewee also connects the initiatives to two specific organisations in the UK non-profit sector, Data Kind and Data Orchard. These two organisations were frequently mentioned and were already mentioned in a quote above. In my interviews they were often seen by the interviewees as the two most prominent UK non-profit sector organisations affiliated with Data for Good. Members of these organisations were also interviewed for the study.

Not all my interviewees saw themselves as part of Data for Good initiatives or even liked the concept. Many interviewees who worked professionally to promote the use of data or were professional data analysts were sceptical towards the use of Data for Good as a label for their work or as a name for a loose network. The reasons for this scepticism ranged from general dissatisfaction to articulate critiques of its ideas and background. These sceptical views towards Data for Good are relevant for my analysis because they often suggested a paradox whereby interviewees critiqued Data for Good initiatives but were themselves professionally involved in promoting the use of data in the non-profit sector. I suggest that this paradox, which I illustrate below, is key to understanding Data for Good initiatives as a loose network that serves as an entry point to the use and promotion of novel data practices in the UK non-profit sector.

One critic of the Data for Good concept underscored their disagreement with its origins in the U.S. philanthropy. The perspective of this interviewee is interesting because they worked for an organisation that was an active participant in Data for Good as a network of organisations.

> *"I actually don't like the phrase data for good. [--] I just don't think there's a good definition of data for good. Because the first one was done by Bloomberg, so I have reserves about that been done by Bloomberg. We think that [Data for Good is] very black and white, but it's not. Good for me, not necessarily good for someone else. I don't believe it's data for good, it's data for promoting something." (Interviewee 32, Product & Programmes manager, Facilitator organisation, Female, 5+ years of relevant experience)*

The thrust of the interviewee's critique is aimed at the Bloomberg Data for Good Exchange organised by billionaire philanthropist Michael Bloomberg in 2014.[10] The first Bloomberg Data for Good Exchange aimed at bringing together non-profit leaders and computational researchers, and was organised in conjunction with an annual, academic ACM Knowledge Discovery and Data Mining conference. In this passage, the interviewee questions whether it is sensible to demarcate between what is or is not good. The interviewee instead seems to imply that the definition is meant to promote particular interests, and this makes the interviewee suspicious of the Data for Good phrase. What is interesting, however, is that the interviewee was an active promoter of quantitative data analysis, digital data collection, and data science in the non-profit sector. The interviewee had worked for multiple civil society organisations specialising in digital

[10] Bloomberg Data for Good Exchange in 2014 was one of the first prominent uses of the concept, but the concept and its variations such as Data Science for Social Good were used before the Bloomberg conference (Aula & Bowles, 2023).

technology. The critique therefore appeared to be aimed at the origins and ideas associated with the U.S. origins of the phrase, but not at the actual use of data in the non-profit sector in the UK.

Another common critique of Data for Good initiatives was linked to their ambiguity, which I have mentioned above. In the following passage an interviewee delivers a stark rebuke of the concept:

> *"To me, it's something that I don't use. I wouldn't use data for good as a moniker or slogan or in any way. It's one of those terms that really don't mean anything. Data, ultimately, what does that mean? But, Good, what does that mean?" (Interviewee 18, Entrepreneur, Facilitator organisation, Male, 20+ years of relevant experience)*

The point of the critique for this interviewee is that terms like Data for Good "*really don't mean anything*." The interviewee seems unsure about both data and good and asks rhetorically "*what does that mean*." The wording emphasises the interviewee's opinion that Data for Good does not mean anything. Nevertheless, it is again worth emphasising that the interviewee worked professionally to promote the use of data and digital technology in the non-profit sector. Indeed, elsewhere in the interview they were eager to profess how they were committed to the use of data and how they saw data as the linchpin of all non-profit work. The ambivalence of the interviewee seems to suggest that non-profit data professionals can at the same time believe in the value of data practices in the non-profit sector but be critical of Data for Good initiatives as a vehicle of their promotion.

Indeed, as will be shown in Chapter 6, criticism of Data for Good or shortcomings of data do not necessarily imply that the interviewees would be *against* the increased use of data in the non-profit sector. Almost every interviewee, including most of the critics discussed above, expressed positive views about the benefits of non-profits becoming more proficient in their use of data. They appeared committed to the potential of quantitative measurement and digital data in helping non-profits do their work. While non-profit data professionals might be critical of Data for Good as a phrase or set of initiatives, these criticisms did not necessarily extend to the use of data as such. Thus, the critics of Data for Good cannot be assumed to be critical of non-profit data as such. These contradictions within the interview sample highlight the complexity of how interviewees value data. They call for a more nuanced analysis of how non-profit data professionals understand the value of data and how normativity is entangled with the use of data.

Based on the above analysis, I suggest that the important insight about Data for Good initiatives in the UK non-profit sector is not about who does or does not use the phrase, but that it does offer an entry point to the loose network of people and organisations that are professionals in non-profit data practices either through their own involvement with data analysis or through their work to promote the use of data. Some organisations promote the use of data by coordinating the Data for Good network. Others do the same without any link to Data for Good initiatives but participate in events relevant to their goals. What matters for my analysis is the *data practices and methods assemblages that they promote,* and the way the interviewees are found to justify the value of data and use data to justify the value of non-profit work. This is also the reason that the conceptual focus of the thesis is on methods assemblages and justification rather than on the initiatives themselves.

To shift analytical attention towards specific methods assemblages and data practices, I next outline two empirical anchors regarding how Data for Good initiatives in the UK non-profit sector connect to specific data practices. The first anchor is the work of DataKind UK in promoting data science in the UK non-profit sector which links the initiative to the innovative potential associated with new computational data analysis techniques. The second anchor is the launch of the Data4Good Festival in 2018 by the non-profit sector data consultancy, Data Orchard, which is shown to promote a very inclusive view of data as any quantitative or digital measurement practice.

5.3. DataKind UK as an entry point to data science in the UK non-profit sector

Interviewees in my sample frequently associated Data for Good with the promotion of data science in the UK non-profit sector. Specifically, the interviewees associated Data for Good with the data science volunteering schemes organised by an organisation called Data Kind UK. The association could be immediate, as in the following quote from an interviewee who worked as the Director of Impact and innovation with over a decade of experience in the non-profit sector and over five years of specialisation in digital technology and data. The interviewee explained that "w*hen you mentioned [Data for Good], my automatic thought is, 'That's the DataKind thing,' "(Interviewee 30, Director of Impact and Innovation, Service-providing non-profit, Female, 5+ years of relevant experience).* Indeed, DataKind UK has frequently used Data for Good in their blogs, public communication, and branding. For example, a blog published in 2020 asks in the title "What is it like to be a Data for Good volunteer" and uses a #dataforgood hashtag.[11] In the course of my data collection I interviewed three people who were, or had been, directly employed by DataKind UK and discussed DataKind UK with several other interviewees familiar with their work.

Data Kind UK is a data science volunteering program founded in 2013. Their work concentrates on promoting the use of data science to address social problems by providing non-profit organisations with programmers and quantitative analysts through a variety of volunteering schemes. My analysis of the interviews indicates that DataKind UK was the first organisation to systematically start promoting the use of data science in the UK non-profit sector and played a central role in introducing Data for Good as a concept. Furthermore, DataKind UK is a local chapter of the U.S.-based originator of data science volunteering schemes, DataKind Global, which informs a link between

[11]https://medium.com/datakinduk/what-is-it-like-to-be-a-data-for-good-volunteer-9063859659c5

simultaneous U.S. developments in using data science in humanitarian and social contexts. DataKind Global was founded in 2011 with the name "Data Without Borders" as an experiment to recruit volunteer data scientists through civic hackathon events to use their data science skills to address social issues. Data Without Borders later changed its name to DataKind UK and adopted Data for Good as its slogan. When DataKind UK was founded in 2013, it brought with it both the idea of recruiting data science volunteers for the non-profit sector, but also the idea of calling this "Data for Good". The label Data for Good gained prominence in 2014 when it was adopted as the title of a conference "Data for Good exchange" organised by Michael Bloomberg as a side-event for the scholarly NeurIPS data science conference to bring together philanthropists, data scientists, and civil society organisations. This illustrates how DataKind UK and Data for Good have a direct early link to the idea of data science as a set of computational tools that can be used to address social problems. As discussed below, DataKind UK is still focused on the idea of data science as a tool for social betterment, although this focus is not shared by everyone.

An understanding of Data for Good as an effort to focus on the opportunities and innovations of data science is exhibited in the following passage. The passage quotes an interviewee who volunteered for DataKind UK as a data scientist and had risen to a leadership role within the organisation. The interviewee had a background in natural science research where they had learned sophisticated computational and statistical techniques that they put to use through projects at DataKind UK. As a data scientist and a leader within DataKind UK, the interviewee proved to be invested in the idea that data science provides an important new opportunity for non-profit organisations. The interviewee had little experience of the non-profit sector, but they explained that Data for Good was about introducing techniques developed in technology-intensive private businesses and research to the non-profit sector.

> *"In a nutshell, [Data for Good is] the idea that we can use the same techniques that are applied to harvesting value from our personal data by very large and powerful corporations to great effect, generally to sell*

> *us things. We can use those same techniques to improve the status of society, so for humanitarian and environmental projects." (Interviewee 7, Data Scientist, Facilitator organisation, Male, 2 years of relevant experience)*

The quote suggests that the point of Data for Good is that the data-driven techniques known for their use by large technology corporations can also be used to tackle social and humanitarian issues. According to the interviewee, Data for Good links to the innovations and progress in computational techniques that are typically associated with digital business, because they have used them "*to great effect*" and have grown large and powerful using them. The interviewee explains that the same techniques that are "*harvesting value from our personal data*" for private corporations can also be repurposed to "*improve the status of society*." This juxtaposition of private corporations and humanitarian interests suggests that there are technical innovations coming from the private sector that should be transferred to the non-profit sector, where they are also expected to be a source of innovation and progress. The interviewee frames data science techniques as an intervention that in itself can help solving social problems, and their work at DataKind UK was depicted as a means to achieve this in practice. Furthermore, the interviewee's emphasis on data science techniques used by technology corporations as inspiration connects Data for Good and data science to very specific methods assemblages that draw upon digital infrastructures and new computational methods that can be used to analyse the data generated by the infrastructures.

Overall, DataKind UK was found to place heavy emphasis on the potential of data science in the non-profit sector. According to their website **"***DataKind UK helps social change organisations use data science to have more of an impact. We do this by connecting them with some of the UK's best data scientists for free*." [12] On the one hand, this definition highlights data science, referring to it as something that non-profits can *use* and that can help them have more impact. It implies that data science is a set of

[12] https://datakind.org.uk/what-we-do/

tools and techniques that non-profits can start using if they want, and that the tools will have a positive effect on non-profit work. On the other hand, it highlights the role of data scientists in achieving this. This emphasis on data scientists is at the heart of DataKind UK's work because the organisation coordinates a network of volunteers who are assigned to work with individual non-profits in projects ranging from weekend-long hackathon events with dozens of volunteers to months-long collaborations with small teams of volunteers. The volunteers, who are advertised to non-profits as data scientists, use novel data science tools in their day-jobs outside the non-profit sector.

To understand what this means in practice, it is necessary to look more closely into what DataKind UK means by data science and who the data scientists are who volunteer through the organisation. Exploring the role of data scientists is especially important because there is no general agreement in research literature on what skills, training, or professional values constitute the emerging data science profession (Dorschel, 2021; Fest et al., 2023; Muller et al., 2019). According to a presentation "What is data science?" by DataKind UK in the 2021 Data4Good Festival: "*Data science is the use of analytical and computational techniques to extract meaning from novel data sources for the sake of supporting organisational decision making*"[13]. This definition highlights two elements: the technical element of the techniques used in data science and the novelty of data sources that can be analysed with the new techniques. In other words, the definition suggests that data science is defined both by its analytical tools and by their application to specific data sources. The purpose of data science in this definition is anchored to decision making, which invites non-profits to understand it as something that changes how non-profits are managed. While this definition is still broad, it does link data science to the idea of technical innovation and its effects on management.

[13] Source: Fieldnotes from Data4Good festival 10.5.2021

Further evidence on what is intended by references to data science comes from interviewees in my sample who offered their views on data scientists. If data science is a tool that non-profits can use, those tools can be known by analysing the tools used by people who are understood to be data scientists. Here are two definitions of a data scientist offered by the interviewees:

> *"I think that a data scientist is somebody who has got programming language skills on top of what a normal data analyst has, is someone who analyses data. The other thing is data scientists do a lot of predictive analytics using existing data to predict future trends. [--] A lot of data scientists have some sort of science degree or mathematics degree and then they learn the programming bit by themselves on top of that." (Interviewee 13, Data Manager, Facilitator organisation, Male, 5+ years of relevant experience)*

> *"These were professional data scientists who tended to have PhDs in maths or stats or physics" (Interviewee 19, Senior manager, Facilitator organisation, Female, 5+ years of relevant experience)*

These definitions flag data scientists as people who have quantitative scientific training, possibly on postgraduate level, and programming skills. The quotes suggest a data scientist is more than a data analyst and able to bring in something more sophisticated. For my analysis, these positionings of data scientists as having advanced skills is particularly important because it offer suggestions regarding what kinds of methods assemblages and data practices they might engage with. The first interviewee identifies predictive analytics as a skill of data scientists which echoes the quote at the beginning of this section on the origin of data science tools in large technology corporations whose business deals with personal data. The second interviewee highlights academic research training in natural sciences as a hallmark of data scientists. Together these definitions of data science highlight how the interviewees associated data science with technical sophistication in the statistical and computational analysis techniques that data scientists might use.

However, some interviewees were uncertain about what a data scientist is or what skills they bring to the non-profit sector. One interviewee was especially sceptical of data scientists and the way DataKind UK framed itself as a volunteer data scientist service: "*I don't like to say data scientists, because I don't think it's a science. I think 90% of data analysts at DataKind are data analysts. They're not data scientists. Machine learning is not what they do."* (Interviewee 32, Product & Programmes manager, Facilitator organisation, Female, 5+ years of relevant experience) According to this interviewee, who also worked to promote the use of data in the non-profit sector and had training in advanced statistics, most people who volunteer at DataKind UK would not qualify as data scientists and they do not use the techniques that would mark them as data scientists. The interviewee reserves data science status to truly advanced techniques.

Another interviewee, who had PhD-level training in quantitative social sciences and had worked in multiple analysis and research roles in the non-profit sector, reflected on data scientists on the following way:

> *"I think the term data scientist is so broad anyways, isn't it? I came across that when I was working at [previous organisation]. People would say they're a data scientist, but they do completely different things than I did. [--] I think it was off-putting to a lot of people who wanted to get into data. It makes it seem like this thing that you can only do if you've got loads of education and skills, and you've sat in a dark room for most of your adolescence going on your computer. Actually, in terms of basic skills, it doesn't take too long to get up to scratch" (Interviewee 16, Data & Research Lead, Facilitator organisation, Female, 5+ years of relevant experience)*

This interviewee offers a quite different definition of data science in comparison to the above definitions that focused on the sophisticated techniques they associated with data science. The interviewee suggests that the category "*is so broad anyways*" and that people with dissimilar skill sets can still call themselves data scientists. Furthermore, the interviewee argues that advanced training is *not* needed for people to get started with data. The interviewee recognises that data science is stereotypically associated with a special skill-set which is characterised as "*loads of education and skills, and you've sat in a dark room for most of your adolescence*", but this description was used to distance this stereotype from the interviewee's own understanding of data and data science in the non-profit sector. The passage suggests that the interviewee believes that while advanced computational skills are useful, non-profits should not get hung up on the most advanced techniques when much simpler data practices might be more relevant for an organisation getting started with data.

The criticism that data science is a nebulous concept and that DataKind UK might not in fact have access to sophisticated data scientists can be explored by analysing whether the past projects of DataKind UK fit the ideals of technical sophistication and innovations. Surveying past projects by DataKind UK on their online project archive reveals that some projects do use computational techniques like machine learning and predictive analytics. An example of such tools is a project to develop an early prediction system for food bank dependency to administer timely interventions.[14] However, in most flagship projects the focus is on analysing novel data sources such as geolocation and demographic data,[15] textual data,[16] or administrative data in non-profit databases.[17]

What non-profits get out of these projects is not new computational products and innovations but novel analysis of data they have already collected or that is publicly available. Because these projects are included in their archive of flagship projects, they can be regarded as particularly successful cases of data science volunteering. The projects do exhibit the use of computational techniques, programming, and use of what can be characterised as novel digital data sources, which strongly suggests they are data science projects as understood by the interviewees. Yet it is not immediately evident from the projects that volunteers need post-graduate level training in programming and quantitative analysis or other exceptional skills to produce such results. Some of the observations of the interviewees regarding the elusiveness of the data scientist

[14] https://datakind.org.uk/portfolio-item/welcome-centre/
[15] https://datakind.org.uk/portfolio-item/mental-health-bame-sobus/ and https://datakind.org.uk/portfolio-item/ca-lewisham/
[16] https://datakind.org.uk/portfolio-item/action-children/
[17] https://datakind.org.uk/portfolio-item/15000-volunteers-sja/

profession therefore seem warranted. However, the projects surveyed above do require specialist skills in programming, data scraping, and analysis. A person with little to no training in data analysis would not be able to complete the projects. An organisation that collects little digital data or runs only small-scale services might find difficulty tapping into the potential of data science.

The above analysis highlights that the work of DataKind UK to promote data science in the UK non-profit sector can be connected to a distinctive set of data practices that either use advanced computational techniques or tap into new digital data sources as sources of innovation in the non-profit sector. In other words, the work of DataKind UK on data science is suitable for identifying cases of new methods assemblages being introduced to the non-profit sector under the banner of Data for Good. The work of DataKind UK serves as one empirical entry point to analyse how the value of the new techniques is justified by my sample of non-profit data professionals and how they use these methods assemblages to enact objects of interest and justify the value of non-profit work.

5.4. Data for Good as an entry-point to diverse data practices in UK non-profit sector

Data science is not the only empirical anchor for data practices promoted by people and organisations participating in the Data for Good network. In this section I show that another empirical anchor can be found in the way the non-profit data professionals use data as shorthand for a variety of quantitative and digital measurement techniques that predate new developments in the 2010s. Indeed, during my interviews with non-profit data professionals it became evident that the potential they saw in data could often be understood as a continuation of much older measurement practices, which the interviewees presented as a first step towards more sophisticated uses of data.

The following quote offers an example of how interviewees connected Data for Good initiatives with broader themes of evidence and measurement that long predate a special interest in data science or digital data. This interviewee worked for an organisation that connects volunteer statisticians with non-profit organisations to help them collect and analyse data. The interviewee depicted the goals of their organisation as being aligned with the Data for Good network, although the organisation was not a central actor in the network. According to the interviewee, this alignment arose from a similar interest in providing especially smaller non-profit organisations with access to experts in quantitative measurement which, as an operating model, was similar to that of DataKind UK. In the following quote the interviewee describes what they mean by Data for Good.

> *Interviewer: "In your own words, what does it mean?*
>
> *Interviewee: I think it's just using data for public good. It's a way of just saying that data is used in a positive way. It's used to reinforce the message for evidence. It's just that idea that data is good. It's good, it's the way that any organization should operate, should work. It should always be part of the conversation whenever you're thinking about what you want to provide or put out there. (Interviewee 26, Member Engagement Manager, Facilitator organisation, Female, 5+ years of relevant experience)*

According to this interviewee, the goal of Data for Good is to "*reinforce the message for evidence*" and "*it's just that idea that data is good*." This suggests that, in addition to data being useful in serving "*public good*" in the non-profit sector, data itself is deemed as good. The interviewee seems to suggest that data is something that is valuable in its own right in addition to being useful in helping non-profits reach their goals. Furthermore, the interviewee proposes that Data for Good is not just about data, but about evidence more broadly. The way the interviewee appears to understand Data for Good is not only about data science, as was the case for DataKind UK, but about quantitative measurement more broadly. In the case of this interviewee, their understanding of data practices can be seen to align especially with the ideas of EBP, because the goal of the organisation was explained as bringing professional statistical expertise and statistical methodologies to non-profits that did not themselves have this expertise. For my analysis, this quote is important because it suggests a significant broadening of what methods assemblages might be promoted in the Data for Good network. In other words, this interviewee beckons towards a more expansive and diverse view of what data practices are valuable for non-profit organisations.

To further explore how this broader, more inclusive understanding of Data for Good links to diverse data practices, I discuss the Data4Good Festival organised by Data Orchard. Many interviewees suggested that the key arena for Data for Good in the UK was the Data4Good Fest organised in 2018, and again in 2021. The event was a collaboration between several organisations that promoted the use of data in the non-profit sector, but a coordinating role was played by a non-profit data consultancy, Data Orchard. Data Orchard is a consultancy founded in 2013 that focuses on non-profit data. They developed a popular framework to assess the readiness of non-profits to use data, which they called a "data maturity model."

The focus of the Data4Good Festival was very different from the focus on data science presented by DataKind UK. One of the organisers of the event who worked in a leading role in Data Orchard with more than fifteen years of experience in the UK non-profit sector explained the rationale behind the event.

> *"It was meant to be a meeting of people who love data with leaders of not-for-profit organizations, and also potentially lone data experts, or nerds in an organization to be part of a wider community, especially if they're the only person in a small organization. Also, for people who didn't know anything about data to come along and hear some of the stuff that goes on to inspire them to become more data-savvy, or to get a grip on data, and in a friendly way, not a scary way [--] It's trying to inspire people about different parts of that. That was the idea of it. I think we succeeded in that, bringing a whole bunch of people together from different perspectives, but around that common goal of using data for social good." (Interviewee 27, Senior manager, Facilitator organisation, Female, 15+ years of relevant experience)*

This passage describes in detail how the organisers of the event wanted to bring together a wide range of people who would have an interest in data. This could range from "*leaders*" to "*lone data experts*," "*the only person in a small organisation*" working with data, and even "*people who didn't know anything about data*." In other words, the event aimed to cast the widest possible net around people working in the non-profit sector, because it was aimed at "*inspiring people*" to become interested in different ways that data might support the work of non-profits. The adoption of Data for Good as the name for the conference helped the organisers communicate their broad interest in data in the non-profit sector. The Data4Good Fest of 2017 and 2021 adopted the phrase to serve their purpose of establishing a venue to promote learning and exchange of ideas regarding non-profit data in broadest possible terms.

The above retelling of the Data4Good Fest as an inclusive event for people with various levels of experience with data was corroborated by other interviewees. Many interviewees saw it as a turning point in the public profile of non-profit data, bringing together for the first-time organisations that had worked on non-profit data independently. One interviewee with no affiliation with the event but several years of experience in promoting the use of data in the UK non-profit sector explained that the event "*brought together a lot of different organisations, and it was about both how to use data and how to use new approaches to collecting data [--]. That was more broad." (Interviewee 16, Data & Research Lead, Facilitator organisation, Female, 5+ years of relevant experience).* The quote echoes insights suggesting an inclusive focus with a broad set of interests and participating organisations.

The same point was re-iterated by another interviewee, who worked for one of the key organisations promoting the use of data in the UK non-profit sector. The person had not attended the event, but having worked extensively with non-profit data and with many of the key organisations, had insights into how the event was positioned in the broader landscape of the UK non-profit sector:

> *"I didn't go to that conference, but I'd spoken to people who went and did say it's a little bit broad. It's a little bit of a kind of bucket that anyone who is sort of connected to the charity world taking an interest in data can put into, and then maybe it will take a little bit of time to coalesce where there will be separate, lots of different identities or whether they'll kind of become core around it. But that's inevitable with an early thing like that." (Interviewee 6, Support & Engagement Manager, Facilitator organisation, Female, 10+ years of relevant experience)*

The interviewee explains that the event framed data in a way that almost anyone in the non-profit sector can be interested in. Furthermore, the interviewee reflects that although it was "*a little bit broad*," this was to be expected "*with an early thing like that*" and "*it will take a little bit of time to coalesce*." The interviewee would appear to mean that the event was pioneering in starting a process where interest in data would grow over time and the networks around it would become more established and specialised. In other words, despite its breadth the interviewee saw the event as a first step towards something new, as an important touchstone for non-profit data professionals in the UK and as the promotion of data in the UK non-profit sector.

Although the focus of the Data4Good Festival and the network of organisations linked to it was very broad, my analysis shows they shared a belief in the power of data to be a positive force in the non-profit sector. Despite having less inclination towards technical sophistication than DataKind UK's focus on data science, this did not imply that the promises of innovation and improvement were diminished. Indeed, the shared goal of all non-profit data professionals that promoted the use of data and were interviewed for the study appeared to be to help non-profits adopt data as a fundamental part of non-profit work. This goal meant quite different things depending on how a non-profit was already using data, but my analysis confirms that the direction promoted by Data for Good initiatives is clear: non-profits should place more value on data as part of their work.

The aspiration towards non-profits using more data in every aspect of their work is evident in a quote from an interviewee who was one of the organisers of the

Data4Good Festival and had long experience of helping non-profits use data. In the quote this interviewee underscores that non-profits need to understand that investment in data requires systematic work and long-term investment. I invite particular attention to how the interviewee does *not* wish to oversell the short-term benefits of data. This distances the views of this interviewee from technologically focused interventions in non-profit work and instead connects data practice to *cultural* aspects of non-profit work.

> *"Becoming masterful, data is at a long-term strategic endeavour, but it's too much for a lot of organizations in one go and sometimes, they focus on specific projects. It might be about evidencing needs and understanding their services better so that they can get more funding. There aren't necessarily quick-win prizes, even if you found evidential impact, it's not like somebody gives you a million-pound prize because you've proved that. It's something that they have to work out all the time and they can reuse and reuse that data in a versatile way to reach different audiences. A lot of it ties up with the culture and leadership of the organization." (Interviewee 28, Senior manager, Facilitator organisation, Female, 20+ years of relevant experience)*

In this quote the goal suggested for all non-profits is to embark on a "*long-term strategic endeavour*" that will have different foci at different times. The use of data is expected to take different forms depending on what the non-profit is trying to do, and this aligns with the inclusive and broad-based strategy that the organisation had adopted in promoting the use of data in the non-profit sector. However, according to the interviewee, the motivation for this work should focus on cultural change where non-profits "*have to work out all the time*" on how they inform their work with data. The message of from this interviewee seems to be that they seek to promote a new data-driven culture in the non-profit sector, rather than a narrow set of specific data practices. The interviewee explains that there "*aren't necessarily quick-win prizes*" because the benefits of the "*strategic endeavour*" towards "*becoming masterful*" are not always immediate. I will return to this cultural aspect of promoting data practices in the next chapter, where I show that it exhibits a particular way of valuing data.

The analysis so far suggests that Data for Good initiatives are an entry-point, not only to data science in the non-profit sector, but to a diverse set of measurement and data collection practices. The evidence from the Data4Good Festival encapsulates this approach, but the ideas promoted in the event were present across the interviews. Data for Good can therefore also be seen as an attempt to build a loose network of non-profit data professionals. Most importantly, the goal of this broad-based campaign is shown to promote the idea that data itself is valuable for non-profit organisations while leaving it open as to which data practices would be valuable in a given context. Nevertheless, the breadth of this strategy suggests that the data practices discussed by the interviewees are linked to a variety of trends in quantitative measurement beyond the hype around new computational methods. In the next section I situate the two entry points I have outlined in this section in the broader setting of quantitative measurement in the UK non-profit sector.

5.5. Situating data practices in the domestic UK non-profit sector

So far in this chapter I have explored what kind of an entry point Data for Good initiatives offer to data practices in the UK non-profit sector. In this section I situate this analysis in what is known about the UK non-profit sector as the wider empirical context that I have reviewed in Chapter 3. I focus here especially on the presence of a continuity of NPM and EBP in the data practices discussed by my interviewees, as well as the influence of Big Data and technological solutionism on the promotion of data science in the UK non-profit sector. Furthermore, I highlight that the experience of data practices in the case of Data for Good initiatives has important differences in comparison to studies of data practices in humanitarian and development contexts, which has implications for the interpretation of my findings in the context of Critical Data Studies literature discussed in Chapter 2.

The broad-based approach to use of data in the non-profit sector, which I have outlined above, is intricately linked to NPM because the culture of appreciating data that was illustrated by my interviewees is in practice shaped by demands of NPM for grant reporting and managerial quantitative measurement. In this sense, the way non-profit data professionals value data practices cannot be separated from the demand for data practices that respond to funding requirements and support managerial quantification. In other words, the appreciation of data promoted in the Data for Good network I have examined is inflected by the power asymmetries of the UK non-profit sector and the way they have pushed quantification. These asymmetries arguably force non-profits to adopt data practices set out by funders and to idealise management by numbers as popularised in the public and private sectors since the 1980s. I delve more deeply into the power asymmetries and data practices in grant-making in Chapter 7, whereas the managerial ideals of improvement through quantification are discussed in Chapter 8.

My analysis shows that the new data science practices promoted by DataKind UK were also influenced by this legacy on NPM. The methods assemblages DataKind UK promotes were not the same as the managerial practices traditionally associated with NPM, but they appeared to follow the same logic of private sector data practices serving as the model for non-profit sector data practices. In the case of data science, this model comes especially from the digital technology sector, which has been a pioneer for the use of data science in their operations and that has actively promoted the idea that their data science tools can be transferred to the social sector and humanitarian contexts to improve their work. However, my analysis of the work of DataKind UK in section 5.4. suggests that this influence is not transmitted through coercive power asymmetries that push non-profits to adopt new data practices to secure funding, but through a more subtle influence of non-profit data professionals who value data science for its computational sophistication and its associated potential for innovation. The way non-profit data professionals value data science is explored more closely in Chapter 6, and their role in extending managerial measurement practices is discussed in Chapter 8.

The ideas and practices relating to Big Data also are found to have had a profound impact on the way my interviewees approached data practices. The fact that Data for Good initiatives use “data” as their keyword is likely attributable to the popularisation of Big Data as a point of reference for digital data and the role played by digital infrastructures in producing digital data. The way my interviewees emphasise how data is valuable for non-profits also appeared to be indebted to the Big Data boom of the early 2010s, which emphasised that data is valuable in its own right and organisations should seek to collect as much data as they can even if they do not yet know how to use it. This idea is also linked to the tendency to treat data generated by digital systems as an objective source of knowledge on human behaviour, which has emerged as an idea alongside Big Data, despite the fact that such data is always shaped by the methods assemblages that produce it (Gitelman, 2013; Ruppert et al., 2013; van Dijck, 2014). Furthermore, the use of data science that seemed to be promoted by my interviewees depends on access to digital data sources which non-profit organisations have only if they have built extensive digital infrastructures with large user bases or if they have access to external data sets. As I will discuss in Chapter 6, such data required for successful data science applications are not always available to non-profits, which limits the usefulness of data science in the non-profit sector and the allure of Big Data. Nevertheless, the ideals of innovation and technological potential associated with Big Data were prominently a factor behind the promotion of data science and the way non-profit data professionals value data in my analysis.

Data practices promoted by the EBP movement were also present in my above analysis of Data for Good as an entry point to data practices in the UK non-profit sector. The way the interviewees promoted the use of data seemed in several ways analogous to the ideals of evidence-hierarchies promoted in EBP which value quantitative and statistical measurement over other ways of knowing. In EBP, quantitative measurement is often treated synonymously with evidence, and the goal is to use as rigorous evidence as possible. The broad-based attempt to promote data practices in the non-profit sector can therefore be seen as a continuation of EBP, with the key difference being that the emphasis on evidence is replaced by a focus on data. However, the statistical and experimental techniques common in EBP did not have a major presence in the broad-based promotion of data that I discussed above which was focused on practices inspired by NPM and Big Data. Furthermore, key promoters of data science in my sample were not focused on the statistical methods associated with EBP, but rather on the new computational data practices made possible by new digital data sources and statistical computing. Thus, while data practices associated with EBP were present in my interviews, they were not central to either the promotion of data science or the broad-based promotion of data in the non-profit sector discussed by my interviewees. Nevertheless, in Chapter 6 I discuss how the interviewees did seem to value data and promote a quantitative understanding of social problems in a way that closely aligns with EBP, although this did not always feature heavily in the data practices or methods assemblages discussed by the interviewees.

Finally, I discuss how my analysis of Data for Good as an entry point to the UK non-profit sector data practices can be positioned in relation to scholarship on Data and AI for Good initiatives in the humanitarian and development contexts, which I have discussed in Chapters 1 and 3. There are commonalities insofar as the promotion of data science as a solution to social problems aligns with the promotion of data science and AI in international development and humanitarian aid sectors (Aula & Bowles, 2023). However, there are differences. For example, DataKind UK, a vocal supporter of data science in my study, was exclusively focused on domestically operating non-profit organisations in the UK with no international projects. My interviewees who were engaged in broad-based promotion of data practices were working principally with domestic social sector and health sector charities, or these sectors were the main clients for training, facilitation, and consulting. There were no indications of links to international NGOs or international philanthropy, and the data practices discussed by the interviewees appeared to be more closely linked to trends in the UK social and health sectors than to those reported in the literature on development and humanitarian sectors.

Pushing non-profits to make more use of data appears to have a different power-dynamic than that reported in similar attempts to introduce digital innovation and data in the humanitarian context which have been criticised for their post-colonial power-structures between aid organisations and local recipients (Madianou, 2019, 2021), the power of individual philanthropists that set agendas and promote their own interests (Jenkins, 2010), and the promotion of digital and computational technologies as a solution to social problems (Haven & Boyd, 2020; Magalhães & Couldry, 2021; Schelenz & Pawelec, 2021; Taylor & Broeders, 2015). The UK non-profit sector, of course, has its own power structures, powerful philanthropists, and the discourse of technological solutionism, but my analysis did not reveal data practices marked by global inequalities or by significant presence or funding from technology corporations. The implication is that the analysis of Data for Good initiatives in this thesis cannot be generalised to experience in the wider global humanitarian context.

5.6. Conclusions

In this chapter I have analysed the origins of Data for Good initiatives in the UK as an entry-point to non-profit sector data practices to reveal my interviewees insights on the networks promoting use of data in the non-profit sector. This analysis revealed two distinctive entry-points to data practices. First, DataKind UK's work to promote data science provides an entry point to the use of computational methods in the UK non-profit sector. Promotion of data science, however, has been shown to constitute only a small part of wider efforts to promote quantitative data practices and digital data collection. Data for Good is also revealed as a loose network to promote diverse uses of data, as captured by the Data4Good Festival. Thus, broad-based attempts to promote the use of data in the non-profit sector offers a second entry point into how non-profit data professionals *value* data. Broad-based campaigns to promote the use of data in the UK domestic non-profit sector were shown to be focused more on getting non-profits started with *some* data practices than on proposing advanced computational techniques as a solution to social problems. The findings highlight that there are numerous data practices that non-profits might adopt, but among my sample of non-profit data professionals there is a shared agenda that data is valuable, and non-profits should learn to value data. Data science is but one part of a diverse set of data practices, albeit with an elevated position. This insight is the starting point for my analysis in the next chapter on how non-profit data professionals assign value to specific data practices and how their value is compared.

Chapter 6

"What we knew, but we didn't have evidence for" – Data and the need for better proofs

6.1. Introduction

In this chapter I focus on data and justification by exploring how non-profit data professionals assign value to different quantitative measurement techniques that they use or promote. The analysis is responsive to contributes to all the research sub-questions outlined in Chapter 2.

My conceptual framework guides an analysis that elicits a common assumption that informs the discussions, examples, and descriptions of data practices offered by my interviewees, whose simplicity can elide its theoretical ramification: *data practices in the non-profit sector are about strengthening knowledge claims with new quantitative methods assemblages*. On the surface this observation is trite, and widely established in earlier literature. But from the perspective of justification and methods assemblages it has two important implications.

The first is that data practices in the non-profit sector are always part of dispute about the strength of claims to knowledge. Following my conceptual emphasis on the importance of ‘situations of dispute,’ the existence of such disputes means that there is a need to determine better and worse claims. In the analysis in this chapter, I suggest that debates about the opportunities of data in the non-profit sector can be understood as *epistemic disputes* where *epistemic value* is assigned to claims based on techniques and technologies of knowing. The analysis shows that non-profit data professionals appear to believe that quantitative and digital data practices have greater epistemic value than other forms of knowledge. Yet, because the methods assemblages to enact a version of reality are always relational, partial, and performative, no quantitative or digital data practice can once and for all close disputes about epistemic value. Despite aspirations of non-profit data professionals to use data to achieve certainty and clarity that might justify claims made by non-profit organisations, in practice non-profits cannot achieve certainty due to challenges revealed in this chapter.

The second implication of the analysis in this chapter is that epistemic value in the non-profit sector is always relational and rarely serves epistemic purposes alone. Instead, it is shown to be entangled with substantive debates about what non-profit organisations want to demonstrate. Thus, epistemic value is rarely the primary interest of the non-profit organisations I study, although the non-profit data experts in my sample are highly engaged with it. The forms of value that non-profit organisations are interested in demonstrating are tied to their goals of social betterment and the obstacles they face when trying to achieve it. However, in practice the non-profit organisations are constrained by their institutional environment and the society around them. In the UK non-profit sector this environment has been shaped by years of NPM, EBP, Big Data, and austerity policies (see Chapter 3). These have shaped the UK non-profit sector in ways that make some disputes over value unavoidable, such those concerned with economic efficiency, accountability, and the effectiveness of non-profit work. My analysis provides a basis for arguing that these disputes call for a variety of data practices to demonstrate value, rendering specific quantitative measurement techniques relevant in some disputes, but not in others.

The pursuit of greater epistemic value and the disparate requirements of substantive disputes in non-profit work are found to often be in tension. In the chapter I show that the promotion of data science in the UK non-profit sector, a key component of Data for Good initiatives (see Chapter 5), is a case that illustrates such tension. I find that while non-profit data professionals report that they see data science as a source of great epistemic value, in practice, data science is rarely deemed to be useful for non-profits. The reasons for these challenges are both weak non-profit capabilities to use data science meaningfully, and the absence of clarity about what non-profits would demonstrate by turning to data science practices. The findings of the chapter therefore suggest that innovations in data practices to achieve greater epistemic value at the time my research was undertaken were of limited relevance for the non-profits in my study.

6.2. Data in epistemic disputes

In this section I analyse how the interviewees in my sample discussed data in terms of knowledge claims. My analysis of the interviews, as already suggested in Chapter 5, indicates that discussions about data do not necessarily refer to specific set of techniques or sources of data, but to the general idea that the proliferation of quantitative and digital data can be valuable for non-profit organisations. In the section I show that this knowledge-focused aspects of the value of data practices can be understood to be part of a specific situation of dispute, epistemic dispute, where epistemic value must be demonstrated.

The following passage quotes an interviewee working in an organisation facilitating the use of data and running training events to encourage and teach the use of data. In the quote the interviewee explains their goals for a training event with participants from charities and grant-makers in a specific small locality where participants were expected to have knowledge about the area. The goal of the event was to help the participants find new data sources and use data analysis to guide their charitable work in the area. The quote offers insight into the goals of the event and, more importantly, about the relationship between data and local knowledge.

> *"We were aware that a one-day long [data training event] isn't going to unearth or uncover loads and loads of answers that we didn't know about. It might just start building a picture of maybe what we knew, but we didn't have evidence for before." (Interviewee 1, Civil Society Data Officer, Facilitator organisation, Female, 4 years of relevant experience).*

This interviewee argues that a data training event is the start of a journey in understanding how non-profits can better use data. What is interesting is that data is argued to help in figuring out "*what we knew, but we didn't have evidence for*." In the broader context of the interview and the event in question, this referred to the relationship between local knowhow and different data sources on that locality. The juxtaposition of what was already known and data as evidence suggests a *hierarchical* relationship between different methods assemblages. In this context, the use of data did not necessarily refer to the potential to reveal something new, but to the possibility of providing greater certainty through the use of data as evidence. The views of this interviewee can be interpreted to frame data as a means of demonstrating something that was already known in other ways, but for some reason could not be confirmed. According to the interviewee, the data collected and analysed for the event would help establishing whether this knowledge is correct. In other words, the interviewee seems to suggest that quantitative and digital data practices would provide better knowledge than other, non-quantitative ways of knowing.

In my interviews, it was common for non-profits data experts to assert that the use of quantitative data can offer a stronger proof than other, non-quantitative sourced of knowing. The following quote is an example of how the expertise of people working in non-profits might be respected but deemed less convincing than quantitative data on the same issue. The interviewee in this case was a volunteer data scientist at DataKind UK and motivated to increase the use of data science in non-profits. This quote offers insight into how a data scientist in the non-profit sector approached the value of data in relation to other sources of knowledge in non-profit work.

> *"[non-profit employees in front-line services] have a lot of embedded wisdom, a lot of expertise about how to help those people on the frontline. I think what the data gives them is a way to monitor whether that expertise is still relevant [--] They might be offering particular services without necessarily a good understanding of the uptake of those services or they might be positioning a program for a particular purpose and not be aware of whether it's fulfilling that purpose or not. The data allows them to check their assumptions." (Interviewee 7, Data Scientist, Facilitator organisation, Male, 2 years of relevant experience)*

This interviewee questions the value of "*embedded wisdom*," suggesting that the use of quantitative data can determine "*whether that expertise is still relevant*" and to "*check their assumptions*." Furthermore, the interviewee suggests that despite the knowledge people working in the non-profit sector might develop through practical work, non-profits might not have "*a good understanding*" of the services they provide. Even if the purpose of offering a specific service is justifiable, the interviewee argues that non-profits might "*not be aware of whether it's fulfilling that purpose*." This suggests that the interviewee values knowledge based on quantitative data as being superior to knowledge that is not. In other words, the use of quantitative data is taken to offer a stronger justification that things really are the way that a non-profit claims.

The following quote is an example of how an interviewee from a grant-giving organisation framed the value of using quantitative data in their work. The interviewee worked as a grant manager in a small grant-giving organisation. The interviewee described how they have started to use more and more data to guide their grant-making, even though the organisation had an exclusive focus on a geographically small area that the organisation was embedded in. The passage offers insight into the value of data from someone who knows the communities and non-profit organisations in the area well, but is keen to learn how quantitative data might improve that knowledge:

> *"Data is really useful, even from a grant making perspective, because it lets us see… it's the level of intelligence it can give you. It gives you information about what is actually happening. It can give you numbers and it can build up that intelligence. [--] there's a danger that we forget what's not in the data as well and data does decontextualize everything. It doesn't account for, what's going on in the wider context." (Interviewee 22, Senior manager, Grant-giving organisation, Female, 10+ years of relevant experience)*

The quote includes several elements that can indicate different aspects of data in debates about knowledge claims. Most importantly, it shows that 'data' is understood as a resource that can help non-profits "*build up that intelligence*," although it has the problematic tendency to "*decontextualise everything*." Furthermore, this kind of "*intelligence*" is valuable to non-profits because it helps them know "*what is actually happening*." This choice of words suggests a profound meaning regarding enactment of versions of reality consistent with understandings of methods assemblages: quantitative data "*gives information"* about what is *really* going on in the world. This juxtaposes the use of quantitative data with other ways of knowing that it is suggested, might not tell the interviewees what *really is* going on. This places quantitative data in the realm of revealing something new about the world, something that helps non-profits have better knowledge about the issues they work with. Yet the interviewee recognises that quantitative data often decontextualises knowledge. Such data might miss things, painting only a narrow picture, although the information it provides is deemed to be valuable. Interpreting this through my conceptual framework, the interviewee frames the use of quantitative data as a resource that helps non-profits have a better understanding of the world but acknowledges this is just one version of empirical reality which has shortcomings.

Based on the above analysis, I suggest that it is possible to conceptualise the knowledge-related assessment discussed by the interviewees as part of epistemic disputes where the strength of claims is compared and assessed. I suggest that when the interviewees discuss specific quantitative and digital data practices as more credible sources of knowledge than others, this can be conceptualised as assignment and comparison of epistemic value. Greater epistemic value makes knowledge claims more credible and leads to their enactments being taken as "real." Most importantly, epistemic value is negotiable and can be strengthened and weakened depending on how claims are made and what practices and techniques are involved with them. Some data practices are almost by default assumed by the interviewees to provide greater epistemic value, but the interviewees also indicate that it is necessary to compare different data sources and perspectives.

Although my analysis indicates that it was common among the interviewees to make claims about the evidential value of quantitative data in epistemic disputes, these claims were often positioned as being open to critique through recourse to other sources of knowledge, such as expertise accumulated through experience. When the versions of reality enacted with quantitative data and other sources of knowledge, the result is a dispute where the strength of the proofs is assessed by the participants in the situation. This indicates that knowledge claims made with quantitative data are open to dispute if this data is not thought to offer anything new or valuable, or if there is contrasting evidence. Thus, it was not a given that professionals working in non-profit organisations would report that 'stronger' quantitative evidence is required to confirm what they already know.

One interviewee working for an organisation facilitating and promoting the use of quantitative data in the non-profit sector recounted a story of what happened when non-profit professionals rejected the need for this data. The interviewee had worked for five years in data-related roles in the UK civil society but had only recently started working specifically with non-profit data. In the interview this interviewee appeared to be motivated to convince non-profits of the value of data to overcome obstacles in its adoption. One such obstacle discussed by the interviewee was when training participants disagree with and even resist the idea that non-profits need quantitative data. The interviewee found this resistance frustrating, as indicated by the quote below.

> *"We did a data training event in Birmingham, and it was a colossal fail, because we didn't divide the people well. There were two really powerful women who said, "We don't know the data. We don't need the data to know where are the most deprived places in Birmingham, we all know in our head." "Well then great, so how will the council know?" "They know also in their heads, so we don't need to share with them where is the most deprived areas for them to give the money to us." We were like, "How do you know though that it's the most deprived area? Beside knowing in your brain, what was the data that told you this is the most deprived and need help?" They can't answer you that. They said, "We know that this is the place that need most help." (Interviewee 32, Product & Programmes manager, Facilitator organisation, Female, 5+ years of relevant experience)*

The interviewee seemed frustrated with the reluctance of their audience to acknowledge that the use of quantitative data can offer better proof of the needs for intervention than their first-hand knowledge. The interviewee was committed to the idea that quantitative data will help non-profits make stronger claims about what the most deprived areas in Birmingham are like, but some members of their audience did not see the need for stronger claims based on quantitative data. In other words, the interviewee indicates that they rejected the idea cherished by non-profit data professionals that data offers proof of "*what we knew, but we didn't have evidence for*." For the members of the audience criticised by the interviewee, it was enough that they and their collaborators knew based on their first-hand knowledge. In the above quote, the interviewee is perplexed by this rejection and uses the example as a negative experience regarding the difficulties of making non-profits value quantitative and digital data practices. The value of these data practices is in dispute, and the interviewee has difficulty convincing their audience that quantitative digital data practices are more valuable than other ways of knowing, such as local knowledge and professional experience. In the example, even when the interviewee evokes different relational situations where quantitative data might be used, such as whether the local council is convinced by local knowledge, the audience still rejects the arguments of the interviewee because they consider knowledge of deprived areas to be common knowledge. In brief, the audience in this interviewee's view does not expect the local council to disagree with claims about deprived areas if they are based on a shared geographic understanding of deprivation in Birmingham. The story is important because it demonstrates that the value of data in providing superior proofs might not be appreciated by everyone.

Yet, my analysis of the interviews does suggest that non-profit data professionals do value quantitative data for its role in justifying knowledge claims. In many instances, quantitative data was understood as demonstrating *value in epistemic disputes*, acting as a resource to justify why one knowledge claim is more accurate than another or why some other claim is not the whole truth. The interviewees suggested that claims based on local knowledge and practical experience cannot always be trusted, whereas the use of quantitative data was seen as offering a path towards greater certainty and more robust evidence. In other words, these non-profit data professionals typically accorded quantitative data *more value* than other ways of knowing.

The understanding exhibited in the above quotes suggests that quantitative data can be characterised as a resource in a variety of situations of dispute where value needs to be demonstrated. This insight is consistent with Boltanski's and Thévenot's idea of reality tests being central to rendering demonstrations of worth natural (2006, pp. 40, 133–144; see Chapter 2). This insight is also consistent with Law's work on how different methods assemblages enact versions of empirical reality. Different methods of knowing, such as expert knowledge, first-hand experiences of front-line non-profit workers, quantitative data collected by non-profits about beneficiaries, and statistics generated by authorities, all can be understood to enact different versions of the issues that non-profits are interested in. Their relative worth in epistemic disputes shapes what is taken to be a more "real" or "true" claim. Thus, for the non-profit data professionals in this study, the use of quantitative data does not present the whole truth, but it takes non-profits closer to it if non-profits commit to achieving higher status in hierarchies of epistemic worth. Knowledge presented without quantitative data is thought to be deficient in that it does not meet the ideal of 'good' knowledge. That quantitative data was valued in this way by the interviewees is unsurprising because the interviewees were selected based on their activity in using or promoting data in the non-profit sector.

6.3. Making non-profits value data

Non-profit data professionals are a unique sample of people working in the non-profit sector. The views of my interviewees on epistemic value and the value of data may not be shared by others working in the sector, as I suggested in the previous section. Non-profit data professionals must therefore try to convince other people working in the sector that the use of quantitative data indeed is worth caring about. In Chapter 5 I showed that Data for Good initiatives provide an outlet to do this by promoting both quantification generally and data science specifically.

In this section I further explore the sociocultural element of how non-profit data professionals try to convince non-profits to appreciate the use of quantitative data. I show that it was common for non-profit data professionals in my sample to assess the worthiness of entire non-profit organisations through their level of commitment to valuing specific data practices. The analysis is used to suggest that although quantitative data practices always have a material element, the epistemic value that is assigned to them is a product of sociocultural change that Data for Good initiatives promote. I focus especially on how some of my interviewees used concepts like "data culture" and "data maturity" as shorthand for the level of commitment to the standards of epistemic value held by non-profit data professionals. [18] However, valuing quantitative data in general can be put into practice through various quantitative data practices whose relevance and value I show is relational. There is no single quantitative measurement technique

[18] In this section I assess "data culture" and "data maturity" as themes that can be detected in the interviews as evidence of the way non-profit data professionals exhibit the logic of epistemic value in their thinking. The concepts have a longer history and there is already critical analysis of concepts like "digital maturity". The argument here is not about the concepts themselves, but about how they are exhibited both in the vernacular of non-profit data professionals and are sometimes used as models for developing the appreciation for epistemic value.

that will work in all possible situations of dispute, which is why in the later sections and chapters I look more closely into the material, relational, and performative elements of methods assemblages. Before this, however, I want to underscore the way non-profit data professionals push other people and organisations in the sector to adopt the ideals of epistemic value that quantitative data practices are understood to serve.

"Data culture" was a concept used by some of my interviewees to highlight the organisational aspects that support the use of quantitative data. The passage below offers a definition of data culture by one of the interviewees who was employed by an organisation that used data culture as one of their keywords in helping non-profits use data. The interviewee worked in a facilitative role, meaning that they did not do data analysis themselves but actively worked with non-profits through trainings and events. These services were free for the clients and publicly funded, which meant that neither the interviewee nor the organisation gained direct financial benefit from promoting the use of data.

> *"What we mean by data culture is do people, do these organizations underpin their work with data, with evidence-base? Do they, or is it just assumption-based? Is it anecdotal? Was it just like I know because I am a professional in working with these communities? How do you evidence that to somebody who wants to see the numbers? It's almost like the data culture is like are they an organization who automatically say, "But where's your evidence for that?" Or are they an organization who shy away from using data at all. The data culture is where are you on that spectrum." (Interviewee 1, Civil Society Data Officer, Facilitator organisation, Female, 4 years of relevant experience)*

In the quote the interviewee defines data culture on a spectrum between two types of knowledge. In one end of the spectrum knowledge is regarded as "*assumption-based*," "*anecdotal*," or based on personal expertise of being a "*professional in working with these communities*." This type of knowledge is what the interviewee says they try to surpass. In the other end of the spectrum quantitative data is meant to interrogate and critique assumption-based and anecdotal knowledge. According to the interviewee, the use of quantitative data is meant to satisfy critical people "*who automatically say,* *'But where's your evidence for that"* and people who "*want to see the numbers*." This distinction implies that this interviewee sees quantitative data as offering superior proofs to strengthen knowledge claims. The use of this kind of data is meant to counter doubt and to encourage non-profits to test their knowledge in more rigorous ways. In sum, the interviewee appears to believe that using quantitative data offers better, stronger, and more certain knowledge than not having this data available to underpin knowledge claims. Organisations with a developed data culture are expected to enrol resources, justifications, and proofs to defend their claims against criticism. Furthermore, organisations with a developed data culture are better positioned to mount data-based denunciations of competing claims, arriving at superior knowledge claims in their own debates or to deflect external criticism.

The holistic framing of data culture is further elaborated in the following quote from a different interviewee from a social sector non-profit who discusses the importance of quantitative data throughout non-profit work. The interviewee worked as the head of data science and had a small team working under them. The interviewee was focused on helping their organisation become more 'data-driven' by collecting better quantitative data and using more data in their decision-making. In addition to the technical aspects of this goal, the interviewee emphasised the cultural side of what it means to be data-driven.

> *"There's something about the data culture of the organization at every level in terms of people at every level feeling more informed, being more comfortable working with data, being able to make explicit links between data and decisions or actions taken. I think it's also common in organizations to measure lots of things rather than measure the right things. Of course, that measurement activity comes at a cost and really if you aren't making decisions based on your measurement, you probably shouldn't be measuring. A lot of room for improvement there for building a strong data culture." (Interviewee 31, Senior manager - data science, Service-providing non-profit, Male, 5+ years of relevant experience)*

According to the interviewee, data culture should be developed "*at every level*." The goal of developing data culture is to help non-profits make "*links between data and* *decisions or actions taken*." This take on data culture emphasises the active role of using quantitative data in guiding what non-profits do, shaping how their goals are enacted and pursued. Furthermore, the interviewee suggests that it is typical for non-profits to "*measure lots of things rather than measure the right things*." Part of data culture therefore is the skill of non-profits in determining what is important for the success of their work. The interviewee seems to suggest that the use of quantitative data is key to the success of non-profit work, but that non-profits also must know for themselves what would be the data that can help them better tackle social problems and contribute to social good. The interviewee, however, says that there is "*a lot of room for improvement*" before non-profits have a "*strong data culture*," suggesting that non-profits are currently unable to build such a culture. The interviewee therefore suggests that non-profits lack skills and knowledge about what sorts of data would be needed and how data might inform their work. Nevertheless, having a better data culture is presented not only as helping non-profits have better knowledge, but to know the "right" things to measure and help them to rethink non-profit work based on their use of quantitative data.

My analysis of discussions on data culture with the interviewees indicates that building a data culture was predominantly aspirational: the interviewees appeared to believe that non-profit data culture must be strengthened. The following passage is a quote from an interviewee who discusses the importance of data maturity and whether non-profit organisations possess it. The interviewee worked as a team lead in an organisation facilitating the use of data, and their worked was focused specifically on helping non-profits use more data. The interviewee was not an expert data analyst by training but had acquired skills relating to the use of quantitative data as part of other roles. The person had worked as the team lead in facilitating data use only for a few years but had already seen some changes in their strategy.

> *"We realized early on that data maturity framework where majority of civil society is, is really right at the beginning of that. We need to understand what's the value of data in the first place, why is it something*

we should potentially invest in and think about creating systems around? Most of the things we've done have been trying to find ways to demonstrate the value of data and make it more accessible and think about how we can create that cultural shift in civil society." (Interviewee 11, Community Engagement Manager, Facilitator organisation, Female, 5+ years of relevant experience)

The quote includes several keywords that are central to the themes of this chapter. The interviewee says their organisation tries to "*demonstrate the value of data*" and "*create that cultural shift*" towards more appreciation of data. The passage acknowledges the role of cultural foundations that need to be in place if the epistemic hierarchies cherished by non-profit data professionals are to take root more widely in the sector. Non-profits who have built these foundations are expected to understand the value of quantitative data and "*invest in and think about creating systems*" to support their collection and the use of data. However, the interviewee says that at the time of the interview non-profits were "*really right at the beginning*" of developing data maturity that would indicate they have adopted both the culture and practices of being a data-driven non-profit. A strong data culture was therefore framed as a precondition for developing the data maturity of non-profits, which requires that non-profit organisations value methods assemblages relating to digital and quantitative data.

Another interviewee with extensive experience of various non-profits provided a longer discussion on the state of data maturity in the non-profit sector. This interviewee worked as a senior manager for data and impact in a medium-size service-providing non-profit organisation in the social sector. The interviewee had worked with non-profit data since the early days of the Big Data boom and had held data-related positions in several non-profits. In the quote the interviewee reflects on whether, in their experience, there had been development over time in how non-profits use quantitative data, given the attention it has received.

"You quite often see the role of digital analyst or data analyst that just look at the performance and report on performance and doesn't do much more than that. [--] I think the awareness is still quite low and people like to make big sweeping statements now. They're like, 'we've

got loads of data, we have to leverage our data, we want to be data driven.' Most people don't really know what they're talking about. [--] I can see an increase in maturity, but I'm quite struck by how limited that's been over the last say 12 years compared to the increase in digital maturity, which has been really huge actually." (Interviewee 30, Director of Impact and Innovation, Service-providing non-profit, Female, 5+ years of relevant experience)

This quote suggests that progress towards data maturity has been "*limited*," and non-profits have been more successful in digitalising their work than making use of the data generated by the newly founded digital infrastructures. The interviewee suggests that analysts employed by non-profits "*just look at the performance and report on performance*," which is framed as a somewhat unremarkable way of using quantitative data. Moreover, the interviewee seems sardonic about sweeping claims of progress around data-drivenness, quipping that "*most people don't really know what they're talking about*." I suggest that the scepticism displayed in this interview stems from the interviewee's status as an experienced professional in digital data analysis, which made them interested in new ways of collecting and using digital data. From their perspective, few non-profit organisations were making use of the tools and techniques the interviewee was proficient in.

My above analysis of how interviewees in my sample discussed data culture and data maturity offers a glimpse into how non-profit data professionals think about the ideal state of non-profit data. My analysis paints a picture of what a non-profit organisation would be like if it had thoroughly embraced a culture that values quantitative data. What is at stake is not only the actual uses of data, but the attitudes and ethos of the organisation. Proponents of a strong data culture argued that non-profits must learn to think about their work *through* data. Non-profits that collect more data and use it in versatile ways are accorded an aura of being "good" non-profits in the eyes of non-profit data professionals. Those non-profits that do not collect quantitative data or only use it in limited ways are thought to be behind, because they lack the practices and resources that would signal what is "good." In other words, non-profit data professionals appear to believe that non-profits whose work is *more* informed by quantitative data are better non-profits. According to the proponents of a stronger data culture, the value of this kind of data will only be realised when non-profits have acquired the cultural beliefs and practices that value data. The two concepts – data culture and data maturity – are positioned as offering a way for non-profit data professionals to guide non-profits towards appreciation of higher epistemic worth at the same time as justifying the pursuit of a superior kind of knowledge with the benefit it offers in practical debates.

6.4. What non-profits justify with data?

Although non-profit data professionals have been shown to value quantitative data for its own sake, non-profit organisations more broadly are not only be focused on epistemic issues. This is where the relational element of methods assemblages, situations of dispute, and justification is crucial in understanding the value accorded to quantitative data. In this section I draw on my analysis to suggest that, ultimately, the new data practices that my interviewees argue are valuable to non-profit organisations are valuable only insofar they help non-profit organisations succeed in disputes that have real consequences for achieving their goals of social betterment. In this section I therefore focus on situations of dispute beyond epistemic value. To make a difference, the use of quantitative data must be *about* something that non-profits find valuable, helping them prevail in situations of dispute where the perceived strength of evidence matters. Data must enact *something* that demonstrates value in these disputes. This is where the institutional environment of the UK non-profit sector and its legacy of NPM and EBP enter the picture by influencing what kinds of disputes non-profit organisations face.

The need for non-profits to use quantitative data to prevail in specific disputes about the value of non-profit work is captured well in the following quote. In the passage, an experienced interviewee working in a leading position in a consultancy that uses data maturity frameworks discusses their motivation to facilitate data use in the non-profit sector. The interviewee is particularly important because their organisation held a central position in the founding of Data for Good initiatives in the UK, which makes their thinking influential beyond the organisation itself or their clientele.

> *"I still feel very passionate that unless you have got data and a grip on data, you won't be able to evidence your need and to get funding or to get political will to change the world as you see it. [--] unless you have data and can tell your story and articulate why it is what you do because of this problem, and why are you having an impact, why it's worth investing some money with us to do this thing, whether it's about helping vulnerable people or saving the environment or whatever, we're never going to achieve those things or continue to do social good [unless you have data]. I think there's just increasingly going to be the need to evidence what it is that you do." (Interviewee 27, Senior manager, Facilitator organisation, Female, 15+ years of relevant experience)*

The quote displays an impassioned explanation of why non-profits should use more quantitative data and why they need to develop their data maturity. The interviewee cycles through a series of things that non-profits will *not* be able to achieve if they do not embrace new data practices. Most importantly, the passage recognises that the use of data often happens in relation to other actors, and non-profits need to learn to use data to achieve their goals in a changing environment. To succeed, non-profits must be able to incorporate the use of quantitative data to address different normative questions such as "*what you do because of this problem*" and "*why it's worth investing some money*." According to the interviewee, it is imperative that non-profits "*got data and a grip on data*," because otherwise non-profit will not be able to "*change the world as you see it*." Without quantitative data non-profits are "*never going to achieve those things or continue to do social good*." The interviewee says that they "*feel very passionate*" about the issue because, in their view, failure to make better use of data will endanger the very foundations of non-profit work.

In the above quote the rationale for the dire appraisal of the fate of the sector can be interpreted as evidence of an increasing demand for quantitative data by external stakeholders and as the interviewee seeing quantitative data an indispensable part of non-profit work. Given the pressures, the interviewee sees no way out of the need to use more data. Thus, the interviewee suggests that non-profits must make better use of quantitative data if they are to demonstrate their capability to change the world for the better. The passage therefore ties together the cross-cutting aspirations for better knowledge, the demand for data by funders and policymakers, and the need to justify claims in a variety of situations.

The quote also testifies to the ongoing influence of NPM and EBP in the UK non-profit sector. The interviewee anchors the need to use quantitative data to the question of "why it's worth investing into you," which highlights an economic logic of assessing the cost and the benefit of non-profit work that is emblematic of NPM. The interviewee's argument that this kind of data is needed to bolster political will also anchors the use of data to the philosophy of EBP that has profoundly influenced social and health policy debates in the UK (see Chapter 3). My analysis suggests that the economic and policymaking requirements for quantitative data outlined by the interviewee can be seen as external pressure that challenges non-profits to justify the value of their work in specific ways and with specific kinds of data. These external pressures coming from the institutional environment of the UK non-profit sector add to the *internal* pressure applied by non-profit data professionals themselves to make non-profits place epistemic value on quantitative data. This dual dynamic is identified in earlier research on performance measurement in the non-profit sector (MacIndoe & Barman, 2012), and it speaks to the multiple sources of public pressure that call upon non-profits to demonstrate the value of their work.

The above interviewee was not alone in framing the need for funding and demands by policymakers as factors urging non-profit to use more quantitative data. Another issue frequently discussed by the non-profit data professionals, but not mentioned by the above interviewee, was use of data to improve the services provided by non-profits. In the following quote an interviewee from the same consultancy as the previous interviewee argued that non-profits approach them because they are interested in demonstrating the value of their work to funders and policymakers, and to assess and improve their own work. According to the interviewee, the clients of the consultancy call for help with using quantitative data because they are:

> *"changing the way they deliver services using data, or questioning the impact that they're having or trying to evidence the impact that they're having in order to gain more funding, or to be able to argue with commissioners that what they're doing is based on evidence." (Interviewee 28, Senior manager, Facilitator organisation, Female, 20+ years of relevant experience).*

The quote identifies three different themes that guide non-profit interest in data. First, the interviewee mentions service delivery and the possibility of changing services based on quantitative data. Second, they mention the need to use quantitative data to demonstrate the impact of their work. Third, the interviewee mentions funders and policymakers, suggesting that quantitative data can demonstrate that the work of the on-profit is "*based on evidence.*" This last point implies that being based on evidence is desirable and even expected by funders and policymakers.

When asked the same question, an interviewee from a non-profit data facilitator and promoter organisation discussed a similar way of categorising what non-profits need help with: "*data about clients, customers [--], data about charity operations and services, and data about funding*." (Interviewee 7, Data Scientist, Facilitator organisation, Male, 2 years of relevant experience). Here we again find funding and services as priorities, but the interviewee also adds a category for knowledge about clients and customers.

The above quotes illustrate the recurring issues that non-profits were found to use quantitative data to address. The interviewees typically presented the key areas of concern regarding non-profit data as a coherent list. While they might meander from one issue to another, jumping from one way of using data to a completely different example, the above passages present the issues a list. The coherence and overlap between the lists provided by representatives of different organisations, suggest that these issues stand out as areas where quantitative data is treated as being particularly important.

However, the interviews did not suggest that all non-profits place similar value on all these issues. The following quotes from two interviews give opposite views of how quantitative data was used in their experience. An interviewee working as the Director of Impact and Innovation in a medium-size non-profit with earlier experience with several small and mid-sized non-profits said that *"everywhere else I worked the focus was on communicating outwards far over and above improving what was happening internally, or changing what was happening internally"* (Interviewee 30, Director of Impact and Innovation, Service-providing non-profit, Female, 5+ years of relevant experience). The quote suggests that in their experience, an external focus on communication was more predominant than an internal focus on improving their own work. In the interview this juxtaposition was elaborated by emphasising how in their current organisation the focus was more balanced and included internal improvement. Through this comment the interviewee emphasised that the internal focus on quantitative data on beneficiaries and service delivery was not a given.

Another interviewee commented on similar imbalances within their own organisation. This interviewee worked for a social sector non-profit as the head of data science and was motivated to find new ways to use quantitative data in their work:

> *"There's a split between the operational side, and the policy side and also the business development side because of course as a charity, in particular one that [has] ongoing need to bring in money and also justify continued investment, the evidence that we're gathering, the data that we're gathering feeds into that. We have many channels, but broadly speaking the data that we're gathering is for decisions by our executive team and our trustees. That's how it flows really." (Interviewee 31, male, service-providing organisation)*

The quote identifies a "*split*" between different facets of how a non-profit can use quantitative data, distinguishing between an "*operational side*," "*policy side*," and "*business development side*." Interpreting these "sides" in the light of the interview as a whole, the facets link up with the themes of service delivery, fundraising, and policy-focused communication that have been identified above. The split mentioned by the interviewee suggests a difference in how this kind of data is used in these areas, which underscores the distinctive roles that data might play. For the interviewee, however, the focus of their work was on using data internally, and the interviewee elsewhere suggested that "*my role is to ensure that the raw material that we're working with is the best it can."* The data used on the "*policy side*" and "*business development side*" could be different from the internally focused "*operational side*" where "*the data that we're gathering is for decisions by our executive team and our trustees*." This quote not only corroborates the importance of a small number of salient issues in my sample but also underscores differences in how data is used to deal with issues. In other words, the interviewee suggests that the use of quantitative data is far from uniform among non-profits. This points to the need to consider the value of data separately in these areas.

In Chapter 2 I proposed that the politics of data should be understood through the way quantitative data is used to demonstrate value in situations of dispute. In this section I have highlighted a relatively short list of the things non-profits try to achieve with this kind of data, which also exhibits broader trends in quantitative measurement in the UK non-profit sector that I reviewed in Chapter 3. If the value of data is contingent on situations, the findings suggest that the cross-cutting value of data in epistemic disputes might contribute to diverse normative and political aspirations depending on the situation. Stronger claims made with quantitative data end up justifying different things and therefore can be understood to *demonstrate value in different situations of dispute*.

As suggested by some of the above interviewees, data can be used to intervene in a variety of relational contexts where value needs to be demonstrated. A non-profit may collect quantitative data on its impact for the purposes set by the organisation itself, combining an aspiration for better knowledge about social change with aspirations as defined by its interpretation of its charitable goals. A non-profit can also collect this kind of data to demonstrate value to external audiences such as funders, local governments, policymakers, and collaborators. The situation of a grant-giver evaluating which organisation should receive a grant and the situation of non-profit managers evaluating different options to organise services suggests the use of different assessment criteria in reaching the "best" decision. Depending on what forms of value are in dispute, different demonstrations and different types of data and evidence might be needed. The credibility and trustworthiness of claims made with data end up offering demonstrations in a variety of situations of dispute.

The above analysis offers initial insight into the way quantitative and digital data practices are used to bolster claims in different situations of dispute. The way that data is used to demonstrate value in these situations of dispute is further explored in subsequent chapters. In Chapter 7 I focus on grant-making and in Chapter 8 on social value and identification of needs. In the next section, however, I review how the need to demonstrate value in diverse situations limits the extent that sophisticated computational techniques or new data practices are useful.

6.5. Balancing pursuit of epistemic value with resources

The relationality of data practices vis-à-vis specific disputes where quantitative data is used to demonstrate value is not the only constraint on non-profit data practices. It was common within my sample to reflect on the resource and capability constraints that non-profits face when using this kind of data. Indeed, the non-profit data professionals in my sample frequently discussed how the lack of non-profit resources dedicated to the use of data is a key obstacle to their work. This constraint is familiar in earlier research on the use of digital technologies in the non-profit sector (e.g. Harmon et al., 2017; Schneider, 2003), and it was discussed by a large number of interviewees.

A lack of resources in the non-profit sector is widely discussed in the research literature (Bach-Mortensen et al., 2018; McCosker et al., 2022). Dependency on public contracts and grants often means that non-profits are only paid to deliver a specific service and must focus all their work on delivering results in a way that satisfies the quantitative metrics required by the donors (B. Evans et al., 2005; Hall et al., 2015; Moxham, 2010). The outcome of this dynamic is that non-profits typically have neither resources nor the capacity to spend on issues relating to these data practices.

Lack of resources has direct implications for the pursuit of the higher epistemic value accorded to evidence based on quantitative data because non-profits are tied to the disputes about resources, policy, and improvement, and they must balance their investment in data practices with the overall availability of resources. As a result, the aspiration towards greater epistemic value exhibited by my interviewees is curtailed by what non-profits can achieve given their current resources. This makes investment in data practices and cultural work aimed at greater appreciation of the value of quantitative data a constant negotiation given the austerity-stricken challenges of non-profit work in the UK.

My analysis of the interviews indicates that the lack of resources was acknowledged either as a general observation about the non-profit sector or as a description of how resource constraints influence the organisation of the interviewee. In the following quote an interviewee addresses the lack of resources as a general problem in the non-profit sector, which is then seen to lead to a lack of resources in data-related work. The interviewee worked as the head of digital innovation in a large non-profit sector consultancy and had an extensive career in the non-profit sector. They had worked both for major grant-making organisations and as a non-profit sector consultant for over ten years, which gave them a breadth of knowledge about the state of the sector in the UK:

> *"I think there's a lot of focus on building stuff. Everyone wants to build new stuff. Everyone wants to run events, or do capacity building, or training. I think those are all sticking plaster over the core problem with*

> *the charity sector, which is about money, bluntly. Charities are trying to fund the bit that no one cares about. That means charities are generally under-resourced" (Interviewee 25, Principal consultant - digital innovation, Facilitator organisation, Male, 10+ years of relevant experience)*

In this quote the interviewee suggests that "*everyone*," referring to people promoting the use of quantitative data, wants to organise projects to support non-profits in their use of data through events, trainings, and programs. This observation on the focus on capacity building suggests an allusion to work to promote a data culture and data maturity discussed above. Given that the majority of my interviewees worked in facilitator organisations, there was extensive discussions on such support schemes. The interviewee also refers to keenness to "*build stuff*," which in the context of the interview referred to development of projects, apps, online tools, and experiments that might leverage digital technology or digital data. Nevertheless, the interviewee suggests that this work is, however, "*sticking plaster over the core problem*" of non-profits not having enough money to do things the way they would want. According to the interviewee, attempts to support the data practices of non-profit organisations or to help them build individual projects or tools only provides a superficial solution to the more fundamental issue of non-profits having a chronic lack of resources. Thus, the interviewee suggests that while data might help non-profits bring about more social change, it will ultimately *not* compensate for a general lack of resources in relations to the scale of social problems to be solved.

The trade-offs in resource allocation between service delivery and the development of digital and data capabilities were acknowledged by an interviewee working for a small non-profit in the social sector. This interviewee worked as a service manager in an organisation focusing on elderly people and was one of the few interviewees in the study whose work did not focus on quantitative data, but who participated in data-related events and was keen to learn new ways to use this kind of data. For the interviewee, the potential value of quantitative data needed to be negotiated with the resources that were available, and the need was to focus on actual service delivery:

> *"I am really aware that data is key, but also you have to balance out against the amount of time and money that we spend collecting data which can take us away from actually delivering a service. There's constantly that tension there between keeping it proportional to what we're doing." (Interviewee 4, Director of Services, Service-providing non-profit, Female, 15+ years)*

The interviewee indicates an awareness of the costs involved with collection and the use of data, arguing that even if they wanted to spend more resources on new data collection and analysis practices, and knew it would help them improve their work, it would still need to be "*proportional to what we're doing*." The interviewee hesitates to spend more resources on using data if it starts to weigh on their service provision. More and better knowledge of this kind is therefore not deemed to be something that non-profits want to invest in for its own sake. In other words, there appears to be a limit to how much better non-profits want to do in addressing epistemic disputes for its own sake. The implication is that the value of quantitative data in disputes over substantive matters might not be enough to warrant further investment even if more quantitative and digital data collection is believed to provide better knowledge.

The effects of scarce resources were further elaborated by an interviewee working as a coordinator in an organisation that connected volunteer experts with non-profits to help them with quantitative data and data analysis. Although the organisation offered its services free of charge, limited resources, and the need to prioritise service delivery was a frequent obstacle in data-related projects.

> *"The difficulty is just the lack of resources within the sector. A lot of organizations are still focused on just delivering their day-to-day needs for their beneficiaries. Data sometimes can be in the backburner." (Interviewee 26, Member Engagement Manager, Facilitator organisation, Female, 5+ years of relevant experience)*

In the quote the interviewee echoes the message of the other interviewees: non-profits lack resources and focus on the actual delivery of services. In saying this the interviewee acknowledges that non-profit organisations allocate their resources to the core work towards social betterment rather than supporting functions such as data collection and analysis. This focus was rarely a choice made by the non-profit themselves because grants and contracts are awarded for service delivery and publicly used metrics of non-profit work can be a punishing drain on resources for non-service-related expenses. All this leads to a situation where the use of quantitative data is "*in the backburner*." This creates a conundrum for this interviewee whose organisation is providing non-profits help with data collection and analysis free of charge: even with the volunteer service they offer, the demand for their work can be limited by the lack of attention and interest in quantitative data on the part of their clients. The fact that non-profit organisations do not necessarily value this kind of data, which Data for Good initiative and non-profit data professionals try to overcome, is an obstacle also for the attempts to make them value data.

The conundrum of non-profit organisations not having resources, time, or an interest in data is not easy to overcome. It serves as a powerful reminder that in the big picture of non-profit work, the non-profit data professionals interviewed for the study are a unique group within the sector. While non-profit data professionals would gladly see their resources expanded and quantitative data being valued more highly in the sector, they report that they can rarely realise these goals in their work.

I suggest that this lack for resources makes the sociocultural character of how non-profit data professionals value data especially interesting, because it does not necessarily reflect the way other people in the non-profit sector value non-profit work. The dilemma was addressed by an interviewee who worked for a facilitator organisation to help non-profit organisations get started with the use of quantitative data. The interviewee was trained in advanced statistical methods and held a PhD in a social science, which suggested that they were personally invested in the value of data. The interviewee explained to me that "*When I speak to charities, you do sympathize, and I can't say, 'No, fire your frontline staff. Hire a data scientist.'*" (Interviewee 16, Data &

Research Lead, Facilitator organisation, Female, 5+ years of relevant experience). The quote voices a distinction between what might be valued by non-profit data professionals who want to promote the use of quantitative data and what is relevant for charities and non-profits who focus on delivering services. This interviewee might prefer more investment in data practices but recognises that it is difficult to justify why services should be cut to have more resources for data-related work. Knowledge of this discrepancy means that non-profit data professionals need to work hard to convince their organisations to invest in the uncertain enterprise of new data practices and the promise of possibly improving the fortunes of the organisation.

6.6. Limits of data science

Given that non-profit organisations have been shown to lack resources to invest in data, the promise of DataKind UK to provide non-profit organisations with volunteer data scientists would seem to be an attractive option. If a non-profit organisation has adopted way of valuing data as proposed by my interviewees but lacks resources, a project done by volunteer data scientists would seem desirable. Indeed, the premise of DataKind UK (see Chapter 5), was shown to be that data science can help non-profits better achieve their goals of social betterment and that volunteer data scientists can be useful for non-profits even in short-term projects.

In this section I show that the promise of data science, either as a set of data practices or in the form of volunteer data science projects, faces major difficulties in being achieved in practice in the UK non-profit sector. My analysis indicates that the way data science is meant to be useful for non-profits rarely matches their existing capabilities or helps them in demonstrating the value of their work. Although the interviewees are found to see data science as a particularly advanced and sophisticated form of data practice, therefore giving it an aura of high epistemic value, in practice, this is not found to lead to non-profit organisations necessarily becoming any more successful in their work or in prevailing in disputes about the value of non-profit work.

I begin my analysis by discussing insights from interviewees who worked for DataKind UK and therefore could be expected to have special insights about the opportunities and limitations of data science in the UK non-profit sector. In addition to being enthusiastic about the opportunities provided by data science, all three interviewees from DataKind UK who participated in the study voiced critical remarks on the challenges they faced and their implications for the value of data science. They reported an abundance of volunteer data scientists but faced a bottleneck when trying to find good uses for this supply of technical expertise.

In the following passage an interviewee who worked in a leading role at DataKind UK reflects on whether data science is useful for non-profit organisations. Having a leading role at DataKind UK meant that they were a keen promoter of data science and had seen numerous examples of data science projects with non-profit organisations. The fact that DataKind UK promotes the use of data science gives weight to the critical remarks made by the interviewee since they go against the organisation's public message. Any non-profit organisation working with DataKind UK is likely already to have a special interest in new digital and computational data practices and may be expected to value the contribution it can make to their work. Yet in the following passage the interviewee is open about the challenges of introducing data science to non-profit organisations.

> *"Our problem was actually finding projects that needed data science because honestly, most UK charities just needed help better understanding the data they were collecting in really basic ways. They did not need machine learning. There was always a bit of a discrepancy between the skillset of the volunteers and what the [charities wanted]. Also, the volunteers wanted to do something technically interesting. They were volunteering, whereas what charity needed was help cleaning up their self-support database. "(Interviewee 19, Senior manager, Facilitator organisation, Female, 5+ years of relevant experience)*

The passage suggests a tension between technologically sophisticated volunteers who are experts in data science and what non-profits needed. According to the interviewee, actual data science skills were not necessarily something that non-profits were looking for or capable of using, although they were interested in data. In contrast, the interviewee suggests that the data science volunteers were keen to do something that would be "*technically interesting*," which could be too sophisticated for non-profits. The quote suggests that the techniques volunteer data scientists claimed to be valuable were beyond what was relevant for many non-profits given their capacity. The elements of sophistication, novelty, and innovation that would demonstrate value for data scientists might catch the attention of non-profits but not fit their needs. Whether this was due to lack of resources or lack of perceived value in pressing practical debates frames the problem in different ways, but both suggest that the level of sophistication that data scientists worked at was not relevant for most non-profits.

A complementary perspective on the problems of a data science is present in the following quote from the same interviewee, this time describing a successful case of data science volunteering. The interviewee describes how one of their first major projects at DataKind UK involved a large social service sector non-profit organisation, with whom the interviewee worked over an extended period of time. The organisation already had extensive databases, especially digital text data and transactional service data, and wanted help in analysing them because they had little prior experience of doing so.

> *"We produce all kinds of really nice snazzy prototypes and dashboards. We pulled in their data from those two different places and put it into one place and showed them analytics for the first time. It wasn't complicated data science, but it was just solid. You've got good data, let's put it together and show you, let's see what's in it."* (Interviewee 19, Senior manager, Facilitator organisation, Female, 5+ years of relevant experience).

The interviewee describes the project as a success that produced useful insights for the client. Nevertheless, the success is not located in the sophistication of the data science techniques, which is what DataKind UK promotes: "*it wasn't complicated data science, but it was just solid*." This assessment suggests that even if the volunteers might also have used more sophisticated techniques, they tempered their aspirations and worked with more basic data analysis techniques. They opted for something that was useful for the non-profit rather than what the volunteer would find exciting. Yet they did establish a new methods assemblage that includes new ways of collating, reporting, and visualising data already collected by the organisation, therefore allowing digital and quantitative data practices to change their way of working. This suggests that the use of these less sophisticated techniques could deliver new and relevant knowledge according to the needs of the non-profit, despite not being the most advanced tools from the perspective of the volunteers. If interpreted in conjunction with the previous quote, the interviewee seems to suggest that it would not have been useful to push the non-profit to adopt latest computational tools just for the sake of it. This example is important because it signals that the value of quantitative data is always situated and relational, and that even interviewees who had a vested interest in promoting data science could take pride in projects when they were valuable on their client's terms rather than providing an instance of the most powerful uses of the supposedly useful data science.

Another interviewee working in DataKind UK in data science volunteering reflected on this challenge by using a metaphor of a white elephant. The interviewee was participating in data science volunteering projects and held a position of leadership within the community. They had PhD-level training in natural sciences, which gave them skills in statistical programming and data management beyond most of the other interviewees in the study. In the following passage, the interviewee discusses how DataKind UK had to decide what to do in response to the rising hype around Artificial Intelligence (AI), and how their approach reflects the interviewee's broader approach to use of data science in the non-profit sector.

> *"We actually had some soul searching about whether we should rebrand or whether we should use AI in our funding applications. The reality is that we generally find that the most impactful solutions are ones that are*

> *understood by the people who are trying to apply them. Otherwise, you're passing over a white elephant. [--]. This white elephant is a large, and expensive, and splendid, but totally useless thing, which becomes a massive burden. Basically, there's a tendency to try and apply the sexiest, newest technique, the best algorithm you can. Something that you maybe want to try to work, but you haven't found a use for it yet, you're like, "Yes, I can totally apply this to this charity's problems." It's almost always overkill. If it's not understood by somebody in the beneficiary organization, then it's going to die." (Interviewee 7, Data Scientist, Facilitator organisation, Male, 2 years of relevant experience)*

The quote demonstrates a discrepancy in data scientists' interest in the latest tools, portrayed by the AI white elephant metaphor. Again, data scientists might have an interest in applying "*the sexiest, newest technique*," which indicates that the data scientist is likely to be interested in the novelty and innovativeness of a solution rather than what is relevant and needed by the organisation. The sophisticated new tools that interest individuals with a high level of technical expertise can be burdensome to their users. Applying the "*best algorithm you can*" might not be understood by non-profits. The use of these tools can be an "*overkill*," suggesting that they deliver much more than what is needed.

Interviewees working for DataKind UK were not the only ones commenting on the mismatch between sophisticated tools and the needs of non-profits. Several other non-profit data professionals offered opinions on the use of sophisticated tools and data science volunteering. An interviewee who worked in a large non-profit sector consultancy and had extensive experience in digital innovation commented on their impressions of data science volunteering by saying that "*The big problem [--] was the capacity within organizations to do anything with their pro bono support. [many organisations have] no ability to do anything with its findings or embed that into their ongoing processes*. (Interviewee 25, Principal consultant - digital innovation, Facilitator organisation, Male, 10+ years of relevant experience). Just as in the above quotes, the interviewee recognises the lack of traction of the solutions proposed through data science volunteering. The interviewee identifies problems with both the insights provided by data science volunteers and the ability of non-profits to put them into practice in their work.

A different wording of the same perspective comes from another interviewee who worked in a data consultancy and held a leading role in the Data for Good movement in the UK: “*Well, our experience is, there’s data science and algorithms, and artificial intelligence, but most people are just struggling to make sense of their one hundred spreadsheets in an organization. There’s a huge gap.” (Interviewee 27, Senior manager, Facilitator organisation, Female, 15+ years of relevant experience).* This quote explicitly acknowledges that the newest computational technologies might not match the needs and capacity to use data in non-profits. The interviewee seems to suggest that the methods assemblages of digital data collection used by most non-profit organisations are a far-cry from the digital infrastructures and statistical programming techniques that underpin latest developments in data science. In other words, they suggest that most non-profit organisations do not have the technological foundations to build methods assemblages that would leverage new techniques in data science. According to yet another interviewee, work with data science in the non-profit sector “*should be mainly about myth-busting. [--] There are definitely possibilities in those spheres, but people must get the basics right first before you can think about what machine learning might be adding to a process*.” (Interviewee 5, Product Lead, Facilitator organisation, Male, 10+ years of relevant experience). In the context of the interview, the “*myth-busting*” suggests the need to discriminate what is just hype, what actual benefits sophisticated new techniques can offer, and what needs to be in place for those benefits to materialise.

A third interviewee reported hearing that data science volunteers are often “*frustrated*” (Interviewee 1, Civil Society Data Officer, Facilitator organisation, Female, 4 years of relevant experience) with the mismatch between what they think is valuable and what is realistic for non-profits, because “*there is such a mess that they have to spend all their time just cleaning their data and hardly doing anything exciting*.”

(Interviewee 1, Civil Society Data Officer, Facilitator organisation, Female, 4 years of relevant experience). The quote includes references to several themes discussed in this section. On the one hand, it recognises the "*mess*" of poor data practices as an obstacle. On the other hand, it addresses how the interests of data science volunteers can be focused on what are "*exciting*" techniques. However, what experts in data science find "*exciting"* might not be particularly useful for non-profits. The problem with lack of demand for sophisticated analysis was recognised beyond data science volunteering. An interviewee working with professional statisticians volunteering for non-profits explained that they "*hear a lot of [volunteers] say, "Oh, this is not statistics. This is not what they would do on a day-to-day. [--] They're using potentially 2% of their skills to what the organization is asking. (Interviewee 26, Member Engagement Manager, Facilitator organisation, Female, 5+ years of relevant experience).* Like the interviewees commenting on data scientists, this interviewee suggests that the techniques cherished and used by professional quantitative analysts tend to be beyond what is relevant for most non-profits, at least in this study. In other words, it seems that quantitative data practices that would be considered epistemologically superior by professional analysts do not necessarily find their way to the sector due to the lack capacity and demand. The interviewee appears to suggest that even when skills to perform such analysis is available through volunteering schemes, non-profit organisations might not try to make use of it.

I suggest that the above analysis, combined with an understanding that the value of data can be treated as part of a variety of normative disputes, offers evidence on why sophisticated computational technologies do not always find much use in the non-profit sector at least at the time of writing. The mismatch between sophisticated data science and the needs of non-profits suggests that people who try to bring their technical skills in computation to the service of non-profits might *value* different things than non-profits. Experts in data science might be interested in the technical innovativeness of computational tools, but such perceptions of value might not be shared more widely in the non-profit sector. Nevertheless, the innovativeness and sophistication of the new techniques might be beside the point for non-profits that are engaged with practical questions that riddle their work. To tackle these questions with digital and quantitative data practices might not need the introduction of methods assemblages that underpin sophisticated data collection and analysis in other contexts. It therefore appears that non-profit data professionals and other professionals in the UK non-profit sector do not have a shared understanding of the epistemic value assigned to specific methods assemblages. Whether some methods assemblage is more advanced than another might be relevant for some non-profit data professionals, but for other people with a different understanding of their value such differences might have little meaning.

6.7. Conclusions

In this chapter I have analysed the way non-profit data professionals in my study demonstrate value with recourse to quantitative data in epistemic disputes. Based on the analysis I suggest that specific ways of collecting and analysing data are among many different methods assemblages to enact versions of reality and establish which claims have greater epistemic value. What Data for Good initiatives and non-profit data professionals are shown to want to achieve is for non-profits to embrace these ideals about the value of data. By doing so they echo ideals that are familiar in Critical Data Studies research on the potential of data to induce innovation and improvement which, as a narrative, can be somewhat distinct from the practices relating to use of data (Beer, 2016; boyd & Crawford, 2012; Elish & Boyd, 2018; van Dijck, 2014). They also echo the long history of quantitative measurement being claimed to be more objective and rigorous than other forms evidence (e.g. Porter, 1995; Desrosieres, 1998).

However, my analysis emphasises that the value of data in the non-profit sector is not established solely by whether it is thought to offer stronger or weaker evidence in epistemic disputes. The value of data is also assessed by whether it provides opportunities to succeed in other situations of dispute that non-profits face, as discussed above. Based on the analysis of the interviews with non-profit data professionals, a small number of situations appear to dominate the concerns of non-profits. These situations guide what data non-profit data professionals report they believe to be important and useful. The analysis does not provide sufficient evidence to define an exhaustive list of such situations, but recurring themes have been identified. The interviewees strongly suggest that applications for funding and the management of services are among the situations that non-profits must constantly deal with. The influence of NPM and EBP seems substantial in these situations. Because these macro-level trends have reshaped the institutional, political, and cultural landscape of the UK non-profit sector it has also influenced what kinds of doubts and requirements non-profit organisations are faced with. The way quantitative data is used in the non-profit sector is influenced by expectations and needs shaped by these macro-level trends. To further explore the value of data in the non-profit sector, in the following chapters I turn to these situations and the way this kind of data is valued in them in situations of acquiring funding and the situations of managing non-profit work.

The findings of this chapter also offer insights on the limitations of data science in the non-profit sector. I have shown that data science is often misaligned with the concerns of non-profits. Even interviewees who specifically worked to promote the use of data science explained that they faced constant challenges in finding uses for data science. The way these interviewees were found to understand the value of data aligns with what Gabrys, Pritchard, and Barrett (2016) call "good enough data", by which they mean data that might not comply with scientific standards, but is rigorous enough to help citizens and civil society organisations to engage with governmental and regulatory stakeholders with the evidence that they are expecting. The findings also align with earlier research on the role of social and cultural factors in shaping what counts as "good" or useful data (e.g. Cruz, 2023; Garnett, 2016; Kennedy & Hill, 2018). Likewise, the reflection by non-profit data professionals on the shortcomings and weaknesses of the use of quantitative data suggests that they display an element of critical awareness about their practices, similar to what has been called for in earlier research on civil society uses of data (Fotopoulou, 2021; Gray et al., 2018; McCosker et al., 2022). My analysis of the sample of interviewees provides little indication of a radical techno-solutionist agenda pushed by global technology corporations as seen in the humanitarian and development policy context, however. While some of the interviewees were keen to promote technological innovations, most prominently those working for DataKind UK, even they indicated that they did not see data science as a solution that would in itself address the social challenges of the non-profit sector or radically transform the non-profit sector's ability to achieve its goals.

Finally, I reflect on these findings given the unique nature of my sample. The way of valuing data I revealed in this chapter was common among the non-profit data professionals interviewed for my study. However, this group is but a small fraction within the larger population of people working in the non-profit sector, and they have unique professional interests related to their focus on quantitative data. Their valorisation of data might not be shared beyond non-profit data professionals. Indeed, in this chapter I have shown how it was common for the interviewees to report that non-profits are "behind" in their work with data and that a "cultural shift" is required to make non-profits place more value on this kind of data. This suggests that non-profit organisations and those working in the sector do not necessarily share the appreciation of the epistemic value of quantitative data held by my interviewees for assessing the strength of claims they need to make. I suggest that this is the reason that the non-profit data professionals in this study placed so much emphasis on a need for a cultural shift towards a greater appreciation of quantitative data: all non-profit organisations face epistemic disputes in their work, and the interviewees aspire for these disputes to be solved with this kind of data.

Chapter 7:
“You’ve got to bring the data to be able to write your papers” - Data and disputes over funding

7.1. Introduction

In the previous chapter I showed that the non-profit data professionals in this study tend to promote a specific way of valuing data as a resource in epistemic disputes. Yet non-profits cannot limit themselves only the epistemic concerns. They must also focus on how data may help non-profits to deliver on their goals of social betterment. In this chapter I focus on the role of the use of quantitative data in awarding grants in the non-profit sector, which according to the interviewees is one of the most important uses of data. The analysis shows how disputes over funding are entangled with epistemic disputes, which place data in a central position in assessing the credibility and trustworthiness of the claims made by grant applicants. The findings contribute to answering two research sub-questions: “*In what situations of dispute do data practices justify value*” and “*How is the demonstration of value entangled with methods assemblages in these disputes*.”

Although non-profits do not generate profits, they need money to organise operations, cover expenses, and ensure the continuation of their work. Non-profits proactively seek funding through donations, grants, and contracts to fulfil their mission of social betterment. The total income of the UK non-profit sector in financial year 2019/2020 was £58.7 billion, up 3% from the previous year (National Council for Voluntary Organisations, 2022). Nevertheless, non-profits are not in equal positions to receive funding. Donors, philanthropic foundations, and governmental funders value some causes over others. Some non-profits have seen their revenues grow whereas for others they diminish. This makes it imperative for non-profits to *demonstrate their worthiness of funding*. Successful demonstrations of worth can help non-profits receive grants and donations. Organisations with lacklustre demonstrations may not make the cut to receive grants.

The chapter focuses on the process of awarding of grants. I analyse the use of quantitative data in grant-making and grant applications as a situation of dispute where grants are awarded based on how well applicants can demonstrate value with data. The goal of is to identify different ways that non-profit data professionals understand the value of data in justifying why they should receive funding, and to analyse the objects that are enacted through data practices.[19]

The chapter identifies three ways that data practices are used to demonstrate value in disputes about funding. Data practices will be shown to enact different objects that demonstrate value. On the one hand, the uses of quantitative data can serve as a demonstration of accountability regarding how a grant is used. On the other hand, data can be used to demonstrate that the work of a non-profit has a real impact on the lives of the people they help. Lastly, data is used to demonstrate the need for interventions. In each of these cases data is used to enact different objects and demonstrations to buttress the claims that one is worthy of money.

[19] By choosing the application and awarding of grants as the empirical situation I exclude some other situations that also display tests of worthiness of money. The chapter does not analyse soliciting donations directly from the public. The relationship between a single grant-giver and a handful of applicants is likely very different from the relationship between a single charity and a thousand small donors. The process of assessing worthiness in such situations might be expected to follow different conventions than in a grant-giving situation.

The observation that data plays a key role in grant-making is not a surprising finding. Much has been written about reporting practices in grant-making and effects of NPM, which I have reviewed in Chapter 3. Non-profits increasingly frame their work as product-like projects that can be “sold” to grant-givers and “bought” by funders, with the ability to quantify results playing a key role in designing projects (Krause, 2014). Thus, the findings in this chapter align with earlier work in the UK and abroad indicating that eligibility for grants and contracts often requires non-profit organisations to adopt extensive reporting systems.

My analysis elaborates on the way the justification of epistemic value intersects with the need to justify non-profit work to grant-makers. Based on my analysis, I suggest that the ideals of achieving complete trustworthiness and certainty through the use of quantitative data cannot ultimately be achieved, despite this sometime being suggested by actors involved in the non-profit sector. My analysis highlights how increased use of quantitative data and data analysis in grant-making rather can produce new forms of uncertainty and tension. Nevertheless, the ideals of trustworthiness and certainty work to sustain power asymmetries in the non-profit sector, as discussed in Chapter 3. Here, I show that while my interviewees were keen to recognise that power asymmetries create challenges, these concerns are compartmentalised from their claims of the transformative potential of data. As a result, the proponents of Data for Good initiatives and the interviewed non-profit data professionals see various quantitative reporting requirements as “bad” data practices that distract non-profits from the “good” data practices that the interviewees want to promote.

7.2. Data and uncertainty in disputes over funding

A grant-giving situation has two sides: an organisation awarding the money and those who apply for money. To determine which organisations should be funded, grant-maker must put non-profits into some order. This makes grant-giving a situation where value is in dispute and needs to be demonstrated in the way conceptualised by Boltanski and Thévenot (See Chapter 2) and empirically analysed in Chapter 5. In this chapter I define grant-giving as a situation of dispute insofar it involves the assessment and ranking of claims about why an organisation should receive a grant. Based on the analysis of the interviews, data practices are highlighted as a key component of how applicants can make a case for funding for grant-makers.

The following quote is an example of how the value of data for funding applications was brought up by an interviewee from an organisation supporting non-profits in using data. The interviewee worked as a manager for an organisation specialising in helping small non-profit organisations use data as part of their work. She was a woman in her forties, worked as the manager of the non-profit, and had over a decade of experience in helping non-profits with questions of digital technology. However, in the recent years their focus had shifted to helping non-profits with data-related practices. In the interview, acquisition of grants was presented as one of the most important things small non-profits might do with data:

> *"It might be that you're just using that data to source funding, to expand your service. You prove that there's the need, and you prove that you're an effective delivery organization. Because you can show that you've been fronted to do some other work and you've been effective. You can show the evidence, outcomes." (Interviewee 2, Manager, Facilitator organisation, Female, 15+ years of relevant experience)*

The quote provides an illustration of non-profit data practices to justify their worthiness of funding. The use of quantitative data is here configured as evidence on how well a non-profit is doing its job. Data presented as a form of evidence appears in the quote as part of a practice aimed at demonstrating that the non-profit has qualities that should be desirable to someone considering who should receive funding. In other words, the interviewee recognises the epistemic value associated with data (see Chapter 5) and connects it to grant-making practices. The interviewee suggests that it is not enough just to be effective or to identify a need to be tackled, but to "*show the evidence*" and "*prove*" it by collecting and analysing data. The passage implies that funders take enactments using data practices to be more credible than enactments using other types of methods assemblages.

The contingent role of data practices in demonstrating worthiness of funding can be found in the following quote from a senior-ranking interviewee in a data consultancy that played a leading role in the Data for Good initiatives. The interviewee was a woman in her forties and a founder of the organisation. The interviewee and their organisation promoted the use of data and offered data-related services for a fee. This gives them an economic rationale for promoting the use of data in addition to more altruistic goals of helping the non-profit sector. In the following passage, the interviewee describes that it is not a given that a grant-maker would be swayed by quantitative data.

> *"If there's a funder that wants evidence and that's how he makes his funding decisions, then data will change that dynamic. If it's a funder that wants to feel good, then data won't change that. The data is only relevant if the funder cares about the data. [--] I'm not being especially critical of funders. I think it's just a reality that funders have all sorts of different motivations and evidence is only ever a part of that mix." (Interviewee 29, Senior manager, Facilitator organisation, Male, 15+ years of relevant experience)*

The interviewee argues that data-based justification only changes the outcome of funding calls if funders care about data. They suggest that the value of data as a form of proof is not a given. In the words of the interviewee, "*funders have all sorts of different motivations*" that guide their decisions. When assessing the fitness of applicants against those motivations, quantitative and digital data collected by the applicants might or might not play a role. In the words of the above interviewee, "*If it's a funder that wants to feel good, then data won't change that.*" This quote acknowledges that funders have their own rationales to determine who is worthy of their money. Yet this interviewee seems somewhat sceptical of funders who do not value data, questioning their motivation to do so as "*feel good*." The words of the interviewee may imply that there is something suspicious about other motivations that might be interfering with the epistemic aspects of demonstrating the worthiness of funding.

Nevertheless, even if grant-makers do ask for quantitative data as evidence from applicants to support their applications, the applicants might not provide it. What should grant-makers then do in such a scenario if they are committed to the ideal that data provides the best 'proofs' of the claims made by applicants?

This problem was addressed by an interviewee working as the head of community investment in a small place-based grant-maker. Being place-based means that the activities of the organisation focus on a single geographic area which, in this case, is a specific London borough. I conducted two separate interviews with members of the organisation. The following passage is drawn from my exchange with the head of community investment on whether grant applicants comply with the expectation of the grant-maker that applications should be backed up with data. The head of community investment was an older woman who had over a decade of experience in the UK non-profit and development sectors.

> *Researcher: Do you get this kind of information from the people who apply for the money? That they would show that, okay, there is this kind of survey or series of interviews or some other research?*
>
> *Interviewee 12: We do get some of it. We do get some. It depends on the organization, and it also depends on the subject area, as to whether that information is available. I think, generally speaking, charities don't tend to use data and evidence as much as they possibly should. That we have a question in our application form that reads, 'please provide the evidence that this intervention is needed.' In a lot of cases, they will not provide data to back up the application [--] but we're always flexible because we are based in [the locality], and we know [the locality], we have a good grasp on what the issues and the needs are. It won't knock*

an organization back. For example, if an organization would like a grant to work with an NRPF[20] clients in [the locality], and they can't find the data on the NRPF, we wouldn't go back to them and say, 'We're rejecting your application because you don't have it.' We would say, 'We know that this is an issue even though we don't have the data.' (Head of Community Investment, Grant-giving organisation, Female, 25+ years of relevant experience

Here, the interviewee suggests that although the grant-maker wants applications to be backed up with data and evidence, it can sometimes relax this requirement. Specifically, the interviewee refers to their local knowledge and experience of tackling social issues as a resource that allows applicant claims to be judged even when no quantitative evidence is provided. This is important for the arguments of this chapter because it illustrates how the grant-maker uses its independent judgement about the trustworthiness and credibility of the claims made by the applicants. The grant-maker may deem claims credible if they use alternative sources of evidence to confirm the issue is real and needs attention. An example given by the interviewee is that if an applicant wants to help immigrants in a precarious position, acquiring quantitative data on this group is particularly difficult and the interviewee would consider it an unnecessarily stringent requirement to demand this kind of data under such circumstances. In other words, the grant-maker in this case appears to prioritise how well the organisation overall demonstrates its worthiness for funding, rather than tightly coupling this with a specific way of demonstrating epistemic value.

The analysis confirms that data practices are closely associated with the grant-making practices in the non-profit sector, as is indicated in earlier research (see Chapter 3). Furthermore, my analysis suggests that data practices are connected to the credibility of the claims made by non-profit organisations, thus introducing the

[20] NRPF refers to a type of immigrant status and is short for "No Recourse to Public Funds", which means that this type of immigrant is not entitled to most social and health benefits usually available for UK citizens. Because of their tenuous position, little formal statistical information is collected or available on this group.

assessment of epistemic value into the grant-making process. The above interviewees report that they assign greater epistemic value to quantitative and digital data practices than to those claims that are not backed by such data, and that using data practices to support grant applications can make a difference between success and failure. The analysis suggests that assessing worthiness of funding is closely entangled with the epistemic worthiness of the claims made by applicants.

However, it is important to remember that using quantitative and digital data practices does not in itself close disputes over worthiness. In Chapter 6 I showed that even strong claims to epistemic value are marked by uncertainty and tensions when the provenance of data is considered, and new evidence is presented. Data practices are a resource in disputes over worthiness of funding, but do not put an end to the disputes. Indeed, there seem to be uncertainties and tensions that undermine some of the ideals of epistemic value that undergird the expectation that grant-making should be use more quantitative data.

A common worry among my sample of non-profit data professionals was that data can be used to game measurement systems. This was believed by some interviewees to degrade the original purpose of using quantitative data. Gaming here referred to the use data to superficially satisfy formal requirements while knowing acknowledging that the data used to do this offers a misleading or one-sided view of an issue it seeks to portray. If the goal of using data is to achieve greater levels of certainty in epistemic disputes and accurate knowledge about the world, gaming the numbers undermines this goal. As I show below, the problem of gaming in disputes about funding is important because it indicates that increasing the use of quantitative data *does not necessarily lead to the goal of increased certainty and credibility in epistemic disputes*.

In the following passage, an interviewee working as a learning and evaluation manager in a large grant-maker organisation discusses the problem of overclaiming in the non-profit sector. Throughout the interview they had painted a mixed picture of the benefits and burdens of data practices. However, in the following quote the interviewee introduces an element of epistemic uncertainty into data use by grantees and frames this issue through the question of *morality.*

> *"I have a wider moral point that the charity sector overall vastly overclaims, and over time that undermines the very trust and credibility of the public about charities because they see all these huge numbers going out and yet the need is so great, so what have you actually been doing if you've supposedly helped three million people or whatever?" (Interviewee 34, male, funding organisation)*

In this quote the interviewee frames the problems of overclaiming and mistrust as something that is morally wrong. Even if data analysis portrays a large *size* of impact, which is desirable in demonstrating worthiness of funding, this claim might not have *credibility* if there are questions about the measurement and the data backing up the claim. According to the interviewee, misleading numbers undermine "*the very trust and credibility*" that non-profit work relies upon for its legitimacy. What the interviewee seems to want is truthful and trustworthy claims of impact, which can be undermined by unreliable uses of quantitative data. Importantly, the credibility of demonstrations is here interpreted as a moral issue, implying that fidelity to accuracy is something that should be valued for its own sake. Furthermore, in the wider context of the interview the moral problem of overclaiming is linked to the legitimacy of non-profit organisations as recipients of funding. The organisation the interviewee was working for gained most of its funding from donations from the public that were then used to give grants for other non-profits, which made the organisation reliant on public trust. To uphold this trust, the person was worried that overclaiming would undermine this trust, which encouraged them to be careful with the claims made by their grantees. In other words, achieving high epistemic value in grant-related claims was framed by the interviewee as a question of public morality, not just a problem arising when evaluating individual applications.

In the following sections I analyse how epistemic uncertainties play out in specific instances of non-profits using data practices to demonstrate worthiness of funding. The analysis focuses on three aspects of what non-profits enact when trying to demonstrate their worthiness: accountability, impact, and needs. I show that epistemic uncertainties play out in different ways depending on what non-profits try to enact. I look into the quantitative and digital methods assemblages that are used to demonstrate worthiness of funding, and how methods assemblages shape how this worthiness can be demonstrated. Furthermore, I suggest how power asymmetries sustain uncertainties and lead to the paradox that quantitative methods assemblages are both criticised and appreciated as an epistemic resource when demonstrating worthiness of funding. As will be shown, some methods assemblages are also more central to demonstrating worthiness of funding in specific ways, which leads to differences in how important those methods assemblages are for non-profit data professionals in my sample.

7.3. Demonstrations of accountability

When experts of non-profit data interviewed for this study discussed the use of data, they often identified reporting requirements of funding bodies as the most prevalent motivation to adopt data practices and collect a particular kind of data. This aligns with earlier evidence on the pressure from external stakeholders often being the driving force behind quantification, as discussed in Chapter 3 (e.g. Hall et al., 2015; Moxham, 2010). Grant-makers in the UK and globally are under pressure to show that the money they raise from the public is used efficiently and with integrity (Barman, 2007; Krause, 2014).

For example, an interviewee who had over twenty years of experience working in the non-profit sector and who held a leading role in a non-profit data consultancy that was central to the Data for Good initiatives explained that "*there's always been a real grind for organizations around monitoring and evaluating their work because they have to report externally, usually to funders or regulators. That's been there forever*"

(Interviewee 28, Senior manager, Facilitator organisation, Female, 20+ years of relevant experience). This interviewee not only suggests that quantitative monitoring requirements set out by external funders are common, but that it is a "*a real grind*" that has "*been there forever*." The wording suggests that using quantitative data for reporting has both a long history and demands constant attention and resources. A similar message was given by an interviewee in a small non-profit that organised trainings and events to help other non-profits to get started with developing their data practices. This interviewee had over a decade of experience in working with non-profits on digital technology, with digitised data being a recent new focus area, but the interviewee observed that "*reporting back figures to funders as funding reports [--]- is obviously a priority for groups. Because they need to." (Interviewee 2, Manager, Facilitator organisation, Female, 15+ years of relevant experience)*. The importance of using quantitative digitised data for external reporting is here framed as a priority over other kinds of data and other ways of using it. The interviewee also suggested that non-profits have little choice if they want to receive grants and contracts from funders that require extensive reporting.

Accountability was highlighted by several interviewees as driving the requirement for monitoring and reporting. The term accountability was used especially by those interviewees working with or for funding bodies. One interviewee working for a non-profit organisation that advised other non-profits on transparency in grant-making, which gave them a wide understanding of how grant-makers work, noted that "*I come from the grant-making world [--] from what I understand, [use of data is] very much driven by government, driven by transparency and accountability concerns* (Interviewee 6, Support & Engagement Manager, Facilitator organisation, Female, 10+ years of relevant experience). Accountability is here linked to the need to be transparent, i.e., for the details of non-profit work to be visible and legible for external actors. Funders often require non-profits to collect this kind of data so that they can monitor what was done with the money.

Interpreted though the lens of my conceptual framework's emphasis on enactments and justification, the above quotes show how non-profits demonstrate worthiness of funding through demonstrations of accountability using a variety of quantitative data practices. When grant-givers award money, they want to make sure that the recipient spends the money as promised. To achieve this, they demand justification for the claims made by applicants. Successful demonstrations of accountability mean that funders are more likely to trust the recipients to handle the money they have been given. Failure to comply with the requirements for demonstrating accountability is likely to raise questions about the propriety of the organisation.

But what kind of data do organisations submit as part of such reporting? I next dive deeper into the materiality and provenance of the data that is submitted to grant-makers.

The following analysis draws from two interviewees in the same organisation, both working in a managerial position relating to the use of data in grant-making. In the passage below, the interviewee who works as an evaluation and learning manager in a large grant-giving body describes what reporting requirements they have for their grantees. Throughout the interview he emphasised that reporting should not be too onerous. In the passage the interviewee describes the way they try to achieve a "*light-touch*" approach to reporting

> *"We have very light-touch reporting. It's basically what have you done, what's been successful, what have been the challenges and some safeguarding and governance aspects at six months. Then at 12 months, we ask for a report against their outcomes and in those 12 monthly reports, we ask for basic activity plans, what are your top 10 activities that you're likely to be doing over the next year, not as a rigid thing to absolutely hold them to delivering because, again, we know, things will change, they might realize two months in that 50 needs to change. That's fine as long as I can explain that. That's the only level of output data we ask for [--].* (Interviewee 34, Evaluation and Learning Lead, Grant-giving organisation, Male, 15+ years of relevant experience)

The interviewee emphasises that every six months the organisation wants grantees to report "*what have you done*" and general information on how their work is faring. This does not necessarily require numerical data. Nevertheless, in the context of the interview it was clear that the grant-maker expected some quantitative data to be included in these reports. Furthermore, once a year the grantees must submit a report that focuses on their "*activities*." The description of what these activities might be is somewhat vague, but again it suggests that they focus on what an organisation has done, which does not automatically call for quantified measurement.

However, elsewhere in the interview the interviewee was clear that they very much expected grantees to have a formal measurement system at place and report to the grant-maker at regular intervals. In fact, the interviewee was happy to give examples of what kinds of quantitative data they would expect from the grantees as part of this learning and reporting.

> *"What we do ask for is outcomes and indicators. It will be, for example, mental health, quite a few organizations might use the Warwick and Edinburgh Mental Health and Well-being Scale with their beneficiaries. They would use that and have a series of indicators around beneficiaries' improvements to their mental health. For homeless projects, for example, it may be how many homeless people a shelter is able to refer on to other specialist services, and how many of those referrals are actually taken up, or how many homeless people they've been able to support into employment or whatever it may be, whatever the project is looking at."* (Interviewee 34, Evaluation and Learning Lead, Grant-giving organisation, Male, 15+ years of relevant experience)

In this passage the reporting requirements have a decidedly data-driven form. The interviewee even discusses what "indicators" the grantees use to measure outcomes in the area of mental health and homelessness.

One of the indicators mentioned here is the Warwick and Edinburgh Mental Health and Well-being Scale, which is a questionnaire developed by academic researchers and consists of 14 discrete items that together produce a single estimate score for individual mental wellbeing (Tennant et al., 2007). The framework was developed by researchers in the two eponymous universities and is widely used in the UK. If interpreted as a methods assemblage, this type of questionnaire-based indicator can be understood as enacting *individuals* that might have some level of mental health issues and therefore be classified as having mental health problems or indicate whether their symptoms becoming better or worse. Administering this test to beneficiaries requires systematic practices of data collection by front-line staff who need to have training in the application of the framework. Successful implementation also requires service process management that allows tests to be taken at regular intervals and stored securely given the sensitivity of the topic. Building a methods assemblage like this from a scratch is far from simple, which contradicts the view of the grant-maker that they take a very "*light-touch*" approach to measurement.

The other type of outcome data described by this interviewee is data on services for homeless people. In this case the measurement indicator is focused on whether and how individuals *use and exit* the service. The methods assemblage in this case consists of the front-line staff interacting with beneficiaries and records their encounters in a database. The other interviewee working for the same organisation elaborated on their data collection on homelessness, suggesting that they collect data "*not just [to] say how many people they've reached, but how many people have they managed to get into long-term housing? How many people have they supported to access training*" (Interviewee 35, Transparency and reporting lead, Grant-giving organisation, Male, 2 years of relevant experience). What is recorded by the grantees depends on how, and how often, a beneficiary might interact with the service, and the categories are determined by the desired outcomes of the service provider and the grant-makers. Furthermore, recording any outcomes of a service for homeless people requires that the organisation can ask these questions from people leaving the service, which is not a given for a target group like homeless people. As a result, although the data requirements described by the interviewee might seem relatively simple, they still require an extensive service management system to be in place and the system is prone to various challenges.

The demands for accountability have material consequences for the recipients of the grants. When grant-makers use their asymmetric power to push non-profits to adopt quantitative measurement, non-profit organisations must build the material and digital infrastructure for data collection. The materiality of data is a key theme in Critical Data Studies (Kitchin & Lauriault, 2014; see also Bowker & Star, 1999) and in the study of methods assemblages (Law et al., 2011; Ruppert et al., 2013) as discussed in Chapter 2. The following passage highlights what the adoption of a new system means from a practical perspective. This quote is from an interview with a person working as the head of services in a medium-sized non-profit organisation specialising in elderly people's services. This interviewee was interviewed twice for the study during the first stage of data collection. They explained that the organisation was required to adopt a new measurement system as part of new grant arrangements. The passage describes the shift in data collection mandated in a new contract between the organisation and a local government that was procuring services from them:

> *"We're going to go from a situation where [current funder] really don't require much data at all from us. Literally, what have you done? How many people have attended? That's pretty much it at the moment. We're going to change to a system where we will have to use an external database to put our detail or put our members information in and we will have to record every time we answer any inquiry or every time someone phones us, so everything literally. If someone sneezes, we're going to have to put it on a database because we will be measured on all of the things that the team currently do, but they don't record anywhere. (Interviewee 4, Director of Services, Service-providing non-profit, Female, 15+ years)*

The interviewee describes how the new reporting requirements go deeply into the fabric of the day-to-day operations of the organisation. The organisation had to adopt a new way of working with their beneficiaries to record the information to the new system. A key passage in the quote is where the interviewee describes that they will measure "*all of the things that the team currently do, but don't record anywhere*." This passage suggests that the focus of the new system is to generate data on work that the organisation is *already* doing. The services and help provided for the beneficiaries might not be changing much, but a new methods assemblage was built to enact what was being done for them. The data generated in this way can be used in various ways beyond reporting, which I discuss further in Chapter 7, but the interviewee suggests that the data collection requirements of the local council drive the configuration of the system.

The new system used by the organisation is called *Charitylog*, which is a proprietary system of a small private company that exclusively works with non-profit organisations in the UK.[21] According to the interviewee, implementing this system "*is a huge requirement on resources*" (Interviewee 4, Director of Services, Service-providing non-profit, Female, 15+ years). Getting started with the system required both money and work by staff-members. The interviewee explained that the level of detail for inputs to the system is high, and they will "*record every time we answer any inquiry or every time someone phones us*" (Interviewee 4, Director of Services, Service-providing non-profit, Female, 15+ years). This means that the interactions that were so far only known by the front-line staff will be recorded on the system according to features of the new database. The classification and descriptions were defined by the requirements of the funders as was explained by the interviewee. The information on beneficiary interactions logged by the front-line staff is what constitutes the *data* in the new system. The data that will demonstrate accountability to the funders is ultimately in the form of notes and records made by the front-line staff. This data is marked by all the uncertainties that accompany the record-keeping practices of the front-line staff and captures but a small part of the interactions with beneficiaries. Yet the system is expected to generate the data that will allow the organisation to demonstrate their accountability to funders.

The dynamics of accountability described here are recognised in earlier research. In the past few decades, audits and other systematic ways of requiring demonstrations

21 https://www.charitylog.co.uk/

of accountability have grown from isolated experiments into *de facto* standards for how trust and distrust are negotiated between and within organisations (Power, 1999, 2000; Strathern, 2000). The non-profit sector has faced internal pressure to adopt data collection for accountability (Barman & Maclndoe, 2012; MacIndoe & Barman, 2012). Monitoring techniques in relation to accountability are particularly prevalent in the UK, where government service contracting has forced new measurement systems onto non-profits (Alcock, 2016).

My analysis deepens these insights by highlighting the tensions in how demonstrations of accountability become entangled with epistemic disputes about what constitutes credible proofs of accountability. When grant-makers call for data for accountability purposes, they typically subscribe to the view that certain kinds and configurations of data are more reliable forms of evidence than other epistemic resource. My focus on methods assemblages stresses that even such data is ultimately constructed through the interactions between front-line staff and clients, are translated into the recording of encounters in an electronic system that invites information to be inserted in specific pre-defined ways. Because data plays a fundamental role in ensuring accountability, the idea of accountability itself has come to be shaped by quantitative data practices. When accountability data is interpreted through the concept of methods assemblages and enactment, specific types of data not only operate as a demonstration of epistemic value but also *enact* a version of the organisation as accountable. When accountability is understood to be measured with certain types of data, accountability becomes what the methods assemblages enact. However, as I have argued in Chapter 5, data practices never offer the final proof of epistemic value, but a resource in epistemic disputes which leaves any claim of accountability still susceptible to critique and doubt regarding the details of those data practices.

7.4. Demonstrations of impact

Most social sector charities try to contribute to social change. However, for well over a century there have been debates about the ability of UK-based non-profits to reach their goals of social betterment (Barman, 2007). Debate on the outcomes of non-profit work carries on today and is intricately connected to the way grants and funding are awarded. *Impact* is a keyword that non-profit data professionals in my interview sample frequently used to discuss whether non-profits make a difference.[22] Furthermore, interviewees frequently connected impact to the grant-making and fundraising.

To begin this section, I give examples of how interviewees framed the connection between impact, funding, and data practices. One interviewee, who worked as a non-profit data consultant, noted that non-profits are "*trying to evidence the impact that they're having in order to gain more funding"* (Interviewee 28, Senior manager, Facilitator organisation, Female, 20+ years of relevant experience). Another interviewee working in a small grant-making organisation remarked that the non-profits they worked with "*want more data on their operations and the environment so that they can apply for funding and showcase the impact. (Interviewee 12, Head of Community Investment, Grant-giving organisation, Female, 25+ years of relevant experience).* A third interviewee, whose work focused solely on economic measurement of non-profit work, observed that "*[data] can be helpful in applications to trusts and grants. When [non-profits are] applying for it, they can say, "Look, we've got some evidence or this is our broad economic impact," then a number of funders can look quite favourably on that*.

[22] Impact is part of a larger lexicon of social change. Some interviewees made a strong distinction between impact, outcomes, and outputs. When such a distinction was made, impact was understood as more long-lasting social change that is difficult to measure. However, an analytical distinction between impact and outcomes was not present in all the interviews. Most interviewees used impact as the overall concept for the difference made by non-profit work. In this section impact is discussed using this general meaning rather than the specialist definition that gives specific meanings to impact, outcomes, and output.

(Interviewee 23, Chief Economist, Facilitator organisation, Male, 2 years of relevant experience). These quotes would appear to underscore the value of impact data in acquiring funding. They suggest that this kind of evidence on the difference made by non-profits is valuable information for funders. The interviewees suggest that being able to offer ‘proof’ of impact helps non-profits receive grants and funding. When numerical data is thought to offer stronger proof of claims, making claims of impact with data is deemed more credible in the eyes of the funders. Enacting impact with this kind of data lends credibility to the claims. As illustrated by the above quotes, funders increasingly expect non-profits to provide data on the impact and outcomes of their work.

For some interviewees, impact has become almost unthinkable without the use of numerical indicators. For example, one interviewee working as the head of data in a large for-profit consultancy specialising in non-profit organisations argued that “*You cannot think about impact without thinking data [--] Do you want to be able to prove whether you’re having a positive or negative impact?” (Interviewee 24, Data Lead, Facilitator organisation, Male, 5+ years of relevant experience).* This example was a particularly strong argument in favour of the use of quantitative data among the interviewees because it leaves little or no room for discussions on impact without quantitative data. As someone responsible for data-related services in a large non-profit consultancy, the interviewee can be interpreted as having a strong interest in tightly coupling quantitative data with impact, because this is what their commercial services are about. In arguing that this kind of data is essential for thinking about impact, the interviewee displays deep trust in the ability of the presentation of data to discriminate between stronger and weaker claims of worthiness. The quote offers insight into how quantitative data indicators help non-profits argue that *their* claims about impact are valid despite possible doubts. It implies that the measure of impact they are enacting is credible. Using this kind of data to enact proofs of impact and demonstrate the value of impact helps non-profits in my sample to settle debates by resorting to proofs and resources that are believed to be more accurate and credible than those made without this kind of data.

In other words, my analysis suggests that both grant-makers and applicants consider impact to be an important factor in demonstrating worthiness of funding. Furthermore, the need to demonstrate impact unfolds against a backdrop of non-profit impact being at times disputed and, therefore, in need of demonstration. This connects the demonstrations of impact back to assessing value in epistemic disputes (see Chapter 5). Thus, an element of epistemic dispute is entangled with disputes about impact. Applying my conceptual framework, data practices are expected both to enact versions of reality and to act as proof in epistemic disputes. Successful demonstrations must be considered trustworthy and 'truthful' if funders are to follow them in awarding funding, and they must counter doubt and uncertainty.

Against this background of quantitative indicators being expected to deliver more certainty and credibility, it was surprising that interviewees could be at times very *critical* of impact measurement. Indeed, there were signs of ongoing debate among non-profit data professionals about how much epistemic value should be assigned to quantitative data when it is used do demonstrate worthiness of funding. Interviewees who were active members in the Data for Good initiatives and enthusiastic promoters of an emphasis on quantitative data indicators in the non-profit sector also voiced scepticism when discussion turned to impact measurement. This observation is important because it illustrates how promoters of non-profit data engage with critical reflection regarding what they consider to be *better or worse evidence.*

Numerous examples can be given of the way interviewees were critical of impact measurement as part of grant-making. An interviewee, who worked as an evaluation and learning manager in a large grant-maker, and who was quoted in the previous sub-section, suggested that *"We try to avoid the term impact and we say to grantees, "We are not collecting your impact [data] because technically impact is way down the line. It's beyond your three-year program."* (Interviewee 34, Evaluation and Learning Lead, Grant-giving organisation, Male, 15+ years of relevant experience). The framing is negative towards the concept and measurement of impact. However, in the wider context of the interview this person was keen to collect *outcomes* data from their grantees. The demarcation between outcomes and impact was often unclear in my analysis, but for this interviewee there seems to be clear difference.

Yet another interviewee helping funders make better use of data echoed this message about uncertainties around quantitative measurement of impact. This interviewee was a data specialist in a non-profit organisation working with grant-makers to increase the transparency of their grants and help them make better use of data. They had extensive experience with Open Data and measurement in the non-profit sector prior to this position.

> *"The thing with impact is that everyone looks at impact differently within the trust and foundations. Specifically, impact, is something that can take, for your social scientist, can take years or decades [to happen]. Are we actually looking at outcomes and outputs, against what? It's not like a clinical trial for a vaccine."* (Interviewee 32, Product & Programmes manager, Facilitator organisation, Female, 5+ years of relevant experience)

The interviewee points out that there are considerable differences in how grant-makers consider impact and how they measure it. Here impact appears to be understood as something that is much larger scale than what a single organisation can achieve. Furthermore, by asking the question "*against what*," the interviewee opens a space for reflection on counterfactuals and points of comparison that are needed to assess whether something has improved. This framing suggests that it is possible to find a reference to epistemic disputes, with the interviewee considering large-scale measurement of social change over time as the proper yardstick for measuring impact rather than resorting to data collected on the level of an individual organisation. The interviewee's scepticism seemed to stem from their opinion that non-profit organisations are not able to measure impact to the standards that the interviewee would consider as evidence of *real* change.

The above analysis is theoretically important because it points towards an element of epistemic dispute in impact measurement. While the overall idea in Data for Good is that quantitative data is a superior source of evidence and helps non-profits secure funding, the problems with impact measurement highlighted by my interviewees suggest that data-based claims are not taken for granted. They suggest instead that the simplicity of ordering non-profit worthiness of funding according to data-driven demonstrations of impact is recognised by my interviewees as being potentially misleading. Nevertheless, all my interviewees who discussed this issue appeared to believe that the collection of quantitative data was crucial to understanding and demonstrating impact. Yet they were sceptical of quantitative impact measurement alone being able enact an accurate image of social change for funders. This doubt suggests that enactments made with this kind of data do not necessarily correspond to what is perceived as "real" impact. This observation brings us back to justifications and denunciations in epistemic disputes: the practices in the use of quantitative data do not close all disputes, although they may be sufficient to settle some individual disputes (See Chapter 5).

7.5. Demonstration of needs

A third way to demonstrate worthiness of funding is to demonstrate that there is a *need* for the work done by applicants. My analysis of the interviews indicates that to do so, non-profit organisations must enact a need and convince funders of its importance. Even if a funder already has recognised a general need a non-profit wants to address, applicants often must show that their work will reach a certain group or a location where that need exists. Under these circumstances success or failure in demonstrating needs is reported by the interviewees to influence which non-profits should get funded. The way articulation of social problems motivates the use of quantitative data in many non-profits is the topic of Chapter 7, but here I analyse these problems to illustrate further the role of value in disputes about funding. Earlier literature on the non-profit sector stresses that needs hold a central role in the self-understanding of charities and non-profits. NPM and austerity policies in the UK have led to increased inequalities along with decreased government funding for non-profit organisations (Alcock, 2016; Clifford, 2017; Smith, 2011) which has motivated charities and non-profits to call for more voluntary and donor-led action. Indeed, the identification of populations in need has become a defining feature of humanitarian funding which Krause (2014) characterises as a market for projects where populations are quantified as beneficiaries whose needs can be tackled with grant funding.

Let me begin with the way promoters of the use of quantitative data in the non-profit sector in my study reported on how the demonstration of needs is considered to be important in awarding funding. In the following passage, an interviewee discusses the importance of needs in justifying who receives grant-funding. The interviewee was an experienced manager in a facilitator organisation that specialised in helping small non-profits get started with digital and data-related skills. Their experience was primarily from the applicant-side of grant-funding and a large part of their own funding came through grants. Throughout the discussion, the interviewee sympathised with the lack of resources and data-related skills among small non-profits. Yet in the following passage they suggest that grant-funding should be directed to where there is the most need and applicants can be prioritised according to how much their work is needed.

> *"If you take a step back, charities shouldn't be there just for the sake of it. They shouldn't continue being just because they've always been there and done the same thing. [--]. What's most important is finding out where there's most need in [the area] and delivering services and supporting the people that live there and putting some resource in there. It's a tricky one, because then that might be at the expense of other stuff that's been funded before." (Interviewee 2, Manager, Facilitator organisation, Female, 15+ years of relevant experience)*

The passage contains two distinct elements concerning the enactment of needs and the specification of needs to demonstrate worthiness for funding. First, the interviewee argues that non-profit work should not exist "*just for the sake of it*." Instead, the interviewee suggests that the legitimacy of non-profit work must be earned in some way. In this quote the justification for non-profit work comes from serving "*where there's most need*." The existence of needs here seems to be taken to demonstrate the need for non-profits as well. Furthermore, this interviewee elaborates that anchoring non-profit work in needs specified through quantitative indicators means that there can be changes in what and who is funded; that is, refocusing funding based on needs means that new areas of interest "*might be at the expense of other stuff*." Second, it is suggested that successful demonstrations of needs in this way may justify taking money *away* from someone who is less successful. In other words, the interviewee suggests that a ranked hierarchy can be established between different demonstrations of needs when they are specified through the practices of data collection and presentation. In this competitive dynamic of grant-making, inadequate demonstrations of need can lead to non-profits not receiving funding when more pressing needs are prioritised.

The rationale for funders to consider needs as a justification to allocate resources is captured well in the following quote from an interviewee from a small place-based grant-maker. The interviewee was an experienced grant manager who had worked in grant-making for over two decades, with ten years in their current locality. I quoted this interviewee and another from the same organisation at length earlier in this chapter when discussing the juxtaposition of local knowledge and quantitative data. In this quote the interviewee sees a strong connection between the use of quantitative data and the trustworthiness of claims, although they also acknowledge that quantitative data might not be the only source of knowledge on needs.

> *"We do look at whether the project is needed, the extent to which it's providing significant benefit for people in [locality of the organisation]. Data like this would come in really useful in terms of whether it's needed. Now, we will probably know, for some projects, whether that intervention was needed, just through our local knowledge. When you can back it up with statistics, it makes it easier to report to senior management trustees. [--] Basically, you've got to bring the data to be*

able to write your papers" (Interviewee 9, Grants Manager, Grant-giving organisation, Male, 20+ years of relevant experience)

In this quote the interviewee recognises that as a place-based local organisation the funder knows plenty about the needs in the area, but they would still expect applicants to demonstrate the need for interventions using quantitative data. This suggests the presence of a complex negotiation between the local knowledge of the grant-maker and the ideal that grant-makers should be led by quantitative data, which in this quote is discussed as statistics. I discussed the unique position of this place-based funder earlier in this chapter. Nevertheless, even when recognising that local knowledge plays a role, the interviewee emphasised that applicants have "*got to bring the data to be able to write your paper*," illustrating the premium they put on quantitative data on needs.

The importance of public quantitative data sources was stressed by several other interviewees. In the following example an interviewee working as a facilitator of quantitative data skills in the non-profit sector offered a practical example of how data on needs can be used to demonstrate worthiness of funding:

> *"[a useful way of using data is] projections and predicting the needs in your area which is relevant to your service users. For example, the London Data Store, there's data on there which by ward predicts the growth rate, the population projections for age groups. [--] if [charities] are applying for funding next year, they're able to say, well, the London data set and they have evidence. Actually, it's telling me that number of young people aged 15 to 18 is going to grow by 20%, so we deserve funding—" (Interviewee 1, Civil Society Data Officer, Facilitator organisation, Female, 4 years of relevant experience)*

Here the example of externally collected data using quantitative indicators is used as a way of justifying funding. The logic of using this kind of data to evidence needs is simple here: an increase in the specific age group that is associated with an increase in a specific need that the applicant tries to tackle is used to bolster the claim that they deserve funding. According to the interviewee, data coming from an official data source such the London statistical data repository is said to grant the claim credibility and gravity. In this case the interviewee highlighted data available on the London Data Store, which is the Open Data hub of the Greater London Authority which publishes periodic official and unofficial statistics and data sets on a wide range of socio-economic phenomena.[23] The interviewee's mention of these data sources was not a surprise in the context of the interview: part of their job was specifically to promote the use of the data that is already gathered in London and to familiarise non-profits with the opportunities it provides.

The materiality of the statistical data available on London Data Store demands critical scrutiny. For the data to be available, the entire methods assemblage of categorisations, data collection, and storage needs to be performed by someone. This work is costly and includes choices about classifications and categorisations that lead to omissions and invisibilities (Bowker & Star, 1999; Law, 2004; Law et al., 2011; Ruppert & Scheel, 2021). For example, an interviewee working as the head of community investment that I have cited several times commented on the weaknesses of the demographic statistics of London.

> *"A lot of the demographic information we have to inform what we do is based on a census which is 2011 [the interview was conducted in 2019]. Obviously, things have changed quite a lot since then. For example, we do not know the number of the Latin American population in [the locality], and we know that it is significantly big. Even in the last census, the Latin American population wasn't even picked in the population group, and there's no data on that particular demography." (Interviewee 12, Head of Community Investment, Grant-giving organisation, Female, 25+ years of relevant experience)*

This quote suggests that recent changes in social issues are not captured in the kinds of data available from the official statistical authorities in London. As a result, it cannot be used to support grant-applications by organisations that focus on those groups that are left out of the census. In other words, while official data with its associated credibility among my interviewees is available on some issues, other issues

[23] https://data.london.gov.uk/

are not covered and non-profits working on these issues do not enjoy the same opportunities as others to support their applications in this way. This shortcoming is important, because it means that those social groups that are not represented in official data sources must be enacted by using other sources or by non-profits collecting their own evidence on needs.

The analysis so far leaves some questions unanswered regarding the role of needs data in demonstrating worthiness of funding. While it was possible to confirm that needs data is important in funding decisions, the interviewees were more circumspect about the role of quantitative data in assessing hierarchies of needs-based claims. Furthermore, my analysis provided no clear insights into how applicant claims of needs are compared against each other. It was not feasible to assess whether evidence on the *magnitude* of needs is used to construct a hierarchical ranking of claims, although this was implied by interviewee observations that bigger needs should have priority over smaller ones. Nevertheless, there was a clear indication that data on needs does have a role regarding the credibility of claims. This last observation stands in contrast especially to my analysis of the role of impact data, where is showed that the interviewees indicated a much clearer hierarchy relating to the magnitude of impact and the credibility of the claims.

What do these findings mean in relation to existing studies of the role of needs in non-profit work and grant-making? My focus on methods assemblages and justification brings to light the constructed nature of any evidence that non-profits might provide on needs. Furthermore, my analysis has emphasised that the data practices deployed to establish needs are not just deployed as evidence that represents social problems but serve as a way of enacting needs out-there in the world so that the existence and intensity of need itself invites support from grant-makers (see Law 2004). In this strategy of justification, enacting a version of reality where there is demonstrated need evokes a sense of injustice and solidarity among grant-makers.

I have shown that the practices involving data on needs are seen by the applicants and grant-makers as including a moral element of solidarity that can be distinguished from the use either of accountability or impact as justifications. These findings build on the Latourian arguments of Clarke and Parsell (2022) about how the enactment of populations in need renders them as resources of solidarity and as objects of the moral duty of those who make funding decisions. My analysis also elaborates on the data-element discussed by Krause (2014) concerning how the target populations constructed by humanitarian organisations are a means that facilitates the end goal of showing solidarity to those populations by administering aid. Quantitative data on needs allows its audiences to witness injustices through numbers, graphs, and tables in a similar way that visually striking images of poverty or hunger are used in humanitarian communication to prompt a sense of urgency and a need for support, despite the performative nature of such images (Chouliaraki, 2013). My analysis in this chapter suggests that when needs are evidenced with quantitative data, the applicants appeal not only to the solidarity of the grant-makers, but to their aspiration of maintaining high epistemic standards in ascertaining the veracity of those needs and their intensity. Yet, at the same time, this exposes the process of identifying needs to all the shortcomings and invisibilities of various quantitative data collection and analysis techniques.

7.6. Power asymmetries and ‘bad’ data practices

So far in this chapter I have focused on analysing *what* and *how* is demonstrated through quantitative data practices to convince grant-makers and how epistemic value and worthiness of funding are entangled with each other. Any such demonstrations, however, happen within an asymmetric power relationship between grant-makers and the applicants. Indeed, the applicants have little or no choice but to fulfil the expectations and standards set by the grant-makers if they want to secure grant funding.

The negative implications of this dynamic were discussed in Chapter 3. For example, reporting has been found to incur significant costs for the applicants, which takes resources away from the actual charitable goals, and the increasingly quantified nature of grant-making has been found to favour organisations and causes that lend themselves more readily to quantification (Arvidson, 2014; Krause, 2014; McHugh et al., 2013). In this section I discuss the findings in earlier sections against the backdrop of a recognition of power asymmetries in grant-making.

Asymmetries of power were widely recognised by my sample of interviewees. In fact, these asymmetries were found to be a source of significant frustration among some interviewees. An interviewee who had worked with small non-profit organisations for nearly two decades noted the challenges of disparate reporting requirements coming from grant-makers, which force non-profits to run duplicate data collection practices to cope with the requirements. The interviewee pointed out that "o*bviously there are different reporting requirements for different funders. Sometimes that's not helpful if you're being asked to collect different things or report different things."* (Interviewee 2, Manager, Facilitator organisation, Female, 15+ years of relevant experience). The interviewee gives a negative framing to differing reporting requirements, suggesting that it is "*not helpful*." While this may be an understatement, it identifies duplication in reporting as a source of problems for the small non-profits that the interviewee worked with.

Small non-profits are not the only organisations that can face difficulty with reporting requirements. An interviewee working for a data consultancy with a leading role in the Data for Good initiatives used more severe words to discuss the same issue. In the following quote the interviewee comments on how even large non-profit organisations can face challenges with reporting requirements.

> *"The larger organizations [--] who are competing for massive multimillion-pound government contracts. They are absolutely inundated with regulatory reporting data requirements onto the external systems, and everyone can see they have no sense of ownership of the data." (Interviewee 28, Senior manager, Facilitator organisation, Female, 20+ years of relevant experience).*

Here, non-profits can be "*absolutely inundated*," suggesting that reporting is a heavy burden. Furthermore, the interviewee suggests that grantees might have "*no sense of ownership of that data*." This suggests that organisations must focus on complying with requirements and have no control over what indicators are used to collect data or why it is collected. This highlights that it is not only small non-profits that face challenges with reporting, but large organisations as well.

The critical sentiment towards reporting requirements was shared by some of the interviewees from grant-making organisations as well. In the following passage, an interviewee who works as an evaluation and learning manager in a large grant-giving organisation describes their reporting requirements for their grantees. I quoted the reporting practices of this grant-maker in the sub-section on accountability, where I suggested that their self-professed light-touch approach to reporting still embraced a considerable quantitative element. This interviewee indicated that their approach had two parallel approaches to quantitative data collection. On the one hand, it was emphasised several times how *little* they dictate reporting requirement. On the other hand, it was stressed how *much* they want grantees to develop their own data collection practices to improve their work. In fact, this interviewee appeared to claim that strict adherence to prevailing reporting requirements can be an obstacle for learning and change. In the following quote the interviewee makes just this argument:

> *"I think the vast majority of charities have been conditioned by funders over 20, 30 years. They use [data] to prove their success rather than as a means to learn and adapt for themselves." (Interviewee 34, Evaluation and Learning Lead, Grant-giving organisation, Male, 15+ years of relevant experience).*

This learning-focused position was offered as part of a longer conversion where the interviewee explained that in their vision for use of quantitative data in grant-making the goal is to enable learning and improvement. To drive this point home the interviewee later expanded on their views:

> *"[we try to] to encourage organizations and charities to try and fight against that conditioning of using [measurement frameworks] to prove success, which means you don't talk about failure, you overclaim, you are scared to change targets, even though they've become completely irrelevant to what your project's actually delivering." (Interviewee 34, Evaluation and Learning Lead, Grant-giving organisation, Male, 15+ years of relevant experience).*

In the quotes, the interviewee expresses a worry about grantees trying to maximise performance according to the metrics that count for grant-makers. Despite grantees knowing these metrics are divorced from the change an organisation is trying to make. The interviewee suggests that past demand by grant-makers for strict measurement frameworks as a condition of funding has led non-profits to try to "*prove their success rather as a means to learn*."

I suggest that this criticism includes two elements of mistrust that stem from asymmetric power relations. On the one hand, it would seem to suggest that grant-makers can be suspicious of the quantitative data provided by non-profits because they know the numbers provided by grantees can be misleading. On the other hand, it suggests that applicants can be suspicious of changing the way they demonstrate worthiness of funding with data because part of their credibility depends on following the agreed-upon data collection techniques. According to the interviewee, this double mistrust that stems from a power asymmetry and the reporting requirements is taking non-profits away from using quantitative data in ways that would help them learn and improve their work. Despite working for grant-makers, the interviewee positions themself as someone who is trying to help grantees make better use of quantitative data for themselves rather than just to comply with rigid monitoring requirements. In other words, the interviewee presents both as a critic of the power asymmetries in data collection and as a proponent of data as a tool for improvement. I suggest that this emphasis on learning does not change the power asymmetry between the grantees and grant-makers. At the end of the day, the grantees of the organisation have a duty to report according to the agreed upon measurement frameworks, even if this might be developed collaboratively and with an eye for learning rather than being dictated unilaterally.

But what exactly do the non-profit data professionals see as the problem in the asymmetric power relations that drive the burdens of reporting? After all, it would not be difficult to conceive of arguments to defend grant-maker reporting requirements for pushing non-profits towards a quantitative direction that most of my interviewees said was desirable. Yet it is hard to find such sentiments in my interview corpus. Even the interviewees working for grant-makers were found mostly to approach the benefits of quantitative data from the perspective of making better grant decisions and emphasised their light-touch and learning-focused approach to measurement, as I have indicated above.

An explanation for this apparent paradox may be that the vast majority of the interviewees in my sample was found to share a particular vision of the value of quantitative data which did not align with mandatory reporting requirements. As I suggested in Chapter 4, a key fundamental of the Data for Good initiatives in the UK is a commitment to the idea that quantitative and digital data practices will help non-profits do their work *better* and help them achieve their goals of social betterment. In Chapter 5 I elaborated on this insight to show how it is possible to identify an appreciation for quantitative data as a source of epistemic value based on my analysis which shows how the interviewees aspire to encouraging non-profits to rethink their work through data as an opportunity for innovation and improvement. However, since this was only a general approach towards quantitative data-related practices, there is considerable leeway regarding *what kind of quantitative or digital data* is helpful in achieving this.

As I have shown in this section, the interviewees do not seem to think that a specific requirement for reporting to funders yields the kind of quantitative evidence that will help non-profits. The interviewees differentiated a compulsory *need* to collect reporting data from the aspirational potential of what non-profits *could and should* do with quantitative data. It is this latter aspirational aspect that that seemed to motivate the non-profit sector data professionals to promote the use of quantitative measurement and digital data collection despite their shortcomings. Accountability might be expected by funders when assessing worthiness of funding, but many non-profit data professionals in this study considered it perfunctory or even damaging. To support this observation, I offer selected quotes from the interviews that highlight different aspects of what makes mandatory quantitative reporting requirements disappointing even for those who otherwise claimed to believe in the transformative potential of quantitative measurement more broadly.

The following quote reiterates the above point in the words of one of the interviewees. The interviewee had worked for several years in different data-related roles in the non-profit sector, especially in organisations that facilitated the use of data through trainings, events, and consulting services. The interviewee was exceptional in my sample for having advanced training in quantitative research methods and having worked in both data science and more general data roles in the non-profit sector. The person was closely aligned with the Data for Good initiatives and their promotion. In the following quote the interviewee describes how they feel about the reporting requirements and power asymmetries in the sector.

> *"Often enough charities are collecting the data that will enable them to get funded. Whereas the data that's really needed in order to progress with the charity might be different from what is required by funders. In essence, charities need to be collecting data that's going to help them, really should be collecting data that's going to be focusing on [--] providing the best services. For me, it's a broken power system that takes place where beneficiaries are the least served when it comes to that [--] It's an understandable struggle when charities have to collect data for several funders in several different types of way. That takes away the attention from them to collect data that is needed to better understand the beneficiaries" (Interviewee 21, Data Science manager, Facilitator organisation, Female, 10+ years of relevant experience)*

In this quote the interviewee says that focusing on data to acquire funding takes away attention from using data to "*understand the beneficiaries*" and *"provide the best services*." According to the interviewee, non-profits should not focus on the requirements set by grant-givers but on "*data that's really needed in order to progress*." Furthermore, the interviewee suggests that it is in the interest of the *beneficiaries* that non-profits collect and use the right kind of data. This quote therefore exhibits both the ideas that power asymmetries in grant-making are damaging for non-profit work and that quantitative measurement is crucial for non-profits to tackle social problems.

Another argument against extensive reporting requirements comes from an interviewee working as the head of digital innovation in a major non-profit sector consultancy. The positionality of the interviewee is interesting, because as a consultant who is paid to help non-profits improve their use of data, this interviewee might be expected to be a keen promoter of data. However, they were keen to emphasise critical points about the harmfulness of non-profits tailoring their data collection to satisfy funders. In contrast to the above interviewees who proposed collecting different data, this interviewee went in a different direction and proposed less data collection overall.

> *Interviewee 25: One thing, as a practical thing I would suggest the rural funders, state funders, or foundations, is to move away from their current model of evaluation and measurement. At the moment, we've got an understanding of results-based performance management which is about constantly measuring service delivery, whatever kind of service that is. You're constantly recording stuff, creating big datasets. You could instead think of running it more like a health system. GPs do not follow updates from their patients, instead they just do what works. Rather than constantly revalidating the models, you just adopt models that work and do them and then you just have to show that you did it. Whereas instead, we're in this model of constantly measuring impact or the change to charities beneficiaries, which is merely just a load of numbers that turn up in a PDF and then go into a file folder somewhere that no one reads. (Principal consultant - digital innovation, Facilitator organisation, Male, 10+ years of relevant experience)*
>
> *Interviewer: You would say that the impact data or the evaluations, none of that is used?*
>
> *Interviewee 25: No. I worked at a funder for years and years. People send these things in, and they just get saved in a drive, no one reads them.*

In the passage, the interviewee proposes that grant-makers should distance themselves from extensive data collection because "*no one reads*" the reports sent by grantees. The constant measurement of change mandated by grant-makers, which is part of "*results-based performance management*," is depicted as not being actually used for any practical purpose other than documentation. The alternative proposed by the interviewee is that grant-makers should follow a standards-driven approach that does not require data-drivenness at the point of service-delivery or as a requirement of funding. Interpreting this from the perspective of epistemic value, the interviewee is seen to question the value of data in grant-making and calls for *alternative* ways to assess the worthiness of funding. Yet following this alternative model would go against the very system of valuing quantitative data for its epistemic worth that seemed to be cherished by many non-profit data professionals.

My argument in this section is that the analysis of power asymmetries in grant-making provides a case in point about why the interviewees of my study can critique some aspects of using quantitative data in the non-profit sector while retaining a strong belief in the overall importance of this kind of data. I suggest that, while the demands for data by grant-makers favour causes that are easier to quantify and organisations that have more resources for data collection, my interviewees were inclined to treat these issues as an exception to the benefits of data rather than as a fundamental critique of reliance on quantitative data. The power asymmetries that give grant-makers the right to determine what kind of data should be collected seemed to irritate many of the interviewees who suggested that this results in foregoing the opportunities that promoters of Data for Good initiatives position at the heart of their activities. As a result, the power asymmetries seem to lead the non-profit sector to collect the "wrong" data and its use for the "wrong" purposes from the perspective of those who are committed to the transformative potential of data. These problems are difficult to avoid given the evidence in this study of the close entanglement between the numerical data-driven understanding of epistemic value and the dominant strategies of assessing worthiness of funding. I suggest that the criticisms of power asymmetries exhibited by the interviewees are relatively toothless in tackling the root of the problems they describe. Many interviewees seemed to claim that it could be possible to steer clear from “bad” data practices and focus on the “good” ones. However, this does not fully account for how deeply the data practices in grant-making are rooted in the ideals of epistemic value that my interviewees were promoting.

7.7. Data science and grant-making

The findings on using data to demonstrate worthiness of funding speak of certain absences: the interviewees mostly did not discuss the use of novel data science tools in the context of grant-making. Interviews with non-profit data professionals suggest that expanded collection of data can help non-profits secure funding, but there was little indication that sophisticated programming or machine learning techniques would do the same. In fact, the most detailed discussions on more sophisticated analytic techniques were about experimental designs and, in some cases, the use of econometric techniques to model the value of social investments.

The following quote from an interviewee working in a leading position in a non-profit sector data consultancy that was central to the Data for Good initiatives discusses why grant-making practices might disincentivise non-profits from improving their data analysis techniques. In the quote the interviewee links the need to secure grants to whether investment in data capabilities is useful for a non-profit

> *“The incentives are highly complex. [--] let’s say, you want to invest in improving impact management scene, and so you’ve put a lot of effort into measuring impact, and you find that your impact is not bad, and you find ways to improve your impact. Does that lead to your supporters giving you any more money? Does it lead to funding? If it doesn’t, what’s the logic for investing? When everybody’s strapped for cash, what’s the logic in investing in that? (Interviewee 29, Senior manager, Facilitator organisation, Male, 15+ years of relevant experience)*

The message of the interviewee seems simple: if adoption of more sophisticated quantitative techniques of measuring impact does not bring any more money to non-profits because they are anyway doing well in funding calls, the logic of investing in these techniques is questionable. While the passage highlights impact measurement, the insights can be extrapolated to the incentives of non-profits to invest in any other sophisticated techniques such as data science: if funders do not perceive the use of sophisticated techniques as providing better demonstrations of the worthiness of funding, non-profits have little incentive to spend their resources on adopting those techniques. The interviewee seems to suggest that there is a limit to how much competition for funding can drive investment towards practices that would help non-profits achieve higher levels of epistemic value. Furthermore, if grant-makers start rolling back extensive quantitative measurement requirements, a theme discussed in the previous section, this would reduce the pressure on non-profits to invest in new techniques.

Thus, the requirements set by funders have a two-pronged effect on non-profits. On the one hand, they incentivise applicants to adopt data practices to better demonstrate value in disputes about funding. On the other hand, non-profits that are successful in demonstrating their value in disputes about funding no longer experience the same pressure to further develop their uses of quantitative data. One consequence of this is that the competitive dynamic of grant-making which, in principle, is meant to lead applicants to improve their data practices to comply with higher standards, might not have this effect. It might disincentivise the improvements sought by promoters of Data for Good initiatives and incentivise a gaming of numbers that undermines the epistemic value of this kind of data.

7.8. Conclusions

In this chapter I analysed the value of data in demonstrating worthiness of funding. The analysis shows that data plays an important role in demonstrating qualities that funders appreciate when awarding grants. Data is used to determine whether non-profits are *accountable* and can be trusted to do what they promise with the money they are given. Non-profits are encouraged to use data to demonstrate that there is a specific *need* for social intervention that an applicant can deliver. Furthermore, quantitative data are used to demonstrate that the work a non-profit does really has an *impact*, i.e., to deflect accusations of ineffectiveness and to 'prove' that interventions lead to real social change. These uses of data enact different versions of reality, but each contributes towards the overall goal of demonstrating why one organisation is more worthy of grants than another. The findings show that in each instance quantitative measurement is intended to make a stronger demonstration of worth than would occur in a demonstration without quantitative data.

Nevertheless, because epistemic worth is subject to its own shortcomings and critiques, there is also uncertainty around these claims. I have stressed uncertainties about the epistemic value of data in disputes about funding and uncertainties about the effects of power asymmetries. My analysis suggests that using quantitative data does not close epistemic debate despite the ideals behind its promotion. It rather creates new points of critique. The hope that quantitative data practices would increase the credibility and trustworthiness of claims made to demonstrate worthiness of funding was routinely questioned by the very same people who promote the use of data. The methods assemblages generating the proofs can always be subjected to critical scrutiny that reveals the constructed and limited nature of any quantitative evidence. My analysis confirms that the non-profit data professionals in my sample were aware of these shortcomings, but, at the same time, enthusiastic about the general promise of new data practices for providing greater epistemic value. My interviewees often framed reporting requirements as "bad" data practices and called for better use of quantitative data as a tool of improving non-profit work. Their perspectives were also informed by their insights into power asymmetries in the non-profit sector. However, the criticisms of reporting requirements and power asymmetries voiced by interviewees rarely extended to the overall value they assigned to data practices in epistemic disputes. Their criticisms therefore retained intact the core assumption that non-profits should embrace quantitative data practices.

These findings build on earlier research by elaborating on the pressures that push non-profit organisations to use data. They provide insight into how the pressures of NPM, EBP, and arguably neoliberalism more broadly, manifest in grant-making. My analysis elaborates on Barman's (2016) insight that social value can be economised through a range of quantitative measurement strategies that serve different purposes. More precisely, it highlights that demonstrating worthiness of funding involves multiplicity in *what is demonstrated* with data and differences in *what kind of data practices* these demonstrations require. Because methods assemblages are relational and enact different versions of reality, it makes a difference whether non-profits try to demonstrate their compliance, impact, or need for their work. Each of these elements has been recognised in earlier research (for an overview, see Rottenburg et al. 2015), and special attention has been given to the enactment of needs by quantifying beneficiaries (Krause, 2014), compliance to public standards of accountability (Power, 1999), and calls for effectiveness and impact in non-profit work (Barman, 2007; 2016). However, I suggest that there has been inadequate appreciation of the incommensurability of the different goals non-profits aim to achieve when they seek to justify their value for grant-makers. These differences were meaningful to the interviewees of my study and suggest different logics of what is valuable about non-profit work. And yet there is a further level of incommensurability in the grant-applicants' different approaches to submitting the numbers they generate using their own methods assemblages. Indeed, as I have underscored in my analysis of enacting impact and needs, assessing the relative value of applications is difficult even when they are supported by quantitative data that is expected to bring commensurability, clarity, and certainty to grant-making.

The findings of the chapter echo the insight in the previous chapter about the sociocultural project of making non-profits appreciate the epistemic value of data: using data in grant-making provides a way to affirm organisational adherence to the expectation that value should be demonstrated with quantitative data practices. Thus, using quantitative data practices may be more about demonstrating that an applicant is a "good non-profit" that follows shared standards than about whether numbers supplied by the applicant can withstand critical scrutiny. In other words, it seems that in some cases the mere adoption and use of specific methods assemblages is enough to demonstrate epistemic value and worthiness of funding. This suggestion elaborates on Power's (1999) arguments on the ritualistic nature of audit and compliance, highlighting how quantitative and digital methods assemblages in themselves can signal value in grant-making.

It is worth noting that the interviewees provided little evidence that data science plays an important part in disputes over funding. While non-profits are certainly pushed to collect more data, it was unclear what value the sophisticated computational techniques have in disputes over the worthiness of funding. Nevertheless, it is possible that data science provides other types of proof that can sway grant-makers, such as a demonstration that an organisation values data in the way that is appreciated by non-profit data professionals.

I finish this chapter by reflecting critically on how value is demonstrated in disputes over funding. My analysis of the risks of gaming and redundancy of accountability data painted a bleak picture of competitive funding. They pose a challenge to the idea that data can help grant-givers rank non-profits in a meaningful order that reflects the potential they have to contribute to social betterment. The findings highlight how enactments with data, which in principle are thought to be more credible than claims without data, can fail in providing a picture of non-profit work that non-profit data professionals report as being adequately "real." Overreliance on quantitative data therefore on the basis of my evidence can lead non-profits and grant-makers to paradoxically *fail* in what Boltanski and Thévenot call the reality tests in justifying value. Yet the interviews also suggested that uncertainty might itself be a source of demand for *more* data to substantiate claims, which further induces opportunities of gaming the numbers. The insight here is that non-profits and non-profit data professionals should be careful not to lose track of what is supposed to be measured with data, i.e., what it tries to enact. If only enactments with quantitative data are thought to be credible justifications or denunciations of value in situations of funding, then other enactments are relegated to a secondary role that might be treated as only private thinking that cannot feature in official grant-making. Without recognition for these other ways of demonstrating epistemic value, it is possible that overreliance on quantitative data practices will guide funding to those best aligned with the rituals of funding, not those with the most potential for social change.

Chapter 8

"We are making the organisation demonstrably more efficient" – Data and disputes about social value

8.1. Introduction

In this chapter I examine the way non-profit data professionals discuss using data practices to manage and improve non-profit services. The findings contribute to answering two research sub-questions: "*In what situations of dispute do data practices justify value*" and "*How is the demonstration of value entangled with methods assemblages in these disputes*."?" I elaborate on one of the key concerns that non-profits address with data that was identified in Chapter 6: the use of data practices to demonstrate value in situations of dispute about the best ways to tackle social issues.

Quantification of social value has long history, which I have reviewed in Chapter 3. Since the 19th century, statistics have shaped the understanding of society and social problems (Desrosières, 1998; Hacking, 1990; Porter, 1986), which has also meant a strong union between quantification and justifications of social value (Boltanski & Thévenot, 2006). While attempts like Social Impact Investment and outcome-based funding, are focused on combining the quantification of society with economic assessment of its value (Bourgeron, 2020; Williams, 2023b, 2023a), digital infrastructures themselves are also methods assemblages that quantify the social and measure social change (Ruppert et al., 2013). In this chapter the focus is on the role of digital tools in measuring social value in the non-profit sector, not on the practices of economising or marketising social value. This rationale is supported by my discussion in Chapters 5 and 6, where I indicated that Data for Good initiatives which served as my entry point to the UK non-profit sector have a special, if broad, interest in digital technology that takes a variety of forms.

The question of how to tackle social issues is understood here as a dispute about social value. The interviewees for this study were almost exclusively working in the social sector which informed their insights about the value of quantitative data in tackling social issues. I find that non-profits can use data practices to demonstrate that their work has social value, and that using quantitative data can help non-profits to justify their choices and deflect criticism. What I mean by social value here is akin to Barman's (2007, pp 37-42) discussion on how outcomes measurement is treated as a measure of social value, although what that value is about depends on the social change the organisation is seeking. Non-profits must assess and demonstrate the value of alternative courses of action towards their goal of social betterment. Such demonstrations have different audiences, but in this chapter the focus is on internal disputes that deal with management and the improvement of non-profit work. The justification for this choice is in Chapter 5 where I identified internal disputes about service management as a key concern among non-profit data professionals.

The disputes and demonstrations of value in this situation provide a different picture of non-profit data in comparison to the disputes about funding (see Chapter 6). When using quantitative data to improve their own work, I show that non-profits do not appear to try to convince anyone else about the value of their work. This gives demonstrations of value a different form than when there is a clear-cut distinction between awarding or rejecting a grant. The analysis of internal disputes highlights the way the quantitative data practices are entangled with ideals of social value among the non-profit data professionals interviewed for the study. These ideals are not necessarily pushed coercively onto non-profits, as is often the case in grant-making. It is rather the case that the ideals of quantified epistemic value promoted by many non-profit data professionals push non-profits to voluntarily adopt the quantification of social value as a foundation for their work. This chapter elaborates on the findings of Chapter 5 on epistemic value by showing how they can shape the self-understanding of non-profit organisations.

In this chapter I focus on how particular kinds of data are used to enact *needs,* and how data on needs is used to demonstrate, assess, and compare the value of alternative courses of action. The analysis identifies two different types of needs that methods assemblages of quantitative data are used to enact. On the one hand, this kind of data is used to enact *collective needs* as objects of social amelioration. On the other hand, data is used to enact *individual needs* to be served with specific interventions and services. In this latter form, data is reported by non-profit data professionals to provide knowledge that serves the better *management* of services. Non-profits enact both as part of trying to deliver "more" social good by meeting the collective and individual needs of their beneficiaries more efficiently and effectively. Yet I also identify uncertainties and tensions that call into question whether the enactments of different types of needs coalesce into a meaningful whole.

The chapter complements earlier research by highlighting the importance of methods assemblages in enacting needs, and how the multiplicity of enactments can lead to incoherence between attempts to address collective and individual needs. Furthermore, the analysis suggests that if non-profit organisations rely exclusively on managerial measurement for tackling individual needs, this can lead them away from understanding social change on the collective level. Furthermore, the findings suggest that if needs are understood solely through what can be measured with quantitative and digital data practices, then it becomes more difficult to think about social value beyond what can be enacted with the data practices the organisation is using. Data science makes it possible for non-profits to measure users and manage services in new quantitative ways, therefore pushing non-profit organisations to adopt more managerial understandings of social value.

8.2. Data and disputes about social value

Non-profits that work in the social sector identify social problems and seek opportunities to tackle them.[24] The justification for this work can often be found in the broader goal of social betterment. What these goals mean in practice for the interviewees in my study is, for example, elderly care, mental health support, poverty alleviation, social housing, support for certain ethnic or identity groups, etc. As indicated in Chapter 6, non-profit data professionals typically understand service delivery and improvement of non-profit operations as one of the key areas where the use of data can change non-profit work. In other words, non-profits must attend to the question of *how* to organise their own work to fulfil their goals. They must decide which issues are more deserving of attention and which groups, communities, localities, or individuals should receive their help. Their work can also be criticised for not doing enough or not using the interventions that would help the most.

Based on my analysis of the interviews, non-profit data professionals can be understood to place great value on quantitative data as a tool to understand and *improve* the work of non-profits. Furthermore, many interviewees seemed to

[24] It is important to note that phenomena such as poverty, homelessness, and hunger are social problems insofar as they are assessed through a statistical conceptualisation of society that emerged in the 19th century. The current understanding of what is a "social" problem in comparison to, for example, an economic or psychological problem, is a continuation of these developments. For the purposes of this chapter, the social nature of problems is assumed rather than questioning what the "social" element of these problems is. For a discussion on how poverty and other adverse conditions in a population have come to be treated as questions for society, see Burchell et al. (1991), Miller and Rose (2008), and Hacking (1990).

understand the *management* of non-profit services as a separate situation of using data in comparison to disputes over funding. As I show below, the measurement of social value through quantitative measurement of needs is closely connected to these managerial ideas of improvement.

The following quote from an interviewee working as the head of data in a large non-profit sector consultancy that offers its services for a fee elaborates on the value of quantitative data in informing and improving non-profit services. As a consultant the interviewee was invested in promoting the use of data and was enthusiastic about the opportunities it offers to improve non-profit work. The passage was preceded by the interviewee explaining the importance of quantitative data in demonstrating accountability for external actors, then changing the focus to discuss the way interest in quantitative data practices has started to take on a more internal and managerial focus.

> *"The narrative now is slightly changing. Now it's not just a matter of being accountable for what you do, but it's also using data to become more effective, to better understand your users, where they're coming from, what kind of things they've been struggling with. Then there is the operational side of things. How long does it take your charity to support a young person in London who has been in touch with you last week, right? To support, you need X, Y, and Z provision. If you ask me, we're still far, far, far, far from using data in a smart way" (Interviewee 24, Data Lead, Facilitator organisation, Male, 5+ years of relevant experience)*

In this passage, the interviewee suggests that data is valuable for non-profits because it helps them "*better understand your users, where they are coming from*." Furthermore, the interviewee recognises the "*operational side of things*," which refers to knowledge about service provision itself and the interactions beneficiaries have with the service. The goal of these practices is to use "*data to become more effective*." Yet according to the interviewee, these goals are far from being fulfilled, and non-profits are "*far, far, far, far from using data in a smart way*." These goals of better understanding, better management of services, and better effectiveness suggest an overarching goal of helping non-profits to better identify opportunities for intervention and become better at administering the interventions. Interpreting these goals a step further, the "*smart way*" of using data refers to the ways that data could help non-profits better understand and achieve social value by tackling social problems. A further interesting element in the quote is that it aligns with the insight in Chapter 7 on how the grant-makers interviewed for the study underscored their aspiration to move from tests of accountability towards facilitation of learning and improvement.

The non-profit data professionals interviewed for this study were in broad agreement that having more quantitative data is beneficial to the ability of non-profit organisations to do their work. As suggested in Chapter 6, non-profit data professionals claimed that quantitative data is more valuable than expertise and first-hand knowledge in disputes about knowledge. An interviewee working as a data scientist for DataKind UK put this sentiment into words in no uncertain terms: "*If you want to make informed decisions, you need data. If you want to know the impact of those decisions, you need data*. (Interviewee 7, Data Scientist, Facilitator organisation, Male, 2 years of relevant experience). As a data scientist working with data and promoting the use of data, it is unsurprising that this interviewee positioned numerical data as an essential part of decision-making. According to the interviewee, it is not possible for non-profits to make informed decisions or to know the consequences of those decisions without quantitative data. Data is therefore regarded by the interviewee as crucial in demonstrating whether a non-profit is delivering social value.

Below, an interviewee working as the head of data science in a social sector non-profit discusses the role of data in improving their work. The interviewee was enthusiastic about the value of numerical data in improving the services of the organisation and keen to make more use of data in their decision-making. The organisation collected extensive amounts of data from its beneficiaries as part of the services in addition to using extensive digital systems to manage the service workflow. In the passage the interviewee describes how they would want this data to be used:

> *"Really the dream scenario for me is just to know that we're making continuous improvement. We want to be on a path where we are making the organisation demonstrably more efficient and more effective. We mentioned those feedback loops [between data collection and action]. I would like to tighten those feedback loops and also to be in a position where we can have greater foresight by identifying trends as they are happening in society and then being able to act." (Interviewee 31, male, service-providing organisation)*

Here, the "*dream scenario*" is one where the non-profit is on a road to "*continuous improvement*." In framing their view as a "*dream scenario*" the passage offers a view into the aspirations and hopes of a data science professional responsible for making data science useful for their organisation. This scenario is framed as a "*path*," which indicates an ongoing process where progress is made towards a set target. Words like "*improvement*" and "*path*" indicate a sense of movement towards a goal or a target, which, in this case, can be interpreted as the ideal state of delivering as much social value as possible. The way the interviewee wants to use data is therefore to assess and demonstrate value when comparing alternatives in providing and managing services. Furthermore, by suggesting the need to "*tighten the feedback loops*" between service management and this approach to data collection, the interviewee suggests that data plays a crucial role in influencing what counts as more valuable services. At the end of that path the organisation would be "*efficient*," "*effective*," "*have greater foresight*," and "*able to act*," with data configured to serve as a key resource in knowing what they mean and what would demonstrate the organisation's contribution towards them. The non-profit would not only know what better looks like but be able to act and organise their work according to what would best serve it. In other words, using data to measure these qualities is positioned as a way of enacting them as goals, setting the standards for what it means to be doing better or worse in relation to them, and pushing the non-profit to have better results according to these metrics.

However, what is deemed to be most important by this interviewee is that the non-profit has the tools and practices to know whether it is progressing towards the ideal state. In other words, the interviewee appears to frame the dream scenario as the ability to know what "more" social value means in their work and be able to contribute to it. The interviewee aims to make the non-profit "*demonstrably more efficient and more effective*." By suggesting that the non-profit should become "*demonstrably*" better, this interviewee assigns to quantitative data the power of assessing whether things really have become better. In other words, the interviewee is evoking the language of computational proofs that demonstrate value. "*More efficient*" and "*more effective*" are given as the indicators of what needs to be demonstrated, bringing quantitative data into a managerial frame of organising and steering non-profit work. In other words, the demonstrative value of quantitative data in epistemic disputes is here used as a proof of value in disputes about how to organise, manage, and improve services. The ideal state of being on a path of improvement is therefore depicted as a path of managing the relationship between service provision and the social issues. This relationship is understood as something that can be known, managed, and improved with data. For this interviewee, this process of improvement would not be possible in the same way if they did not use data to enact how well they are doing according to various metrics of their work.

The internal disputes over social value and improvement that I discuss here are markedly different from the need to demonstrate worthiness of funding. Although similar data can be used to serve non-profits in both kinds of normative disputes, the interviewees clearly conceptualised these as separate realms. As argued in Chapter 6, using data to demonstrate worthiness of funding can lead non-profits to overclaim and game reporting to 'prove' their success rather than trying to learn from their past work, which was shown to frustrate many of the interviewees.

The analysis here highlights the way non-profits value particular types of data through its role in disputes about social value. Based on the analysis, delivery of social value and promotion of data practices are strongly entangled. The commitment to improve data culture and maturity discussed in Chapter 5 is here combined with the commitment to the pursuit social betterment. Through their entanglement, I suggest that the interviewees participating in Data for Good initiatives and working in data-related roles in the UK non-profit sector consider that more quantitative data and better knowledge will help non-profits closer to their broader goals. The disputes over more or less social value and stronger or weaker evidence of social value were seen by non-profit data professionals as an opportunity to improve non-profit work. Words and phrases like "*progress,*" "*continuous improvement*," and data as "*fundamental to helping deliver their goals*" suggest that the interviewees do understand the pursuit of social value in hierarchical terms where data demonstrates value so that alternatives can be ordered, and the best course of action chosen. If someone within a non-profit organisation proposes that an alternative course of action might contribute more to social betterment, data metrics are increasingly taken as the yardstick for deciding which option to choose. When interpreting non-profit data practices in this way, working towards social betterment can be understood as being shaped by quantitative data practices and what can be enacted with them. Finally, within these disputes, data presentations are also meant to *demonstrate* what choices would lead non-profits towards more social value. The above dynamics are not limited to Data for Good initiatives but driven by a broader set of factors that I discussed in Chapter 3. The influence of NPM in the UK and the ideals of EBP cannot be overlooked as significant drivers that predate the current interest in digital data and data science. As indicated in Chapter 5, Data for Good initiatives tap into these broader developments, adding the promise of digitalisation and data science as sources of innovation and improvement.

In the following two sections I focus on the methods assemblages and enactments in the quantification of social value by analysing how non-profit data professionals in this study reported using various kinds of data to enact collective and individual needs as their measure of social value. The goal of this analysis is to show that responding to collective and individual needs can be seen as different facets of what it means for non-profits to provide "better" services, but they also contain their own ambiguities and uncertainties.

8.3. Uncertainty in enacting needs

The above analysis suggests that there are tensions between different "proofs" and resources to demonstrate social value. Tensions are found especially between enactments of collective and individual needs. The most important insight is the discrepancy the analysis reveals between how needs are enacted and how responding to needs might or might not translate into measurable social change. Trying to maximise measurable social change on the level of individual beneficiaries might not translate into increased social value on the collective level; better knowledge that personalises services and experiences of individuals might not be the same kind of knowledge that helps non-profits achieve wider social change.

Trade-offs in using digital data from service provision to guide non-profit work were discussed by an interviewee who worked for a large grant-maker as a specialist in investment into digital technology. According to this interviewee, non-profits' ability to generate data on individual needs and to respond to them is enhanced when they adopt digital tools, but the interviewee also identified risks in taking this too far.

> *"Where I think data plays a useful role, [--] is obviously in trying to continually adapt services in terms of service delivery, who's using this at what time of day, how could we start to deliver more personalized services to this type of user in this way. The design of digital services can be greatly improved and made more targeted around peoples' needs. What I worry about is we don't think about the wider context when we use data in that way, and often we start to look at data as a how has someone used this service? Have they had a good experience, but having a good experience doesn't mean the same as a good outcome, unless the outcome was about just having a good experience." (Interviewee 22, Senior manager, Grant-giving organisation, Female, 10+ years of relevant experience)*

The interviewee poses a dilemma in identifying individual needs and personalising services according to them. On the one hand, the interviewee suggests that digitalisation and digital tools are crucial in collecting individual-level data and adjusting service delivery accordingly. More data and data-driven design of services is therefore assumed to deliver more social value. On the other hand, the interviewee suggests that they "*worry about*" individual level data and personalisation possibly obscuring the wider social context that surrounds beneficiaries. What is good for personalisation and managing service delivery might not lead to good outcomes in the broader context. The interviewee refers to this as the tendency to focus on "*how has someone used this service*" rather than what the service is meant to achieve. An extreme example given is that "*having a good experience doesn't mean the same as a good outcome*," which implies that personalised service delivery can become focused on details of individual encounters rather than on broader social change. The interviewee's reflection suggests a discrepancy between data on personal service delivery and data on collective needs.

Difficulties of measuring whether client needs have been addressed were also addressed by an interviewee working for a medium-size non-profit specialising in elderly people's care. In the following quote the interviewee working as the director of services describes the challenges of using data to measure individual needs and improvements in elderly care in comparison to another area that they had previously worked on.

> *"[in the past] I worked for a charity that had a very clear outcomes framework measurement tool. [--] You got the measurement at the beginning, measurement as you went along at regular intervals and measurement at the end. It doesn't work like this [in elderly people's services] just because we're working with a very different need group. [--] There isn't a measurement that we can go back to for how things were at the beginning and now, six years on, how are things now? It's not really like that. It is different from the mental health and wellbeing project, where there is a clearer start for people and a clearer end sometimes [--]. It's not a linear journey that [elderly people] are on, it's kind of up and down and their needs change and then they're ill for a while, they get better again. Anything can happen really." (Interviewee 4, Director of Services, Service-providing non-profit, Female, 15+ years)*

In the above passage the interviewee juxtaposes use of regular measurement in elderly people's services with their earlier experience in mental health and wellbeing services. In some areas of the social sector, they observe that it is possible to construct a measurement of beneficiary progress because they have a "*clearer start for people and a clearer end*," whereas in elderly people's services "*it's not a linear journey*." By comparing these two cases it is suggested that measuring client progress is not as useful in elderly people's services because it does not necessarily have clear interventions and outcomes that would measure something that can be framed as progress. In other words, the interviewee seems unsure about whether it possible to measure beneficiary progress reliably, let alone extrapolate evidence on wider social impact on the collective level.

In the interviews discussion on non-profits tapping into non-quantitative ways of knowing seemed to concentrate on the frontline of working directly with people in need. Following Law's notion of methods assemblages, frontline staff encountering people in need is no less a method of knowing needs than is the collection of quantitative data. Yet they do not seem to command similar epistemic authority in the eyes of the non-profit data professionals interviewed for this study. Yet some interviewees were supportive of not always relying on quantitative data to determine what is the best way to advance social betterment. In fact, an interviewee working in a senior data-related role for a large consultancy specialising in non-profit work voiced their worry about focusing too much on quantitative data collection in service provision. The positionality of the interviewee gives this quote extra weight, because their work might suggest that they would be expected to be enthusiastic about data:

> *"We see greater investment in measuring, monitoring, and doing the processes of management rather than doing the processes of delivery. I actually think for a lot of charities, they don't really need a lot of data. They just need to get on with their thing. They need to run their care home. Actually, adding layers of data and management is just adding more layers of bureaucracy on top." (Interviewee 25, Principal consultant - digital innovation, Facilitator organisation, Male, 10+ years of relevant experience)*

Here, the interviewee is worried that non-profits are investing more in management measurement while the actual delivery of services receives less attention. Furthermore, it is observed that many charities "*don't really need a lot of data*" because they should focus on getting "*on with their thing*." This observation suggests that most non-profits already know enough about how to deliver services and there is no need for them to closely measure needs and effectiveness. This interviewee therefore appears to challenge the ideal that collecting more quantitative data will help delivering better services that will lead to more social good.

These criticisms of quantitative measurement in managing and improving non-profit work cast doubts on the idea that data-driven service management will lead non-profits any closer to broader social change. Indeed, earlier research has charged reliance on Big Data in social contexts with producing an atomistic and individualistic worldview that emphasises individual data points rather than their relation to broader social processes and phenomena (Lake, 2017). While non-profits that embrace quantitative data in their service provision may claim that they are more efficient and effective than ever, this might not be the case outside the enactments generated through service provision itself. The paradox is that by focusing on improving their *work*, non-profits may leave unaddressed the underlying factors that are the cause of the needs. Non-profits might tackle more detailed individual needs but fall short of achieving broader social change. This aligns with Krause's (2014) suggestion that a managerial orientation of counting beneficiaries and transactions can lead to a situation where individual non-profits help people in a very circumscribed way that is the easiest to measure and report with data.

Why do such tensions persist if non-profit data professionals are committed to stronger 'proofs' in epistemic disputes that will influence whether needs are tackled? Law's work on methods assemblages provides a possible explanation for this conundrum. When the measure of "true" and "real" social value is understood to be a result of specific methods assemblages, it is not possible to use external criteria to determine what ultimately is "real" and "true." What counts as real social value is assessed with the data collected and configured by non-profits, which ranges from managerial data on service provision to statistical data provided by governments. However, for data collected as a by-product of non-profit services to be challenged, there needs to be an alternative source of epistemic claims that is recognised by the non-profit. If no such source exists or it is disregarded, then the goals of non-profit work become increasingly aligned with what can be enacted with data as illustrated by my analysis. However, while it was common among the interviewees to extol the benefits of managerial quantitative data on needs, the fact that many interviewees voiced uncertainty about this indicates that not all non-profit data professionals take this kind of data as everything there is to assert social value. In the next two sections I examine how the uncertainties around quantitative and digital data play out in two scenarios: identifying the individual and collective needs to be tackled with non-profit work.

8.4. Enacting and managing individual needs

To achieve their goal of social betterment, social sector charities provide services that are intended to help some *people*. The first set of methods assemblages I discuss is the use of data to know individuals as people who have needs that can be tackled by non-profits. More precisely, the analysis here focuses on how data is configured to *enact individuals* as targets of services and *manage services* that respond to those needs.

One of the flagship examples of data science in the non-profit sector advertised by DataKind UK is a food bank dependency project that was hosted by The Welcome Centre foodbank in Huddersfield, UK.[25] I encountered this example while conducting fieldwork in an event organised by DataKind UK, where I heard a presentation on the project by the volunteers who participated in it. The case was subsequently discussed

[25] https://www.datakind.org/2022/02/23/identifying-food-bank-dependency-early/ last accessed 26.9.2024.

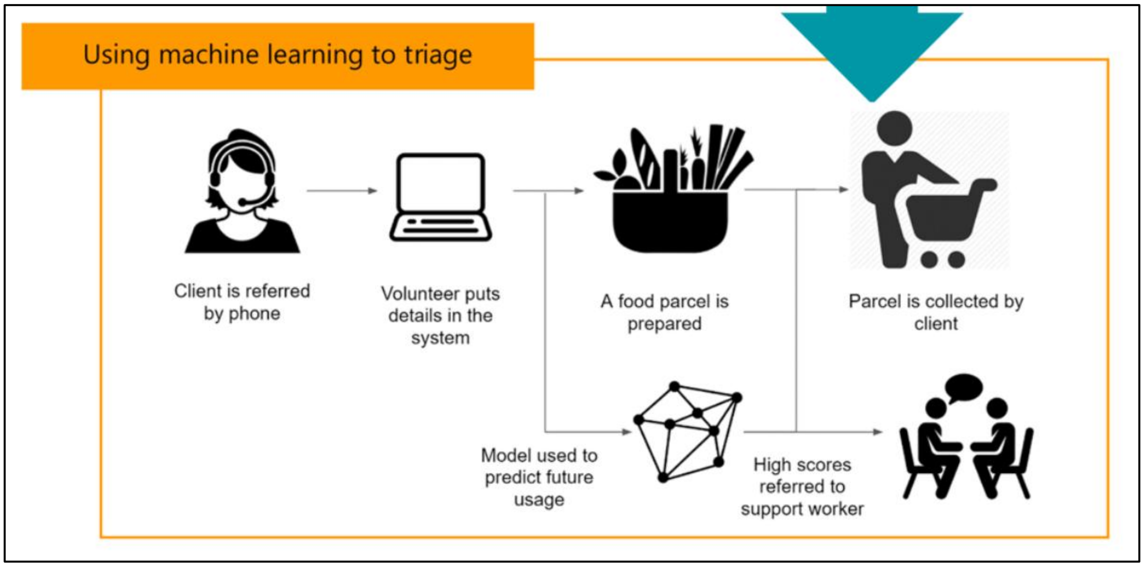
with interviewee working for DataKind UK. Information on the case was also available online on DataKind UK's website. I discussed this project in Chapter 5 where I used it as an example of the way data science has been integrated into non-profit sector methods assemblages. Here I take a different perspective, focusing on what the methods assemblage enacts.

The project addressed the problem that while foodbanks are meant to be short-term and temporary sources of help, some people become dependent on them for a long time. In the project data science volunteers from DataKind UK developed a machine learning algorithm that estimated the individual-level risks of food bank users becoming dependent on it. The algorithm was integrated into the information systems of the non-profit and flagged at-risk users so that they could proactively be given more support.

The operating process of the Welcome Centre foodbank in Huddersfield is depicted in the picture below provided by DataKind UK and described by the organisation itself on their website.[26] To receive help, clients need to be referred by a social worker or other social support professional, but referrals can also be given directly on the phone. After a referral has been made, a food parcel is prepared for pick up from the food bank. When picking up the food parcel, some clients receive further support from the members of the foodbank. To better identify people in need of extra support by the staff, the food bank partnered with DataKind UK to use data and analytics to identify people who are at risk of becoming dependent on the food bank that is supposed to be only of temporary help. To do so, the volunteer data scientists trained an algorithm using data from past foodbank referrals and a Random Forest machine learning classifier to calculate the predicted risk of the referrals increasing in the future. This future-oriented risk score was then used to decide which clients should receive extra support from the staff, replacing an earlier strategy of prioritisation based on frequency of use.

[26] https://www.thewelcomecentre.org/pages/need-our-help last accessed 26.9.2024.

Picture 1. The Welcome Centre Huddersfield food bank service process. [27]



The food bank dependency algorithm is a case of a methods assemblage that enacts the claimed needs of individual clients. The score generated by the machine learning model based on earlier food bank records ranks each client according to a measure that is interpreted by the organisation as their predicted need. Furthermore, needs are enacted through three different strategies. In the first strategy, need for the service is assessed at the point of providing clients a referral, which demarcates between those entitled to the food bank support and those who are not. The result is that those classified as in need are enacted as clients of the food bank. In the second strategy the food bank measures the intensity of the need by tracking the frequency of the referrals, which is generated as a by-product of managing the service itself. This allows the food bank to classify and enact some people as clients in greater need than others and therefore in need of extra support. In the third strategy that was developed with DataKind UK, the new predictive scoring system takes all the data collected by the food bank and enacts some of clients as *at risk* of becoming in need of extra support. This last strategy therefore does not only look at past behaviour but tries to predict

[27] https://www.datakind.org/2022/02/23/identifying-food-bank-dependency-early/ last accessed 27.9.2024.

future possibility of becoming dependent on the foodbank. Each of these strategies therefore enacts a different version of who is in need.

Furthermore, the adoption of predictive scoring is taken by the organisation to be an *improvement* of their service because it provides a new assessment of need that they claim is superior to earlier assessments. According to the DataKind UK report on the project, the goal was to "*improve the accuracy and efficiency of the targeted work that the support worker undertakes.*"[28] This implies that a new assessment of needs will lead to higher efficiency of the work. Nevertheless, because the new scoring system enacts a possible trajectory that has not yet happened, a different measurement would be needed to assess whether extra help changes the trajectory of the clients. This kind of information was not provided by the food bank or DataKind UK. In other words, it is not possible to assess whether the predicted trajectory would happen without the support, whether it improves the outcomes of the service, or whether some other indicator beyond past service use would be a good predictor of risk.

The above case is an example of how changing service provision based on a new measurement of needs is taken by a non-profit to be an improvement in itself even without data on its outcomes beyond the data that is used to train and test the model. In other words, the credibility of the score relies on the new *analysis* and the data science techniques used to perform it. The uncertainties in accuracy and of usefulness of the data collected by the foodbank are therefore compounded by the uncertainties about whether the statistical model producing the score is accurate and trustworthy. Introduction of the algorithm is thus far from a simple step to increase the accuracy and credibility of identifying food bank dependency because it introduces new sources of uncertainty at a time when the use of machine learning models is coming under increasing scrutiny in public debate. This food bank case therefore testifies to the

[28] https://www.datakind.org.uk/stories-news/welcome-centre

difficulties of achieving greater credibility and trustworthiness through the use of novel data science techniques.

To generate data on individual needs, non-profits require a system where information on beneficiary needs can be inserted. For many non-profits, this system is the wider digital infrastructure that the organisation is using as part of providing services. To illustrate how such digital infrastructures are used to generate data on individual needs, I examine how Citizens Advice, a large nationally operating social sector non-profit, has used their digital infrastructures to collect data on their beneficiaries and used this data in an effort to understand their users. The following quotes are from an interviewee working in a managerial role relating to data, and further details were confirmed from public data sources such as non-profit websites, blogs, and reports published by the organisation. Citizens Advice had also collaborated with DataKind UK and interviewees from DataKind UK discussed the case, which allowed triangulation. In the following passage the interviewee reflects on the data they have. The interviewee is here referenced with a pseudonym "Interviewee A" to prevent their anonymity being breached elsewhere in the thesis.

> *"What special data do we have, it's the data that we get from our clients, so being a client-facing service. I work for national Citizens Advice and then there are 270-odd local branches, so independent branches in their own right, all over England and Wales. We essentially gather data as a by-product or function of the service that we provide. This data is sensitive. We have to maintain confidentiality and ensure that we're trusted. It's relatively high volume because we're seeing large numbers of people. It's relatively unstructured. For example, a lot of the insight might come out of the narrative. If a client is seen face to face, then an advisor will write up the interaction. There's also our advice itself which is almost like our product. Because we offer a broad range of services, that content is also high volume and quite complex and can be difficult to manage." (Interviewee A)*

This interviewee describes how the data they now generate is a "*by-product*" of their service provision. This data takes multiple forms. The interviewee highlights that "*insights might come out of the narrative*," which refers to textual data recorded by front-line staff on the interactions they have with beneficiaries. Another source of data the interviewee highlights is "*our advice itself*," which refers to the instructions and counsel provided by the staff which is a textual report recorded by the case worker accompanied by a classification of the issues and needs reported by the client. Both sources are information on the needs of their beneficiaries because this "*narrative*" data is the information provided by the beneficiaries on what kind of advice they need, and the "*advice itself*" is a response to what the staff believe is the advice the person needs. Both sources of data, however, are by-products of the service which means that they are shaped by all the choices that go into organising the service provision itself. The methods assemblage that generates data on individual needs is therefore not just what is recorded by the staff in the interactions, but also the digitalised service provision process.

The challenges of relying on data on individuals as a measure of social value come to the fore when the analysis is expanded to measuring the *change*. In the following quote, the interviewee from Citizens Advice reflects on the difficulty of measuring whether their services solve the problems beneficiaries have:

> *"A lot of the issues that we work with, we're trying to help people to resolve them, but we don't always know exactly whether the issue has been resolved. We're not always dealing with those workflows that have a start and an end as it were." (Interviewee A)*

According to the interviewee, the way they work with people in need does not always have "*workflows that have a start and an end*." In the context of measuring change, this quote suggests that it can be difficult to categorise problems of individual users as "*resolved*" or even to assess whether their situation has improved with the service. Measuring change between initiation and termination of the contact with an individual beneficiary is not necessarily possible even if large quantities of records are generated for the individual. Responding to needs does not yet mean that problems are solved although a better response to individual needs is a central plank of using data to improve non-profit work.

An interviewee working for DataKind UK provided insight on the data generated by Citizens Advice. The organisations had partnered multiple times to discover new ways to use the data, and the interviewee was familiar with their work.

> *"They already had good data because they're Citizens Advice and so all they do is talk to people about their issues and very carefully log it all. They had data, they had just had no idea what to do with it. We helped them analyse it, that we worked with it over the years. [--] We pulled in their data from those different places and put it into one place and showed them analytics for the first time. [--] . We found lots of weird issues that meant stuff to them. I think we found that there was surprising number of people having issues with the heating that hadn't been picked up. For them, it was the issues that were new and were occurring in the UK. Something like payday loans were actually tagged "any other category" in their database because they didn't yet put it as a category. We were helping them understand that problem by doing a lot of text analysis." (Interviewee 19, Senior manager, Facilitator organisation, Female, 5+ years of relevant experience)*

The interviewee's insights elaborate on what kind of data Citizens Advice collects by recording encounters with clients to digital systems. The quote highlights that data was being collected before there was knowledge of what to do with it which is common when data is generated as part of a digitalised service provision process. Nevertheless, the interviewee indicates that such data often misses key details when it does not fit into the basic categories used by the service. In this case the interviewee suggests that heating and pay-day loans had not been identified as areas of need in the data generated through the system, but the analysis helped Citizens Advice to address them as potential areas of need. The analysis therefore provided not just new insights but prompted changes in how needs were being recorded. However, it is not clear from this example what actions were taken after the analysis. The ideals of improving non-profit work with the quantification of social value and identification of needs would, nevertheless, suggest that the assumed benefit of the analysis is the reorganisation of the services. After all, data and knowledge are not yet interventions that change lives, although it was common among the interviewees to claim that it is a step towards it (see Chapter 5).

To better understand how Citizens Advice uses methods assemblages to enact beneficiary needs, I take a step back to consider the broader service provision process of the organisation. As suggested by the interviewees, the primary goal of Citizens Advice is to provide designated services and data is collected as a by-product. The digital infrastructure supporting service provision is designed according to the goals of service provision, which are not determined by Citizens Advice alone. In fact, according to their Annual Reports, most of the services are provided in partnership with the UK government and other partners, and income from these partnerships amounts to three quarters of the total annual income of Citizens Advice. These partnerships have a narrow focus on the money from individual government departments that is earmarked for specific advice services, or partnership with donors and other charities focusing on just one locality. These partnerships shape the way Citizens Advice categorises their areas of advice and the needs they respond to. As argued by Critical Data Studies scholars, data is never raw and shaped by what organisations do in the first place and what they find relevant to include in the design of their digital infrastructures (Gitelman, 2013; Kitchin, 2014b). Indeed, I suggest that the data on individual needs is but a small elaboration of the way the service itself assumes certain needs should be responded to. Data-driven discovery of individual needs is seen as only fine-tuning the advice the organisation has committed to provide as part of its strategic choices and partnerships. It was therefore uncertain how much the new analysis of data would ultimately improve the quality, effectiveness, or efficiency of the service.

The above analysis on the enactment of individual needs highlights the way digital data collected and generated as part of service provision is changing the way non-profits understand social value. Based on the interviews with non-profit data professionals, their vision for management and improvement of non-profit work is based on collecting detailed data on the needs of their users and shaping non-profit work to better respond to them. In other words, their understanding of social betterment focuses on better response to the needs of individual beneficiaries which are enacted with the digital, mostly quantitative data, collected through service provision itself.

These findings corroborate earlier research suggesting that non-profit sector ideals of measurement and improvement walk hand in hand, although it is often unclear if they actually improve non-profit work (de Waal et al., 2011; Melnyk et al., 2014; Moxham, 2010). Indeed, based on my analysis I suggest that extensive reliance on digital service provision data as a measure of social value is likely to lead organisations to have a narrower, not richer, understanding of social change because it reduces it to the interactions non-profits have with their beneficiaries. As an ever-partial enactment of social value and beneficiaries, this reliance can lead non-profits to focus on narrowly optimising the management and measurement of their own processes, rather than focusing on the wider goals of social betterment. Exclusive reliance on the quantitative data can lead to other ways of understanding social value or beneficiary needs losing their clout. If non-profits solely use managerial quantitative data to enact a version of social change, then this can become the whole reality of what social change means to them, despite the partiality of that data and the version of reality it enacts. These insights on enacting individual needs join long-standing critiques of introducing managerial practices and measurement into non-profit work (see Chapter 3). In the next section, however, I show that this is not the only way that non-profit data professionals in my study understood the use of quantitative data in enacting needs and that non-profit sector data professionals also look beyond their own data sets to understand the needs of the population.

8.5. Enacting and tackling collective needs

Based on my analysis, digitised data is confirmed as playing a key role in how non-profits enact social problems as *collective needs* that non-profits can tackle. The importance of data on collectives and their needs was often discussed by the interviewees. In the following quote an interviewee working in a leading role in a non-profit sector data consultancy explains how grant-makers can be more interested in data on a certain community than in any data provided by grantees. The quote is part of a longer discussion on what kinds of data the clients of the organisation are interested in using. In the quote the interviewee discusses the interests of community foundations, which are a type of grant-giving organisations that focuses on a specific locality:

> *"[community foundations] are interested in trying to understand the need of the community, of the geography. They're not necessarily interested in their specific grantees [--] Sometimes they're just wanting to evidence what social context is, or what the social problems are or the geographic barrier where they're wanting to work." (Interviewee 28, Senior manager, Facilitator organisation, Female, 20+ years of relevant experience).*

This interviewee juxtaposes "*community*" and "*grantees*" as objects of data and argues that community foundations are more interested in the former than the latter. The data on "*needs of the community*" is what I analyse here as data on collective needs, because it identifies the needs of a larger social unit than the identification of individual needs discussed in the previous section. The quote underscores the role of quantitative data in enacting collective needs of the community which is used as evidence on the needs and problems that require attention. Furthermore, it emphasises that evidence on individual-level needs that is often collected by non-profits themselves, is not necessarily interesting for all non-profits and charities because their unit of intervention to tackle social issues might be a specific wider locality, community, or social group.

Some of my interviews suggested that certain data sources on collective needs are more authoritative than others. For example, the UK indices of multiple deprivation, a data set maintained by the UK government that maps various dimensions of inequality and poverty in a single geographic representation, was held in particularly high regard by many interviewees. Its status as an official government statistical set of data contrasts it with data collected by individual non-profits. The value of this data was stressed by multiple interviewees. The following passage is an example of how the head of data science in a social sector non-profit organisation discussed the value of external data sets, with indices of multiple deprivation as one of them. For the interviewee, the use of external data sets was expected to complement internal data sets, which are focused on service delivery.

> *"Making use of external data sets, we do that, particularly things like data sets from the Office of National Statistics. In particular the geographic data sets and things like The Indices of Multiple Deprivation [--] As a general principle, there are several data sets in the UK—several official data sets that really help to enhance the strength of your analysis." (Interviewee 31, male, service-providing organisation)*

It is suggested here that indices of multiple deprivation are valuable because of their geographic orientation and ability to "*enhance the strength of your analysis*." In the wider context of the interview, what is deemed to be enhanced by the indices is the analysis of data collected by the organisation itself. The data provided by the indices is understood to be particularly strong evidence on the needs of specific geographic areas. The interviewee recognises indices of multiple deprivation as one of "*several official data sets*," which they use to complement their own data. In the framework of the analysis of epistemic disputes, the interviewee can be seen as comparing the legitimacy and value of different data sets. In this case, the interviewee suggests that the two sources complement each other and can help the organisation achieve greater levels of accuracy and credibility on changing needs in the society.

The data set under discussion here, the *Index of Multiple Deprivation*, is a very different data set than what I discussed earlier in this chapter. The index consists of 39 separate indicators drawn from official statistics and compiled into a single weighted score that reports *relative* deprivation between the 32,844 geographic units that the score is calculated for. Collection of the data and publication of the results is coordinated by the UK Ministry of Housing, Communities & Local Government, making it part of the official statistical research by the government The indices and the data have been released periodically since the year 2000, with the latest report published in 2019 just before the interviews were conducted. The data set is openly available for everyone without cost and key findings are available on interactive websites and reports. The indices are part of a methods assemblage consisting of the wider statistical machinery of the government that no non-profit organisation would be able to produce, giving it unique epistemic authority as an official government data set. What makes the index interesting for my analysis is that its existence has nothing to do with either digital data or data science because their collection and configurations predate the prominence of either. Nevertheless, it is still considered a key data set for enactment of collective needs. In the case of enacting collective needs, official statistics are a major epistemic resource in the same way that statistics have been for decades. However, it is important to note that the availability of the data set itself as open data is not a given, but it is this openness that allows the data set to be combined with other data that a non-profit might have. Non-profits that have built their own data capacities can therefore tap into the data set in their own work and either refine their own data with the index or refine insights from the index with their own data, thereby producing a new enactment that goes beyond official statistics.

So far in this section I have discussed the importance of enacting collective needs and the importance of official statistics. This corresponds to the traditional role of statistics in public debate over social policies. However, it was also clear that data collected as part of service provision itself is also used by non-profits to enact collective needs. More precisely, non-profits were found to collate data on individual needs identified through service provision to build a picture of collective needs.

An illustrative case of data generated through service provision also serving as data on collective needs comes from an interviewee working for a medium-size social sector charity. The organisation focused on providing help for people in financial distress, advising on welfare benefits, and providing financial support. The interviewee had over a decade of experience in the non-profit sector, and they explained how their career had focused on "*how we can measure the performance of different platforms, website or other digital tools, apps, and through measuring that performance make improvements.*" (Interviewee 30, Director of Impact and Innovation, Service-providing non-profit, Female, 5+ years of relevant experience). This was also the focus of their current job where they led the non-profit's work on data. In the following passage the interviewee describes how they use data collected through online tools to understand changing needs

> *"We focus dominantly on our understanding of people affected by poverty and what we can learn about people's changing needs as a result of the data we collect through our main tools. We have a website that has a lot of information on the benefits system, on how to go about claiming welfare benefits, on your entitlements and what to do if your own financial hardship. We also have a benefits calculator that will help you calculate your benefits. [--] Then we also have a grant search, which allows you to search a database of thousands of grant funds around the country that you could be entitled to as an individual to claim accounts. [--] All of these tools, obviously the website information isn't really a tool, but we're generating data from that as well. Through those, we can build up a picture of the changing needs of people that come to our channels and just purely by what they tell us through filling out their various questions." (Interviewee 30, Director of Impact and Innovation, Service-providing non-profit, Female, 5+ years of relevant experience)*

In this quote the interviewee explains how their online tools and service logs generate data on who is seeking their help. The primary goal of these online tools is said to be to disseminate useful information to beneficiaries by personalising the advice based on their personal attributes, but they also double as technologies of data generation. To receive advice, beneficiaries using the tools must insert information on their social status and background to determine their eligibility for specific benefits. Elsewhere in the interview the interviewee explained that this includes categories such as age, gender, nationality, income, family situation, immigration status, and home address. Data on the applicants can then be connected to categorical data on what kind of support they are looking for or what problem they are facing. According to the interviewee, combining these two elements allows the organisation to "*build up a picture of the changing needs*." This, I suggest, can be rephrased as suggesting that the data is taken by the interviewee to enact and articulate versions of social problems, revealing changes in collective needs. As in the previous case, information provided by individual beneficiaries is aggregated not just as measures of individual need, but as representative of wider changes in collective needs.

To elaborate on what enactment of collective needs with these kinds of data from online tools means in practice, I quote the same interviewee on what insights the organisation has drawn from the above-mentioned data.

> *"At the moment, we can see the huge spike in demand from self-employed people, we can see that the demographics are shifting on the people who use our tools. We were previously very underrepresented around white European people because people coming to this country from say Eastern Europe weren't searching for and weren't claiming benefits. They were working, but right now they could have right to remain there in the UK, they're staying here through the [COVID-19] crisis and they're going on and claiming benefits. We can see that single parent, there's a real spike in demand for single parents. There's a real correlation with younger people as well and women.*

The interviewee explains that demographic information on who is using their tools and what support they are looking for offers insights on the social groups that are facing financial hardship. For example, it is suggested that Eastern European nationals have emerged as a group looking for support due to the pandemic, whereas earlier this group did not do so. It is also suggested that single parents, women, and younger people have emerged as new groups looking for support based on their increased numbers in using the online tools. In other words, the interviewee considers the data generated through their online tools to represent real needs in the society, with changes in the data reflecting changes in the broader society. For this interviewee, online tools are positioned as components of a methods assemblage to enact collective needs in the same way that statistics do.

Based on my analysis, I suggest that the way these interviewees extrapolate data on individual users as a representation of collective needs is connected to the ideals of Big Data that became popular in the early 2010s; that is, that digital data generated as a by-product offers reliable information on social phenomena, despite not being a representative random sample (c.f. Mayer-Schönberger & Cukier, 2013). Assessing these online tools as components of a methods assemblage highlights that for many users this data is good enough to guide their work, and that they do enact a version of social reality that organisations consider valuable. Researchers, however, have highlighted that such data is not the same as representative random sampling of a population because data from digital platforms is shaped by the digital infrastructure itself and the self-selection of the users (Marres, 2017; Ruppert et al., 2013). The data collected with the online tool that I discussed above is arguably liable to *more* uncertainties than either official government statistics or representative statistical samples, although it is perceived by my interviewee as a valuable new source of data on collective needs. Indeed, my analysis suggests that digital exhaust data is used precisely to enact collective needs despite its shortcomings and uncertainties. The result of this extrapolation is that non-profits that rely on their own service data to understand collective needs are at risk of enclosing themselves within a perception of social change that is enacted by the organisation itself unless external data sources are used to complement it.

The analysis of the interviews highlights that non-profit data professionals can use external data sources as well, such as the Indices of Deprivation or, as I showed in Chapter 6, open data from London Data Store, which reduces the risk of relying on repurposed data on individual needs. Nevertheless, what is important is that non-profit organisations did seem to use their own data sets to enact a version of collective needs and to manage and improve their services no matter their credibility and trustworthiness to possible outside actors. My focus on enactments and justifications stresses that such practices influence how non-profits operate and how alternative courses of action are justified. The interviewees have been shown to place epistemic value on their own enactments of collective needs and to prefer using such data to not using it, no matter how much uncertainty is involved with this.

8.6. Power asymmetries

I next turn to the power asymmetries that these data-driven ideals of social betterment embed. In Chapter 6 in my discussion of disputes over funding I suggested that the power of grant-makers over grantees is asymmetric and challenges the use of certain kinds of data. When it comes to the quantification of social value, no such coercive dynamic appeared to be present. People participating in Data for Good initiatives have been shown to push non-profits to adopt data as the way of measuring social value because they believe it to be a superior epistemic resource that improves non-profit work. Whether this actually is the case is disputed as I have argued above. Power asymmetries come into play when we dig deeper into where this ideal comes from and how it is promoted as discussed in Chapter 5.

A common dynamic in Data for Good initiatives revealed by this study is that people and organisations with advanced data analytic capacities serve as models for others. Non-profits with little prior expertise in quantitative or digital data collection or analysis are encouraged to collect more data, invest in digital systems, and hire professionals to analyse the data. The data maturity models that I discussed in Chapter 5 are deficit models where some non-profits are deemed to be "leaders" whereas others are said to be "behind" the ideal practice and therefore need to "catch-up". As it happens, the ideal models of data-driven non-profit work then come from large non-profits with resources to develop the systems and from data professionals who have honed their skills in the private sector, governments, or universities. The power asymmetries of quantifying social value can be found in how these factors relate to the actual state of the use of quantitative data in most non-profits.

I suggest that a key power asymmetry in disputes over social value is that investment in data collection and computational capacities is itself taken to be a sign that non-profits are serious about social value. Having extensive digital service management systems and data on individual and collective needs was taken by many of the interviewees in this study itself to be a goal despite unclarity on whether this makes a difference on the broader societal level. If non-profits cannot collect numerical data and lack digital systems, critics can raise questions about whether they can achieve their goals of social betterment. The power asymmetry therefore lies in large non-profits becoming the models for social betterment on the premise that they have more quantitative data, whereas small non-profits are treated with distrust for lacking data. The result of this dynamic is that bigger non-profits are considered better non-profits almost by default because they are more likely to be able to demonstrate their social value with this kind of data. Yet as indicated above in the discussion about the uncertainties of achieving collective change through the management of individual needs, data-driven management of non-profit services does not necessarily lead to social betterment or an improvement of social conditions.

Another aspect of power asymmetry can be found in the dynamic between non-profit data professionals and people who are not experts in quantitative data collection and analysis. As indicated throughout this chapter, this kind of data is valued as a measure of social value and needs. This means that the people who can work with data and analyse it have a special position in the internal debates non-profits are having about their social value. I suggest that if only claims made with quantitative data are appreciated in disputes about social value, this grants non-profit data professionals an asymmetric power position over other experts in non-profit work, such as community leaders and front-line staff. After all, if all decisions on managing and improving services need to be based on particular types and presentations of data, the people responsible for data analysis are very likely to have considerable influence over the entire organisation. Indeed, it is worth remembering that in Chapter 5 I indicated that an explicit goal of Data for Good initiatives in the non-profit sector has been to build a new professional community that has hitherto not existed.

I suggest that one outcome of this power of data professionals is that non-profits are likely to increasingly embrace two ideological underpinnings often criticised by

Critical Data Studies researchers. The first is techno-solutionism which refers to the idea that social problems can be solved with technological innovation (Madianou, 2021; Morozov, 2011). The second is dataism which refers to uncritical deference to digital and online data as a neutral or objective source of knowledge and the aspiration to collect as much data as possible even if the purpose of its collection is unclear (boyd & Crawford, 2012; van Dijck, 2014).[29] The challenge that these two ideals present to non-profit work is that they celebrate a specific way of working and organising which is justified by the promise of innovation and improvement. This is despite mounting evidence of the problematic and outright harmful implications of embracing technology-centric approaches to social betterment. Placing a premium on techno-solutionism and dataism can lead to the devaluing of non-profit work that does not seemingly condone with these ideals. In contrast, performative uses of technology that align with these ideals are valued even if there is uncertainty about its implications or usefulness. Power asymmetries therefore manifest in the status of different ways of doing non-profit work even if their social contribution is identical.

Furthermore, because techno-solutionism and dataism are vigorously promoted by large technology corporations in their own philanthropic work in humanitarian and development contexts (Madianou, 2021; Magalhães & Couldry, 2021), non-profit data professionals who follow such ideals end up promoting the interests of large technology providers. As a result, the power asymmetry between non-profit data professionals and other professionals in the non-profit sector can increase the influence of actors that are quite remote from the goals of social betterment through charity towards people in need, in this case, in the UK, and can contribute to inequalities that they claim to address. Researchers have highlighted that such expansion means that the interests, values, and operating practices of technology companies are pushed into new spheres of society, thereby transforming what it means to contribute to the betterment of

[29] It is important to recognize that these two ideals are related to but more specifically related to digital technology than the wider belief in the neutrality and objectivity of numbers (Porter, 2001).

society (Magalhães & Couldry, 2021; Sharon, 2018; Taylor et al., 2023). The people interviewed for this study as a sample of non-profit data professionals participating in Data for Good initiatives can also be seen as promoters of these new ideals that have a profound effect on the more traditional goals of charity as a form of solidarity and its conceptions of social value.

Finally, it is worth stressing that the interviews elicited little evidence of large technology companies such as Google, Microsoft, or Facebook being *directly* involved with the Data for Good initiatives in the UK non-profit sector, although they are indirectly implicated in the promotion of data science as tool of social betterment. In fact, several interviewees who were active promoters of Data for Good initiatives voiced criticism of the possibility of large technology companies becoming directly involved with the network. This means that while it is evident that many of the interviewees of the study promoted the use of digital technology a computational tool, this did not mean that the initiatives or the practices promoted in them were a direct extension of large technology companies or would benefit from grants awarded by them. In this respect the analysis of the interviews seems to suggest that the involvement of large technology companies or their techno-solutionist approaches o social problems has not gone as far in the UK non-profit sector as in the context of humanitarian and development aid, where large technology companies and philanthropic foundations of technology entrepreneurs are already major actors.

8.7. Conclusions

In this chapter I have sought to clarify what it means when social value is reimagined based on quantitative data on needs. Unlike in disputes over funding, which have an external focus and fairly clear cut-off between success and failure, the internal debates about how to contribute more to social good do not necessarily have similar distinctions between success and failure. What counts as satisfactory is determined by the organisation *itself*. Therefore, the question the non-profit data professionals in this study tackled with their promotion of the use of data is whether non-profits could be *even more* efficient, effective, and impactful in delivering social value. The use of data, then, provided a key strategy for identifying such opportunities and measuring whether improvement "really" occurred. The observations about stronger or weaker evidence in epistemic debates was shown in this chapter to help non-profits to get closer to "real" and "true" social value.

I suggest that as attention to data-driven improvement expands its reach, it is increasingly difficult for non-profit organisations to consider social value beyond what can be enacted with quantitative and digital data practices. In the world that Data for Good initiatives aspire to, there might not be any "goodness" beyond what can be demonstrated with the use of data. Other ways of measuring social value and improving non-profit work become increasingly suspicious because of the perceived weakness of the proofs about impact and progress.

In Chapters 6 and 7 I suggested that there are limitations to the usefulness of data science in the non-profit sector. However, in this chapter the way data science might help non-profits becomes clearer: with even more data and even closer management of non-profit work come opportunities to use data science to analyse beneficiary needs. The computational techniques celebrated by data scientists find their non-profit sector use-cases in the closer management of beneficiaries. The use of data science has been shown to enact and rearticulate both individual and collective needs by using new data sources and new data analysis techniques. These can create new versions of what it means to respond to needs and therefore contribute to social value. Critical reflection on these findings suggests that changes in whether data is or is not valued in disputes over social value could lead to differences in what needs are tackled and what issues are deemed worthy of intervention. What this means in practice is that that rethinking of needs and social value through the lens of quantitative data means prioritising those social issues that are easiest to quantify. It risks disregarding social issues that are less amenable for quantification. These findings corroborate earlier studies of use of data in the non-profit sector (Heeks & Shekhar, 2019; Krause, 2014).

Furthermore, my findings question whether closer measurement and management of individual needs necessarily leads to collective change. This is bad news for the legitimacy of non-profit work because divorcing service management from collective change has been shown to potentially undermine the rationale of social betterment. Putting too much emphasis on measurement and management of individual needs can lead to more stirring of the surface while the deeper currents of social issues remain unchanged. This is hardly desirable for non-profits, although doing so might align them with the expectations of a strong ‘data culture’ and greater ‘data maturity’ promoted by non-profit data professionals (see Chapter 5).

Finally, I want to emphasise the implications of the analysis in this chapter for the notion of epistemic value. In previous chapters I have suggested that increasing the use of quantitative data does *not* eradicate uncertainties in knowledge claims despite many interviewees claiming that data can deliver higher levels of epistemic value. In this chapter I have shown how the interviewees could both promote the use of digital and quantitative data while identifying weaknesses in enactments made with that data. Although this kind of data was associated with credibility and with the ideal that it will provide the best knowledge, it ultimately was seen as failing to offer a stable epistemic foundation for non-profits aiming to improve their services. This failure was ascribed to the shortcomings and loopholes that can be identified with any data set and is therefore not limited to the data practices discussed in this section. Thus, the use of data is not the final word on epistemic disputes, but a resource to be used when justifying claims. Following my interpretation of John Law, methods assemblages enact partial versions of reality that can be fit for a specific need to justify claims, but they are ever partial. Social value, identification of needs, and improvement of non-profit services can never be fully captured in their complexity, which leaves claims about them open for critique even when the most sophisticated forms of data and data science are employed.

Based on these reflections, I suggest that expanding the use of data science in service management might not always help non-profits to achieve collective social change. With closer focus on data science and service provision data, non-profits might seal themselves off from the larger context of social change. If followed too closely, data collected by an organisation through service provision risks becoming everything there is to social change. This also creates opportunities similar to the gaming that was identified in Chapter 7, but here within internal debates and with more profound consequences for the self-understanding of non-profits. Evidence on serving beneficiary needs has been shown to be turned into evidence that *legitimates how well the non-profit is already doing its work*, rather than spurring it towards improvement that is the stated aim of collecting more data. After all, if data science approaches help non-profits collect more data on their success, this can grant non-profit managers considerable legitimacy in their work. Legitimacy, however, can be fragile when doubts emerge. The analysis of my interviews suggests that doubts and critiques are stirring among non-profit data professionals. However, these critical reflections have mainly found an outlet in calling for more and different data to be collected as a remedy to the shortcoming of earlier data collection.

Chapter 9

Conclusions

9.1. Introduction

The goal of this thesis was to analyse the politics and practices of data in the UK non-profit sector, which I approach by drawing upon insights in the Critical Data Studies field. The motivation to explore this topic stemmed from the recent pushes to introduce new quantitative and digital data practices to the non-profit sector as part of wider trends in the society that are promoting data science and Big Data. My conceptual framework combined John Law's arguments on methods assemblages in the ANT tradition with Luc Boltanski and Laurent Thévenot's insights on justification and value. As explained in chapter 2, this combination was motivated by my goal of elaborating on Ruppert, Law, and Savage's work to develop a strategy for addressing normative concerns, while retaining key ideas in ANT. The aim of developing this framework was to enable a symmetric analysis of sociotechnical data practice and the normative promises of social betterment through the use of quantitative data in the non-profit sector. The conceptual framework operationalised the empirical part of the thesis consisted of three concepts: methods assemblages, situations of dispute, and demonstrations of value. Empirical data collection combined interviews with 35 non-profit data professionals with supplementary materials from fieldwork observations and online information search.

In this concluding chapter I review the findings and key arguments. I open the chapter by offering my answer to the primary research question and research sub-questions. I then discuss the contribution to earlier literature with separate components regarding the empirical research on non-profit sector data practices and theoretical debates within the Critical Data Studies field. In the penultimate section, I discuss the limitations of the study, alternative interpretations of my evidence, and opportunities for further research. The thesis finishes with a short reflection.

9.2. Answering the research questions

The primary research question was *"How are data practices used to demonstrate value in the UK non-profit sector?"* Based on my analysis in the preceding chapters, data practices demonstrate value by either serving as proof in epistemic disputes or by enacting versions of reality that demonstrate value in other situations of dispute. I proposed the concept of epistemic value as a way of understanding how data itself is used to assert value and act as a "proof" that substantiates claims. Furthermore, I proposed that assessing the epistemic value of data practices is likely to be subject to its own rules of justification and denunciation that often intersect with the need to demonstrate other forms of value as well. This means that if some data practices are thought to be successful in demonstrating epistemic value, they can be used in different situations of dispute to enact objects that serve as proofs of value. For example, when non-profit organisations use quantitative data practices to demonstrate their impact when applying for grants, they enact a version of reality where the work of the non-profit produces social change, and the credibility of this claim is bolstered by the techniques that were used to make it. In other words, the methods assemblages are used to enact a version of reality that supports the claims of the organisation making them. This also means that different data sets and analysis techniques can enact different versions of whether the organisation is impactful, possibly casting doubt and uncertainty over such claims made with other methods assemblage. In the empirical analysis I have shown instances of such doubt and uncertainty throughout Chapters 6, 7, and 8, suggesting that the interviewees often voice critical remarks on the credibility of specific data practices. My analysis confirms that analysing the entanglement of methods assemblages and justification provided a useful vantage point to investigate data practices in politicised and decisively normative contexts such as the non-profit sector.

The basis for this conclusion was built iteratively throughout the thesis. In Chapter 2 I established the theoretical foundations for this argument by combining the ANT idea that methods assemblages enact competing versions of reality with Boltanski's and Thévenot's arguments on the centrality of reality tests in all demonstrations of value. Based on this foundation, I outlined three research sub-questions to guide the analysis. I will answer each of them in turn before returning to the primary research question.

The first research sub-question was "*What new quantitative or digital methods assemblages are promoted in the UK non-profit sector*?" This question is important, because the part of the motivation for the study was my interest in the promise of Data for Good initiatives that new quantitative and digital data practices provide an opportunity for innovation and improvement in the non-profit sector. To understand how data practices demonstrate value, it is necessary to first identify and analyse the data practices present in the case.

The initial answer to the first sub-question was given in chapter 5, in which I analysed Data for Good initiatives as an entry point to non-profit data practices. I showed that data science, which often is central in research on Data for Good initiatives and in the public imagination, is only a small part of the overall push to promote quantitative and digital data practices in the UK non-profit sector. Based on my sample of interviews, Data for Good initiatives in the UK non-profit sector were shown to focus much more on gradual development of quantitative data collection and analysis skills.

In the next three chapters, which focused on different situations of dispute, I showed that the value of data science was uneven across these disputes.

A key finding concerning data science in the context of the first research sub-question is that the methods assemblages associated with data science have often proven far less relevant for non-profits than their proponents might want. In Chapter 6 I showed that even interviewees who had long worked to bring data science to non-profit sector could be sceptical of its value. The value of data science appeared to be limited not only by a lack of skills and resources in the non-profit sector, but also by the lack of digital infrastructures that would provide the data for analysis. Furthermore, the analysis of the interviews suggested a mismatch between what makes data practices valuable for non-profits and what data scientists find valuable in their work. My analysis of the data science volunteering scheme of DataKind UK suggested that experts of data science might be interested in the technical innovativeness of computational tools, but such perceptions of value were not always shared more widely among my interviewee and their experiences of non-profit data practices.

The second research sub-question was "*in what situations of dispute do data practices justify value*." Answering this question is a central part of my approach to the politics and normativity of data practices. Chapter 6, 7, and 8 each focused on one situation of dispute that was identified in the interviews.

In Chapter 6 I showed how non-profit data professionals understand data practices as a way of achieving higher epistemic value when it is in dispute. I called these situations epistemic disputes and showed how my interviewees tend to associate digital and quantitative data practices with higher epistemic value. Epistemic value and data practices are therefore closely connected, because the choice of methodologies and ways of knowing are part of assessing epistemic value, and use of quantitative data practices is thought by most of the interviewees to be a better demonstration of epistemic value than non-quantitative ways of knowing. However, I also found that epistemic value is rarely the main concern for the non-profit organisations in my sample and data practices were ultimately used to support substantive claims about the value of non-profit work. The methods assemblages used by non-profit organisations were shown to enact different versions of reality that are tailored to demonstrate value in specific disputes.

After establishing epistemic disputes as a focal point of data practices and value, I then turned my attention to two areas where my interviewees observed that data practices were particularly valuable: grant-making (Chapter 7) and measurement of needs (Chapter 8). The analysis does not exhaust all the situations of dispute that arise where data might be used in the non-profit sector, but my analysis suggests that these two situations are highly salient due to the extensive treatment they were given in the interviews. Their existence is also supported by earlier empirical research on quantification and data practices in the non-profit sector, which has extensively discussed the effects of marketisation and managerialism in non-profit work (see Chapter 3). In my analysis I showed that the same quantitative and digital data practices can be used across situations of dispute, which means that the same measurement techniques end up substantiating different forms of value. For example, quantitative measurement of needs can be used to demonstrate worthiness of funding when applying for grants, but it can also be used to debate whether the organisation contributes to broader social change or whether the service of a non-profit organisation is meeting the needs of its beneficiaries. In all these cases methods assemblages are used to enact needs, but their function in demonstrating value is different.

Throughout Chapters 6, 7, and 8 I suggested that data practices in the parts of the non-profit sector I examined ultimately appear to fail to provide a stable and unified epistemic foundation for all non-profit work, although the aspiration towards higher epistemic value often treats quantitative and digital data practices as a way of achieving this goal. Even the most advanced new computational data practices, which I analysed especially in Chapter 6 and 8, were not found to provide a stable epistemic foundation that their proponents hope they could provide. In other words, strengthening the epistemic value of claims only settles local epistemic disputes, but these demonstrations remain susceptible to criticism when new evidence is enrolled or the assumptions and practices that underpin the analysis become points of criticism. In fact, pursuing higher epistemic value purely for the sake of it often seems to miss the point on what non-profits try to do with data in disputes about worthiness of funding and social value.

The third sub-question is "*how is the demonstration of value entangled with methods assemblages in these disputes*." A response to this question is particularly important for my answer to the primary research question because it builds on the methods assemblages identified in response to the first research sub-question and explores their interaction with the situations of dispute identified in answer to the second research sub-question.

In Chapter 6 I showed that methods assemblages and epistemic value are closely entangled because some methods assemblages are thought to provide better and more credible "proofs" than others. Because of this entanglement, the use of specific data practices to make a claim is often itself taken as a sign of credibility. The analysis suggested that the non-profit data professionals I interviewed push non-profits to prioritise quantitative methods assemblages in enacting objects and phenomena of interest, and to offer quantitative, rather than non-quantitative, 'proofs' when the value of non-profit work is in dispute. Based on my analysis, the way value is attributed to data practices makes them desirable across different situations of dispute and ends up shaping what it means to demonstrate value in these other disputes.

The push by non-profit data professionals to make non-profit organisations value data practices has consequences for the way social betterment and the goals of non-profit work are understood. In Chapter 7 on grant-making and Chapter 8 on social value I suggested that the goals pursued by non-profits are increasingly shaped by data practices that are supposed to have higher epistemic value than non-quantitative demonstrations. In these two chapters I identified a variety of qualities that non-profits enact with data practices and that are therefore shaped by quantitative and digital methods assemblages. These include the accountability of organisations, impact of interventions, needs to address with grants, collective needs to be tackled, and individual needs to be served. All these enactments were shown in different ways to justify the value of non-profit work. In each of these instances, data practices were crucial in demonstrating that the claims made by non-profit organisations are epistemically worthy.

By pushing for more use of data and greater appreciation of data, non-profit data professionals were shown to want non-profits to *rethink* their work through data and therefore to *reshape* demonstrations of value. What social change looks like appeared to become more akin to what versions of social change can be enacted with data. What beneficiaries and clients need was being transformed into what needs can be enacted with data. What is good management of non-profit work was also evidenced as being transformed into what data can show about it. Furthermore, the push was not only about reaching higher epistemic value but also about changes *to what non-profit organisations want to achieve*. Based on my analysis in this study, the goal of making all non-profit organisations proficient in data practices and to value data might, therefore, ultimately not be about making non-profits succeed in their own goals. Instead, the goal might be about making non-profit organisations conform to specific goals, interests, and values that align with the aspiration to use more quantitative data practices. Promotion of quantitative and digital data practices might either purposefully or inadvertently de-legitimise successful non-profit work whose value is difficult to capture with quantitative measurement techniques available to non-profit organisations.

However, the entanglement of value and methods assemblages also means that data practices are shaped by situations, and not every quantitative or digital data practice is equally important in all situations. To emphasise this point, in Chapter 6 I discussed how the non-profits data professionals in my sample care about some situations of dispute more than others. In the same chapter I highlighted the challenges of limited resources and skills in the UK non-profit sector, which has led to data science being less relevant for non-profit organisations than its promoters have wished. Indeed, a discussion of data science was almost absent from my analysis of grant-making practices in Chapter 7. However, data science played a prominent role in my analysis of data practices and management of social value in Chapter 8. Altogether the three chapters therefore highlight variance in how data science is entangled with demonstrations of value.

Returning to my primary research question, the empirical analysis in the thesis suggests that the value of data practices is not clear cut and faces numerous challenges. The findings suggest that rethinking the pursuit of social good in terms of what can be demonstrated with the use of quantitative data can create contradictions that undermine the very ideals that guide the promotion of this data by non-profit data professionals. Crucially, the non-profit data professionals in my study were not strangers to the tensions and contradictions, which were extensively discussed. I found that these non-profit data professionals often voiced doubts and uncertainties about reliance on data practices, especially when there was a need to compare versions of reality that do not fit together. These uncertainties, however, did not necessarily shake the assumption among most interviewees that non-profits should anyway try to use more data or that they have no alternative to using more data.

My conceptual framework – with its focus on the concept of epistemic value – was very helpful in explaining this contradiction. While the general standards for assessing epistemic value that I infer in my analysis may favour quantitative and digital measurement practices, the methods assemblages used in specific relational contexts are shown to always be partial and liable to shortcomings. Use of data to demonstrate value does not close disputes once and for all, although it provides support for claims about value in specific situations of dispute. The shortcomings of specific enactments appeared to be widely recognised by the non-profit data professionals interviewed for my study. In some cases, recognition of shortcomings led non-profit sector data professionals to criticise or denounce specific data practices as *unrealistic* and not corresponding to what they contended should *really* be done (see Chapters 6 and 7). The response to epistemic tensions and contradictions arising in quantitative data practices was often to recommend the collection of more and "better" data to overcome problems, or to refocus on "better" uses of data. Thus, a common response to criticism of specific quantitative methods assemblages that serve as demonstrations of epistemic value was found to be to configure better quantitative methods assemblages rather than to rethink the normative premises accompanying the valorisation of quantitative data practices.

9.3. Contributions to research on non-profit sector data practices

The analysis in this thesis complements sociological research on quantification in the non-profit sector by building on ideas from Critical Data Studies and the work of Law, Ruppert, and Savage (2011;2013) on methods assemblages. The conceptual framework (Chapter 2) complements earlier studies on non-profit sector data practices (Chapter 3). The study responds to Rottenburg et al.'s (2015, pp. 21-22) call for sociotechnical bottom-up studies of quantification and expands on Barman's (2016) work on quantifying social value. It also aligns with Mennicken and Salais' (2022) insights on how researchers must look beyond techniques of measurement and macro-level politics to understand how politics and measurement are entangled in specific cases.

The findings expand on Barman's (2016) arguments on the diversity and relationality of measuring value with quantitative techniques, especially how specific measurement techniques can be tailored to specific relational contexts where value needs to be measured. The analysis shows how Barman's arguments on the co-constitution of measurement and value in the context of economic measurement can also be applied when the analytical focus is on data practices more generally. Since the empirical anchor in my thesis is data practices revealed through the lenses of non-profit data professionals and the situations of dispute where data is used, both the data practices and the attempts to demonstrate value are revealed as being more diverse than in Barman's study. Indeed, my findings suggest that debate about the social value of non-profit work takes many forms beyond financialization and economisation of social value, which were the focus of Barman's study. I suggest that diverse forms of valuation can be present even if relatively similar techniques are in use because it is the situations of dispute in which non-profits must justify their value that ultimately anchors the substance of what non-profits enact with measurement techniques. An example of this in my study is the way the measurement of needs is deployed to justify different aspects of value depending on whether it is assessed as part of grant-making or internal managerial discussions, although the methods assemblage enacting the needs might be the same in both scenarios (see Chapters 7 and 8).

My findings confirm that Krause's (2015) findings on the quantification of target populations in international humanitarian grant-making are also seen in the context of the UK non-profit sector. In Chapter 7 I showed that enacting needs to justify worthiness of funding is one of the most important ways that the interviewees in my study understood the value of quantitative data. However, this was not the only way that data practices were shown to enact needs. In Chapter 8 I showed that there are competing ways of enacting needs when non-profit organisations engage in internal discussions on the social value of their work.

My analysis also reveals and confirms the importance of power asymmetries in the non-profit sector as discussed in Chapters 6, 7, and 8. It highlights that non-profit data professionals report adopting different strategies in navigating the need to justify value depending on the power dynamics: non-profit data professionals in this study did not advocate for greater use of quantitative data just because grant-makers demand it or due to blind faith in quantitative measurement. Thus, I suggest that the quantification and enactment of needs observed in this study was not only tied to market-like dynamics of grant-making but was also important for internal discussions on how to improve and manage non-profit contributions to social change. Thus, the findings highlight the need to understand the relationality and variability of the politics of data practices.

Using data practices to enact populations in need was found to be linked to multiple different strategies to justify the value of non-profit work. As shown in my analysis in Chapters 7 and 8, demonstrations of needs and impact that are enacted to secure funding can diverge from the needs and impact that are enacted when managing services or advocating for social change. In the light of these results, it is likely that such differences might be present in other cases of enacting needs as well. If non-profits enact radically different versions of social need depending on whether the enactments are used to secure funding, manage services, measure collective social impact, or advocate for social change, this begs the questions of how aware people working in a non-profit are of these differences.

My findings complement research on civil society and activist uses of data. Past research has identified new sources of data as a resource for Data Activism and civil society action, although using novel data practices requires critical reflection on the situatedness and partiality of quantitative and digital measurement (Beraldo & Milan, 2019; Bruno et al., 2014; Crooks & Currie, 2021; Currie et al., 2019; Gabrys et al., 2016; Marres, 2012; Milan & van der Velden, 2016). Scholars have urged civil society and non-profit organisations to develop both their capability in using data and their critical awareness of the shortcomings (Fotopoulou, 2021; Gray et al., 2018; McCosker et al., 2022). Non-profit organisations in the UK are key members of the civil society and advocate for social change in addition to providing services that tackle social issues, and this research is relevant for the sector.

My analysis contributes to this literature by underscoring that while the non-profit data professionals in my sample associated data with various ways of contributing to social betterment, many also expressed criticism regarding data practices. The findings therefore confirm that struggles to achieve social betterment are increasingly being fought through the deployment of quantitative data practices. Indeed, the high epistemic value associated with these data practices means that the non-profits in my study were adopting new data practices to increase the credibility of their messages and to argue their case with greater epistemic legitimacy. Moreover, the non-profit data professionals interviewed for the study frequently criticised some uses of data while promoting others and frequently addressed the shortcomings of quantitative measurement in non-profit work. Based on the interviews, I suggest that critical awareness of limitations, which has been called for in several earlier studies, is already present in the UK non-profit sector, but that the non-profit data professionals respond to shortcomings by calling for more and better quantitative data rather than rethinking of whether quantitative measurement is needed in the first place.

In this thesis Data for Good initiatives were studied as an entry-point to non-profit sector data practices. Yet the findings also contribute to the emerging literature on Data for Good and AI for Good initiatives. I concur with Moore (2019) and Green (2019) that it is mistaken for proponents of Data for Good initiatives to frame the non-profit sector itself as a domain that where all data practices in the sector are inherently "good". My analysis confirms that the politics of data in the non-profit sector are much more complicated than this. Nevertheless, in contrast to the above authors and to Cowls (2021; Cowls et al., 2021) and Berendt (2019) who suggest that it is possible to outline ethical or political guidelines that would provide data scientists with a stable normative foundation that guides them towards "goodness", I argue that it is not possible to outline one set of practices and values that would pin down the politics of data science across different contexts. This follows from my theorisation of the politics of data practices as always relational.

My findings on Data for Good initiatives in the UK (see Chapter 5), paint a markedly different picture of Data for Good initiatives compared to similar initiatives in humanitarian and development contexts (Espinoza & Aronczyk, 2021; Holzmeyer, 2021; Madianou, 2021; Magalhães & Couldry, 2021). My study does identify data science as one part of Data for Good initiatives in the UK non-profit sector, but their role was much less prominent than might be expected given their reported prominence in international initiatives. Non-profit data professionals, even those directly involved in the promotion of data science, were often critical of their relevance. My interviewees views differed markedly from those identified in some analyses of international initiatives where techno-solutionist underpinnings are found with data scientists and technology corporations aggressively pushing for the adoption of data science.

In this study of Data for Good initiatives in the UK non-profit sector there was little or no evidence of the influence of large technology companies, such as Google, Microsoft, or Facebook, or technology-focused philanthropic funders, such as Gates Foundation, that are behind some of the international initiatives in humanitarian and development contexts. I found activities associated with Data for Good in the UK – at the time the study was undertaken - to be more of a collaborative effort driven by non-profit data professionals working in a variety of organisations and with a variety of goals.

9.4. Value of the conceptual framework within Critical Data Studies

In this thesis I have used ideas from Critical Data Studies to explore non-profit data practices. I developed a conceptual framework that elaborated on the ideas of Evelyn Ruppert and John Law concerning the need to study the politics of data through data practices and paying close attention to the relationality and normativity of methods assemblages (Law, 2004; Ruppert et al., 2013; Ruppert & Scheel, 2021; Mol, 2002). I also aimed to analyse the politics of data informed by insights from the Critical Data Studies field and by bridging between concepts from ANT and the pragmatic sociology of values. The intention was to complement research on Data Activism (e.g. Milan & van der Velden, 2016) and Data Justice (Dencik et al., 2016; Taylor, 2017), which explores the use of data in politicised contexts such as civil society and the non-profit sector. This application of my framework has been very helpful in emphasising the ways data practices can be deployed to justify or denounce value in normative disputes, and how the value of quantitative and digital data itself can be justified and disputed. In this section I re-iterate the strengths and contributions of the approach I have used, whereas the next section will discuss its limitations.

First, the conceptual framework shifted my attention analytically towards the *politics of what is enacted* with methods assemblages and how those enactments are used in situations of dispute. My analysis provided numerous insights into why the politics involved with data practices come to light when analysed through the need to demonstrate value. My conceptual framework called for an analytical approach that differs from Critical Data Studies scholars' efforts to analyse how politics are involved in the collection and generation of data (e.g. Kitchin, 2014) or the power asymmetries between data subjects and those who collect data (Andrejevic, 2014). My conceptual framework was also helpful in enabling me to distance myself from the need to make assumptions about whether specific data practices or the objects they enact are "good" or "bad" as such, or whether they contribute to, or constrain, the pursuit of social justice. My framework foregrounded how normative conundrums present themselves to non-profits in the UK through their practical work. Thus, my conceptual framework highlights vernacular understandings of the data practices of non-profit data professionals and how they report the benefits and problems of using quantitative data. Crucially, the framework allowed me to integrate justifications and critiques in the same empirical analysis, avoiding the pitfall of drawing stark oppositions between affirmation and rebuke.

Second, my conceptual framework and its application suggests a need within the Critical Data Studies field for reflection on whether quantitative data practices have a *depoliticising* effect on all non-profit work. In Critical Data Studies the accusation of depoliticization has been common and is often accompanied by critical assessments of how practitioners might believe that data is objective or neutral and whether there is a need to re-politicise data practices (boyd & Crawford, 2012; Iliadis & Russo, 2016). The goal of re-politicising data is often explicit in Data Activism and Data Justice approaches. In my conceptual framework, the use of data cannot be charged with depoliticising disputes, because settling debates through recourse to quantitative data tends to relegate the debate to the realm of ontological politics. As argued by Boltanski and Thévenot (2006), all normative disputes resort to reality tests in assessing proofs of value. In my framework enactments with data are not treated as being any more "objective" or "neutral" than enactments through personal encounters with beneficiaries or recourse to qualitative evidence. The latter is not deemed to be any "richer" or "authentic" than the former. Unlike some work in Critical Data Studies calling for more attention to the lived experience of communities and front-line workers (e.g. Fotopoulou, 2021), in my framework, data practices' political and normative nature is the starting point for an empirical analysis that is attentive to the normative positions of the practitioners who use data.

Third, my conceptual framework emphasises specific situations of dispute as the site of inquiry into politics, in contrast to an emphasis on structural notions of politics that is present in some work in the Critical Data Studies tradition (e.g. Andrejevic, 2014; boyd & Crawford, 2012; Dalton et al., 2016; Dencik et al., 2016, 2019; Taylor, 2017). This meant that macro-level themes discussed in earlier literature in Critical Data Studies, such as marketisation and neoliberalism as well as Big Data and technological solutionism, were identified and analysed through the way the themes manifested in the vernacular understanding of data practices by my interviewees. This conceptual strategy also complements more normative analytical strategies that set out to explicitly critique, reject, or seek alternatives to the use of quantitative data (Couldry & Powell, 2014; Dencik et al., 2019; Luka & Millette, 2018; Milan & Treré, 2019). Instead of myself building a normative case for the critique of data, I aimed to allow uncertainties and contradictions to emerge from my analysis of the way non-profit data professionals in my interviewee sample themselves justified and doubted the value of data (See Chapter 6). Instead of seeking evidence to argue why quantitative data has harmful consequence when used in competitive grant-making or critiquing its embodiment of neoliberal tendencies, the conceptual strategy allowed me to show how my interviewees were worried that uncertainties related to data practices are undermining the goals of demonstrating accountability, impact, and needs (see Chapter 7). Rather than building an argument against the quantification of social value through the measurement of needs, I showed how tensions within these disputes mean that non-profit data professionals report hesitancy about whether data-driven service management will eventually make a difference to changes on the collective level (See Chapter 8). Most importantly, my conceptual framework was helpful in revealing that doubts and uncertainties could still be turned by the interviewees into an opportunity to champion "better" data practices. The analysis therefore contributes to earlier research in Critical Data Studies by showing how non-profit data professionals themselves deal with the shortcomings and uncertainties around data, and how macro-level political dynamics identified in earlier literature are understood on the level of individual people working with and promoting the use of quantitative and digital data.

Fourth, the inspiration for my conceptual framework which was drawn from Boltanski and Thévenot's work emphasised a symmetric approach to normativity. I suggest that this approach can encourage researchers in the Critical Data Tradition to follow Boltanski and Thévenot in reflecting on why the critiques in the tradition of critical sociology and critical theory often fail make a difference in practice (Boltanski & Thévenot 2006; Boltanski 2011) and on why some of the *targets* of critique might be able to integrate those criticisms into their practices (Boltanski & Chiapello, 2018). This issue is also addressed in the ANT tradition (Latour 2004) (see Chapter 2). My conceptual framework was applied in a way that encourages such reflection, and it insists that researchers do not have a normatively or epistemologically privileged position in crafting critiques of data practices. The question then is what normative resources are drawn upon to deflect criticism of quantitative data practices, and to what extent are criticisms co-opted by data practitioners and disarmed? As discussed above, the critique of "bad" quantitative and digital data practices can be turned by non-profit data professionals into a plea for more “good” data practices that it is hoped will overcome the problems of the earlier practices. Reflecting on these questions could offer Critical Data Studies researchers the opportunity to cater to practitioners’ needs for novel resources to facilitate critical reflection on the opportunities and shortcomings of data practices.

9.6. Limitations of the conceptual framework and alternative interpretations

Every conceptual framework is limited as far as it is bounded by a set of theoretical starting points and choices in research design. In this section I highlight some weaknesses that came to light relating to my conceptual and methodological choices and challenges discovered when applying them. I also discuss alternative theoretical framings and their relevance for future research.

The first limitation concerns my focus on social over material aspects of methods assemblages. Although my expansion of the original work in ANT in a more sociological direction offers several benefits, I also found that analysing the interaction between data practices and justifications would benefit from more first-hand observation of the materiality of methods assemblages. Without this access, I often faced difficulty in getting deeper into the entanglement of methods assemblages and justification. Whilst the thesis shows the value of my approach, it also demonstrates that too much emphasis on the social side can be at risk of shallow observations when it comes to the ways that data practices shape demonstrations of value. I suggest that future studies should operationalise the framework with a stronger ethnographic or case-study component.

A second limitation of the conceptual framework is that its inductive focus can overlook some political and normative ramifications of data practices. The framework foregrounds issues that are explicitly recognized by interviewees or that can be readily identified in interviews. Conversely, the strategy can overlook those aspects of political and normative debate that are either not recognized by interviewees as relevant in their work, are unknown to them, or they deliberately choose to omit. The framework can likewise face challenges if used to explore scholarly issues that interviewees would not be aware of.

A third limitation concerns with the conceptualisation and boundaries of situations of dispute. Because the framework is permissive in terms of how a situation of dispute is identified and focuses on close interpretation of practices, it follows that studies might not draw the boundaries of situations in the same way. For example, in Chapter 8 it could also be possible to see the analysis of individual and collective needs as part of separate disputes, although they are here discussed as different aspects of social value. The collection of different materials, interviewing different people, or conducting the study at a different time might all have suggested different boundaries being drawn between analytical units in this study. Future studies should elaborate on the malleability of my key concepts and always ensure that the data collection and analysis follow rigorous standards.

A fourth feature of my conceptual framework is that the analysis balances between description and interpretation. On the one hand, the power of the framework is in using close description of data practices and justification. On the other hand, operationalisation of the framework requires interpretation of meanings. While in the empirical analysis I have shown that it is possible to focus on both at the same time, I acknowledge that the majority of my analysis is interpretative, and interviews were not always an optimal data collection strategy for close description of data practices. Future studies should explore different balances between description and interpretation.

Having discussed some of the limitations of my conceptual framework, I turn to limitations in the methodology of the study. Some of these limitations have already been discussed in Chapter 4 on methodology. The choice in the research design to focus on non-profit sector data professionals as a source of information meant that the analysis is limited to people who professionally work with or promote the use of data. This involved identifying organisations participating in Data for Good initiatives and recruiting interviewees using snowball sampling. The sample of interviewees is skewed strongly towards people who are committed to advancing the use of data or whose professional work focuses on quantitative data uses. This focus seemed justified given my interest in Data for Good initiatives, but it limited what can be said about data practices in the non-profit more broadly. It means that the critical reflection voiced by the interviewees is that of the data professionals themselves, and it is likely that including other professional groups from the non-profit sector would produce different concerns about the value of data. For example, having more interviewees from volunteer and front-line roles might have led to more comparisons between quantitative data practices and first-hand personal experience. Including more interviewees with managerial and leadership roles might have provided more insight into organisational and political considerations that influence the way non-profit organisations value data. Including these other groups would have also allowed a comparison of the views of different groups, which was not possible in my design given its focus on one group of interviewees.

The interviewees in this study were drawn primarily from various UK facilitator organisations that support the use of data in non-profit organisations but did not provide their own frontline services to beneficiaries. Only four interviewees were recruited from service-providing non-profits with seven from grant-giving organisations. Recruiting more interviewees from service-providing non-profits might have shed more light on the way data is used and repurposed as part of non-profit work. This limitation is felt particularly in Chapter 8 on disputes about social value, where further interviews or participant observation would have provided a wider scope for my analysis. On the other hand, since interviewees from facilitator organisations mostly worked with service-providing non-profits, this was not a major limitation.

My analysis of the interview material might be open to alternative interpretations with a slight shift in focus. In Chapter 8, for example, on disputes over social value, I focused on the enactment of collective and individual needs emphasising how they are shaped by the way non-profit work is managed. However, it would also have been possible to focus more closely on data practices and methods assemblages in managing front-line services. This was not done since I lacked interviewees and access to service-providing non-profits and their work, and my analysis of needs and social value focused on showing where non-profit data professionals understood data to be particularly relevant.

In the interviews with non-profit data professionals many were willing to share critical reflections on the limitations of using quantitative data in the non-profit sector. These critical reflections on the tensions and uncertainties relating to data practices in specific disputes feature prominently in my analysis. However, how well they represent the reflections that non-profit data professionals display in their actual work is not addressed in my study. Some of these reflections might be attributed to the context of the interview that specifically invites reflection but is disconnected from their day-to-day work. The critical reflections voiced by the interviewees may play a smaller role in the actual use of data in the non-profit sector. It may be that such uncertainties are glossed over in the actual work of the interviewees. Nevertheless, in my analysis these critical comments were important in showing how versions of reality do not always fit together and how the non-profit data professionals in my sample themselves critique their work involving data practices. I interpret critical reflections as providing insight into justifications and denunciations regarding data practices, but I acknowledge that alternative interpretations are possible.

A limitation of the empirical component of my study is that I was not able to attend as closely as originally planned to the materiality of the methods assemblages, as explained in Chapter 4. My study opened with fieldwork and participation in data-related events in the non-profit sector, but in later stages the focus turned to interviews and my fieldwork ended with the onset of the COVID-19 pandemic. I had only limited opportunities to observe data practices as they unfold within UK non-profit organisations or in their relationships with other organisations. Such observation would potentially have revealed more information on how the use of data is promoted and justified in Data for Good initiatives, as well as the material aspects of data practices. Instead, I was limited to analysing the materiality of data assemblages through the insights of interviewees and additional data collection. A further limitation is that I was not able to arrange participation in data science volunteer events organised by DataKind UK, one of the key promoters of data science in the UK non-profit sector. While I had interviewees from the organisation, it would have been beneficial to penetrate more deeply into the events and the community of volunteer data scientists. This would also have helped to get closer to the material aspects of data science.

The study being set in the UK non-profit sector also poses limitations to generalisability. The UK non-profit sector is particularly affected by market competition for non-profit funding and managerial monitoring requirements, and the findings reflect these broader conditions that were discussed in Chapter 4. The findings therefore might not be applicable in country contexts where the structure and culture of the non-profit sector has a different background. Furthermore, the focus on domestic social and health sector non-profit work means that the findings of the study might not be directly applicable in the context of international humanitarian and development aid. While the conceptual strategy is transferable to the international context, the findings themselves might be different given the different institutional dynamics and power asymmetries influencing non-profit data practices.

I now turn to a critical reflection on possible alternative strategies for similar studies. First, because I eschewed more structurally focused critical approaches to data practices, favouring a normatively symmetric approach, certain common arguments about data practices and non-profit work were not explored. Crucially, I did not seek to criticise the use of data or data practices as such or to propose alternatives. Had this been my goal, I might have framed my analysis in the light of social justice (Dencik et al., 2016, 2019; Taylor, 2017), feminist technoscience (Haraway, 1990, 1997) or de-colonial perspectives (Madianou, 2019, 2021). Because I did not explore these directions, I did not analyse the situatedness of my findings in the context of modernist Western cosmologies, neoliberal values of the Anglo-American cultural context, power asymmetries between data scientists and charity beneficiaries, the imaginaries of data-driven solutionism, or the gender-dynamics in UK non-profit and social sector work.

Second, my conceptual choices also meant that I touch only briefly on the enduring implications of NPM, EBP, financial austerity policies, and neoliberalism. As discussed in Chapter 3, each of these phenomena has had a deep effect on the non-profit sector in the UK. Indeed, if analysed more closely against this historical background, the findings presented in Chapters 7 and 8 could be interpreted to provide a sharp commentary on increased reliance on quantitative data in a neoliberal non-profit sector. This might have yielded deeper reflection on the extent to which the goals of UK non-profits are dictated by the interests of government contracts and philanthropic grants. Similarly, interpreting the findings through an analysis of the political economy of the non-profit sector might have highlighted the uncertainties and tensions associated with grant-giving processes.

9.7. Conclusions and final reflections

One of the interviewees criticised UK Data for Good initiatives by saying that "y*ou can deliver the performativity of good, without the substance of good*" (Interviewee 26, Member Engagement Manager, Facilitator organisation, Female, 5+ years of relevant experience). This interviewee was critical of the idea that data practices can themselves do "good" in the non-profit sector. Furthermore, she implies that the performativity of "good" is somewhat illusory in comparison to the substantive aspects of "good."

However, distinguishing between performativity and the substantive can be exceedingly difficult. When data practices and the assessment of their epistemic value serve to establish what is “real” and “true,” it can be difficult to establish a vantage point that caters to a credible denunciation of a given data practice.

Yet data practices are open to denunciations as I have shown throughout this thesis. My analysis illustrates that data can be gamed, data can distract, and that data might not always lead non-profits where they think it will. These criticisms suggest that the non-profit data professionals in this study did not consider quantitative and digital data practices to be all there is to establishing truth or achieving social betterment. Yet my interviewees were content to use this kind of data when it was deemed to help them to secure funding for a good cause or to identify opportunities for interventions. My relational approach to politics and practices emphasised such contingencies that stem from the situatedness of data practices, which can lead to tension and paradox when comparing different situations.

The epistemic value concept that I developed in this thesis offers a way to understand contingency and relationality in how quantitative data is valued. Even if quantitative and digital data practices carry an aura of objectivity and rigour for some, they ultimately do not offer a stable epistemic foundation for non-profit work. Indeed, in this study they were criticised by the same people who promote them. Thus, my analysis shows that a focus on demonstrations of value and situations of dispute provides a fruitful way of investigating the politics and practices of data. The results points to a way forward in considering justification and critiques of data practices across other contexts through the lens of a conceptual framework that has yielded considerable insight. This paves the way for further analysis on how and why practitioners think the use of quantitative data is valuable even when they acknowledge that these data practices and their associated data assemblages have various shortcomings.

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Appendix 1 – Interview guide in the first stage of data collection

This interview guide was used as part of fieldwork and ethnographic participation in a focusing event. The interview guide was significantly changed for each interview to focus on the special characteristics of the organisation/interviewee. The guide presented here covers some of the key themes discussed in the interviews. For example, interviews with participants focused on how their organisations use data, what they with data in the event, and what they think of data in the non-profit sector more broadly. On the other hand, interviews with facilitators focused on the dynamics of the event, what difference data makes to non-profits, and what are the broader dynamics of data in the context of the sector. Interviews before and after the event focused on different things.

1. Warm-up
   1.1. What does your organisation do?
   1.2. How did you come to work with data?
2. Event and facilitation [if interviewed before the event]
   2.1. Can you describe the background and the build-up of the events?
   1.1. Why this form of event? What difference do they make?
      - Who are the collaborators? What are their roles?
   2.2. What outputs and outcomes do you expect to come out of the event?

3. Your attendance to the event [If interviewed before the event]
   3.1. Why did you want to attend the event?
   3.2. Why do you think the event is organised? What appears as be its goal to you?
   3.3. What expectations did you have for the event?

4. Data sets
   4.1. What data sets will be used in the event? / What data sets did you use?
      - Have you personally worked with these data sets before?
   4.2. How did the data sets come to be?
      - Who compiled them?

- Who administers them?
- How are they used now?

4.3. How are the data sets connected to the theme of the event??
4.4. What do you expect to be done with the data sets in practice?

5. Capacity
   5.1. The event aims at capacity building. What does this mean to you?
   5.2. What difference can the use of data sets make?

6. Event walkthrough
   6.1. How do you feel after attending the event?
   6.2. How did it compare to any other forms of facilitating data in charities?
   6.3. What was the most useful or important thing to you?
   6.4. What exactly did you do with the data sets in the event?
   6.5. What kind of quirks and gaps did you encounter with the data?
   6.6. Who would this information be useful to? What can be done with it?
   6.7. What was the most useful or important thing to you?
   6.8. Did the event encourage you to do something differently, or think about some new questions?
   6.9. To simplify matters, do you think the outputs, or the process of the event was more important?

7. Charity data in general
   7.1. How would you describe use of data in the charity sector right now?
   7.2. What are your thoughts on different styles of intervention to support use of data?
   7.3. What do you think are the most pressing questions in the charity data context?
   7.4. what interventions could help charities make more use of data?
   7.5. What difference can the use of data make in the charity sector?

8. Wrap up
   8.1. Who would be useful further contacts?

Appendix 2 – Interview guide focusing on the second stage of data collection

1. What do you do?
   1.1. What work does your organization do?
   1.2. What did you do before?
   1.3. To get things started, what does use of data mean for you in your work?
   1.4. Can you give me examples of how <u>you</u> use data?
      Prompts and follow-ups: What is the goal of this practice? How did you get the idea? What is the use of data changing in this case? What can be done differently because of data?
   1.5. Do you know of other examples of how data is used in the charity sector?
      Prompts and follow-ups: What is the goal of this practice? What is the use of data changing in this case? What can be done differently because of data?
2. Context of non-profit data
   2.1. In your own words, why should charities and non-profits be interested in use of data?
   2.2. Where does the interest in data in the non-profit sector come from?
      Prompts and follow-ups: What is your earlier memory of data being a "thing" in the non-profit sector? Can you tell me why it was relevant back then? Is the current discussion similar or different from that time?
   2.3. Are there any particular organisations, events, or people that have been important for the emergence of data as a question?
   2.4. Issues around use of data do not exist in a vacuum. What other phenomena, opportunities, problems, or issues is data connected to in the non-profit sector?
      2.4.1. **Prompts and follow-ups:** Has there been any significant changes to the environment that charities work in? How is use of data related to wider interest in digital tools, internet, and social media? What is the relationship between data and the interest in impact? How is data connected to competition between charities for funding?

3. What are your thoughts on the concept "Data for Good"?
   3.1. What does "Data for Good" mean to you?
      Prompts and follow-ups: What practices would you associate with "Data for Good"? Why has this kind of a concept emerged? What is its connection to the "Tech for Good"?
   3.2. What makes someone or some organization a part of the "Data for Good"?

3.3. Who could not say that they are part of “Data for Good”?
3.4. What is the difference between charities, companies, and governments saying that they do “Data for Good”?

4. Facilitation and interventions
 4.1. What would help charities make more use of data?
 4.2. What interventions / tools of facilitation work?
 4.3. What legitimates investment of resources into data skills?
   Prompts and follow-ups: Many people have said that charities do not have resources to do this, so where should the resources come from?
 4.4. What do you think of the role of facilitator and consulting organisations?

Appendix 3 – Interviewee background information

Interviewee pseudonym	Job Title	Type of experience in the non-profit sector	Relevant experience	Category	Gender
Interviewee 1	Civil Society Data Officer	Community engagement	4 years	Facilitator	Female
Interviewee 2	Manager	Director of an organisation supporting digital and data skills	15+ years	Facilitator	Female
Interviewee 3	Digital Adviser	Digital and data skills training in the non-profit sector	5+ years	Facilitator	Female
Interviewee 4	Director of Services	Frontline work, trainings, and non-profit service management	15+ years	Service-provider	Female
Interviewee 5	Product Lead	Research, analysis, and data science in the non-profit sector	10+ years	Facilitator	Male
Interviewee 6	Support & Engagement Manager	Database skills expert and trainer	10+ years	Facilitator	Female
Interviewee 7	Data Scientist	Data science volunteer, background in natural sciences	2 years	Facilitator	Male
Interviewee 8	Data & Research Lead	Research and analysis in the non-profit sector	1 year	Facilitator	Female
Interviewee 9	Grants Manager	Charity grant management	20+ years	Funder	Male
Interviewee 10	Senior Commissioning Officer	Local council procurement in social and housing sectors	20+ years	Funder	Male
Interviewee 11	Community Engagement Manager	Community engagement	5+ years	Facilitator	Female
Interviewee 12	Head of Community Investment	Grant management and project management	25+ years	Funder	Female
Interviewee 13	Data Manager	Data analyst and database manager	5+ years	Facilitator	Male
Interviewee 14	Entrepreneur and activist	Database management and data analysis	5+ years	Facilitator	Male
Interviewee 15	Entrepreneur and activist	Volunteer in digital innovation	1 year	Facilitator	Male
Interviewee 16	Data & Research Lead	Research, analysis, and data science in the non-profit sector	5+ years	Facilitator	Female
Interviewee 17	Entrepreneur	Volunteer in data analysis	2 years	Funder	Male
Interviewee 18	Entrepreneur	Consulting and training for digital technology and impact in the non-profit sector	20+ years	Facilitator	Male
Interviewee 19	Senior manager	Research, analysis, and data science in the non-profit sector	5+ years	Facilitator	Female
Interviewee 20	Head of Data and Analytics	Research, analysis, and data science in the social and health sectors	5+ years	Service-provider	Male
Interviewee 21	Data Science manager	Research, analysis, and data science in the non-profit sector	10+ years	Facilitator	Female

Interviewee 22	Senior manager	Consultant and facilitator in digital social innovation	10+ years	Funder	Female
Interviewee 23	Chief Economist	Analysis, research, and evaluation	2 years	Facilitator	Male
Interviewee 24	Data Lead	Research, analysis, and data science in the non-profit sector. Facilitation and consulting.	5+ years	Facilitator	Male
Interviewee 25	Principal consultant - digital innovation	Grant management, non-profit consulting, data science	10+ years	Facilitator	Male
Interviewee 26	Member Engagement Manager	Community engagement	5+ years	Facilitator	Female
Interviewee 27	Senior manager	Research, analysis, and data science in the non-profit sector. Consulting and facilitation of skills.	15+ years	Facilitator	Female
Interviewee 28	Senior manager	Research, digital innovation, and management in the non-profit sector. Consulting and facilitation of data analysis skills	20+ years	Facilitator	Female
Interviewee 29	Senior manager	Digital technology, marketing, management, data analysis in the social sector	15+ years	Facilitator	Male
Interviewee 30	Director of Impact and Innovation	Digital technology, digital innovation, data analysis, charity management.	5+ years	Service-provider	Female
Interviewee 31	Senior manager, data science	Data science, database management, management	5+ years	Service-provider	Male
Interviewee 32	Product & Programmes manager	Data analysis, database management, data skills facilitation	5+ years	Facilitator	Female
Interviewee 33	Programme Director	Data analysis, data skills facilitation	5+ years	Facilitator	Male
Interviewee 34	Evaluation and Learning Lead	Project management, grant management, grant evaluation and monitoring.	15+ years	Funder	Male
Interviewee 35	Transparency and reporting lead	Data analysis and grant management	2 years	Funder	Male