Discover Sustainability

Research

Advancing social value analysis: challenges and opportunities to understanding social outcomes in the United States and in the United Kingdom

Diana Bozhilova[1]

Received: 14 July 2024 / Accepted: 4 November 2024
Published online: 25 November 2024

Abstract
This paper addresses the comparability and related scalability constraint of Maier et al. (VOLUNTAS 26: 1805–1830, 2015) of social impact measurement by deploying experimental mapping of the Sustainable Development Goals (SDGs) target indicators onto social return on investment (SROI) data proxies. Datasets on the unit cost database model hosted by the Greater Manchester Authority are derived for the UK and for the US. Discreet differences in data terminology between financial proxies in the UK and in the USA are translated with a contextual approach for data optimization. The resultant mapped datasets of financial proxies offer early evidence in support of the scalability of SROI. This is valuable for local measurement of progress towards the global 2030 Agenda for Sustainable Development. This research finds that there are comparatively wide differences in sufficient data both within and across the UK and the US datasets. Yet, mapped data counts show sufficient cross-geographic financial proxy overlaps, pointing to the viability of data collection with financial proxy sampling and mapping both for the better understanding of place-based social value creation and for comparative localised social value contribution. This paper concludes that initial mapping of data onto the SDG target indicators improves the comparability constraint of SROI.

Keywords Social value · Financial proxy · Sustainable development · Global goals · SROI · SDG

1 Introduction

The goal of this paper is to contribute to the discussions of the comparability and related scalability constraint of social impact measurement, specifically the SROI approach [17]. Common concerns further relate to over-claiming and data assurance, summarised as 'silver bulletism' or the seeking of a 'special number' by Gair [12]. Diving directly into the potential limitations of SROI does not obfuscate its benefits. Indeed, Maier et al. [17] state that the appropriate departing context for discussion of the SROI limitations is the understanding that all social accounting methods suffer from criticism. Therefore, SROI is not unique in this regard. SROI is, however, far more widespread than other social accounting methods [34]. It is also a method in continuous development,[1] which is why addressing its limitations is a worthy endeavour. This paper contributes to the discussion on one of the two fundamental criticisms of SROI as defined by Maier et al.:

[1] Unit Cost Database Model: https://www.greatermanchester-ca.gov.uk/what-we-do/economy/social-value-can-make-greater-manchester-a-better-place/ (site last accessed 22 September 2024).

✉ Diana Bozhilova, diana.bozhilova@nulondon.ac.uk | [1]Northeastern University London, London, UK.

"commensuration" [17]. Under "commensuration", Maier et al. [17] develop a series of arguments around SROI limitations, classifying these as (1) fundamental, (2) inherent but not prohibitive, (3) technical solvable. Comparability is classified by the authors as (2) inherent but not prohibitive and is defined as: "comparison of… different scale and different environment." [17] The arising questions is how to minimise misleading SROI value comparison narratives and support the SROI scalability (scalability defined as improving on SROI limiting factors, such as knowledge, capacity, resource, data quality [1]). This paper suggests that cross-geographic (UK, US) data mapping via the conduit of the SDG target indicators increases our ability to better understand both place-based social value creation and comparative localised social value contribution. To be sure, the paper does not claim to have evaded discretion or subjective judgement altogether [17] in mapping proxies onto the SDG target indicators. However, both improve through the finite nature of the SDG target indicators [24].

Over the last two decades, UK organisations initially from the first and third sectors, but increasingly also from the second and fourth sectors, have had to respond to societal concerns about the social return on the investment of public funds. This requires embedding social return in organisational frameworks, such as Corporate Social Responsibility (CSR) and across supplier engagement strategies [23]. Following recent COPs, there is an increased focus on climate change and environmental regeneration [16, 30]. For example, from 1 April 2022 the National Health Service (NHS, UK) introduced a mandatory minimum 10% weighting for social value in all procurement [2, 19–21]. Acting locally whilst thinking globally to create net-zero (in some instances net-positive) services and supply chains requires robust measurement of progress and clear mapping of outcomes onto nationally determined contributions (NDCs) (where applicable) of/and towards the United Nations Sustainable Development Goals (UN SDGs, also referred to as the Global Goals).

This study has two objectives. First, it sets out to create corresponding SDG (CSDG in the datasets) target indicator mapped national databanks of financial proxies[2] for social outcome measurement in the UK and in the USA. These can be used to scale up the Social Return on Investment (SROI) method by better understanding the SROI comparability constraint [17], supporting a more robust local assessment of progress towards the global 2030 Sustainable Development Agenda. Second, the study comparatively analyses the resultant CSDG mapped financial proxy data and outlines some of the challenges and opportunities to understanding place-based social value creation within a global context framework. The main questions which this research raises concern the scope for comparability and scalability of SROI. Whilst SROI was first developed in the USA in the 1990s, it has been significantly enhanced in the UK since (especially noting the UK Green Book and the Social Value Act) [27]. This justifies the geographic focus of the present research. Furthermore, the study is timely, with just half a decade left to fulfil the targets of the 2030 UN Agenda for Sustainable Development (SDGs) [24].

Reporting on the SDGs performance at the organisational level is often done by using social impact frameworks to produce a 'complete social impact account' or a 'Social Return on Investment' (SROI) analysis (SVI & EY 2019, 19). Organisations producing a social impact account have done so either through SROI analysis (or similar method) or an SDGs impact analysis (by systematically considering the relevance and significance of each SDG [25]. By mapping the financial proxy values of a SROI analysis onto the SDGs' target indicators, this research elucidates on the complementarity between the two frameworks [25]. In doing so, the research addresses the comparability constraint of SROI [17]. To be sure, this paper does not discuss all stages of a SROI analysis (Fig. 1) but looks specifically at the data collection stage by adding the mapping of SDG target indicators to existing (UK) or modelled (US) datasets. This experimental approach delivers similar findings, but at significantly greater scale, to a previous study focusing on incorporating SDG (Goal 3) indicators in the SROI method, which also concluded that the approach offers "standardised ground for comparison" [7].

The approach of this study involves both manual and computational methods for data research (UK), harvesting, and selection (US) through existing national-level statistical databases. Results reveal insights into differences of governance and infrastructure in the UK and in the US concerning social outcomes measurement. In the process of data sampling (US) and data mapping (UK, US), decisions were made about which statistical data is sufficient, insufficient, or unusable for financial proxy (cost saving) mapping with SDG target indicators. The UK dataset provides tables listing the categories used, a separate data tab for each category, and the data used to uprate historical costs to account for inflation (GDP price deflator[3]). The data was largely extracted from the Unit Cost Database hosted by the Greater Manchester Authority [13], adjusted for inflation.[4] Each category tab is followed by the same category tab and the numbering 1. Whilst the

[2] Supplementary Green Book Guidance: https://assets.publishing.service.gov.uk/media/60fa9169d3bf7f0448719daf/Wellbeing_guidance_for_appraisal_-_supplementary_Green_Book_guidance.pdf (site last access 22 September 2024).

[3] https://www.gov.uk/government/collections/gdp-deflators-at-market-prices-and-money-gdp (site last accessed 22 September 2024).

[4] https://www.greatermanchester-ca.gov.uk/what-we-do/economy/social-value-can-make-greater-manchester-a-better-place/ (site last accessed 22 September 2024).

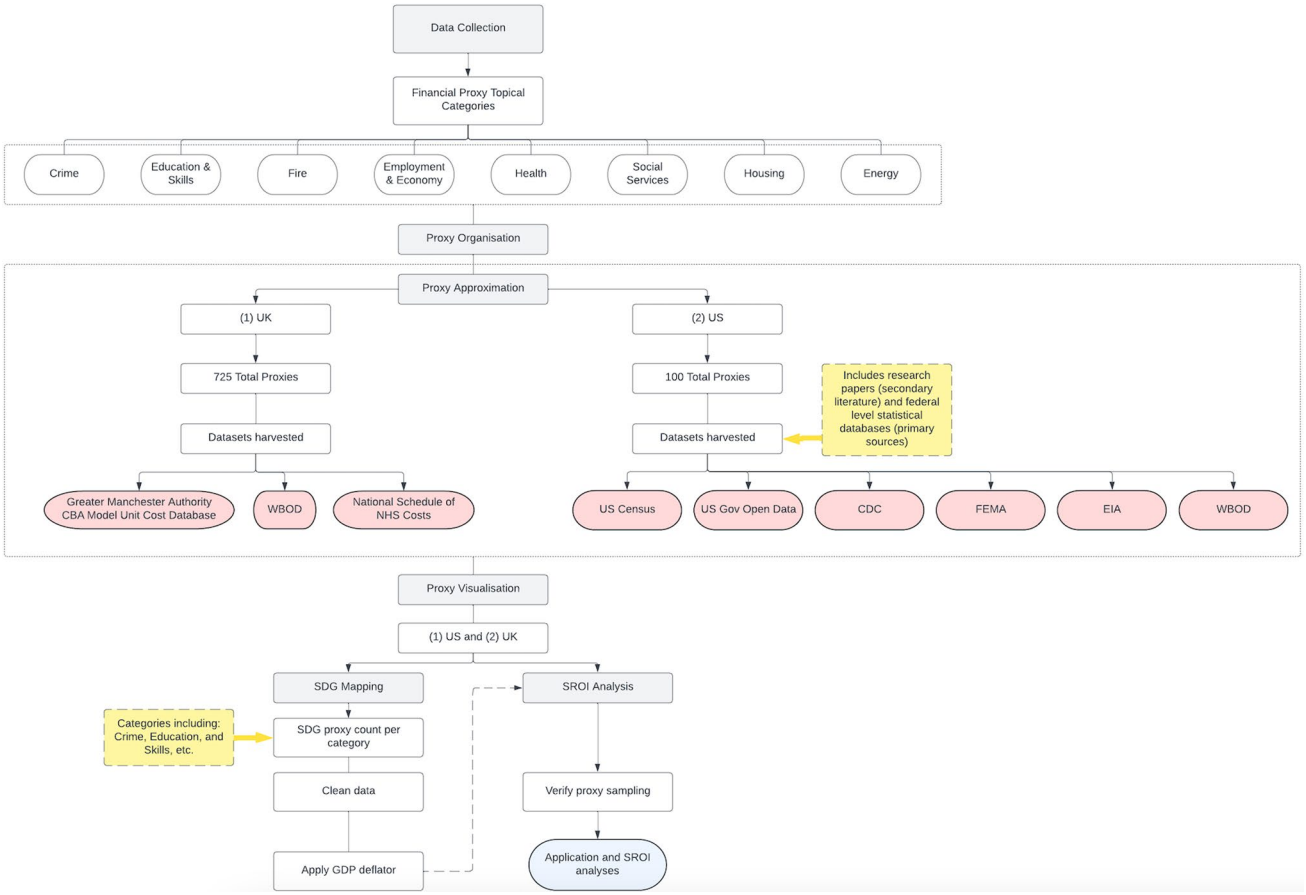

Fig. 1 Methodological procedure: from data collection to SDG mapping and SROI analyses. The dotted line shows possible onward procedures from this research, subject of future directions of study

former shows the fully extracted category data, the latter shows only the total unit cost, extracted with a script. Total unit cost covers the public value case, accounting for fiscal, economic, and social value benefits [ibid.]. The Unit Cost Database [13] allows for economic cost benefit analyses and for SROI analyses [ibid.]. The latter is served by the total unit cost value column [37]. Mapping of proxies (cost savings) to SDG target indicators (CSDGs) is not part of the original Unit Cost Database and has been added to the derived dataset manually. After each category table, a further table has been added manually summarising which closest corresponding SDG target indicators were mapped. This is then shown in detail as a separate column both in the category tab and in the category tab followed by the numbering 1. The US dataset is modelled on the UK dataset to enable comparative analysis through the medium of mapped SDG target indicators. It provides a separate data tab for each category. The first tab shows the comparison of UK and US outcome proxies. The cost savings data was largely extracted from the US Census and cross-referenced in other federal level databases (equivalent to UK dataset Level 1 data inputs) [6, 10, 11]. For each US data input, the corresponding database source is shown in column C. Each category tab is followed by the same category tab and the numbering 1, extracted with a script. Mapping of proxies to SDG target indicators (CSDGs) has been added manually.

Discreet differences in data terminology between the UK and US outcomes were translated to enhance the number of sufficient data in the national datasets. Using the UK dataset category model, US financial proxies were harvested for which either direct equivalency between data terminology in the national datasets existed or discreet differences in data terminology could be translated with a contextual approach. This relies on ideas from House [15] which offers examples of how context can inform text. Per this approach, the context ought to be provided [15]. In the US dataset, under category tabs, the context is served by relevant research paper references in column C which work with the same

federal level data as sampled by the dataset. For example, whereas a distribution system of insulated pipes was described as a 'heat network' in the UK, in the US it was more commonly referred to as 'district heating'.[5] This can be also observed in the instance of electricity costs. Whereas in the UK the 'domestic' electricity price is the reference value, in the US this is described as the 'residential' cost. In the latter example of 'domestic' and 'residential' costs, the translation was more easily acquired as there was an obvious and trivial adaptation between UK and US vocabulary. In the former example of 'heat networks' and 'district heating' the translation required a more considered analysis into the technical definitions of the terms.

This approach to dataset sampling and optimization (US) has yielded valuable comparative dataset results, including on discreet inequality [35]. For instance, one of the most noteworthy financial proxies in the US dataset sampled from the EIA database was the aggregate social cost of carbon, which acts as an alternative proxy to the aggregate traded price of carbon in the UK dataset. The social cost of carbon measures the long-term damage done by a tonne of carbon dioxide emissions each year, compared to the UK financial proxy which instead relies on economic measures to reflect changes in carbon emissions. The discreet translation enhances the number of sufficient financial proxies in the SDG mapped datasets by accounting for activities of organisations which report on energy use but not necessarily on carbon emissions.

The resultant UK and US datasets offer early evidence in support of the comparability and scalability of the SROI method. This is valuable for local progress and its links to the global 2030 Agenda for Sustainable Development. By creating national datasets of CSDGs mapped financial proxies (cost savings) for social outcomes and translating discreet differences of terminology between national geographic contexts (UK, US), this study contributes to the body of work addressing the comparability constraint, sub-category 'inherent but not prohibitive' [17] , in social impact measurement. Overall, the resultant national datasets suggest that there are differences in sufficient mapped data for NDCs (where applicable) and SDGs, both within (under thematic categories) and across the UK and the US datasets. Equally, the fact that the sufficient data count visualisation shows cross-geographic financial proxy overlaps when using the conduit of SDG mapping (CSDGs in the datasets), points to the viability of financial proxy sampling both for place-based social value creation and for comparative localised social value contribution (Fig. 2).

2 Social value, social return on investment (SROI), and the sustainable development goals (SDGs)

In tracking the genealogy of social impact investment (SII), Mitchell shows how social return on investment metrics were driven largely by the US private sector [18]. Over the years, this has led to the development of a systemic approach which the author describes as 'philantro-capitalism' [18]. It expanded through partnerships from all sectors of the economy, 'including business, finance, NGOs, nonprofits, and both national and supranational governments.' [18]. Its spread across the Atlantic intensified since the turn of the century. Both then prime minister David Cameron's presiding agenda over the G8 in 2013 and the European Investment Bank's approach to the African, Caribbean and Pacific countries (ACP) were cited in the growing evidence of "cross-Atlantic fertilisation" to foster SII [18]. This drive has been progressively dressed in concrete policy instruments in the UK, such as the Public Services (Social Value) Act (GOV.UK 2012) [21] and the Social Value Model (GOV.UK 2021) [28]. Similar regulatory equivalents did not emerge in the US context, despite the model origination, highlighting the development of a specific and more marked governing grip on SII in the UK over the last decade.

Arvidson et al. [3] explain how the benefit of public spending is often intangible. This makes the investment returns of publicly funded health, housing, social services, amongst others, harder to quantify. It limits our understanding of social justice progress at national and supranational level as we try to appraise impact measurement of publicly funded projects (in the context of national and supranational frameworks) which advance social justice, such as the UN 2030 Agenda for Sustainable Development and applicable NDCs. For non-traded returns where clear pricing is often lacking and there are insufficient human resources to run bespoke cost–benefit analyses (CBA), SROI has gained in prominence. As the authors note, SROI does not differ technically from CBA: 'SROI is described as an approach towards identifying and appreciating value created… The approach is focused on attributing financial value to inputs and outcomes… In order to estimate the positive (or negative) social value… the SROI model uses financial proxies.' [3]. This logic informs the Cost Unit Database Model of the Greater Manchester Authority as well [13].

[5] UK Department for BIS clarifies that heat networks and district heating can be used interchangeably: https://assets.publishing.service.gov.uk/media/5abccf5f40f0b6026d7ecefb/HNIP_What_is_a_heat_network.pdf (site last accessed 22 September 2024).

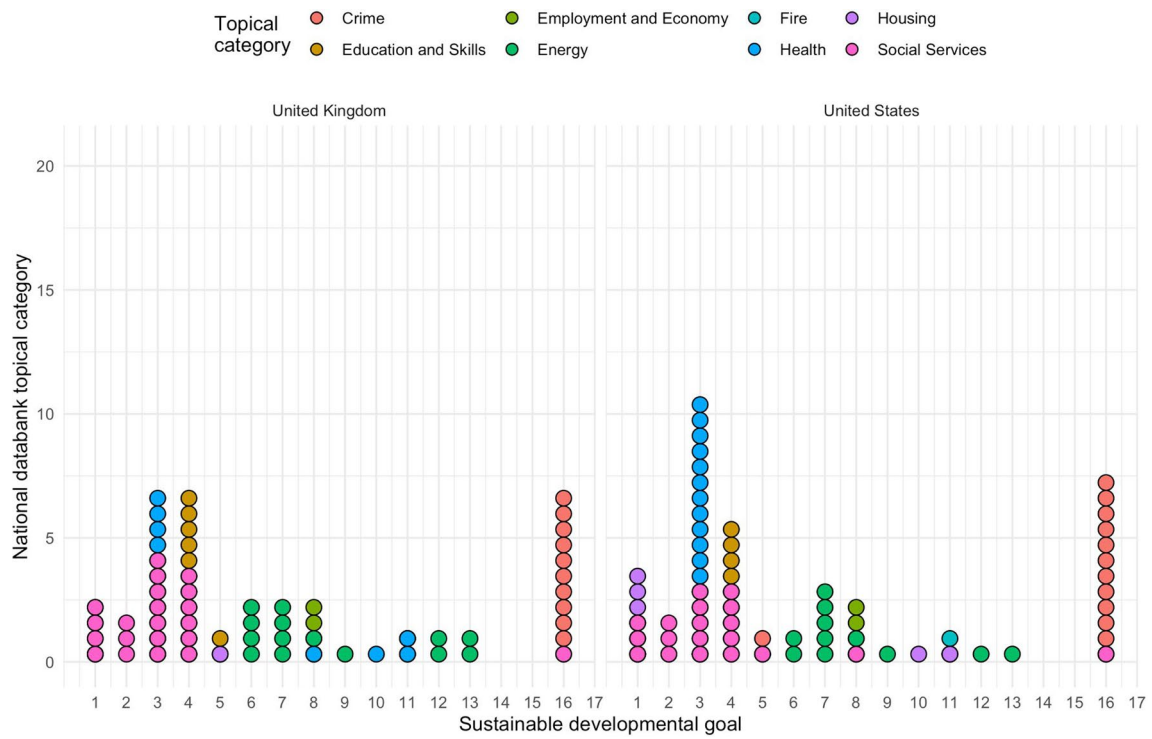

Fig. 2 Count of SDGs mapped in financial proxy topical categories in the UK and US datasets. All 17 SDGs are presented. Using colour coded dots for each topical category in the respective national financial proxy datasets, the figure shows where and how many different financial proxies within topical categories have been mapped on the Global goals (e.g. how many times Global goal 2 maps onto the 'Crime' topical category in the UK and US national financial datasets)

From this definition, it becomes clear that some of the key challenges for the comparability and scalability of the SROI method are the mapping of outcomes (noted as cost saving detail in the datasets) and financial proxies (total unit cost in the datasets). This research addresses some of these challenges to comparability and scalability of social outcome measurement by, first, constructing national financial proxy datasets (US) (UK-derived dataset) and, second, mapping financial proxies (within topical categories) onto the SDGs and their respective target indicators (CSDGs). Drawing on the work of Van der Meer [33] Arvidson et al. [3] note that SROI provides not only a framework for systematic assessment, but also neatly fits into a theory of evaluations as social constructions. Whilst the research focuses in the main on addressing challenges to the comparability and scalability of SROI, it also highlights the need and significance for qualitative analysis within quantitative datasets [35] (e.g. translation of discreet data terminology differences for optimising national datasets).

Social value analysis uses qualitative and quantitative data, often to illuminate the causality between investment and social value. It aims to bring about sustainability by addressing social justice where sustainability is defined as 'results from the marginal benefits for human development through which incomes, due to the process of redistribution, support human development' [4]. In a recent technical paper, SVI and EY showed how to perform impact focussed SDG reporting [25]. For both SROI and SDGs analyses, stakeholder engagement for social outcome mapping is a critical stage of the social impact account. SVI and EY define the SDGs as (quasi) outcomes (a mix of outcomes, activities and issue areas) by global stakeholders [25]. They acknowledge that the SDGs are not always presented as outcomes but rather guide organisations to consider their specific impacts [25]. The authors see SROI as that framework which guides the organisation to'translate the SDGs agenda into their local context.' [25] Furthermore, the authors note that 'by engaging with… local stakeholders, an organisation can map, causally link and prioritise its outcomes to the SDG framework.' [25] The present research tests this hypothesis by using SDGs mapping of SROI financial proxies in the UK and in the US context. In addition, mapping financial proxies on the SDG target indicators offers a medium through which to discuss variations in counts of sufficient data (data density) within different national contexts. Whilst the research is mindful of established scholarship conventions of cautioning against comparative analysis of SROI outcomes, the medium of the SDGs framework enables a comparative discussion of national financial proxy counts without overlooking the need to avoid comparative SROI outcome analysis. In this way, we can better understand a social value report beyond the local

context and the stand-alone case study but without doing away with the focus on place-based value creation. Where SVI and EY [25] developed a technical paper on the complementarity of the SDGs and SROI, this study presents practice research to enhance understanding of social impact accounting.

Practice research from concurrently working with the SROI and SDGs frameworks is not entirely novel. It has emerged in recent years, in particular in the healthcare sector. Consistent with the findings of this paper, healthcare offers a large repository of open access data, including data which can be interpreted and designated as financial proxies. In a World Health Organisation Europe paper, Dyakova et al. [9] set out to investigate the following question: 'What is the evidence for social return on investment from public health policies to support implementing the Sustainable Development Goals by building on Health 2020?' [9] The findings show, inter alia, that SROI of health investments strongly supports specific target indicators across nine of the 17 SDGs and a total of 35 target indicators, whilst investments in NCDs advance seven of the SDGs and 14 target indicators [9]. The findings report usefulness of some local (targeted) interventions whilst advocating for universalistic others and which are deemed as more meaningfully advancing the SDGs through a SROI assessment (e.g. in the area of mental health) [9]. The authors conclude that targeted SROI for sustainable development was still rare despite SROI being both useful and suitable in 'providing a common methodology to measure the wider social, economic and environmental value of interventions' [9]. The utility of measuring non-monetary social benefits was highlighted which pointed to the dearth in financial proxy research. Consequently, the present paper is timely and appropriate in advancing the better understanding of SROI.

The intersection of SDGs and SROI research presents some important limitations. This study wishes to be explicit about those and how it has acknowledged them. Whilst the paper has dealt with data sampling limitations (for example by introducing both contextual translation and model topical category organisation of financial proxies within the national datasets), the specific use of the financial proxies is explicitly not within the scope of the present paper. Arising from this framing of the scope of the present research, specific limitations which it does not aim to deal with here include:

(1) Where a financial proxy maps onto more than one SDG (in rare cases) and more than one target indicator within a single issue SDG area (a significant count of financial proxies). Whilst this is explicitly presented in the sampled data of financial proxies visualisation in Figs. 3 and 4 (Results and Discussion section, below), this paper does not prescribe how to deal with this in practice. Broad prescription in this regard can be found in the SVI and EY technical paper [25] and in Tan et al. [26]. They posit that context specific translation of the SDGs is enabled by social impact measurement [25, 26]. From this, it follows that SROI will select the financial proxies which map onto the relevant SDGs after translation into local contexts, known as local indicator adaptation [26]. In other words, place-based models have utility for 'SDG localisation' [26]. Further specific prescription can be the subject of future research.
(2) Debates about sampling average costs of interventions potentially obviating their 'shadow price' or intrinsic value [3]. This research has sought to optimise sufficient data for financial proxy sampling by translating discreet differences of terminologies in the national dataset, leading to the assignment in some instances of more than one value consideration of a given intervention.
(3) Debates about the use of fixed versus variable costs, following from the preceding point [3]. The national datasets, notionally constructed by the present research, use fixed costs because these were much more readily available than variable costs across the sampled existing databases. This paper acknowledges the accepted guidance for those performing SROI analyses to use their discretion when selecting fixed versus variable costs [3].

3 Methodology

National datasets (UK, US) were structured to investigate the potential of existing national open-source access databases to yield sufficient mapped data for financial proxies in the context of the social sciences method of social return on investment (SROI). The main questions which this research raises are concerning the scope for comparability and scalability of the SROI framework, hitherto considered a more bespoke case study impact assessment method. The dataset time collection period for the US was 2021–22. A similar dataset was derived for the UK over the time period of 2020–21. The findings draw on the outcomes yielded by research across national databases, in the US and in the UK, respectively. The methodological procedure for data sampling is shown in Fig. 1.

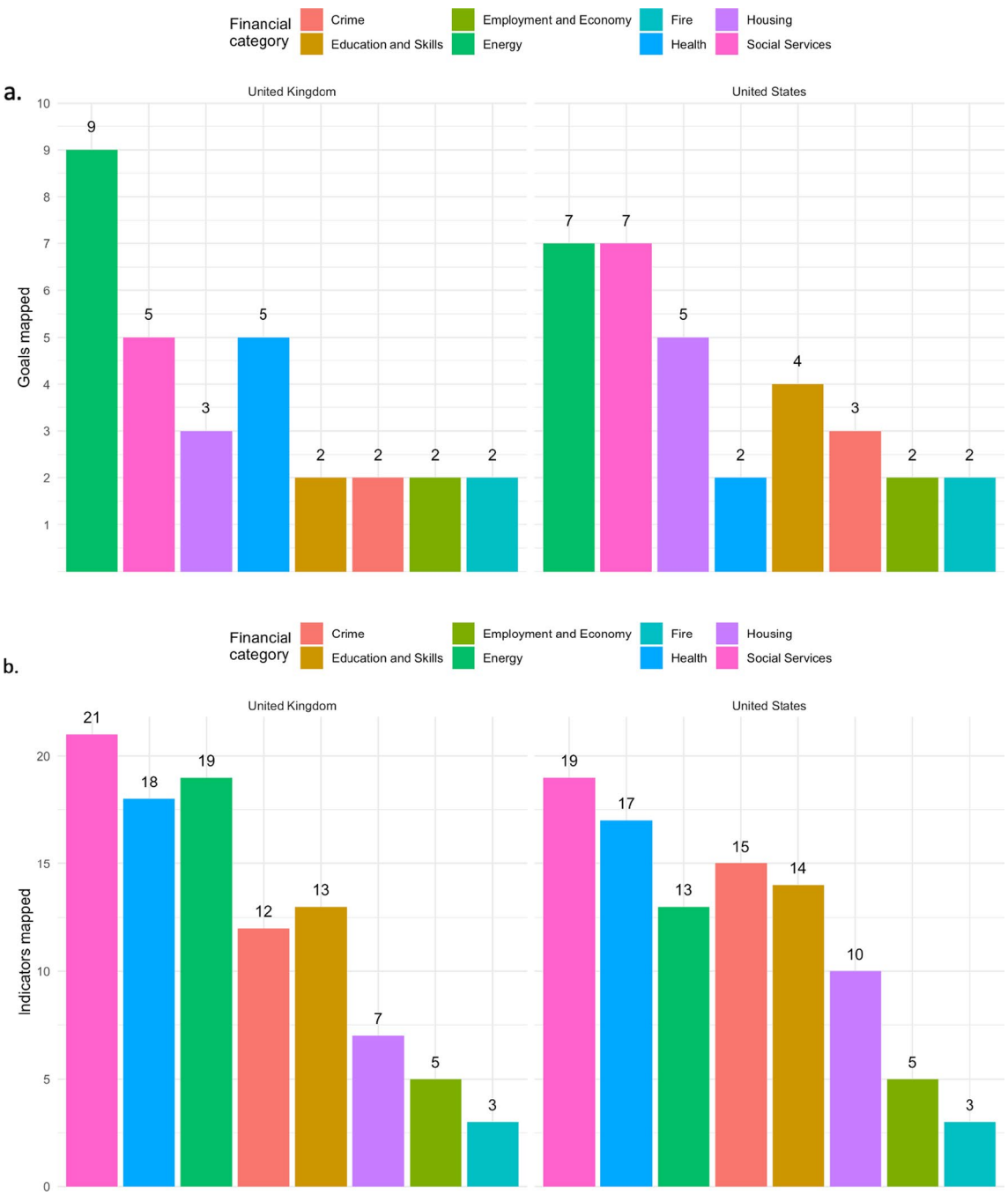

Fig. 3 Global goals and SDG target indicators. **a** - Offers a broader view which explains onto how many SDGs the financial proxies map. **b** - Offers a detailed view which explains how many target indicators in each SDG the financial proxies map onto

3.1 Data collection

Due to the large size of both countries' national statistical databases and the number of financial proxies presented in the datasets, a general overview has been provided of all the databases with specific insights into those that offered sufficient data for mapped financial proxy sampling for SROI analysis. In the US, these databases include: data.gov, CDC public use files, US Census [33] reports, and data provided by the EIA. The UK dataset was derived in large part from the Greater Manchester Authority CBA model unit cost database (2019 edition) [32], with some cross-references to the World Bank Open Data (WBOD) and the national schedule of NHS costs.

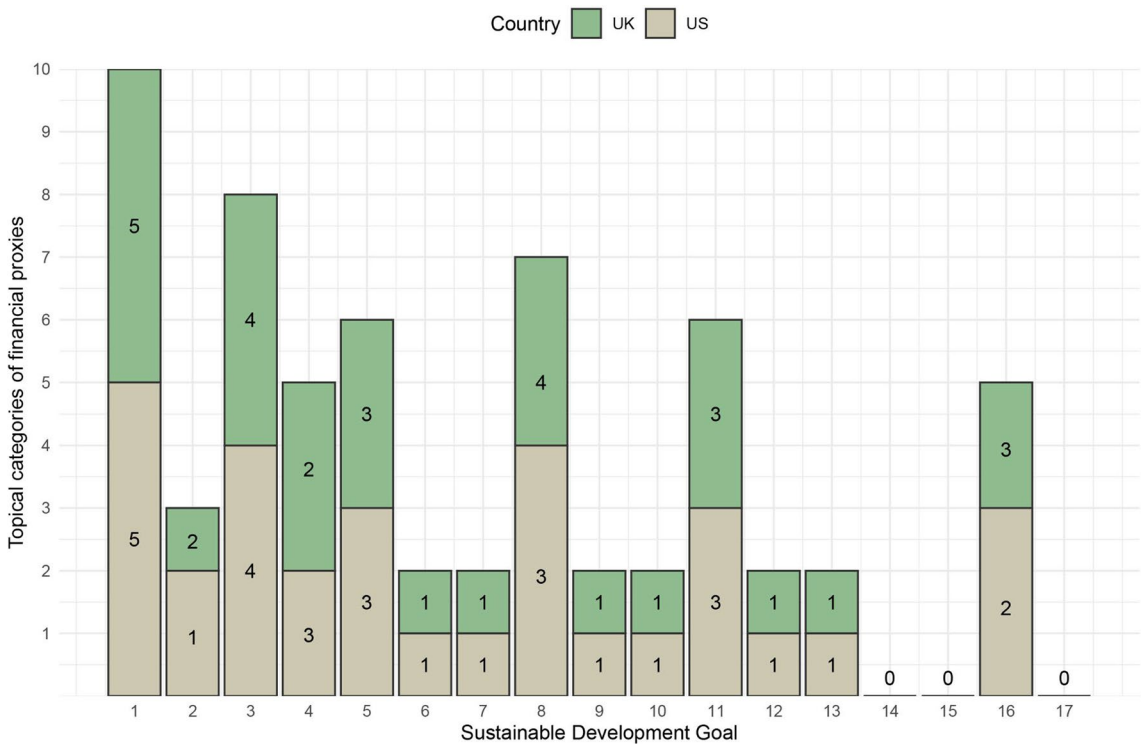

Fig. 4 Total number of SDGs mapped onto sampled financial proxies. This figure provides an insight into the issue areas of the 17 SDGs. Herein is given a unit count of how many times a given Global goal was mapped in each topical category in the US and UK national datasets, respectively (e.g. Global goal 3 was mapped in three topical categories in the US dataset and in two topical categories in the UK dataset)

3.2 Data sampling

The financial proxies of the national datasets are organised into topical categories (e.g. education, energy, housing, crime, fire, etc.) on the Cost Unit Database model hosted by the Greater Manchester Authority [13]. The number of topics was obtained with a qualitative approach and broadly corresponds to the UK Green Book's supplementary guidance of the HM Treasury (UK) (The Green Book 2022) [27] and relatedly, the Greater Manchester Authority CBA model (GMCA 2014), as well as separately, the US Census (US.GOV 2022). Mapping onto the SDGs target indicators (CSDGs) was added manually.

The first national dataset structured by this research was that of the UK (2020–21). The research used the same number of topical categories to work on the data across both the UK and the US datasets, which as the research progressed enabled the standardised organisation of a comparative overview of the sampled, then SDGs mapped financial proxies for the national datasets. The decision to first map UK financial proxies and model the later dataset of US financial proxies on the UK dataset categories was grounded in the fact that the US does not issue the level of detailed guidance on 'value for money' which the UK HM Treasury does (HM Treasury, UK, Green Book supplementary guidance), nor did it have a pre-existing model such as the Unit Cost Database of the Greater Manchester Authority, now a leading national approach.

Each national dataset, for the UK and for the US, respectively, has been organised in such a way as to evidence each source of data individually and describes the social outcome in detail in the comment column. The research used a qualitative approach to translate discreet differences across sufficient financial proxies between the UK and the US. In this process, data from the US was organised referencing the topics inductively developed in the context of the UK model. The utility of topical categories to organise the sampling of databases was validated through strong evidence of their application found in both the UK (The Green Book of the HM Treasury and the Greater Manchester Authority CBA tool) and US (US Census) databases. Within each topical category, US proxies could be counted against the number of sampled UK proxies to enable a comparative overview of the dataset results. The proxy translation where necessary was conducted by searching through key terms and phrases in the 'Comment' section of UK datasets as well as through peer reviewed research papers using data from the same national databases. Gaining a full understanding of the proxy through the detailed comments, enabled discreet translation of variations in terminology between the US and the UK datasets

with the contextual approach [15]. Translation has been central to standard data-gathering procedures and is thus not a novel approach. Contextualising by examining layers of data-linked commentary to reveal cross-cultural similarities was the preferred method of terminology translation for the present research [22]. This approach was found to optimise the sampled financial proxy counts. The data was then 'cleaned' using a script and adjusted both national datasets with the respective national gross domestic product (GDP) deflators (The Green Book 2022). The last step was to map data onto the SDGs, their targets and target indicators, as well as any applicable NDCs, found in datasets column CSDGs. This has led to a re-codification, or transfer of codes, from the original databases into the structured national datasets, by assigning to sampled financial proxies at least one SDG single issue area target indicator where possible [22]. Extracted sufficient data count visualisation shows financial proxy overlaps and national dataset density when mapped onto the SDGs (see Fig. 4, Results and discussion section).

4 Results and discussion

Multiple factors had to be taken into account when structuring datasets of financial proxies in order to maintain a level of standardisation between the US and the UK data. Once a financial proxy had been sampled, adjustments had to be made to enhance data validity. A key aspect of this was adjusting for inflation. To do this for both the UK and the US databanks, a national GDP deflator was used to account for general inflation in the domestic economy of each country. In accordance with the dates of sampled financial proxies, the UK deflator ranged from the price year 1992 until 2023, while the US deflator ranged from 1996 until 2026. This covered all of the sampled proxies in the respective national datasets.

Other aspects of standardisation across the proxies included making adjustments to proxy units. A key example of this was monetising the value of carbon dioxide (CO2) through multiple UK energy proxies. These proxies, such as the 'average amount of CO2 produced via household electricity consumption' and 'carbon emissions of building operations per year', needed to be sampled as financial proxies using the traded price of carbon. This figure had already been provided in the US Census database and was described as the 'social cost of carbon' within the topical category of 'energy'. Combined with other proxies that involved CO2, therefore, it was possible to utilise the traded price of carbon in order to approximate overall costs of carbon emissions.

Owing to differences in governance and infrastructure in the US and in the UK, often the cost-savings details of the two countries showed some variations. Although this did not limit the ability to identify and sample data, in some cases there has been a need to designate a variation on units or programmes in order to represent the same outcome in the two respective national datasets. Where this occurred, it has arisen from the fact that US datasets were sourced from federal level databases, rather than from the state level. The rationale behind this decision was an observation that if data was gathered at state level, then this would have been an inaccurate representation of the US federal level. Because of the marked variations of outcomes between states, a federal outlook offered an averaged-out cost-savings detail across the US (mean). This caveat has limited the data research (count) in some instances. For example, it was established that the large amount of data presented on data.gov resulted from the fact that data was sub-divided state-wise. When searching for only federal level measures in the data.gov database, the number of sufficient data for financial proxies dropped significantly. Whilst aware of some of the limitations to sampling average costs of interventions for fear of not reflecting their 'shadow price' or intrinsic value (Sect. 2), this research has sought to optimise sufficient data through the contextual approach and in a number of cases is able to evidence more than one value consideration of a given intervention [3]. This is discussed at greater length below.

Wording and descriptions used within UK databases often differed from terms used in the US databases. In more negligible instances, this occurred within the EIA (US) database, as terminology for US energy services varied from that in the UK (Sect. 1). Although these differences are discreet, it was important to map the variations in terminology, so that the dataset was optimised, whilst the possibility to run comparative analytical overviews of the sampled mapped data was possible. Research efforts at increasing comparable financial proxy sampling accuracy strictly within the structured national datasets extended to other data, for example when harvesting data on the construction cost of electricity generators. There were a range of photovoltaic systems values in the EIA database. It was important to be precise when matching these values to the available UK financial proxies which specifically reference the use of 'thermal hybrid' panels.

Other forms of terminological inconsistencies between national databases occurred with reference to the type of government programmes from which financial proxies for the national datasets were sampled. For example, whereas 'Meals on Wheels' was used in UK social services, in the US there were limited services of this nature. Instead, a US financial

proxy was sourced that described the cost of a nutritious diet for an elderly person per week. Although this proxy did not reference a specific government programme or intervention, the outcome of such a meal would have been contextually similar between the two countries.

Following an approach to focusing on the UK and the US cost-savings details for a range of outcomes grouped under the categories, the datasets offer more information on how the cost was researched and any additional calculations that were introduced in this process. In some cases (US), the paper researched additional secondary reports where the cost-savings detail was mentioned, in order to provide greater insight into the composition of the value measures. Lastly, the cost per unit type and the price year in the national datasets represent the actual cost. Although an effort was made to sample financial proxies in current prices, in some instances adjustments with the national gross domestic product deflator was necessary to remove the effects of inflation from the time series and instead present it in real terms (The Green Book 2022). For the UK, the GDP deflator in index form is produced by the HM Treasury from data provided by the Office for National Statistics (ONS) (HM Treasury 2022) (ONS 2012) [19]. For the US, the GDP deflator is a measure of inflation in the prices of goods and services produced in the United States, including exports. The gross domestic price deflator closely mirrors the GDP price index (BEA 2022) [5].

The US Census provided the most useful financial proxies for the US dataset [32]. Whereas in other databases, figures were often cited from a different primary source that had to be traced back to the original host, the US Census offers data which could be directly sampled. The data were provided in Excel files, which described statistical data as it was reported by the US government, local authorities, and public bodies. Helpfully, the sections of the US Census also correlate with the topical categories in the US dataset (in turn derived from the UK model), making it easier to harvest data. This is in comparison to using other sources such as data.gov [8], where the large number of databases means that the only viable way to research the data was based on keyword searches.

The US Census yielded sufficient financial proxy results for the topical categories of 'Crime', 'Education', 'Employment', 'Fire', 'Health', 'Housing', 'Social Services', and 'Energy'. The majority of the financial proxies correlate with the UK financial proxies' topical categories, however some adjustments were necessary in order to optimise the datasets' comparability. The most significant adjustment was excluding the Environment category from the datasets, as this category was generally not comparable. Other examples of adjustments refer to contextual translation. In the UK, 'Personal Independence Payments' (PIP) are used as part of the UK government's benefits programme. The US government uses a similar scheme, but in the form of 'Supplemental Security Income' (SSI), which was applied in this research to contextually translate SSI to PIP. Both are funds provided by the respective national government, in the form of monthly payments towards specific recipient groups. For the UK, the group receiving PIP consisted of disabled adults who needed help with the extra costs caused by long-term ill health or disability. In the US, the group receiving SSI was adults receiving financial support due to being 'Aged', 'Blind', or 'Disabled'. There are caveats that distinguish the US and the UK groups. Whereas the UK highlights 'long term' illness, the US does not have bounds concerning the temporality of an individual's illness. It was also understood that the US covered a broader group of individuals, including those who were simply 'aged', without any specific underlying ailments. These caveats are important for the place-based value approach.

Interestingly, it was observed in the data breakdown that the US Census offered data of a more nuanced nature on this type of benefit. The SSI is subdivided into more categories of payments than what was shown in the PIP (UK) data. Conversely, the UK has multiple different schemes for the sub-groups, rather than the more apparently streamlined approach of the US SSI. In the UK, the sub-group specific schemes range from 'Disability Living Allowance' (DLA) to 'Attendance Allowance'. The number of UK schemes, however, did offer other dataset benefits such as allowing for a deeper investigation into the types of costs incurred, conversely presenting opportunities for offsets of these costs through SDGs target indicator mapping. Although the majority of the US SSI data was hosted in a single location and was, therefore, easier to access, the dataset lacked the richness of the cost details that UK databases presented on the individual sub-group schemes.

Other data that held promise was sampled from the EIA database (US). As the EIA presents data in multiple formats, from tables to reports, to presentations, it was harder to identify the primary data than was in the case of the US Census. Despite this, financial proxies were sourced for the cost of: (1) electricity, (2) carbon, (3) electric cars, (4) biomass, and (5) construction materials. The research found that there was an overlap between the EIA financial proxies and the financial proxies sampled from within the 'Energy' section of the US Census dataset. This is because the US Census itself often uses the EIA as a primary data source. The US Census presents the exact figures as given by the EIA in the current price year. However, the source of these figures is slightly different to the EIA section of the database. This is because the US Census typically harvests data from the EIA's Annual Energy Review—a compiled data source for different energy measures. This notwithstanding, when collecting data from the EIA database, it was more suitable to investigate the individual energy

measures by using their designated section on the EIA. This was because the individual EIA sections offered a more complex breakdown of topical categories. Using the conduit of topical categories (Fig. 1), this in turn meant that US proxies were more easily compared to and discreetly translated, where necessary, onto UK such (Fig. 2).

Owing to the approach of the research on sampling financial proxies for energy from multiple primary sources, it was possible to identify sufficient financial proxies for other energy materials in the process as well. Notably, these included propane and gasoline. In turn, these were used to test the utility of the SROI method for energy intensive industries, such as aviation and the heavy industries. The research also yielded sufficient data for financial proxy sampling for the composite cost of crude oil. This was built into the US dataset even though there is currently no equivalent financial proxy in the UK databank. In this instance, comparative data analysis was not possible and the research could only support place-based social outcomes.

One of the most noteworthy financial proxies from the EIA database was the aggregate social cost of carbon in the US, which acts as an alternative financial proxy to the aggregate traded price of carbon in the UK. The social cost of carbon measures the long-term damage done by a tonne of carbon dioxide of emissions each year. By comparison, the UK financial proxy relies on economic measures to reflect changes in carbon emissions. In this instance, the research applied a discreet financial proxy translation in order to optimize the data. In turn, this supported a better understanding of both place-based social outcome creation and comparative localised social value contribution. The discreet financial proxy translation enhanced the number of sufficient financial proxies in the structured national datasets by accounting for the activities of organisations which reported on energy use but not necessarily on carbon emissions.

Financial proxies in the topical categories of housing and social services proved harder to sample and revealed gaps in the data as compared to other topical categories, such as health and energy, where the data was much more dense. Even though households often account for the majority of carbon emissions from a single source (ca. 40% in UK; 20% in the US, 2023), financial proxies for social outcome research in health and energy are much more plentiful as shown in Table 1 and Fig. 5. This is because larger agencies such as the EIA and the CDC are more likely to publish data directly and do so in more accessible formats for research by data sampling processes. Whilst the EIA must publish an Annual Energy Outlook, the CDC has a specified tool to access data from topics ranging as widely as 'alcohol use' and 'environmental health'. In the UK, the NHS acts in similar capacity to the CDC in relation to the datasets sampling research and whilst the private sector in the UK offers more energy data compared to government agencies within the US (EIA), both are equally accessible in terms of sampling financial proxies for national datasets.

In the case of the topical categories of housing and social services, there is less impetus for agencies to publish data in similar ways to the EIA and the CDC. Whereas energy and health data are at the forefront of public awareness as part of discourses on climate and social justice, other areas are not as widely publicised just yet. In the UK, the impact of such under-reporting is possibly less significant than in the US. With a smaller population and economy, the UK published more extensive data from local authorities, for example in terms of community care for adults and children. This finding is reflected in the total number of harvested data and financial proxy sampling. Whereas the U.K. dataset has 725 financial proxies, the US dataset has just 100 financial proxies. In the US, the difficulty in advancing research on the social impact of investments in housing and social services can have proportionally larger effects on broader (global) trends to advancing sustainability agendas. At regional level, both UK and US social outcomes are proportionally significant.

In other areas still, US financial proxies are harder to come by than UK financial proxies. Some of the most informative proxy costs researched within the UK databases have yet to yield comparable designations within the US dataset (Tables 1, 2 and Figs. 5, 3 for unit counts and comparative financial proxy distribution). For example, the UK dataset offers a wide range of cost-savings information on the benefit of obtaining different educational qualifications. Although similar proxies have been researched within the US datasets, these values are harder to establish and assign into the US dataset. As a financial proxy is made up of a number of statistical measures (e.g. gross earnings, employment returns, etc.), it is likely that economic values for educational returns would be sampled through secondary resources (e.g. research papers) rather than through federal level statistical databases (primary sources). Whilst the latter was the preferred data collection approach used in this research, it has yielded comparatively fewer sufficient financial proxies for the US dataset than for the UK dataset. Conversely, the downside to relying on secondary sources for the sampling of financial proxies is that it is much more labour intensive, and therefore, of limited utility to testing the comparability and scalability constraint of place-based social value creation and for comparative localised social value contribution.

Data sources, such as the GSS data explorer and the World Bank Open Data (WBOD) [36] hold limited utility in the context of the two datasets. Although GSS and WBOD offer the most up to date statistical data, these are not correlated to topical categories (Fig. 1) within the nationally designated datasets. For example, the GSS data explorer presents a collection of survey results which are used to monitor social change within the US. Results from these surveys can be

Table 1 Financial proxies and SDGs, unit count

Financial proxy category	Crime	Education and skills	Employment and economy	Fire	Health	Housing	Social service	Energy	Total
Databank (country)									
United States	12	4	5	5	29	6	5	34	100
United Kingdom	214	24	10	7	235	76	131	28	725
Dominant SDG Mapped									
United States	16,5,3	4,1,2,16	8,1	1,11	3,8	1,10,11,3,5	1,2,5,3,4,8,15	7,9,13,6,12,11,8	1,2,3,4,5,6,7,8,9,10,11,12, 13,16
United Kingdom	16,5	4,5	8,1	1,11	3,4,10,11,8	1,3,5	1,2,4,16,3	7,9,13,3,11,1,12,6,8	1,2,3,4,5,6,7,8,9,10,11,13,16

Explanatory note: This table provides a final count of the number of financial proxies within each topical category, US and UK, respectively. It also provides a count of the dominant SDGs mapped within each topical category. The total count of dominant SDGs shows which goals out of the 17 SDGs have been mapped most closely. It should be noted that this table refers to the headline SDGs, not to the individual SDG target indicators

Table 2 SDGs and target indicators, unit count

	Crime	Education and Skills	Employment and Economy	Fire	Health	Housing	Social Services	Energy	Total
Global goals (SDGs) mapped in each topical category									
United States	3	4	2	2	2	5	7	7	32
United Kingdom	2	2	2	2	5	3	5	9	30
SDG target indicator mapped in each topical category									
United States	15	14	5	3	17	10	19	13	96
United Kingdom	12	13	5	3	18	7	21	19	98

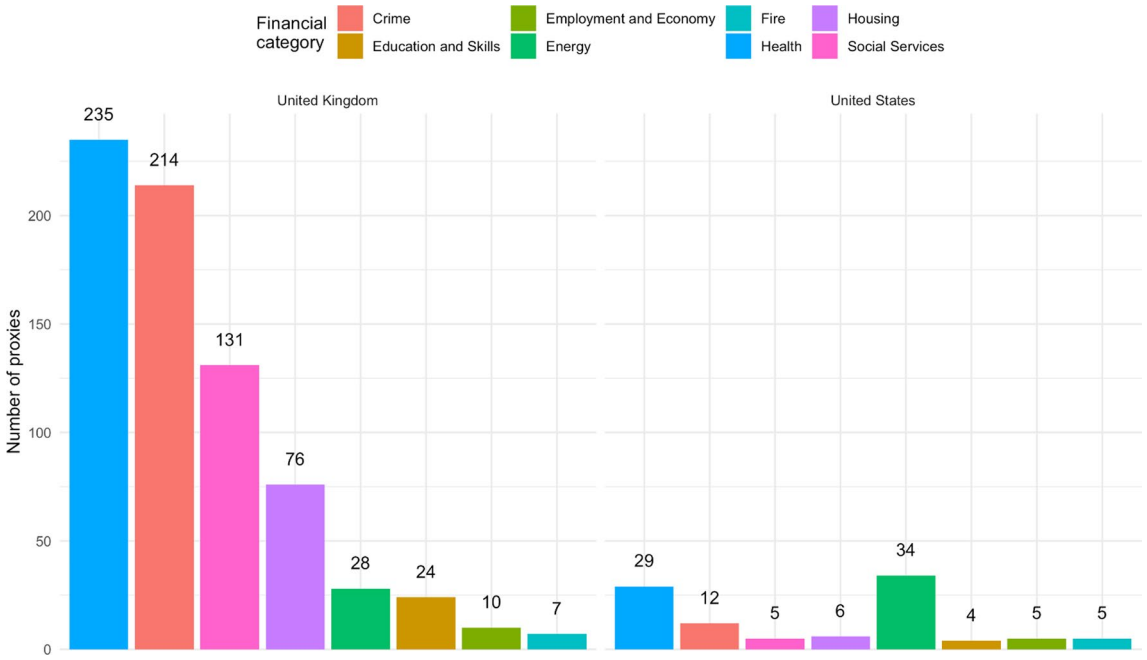

Fig. 5 Financial proxy count. Comparison of the final number of proxies found in the US and UK datasets

used to assess key trends and compare user responses over time. Survey questions concern subjects such as the amount of time an individual works per week, or their marital status. However, this type of data cannot be sampled for financial proxies since it does not include any cost-savings outcomes. Similarly, WBOD offers data which is of limited utility for the purposes of the SROI method research. Although WBOD presents data such as GDP per capita, school enrolment percentages within the national population, and life expectancy rates, amongst others, these measures only have the potential to contextualise social outcome measurement analyses but cannot serve as sampling datasets for financial proxies.

5 Conclusion

This paper analysed a number of existing open access national-level databases in order to sample and map data for the structuring of national datasets of financial proxies. In the US, these databases included: data.gov, CDC public use files, US Census reports, and data provided by the EIA. The UK dataset was derived in large part from the Greater Manchester Authority CBA model unit cost database (2019 edition), supplemented by World Bank Open Data (WBOD) and the national schedule of NHS costs. The study used quantitative and qualitative methods to optimise the counts of sufficient data for financial proxy sampling for comparative (UK, US) data analyses.

The study shows the complementarity of the SROI and SDGs frameworks for data sampling. When using the conduits of (1) organisation through topical categories and (2) SDGs mapping (Fig. 1), the research interprets national datasets as containing greater sufficient data for social outcome measurement. However, when performing an in-depth sampling and mapping against the SDGs target indicators (CSDGs), national datasets reveal varying national patterns of data density. Data density increases the richness of social impact measurement. It also improves the scalability of social impact accounting tools, such as SROI. The research shows that UK national dataset density for financial proxy sampling is greater in some topical categories (but not all) than the US national dataset. The converse is true in far fewer instances. In turn, this begs the conclusion that at present social outcome measurement accounting is likely overall more scalable in the UK, even though not in all topical categories, than it is in the US. This finding is consistent with the emergence of national policy level application of social accounting methods and social value governing in the UK and in the US, respectively, over the last decade where there have been more prescriptive national policy requirements of social value measurement in the UK than in the US. The analysis of data density also contributes to discourses on gaps between the global indicators of the SDGs and local needs and understandings of social outcomes. The comparative variation in sufficient national data density for measuring social outcomes in some topical categories helps explain the difficulty in mapping the Global goals' indicators onto local contexts. This is not helpful to overcoming the comparability constraint of SROI. Plugging the gap in national data density is one way of abridging this space. Comparative data analysis can be limited in areas of particularly 'thin' data and, thus, only support place-based social outcome creation (e.g. composite cost of crude oil). In identifying approaches which optimise existing data, such as data terminology translation and recodification through the conduit of the SDGs target indicators, this study contributes to research and debate on systemic solutions.

The several limitations noted from the outset of this study suggest future research directions. First, beta calculations of social outcome measurement, such as SROI, when using national datasets of financial proxies (including through computational modelling) is one direction of future research which can clarify if and how financial proxies that map onto more than one SDG and/or SDG target indicator are used. This will provide direction towards the complementarity of the SROI and SDG frameworks in practice and offer more insights on the comparability constraint. Second, whilst the research has made tentative efforts at optimising average costs of interventions through contextual translation of terminological differences, where applicable, across the UK and US national datasets, further research is needed into intrinsic costs. Third, the varied and often limited data density which this research found through its analysis, indicates preference to the use of fixed rather than variable costs. Future research into overcoming this limitation is necessary.

Acknowledgements The research of data was partly supported by my former research assistant at Northeastern University London, Phoebe Garrard. The research was generously supported by two Northeastern University Tier 1 seed grants.

Author contributions Diana Bozhilova wrote the full manuscript. A research assistant, Phoebe Garrard, worked on the preparation of some of the data figures, tables, graphs, and annotations.

Funding Open access funding provided by Northeastern University Library. Northeastern University, Tier 1.

Data availability The UK and US datasets are protected and are not publicly available due to active seed grant metrics reporting periods. UK dataset DOI: https://doi.org/10.6084/m9.figshare.27083188 US dataset DOI: https://doi.org/10.6084/m9.figshare.27083182.

Declarations

Competing interests The authors declare no competing interests.

References

1. APHSAI. Social Return on Investment. 2013.
2. Applying net zero and social value in the procurement of NHS goods and services: Version 1. NHS, pp.1–15. 2022. https://www.england.nhs.uk/greenernhs/wp-content/uploads/sites/51/2022/03/B1030-applying-net-zero-and-social-value-in-the-procurement-of-NHS-goods-and-services-march-2022.pdf. Accessed 2022.
3. Arvidson LF, McKay S, Moro D. Valuing the social? The nature and controversies of measuring social return on investment (SROI). Voluntary Sect Rev. 2013;4(1):3–18. https://doi.org/10.1332/204080513X661554.
4. Balaceanu C, Apostol D, Penu D. Sustainability and social justice. Procedia Soc Behav Sci. 2012;62:677–81.
5. BEA. BEA: GDP Price Deflator. 2022. https://www.bea.gov/data/prices-inflation/gdp-price-deflator. Accessed 20 Aug 2022.
6. CDC. Centres for Disease Control and Prevention. 2022. https://www.cdc.gov. Accessed 4 Jul 2022.
7. Chicarelli Alcantara BRUNO. SDG-related indicators to increase SROI comparability: an exploratory study on Italian social enterprises in the health and social care sector. 2022.
8. Data.gov. Data.gov. 2022. https://www.data.gov/. Accessed 27 Jun 2022.
9. Dyakova M et al. Investment for health and well-being: a review of the social return on investment from public health policies to support implementing the Sustainable Development Goals by building on Health 2020. Regional Office for Europe: World Health Organisation, pp. 1–68. 2017. https://apps.who.int/iris/bitstream/handle/10665/326301/9789289052597-eng.pdf?sequence=3&isAllowed=y. Accessed 2022.
10. EPA. US EPA. 2022. https://www.epa.gov/. Accessed 10 Jun 2022.
11. FEMA. FEMA.gov. 2022. https://www.fema.gov. Accessed 17 Jul 2022.
12. Gair C. SROI act II: A call to action for next generation SROI. San Francisco: REDF; 2009.
13. GMCA. Research: cost benefit analysis. Greater Manchester Combined Authority. 2014. https://www.greatermanchester-ca.gov.uk/what-we-do/research/research-cost-benefit-analysis/. Accessed 2022.
14. GOV.UK. GDP deflators: user guide. 2014. https://www.gov.uk/government/publications/gross-domestic-product-gdp-deflators-user-guide/gdp-deflators-user-guide. Accessed 15 Aug 2022.
15. House J. Text and context in translation. J Pragmat. 2006;38(3):338–58.
16. IPCC. Climate change 2022: impacts, adaptation and vulnerability. 2022. https://www.ipcc.ch/report/ar6/wg2/. Accessed 20 Aug 2022.
17. Maier F, Schober C, Simsa R, Millner R. SROI as a method for evaluation research: understanding merits and limitations. VOLUNTAS Int J Volun Nonprofit Organ. 2015;26:1805–30.
18. Mitchell K. Metrics millennium: social impact investment and the measurement of value. Comp Eur Polit. 2017;15:751–70. https://doi.org/10.1057/s41295-016-0081-7.
19. ONS. Balancing the three approaches to measuring gross domestic product. 2012. http://www.ons.gov.uk/ons/rel/naa1-rd/united-kingdom-national-accounts/the-blue-book--2012-edition/art---balancing-the-three-approaches-to-measuring-gdp.html. Accessed 10 Aug 2022.
20. Procurement Policy Note—Taking Account of Social Value in the Award of Central Government Contracts. 2020. [online] Action Note PPN, GOV.UK, pp.1–4. https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/921437/PPN-06_20-Taking-Account-of-Social-Value-in-the-Award-of-Central-Government-Contracts.pdf. Accessed 2022.
21. Public Services (Social Value) Act. Chapter 3. 2012. https://www.legislation.gov.uk/ukpga/2012/3/enacted . Accessed 10 Aug 2022.
22. Rosman A, Rubel PG, editors. Translating cultures: perspectives on translation and anthropology. 1st ed. Oxfordshire: Routledge; 2003.
23. Scelles N, Inoue Y, Perkin SJ, Valenti M. Social impact assessment of corporate social responsibility initiatives: evaluating the social return on investment of an inclusion offer. J Bus Ethics. 2024. https://doi.org/10.1007/s10551-024-05786-w.
24. Sustainable Development Agenda: Sustainable Development Goals Report 2016. New York: United Nations, pp.1–51. 2016. https://unstats.un.org/sdgs/report/2016/ . Accessed 2022.
25. Sustainable Development Goals reporting and the Social Value International framework. SVI & EY Technical Paper. 2019. https://static1.squarespace.com/static/60dc51e3c58aef413ae5c975/t/60f8030e1ea6a807ba854462/1626866448576/EY-and-SVI-SDGs-UPDATED_11112019.pdf. Accessed 2022.
26. Tan DT, et al. Systems approaches for localising the SDGs: co-production of place-based case studies. Glob Health. 2019;15(1):85–85. https://doi.org/10.1186/s12992-019-0527-1.
27. The Green Book: Central Government Guidance on Appraisal and Evaluation.UK: HM Treasury, pp.1–132. 2022. https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/1063330/Green_Book_2022.pdf . Accessed 2022.
28. The Social Value Model. UK: Government Commercial Function, pp.1–31. 2020. https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/940826/Social-Value-Model-Edn-1.1-3-Dec-20.pdf . Accessed 2022.
29. U.S. Energy Information Administration (EIA). EIA.gov, 2022. https://www.eia.gov . Accessed 15 Aug 2022.
30. UK Social Value Portal. UK social value portal: 10 years of the social value act. 2022. https://socialvalueportal.com/resources/insight/social-value-movement/10-years-of-the-social-value-act/ . Accessed 30 Jan 2023.
31. Unit Cost Database Model: https://www.greatermanchester-ca.gov.uk/what-we-do/economy/social-value-can-make-greater-manchester-a-better-place/ . Accessed 22 Sept 2024.
32. US Census Bureau. Census.gov, 2022. https://www.census.gov/en.html . Accessed 5 Jun 2022.
33. der Meer V, Bauke F. Evaluation and the social construction of impacts. Evaluation. 1999;5(4):387–406. https://doi.org/10.1177/135638999400830048.
34. Vik P. What's so social about social return on investment? A critique of quantitative social accounting approaches drawing on experiences of international microfinance. Soc Environ Account J. 2017;37(1):6–17.
35. Weber T. Discreet inequality: how party agendas embrace privileged interests. Comp Pol Stud. 2020;53(10–11):1767–97. https://doi.org/10.1177/0010414020912286.
36. World Bank. World Bank Open Data. 2022. https://data.worldbank.org/. Accessed 3 Aug 2022.

37. Yates Brian T, Mita M. Social return on investment (SROI): problems, solutions and is SROI a good investment? Eval Program Plann. 2016;64:136–44. https://doi.org/10.1016/j.evalprogplan.2016.11.009.