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Capital Allocation in UK Social Impact Bonds:

Sectoral Patterns and Investor Influence

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Abstract

This dissertation investigates how capital is allocated across `Policy Sectors` in the UK's Social Impact Bond (SIB) market. Using a custom-compiled dataset and a Gamma generalized linear model with a log link, the study identifies significant differences in `Capital Raised` by sector, highlighting patterns that may reflect investor behavior, outcome measurability, and policy alignment. Results show that Child & Family Welfare projects attracted the largest median investment, whereas Education, Employment & Training, Health, and Homelessness received 32 – 68 % less; Criminal Justice projects exhibited a positive but statistically non-significant difference (n = 2, p = 0.64). The analysis draws on 76 UK SIBs launched 2010 to 2025 and employs a Gamma GLM (log link) that explains 55 % of the variation (pseudo-R^2) in `Capital Raised`. These findings contribute to ongoing debates about the scalability, design, future policy design, and equity of outcomes-based financing mechanisms like SIBs

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GitHub Repository: `https://github.com/clarezureich/Dissertation`

Contents

1 Introduction - What is a Social Impact Bond?

Social Impact Bonds (SIBs) launched in the United Kingdom in 2010 and represent an innovative financing mechanism designed to channel private investment into public welfare initiatives. Positioned within the broader field of social impact investing, SIBs serve a dual purpose: (1) financing the delivery of social services and (2) generating financial returns for investors. Private capital is deployed to cover the upfront costs of social welfare programs in typical SIB models. A national or local government entity then commits to repaying investors only if the project achieves predefined performance benchmarks. Repayment includes the original investment and a performance-based success payment, both of which are conditional on achieving the specified outcome metrics. The success payment is based on the estimated long-term savings that the government expects to realize from a successful intervention. Therefore, investors are offered a performance-based return in addition to the repayment of principal (Maier et al., 2018). SIBs' main goal are to shift immediate fiscal responsibility away from the public sector and reduce future public expenditure through preventative interventions.

1.1 Cross-Sector Partnerships - Public, Private, and Social

The standard configuration of an SIB involves four primary stakeholders: the commissioner, intermediary, private investors, and the service provider. The commissioner, usually a public authority, establishes the overall framework for the SIB-funded project by defining its social goals, target population, timeline, and how success will be measured. An intermediary then coordinates the interests of the stakeholders' by managing communication and accountability. The intermediary collaborates with service providers to define and then deliver social interventions that align with the commissioner's objectives. Simultaneously, the intermediary structures the investment vehicle to mobilize capital from private investors to fund the program's implementation (Warner, 2013). See Figure 1 below for a chart detailing the

structural relationship of the four main players detailed above, as well as their interaction with the target population in which the service is delivered (Del Giudice & Migliavacca, 2018).

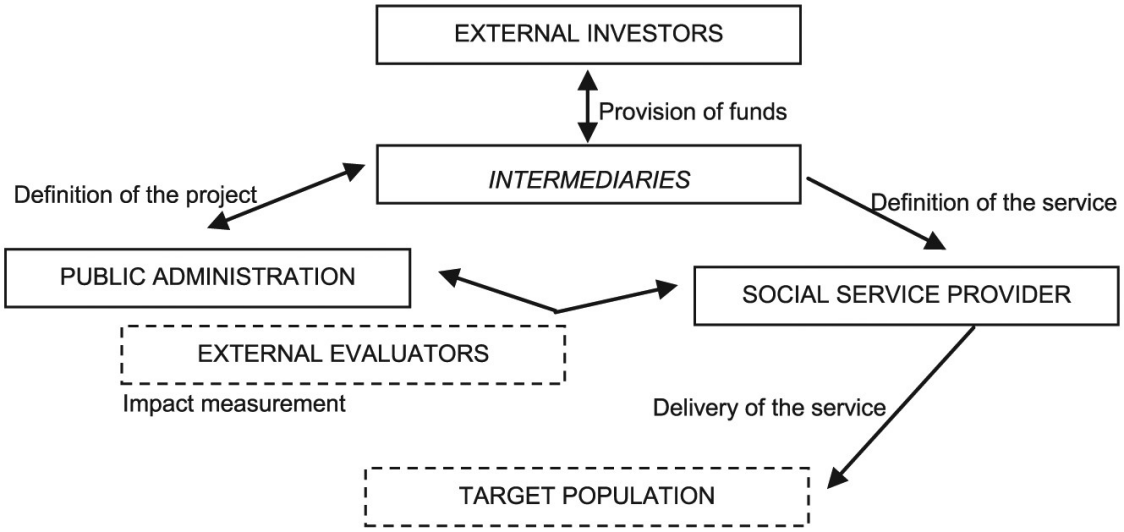


Figure 1: Del Giudice & Migliavacca's (2018) Relationship Diagram of Multi-Stakeholder Interaction

1.2 The Misnomer of "Bond"

The term Social Impact Bond (SIB) is misleading, as these instruments differ fundamentally from traditional financial bonds. Unlike conventional bonds, which offer fixed interest payments and guarantee the return of principal, SIBs do not guarantee fixed returns. SIBs are not subject to interest rate risk, reinvestment risk, or market risk (Chen, 2022). Investors may lose their entire principal investment if the targeted outcomes are not met. If the program succeeds, investors are repaid their principal along with the performance-based success payment. SIBs are not publicly traded, lack a secondary market, and are not listed on any financial exchanges. The government does not act as a borrower in SIBs. Rather, it serves as an outcomes funder, making payments only if the intervention delivers the agreed results. While labeled as "bonds," SIBs function more like outcomes-based contracts or pay-

for-success investments, with risk-return profiles closer to venture capital than fixed-income products (Del Giudice & Migliavacca, 2018).

1.3 Research Questions of the Study

There is limited empirical evidence on how funding is distributed across sectors and what these patterns reveal about investor preferences despite the rapid global growth of SIBs. Existing studies focus primarily on project-level design features and contractual arrangements, leaving questions about sectoral allocation and equity in resource distribution. This study addresses that gap by investigating how SIB funding is allocated across policy areas in the UK, using a statistical model and a gamma distribution to identify patterns in investment distribution. The central and secondary research questions are:

- **RQ1**: How is private capital distributed across policy sectors in UK Social Impact Bonds launched between 2010 and 2025?
- **RQ2**: To what extent do project-level characteristics explain variation in capital raised, specifically (a) scale (service-user count) and (b) investor syndication?

This study provides empirical evidence to inform both theory and practice, supporting or challenging assumptions about how private investment aligns with public social priorities in outcomes-based contracting. It extends the evidence base by shifting the empirical focus from project-level characteristics to sector-level funding patterns. The study also uses the most complete dataset on UK SIB to date. A gamma distribution with log-link model is used to account for the skewed nature of financial data, which is a methodological contribution not found in existing research.

Because private investors supply the upfront capital that makes SIB structures feasible, it is important to understand how their preferences, risk tolerance, and perceptions of value influence funding decisions. The study provides insights for policymakers seeking to design

equal and efficient outcomes-based models by examining these patterns. It also contributes to the limited empirical literature on investor behavior in social impact bond financing.

1.4 Hypotheses

Prior research suggests that investor preferences track the measurability of project outcomes: investors are generally willing to "take on implementation risks, but not model risks" (Warner 2015; OECD 2015). Building on outcome-measurement studies (OECD 2015; Giacomantonio 2017; Gustafsson-Wright & Painter 2025), this dissertation groups UK SIB sectors into *high measurability* (Employment & Training, Homelessness), *medium measurability* (Child & Family Welfare, Criminal Justice), and *low measurability* (Education, Health). Table 1 in section 3.5.1 (Outcome-Measurability Typology) summarizes the evidence for this classification.

> **Hypothesis 1:** *SIBs in high-measurability sectors will raise more capital than those in medium- or low-measurability sectors.*

The secondary hypotheses further explore how project structure influences capital raised:

> **Hypothesis 2:** *Projects with more Service Users (i.e., larger target populations) will raise more capital.*

> **Hypothesis 3:** *Projects with a higher number of investors will raise more capital.*

1.5 Case Study - The First Social Impact Bond

Early implementations of SIBs provide valuable insights into the model's design and operation. Among these, the HMP Peterborough SIB was the first to launch in 2010 and is widely recognized as the pioneering example. Frequently cited in both policy and academic literature, this initiative targeted reoffending rates among short-sentenced male prisoners -

a group that historically received minimal support post-release (Anders & Dorsett, 2017; Rotheroe, 2014; Nicholls and Tomkinson, 2015). The SIB financed the intervention scheme of One Service, an individualized rehabilitation program offering housing, employment assistance, addiction recovery support, and mentorship to recently released inmates (Social Finance, 2011).

In this model, investors contributed £5 million in upfront capital, which was used to fund the delivery of One Service over a six-year period (Social Finance, 2017). Social Finance UK acted as the intermediary by managing the relationship between investors, One Service providers, and government commissioners. The Ministry of Justice committed to repaying investors only if the intervention program achieved at least a 7.5% reduction in reconviction events compared to a national control group, assessed cumulatively across cohorts (Anders and Dorsett, 2017). Independent evaluators tracked performance using national reoffending data. Figure 2 below recreates Del Giudice & Migliavacca's (2018) structural relationship chart of SIB using the specific players from the HMP Peterborough SIB to illustrate the complex relationships defined in the case study.

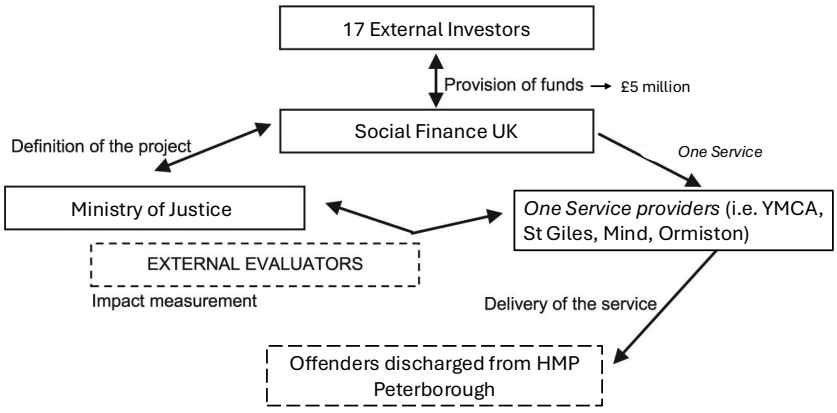


Figure 2: Del Giudice & Migliavacca's (2018) Relationship Diagram: Case Study of HMP Peterborough SIB

The results of the service program were positive: reconviction events among the Peterborough cohorts fell by a combined 9% across all cohorts compared to the national control group (Anders & Dorsett, 2017). All 17 private investors were repaid with a return funded by the government that equated to about 3% per annum for the period of investment, as the measured outcomes exceeded the threshold (Disley et al., 2015; Jolliffe & Hedderman, 2014; Social Finance, 2017).

The Peterborough case illustrates key elements of SIB contracts: risk transfer, repayment tied to performance, and collaboration among multiple stakeholders. However, it also highlights the bespoke nature of early SIB models which later necessitated improved scalability.

1.6 Global Growth and Systemic Evolution

Since the HMP Peterborough launch in 2010, the United Kingdom has become the test-bed for outcomes-based commissioning, deploying 100 SIBs across a diverse range of policy areas (Anastasiu et al., 2024). Worldwide implementation almost doubled from 168 projects in 2019 to $\approx$ 300 today (Gustafsson-Wright & Boggild-Jones, 2019; Anastasiu et al., 2024), signaling a shift from pilot novelty to mainstream policy tool.

Governance has matured alongside this growth. Outcomes funds now pool central-government resources, standardize contracts, and co-finance local commissioners. This slashes the transaction costs that once hindered scale (Social Finance, 2018; Anastasiu et al., 2024). The UK's Life Chances Fund alone commits £80 million to portfolios of local projects, enabling smaller organizations to participate and turning isolated pilots into integrated service models (Social Finance, 2018).

Multi-agency partnerships have replaced single-commissioner deals, embedding programs within broader systems of care and creating shared, long-term accountability. This institutional evolution marks outcomes-based finance's transition from an experimental tool to scalable, adaptive component of public-service delivery.

2 Literature Review

2.1 Defining Social Impact Bonds in Literature

Carter et al. (2024) define Social Impact Bonds as cross-sector partnerships characterized by two defining features: (1) an outcome-based contract that links payment to the achievement of a specified social goal, and (2) up-front third-party financing of the program, with repayment contingent on achieving that goal. Gustafsson-Wright et al. (2015) expand this definition with two additional criteria: (3) enabling legal and political conditions that support service implementation, and (4) a reasonable time horizon for achieving measurable outcomes. Together, these features distinguish SIBs from traditional funding models and underscore their reliance on multi-actor collaboration.

However, scholars continue to debate whether SIBs should be understood primarily as innovative financing mechanisms, instruments of public-sector reform, or manifestations of financialization in social policy (Fraser et al., 2018; Edmiston & Nicholls, 2018). Fraser et al. (2018) identify three prevailing narratives: 1) the public-sector reform narrative frames SIBs as tools to increase efficiency and accountability in service delivery; 2) the financial-sector reform narrative emphasizes their potential to align profit-seeking capital with social outcomes; and 3) the cautionary narrative critiques SIBs for embedding market logics into welfare provision at the expense of equity and systemic change. Advocates of the cautionary narrative warn of the financialization of social services - where public needs may become subordinate to financial interests - and point to perverse incentives such as cherry-picking of program participants to boost success rates. These differing interpretations are not merely semantic; they shape the assumptions embedded in theoretical frameworks and influence policy expectations.

SIBs are inherently multi-faceted instruments - they are simultaneously public-private partnerships for social programs, performance-based contracts focused on outcomes, and impact investment opportunities for private capital. This hybrid nature makes SIBs chal-

lenging to categorize and contributes to the divergent narratives in the literature. Clarity in definition is essential because how an SIB is defined - whether as a contract, a financial product, or a governance innovation - will affect how its success is measured, and which outcomes are prioritized.

2.2 Current Empirical Evidence Gaps

SIBs remain under-examined in both empirical evaluation and theoretical conceptualization, despite the rapid global growth. Walker et al. (2023) emphasize that relatively little empirical or theoretical evidence exists on SIBs' performance, advantages, or disadvantages, and that much of the available literature is thematically driven rather than grounded in robust data. A major constraint to empirical research, as noted by Broccardo et al. (2020), Palcic et al. (2019), and Petersen et al. (2018), is the limited availability of standardized and transparent reporting on SIB design, implementation, and performance. Such data gaps constrain rigorous evaluation and evidence-based policy design (OECD, 2015; Gustafsson-Wright et al., 2015). As a result, much of the existing literature on SIBs is predominantly descriptive, often focusing on case studies of early pilots in the UK, US, and Australia (Cooper et al., 2016; Edmiston & Nicholls, 2018; Fox & Albertson, 2011; McHugh et al., 2013) or offering conceptual analyses of governance and financial frameworks (Carter et al., 2024; Fraser et al., 2018; Gustafsson-Wright et al., 2015). In response to these limitations, recent initiatives have begun to compile more comprehensive data: for example, the Government Outcomes Lab has developed an open-access Impact Bond Dataset to standardize information on global SIB projects. Such efforts are promising (Carter et al., 2024), but the available data remains scarce and imbalanced because of the rapid propagation of SIBs and the voluntary nature of disclosures.

Even the empirical work that does exist analyzes project-level factors rather than systemic funding trends. The limited focus leaves a gap in the understanding of how capital is distributed across policy areas. This is an insight that is essential for evaluating investor

preferences and alignment with policy objectives. For example, Del Giudice and Migliavacca (2018) examine contractual and governance features that influence institutional investor participation. In their analysis of 107 SIBs issued worldwide up to 2017, they found that structural elements - such as the presence of a local public authority as a partner and the use of a special purpose vehicle (SPV) - significantly increase the likelihood and extent of institutional investor involvement. The authors report that institutional investors prefer SIB projects with fewer co-investors since this allows for greater visibility and control, and they avoid SIBs structured purely as grants or donations. Additionally, traditional financial metrics like the internal rate of return (IRR), maturity of the contract, or presence of collateral guarantees showed no significant effect on institutional participation. This suggests that mainstream investors are more concerned with contract design and risk mitigation than with headline financial returns when considering SIB investments. While these findings are valuable, they do not address how SIB funding is distributed across different social sectors or what these patterns reveal about investor priorities. Brookings' 2025 global snapshot reports that most SIBs focus on "easily measurable" issues such as social welfare (79 projects), employment (70), and education (46), whereas criminal justice (14) remain underrepresented (Gustafsson-Wright & Painter, 2025). However, those statistics are based on project counts rather than capital flows, leaving unanswered whether financial resources align with the most pressing social needs. The study that follows seeks to address this gap.

Addressing the break between theory and evidence is essential for understanding whether SIBs deliver on their promise to mobilize private capital toward high-need, high-impact areas, or whether they gravitate toward safer, more predictable domains. This study models sectoral funding allocation in UK SIBs with a gamma distribution to capture the skewed nature of investment data. By focusing on where money actually goes, rather than just the number of projects, the analysis will shed light on whether SIB investments concentrate in certain sectors and what that implies about investor behavior and policy impact.

2.3 Competing Theoretical Perspectives on SIBs

The empirical limitations of SIB research are compounded by theoretical uncertainty. While gaps in data restrict evidence-based evaluation, ongoing scholarly debate over the conceptual foundations of SIBs raises further questions about their role, purpose, and governance. Competing frameworks range from outcome-driven models inspired by New Public Management (NPM) to collaborative governance models grounded in New Public Governance (NPG) and Open Innovation theory. This reflects divergent assumptions about what SIBs are designed to achieve and how success should be measured (Albertson et al., 2020; Olson et al., 2024). For example, NPM-influenced perspectives tend to emphasize features central to the SIB model's pay-for-success structure like performance accountability, efficiency, and quantifiable outcomes. In contrast, an NPG framework relies on multi-agent collaboration, stakeholder engagement, and transparency. As a result, SIBs are positioned as partnerships rather than purely market-based instruments. The inclusion of Open Innovation principles further suggests co-creation and knowledge sharing between public and private actors to address complex social problems.

Critics argue that no single framework fully captures the complexity of SIBs or the trade-offs between financial and social objectives inherent in their design (Maier et al., 2018; Williams, 2024). For example, Olson et al. (2024) critique both NPM and Open Innovation perspectives as insufficient, given the diversity and adaptability observed across SIB projects. The authors promote a social innovation framework that questions whether SIBs truly foster systemic, long-term change or merely repackage existing practices under the rhetoric of innovation. In line with NPM logic, Buffa et al. (2023) propose a model that emphasizes quantifiable impact and measurable performance indicators as the core of SIB assessment. A framework like this reinforces the focus on outcomes as the key accountability mechanism.

Despite these theoretical contributions, skepticism persists regarding the transformative potential of SIBs. Scholars question whether these instruments can meaningfully disrupt traditional public service delivery or financial logics, or if they instead reinforce them (Fraser

et al., 2018; Maier et al., 2018; Olson et al., 2024; Williams, 2024). Williams (2024) offers a critical perspective by examining the limitations of what he terms "hinge mechanisms" - the contractual and financial linkages designed to align investor returns with social outcomes. These hinges are meant to pivot stakeholders toward shared goals by tying repayment to results. This in turn balances risk between public and private parties. However, in practice, hinge mechanisms often create rigidity rather than adaptive governance. By embedding narrow performance targets in contracts, they may encourage compliance and risk-aversion over innovation, which privileges interventions that are low-risk and easily measurable. This dynamic can discourage more holistic or systemic approaches to social problems and undercut efforts to address complex issues that require flexibility and long-term commitment. Frameworks rooted in NPM principles may further exacerbate this challenge: their focus on short-term performance metrics and efficiency can promote quick wins at the expense of deep, transformative change (Maier et al., 2018). The tension between treating SIBs as a tool for managerial efficiency versus a catalyst for social innovation remains a central theme in the literature.

2.4 Intersection of Theoretical and Empirical Gaps

A critical empirical gap intersects with these theoretical debates: the financial distribution of SIB investment across `Policy Sector`s. Although prior research has explored governance challenges and stakeholder dynamics, few analyses exist on how funding flows vary by sector and what this reveals about investor priorities and risk perceptions (Edmiston & Nicholls, 2018; Fraser et al., 2018). This is an important intersection of questions about what SIBs are meant to do (theoretically) and what they are actually doing (empirically). Understanding sectoral allocation is essential for assessing whether SIBs fulfill their promise of mobilizing private capital toward the most pressing social needs, or whether capital gravitates toward "safe" areas with easily measurable outcomes. If funding is clustering in low-risk domains such as employment or recidivism reduction, while complex areas like mental health or sub-

stance abuse remain underfunded, concerns arise regarding equity, cherry-picking of target populations, and the broader social value of outcomes-based finance (McHugh et al., 2013; Warner, 2013). In other words, the cautionary warnings about SIBs privileging metrics over real action prove true if evidence shows that investment flows bypass the hardest-to-serve communities or problems.

Empirical evidence on these patterns is vital for policymakers who are seeking to design incentives - such as pooled outcome funds or risk-sharing mechanisms - to attract investment into underserved sectors (Gustafsson-Wright et al., 2015; OECD, 2016). It also informs the theoretical discussion: for example, a predominance of investment in "safe" areas might support the view that SIBs are driven by financial-sector logic (seeking reliable returns), whereas a broad distribution including high-need areas might indicate that SIBs can align with public-sector reform goals. To date, no study has rigorously analyzed how funding amounts are distributed across sectors or what factors influence these patterns. This study aims to fill that gap by combining the theoretical insights on risk and collaboration with an empirical analysis of funding distribution.

2.5 Theoretical SIB Frameworks

Several conceptual frameworks have been proposed in the literature to explain how SIBs function and what their emergence signifies. Albertson et al. (2020) offer a foundational model that combines elements of New Public Governance (NPG) - an evolution of New Public Management (NPM) emphasizing networked collaboration and trust-based partnerships - with principles from Open Innovation theory. In their view, SIBs embody a hybrid approach: they carry the performance-based, outcome-oriented nature of NPM while also requiring the cross-sector collaboration and information sharing highlighted by NPG and Open Innovation. Under this model, SIBs are seen as structured opportunities for co-creation, where public, private, and nonprofit actors jointly design and implement interventions. The strength of this framework is in acknowledging that SIBs must reconcile divergent interests and account-

ability: governments seek social outcomes and value for money, investors seek a return (and perhaps social impact), and service providers seek to fulfill their mission and secure funding. Albertson et al.'s (2020) model helps illustrate the governance challenges in aligning these interests under a single outcomes contract (e.g., negotiating outcome metrics that are rigorous yet fair, and establishing decision rights among parties).

Olson et al. (2024), however, question whether even these collaborative frameworks capture the reality of SIB innovation. They point out that many SIBs, despite innovative rhetoric, operate within conventional bounds - focusing on interventions that are already known to be effective, or implementing performance management techniques long used in public services. Olson and colleagues propose using a social innovation lens that asks whether SIBs truly create new value or merely rebrand existing financial tools and service models. If SIBs do not promote fundamentally new solutions or address root causes, then their added value may lie only in financing and not in social innovation. Buffa et al. (2023) similarly stress the risk that SIBs emphasize measuring impact over making impact. Concentrating on quantifiable outcomes risks simplifying complex social issues into narrow, measureable targets.

The literature also reflects a persistent undercurrent of skepticism about SIBs' ability to transform service delivery. Fraser et al. (2018) and Maier et al. (2018) situate SIBs within a broader critique of market-oriented approaches to social policy. This again suggests that SIBs might reinforce an emphasis on measurable outputs and short-term results instead of structural change. For instance, a SIB-funded homelessness project might prioritize the number of individuals housed within six months, rather than broader measures of community integration or long-term well-being measures. From this viewpoint, SIBs may inadvertently reinforce the status quo by steering resources toward interventions that can generate data-friendly outcomes instead of those that address deeper systemic issues (Williams, 2024). The tension between innovative promise and cautious practice is thus a key theme: even as SIBs are hailed as "disruptive" social finance, they may simultaneously be constrained by the very

frameworks of accountability that justify their existence.

Giacomantonio (2017) adds further nuance to these discussions by introducing the concept of the 'SIB paradox': projects rational for governments (in terms of social impact and cost-effectiveness) often lack sufficient returns to attract private investors and vice versa. This structural misalignment helps explain why SIB markets remain limited, despite efforts to reduce transaction costs or mitigate investor risk. Giacomantonio (2017) suggests that SIBs are likely a better fit for philanthropic funders than for traditional institutional investors, raising important questions about the model's scalability and its dependence on socially motivated rather than commercially driven capital. This theory links directly to questions of sectoral allocation: if investor-government priorities rarely converge, funding patterns may gravitate toward areas with quantifiable outcomes, sidelining complex but high-need sectors.

2.6 Measuring SIB Performance

A recurring challenge in the literature is the difficulty of establishing appropriate, outcome-based performance metrics for SIB-funded programs (Edmiston & Nicholls, 2018; Wooldridge et al., 2019). While the SIB model aims to link financial returns directly to verified social impact, many targeted outcomes (such as behavioral change, long-term health improvements, or educational attainment) are complex and not easily reducible to a single indicator. This often leads to reliance on proxy measures (e.g., test scores for learning, job placements for economic well-being), which may not capture the full depth or durability of the social change intended.

To address these limitations, scholars emphasize methodological rigor in evaluating SIB outcomes, including techniques such as additionality (measuring benefits attributable solely to the intervention, beyond what would have happened anyway) and counterfactual analysis (comparing results to an estimate of what would have occurred without the intervention). These approaches, however, can be costly, data-intensive, and dependent on complex assump-

tions, which makes them difficult to implement consistently (Fraser et al., 2018). Moreover, the push to produce measurable, short-term results can create tension between financial accountability and the pursuit of genuine social value. In practice, SIB contracts typically have finite terms (often 3-7 years) and predefined metrics, which may incentivize service providers to focus on hitting those targets within the timeframe.

These pressures can generate unintended consequences, including "cherry-picking" (selecting participants who are easiest to help or most likely to succeed), "parking" (neglecting or offering minimal service to individuals with more challenging needs who could lower overall success rates), and "gaming" (manipulating processes or data to meet targets without genuinely improving outcomes). Such practices have been documented as risks in outcomes-based contracting and are a focal point of the cautionary narrative on SIBs (OECD, 2016). The rigid focus on quantitative metrics might privilege interventions that yield quick, easily measured wins, and incentivize cream-skimming and cherry-picking regardless of a project's broader social urgency. These behaviors undermine equity since the most vulnerable or difficult-to-serve populations are exactly those who may be "parked" or excluded, and they divert attention from longer-term or less tangible aspects of impact (such as building community trust or improving life satisfaction). Consequently, while SIB frameworks aim to foster outcome-driven accountability, they risk incentivizing actions that compromise ethical integrity and policy effectiveness. The literature calls for careful contract design (e.g., multiple metrics, rewards for serving high-need cases, independent evaluations) to mitigate these risks, but there is limited evidence on how often such safeguards are implemented or how well they work.

2.7 Investor Influence and Financialization

The role of private investors introduces another layer of complexity in SIB design and implementation. Investor bases can range from philanthropic foundations and high-net-worth individuals to mainstream banks, pension funds, and other institutional investors. The di-

versity brings varied expectations regarding risk, return, and social value. This diversity can enhance resource mobilization and risk-sharing, as different investors can participate according to their risk tolerance and impact objectives. On the other hand, it also creates governance challenges and potential conflicts over priorities (Fraser et al., 2018). For example, a philanthropically minded investor might be willing to accept a below-market return or higher risk for the sake of innovation, whereas a pension fund might require more assurance of capital preservation and demonstrable results, leading to tension in structuring the SIB.

Empirical research suggests that philanthropic capital often plays a catalytic role in early SIBs. Mazzuca et al. (2023) find that the involvement of philanthropic or socially motivated investors correlates with higher overall investment volumes, supporting the notion that these actors help "de-risk" projects and encourage participation by more commercially oriented financiers. However, reliance on philanthropy raises concerns about scalability and sustainability. Projects may remain dependent on below-market-rate finance rather than attracting institutional capital at scale, limiting the SIB model's impact on mainstream public finance. Evidence shows that institutional investor participation in SIBs has so far been modest: Del Giudice and Migliavacca (2018) note that from 2010 to 2017, institutional investors were involved in only a minority of SIBs worldwide, making their role a "marginal phenomenon". One reason is that SIB contracts often lack the risk-management tools and clear governance structures that institutional investors require, such as robust performance data, collateral, or control rights to monitor service providers. In effect, by transferring a significant portion of performance risk to private funders (a core premise of SIBs), many early SIB designs may have deterred mainstream investors who are unwilling or unable to shoulder that level of uncertainty. This paradox highlights a fundamental constraint: SIBs thought as a tap to large pools of private capital for social good, but if the contracts are not structured to align with institutional risk-return profiles, that capital will not materialize.

The growing influence of private finance in social service delivery also raises concerns about the financialization of social policy. Financialization refers to the process by which

financial metrics, actors, and interests come to dominate areas of life that were previously driven by social or public welfare logic. In the context of SIBs, this manifests in contractual terms and performance frameworks that prioritize measurable, investor-friendly outcomes to ensure confidence and repayment security. While such mechanisms may be necessary to attract private capital, critics argue that they risk shifting SIB initiatives from an "impact-first" orientation to a "finance-first" logic, where meeting investor expectations can become the dominant objective (Berndt and Wirth, 2018; Sinclair et al., 2014). This shift not only undermines the transformative ambitions of SIBs but also exacerbates equity concerns. Capital tends to flow toward sectors and interventions with clear, quantifiable outcomes and data (to satisfy investors and auditors), rather than toward messy, complex social challenges where results are harder to measure or achieve in a short time-frame. Taken together, these theoretical and empirical discussions reveal an important blind spot: structural, governance, and investor-related factors shape SIB design, yet the evidence is lacking on how these forces translate into actual patterns of resource allocation across social sectors.

2.8 Why Sectoral Funding Allocation Matters

Given academic discourse and identified gaps, analyzing sectoral funding patterns is critical for evaluating whether SIBs deliver on their promise of mobilizing private capital toward socially urgent and complex challenges. If investment flows are concentrated in "safe," easily measurable domains, this would confirm concerns raised by the cautionary narrative and the SIB paradox, which posits that financial and social priorities rarely align without deliberate design interventions. Conversely, a more balanced allocation would suggest that SIBs can support diverse policy goals even under current market and governance constraints. Understanding these dynamics provides actionable insights for policymakers seeking to design outcome funds, adjust risk-sharing mechanisms, and embed equity considerations into future SIB models. This study, therefore, addresses an essential gap in the literature by providing an empirical analysis of how SIB resources are distributed across sectors in the UK.

3 Data and Methodology

3.1 Data Sources

This study draws on a comprehensive dataset of UK Social Impact Bond (SIB) projects compiled from multiple sources. The core data was obtained from the INDIGO Impact Bond Dataset hosted by the University of Oxford's Government Outcomes Lab. The INDIGO dataset is an open-access, project-level database that is co-created by researchers and practitioners to standardize information on SIB contracts worldwide (Carter et al., 2024). It addresses a critical gap: although SIBs are in principle rich in data due to their focus on measurable outcomes, historically such data have been "sparse, partial and dispersed" (Carter et al., 2024). Walker et al. (2023) describe INDIGO as a collaborative data infrastructure that consolidates previously fragmented SIB information into a common platform, making this effort "the most comprehensive, open and global SIB database" to date.

3.2 Data Cleaning and Sample Construction

Only UK-based SIB projects in the INDIGO dataset were extracted for this analysis to control for cross-country inconsistencies like differing currencies, policies, legal systems, financial markets, and phase of SIB adoption. This subset is comprised of exactly one hundred SIB contracts launched in the UK from 2010 (the year of the first SIB in Peterborough) through present. Each project is identified by a unique INDIGO project ID and includes descriptive fields such as `Policy Sector`, dates, participating organizations, and financial metrics.

3.3 Missing Data and Supplementation

Because initial INDIGO records had notable gaps in some financial and participant fields (consistent with Walker et al.'s (2023) observation that public reporting on SIBs remains limited), additional research was undertaken to make the dataset more robust. Specifically, missing values for `Capital Raised, Policy Sector, Number of Service Users`, and `Number`

`of Investors` were supplemented through manual collection from publicly available investment memoranda, government websites, and press releases. These external sources provided key financial and implementation details that were not captured in the INDIGO records.

The merged dataset offers the most complete picture of UK SIBs currently available. Walker et al. (2023) note that "data pertaining to completed and ongoing SIBs is comparatively sparse," and that disclosure requirements are weak. Combining the INDIGO dataset with targeted supplementary sources helps mitigate these limitations and supports more reliable analysis.

After merging, cases that were still missing any of the four core variables were removed using list-wise deletion. This resulted in a final sample of 76 SIB projects. List-wise deletion was considered appropriate given the relatively small number of incomplete cases and the absence of systematic bias across sectors. A full list of dropped projects (Appendix A Table 4) and missingness by variable (Appendix A Figure 8) are provided. The list of supplementary data sources can be found in the bibliography.

3.4 Descriptive Statistics and Distributional Characteristics

The final analytical sample includes 76 UK-based SIB projects following the removal of projects with missing values in the outcome (`Capital Raised`) or key explanatory variables (`Service Users`, `Number of Investors`, or `Policy Sector`). The original scraped dataset from the INDIGO impact bond dataset included 100 projects, which was merged with supplementary data from official memoranda and government publications to improve coverage. After merging and cleaning, 76% of the initial projects were retained for analysis, representing the most complete and reliable subset of UK SIB contracts.

Descriptive statistics indicate marked skewness across all variables, a pattern commonly observed in financial and investment-related datasets (Manning & Mullahy, 2001; Seneta, 2004). `Capital Raised` ranges from £100,000 to £5.88 million, with a median of £910,000, a mean of £1.18 million, and a right skew of 2.302 (kurtosis = 6.464). `Service Users` also

exhibit a right skew at 2.163 (kurtosis = 3.981). The projects serve as few as 10 individuals and as many as 8,000 (median = 395, mean = 1,308), indicating that most projects are relatively small in scale. The distribution of the `Number of Investors` ranges from 1 to 19 (median = 3, mean $\approx$ 6) with a skew of 0.713 (kurtosis = -0.885). This means that while most SIBs involve small consortia, a few have wide investor participation. These high positive skewness values and leptokurtic distributions justify the use of a Gamma log-link model, which is well-suited for strictly positive, right-skewed data. Descriptive statistics by `Policy Sector` can be found in Appendix B Table 5.

Figure 3 illustrates these patterns through histograms of the raw variables, showing the high degree of positive skewness in all three measures, while Figure 4 presents the same variables after applying natural logarithmic transformation, which substantially reduces skewness and approximates normality.

The study uses only publicly available, non-identifiable financial data; no personal information was processed, so formal ethics approval was not required.

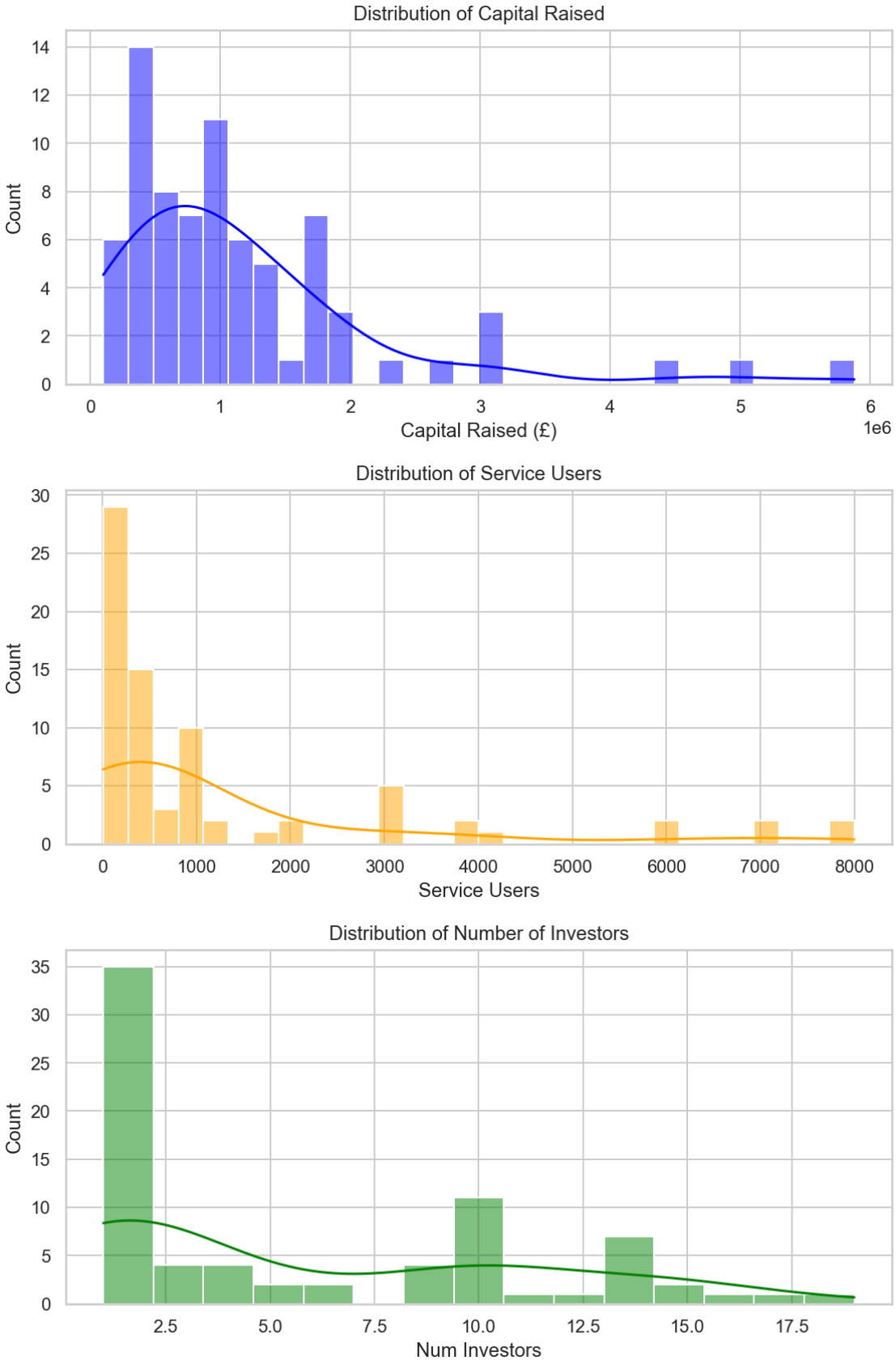


Figure 3: Distribution of Key Variables: Capital Raised, Service Users, and Number of Investors

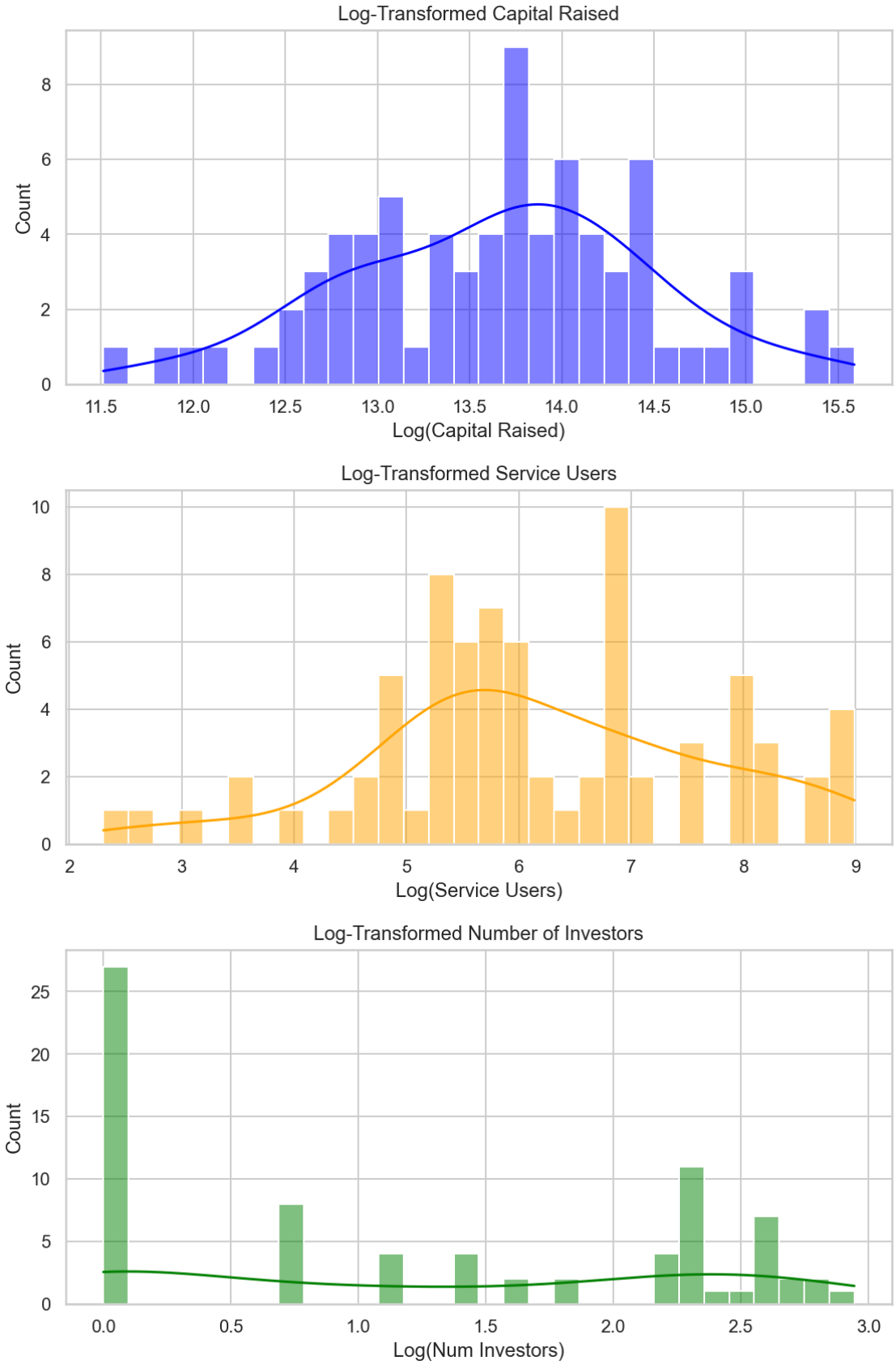


Figure 4: Log Transformed Distribution of Key Variables: `Capital Raised`, Service Users, and Number of Investors

Boxplots in Figure 5 show outliers in `Capital Raised`, where several projects report significantly higher investment levels than others. These cases do not indicate data entry errors but reflect real variation in project scale and financing. Skewness in financial data is common because a small number of large-scale initiatives account for a disproportionate share of capital flows.

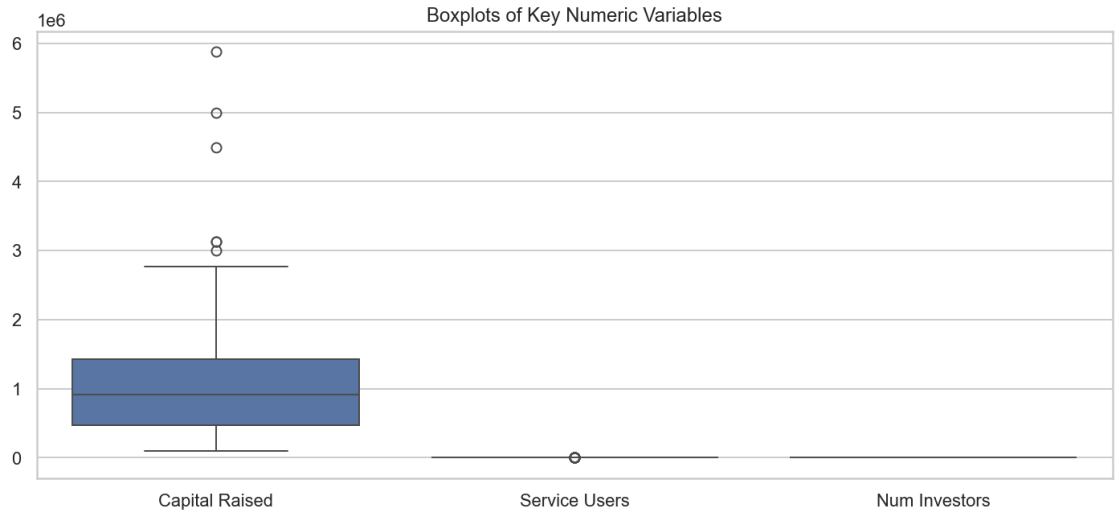


Figure 5: Boxplots of Capital Raised, Service Users, and Number of Investors

These characteristics justify the modeling of a Gamma GLM with a log link as the primary estimation technique and an OLS log-linear model as a robustness check. The log-link in the Gamma GLM addresses the right-skewness of the dependent variable by modeling the expected value of `Capital Raised` on a multiplicative scale. Log-transforming the independent variables ensures proportional relationships and mitigates extreme leverage effects. Gamma GLM is often used to address heteroskedasticity in skewed financial data (Manning & Mullahy, 2001), but a Breusch-Pagan test on the log-linear model suggests homoscedastic residuals (results can be found in Appendix C Table 6). The Gamma model still remains appropriate given the non-normal and strictly positive distribution of the dependent variable.

`Policy Sector` distribution shows that SIB projects are concentrated in a few key domains. Figure 6 shows the largest share of projects falls within `Homelessness` followed by `Child & Family Welfare` . This pattern is consistent with prior research suggesting

that investors and commissioners prefer sectors with measurable outcomes and established evidence bases (Maier et al., 2018; Fraser et al., 2018). However, the variation in funding amounts across sectors underscores the importance of analyzing capital allocation rather than project counts alone. While the dataset provides a rare and relatively complete view of the UK SIB landscape, the limited number of projects per sector (particularly in domains like criminal justice) highlights the need for cautious interpretation of sectoral effects.

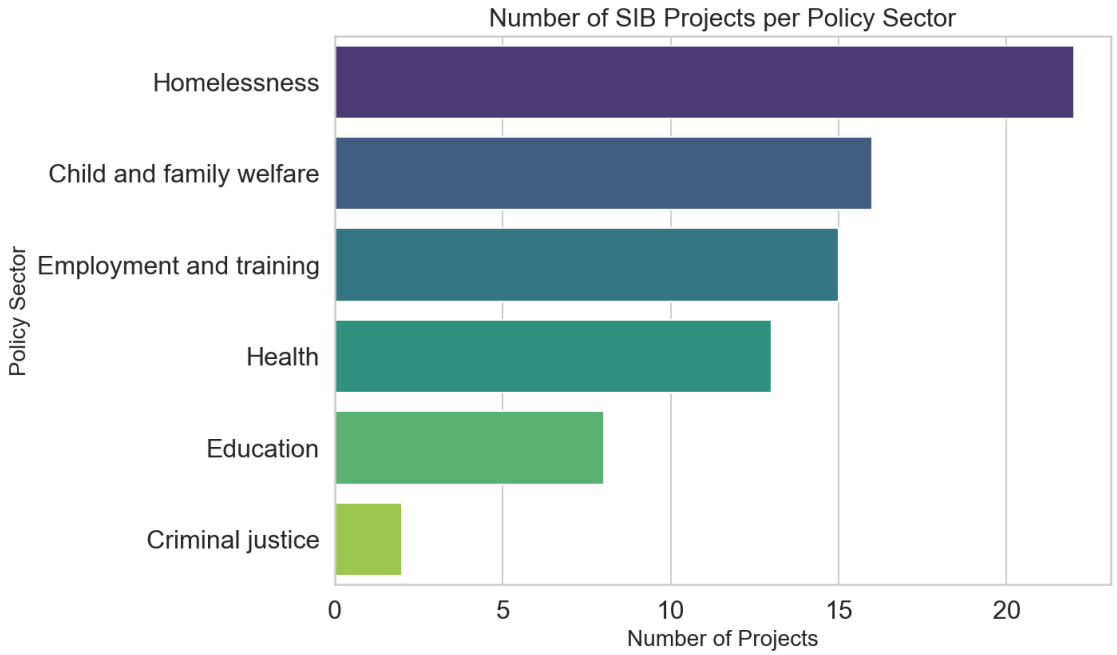


Figure 6: Number of UK Social Impact Bonds per Sector

The 2 Criminal Justice observations are retained in the analytical dataset because its under-representation is substantively meaningful rather than methodologically problematic. The limited number of SIBs targeting criminal justice aligns with long-standing critiques in the literature that investors and commissioners tend to avoid sectors with complex, long-term, or politically sensitive outcomes (Fraser et al., 2018; Maier et al., 2018). Issues such as recidivism or rehabilitation often lack short-term, quantifiable success metrics, making them less attractive under outcomes-based contracting models that prioritize measurability (Albertson et al., 2020). Rather than treating this under-representation as a data limitation, this study views it as empirical evidence of investor preferences and sectoral biases. Including

these projects strengthens the analytical narrative by illustrating not just which sectors receive more funding, but also which are systematically overlooked.

3.5 Operationalizing Key Variables: Theoretical and Empirical Basis

This study operationalizes investor preferences and project characteristics through four key variables: `Capital Raised` (dependent variable),`Policy Sector`,`Service Users`, and `Number of Investors`. Each is theoretically grounded in the SIB literature and related frameworks in public administration, impact investing, and financialization.

`Capital Raised` is the dependent variable and represents the total upfront investment committed to each SIB in GBP. This measure provides the most direct indicator of resource allocation and reflects investor confidence and sectoral preferences (Del Giudice & Migliavacca, 2018). Existing studies often quantify SIB activity by the number of projects, but such counts obscure disparities in financial scale (Gustafsson-Wright & Painter, 2025). Focusing on funding amounts therefore addresses an empirical gap and aligns with critiques suggesting that financialization may drive investment toward sectors offering easily quantifiable outcomes (Fraser et al., 2018). Examining capital flows rather than project frequency provides a more accurate lens on investor priorities and perceived outcome value.

The first independent variable, `Policy Sector` (H1), captures the social domain of the intervention. The sectors are categorized based on the identified Primary Sustainable Development Goals (SGDs) of the SIB, as defined by the United Nations, and can be any of the following: Health, Employment and training, Homelessness, Child and Family Welfare, Criminal Justice, and Education (United Nations, 2015). Sectoral variation is central to SIB theory because measurability, complexity, and time horizons differ across domains, influencing both investor risk perception and contractual design (Maier et al., 2018). Under New Public Management (NPM) logics, investors and commissioners are expected to favor interventions with clear, auditable metrics (such as job placements) over complex issues

like mental health, which pose higher attribution and success measurement challenges (Albertson et al., 2020). Financialization critiques similarly predict clustering in predictable, data-friendly domains (Fraser et al., 2018). Including `Policy Sector` tests whether such patterns are evident when measured by actual funding levels.

While the present analysis includes all reported UK SIBs by `Policy Sector`, it is important to note that some domains are entirely absent from the dataset. For example, Agriculture & Environment and Poverty Reduction sectors with 111 and 3 global projects, respectively, are not reflected in the UK sample (Carter et al., 2024). As these sectors do not appear in the underlying data, they are necessarily excluded from the sectoral analysis in this paper. Their absence may reflect either a lack of commissioning activity or reporting gaps and highlights broader limitations in sectoral comparability.

The second independent variable, `Service Users` (H2), represents the size of the intended beneficiary population. Project scale matters because larger interventions typically require more capital, influence risk-sharing arrangements, and shape investor perceptions of efficiency and social impact (Del Giudice & Migliavacca, 2018). Larger projects may signal economies of scale, reducing per-unit costs and appealing to investors interested in maximizing both financial efficiency and measurable social returns. This variable therefore captures a core determinant of funding decisions within SIB structures. However, service user count may also reflect baseline operational demands rather than investor preference alone. Larger beneficiary groups often entail higher staffing, logistical, or programmatic costs, suggesting that capital requirements are at least partly determined by delivery realities, not just investor signaling (Warner, 2013).

Finally, the third independent variable, `Number of Investors` (H3) reflects the capital structure and the distribution of financial risk across participants. Theoretical and empirical work suggests that multi-investor arrangements reduce exposure for individual investors and may enable higher total funding commitments by pooling resources (Maier et al., 2018). A larger investor base can also serve as a credibility signal, reducing perceived risk and

attracting additional capital (Mazzuca et al., 2023). By including this variable, the analysis evaluates whether syndication and diversity of investor participation correlate with increased funding volumes. No zero values were present in `Service Users` or `Number of Investors`, validating the use of log transformation without adjustment.

3.5.1 Outcome-Measurability Typology

Outcome measurability reflects three attributes: (i) clarity of causal attribution, (ii) frequency and reliability of data collection, and (iii) regulatory acceptance of the metric (Giacomantonio 2017; Warner 2013). Employment SIBs, for example, verify job placements through HMRC wage records and thus score "high," whereas Health SIBs must infer quality-adjusted life-years from multiple datasets and score "low." Table 1 summarizes the evidence base and resulting high/medium/low assignments used in H1.

Given the positive-only, highly skewed nature of the `Capital Raised` variable, a Gamma GLM with a log link is used as the primary estimation model. This approach enables multiplicative interpretation of predictors, ensures positive predictions, and aligns with theoretical models of financial scaling and investor signaling (Manning & Mullahy, 2001; Spence, 1973).

Table 1: Outcome–Measurability Typology by Sector (detailed evidence)

Sector	**Typical outcome metric**	**Evidence of routinely collected data**	**Measurability**	**Key evidence sources**
Employment & Training	• Verified job placement at 13 & 26 weeks • Sustained employment (52 weeks) • Wage progression (£ per week)	HMRC RTI PAYE records matched quarterly; Universal Credit earnings data (monthly pulls)	High	**Hevenstone** (2023) – quasi-experimental study of 37 employment SIBs; **OECD** (2015) – *Social Impact Investment* report, Chap. 4 on wage-record metrics
Homelessness	• Nights in temporary accommodation • Sustained tenancy at 6 & 12 months • Rough-sleeping headcount delta	DLUHC *Rough Sleeping Snapshot* (annual); Housing Benefit administrative data (monthly); HCLIC case-level returns (weekly)	High	**DLUHC** (2024) – official snapshot dataset; **Gustafsson-Wright, Massey & Osborne** (2020) – Brookings outcome-pay analysis (homelessness cases)
Criminal Justice	• Proven re-offending within 12 months • Frequency of re-arrests • Custody vs. community sentence days saved	Home Office PNC-based re-offending dataset (quarterly); Court Service disposals file (monthly); Privacy redaction below 10 cases	Medium	**Disley et al.** (2015) – HMP Peterborough SIB evaluation; **RAND Europe** (2016) – lessons on outcome tracking in the pilot
Child & Family Welfare	• Placement stability (% in same placement $\geq$2 yrs) • Days in out-of-home care • Timely reunification ($\leq$ 26 weeks)	SSDA903 *Children Looked After* dataset (annual); Section 251 LA finance returns (annual)	Medium	**DfE** (2024) – national statistical release; **Carter et al.** (2024) – GO LAB Dataset, 11 UK child-welfare SIBs
Education	• KS2 scaled scores (reading, maths) • GCSE 9–4 pass rate • Attendance & persistent absence (%)	School Census (termly); DfE National Pupil DB exam files (annual)	Low	**Elsby et al.** (2022) – World Bank/Ecorys evidence review of education impact bonds
Health	• 30-day emergency readmissions post-discharge • QALY gain (EQ-5D) • Avoidable A&E presentations	Hospital Episode Statistics (monthly extract); NHS OIS 3.2 readmissions indicator; PROMs repository (bi-annual)	Low	**NHS Digital** (2020) – CCG OIS 3.2 *Emergency readmissions* dataset; **Fraser et al.** (2018) – GO Lab evaluation of health SIB trailblazers

3.6 Model Specification

To examine how investor preferences shape capital allocation in UK Social Impact Bonds (SIBs), this study applies a Generalized Linear Model (GLM) with a Gamma distribution and a log link function. This approach is theoretically and empirically motivated by the nature of the outcome variable, `Capital Raised`, which has characteristics typical of financial investment data: continuous, strictly positive, and heavily right-skewed (Manning & Mullahy, 2001; Seneta, 2004).

The core model takes the following log-link functional form:

$$\begin{aligned}\ln(\text{Capital Raised}_i) = \beta_0 &+ \beta_1 \ln(\text{Service Users}_i) + \beta_2 \ln(\text{Num Investors}_i) \\ &+ \beta_3 \cdot \text{Criminal Justice}_i + \beta_4 \cdot \text{Education}_i \\ &+ \beta_5 \cdot \text{Employment/Training}_i + \beta_6 \cdot \text{Health}_i \\ &+ \beta_7 \cdot \text{Homelessness}_i + \varepsilon_i\end{aligned}$$

Where:

Capital Raised$_i$ is the initial investment amount committed by investors for project i. This variable is in £ millions and log-transformed.

Service Users and *Number of Investors* are both counts and are log-transformed to reduce skew and model proportional effects. `Service Users` in the number of target beneficiaries stated in the contract. `Number of Investors` is the distinct funding entities listed in a contract.

Criminal Justice$_i$, *Education*$_i$, *Employment/Training*$_i$, *Health*$_i$, and *Homelessness*$_i$ are six binary flag variables to create dummy variables for `Policy Sector`s. Child and family welfare is the reference category.

Gamma distributions are well-suited for modeling skewed, positive-valued variables like capital investment, which often exhibit increasing variance at higher values (Manning &

Mullahy, 2001). This approach is consistent with established applications of GLMs to skewed, positive cost data in other fields, where Gamma distributions with log links have been shown to improve prediction accuracy and interpretability (Moran et al., 2007). Their findings reinforce the suitability of the Gamma-log framework for modeling financial amounts that exhibit heteroskedasticity and right-tailed distributions, as observed in this dataset. As Seneta (2004) notes in his analysis of the variance-gamma model, financial variables like investment amounts frequently deviate from normality and exhibit heavy right tails due to the presence of a few high-investment cases. These properties violate core OLS assumptions, making a Gamma GLM with a log link a more appropriate modeling strategy in many financial contexts.

However, a Breusch–Pagan test conducted on the residuals of the OLS log-linear model indicates that heteroskedasticity is not present in the current dataset ($F = 0.98, p = 0.45$). This outcome suggests that the variance of residuals is not significantly related to the predictors. While this result weakens the case for Gamma over OLS on statistical grounds alone, the Gamma model remains justified due to the strictly positive domain and right-skewed distribution of the dependent variable, as well as its ability to model multiplicative effects directly.

Seneta (2004) also shows that when returns or prices follow heavy-tailed or skewed distributions, modeling frameworks that explicitly allow for this (e.g., using Gamma or variance-gamma families) provide better fits and more robust inference. While the dependent variable is capital rather than return, the underlying distributional logic holds, since the variable is continuous, right-skew, and positive-only.

3.6.1 Diagnostics

Model adequacy was assessed using deviance-residual Q–Q plots, Cook's D influence statistics, Pearson residuals versus fitted values, and an over-dispersion test. Diagnostic graphics are provided in Appendix D Tables 9 and 10.

3.7 Multiplicative Interpretation

This multiplicative logic aligns with established economic theories of scale effects and signaling, where larger projects signal credibility or operational capacity and thus attract higher capital investment (Spence, 1973; Del Giudice & Migliavacca, 2018). In these frameworks, perceived impact or risk does not increase linearly with project scale. Instead, funding decisions often respond proportionally or exponentially to perceived success probability or expected return. The log link function naturally captures this non-linear relationship by interpreting coefficients as percentage changes in expected capital.

For example, a 10% increase in `Service Users` is expected to increase `Capital Raised` by a fixed percentage, regardless of the project's original size. This mirrors how investors evaluate proportional risk and return.

3.8 Robustness: OLS with Log-Transformed Dependent Variable

As a robustness check, an Ordinary Least Squares (OLS) model is estimated using the natural logarithm of `Capital Raised` as the dependent variable. This method is widely used in applied econometrics for its interpretability and familiarity (Wooldridge, 2016). However, OLS assumes homoscedastic and normally distributed residuals and does not restrict predictions to be strictly positive. While the data satisfy homoskedasticity assumptions, the OLS model is not used as the primary model because it does not naturally capture the multiplicative dynamics or positive-only domain of capital allocation decisions. These estimated effects are further interpreted in the Results section, where sector-specific and structural predictors of capital variation are examined in detail.

4 Results

Table 2 reports the empirical findings of the Gamma GLM model. Since each row in the dataset corresponds to a unique SIB project, the regression estimates reflect how project-

level characteristics, like sector, scale, and investor engagement, are associated with the amount of `Capital Raised` by individual projects. The Gamma model serves as the primary specification, while the OLS model provides a robustness check. Coefficients are interpreted relative to the omitted baseline of Child & Family Welfare; exponentiated estimates therefore indicate the proportional change in capital when moving from that sector to any other.

Table 2: Generalized Linear Model Regression Results (Gamma, Log Link)

Model Information	
Dep. Variable	Capital Raised
Observations	76
Model	GLM (Gamma)
Link Function	Log
Method	IRLS
Scale	0.39819
Log-Likelihood	-1108.2
Pseudo R^2 (CS)	0.5467
Deviance	26.442
Pearson χ^2	27.1
Iterations	16

Variable	**Coef.**	**Std. Err.**	**z-stat**	**p-value**	**95% CI**
const	12.1083	0.345	35.101	0.000	[11.432, 12.784]
log(Service Users)	0.3595	0.066	5.442	0.000	[0.230, 0.489]
log(Num Investors)	0.0960	0.075	1.283	0.199	[-0.051, 0.243]
Criminal Justice	0.2257	0.479	0.471	0.637	[-0.713, 1.164]
Education	-0.8628	0.281	-3.069	0.002	[-1.414, -0.312]
Employment and Training	-0.7944	0.270	-2.946	0.003	[-1.323, -0.266]
Health	-1.1515	0.314	-3.672	0.000	[-1.766, -0.537]
Homelessness	-0.6378	0.217	-2.943	0.003	[-1.063, -0.213]

4.1 Hypothesis 1: Sectoral Differences in Capital Raised

Hypothesis 1 proposed that SIB funding levels would vary systematically by policy sector based on differences in outcome measurability, complexity, and perceived investor risk. The results provide strong support for this hypothesis.

Figure 7 below visualizes the exponentiated coefficients from the Gamma GLM, showing the multiplicative effects of each `Policy Sector` on `Capital Raised`, relative to the omitted reference category. Projects in the criminal justice sector are associated with a 25% higher capital estimate ($\exp(\beta) \approx 1.25$), though this result should be interpreted cautiously given the small number of observations in that category.

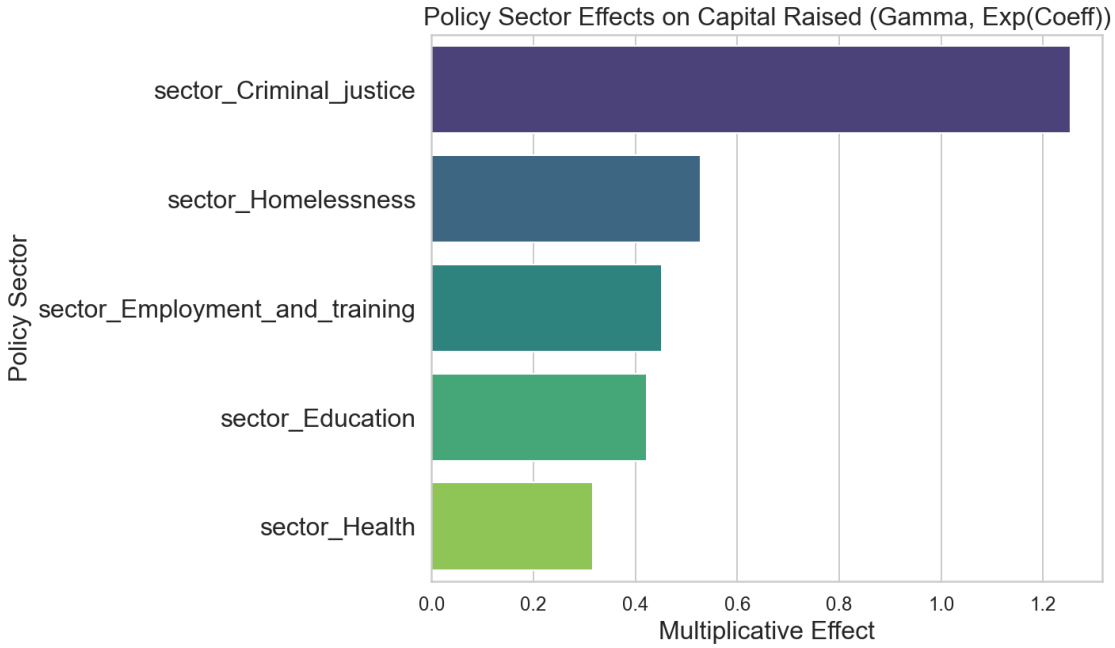


Figure 7: Estimated Multiplicative Effects of Policy Sector on Capital Raised (Gamma Model)

In the Gamma model, several sectors are associated with statistically significant reductions in `Capital Raised`compared to the omitted reference group of `Child and Family Welfare`:

- **Education** projects raised **58% less** capital on average

  (Exp(β) = 0.42, p = 0.0021)

- **Employment and Training** projects raised **55% less**

  (Exp(β) = 0.45, p = 0.0032)

- **Health** projects raised **68% less**

  (Exp(β) = 0.32, $p < 0.001$)

- **Homelessness** projects raised **47% less**

  (Exp(β) = 0.53, p = 0.0033)

The `Criminal Justice` sector showed a positive coefficient (Exp(β) = 1.25), but the effect was not statistically significant ($p = 0.637$), likely due to the small number of projects in this category. While the direction of effect runs counter to theoretical expectations, the wide confidence intervals and low frequency of `Criminal Justice` projects suggest this result should be interpreted cautiously.

To test the influence of potential outliers, a Gamma GLM was re-estimated excluding the two projects in the `Criminal Justice` sector. Results remained highly consistent: sectoral effects for `Education` , `Employment & Training` , `Health` , and `Homelessness` were all significantly negative relative to the reference category, and the positive association between the number of `Service Users` and `Capital Raised` persisted. The `Number of Investors` again did not reach statistical significance ($p = 0.214$), suggesting that this effect is not robust across model specifications. The results are presented in Table 3 below.

4.1.1 Likelihood Ratio Test

To assess the joint contribution of `Policy Sector` variables, a likelihood ratio test was conducted comparing the full Gamma GLM to a reduced model excluding the sector dummies. The result was statistically significant, $\chi^2(5) = 21.47$, $p = .0007$, indicating that `Policy Sector` categories significantly improve model fit. This finding supports Hypothesis 1, suggesting that the policy domain of a Social Impact Bond (SIB) meaningfully contributes to the amount of capital it attracts, even after controlling for project scale and investor participation.

Table 3: Gamma GLM Regression Results (Excluding Criminal Justice)

Variable	Coef.	Std. Err.	z-stat	p-value	[95% CI]
const	12.1378	0.345	35.159	0.000	[11.461, 12.814]
log(Service Users)	0.3548	0.066	5.371	0.000	[0.225, 0.484]
log(Num Investors)	0.0927	0.075	1.242	0.214	[-0.054, 0.239]
Education	-0.8609	0.280	-3.071	0.002	[-1.410, -0.311]
Employment and Training	-0.7885	0.269	-2.931	0.003	[-1.316, -0.261]
Health	-1.1428	0.313	-3.652	0.000	[-1.756, -0.530]
Homelessness	-0.6358	0.216	-2.941	0.003	[-1.059, -0.212]

Model:	GLM (Gamma, Log Link)
No. Observations:	74
Df Residuals:	67
Df Model:	6
Scale:	0.39608
Log-Likelihood:	-1077.3
Deviance:	25.933
Pearson chi2:	26.5
Pseudo R^2 (CS):	0.5070

4.1.2 Ordinary Least Squares as a Robustness Check

Robustness checks using the OLS model produced near-identical patterns, with all significant sectors retaining both sign and magnitude. This confirms that sectoral effects are not sensitive to model choice and are robust to functional form. Thus, the findings on `Capital Raised` by sector are not simply a modeling artifact but reflect a real structural feature of SIB capital flows. The OLS log-linear model results can be found in Appendix E Table 7.

4.2 Hypothesis 2: Project Scale and Capital Raised

Hypothesis 2 posited that larger-scale projects, as measured by the number of `Service Users`, would attract more capital. This is strongly supported by the data.

- In the Gamma model, the coefficient for log(Service Users) is 0.36 ($p < 0.001$), meaning a 1% increase in `Service Users` is associated with a 1.43% increase in `Capital`

`Raised`.

- This effect is mirrored in the OLS model ($\beta = 0.35$, $p < 0.001$), confirming its robustness.

These results align with economic theories of scale and signaling, where larger projects suggest higher credibility, broader impact, or more efficient per-unit outcomes (Spence, 1973; Del Giudice & Migliavacca, 2018). A project's scale may not only reflect its reach but also its administrative complexity, outcome monitoring infrastructure, and visibility to funders. Larger projects may benefit from economies of scale in both delivery and evaluation, making them more attractive to investors seeking predictable and replicable outcomes.

However, these relationships are not unambiguous. As noted in the methodology section, service user count may also reflect operational funding requirements, not just investor preference. A large-scale program inherently demands more upfront capital, and investors may simply be meeting the cost structure rather than responding to perceived value or risk. Thus, while the association is statistically strong, it may partially capture funding necessity rather than investor motivation.

4.3 Hypothesis 3: Number of Investors and Capital Raised

Hypothesis 3 suggested that projects with more investors would raise more capital, due to risk pooling, greater access to funds, or signaling effects. The results offer mixed support for this hypothesis.

In the Gamma model, the coefficient for log(Number of Investors) is positive ($\text{Exp}(\beta) = 1.10$) but not statistically significant ($p = 0.199$).

However, in the OLS model, the effect is statistically significant ($\beta = 0.17$, $p = 0.030$), indicating that additional investors are associated with modest increases in `Capital Raised`.

This discrepancy may stem from the way each model handles distributional assumptions. OLS assumes constant variance and additive relationships, while the Gamma GLM models

proportional effects and accommodates skew. The presence of a significance signal in OLS but not Gamma suggests that the effect of investor syndication may be small and inconsistently influential.

Alternatively, this result could indicate that the type of investors, not the number, is more relevant to capital mobilization. Institutional backers or government co-investors may bring reputational weight that small consortia cannot replicate, meaning that quantity alone does not dictate funding scale.

4.4 Interpreting Key Coefficients

To illustrate the substantive meaning of the regression results, three key coefficients from the Gamma GLM are interpreted below. These examples demonstrate how model estimates translate into percentage changes in `Capital Raised`, holding other variables constant.

Education vs. Child & Family Welfare The coefficient for *Education* is -0.863 ($p = 0.002$), meaning that, all else equal, projects in the *Education* sector raise approximately 58% less capital than comparable Child & Family Welfare projects. This is obtained by exponentiating the coefficient, $\exp(-0.863) \approx 0.42$, which indicates that *Education* projects attract only 42% of the `Capital Raised` by the reference category. This suggests that, despite Education often being considered a highly measurable sector, it still receives substantially lower investment when project size and investor count are controlled for.

Number of Service Users The coefficient for $\log(\textit{Service Users})$ is 0.360 ($p < 0.001$). This implies that a 10% increase in the target number of `Service Users` is associated with roughly a 3.6% increase in `Capital Raised`, calculated as $0.10 \times 0.360 \approx 0.036$. This supports the scale - signaling hypothesis, whereby larger intended reach is linked to higher upfront investment.

Number of Investors The coefficient for log(*Number of Investors*) is 0.096 ($p = 0.199$) in the Gamma model. While this suggests that a 10% increase in the `Number of Investors` could be associated with about a 1% increase in `Capital Raised`, the effect is not statistically significant. This indicates that, holding sector and scale constant, simply increasing the `Number of Investors` does not reliably increase total capital, consistent with the idea that investor type may matter more than investor count.

4.5 Diagnostics

Diagnostic tests (Figs.9 - 10) confirm a well-specified model. The Q–Q plot in Fig. 9a approximates normality, and the over-dispersion ratio in Fig. 9c is 0.40 (< 1), indicating no residual over-dispersion. Cook's D values Fig. 9b) show only two observations above the 4/n threshold; dropping them changes exponentiated coefficients by $< 5\%$, underscoring robustness. Pearson-residual panels in Fig. 10b display no funnel pattern, so heteroskedasticity is not evident for either the Gamma or log-OLS model. Combined with the close alignment of actual and predicted values (Fig. 10a), these checks favor the Gamma GLM over the naive linear alternative.

5 Discussion

This study finds that capital allocation across UK Social Impact Bonds (SIBs) is shaped more by sector and project scale than by purely technical measures of measurability or governance structure. Most notably, Criminal Justice SIBs attract disproportionately more investment than any other sector, while Employment & Training, often described as an "investor-friendly" domain, underperforms relative to Child and Family Welfare. These disparities persist even after controlling for service-user counts and investor mix, revealing a "SIB paradox": sectors with the clearest metrics do not always secure the largest flows of capital.

5.1 Summary of Key Findings

Using a Gamma Generalized Linear Model (GLM) with a log link, and confirming robustness through a log-linear Ordinary Least Squares (OLS) specification, the analysis demonstrates that sector type and programmatic scale are statistically significant predictors of upfront capital mobilization. Larger service-user counts consistently signal efficiency and credibility to investors (Spence, 1973), while certain sectors such as Health, Education, and Employment & Training receive systematically less capital than the Child and Family Welfare reference category.

The OLS results reinforce these patterns, although investor count is only significant under the OLS specification, suggesting its influence is sensitive to distributional assumptions. This mixed result for Hypothesis 3 indicates that while scale and sector are consistent drivers of investment, investor count plays a more conditional role.

Causality remains a caveat. Because commissioners self-select which sectors to finance, and because unobserved contextual factors such as local unemployment, budget cycles, and political salience may influence project initiation, sector coefficients could capture selection effects rather than intrinsic investor preferences. A sector-fixed-effects panel or an instrument such as lagged commissioner budget shares could help address this, but the present cross-section lacks temporal depth.

5.2 Sectoral Disparities and the SIB "Paradox"

The sector-based disparities speaks to a long-standing critique: SIBs favour alignment with investor appetites rather than direct targeting of complex social need (Fraser et al., 2018; Maier et al., 2018). While Health and Education are foundational to social infrastructure, they involve long-horizon, politically sensitive outcomes that often require multi-level governance and regulatory coordination. These conditions are not well-suited to pay-for-success contracts.

The underfunding of Employment & Training contradicts literature framing it as "investor-

friendly" due to measurable indicators (Gustafsson-Wright et al., 2015). This divergence supports the SIB paradox and highlights how perceived political optics can override technical measurability. The results here suggest measurability alone is insufficient to attract substantial capital. One explanation, consistent with interview evidence from UK commissioners (Walker, 2023), is a saturation effect: many such SIBs are capped at $\leq$ £1 m as small pilots, fragmenting investment and preventing the creation of high-profile flagship deals. In practice, this means outcome funders should explicitly recognize sectors at risk of underinvestment and design incentives to attract capital there. Without such interventions, market-led allocation will continue to favor politically visible or administratively convenient sectors over those with high but harder-to-measure social value.

By contrast, Child and Family Welfare projects often focus on outcomes like foster placement stability, school attendance, and early childhood benchmarks. These are administratively feasible, closely tied to observable behavioral change, and readily auditable, making them attractive to both commissioners and funders.

5.3 The Case of Criminal Justice: Outlier or Indicator

Although only two Criminal Justice projects are present in the dataset, their large positive coefficients run counter to broader investor caution toward politically sensitive or attribution-resistant interventions. Possible explanations include novelty effects, higher baseline costs, or public co-financing motivated by a desire to pilot alternatives to incarceration. However, the infrequency of such projects underscores a structural tension: sectors with acute social need may remain underrepresented not because they fail to perform, but because they are perceived as misaligned with the financial and political logic of pay-for-success. This aligns with critiques that outcomes-based finance can inadvertently reinforce selectivity rather than broaden investment reach.

5.4 Model Robustness and Methodological Considerations

The OLS model serves as a useful robustness check, producing broadly consistent results with the Gamma GLM. However, OLS cannot constrain predictions to the positive domain or fully capture multiplicative effects. The Gamma model remains preferred for its fit to the right-skewed, strictly positive capital data, and for its interpretability in percentage terms, a scale more intuitive for policy and funding analysis (McCullagh, 2019).

A Breusch–Pagan test on the OLS residuals yielded $F = 0.98$, $p = 0.45$, indicating no evidence of heteroskedasticity. While this reduces the purely statistical case for the Gamma model, its alignment with the data's distributional properties and its ability to model proportional effects provide a stronger substantive justification.

5.5 Policy and Practice Implications

The persistence of sectoral disparities after controlling for scale and governance variables indicates that market-led allocation will not automatically align with social priorities. In line with financialisation critiques (Fraser et al., 2018; Maier et al., 2018), the results suggest that political optics, ticket size, and historic momentum often outweigh technical measurability in shaping investor decisions.

Targeting under-investment Health and Education, despite high social value, are structurally disadvantaged in attracting SIB capital. Policymakers and outcomes-fund designers could offset this through targeted subsidies, outcome-premium multipliers, or blended-finance guarantees to de-risk contracts in these sectors.

Scaling beyond pilots Employment & Training may require aggregation mechanisms to overcome fragmentation. Pooled funds or larger, multi-site contracts could attract investors seeking scale and visibility.

Investor dynamics Investor count does not linearly increase capital pools, consistent with herding theory (Kahneman & Tversky, 1979; Barber & Odean, 2013). This suggests that lead investor credibility, rather than participation breadth, is the decisive capital signal.

Taken together, these findings confirm that SIBs are not purely technocratic instruments but are deeply shaped by investor preferences and market logic. The SIB paradox, where measurability does not guarantee capital, has clear implications for the design of more equitable and innovation-friendly outcomes-based finance systems.

5.6 Limitations and Structural Constraints

Several factors constrain both causal interpretation and generalizability.

Design This study uses a cross-sectional, observational design. While strong associations are found between sector, project scale, and `Capital Raised`, these cannot be interpreted as definitive causal relationships. Sector coefficients may reflect unobserved cost structures, commissioner mandates, or political context. Without temporal variation, it is impossible to assess how changes in external conditions or project performance influence investment flows over time. A sector-fixed-effects panel model or quasi-experimental designs, such as natural experiments or difference-in-differences, would offer stronger causal leverage.

Data quality and coverage Public reporting on SIBs is inconsistent. Smaller or regionally administered projects are less likely to have comprehensive documentation, which can create visibility bias and under-represent niche or locally focused interventions. In some cases, financial records were reconstructed from secondary sources, and this non-random availability of data introduces the possibility of systematic bias. Missing or incomplete fields, particularly in early SIBs, may distort estimates of capital allocation patterns.

Scope of analysis The analysis focuses exclusively on upfront capital commitments. It does not examine realized outcome payments, investor returns, or long-term cost-effectiveness. As a result, the link between initial investment and actual social or financial performance is not addressed. For example, the large coefficient observed for Criminal Justice should be interpreted with caution, as it is based on very few observations and says nothing about subsequent project success or sustainability.

Contextual effects Sector coefficients can also capture broader economic and political

conditions that are not included in the model, such as local unemployment rates, national budget cycles, or sector-specific policy reforms. These findings may also be context-specific; the UK's centralized outcomes-funding infrastructure and policy priorities differ from other jurisdictions, meaning replication in different settings could yield alternative sectoral patterns.

Together, these limitations mean that while the patterns identified here are robust within the dataset used, they should be treated as indicative rather than definitive. Policy recommendations should be read with these caveats in mind.

6 Conclusion

This study makes three substantive contributions to the literature on social finance and outcomes-based contracting.

First, it provides one of the few quantitative analyses of how capital is distributed across UK Social Impact Bonds (SIBs), applying a structured econometric framework to test hypotheses grounded in financial theory, public accountability, and policy design. While much of the existing SIB literature is qualitative or case-focused, this research systematically evaluates how sector, project scale, and investor participation influence the size of upfront capital commitments. This focus on capital allocation addresses a foundational yet underexplored element of SIB design.

Second, it introduces the use of a Gamma Generalized Linear Model (GLM) with a log link to model `Capital Raised`, which is a highly skewed and strictly positive variable. This method enables percentage-based interpretation of effects, which aligns more closely with how commissioners and investors assess proportional risk and return. By comparing the Gamma GLM with a log-linear OLS model, the analysis demonstrates how distributional assumptions can shape inferences about investment behavior, providing a methodological contribution to the study of financial flows in social policy instruments.

Third, it bridges academic inquiry and practical relevance by identifying structural patterns in capital flows that may reinforce inequities in service delivery. Sectors such as Health, Education, and Employment, although socially vital and often considered measurable, attract systematically less funding than Child and Family Welfare. This misalignment between social need and capital allocation raises concerns about the market-led orientation of SIB investment and highlights the need for targeted interventions to align private incentives with public priorities.

These contributions deepen the understanding of the interaction between investor behavior, sectoral characteristics, and program design. They also underscore the importance of transparent, theory-informed modeling and measurable evaluation criteria in the design and management of SIBs.

Ultimately, without deliberate corrective measures, capital allocation through SIBs will continue to reflect market logic more than social priorities.

6.1 Future Research on Investor Behavior in SIBs

Several opportunities exist to extend this work.

Longitudinal capital tracking Future studies should link initial investment amounts to subsequent outcome payments and investor returns. Tracking SIBs across their full lifecycle would reveal how capital commitments evolve in response to outcome performance, political change, or investor turnover, and whether sectors attracting more capital also deliver proportionally greater returns or social impact.

Disaggregating investor profiles Capital allocation patterns may be influenced by investor mission, governance model, or return expectations. Future work could categorise investors (e.g., philanthropic, corporate, institutional, public-sector) and test whether mission-driven investors behave differently from commercially oriented ones.

Incorporating broader macro-political variables Adding measures such as national unemployment rates, political party control, fiscal constraints, or regional deprivation in-

dices could help disentangle investor preference from contextual necessity. This would allow stronger claims about whether observed disparities are due to market logic or structural policy environments.

Cross-national comparisons Comparing the UK with other countries that operate centralized outcome funds or use alternative outcomes-based finance models could help identify institutional arrangements that promote more equitable capital mobilization across sectors.

Mixed-methods approaches Pairing statistical analysis with interviews or document analysis from commissioners, intermediaries, and investors would provide richer insights into decision-making rationales, particularly in underfunded but socially critical sectors such as Health and Education.

6.2 Next Steps for Policy and Practice

This study also reveals critical gaps in data infrastructure that should be addressed by policymakers and public funders. Because SIBs entail potential future payouts from public budgets, clear documentation of investment terms, service delivery metrics, and performance outcomes is essential for transparent governance. Without standardized reporting protocols, it becomes difficult to evaluate the cost-effectiveness of outcome-based finance or ensure accountability to taxpayers.

Governments and outcome fund managers should consider mandating minimum reporting standards for all SIBs, including disclosure of `Capital Raised`, investor composition, projected versus realized outcomes, and payment schedules. Such efforts would improve evaluability, reduce informational asymmetries, and help build public trust in performance-based funding mechanisms.

In parallel, funders might explore blended finance instruments, tiered risk-sharing, or outcome prepayment schemes to de-risk investment in high-need but underfunded sectors. These strategies could correct current imbalances and align private incentives with public priorities more effectively.

This study offers a granular look at how investor capital is distributed across policy domains, laying the groundwork for more transparent and data-driven SIB design going forward.

7 Appendix

Replication files (cleaned dataset, supplementary data and sources, py scripts, and figure code) are on GitHub at https://github.com/clarezureich/Dissertation, enabling full reproducibility of tables and plots.

Appendix A: Supplementary Data Figures

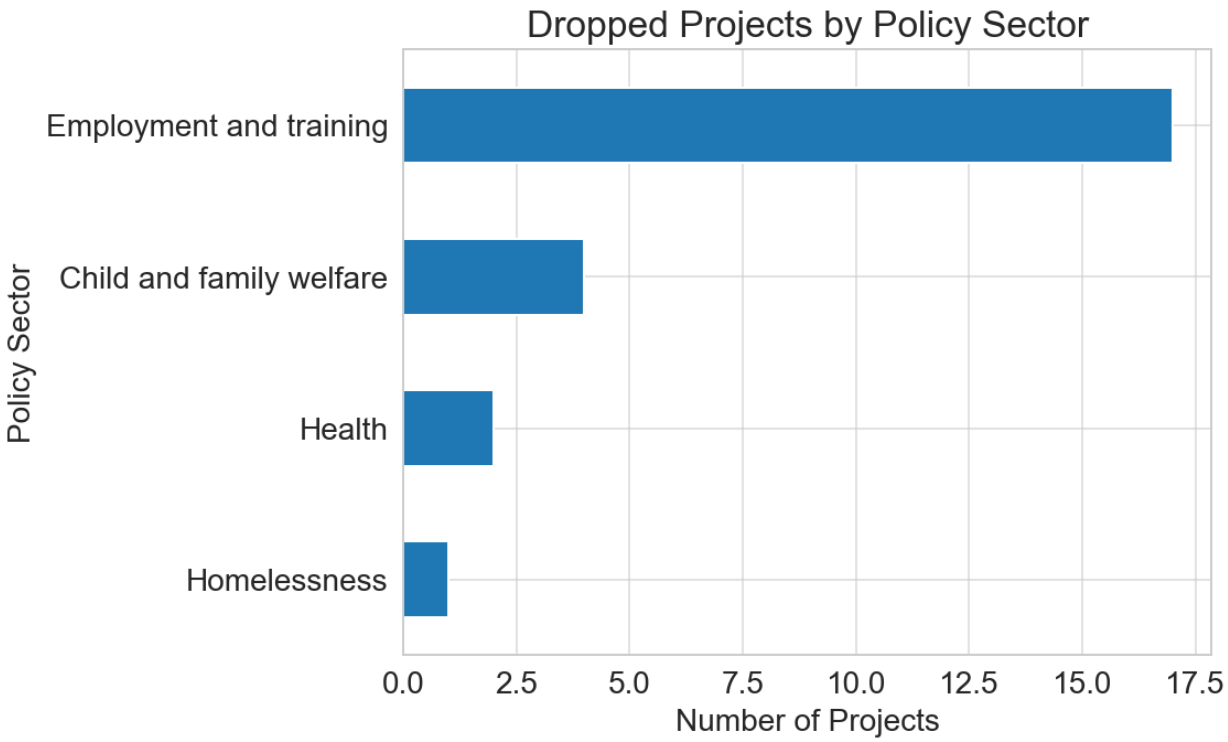


Figure 8: Dropped projects by policy sector (n = 24)

Table 4: Projects excluded from the analytical sample (missing key fields)

Project ID	**Name**	**Policy sector**
INDIGO-POJ-0271	Plymouth Refugee Opportunities	Employment and training
INDIGO-POJ-0282	Refugee Integration Support and Employment (RISE)	Employment and training
INDIGO-POJ-0283	Refugee Transitions — West Midlands	Employment and training
INDIGO-POJ-0284	Greater Manchester Refugee Integration Partnership	Employment and training
INDIGO-POJ-0192	MHEP Tower Hamlets Learning Disabilities	Employment and training
INDIGO-POJ-0193	MHEP Tower Hamlets Community Options	Employment and training
INDIGO-POJ-0236	DWP Local Supported Employment — Blackpool	Employment and training
INDIGO-POJ-0259	DWP Local Supported Employment — Enfield	Employment and training
INDIGO-POJ-0260	DWP Local Supported Employment — Hertfordshire	Employment and training
INDIGO-POJ-0261	DWP Local Supported Employment — Kent	Employment and training
INDIGO-POJ-0262	DWP Local Supported Employment — Northamptonshire	Employment and training

Table 4 (continued)

Project ID	Name	Policy sector
INDIGO-POJ-0263	DWP Local Supported Employment — North Yorkshire	Employment and training
INDIGO-POJ-0264	DWP Local Supported Employment — Nottinghamshire	Employment and training
INDIGO-POJ-0265	DWP Local Supported Employment — Somerset	Employment and training
INDIGO-POJ-0266	DWP Local Supported Employment — South Tyneside	Employment and training
INDIGO-POJ-0267	DWP Local Supported Employment — Surrey	Employment and training
INDIGO-POJ-0268	DWP Local Supported Employment — West Sussex	Employment and training
INDIGO-POJ-0269	DWP Local Supported Employment — Wirral	Employment and training
INDIGO-POJ-0270	DWP Local Supported Employment — Wrexham	Employment and training
INDIGO-POJ-0175	MHEP Durham Community Options	Child and family welfare
INDIGO-POJ-0176	MHEP Shropshire Community Options	Child and family welfare
INDIGO-POJ-0177	MHEP York Community Options	Child and family welfare

Table 4 (continued)

Project ID	**Name**	**Policy sector**
INDIGO-POJ-0144	Home Care — Rochdale	Health
INDIGO-POJ-0155	Entrenched Rough Sleepers — Manchester	Homelessness

Appendix B: Additional Descriptive Statistics

Table 5: Descriptive Statistics of Capital Raised by Policy Sector (GBP)

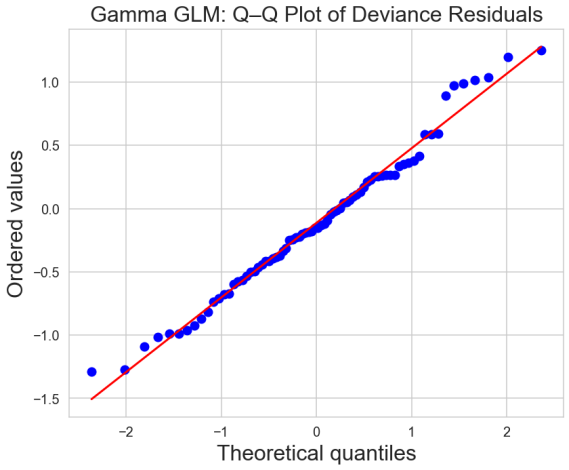
Policy sector	**Mean**	**Median**	**Min**	**Max**
Child & family welfare	1,507,148	1,100,000	150,000	4,500,000
Criminal justice	3,000,000	3,000,000	1,000,000	5,000,000
Education	746,875	682,500	100,000	1,810,000
Employment & training	1,165,109	900,000	300,000	3,000,000
Health	1,013,099	1,000,000	300,000	1,870,000
Homelessness	1,056,025	641,500	160,000	5,880,000

Appendix C: Breusch-Pagan Output Table

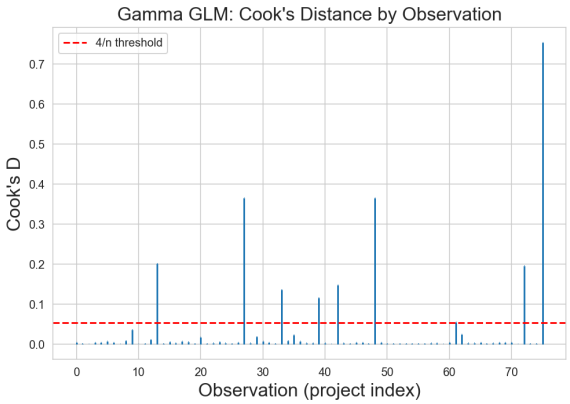
Table 6: Breusch–Pagan Test for Heteroskedasticity

Statistic	**Value**	**p-value**
LM Statistic	7.518	0.377
F Statistic	1.066	0.395

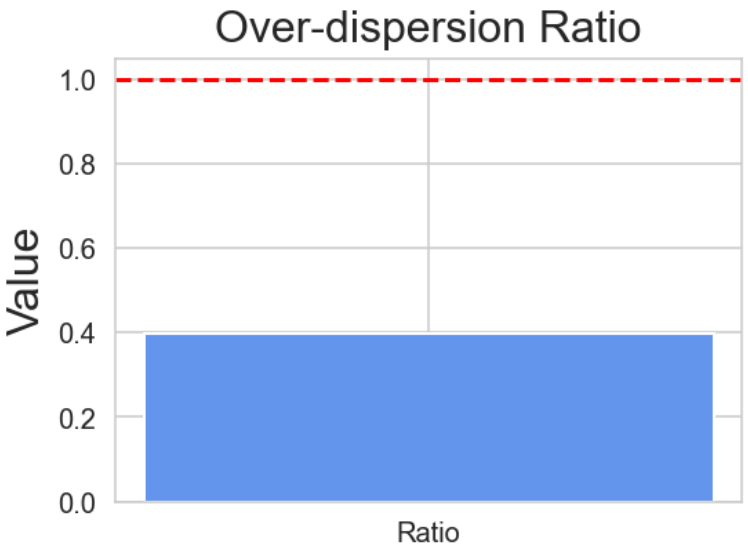
Appendix D: Diagnostic Figures



(a) Q–Q plot of deviance residuals

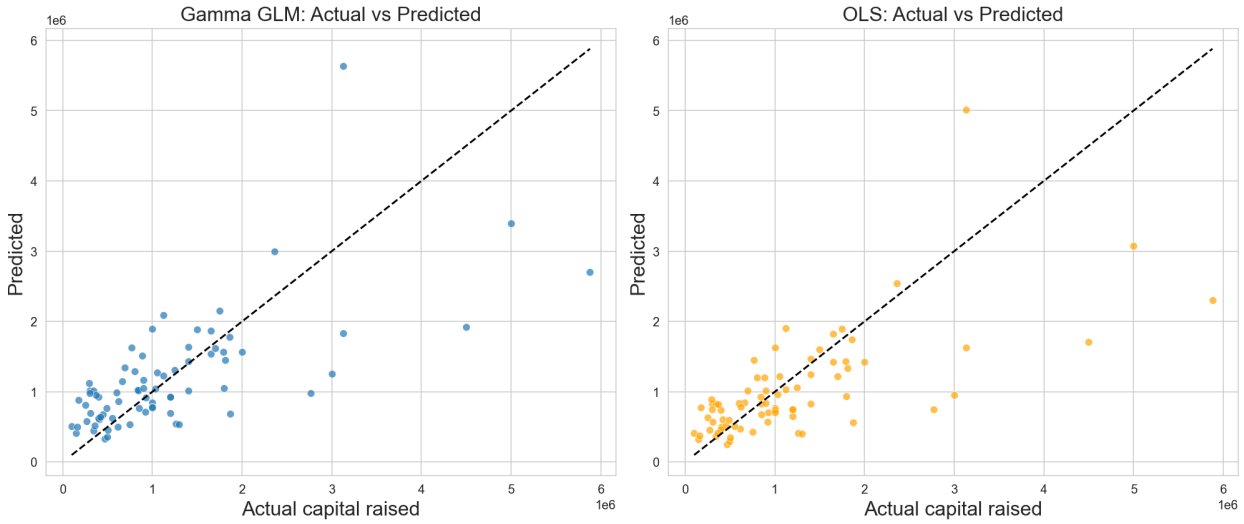


(b) Cook's D influence by observation

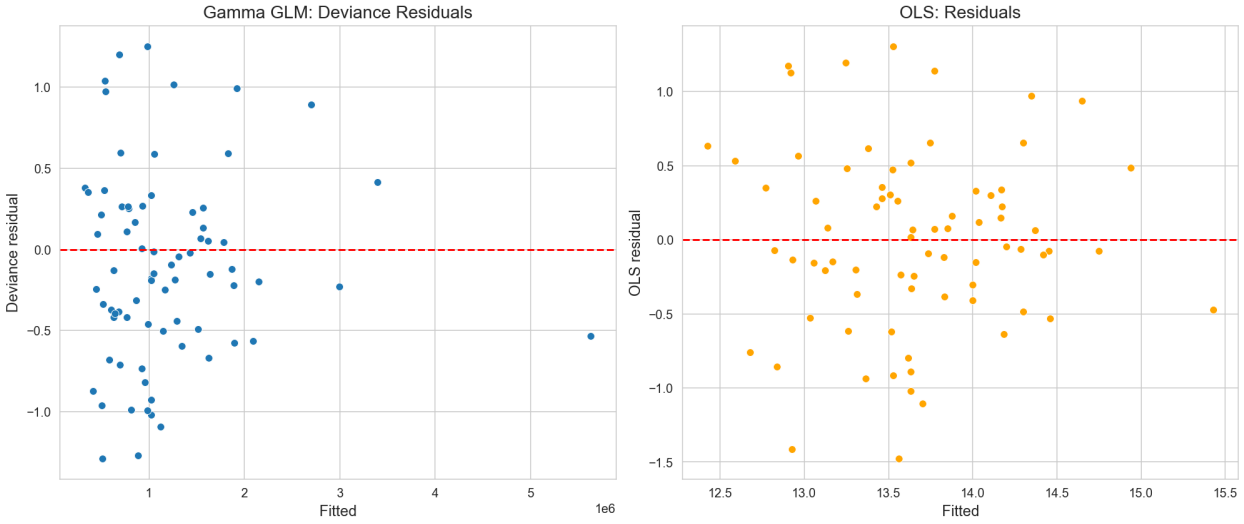


(c) Pearson χ^2/df over-dispersion ratio

Figure 9: Gamma GLM diagnostics. Panels illustrate (a) approximate normality of deviance residuals, (b) limited influence of individual projects, and (c) absence of over-dispersion (ratio = 0.40).



(a) Actual versus predicted capital raised (Gamma GLM on the left, log-OLS on the right)



(b) Studentised Pearson residuals versus fitted values (Gamma GLM on the left, log-OLS on the right)

Figure 10: Gamma GLM fit diagnostics. The top panel compares model predictions with observed capital; the bottom panel checks for heteroskedasticity via residual patterns.

Appendix E: OLS Regression Output Table

Table 7: OLS Regression Results (Log-Linear Model)

Variable	**Coef.**	**Std. Err.**	**t-stat**	**p-value**	[95% CI]
const	11.8675	0.347	34.158	0.000	[11.174, 12.561]
log(Service Users)	0.3524	0.067	5.296	0.000	[0.220, 0.485]
log(Num Investors)	0.1669	0.075	2.215	0.030	[0.017, 0.317]
Criminal Justice	0.2536	0.482	0.526	0.601	[-0.709, 1.216]
Education	-0.8056	0.283	-2.845	0.006	[-1.370, -0.241]
Employment and Training	-0.7736	0.272	-2.849	0.006	[-1.316, -0.232]
Health	-1.0562	0.316	-3.344	0.001	[-1.686, -0.426]
Homelessness	-0.6513	0.218	-2.984	0.004	[-1.087, -0.216]

Model:	OLS (Log-Linear)
No. Observations:	76
Df Residuals:	68
Df Model:	7
R-squared:	0.475
Adj. R-squared:	0.421
F-statistic:	8.806
Prob (F-statistic):	1.15×10^{-7}
Log-Likelihood:	-69.166
AIC:	154.3
BIC:	173.0
Durbin-Watson:	2.083
Omnibus:	0.112
Prob(Omnibus):	0.945
Jarque-Bera (JB):	0.134
Prob(JB):	0.935
Skew:	-0.083
Kurtosis:	2.878

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