Quantifying Hidden Exploitation: Dual-Method Prevalence Estimates of Modern Slavery Risk Among UK Domestic Workers*

Caroline Emberson Scott Moser

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Purpose
The purpose of this article is to demonstrate a quantitative approach to the construction of a risk index of labour exploitation and alternative estimators of the prevalence of exploitation.

Design/ Methodology/ Approach
Using data from a survey of domestic workers based in the United Kingdom (UK), we use statistical techniques, including Respondent Driven Sampling (RDS) methods RDS-I and RDS-II and Network Scale Up (NSUM) methods, to produce an index of labour exploitation risk and estimators of the prevalence of labour exploitation.

Findings
The labour exploitation risk index shows a reverse correlation between the increasing seriousness of exploitation and the number of exploitation cases reported. The various prevalence estimators examined show significant differences in population level exploitation.

Research implications/ limitations
Further research into the application of different quantitative statistical estimators of the prevalence of labour exploitation is urgently required.

Practical implications
Robust estimators are necessary if policy makers are to make informed choices about the appropriate allocation of scarce resources to help to eradicate severe forms of labour exploitation and labour abuse.

Social implications

*Authors' names are listed in alphabetical order.

Even by more conservative estimates, thousands of domestic workers in the UK are subject to labour exploitation. Urgent policy attention is needed if structural vulnerabilities are to be removed.

Originality

We believe this paper is the first to compare the use of RDS and NSUM methods in the quantitative estimation of the prevalence of labour exploitation and to construct a quantitative, composite index of labour exploitation risk.

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1 Introduction

* Why study labour exploitation among UK domestic workers?

* Gap in existing research.

* Contributions: (1) Conceptualisation of exploitation (binary vs. continuous, risk inde

2 Introduction

Labour exploitation has been defined as ‘work situations that deviate significantly from standard working conditions as defined by legislation or other binding legal regulations, concerning in particular remuneration, working hours, leave entitlements, health and safety standards and decent treatment’(**european_union_for_fundamental_rights_severe_2015**). In the operations and supply chain management literature, interest in businesses’ respect for these kinds of employee labour rights began with studies focused upon labour rights transgressions related to risk reduction and risk communication and how to improve employees’ health and safety (**chinander_aligning_2001**; **wolf_operationalizing_2001**). More recently, serious labour rights abuses have come to the fore with studies examining the challenges of severe labour exploitation under the umbrella term ‘modern slavery’ (**gold_modern_2015**; **new_modern_2015**; **benstead_horizontal_2018**; **stevenson_modern_2018**). While this literature offers important insights into severe forms of labour exploitation, particularly in global supply chains, this and the wider social sustainability literature has been criticised for its de-humanised approach to the understanding of workers and their working conditions (**soundararajan_humanizing_2021**). While at least one current project seeks to examine the phenomenon of worker voice in factory settings (**leverhulme_trust_research_2022**), there appears to be little attention paid to severe forms of labour exploitation from the workers’ perspective in the private sphere. Nowhere are the realities of individual workers’ experiences of employer exploitation brought into sharper relief than in the setting of domestic work in private households.

The authors of the Global Slavery Index estimate that there are seventy-six million people employed in domestic work worldwide (**international_labour_organization_global_2022**)). According to **bonnet_domestic_2022<empty citation>**, eighty percent of this domestic work is unregulated and informal. Labour exploitation has been identified as an extensive global problem within the sector, with domestic work identified as one of five private sector groupings which contribute the most to forced labour. Defined in the ILO Forced Labour Convention, 1930 No.29, forced or compulsory labour is ‘all work or service which is exacted from a person under the threat of a penalty and for which the person has not offered himself or herself voluntarily’ (**ilo_what_2024**). Seventy-six percent of domestic workers are women, and these workers represent four percent of the total female workforce (**international_labour_organization_global_2022**). Indeed, women in forced labour are much more likely to be in domestic work than in any other occupation (**international_labour_organization_global_2022**). The ILO suggest that female domestic workers may be coerced through non-payment of wages; abuse of vulnerability; subjected to physical and sexual violence or experience threats against their family members. Such severe forms of labour exploitation may be present alongside other, perhaps less severe but equally illegal, practices which constitute various forms of labour abuse. The criminalisation of both labour exploitation and abuse in a domestic setting has developed in recent times, with legislation enacted in the United Kingdom (UK), Europe, Australia and Norway to criminalise such severe exploitation under the term 'modern slavery'. However, even where modern slavery laws are in place, reliance on traditional, inspection-led, approaches to detection designed primarily to ensure labour rights compliance within communal workplaces such as factories mean that the number of reported cases of labour exploitation in private dwellings may well severely underestimate actual exploitation levels. Though an exploration of labour exploitation within private residences, our research seeks to redress the paucity of rigorous quantitative research in the modern slavery field. Specifically, this article aims to contribute to a more nuanced understanding of how quantitative methodologies may be deployed to improve understanding of the realities of workers' conditions by demonstrating the use of a statistically robust estimation of the nature and proportion of labour exploitation and abuse among domestic workers in the UK. This setting was chosen due to long-standing national legislation criminalising modern slavery introduced to the UK in 2015. Despite, or perhaps because of this legislation, in recent years the number of potential victims entering the UK's National Referral Mechanism (NRM), a scheme which provides government support for those suspected to be modern slavery survivors, has continued to increase. Nineteen thousand, one hundred and twenty-five potential victims were recorded in 2024: the highest annual figure since the NRM began (**home_office_modern_2025**). In 2024, for the first time the number of cases of potential modern slavery among females handled by the charity Unseen, who run the UK's modern slavery helpline, were more prevalent than those among men (**carter_women_2025**). Despite these worrying headline statistics, and the persistence of specific concerns about high levels of exploitation among domestic workers in the grey literature (**kalayaan_new_2008**; **mantouvalou_modern_2016**; **latin_american_womens_rights_service_behind_2023**), to our knowledge no-one has yet estimated the nature and extent of labour exploitation and abuse that may exist among domestic workers in the UK.

In contrast to overseas factory workers in globally dispersed, product, supply chains, many service workers engaged in domestic work have migrated to work in the UK. These transnational workers enter on restricted visas where their employment—and their right to remain in the country—is tied to their continuing employment. It is now ten years since the UK's Modern Slavery Act was enacted. During its passage through parliament, those advocating for the rights of domestic workers were successful in expanding the final category boundaries of the legislation to include, in Section 53, the specific definition of (overseas) domestic workers as modern slavery victims (**caruana_boundaries_2025**). These transnational migrants are at particular risk of exploitation due to regulatory visa restrictions and intersecting structural issues related to their gender, the relative isolation of domestic work and a lack of supportive social networks. This can mean that they fall out of legal migratory status.

Due to the social stigma attached to such illegal working, transnational workers remaining in the UK without the right to work may be considered a hidden, hard-to-reach, population. Extracting a sample of domestic workers which includes this group raises difficulties when trying to employ the normal statistical sampling methods considered necessary for robust prevalence estimation. Perhaps due to these sampling difficulties, we know relatively little about the nature of labour exploitation among this particularly at-risk group of workers. Fortunately, there has been significant interest in the development of alternative methods for prevalence estimation which include such hard-to-reach groups, with many scholars advocating and developing the use of respondent-driven sampling (RDS) techniques to support statistically robust estimators.

In this paper, we make two specific contributions to the operations and supply chain management literature. First, we demonstrate the use of RDS coupled with Network Scale-up Methods (N-SUM) to reach and sample respondents' views of their working conditions among these, predominantly female, transnational migrant domestic workers. We use the data we obtain from these respondents to show how quantitative survey data can be used to estimate the proportion of workers experiencing labour exploitation. Second, we begin to capture the nature and extent of modern slavery as voiced by domestic workers, thus, we believe, expanding the nascent literature on worker voice which has, in the main, focused primarily on factory workers (**stephens_theorising_2024**). These contributions not only extend our understanding of the risks of labour exploitation and abuse among service workers engaged in domestic settings but also show how it is possible to shed light on the severity of the individuals' experience of exploitation through the construction of a novel risk index. The remainder of this paper is structured as follows. our study in more detail, highlighting what is already known about the current population of domestic workers in the UK and the conditions in which they work. Next, we describe our research methods. We review the development of the respondent-driven sampling (RDS) techniques we used and explain why this sampling method is suitable for our study. We then describe our survey methods, including how we designed our survey instrument, contacted our sample seeds and analysed our data. We then present and discuss our findings, detailing the proportional estimate that we calculated and the risk index we constructed. In our discussion, we expand upon the implications of our findings for government policy, enforcement practices and further research, including how these methods may be used in future studies of labour exploitation in other sectoral and geographic contexts. The limitations of our study are outlined, before, finally, we conclude our article.

2.1 Conceptualising Labour Exploitation and the Degree of Risk

- Binary vs. continuous definitions.
- Risk index construction and theoretical justification.

Modern slavery has been criticised by some for its overly extensive scope: encapsulating a broad range of divergent sub-categories of exploitation (**oconnell_davidson_margins_2015<empty c** **gutierrez-huerter_o_change_2023<empty citation>**). For this reason, we used the

International Labour Organization's (**ILO11-indicators<empty citation>**)[1] 'Indicators of Forced Labour' to identify the potential for severe labour exploitation and as a basis for the quantification of our labour exploitation and abuse risk index. The ILO identify eleven indicators designed to help understand how forced labour arises and how it affects victims. These indicators include: abuse of vulnerability; deception; restriction of movement; isolation; physical and sexual violence; intimidation and threats; retention of identity documents; withholding of wages; debt bondage; abusive working and living conditions and excessive overtime. According to the ILO, the presence of a single indicator in any given situation may in some cases imply the existence of forced labour. However, it also suggests that in other cases it may be necessary to look for several indications which, taken together, may point to a case of forced labour. We seek to refine this statement through the construction of a composite index by which means a degree of risk related to the likelihood of a domestic worker experiencing this most severe form of exploitation may be distinguished from the likely occurrence of less severe, though similarly illegal, forms of labour abuse.

3 Evaluating the Degree of Risk

The study of risk management has a long tradition in operations and supply chain management. Initially, the risks under consideration were primarily related to ensuring continuity of the supply of goods and services (see for example, **juttner_supply_2003<empty citation>**). Beginning with **anderson_critical_2006<empty citation>** and **anderson_sustainability_2009<** however, a literature stream of sustainability-related supply chain risk management developed related specifically to the risks associated with the environment and social justice. A normative consensus related to the main stages of supply chain risk management has developed in the literature, with a five-stage sequential model typically presented. There have also been empirical studies of risk management within various industrial supply chains in the United States and India (**tarei_hybrid_2018<empty citation>**; **dellana_scale_2021<empty citation>**), including the quantification of a risk index for the petroleum supply chain (**tarei_hybrid_2018<empty citation>**). Yet, while these authors recognize the need for responsible management and its effect on societal values, in line with other literature in the field they view risk from the perspective of the corporate supply chain rather than examining the risk of harm to the worker.

In our study, we conceptualise the risk of labour exploitation from the workers' perspective. We conceive severe forms of labour exploitation such as forced labour as one end of a spectrum ranging from illegal employment practices that constitute labour abuse, such as wage payments below legal minimum wage levels and health and safety violations, through to the likelihood of criminal exploitation recognized in the UK as modern slavery. Our assessment of this personal risk permits a degree of risk to be assigned to various clusters of forced labour indicators with the more indicators present, the stronger the likelihood that the working conditions may be considered exploitative. Our approach, therefore, includes, but goes beyond, assessing the likelihood of forced labour by simply quantifying the proportion of

[1]CE: No idea if this is the correct reference – it is my best guess.

survivors entering the UK's National Referral Mechanism (NRM): a government system for survivor support set up to identify whether there are positive grounds for the identification of Modern Slavery. In our method, an NRM referral is used as the strongest indicator of modern slavery risk, with lesser risks assessed according to the degree to which cumulative indicators of forced labour are reported.

3.1 Case Setting: Labour Exploitation Risk Among Transnational Migrant Domestic Workers In The UK

Domestic work forms part of a broader industrial category of Personal and Household Service work (PHS). Work in this category includes those employed in 'social work activities without accommodation' and 'activities of households as employers of domestic personnel' (**european_commission_staff_2012<empty citation>**). In 2017, an estimated 980,000 people were engaged in PHS work in the UK (**manoudi_analysis_2018<empty citation>**). **manoudi_analysis_2018<empty citation>** highlight that the PHS sector is dominated by women and migrants, with many undeclared foreign workers. Detailed statistics related to the country of origin of domestic workers migrating to work in PHS in the UK are difficult to isolate before 2019. Since that time, annual migration has fluctuated – falling sharply in 2021 due in part to the COVID-19 pandemic, before later rising again above pre-pandemic levels. In the year to December 2022, the UK Home Office reported that it had issued 18,533 Overseas Domestic Worker visas (**home_office_why_2023<empty citation>**). These domestic workers came from various countries in South America and Asia, including many from the Philippines.

In 2023, **strauss_britain_2023<empty citation>** reported a big shift in the source countries of migrants arriving in the UK on the Overseas Domestic Worker and other types of worker visas. Transnational domestic workers from the Philippines and India accounted for the single largest number of applications granted (10,186 and 3,858 visas respectively), followed by smaller, but still significant, numbers of workers arriving from Bangladesh (465), Nigeria (446), Sri Lanka (444), Egypt (422), and Ethiopia (285). In the same period, smaller numbers of visa applications to work as a domestic worker in the UK were also accepted from workers from other source countries including, but not limited to, the Sudan, Nepal, Ghana, Kenya, Lebanon, Eritrea, Iran, Turkey, Yemen, Malaysia, Thailand, and Morocco. This post-Brexit increase in the diversity of source countries from which transnational workers are drawn makes a more detailed analysis of the risk of labour exploitation in the sector both timely and more urgent.

There is a long history of reports of exploitation in the domestic work sector in the UK. In 2008, the civil society organisation Kalayaan, which was formed to campaign for the formal recognition of migrant domestic workers' rights in the UK, reported on the impact of proposed changes to the UK immigration system on migrant domestic workers (**kalayaan_new_2008<empty citation>**). Their report highlights government recognition of documented and unacceptable levels of abuse and exploitation among domestic workers in the UK as early as 1996. At this stage, new policies, including the development of a specialised visa allowing domestic workers to change employer during their stay were introduced. However, in 2012, these visa conditions were modified, tying domestic workers to a single employer and restricting the length of time that they are permitted to remain in the country to a period of six months (**gower_calls_2016<empty citation>**). Overseas domestic worker visa holders are now, again, permitted to change employers, but not to apply to renew their six-month long visa unless they receive a positive 'Conclusive Grounds' decision related to exploitation considered to be modern slavery through the UK's National Referral Mechanism (NRM) (**romero_blueprint_2025<empty citation>**).

These reports highlight the underlying reasons for migrant domestic workers' vulnerability, including workers' relative desperation for work; their lack of social ties; unfamiliarity with English language and culture; long working hours; lack of knowledge of their legal rights; a lack of oversight of the private home as a workplace; their work forming part of the informal economy; their reliance on their employer for permission to work in the UK; and their lack of recourse to public funds. As a result, migrant domestic workers are vulnerable to abuse ranging from minor breaches of employment and health and safety law, to physical and sexual violence, slavery, forced labour and trafficking.

That these conditions may persist is evidenced by a report from another civil society organisation, the Latin American Women's Rights Service, which describes the results from twelve in-depth interviews with Latin American domestic workers in the UK. This report depicts high levels of isolation, exploitation and abuse including a failure by employers to provide written contracts or payslips; breaches of verbal agreements; a requirement to perform different tasks from those indicated during recruitment; increasing working hours with little or no time off; excessive work days; a lack of paid holiday; many domestic workers not registered with a GP; sexual harassment in the workplace; verbal or physical abuse; employer surveillance; a lack of opportunity to change working conditions; isolation and fear of seeking help; and high reported levels of trafficking for labour exploitation (**latin_american_womens_rights_service_behind_2023<empty citation>**).

Against this backdrop, we used respondent driven sampling (RDS) as a sampling technique to recruit and survey domestic workers in the UK about the working conditions they were experiencing to estimate the nature and scale of abuse and exploitation based upon reports of their conditions by domestic workers themselves.

4 Research Methods

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* Survey and RDS design.

* Sample recruitment and incentives.

* Estimation methods (RDS estimators, NSUM, bootstrap).
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4.1 Respondent-Driven Sampling (RDS) And Survey Method

Comprehensive descriptions and literature reviews of the development and use of RDS to estimate the population size of a hidden population are available elsewhere (**heckathorn_comment_2011<empty citation>**; **gile_methods_2018<empty citation>**). Suffice it to say, the possibilities of the use of a one-wave snowball sampling to allow researchers to obtain a sample of personal networks was posited by **frank_estimating_1994<empty citat** Following the identification of a set of original sample members known as seeds, **heckathorn_respondent-driven_1997<empty citation>**; **heckathorn_respondent-driven_20** advocate the use of a double incentive to recompense participants not only for their involvement, but also for their recruitment of further participants in subsequent 'waves' of participation by drawing upon the social ties through which members of the hidden population are connected to each other.

The typical number of original sample seeds is between two and ten: chosen as heterogeneously as possible (**gile_methods_2018<empty citation>**). Though they may be subject to both systematic and non-systematic errors, the use of snowballing methods for the study of hidden populations, with the support of monetary or symbolic rewards, has been advocated as a way of creating robust recruitment embodying diversity in characteristics such as ethnicity, gender and geographical location (**heckathorn_respondent-driven_1997<empty citation>**; **heckathorn_respondent-driven_2002<empty citation>**). In these papers, Heckathorn advances the development of RDS to include self-reported network size as a population estimator and bootstrapping techniques to support the development of an estimator's confidence intervals, an approach that has since been refined by others (**gile_network_2015<empty citation>**). Such developments derive a new class of indicators for the population mean and define a corresponding bootstrap method to estimate the errors in RDS. The resulting 'network working model' permits the individual's connectedness in the network to be tested, while reducing bias with respect to the composition of the seeds. Snowball sampling is based upon the initial recruitment of the original sample selection by means of convenience. RDS also takes a non-random approach to seed selection, but relies upon the social network structure that exists between participants to produce a non-probabilistic sample (**goodman_comment_2011<empty citation>**). Incentive structure is important—though this weakness is not a feature of our target hidden population, some researchers have identified that younger men with higher socio-economic status are less likely to participate (**mccreesh_respondent_2013<empty citation>**). Perhaps of more concern, RDS has been described as a risky strategy since researchers cannot be sure whether enough respondents have been recruited through subsequent waves to eliminate bias within the original sample members (**vincent_estimating_2017<empty citation>**).

RDS has been widely used to sample a variety of hidden populations, including HIV prevalence, rape and client-initiated gender-based violence among sex workers (**mccreesh_evaluation_2012<empty citation>**; **schwitters_prevalence_2012<empty citation** While the RDS method has proved limited when seeking to provide population heterogeneity by geographical location (**mccreesh_evaluation_2011<empty citation>**), where these population features are of lesser importance, such methods have been used successfully. RDS methods have been used to survey other migrant populations (**tyldum_surveying_2021<empty citation>**), while such network-based referrals have been described as the only viable method to reach many types of labour trafficking victims (**zhang_measuring_2012<empty citation>**) and have been used to research exploitation among low-wage workers in three American cities (**bernhardt_broken_2009<empty citation>**); a study of labour trafficking in migrant communities in the city of San Diego (**vincent_estimating_2017<empty citation>**); examination of the worst forms of child labour in the Indian state of Bihar (**zhang_victims_2019<empty** and the commercial sexual exploitation of children in Nepal (**jordan_overcoming_2020<empty citatio**

The survey instrument included modules on demographic and employment characteristics, social network size and composition, and indicators of labour exploitation. The exploitation indicators were based on the International Labour Organization's framework of forced labour, adapted for the UK domestic work context. These indicators allowed us to operationalise exploitation in two ways. First, we constructed binary indicators classifying respondents as exploited or not exploited, based on threshold criteria. Second, we developed a continuous risk index, designed to capture gradations of vulnerability across the full sample.

In the following section, we describe our methods, including how we designed our survey, contacted our sample seeds, and analysed our data. Our approach can best be described as Web-based RDS (**wejnert_web-based_2008<empty citation>**). We designed a web survey using the JISC online survey interface, suitable for our respondents to complete via a mobile phone. Composite measures to quantify the extent to which respondents were at risk of labour exploitation, including severe forms of exploitation such as forced labour, were constructed from existing exploitation typologies, notably the ILO's Indicators (**ILO11-indicators<empty citation>**). The survey consisted of these 11 composite indicators and included questions related to domestic workers' level of job satisfaction, employment conditions, and demographic data such as nationality, age, and gender. The main survey was conducted in the five months between February and July 2023.

4.2 Initial Sample Selection

We selected our first wave of participants nonrandomly by convenience sampling. Mobile phone numbers were used both to identify seed participants and to act as a unique identifier for those whom they referred. To avoid sample homophily, original sample members were selected from three distinct domestic worker communities. This was facilitated by civil society organisations who represented distinct domestic worker communities. One was an exclusively online community of transnational domestic workers working in the UK, the second represented UK domestic workers of Filipino origin, and the third drew its membership from the Latin American community of domestic workers, also in the UK. Along with other academics with expertise in exploitation within domestic work, representatives from these three organisations also contributed to survey question design and facilitated the piloting of an initial version of the survey (which was translated and made available in four languages: English, Spanish, Tagalog, and Portuguese) to selected domestic workers within each community.

4.3 Survey Incentives: Incentive Design and Participation Verification

A double incentive scheme rewarded respondents both for completing the questionnaire and for each referral who went on to engage with the survey. The challenge of incentive design is to set the incentive at a level that adequately rewards respondents' time and participation, but that also avoids the risk of fraudulent participation due to too high a monetary gain (**jordan__overcoming__2020<empty citation>**). A sum of £10 was provided for survey completion with a further £5 for each successful nomination. While respondents were asked to nominate up to 10 domestic workers within their existing social network, it was the first three of these from whom participation was requested in subsequent waves. This approach is akin to the use of vouchers in face-to-face studies as advocated by **thompson__new__2020<empty citation>**.

The ethical and practical issues related to the design and effective use of incentives for RDS among vulnerable populations has been much discussed in the literature; see, for example, **wang__respondent-driven__2005<empty citation>**; **abdul-quader__effectiveness__2006<empty citation>**; **singer__incentives__2006<empty citatio** **dejong__ethical__2009<empty citation>**; **semaan__ethical__2009<empty citation>**; **brunovskis__untold__2010<empty citation>**; **semaan__time-space__2010<empty citation>**; **platt__adapting__2015<empty citation>**, including the specificities of incentive use within web-based surveys (**cobanoglu__effect__2003<empty citation>**). Following the principles of lottery use established by **brown__you__2006<empty citation>** and **laguilles__can__2011<empty citation>**, we also designed our survey to encourage the maximum extent of participation by entering all respondents completing the questionnaire into a free prize draw for £150. Research suggests that a high lottery provides the most cost-effective incentive for obtaining complete responses (**gajic__cost-effectiveness__2012<empty citation>**). While using incentives to encourage participation would seem to be desirable, it is worth noting the potential downside of respondents fabricating responses to increase their remuneration (**robinson__sampling__2014<empty citation>**). To minimise this risk, mobile phone numbers for each respondent and those whom they referred were collated, and each of these numbers was called by one of the authors of the paper to ascertain the veracity of the respondent as a migrant domestic worker.

4.4 Descriptive Statistics

In total, we received completed online surveys from 97 respondents. Of these respondents, 90 identified themselves as transnational migrants. Forty-five percent regarded themselves as self-employed, 39% identified themselves as employees, and 16% categorised their employment status as that of a worker.

Of the 97 respondents, 64 (66% of the total), and the largest single nationality group, reported that they had a Filipina background. Other nationalities represented included Dominican, Brazilian, Spanish, Colombian, Bolivian, Venezuelan, Cuban, and Panamanian. Female domestic workers made up 97% of the sample, with 3% of the sample comprised of

Table 1: RDS Sample Characteristics by Nationality Cluster and Recruitment Wave. Source: Authors' Own Work.

Table 2: Sample Characteristics by Nationality Cluster

Nationality	N	%	Seeds	Recruits	Mean Degree	Median Degree
Filipino	62	72.9	0	62	11.3	5
Latinx	17	20.0	0	17	6.9	5
Other	6	7.1	0	6	7.5	4

Note: Degree refers to reported network size (Q13: number of domestic workers known).

male domestic workers. The age structure of the domestic workers was skewed towards those over 45 years old, with such workers representing over half of the sample (see Table 1).

Recruitment diagnostics indicate that equilibrium was reached across key demographic variables by wave X. Reported personal network sizes ranged from X to X, with a mean of X and a standard deviation of X. Figure 1 presents the recruitment tree, showing that Latinx respondents generated longer referral chains, while British respondents tended to form shorter, more fragmented networks.

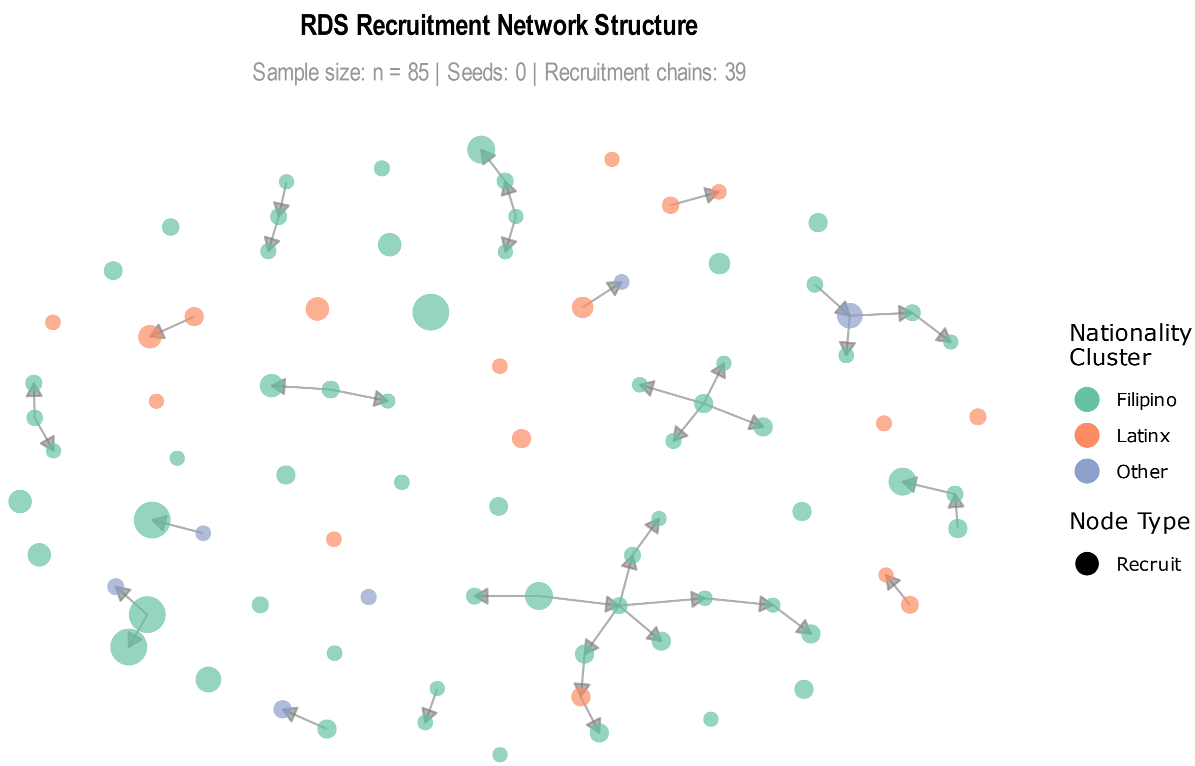

Figure 1: RDS Network Structure: Recruitment chains showing seed nodes (triangles) and recruitment waves. Node colors represent nationality clusters, with node size proportional to reported network degree (Q13). Lines show recruiter-recruit relationships. Source: Authors' Own Work.

Table 3: Distribution of Sample Across Recruitment Waves. Source: Authors' Own Work.

Table 4: Recruitment Wave Distribution

Recruitment Wave	N	%	Seeds	Recruits
Wave 1	46	54.1	0	46
Wave 2	26	30.6	0	26
Wave 3	7	8.2	0	7
Wave 4	4	4.7	0	4
Wave 5	2	2.4	0	2
Total	**85**	**100.0**	**0**	**85**

Note: Seeds are initial participants (recruiter.id = -1). Recruits are referred participants.

4.5 Indicators

creating comparable variables to bridge the Respondent-Driven Sampling (RDS) and Network Scale-Up Method (NSUM) estimations is a key methodological challenge the research team is actively working to solve. The core issue is that the two methods rely on differently framed questions: • RDS estimation uses "egocentric" questions, which focus on the respondent's personal experiences (e.g., "Have you been forced to work?"). • NSUM estimation uses questions about the respondent's knowledge of others in their network (e.g., "How many domestic workers do you know who have experienced…"). The survey questions designed for these two purposes do not always match up directly, making a fair comparison between the estimates difficult. The Strategy: Creating "Linking" Variables To overcome this, the team's strategy is to identify and group questions that cover the same underlying themes, even if they are worded differently for each method. The goal is to aggregate some of the specific "egocentric" questions to make them comparable to the broader "how many do you know" NSUM questions. Based on your sources, several sets of "linking" questions have been identified with varying degrees of confidence in their comparability: • Document Withholding (High Confidence): ◦ RDS Question: Q70 asks if the employer has withheld the respondent's travel and identity documents. ◦ NSUM Question: Q71 asks how many other domestic workers the respondent knows who do not have access to their own documents. • Debt and Pay Issues (High Confidence): ◦ RDS Questions: This involves combining Q39 (having to pay off debt to someone who helped find work) and Q42 (has your pay ever been withheld?). ◦ NSUM Question: Q43 asks how many others the respondent knows who have experienced problems with debt or pay. • Abuse and Threats (Medium Confidence): ◦ RDS Questions: This requires grouping Q45 (forced, deceived, or threatened into poor working conditions), Q47 (employer intimidation or threats), and Q48 (verbal abuse). ◦ NSUM Question: Q49 asks how many others the respondent knows who have experienced the use of threat or force. • Excessive Hours (Lower Confidence): ◦ RDS Questions: Q61 (weekly rest does not last 24 hours) and Q62 (working excessive overtime) are combined. ◦ NSUM Question: Q64 asks about knowing others who work excessive overtime, lack breaks, or lack annual leave. The comparison here is considered "flakier" because the RDS questions do not ask about annual leave, creating a partial mismatch. • Access to Help (Lower Confidence): ◦ RDS Question: Q78 asks if the respondent knows who might help them (coded for "No" answers). ◦ NSUM Question: Q79 asks how many other domestic workers the respondent knows who do NOT know where to go for help. By creating these comparable variables, even if just for one or two highly confident themes like debt bondage or document withholding, the team hopes to perform a fair comparison between the estimates derived from the two different methodologies. This process is considered a crucial step to integrate the RDS and NSUM approaches and to produce more robust findings.

4.6 Ethical Approval

The data collection that underpins the analysis presented in this paper was given favourable ethical approval by the lead author's School Research Ethics Committee in January 2023. All participants were informed about the aims of the study, provided informed consent, and were assured that participation was voluntary and confidential.

4.7 Use of Artificial Intelligence in Research

Large Language Models (LLMs) were used for brainstorming the organisation of the paper and editing of text. Code co-pilot (Claude Code) was used to test and debug R scripts employed in the statistical analysis. No generative models were used to generate or simulate data.

5 Estimation Methods

We analysed the survey sample using multiple estimation models in order to assess robustness and conduct sensitivity analyses (see Appendix XX). The survey instrument contained both ego questions (which capture information about respondents and their personal network ties) and alter questions (which capture information about the people respondents know). These two types of network data enable two fundamentally different estimation strategies: respondent-driven sampling (RDS) estimators and network scale-up methods (NSUM). In addition, we developed and implemented a novel three-step bootstrap procedure to address uncertainty in NSUM estimates, which we describe in more detail below.

5.1 RDS-Based Estimation

RDS estimators use ego-based information. Each participant reported the number of other domestic workers they knew, and this degree information was used to adjust for the over-representation of highly connected individuals in the sample. We implemented RDS-II and Gile's successive sampling (SS) estimator, the latter of which accounts for finite population effects and improves performance when the sample fraction is relatively large (Gile, 2011; Gile and Handcock, 2010). These estimators were used to generate prevalence estimates for binary indicators of exploitation.

For continuous traits, such as the exploitation risk index, we applied model-assisted inference approaches (**gile15-network<empty citation>**, Gile, 2011; Gile, Beaudry, and Handcock, 2018). These approaches combine design-based adjustments with regression models that incorporate auxiliary covariates, producing valid estimates of sample means and distributions of continuous outcomes under the RDS design.

5.2 Estimation Strategy

Given that our data were collected using a respondent-driven sampling (RDS) design, the choice of estimator is critical. We considered several well-established RDS estimators, each with distinct assumptions and applicability.

First, the **RDS-I estimator salg04-samplin<empty citation>** provides an early design-based approach. However, it performs poorly in small samples, is highly sensitive to seed dependence, and requires strong assumptions about equilibrium. Since our sample comprises fewer than 100 respondents recruited from multiple seeds, we regard RDS-I primarily as a historical benchmark rather than a viable option for inference.

Second, the **Volz–Heckathorn (VH) estimator volz08-probabi<empty citation>** offers a probability-based refinement of RDS-I. It is more robust but assumes a large population relative to the sample size and does not adjust for finite-population effects. Although our diagnostic checks indicated approximate equilibrium across key demographics, the VH estimator is best used here as a robustness check rather than the primary estimator.

Third, the **Successive Sampling (RDS-SS) estimator** (also called RDS-II) **gile11-improve<empty citation>** accounts for finite population effects, adjusting for the non-negligible sampling fraction that arises when the target population is not extremely large relative to the sample. This property makes RDS-SS particularly appropriate for our study of migrant domestic workers, and we therefore use it as our primary estimator for binary outcomes (e.g., presence or absence of exploitation).

Fourth, to estimate **continuous outcomes** such as our exploitation risk index, we employ the **Model-Assisted (MA-RDS) estimator gile15-network<empty citation>**. This approach integrates regression modelling with RDS weights, thereby extending inference beyond binary outcomes and improving efficiency by leveraging auxiliary covariates.

Finally, although recent work on **Clustered Successive Sampling Population Size Estimation (Clustered SS-PSE) gamb23-clustered<empty citation>** extends RDS-based methods to estimating the size of clustered hidden populations, our study does not attempt to estimate the absolute number of domestic workers. Instead, we focus on the prevalence and severity of exploitation. As such, Clustered SS-PSE is not central to our analysis, though it remains a promising avenue for future research.

In summary, we rely primarily on **RDS-SS** for binary outcomes and MA-RDS for continuous outcomes, with **VH** used for robustness checks. This combined strategy balances methodological rigor with the substantive goals of our study.

We use model-assisted RDS estimators (**gile15-network<empty citation>**) because they are design-based yet leverage a working ERGM (with degree and homophily terms) to approximate inclusion probabilities conditional on our observed seeds. This approach directly addresses seed bias and homophily that conventional RDS estimators cannot correct, accommodates finite-population effects through successive-sampling logic, and supports valid estimation of both binary and continuous outcomes. By conditioning on the actual seed composition and subgroup structure in our data, the method reduces bias, improves efficiency, and provides design-compatible bootstrap uncertainty, making it particularly well-suited to our small, heterogeneous sample of domestic workers."

5.3 Network Scale-Up Methods (NSUM)

NSUM relies on alter-based information. Rather than depending on respondents' own position in the referral network and their reported degree, NSUM uses information about alters—other people in respondents' networks. Participants reported on the number and characteristics of people they knew who met specific exploitation criteria. These reports were aggregated to estimate prevalence in the wider population of domestic workers.

The key methodological distinction between RDS and NSUM lies in how the social network is used. RDS leverages ego-level network size and recruitment paths to adjust for biases in the referral process. NSUM treats respondents as informants about a larger social universe, using alter data to infer prevalence. RDS depends on accurate self-reporting of degree and on the properties of recruitment chains, while NSUM depends on the accuracy of respondents' knowledge about others and the representativeness of their social networks

5.4 Bootstrap Procedure for NSUM

To appropriately characterise uncertainty in NSUM estimates, we developed a novel three-step bootstrap procedure. This approach resamples respondents, their reported alters, and the exploitation classifications simultaneously, thereby capturing uncertainty at each stage of the inference process. This procedure provides more realistic confidence intervals than those generated by conventional variance estimators, particularly for small samples such as ours. Details of the bootstrap implementation and diagnostic checks are provided in Appendix **app-3step<empty citation>**.

5.5 Comparative Rationale

Respondent-driven sampling (RDS) and network scale-up methods (NSUM) both rely on social network structures, but they exploit different aspects of those structures for inference.

RDS uses ego-based information. Each participant reports the size of their personal network of eligible individuals, and these degree reports are combined with the wave at which respondents were recruited to adjust for unequal inclusion probabilities. The underlying logic is that individuals with larger networks are more likely to be recruited earlier and more often, creating a bias toward highly connected respondents. RDS estimators, including Gile's successive sampling estimator, explicitly correct for this bias by weighting observations according to network degree and recruitment path. For continuous traits, such as our risk index, RDS model-assisted estimators incorporate auxiliary covariates into this weighting process to further reduce bias.

In contrast, NSUM uses alter-based information. Rather than focusing on the ego's probability of inclusion, NSUM treats respondents as informants about the wider hidden population. Respondents are asked how many people they know with a given trait (for example, "How many domestic workers do you know who have experienced exploitation?"). These responses are then scaled up, using assumptions about network size and visibility, to infer prevalence in the broader population. This method does not depend on recruitment chains but instead on the accuracy of respondents' knowledge about others in their social networks.

The practical difference is therefore twofold. RDS estimates are anchored in "who recruited whom" and "how many do you know," while NSUM estimates are anchored in "how many of your alters fit this category." RDS leverages inclusion probabilities tied to ego network size; NSUM leverages alter reports to extend beyond the sample. Applying both methods to the same dataset allows for triangulation across two fundamentally different inferential logics.

Applying both RDS and NSUM to the same survey allows triangulation across two fundamentally different inferential paradigms. For continuous outcomes, such as the exploitation risk index, only model-assisted RDS estimators are appropriate. For binary outcomes, both RDS and NSUM can be applied, enabling direct comparison of results. This dual approach strengthens the empirical credibility of our findings, highlights the conceptual value of considering exploitation both as a binary threshold and as a continuum, and demonstrates the methodological trade-offs involved in studying hidden populations.

6 Results

6.1 Model-Assisted Estimates of the Risk Index (Continuous Conceptualisation)

One of the central contributions of this study is the introduction of a continuous risk index to measure degrees of exposure to labour exploitation. The index was constructed from multiple indicators aligned with the International Labour Organization's forced labour framework, weighted inductively and refined through expert consultation. Rather than treating exploitation as a dichotomy, the risk index conceptualises all domestic workers as facing some degree of potential exploitation, albeit with significant variation in intensity.

Because continuous traits cannot be estimated directly with conventional RDS estimators or NSUM, we employed model-assisted inference methods. These methods adjust for the non-random structure of RDS recruitment while permitting reliable estimation of means and distributions of continuous outcomes (Gile, 2011; Gile and Handcock, 2010; Gile, Beaudry, and Handcock, 2018).

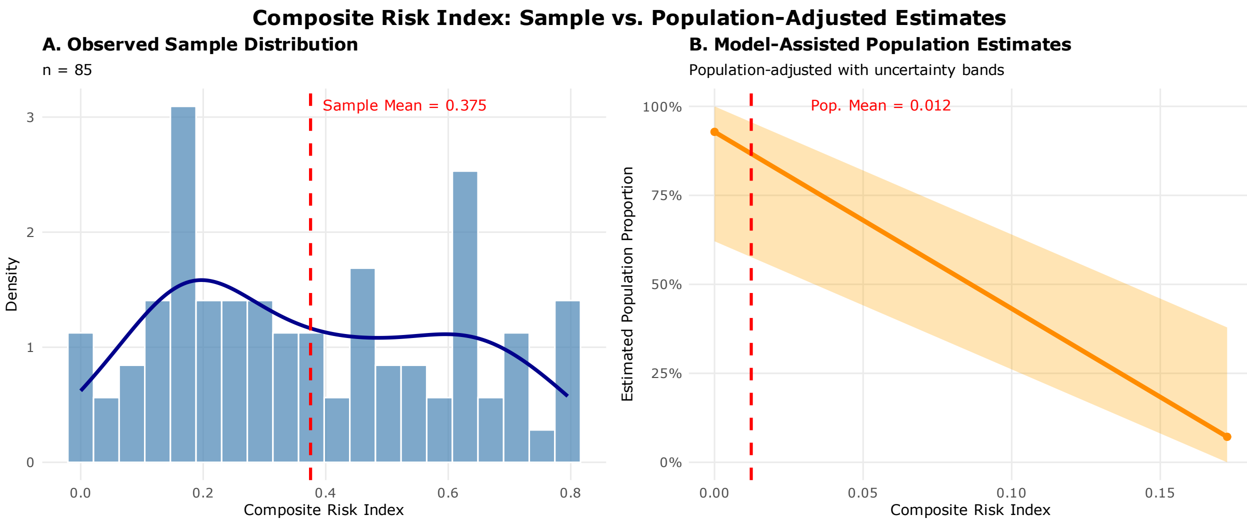

Figure 2: Model-Assisted Estimates of Composite Risk Index: Distribution comparison between observed sample data and population-adjusted estimates. The left panel shows the empirical distribution of risk scores in the RDS sample, while the right panel presents the model-assisted population proportion estimates for specific risk categories with uncertainty bounds (the light band shows confidence intervals around the proportion estimates). Source: Authors' Own Work.

The MA estimate suggests that approximately 92.8% of the population has zero exploitation risk, while 7.2% has moderate risk (0.1725)

The population-weighted average risk is 0.0124 This represents the Model-Assisted estimate of mean exploitation risk in the population, adjusted for RDS sampling bias. It is a design-based estimate that corrects for the non-random recruitment process in RDS. The population-adjusted distribution shows less concentration in the lower risk categories compared to the raw sample, suggesting that the RDS process may have under-recruited higher-risk individuals. Figure **??** presents the comparison between the observed sample distribution and the model-assisted population estimates, demonstrating how the bias correction affects our understanding of exploitation risk in the broader domestic worker population. This pattern reinforces the conceptual claim that exploitation is best understood as a continuum rather than a simple binary condition.

Table 5: Model-Assisted Estimates of Binary Exploitation Indicators: Population prevalence estimates adjusted for RDS sampling bias. Values represent the estimated proportion of domestic workers experiencing each form of exploitation. Source: Authors' Own Work.

Table 6: Model-Assisted Estimates of Binary Exploitation Indicators

Exploitation Indicator	Population Prevalence (95% CI)
Any Exploitation	95.0% (62.2-100.0%)
Excessive Hours	83.7% (71.9-95.6%)
Limited Access to Help	58.3% (46.1-70.6%)
Threats/Abuse	57.3% (35.4-79.3%)
Pay-Related Issues	49.5% (35.6-63.5%)
Document Withholding	34.3% (16.4-52.2%)

Note: Estimates adjusted for RDS sampling bias using model-assisted inference. Confidence intervals reflect design-based uncertainty.

6.2 Binary Exploitation Indicators (Exploited or Not Exploited)

To complement the continuous measure, we also operationalised exploitation as a binary outcome. Respondents were classified as exploited if they met threshold indicators consistent with ILO definitions. This allows estimation using both respondent-driven sampling estimators, which rely on ego-based network data, and network scale-up methods, which rely on alter-based information.

6.2.1 Model-Assisted (MA) Estimates

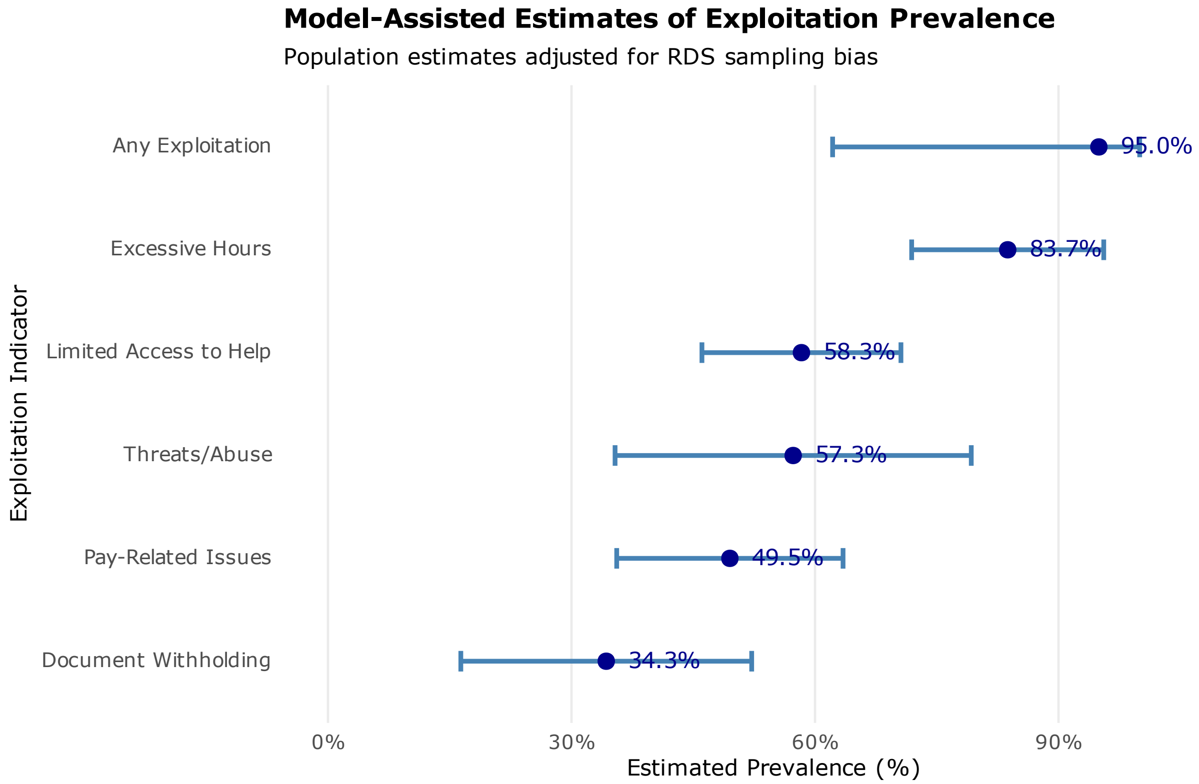

Figure 3: Forest Plot of Model-Assisted Binary Exploitation Estimates: Population prevalence estimates with 95% confidence intervals for each exploitation indicator, ordered by prevalence magnitude. Error bars represent design-based uncertainty in the estimates. Source: Authors' Own Work.

Here are the Clustered SS-PSE prevalence estimates by nationality subgroup:

Subgroup | Document withholding | Pay-related issues |

Threats/abuse	Excessive hours	Limited access to help	
—-	———————	——————————	
Overall sample	0.1% (0–0.7)	0.2% (0–1.4)	0.2%
(0–1.7)	0.3% (0–2.4)	0.1% (0–1.4)	
Filipino	0.4% (0–3.2)	0.9% (0.1–5.1)	1.0%
(0.1–8.4)	1.3% (0.1–9.5)	0.7% (0.1–7.9)	
Latinx	0.1% (0–0.8)	0.2% (0–2.2)	0.2%
(0–2.0)	0.3% (0–3.8)	0.1% (0–1.2)	
Other Combined	0.0% (0–0.3)	0.1% (0–1.0)	0.1%
(0–1.4)	0.1% (0–1.2)	0.1% (0–1.5)	

Key Findings

Table 8: RDS Estimates of Binary Exploitation Indicators: Population prevalence estimates using RDS-II and Successive Sampling (SS) estimators with bootstrap confidence intervals. Source: Authors' Own Work.

```
NULL
```

1. Filipino workers show consistently higher prevalence across all exploitation indicators
2. Excessive hours shows the highest prevalence in all subgroups
3. Wide confidence intervals reflect the uncertainty inherent in hidden population estimation
4. Cluster proportions from MCMC: Filipino (37.4%), Latinx (31.7%), Other (30.9%)

The analysis successfully accounts for nationality-based clustering in the network structure and provides valid subgroup-specific prevalence estimates using the Clustered SS-PSE methodology.

6.2.2 RDS Estimates

6.2.3 Sub-group Analysis

Standard SS-PSE assumes that the underlying social network of the hidden population is fully connected. This means:

- Any member of the population can be reached by any other member through a path in the network
- The network forms a single, connected component
- RDS recruitment can theoretically reach any individual in the population from any starting seed

Why This Assumption Matters

The connectedness assumption is fundamental to SS-PSE's theoretical foundation because:

1. Successive Sampling Logic: SS-PSE models RDS as a "without-replacement random walk through the network"
2. Depletion Detection: The method assumes that individuals with larger network sizes are recruited earlier, and their depletion over sampling waves provides information about population size
3. Inclusion Probability Modeling: The probability model relies on the ability to potentially sample any individual from any starting point

The netclust Solution: Clustered SS-PSE

The **gamb23-estimating<empty citation>** approach addresses clustering through e.g. Clustered SS-PSE Method (implemented in `netclust` **netclust21-ljgamble<empty citation>**):