NSUM

NSUM has been used to estimate the sizes of hidden populations in criminology and public health and has been proved both reliable and easy to implement in studies of religious ideology (Yang and Yang, 2017)

NSUM estimators offer some specific advantages over self-reported responses. Self-reporting within surveys related to sensitive subjects, such as religious views, may suffer from biases including social desirability, personal safety concerns and definitional ambiguity (Yang and Yang, 2017).

GNSUM

GNSUM has the potential to be a very powerful method but is not without its difficulties and limitations. At present, there is limited data on how it performs, particularly when the population of interest is hard to reach. Feehan and Salganik (2016) identify 5 different GNSUM estimates. Limited information is given as to how to select between them.

Given the data we collected, it was not possible to calculate a frame ratio or, due to the lack of enriched aggregated data, the true positive rate.

To estimate the visibility (Feehan and Slaganik (2016 C.1)

The main assumption needed is that everyone in H has a non-zero probability of being observed (= being in the sample). **IF** we are willing to assume/ justify this and *IF* we had a "How many DWs do you know?" and *IF* we had a "How many DWs know you are in H", **then** I *think* we can use what I understand to be Caroline's idea (very clever I just say) to 'build out' a person in H's report of people in F that know they are in H. Then again, this is a bit bizarre because F is the only probe alter group. In any event, I don't think we the necessary questions – but I hope I'm wrong.

True positive rate: is the probability of a positive test result conditioned on the individual truly being positive. This is part of sensitivity analysis. This could be based on the assumption that people who have been in the NRM – and are therefore members of the hidden population -are visible to those who refer them and implicitly may also know the situation of the referees.

Estimates based on social ties

Most social science surveys use a sampling frame which misses certain members, known as hard to reach groups (McCormick et al., 2012). Strategies that have proved successful in reaching the members of these hard-to-reach populations utilise these respondents' social networks. Questions are asked about respondents' connectedness to different groups of known size. This aggregated relational data is then analysed to learn about the size and distribution of survey respondents' weak-tie personal networks (Feehan et al., 2022).

Probe Alter Groups (PAG)

While these authors explain how to estimate the size of these groups from a survey sample, in our study we asked domestic workers how many other domestic workers they knew who had entered the National Referral Mechanism (NRM) (Qu 83 5f15). This probe alter was envisaged to be an appropriate way of generating aggregated relational data since external data on NRM referrals since its inception is made publicly available.

In addition, we investigated the possibility of using a second probe alter – domestic workers working in the UK. While we initially considered estimating this figure based upon people entering on a particular visa know people on that visa. There are networks within each nationality group. NGOs are ethnically linked. There is a complication related to the known number of migrant domestic workers in the UK since migrants may arrive on different visas – so the overall figure is likely to be larger than the total number of Overseas Domestic Worker Visas issued. Instead, we used the EUs estimate of those domestic workers who are part of the Personal and Household Service sector (PHS) made up of 'social work within accommodation' (NACE 88) and 'activities of households as employers of domestic personnel' (NACE 97/ SIC 97). In its 2018 thematic review, the EU estimated the number of NACE 88 workers in the UK at 929,000 and NACE 97 workers at 51,000 (Q3, 2017) (Manoudi et al., 2018, p. 13).

RDS

*See RDS draft paper

We have collected a convenience sample of those workers with a mobile phone engaged in domestic work in the UK in the past 12 months. For a general explanation of RDS sampling see Gile et al. (2018). We have a proper RDS from the frame, F; some of those in sample are in MS (z_i=1 in the language of Gile et al 2018) and some are not and we can use the VH or SH estimators for the _*proportion*_ experiencing MS (pages 71-73 in Gile et all 2018). Properly.

Given that the sampling was not independent, we employed a bootstrap sampling method (Baraff et al., 2016; Yauck et al., 2022; Yauck and Moodie, 2022)

Within our study

U refers to the set of the total number of people in domestic work within the UK. We started by considering this in terms of official ODW visa statistics, but later modified this to... The rationale for this was that the ODW visa estimate is likely to be an underestimation of the population size, given that there are also likely to be some British Nationals in domestic work and also a grey market of indeterminant size.

Our population set U and frame population from which the sample is taken (F) are clear (see (Feehan and Salganik, 2016) for us this is the total number of domestic workers in the UK with access to mobile phones.

The hidden population, H, is the set of those working in domestic work being exploited.

It is possible to calculate two of the three adjustment factors (degree ratio and true positive ratio) suggested by Feehan and Salganik (2016) from our data and then to use these, along with the proposed basic scale up calculation, to estimate the number in the hidden population (as shown in eqn 24). We were not able to estimate the frame ratio - as by definition we could not collect any data on U.

The social networks identified within our study suggest that domestic workers' social ties are unusually sparse, even for a population. We have a large number of initial seeds, and relatively few waves of referrals. 1st wave: 54; 2nd wave: 29; 3rd wave: 7; 4th wave: 4; 5th wave: 3.

We can combine the RDS nature of the sample with an NSUM estimator. I _*think*_. (e.g. actually calculating eqn 23 in F&S 16, but using their appendix B (esp. eqn. B.4, and results B3 and B.4, but estimating the size of F, $\hat{N_F}$ using ad hoc methods from the VH estimator (e.g. the denominator of eqn 3 in Gile et al 2018).[But it may be inefficient}

Assessing risk

The ILO suggest that while the presence of a single indicator in a given situation may in some cases imply the existence of forced labour - a particular and severe type of labour exploitation - while in other cases you may need to look for several indicators (I.L.O., 2011). This enabled us to construct a new variable that indicated the confidence we as researchers have that this particular person is at risk of modern slavery. We have used different questions to identify people in the hidden population, H. These can be compared. We explored combining them in some form of likert scale to estimate the risk of experiencing modern slavery in addition to the dichotomous – y/n variable related to their engagement with the NRM. We posit the use of this risk index variable, calculated from self-reported data, as the DV [dependent variable?] in a regression model.

Rather than focusing on the hidden population, we collected RDS data on the frame population. For this reason, we trimmed our data to include only those respondents who identified that their circumstances could be considered abusive - taking the widest possible spectrum of abuse (i.e. including behaviours such as verbal abuse and all other indicators of exploitation). Since 82% of our sample reported verbal abuse, this approach meant that we could keep a high proportion of our respondents in our analysis

For example, and answer of (0) or (1) on 80. 5f12: Have you or someone you know personally been advised to enter the NRM?

(0) I have been advised to enter the NRM and was referred

(1) I was advised, but decided not to enter the NRM

or 72. 5f4: Do you feel your working environment is safe and healthy?

70. 5f2: Has your employer, or their agent, withheld from you your travel and iden�ty documenta�on?

or 61. 5d8: Does your weekly rest last longer than 24 hours consecu�vely?
or an answer of 0-4 on 55. 5d4-b: Please mark, if you have NOT received any of the following (you can select more than one op�on)

or especially 50. 5d1 to 5d2-a (inclusive)

or espeically 45. 5c2, 46. 5c3, 47. 5c4, 42. 5b7: Has your pay ever been withheld by your employer?

32. 5a4: In your most recent job, have you ever felt that you could not leave your work premises?

30. 5a2: Do you have control over the �mes of the day that you work?

(espeically) 29. 5a1: Have you ever been forced to do any work by your employer or household against your will?

Maybe the following, but likely not. Just some suggestions.

36. 5b1: How much are you paid an hour, before tax and other deduc�ons?

44. 5c1 -44.5c1-b

57. 5d4-c: Please mark if you have NOT received the following informa�on as part of your contract (you can select more than one op�on):

or 63. 5d10: Do you feel you suffer from a lack of privacy in your work? (maybe?)

Possible questions that indicated modern slavery risk were identified and included Q36, Q21/25, Q35, Q83.

At a conceptual level, we treated MS not as dichotomous but that everyone in F has some 'amount' of experiencing MS (even if that number is zero). I.e. everyone has a 'risk index' (call it RI?)

Then, with this conceptualization, we again have a proper RDS sample. I guess the quantity of interest in this case is the distribution of RI in sample, and an estimate of the population distribution of MS. I don't know just yet how to do the later.

Each unique ID within the trimmed sample was coded with a composite risk index between 0-1.

Our analysis

Response data was coded to indicate the wave number of the respondent and by whom they were referred.

We adopted a bootstrap sampling method (Baraff et al., 2016). Initially, following (Yauck and Moodie, 2022), we intended to produce an adjacency matrix, or directed graph, showing the people referring and those who they referred was produced. In fact, we reproduced the procedure detailed in (Yauck et al., 2022).

Data cleaning

Each respondent was given a unique identifier.

A variable was constructed indicating who had referred who

A ‘suspicious’ variable was created for use in robustness testing. This was a binary variable, given the value 1if we had reason to think that the response is suspicious or unreliable. For example, if the responses contained logical inconsistencies e.g. Q86 greater than Q85. Responses were corrected to maximise the data.

Where mobile number were given rather than a count in response to ‘how many people do you know’ questions this was corrected.

Aggregated data can be used to calculate Equation 23 from (Feehan and Salganik, 2016).

We have the average degree from the hidden group to the frame so the data exists to calculate the degree ratio - to 95 CI - can cite those who say this is of interest - what is needed now is a justification for the practical usefulness of this adjustment factor

These can be run through with robust sensitivity checks (See Feehan and Salganik (2016) D.3.2 p. A56, and D.3.1 p. A51, D.3, Table D.2)

Two sub-populations of known size were identified as probe alters: (1) the number of DW in the UK and (2) the number of people going through the NRM (Q 83 5f15)

83. 5f15: Do you know personally of any other domestic workers who went through the NRM system? If so, how many? Numerical value

To support robustness testing, a ‘suspicious variable’ coded 0/1 was created for each response if the response contained logical inconsistencies e.g Q85 and Q86 (Q86 must be no larger than Q85. To mazimise the dataset, where necessary data was modified to ensure logical consistency. Other data cleaning tasks included showing only a number where a mobile phone number had been entered against a ‘how many’ question

Given that social networks tend to exhibit homophily, we also discussed sub-dividing our data into different nationality groupings but we had reservations about the potential for unconcious cultural stereotyping.

Assumptions

Everyone a person $i \in H$ knows that have gone through the NRM, _*also*_ knows that i is in H, In other words, an exploited worker who knows someone in NRM, likely has a reciprocal relationship (?) – the person in NRM likely knows the exploited worker is in H

Limitations

There is no separate sample from the revealed hidden population, so we do not have enriched aggregated relational data. With suitable ethical procedures, this could be addressed in subsequent studies. But, at present this means we are unable to calculate the Frame ratio, [or][is this] (Feehan and Salganik, 2016) equation 7 – or the improved GNSUM equation 23.

Our study identifies only one probe alter – the number of domestic workers known to the respondent who have entered the NRM. Between 5-20 probe alters might be expected in a larger study.

Respondents were asked to identify only contacts from whom they held mobile phone contact details. This was done to reduce the possibility of recall error (Feehan and Salganik, 2016) but it may have had an effect of skewing the data.

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