Estimating Abortion Incidence using the Network Scale-Up Method

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Abstract

A major challenge in the field of abortion research is accurately measuring the incidence of induced abortion in clandestine or restrictive settings. This study tests the application of the Network Scale-Up Method (NSUM), an indirect social-network based measure, to estimate abortion incidence. The NSUM estimates the proportion of respondent's social networks that are members of a hidden population, such as women who have had abortions. Respondents social networks are estimated through a series of questions on how many people a respondent knows who are members of a population of a known size. While the NSUM has been used to estimate other stigmatized behaviors, this is the first study to rigorously test its application in estimating nationally-representative abortion incidence rates. Data for this analysis comes from the 2018 Performance, Monitoring and Accountability (PMA) community-based surveys in Ethiopia and Uganda. We compare the NSUM abortion incidence estimates with women's direct reports and previous abortion incidence estimates in both countries. We conduct a series of robustness checks on the estimated social network size to assess the accuracy of our NSUM abortion estimate. We also conduct a validation check using the NSUM to estimate IUD and implant use, for which reliable estimates already exist.

Introduction

A major challenge in the field of abortion research is accurately measuring the incidence of induced abortion in clandestine or restrictive settings. Standard methods such as using administrative health records or surveying women directly tend to result in an underestimation of abortion incidence (Rossier 2003; Jones and Kost 2007). Over the past several years, the most rigorous and widely used method to estimate abortion incidence is the Abortion Incidence Complications Methods (AICM). The AICM uses estimates of facility post-abortion care caseloads in combination with a multiplier to account for the proportion of abortions that will not necessitate medical attention to create an induced abortion incidence estimate (Singh, Remez, and Tartaglione 2010). This method has been successfully implemented in over 25 countries, including 11 in sub-Saharan Africa (Henshaw et al. 1998; Bankole et al. 2015; Singh et al. 2005; Prada et al. 2016; Levandowski et al. 2013; Polis et al. 2017; Moore et al. 2016; Singh et al. 2010; Sedgh et al. 2011; Basinga et al. 2012; Sedgh et al. 2015; Keogh et al. 2015; Chae et al. 2017; Mohamed et al. 2015; Sully et al. 2018). However, the recent rise in the use of medication abortion, which can be accessed from pharmacies or the black market, and often does not require any interactions with the medical system, has increasingly made traditional AICMs less desirable methods to estimate abortion incidence. In response to these limitations, new methods are being developed and tested through community-based surveys, including list experiments, the confidante method, and modified approaches to the AICM. While promising, these methods lack a clear process for assessing the accuracy and robustness of the estimates they produce.

Another promising alternative, indirect method for estimating abortion incidence is the Network Scale-Up Method (NSUM). The NSUM was initially developed to estimate the number of deaths during the Mexico City earthquake of 1985 (Bernard et al. 1989, 1991). Since then, this method has since been used to improve the measurement of stigmatized behaviors among hidden populations such as female sex workers, men who have sex with men, and injecting drug users (RBC/IHDPC 2012; Salganik, Fazito, et al. 2011; Wang et al. 2015; Ezoe et al. 2012). One previous study has used the NSUM to measure abortion incidence in Iran (Rastegari et al. 2014). However, that study did not include a nationally representative sample, and it did not employ a number of internal validation checks that indicate how well the estimator is performing. The existence of these validation checks is an assuring and rigorous feature of the NSUM, providing an advantage over other newly proposed indirect methods for measuring abortion incidence.

This paper describes the application of the NSUM to measure abortion incidence in Uganda and Ethiopia. An NSUM module was added to the 2018 rounds of the Performance, Monitoring and Accountability (PMA) female questionnaires in both countries. This paper uses the NSUM to estimate abortion incidence in Ethiopia and Uganda, comparing NSUM estimates to other sources of abortion data for both countries, and assesses the application of the NSUM in both settings using validation checks. Overall, this paper will assess the use of the NSUM for measuring abortion incidence through community-based surveys.

Methods

Data Sources and Sample

Data for this analysis come from Round Six of the PMA surveys in Uganda (April-May 2018) and Ethiopia (June-July 2018) (PMA2020 2018). These surveys include a nationally-representative sample enumeration areas (EAs) in each country. EAs are sampled using a two-stage cluster design for rural/urban residential areas and geographic sub-regions. Female respondents residing in the selected EAs are then randomly selected to participate in the survey. In 2018, there were 7,546 women interviewed in Ethiopia and 4,288 in Uganda, half of which (Uganda: N = 2159; Ethiopia: N = 3815) were randomized to answer the NSUM module. In addition, we used 2016 DHS data from Uganda and Ethiopia to identify appropriate characteristics for the “known population” questions. Known population sizes were calculated using the 2016 DHS and the World Population Prospects 2017 Revision’s median variant projection for the population of women age 15-49 in 2018.

Network Scale-Up Method (NSUM)

The foundational assumption of the NSUM is that the underlying social networks of individuals are, on average, representative of the general population. Given this, the proportion of a hidden population among the social networks of a representative sample will approximate the true proportion of that hidden population among the general population. Therefore, in order to estimate the size of a hidden population, one must first determine the size of individuals’ social networks. This can be difficult to do, as most people find it challenging to accurately report the number of people in their social network.

In survey-based NSUM studies, there are typically two methods used to estimate personal network sizes; in this study, we use the “known population” approach (Killworth et al. 1998; McCarty et al. 2001). To estimate personal network sizes using the “known population” approach, each respondent is asked to report the number of people she knows who have a certain characteristic. In selecting characteristics, two criteria must be met: the number of individuals in a population that have the characteristic must be known, and the characteristic must be rare enough that an individual could reasonably count all of the people in her social network with that characteristic. For example, respondents in Ethiopia were asked “how many women do you know who live in a household that owns a camel?” If a respondent reports that she knows 1 women who fits this description, and we know from the most recent Ethiopian Demographic and Health Survey that approximately 529,000 women live in a household that owns a camel, we estimate that the respondent knows 1 out of 529,000 Ethiopians. We can then estimate that the size of her social network is 51 by multiplying 1/529,000 by the total number of women age 15-49 living in Ethiopia (26,737,000). The more “known population” questions asked of each respondent, the more accurate the network size estimate becomes. The formula for calculating personal network sizes using the maximum likelihood method is as follows:

$$\widehat{c_i} = \frac{\sum_j m_{ij}}{\sum_j e_j} * t$$

Here, $\widehat{c_i}$ is the estimated personal network size of respondent *i*, m_{ij} is the number of people with a particular characteristic *j* that respondent *i* knows, e_j is the size of the sub-population with characteristic j, π_i is the inverse probability of selection for respondent I, and *t* is the size of the general population (McCarty et al. 2001; Bernard and McCarty 2009).

In order to prevent outlier responses from unduly biasing social network size estimates, all known population responses will be top-coded at 30, as has been done in previous NSUM studies (RBC/IHDPC 2012; Zheng, Salganik, and Gelman 2006; McCormick, Salganik, and Zheng 2010; Salganik, Mello, et al. 2011).

Once an estimate of someone’s personal network size is reached, the next step in the method is to estimate the size of the key population of interest, which, in this study, is women who have had an induced abortion. Each respondent is asked how many women they know who have ever done anything to successfully induce an abortion. We can use this information, in combination with the personal network size estimates, to estimate the number of women who have had an abortion in each country using the following formula:

$$\widehat{e} = \frac{\sum_i m_{ij} * \pi_i}{\sum_i \hat{c}_i \ * \ \pi_i} * t$$

In this case, $\widehat{e}$ is the estimated number of women who had an induced abortion in each country, m_{ij} is the number of women that respondent *i* knows with characteristic *j* (induced abortion), $\widehat{c_i}$ is the size estimated personal network size of each respondent *i*, and *t* is the size of the general population (McCarty et al. 2001; Bernard and McCarty 2009). In this study the sample and population of interest is only women of reproductive age; as such *t* is defined as the number of women aged 15-49 in each country.

Adjusting for Transmission Bias

One assumption of the NSUM is that all respondents have perfect knowledge about all people in their social network. (i.e. if someone in your social network has cancer, then you know they have cancer). Violations of this assumption are called “transmission effects”. However, abortions are not likely to be known by everyone in someone’s social network. When knowledge about the hidden population is incomplete in a social network, it necessary to estimate the “visibility”, or τ, which can be used to adjust the NSUM estimate for transmission bias. For example, if women who have abortions only told 20% of their social network, then we would consider the visibility of abortion to be 0.2. We then adjust the NSUM estimator by 1/0.2 to account for the transmission rate. Without this adjustment, the NSUM estimator would under-estimate the number of women who had abortions by a factor of 5. The updated NSUM estimator adjusting for transmission bias is as follows (Salganik, Mello, et al. 2011):

$$\widehat{e} = \frac{\sum_i m_{ij}}{\sum_i \hat{c}_i} * t * \frac{1}{\tau}$$

One drawback of the NSUM is the difficulty in determining the value of τ. Several previous studies testing different methods to estimate transmission bias proven unsuccessful for a variety of reasons (Shelly 1995, Shelly 2006, Killworth 2006, Paniotto 2009). The most rigorous and valid estimates of the social visibility of hidden groups are derived from the Game of Contacts, developed by Salganik et al. (2011). This method involves recruiting a separate sample of members of the hidden population of interest and collecting visibility through a game-like activity. While results from this method have been promising, the main downside is the additional resources required to nest this smaller study within a larger community based survey. The Game of Contacts has also only been tested for estimating socially connected hidden populations such as intravenous drug users or men who have sex with men; its applicability to measuring transmission bias for abortion is unknown. The current study tests a novel method for estimating transmission bias that does not require separate data collection. Instead, we ask women who directly report their abortions in the PMA surveys how many people in their social network they have told about their abortion(s). We then use the inverse of this proportion as our estimate of τ.

Measures

Previous NSUM studies have typically used two different methods for defining what it means to "know" someone, which has implications for how someone's social network is identified (RBC/IHDPC 2012). The more conservative definition aims to only include stronger network ties when considering someone's social network. When using this definition, a respondent is asked to think of individuals who they know by sight and name, who also know the respondent by sight and name, who live in a specified geographic area, and who the respondent shared a meal or drink with in the past 12 months. The original intent of this study was to use this "meal" definition. However, during the pilot it was determined that women in Uganda and Ethiopia generally do not socialize with their friends and extended family members in this way, and using this definition would systematically exclude appropriate social ties. Instead, the more basic definition of to "know" was used, which removes the meal/drink requirement and instead stipulates that contact has occurred (in person, by phone, over computer) in the past 12 months (see Appendix A).

Several NSUM questions were added to the 2018 female PMA surveys in each country. First, 12 "known population" measures were included, each using the more basic definition of a social network tie (See Table 1 and Table 2). Appropriate known populations were determined using 2016 DHS data; 5 questions were asked in both countries, and 7 questions were specific to Ugandan and Ethiopia contexts. An additional validation question was asked for the number of women the respondent knows who use an IUD or implant as a form of contraception; the PMA female question collects data on IUD and implant usage, and this information will be used to determine countrywide counts for this population.

The question used to measure induced abortion in both Uganda and Ethiopia was "Of the women you have had contact with in the past 12 months, how many have ever done something to intentionally end a pregnancy?", and "Thinking of these X women who you have had contact with in the past 12 months and who have ever ended a pregnancy, how many have ended a pregnancy in the past 12 months?" Finally, two questions were included to measure transmission bias. Women who self-reported ever having an induced abortion were asked how many women in their social networks know that they had ever intentionally ended a pregnancy. A similar question was asked of women who were current IUD/implant users.

Validity Checks

In order to test the relative accuracy of the NSUM estimates, we use back estimation of the other known population and compare our estimated population sizes to the known size of each population. This back estimation process begins after personal network sizes have been estimated using the known population variables. First, a known population variable is selected to be treated as the new target variable. As an example, women who are current smokers may be selected. Next, we estimate the number of female current smokers within each country using the previously estimated personal network sizes. To test the accuracy of this back estimate, the newly estimated population size is compared to the known number of women who smoke. This can be repeated for every known population variable measured in the survey. The extent to which the back estimates mirror the known population sizes provides confidence in the relative accuracy in the estimates for the size of the hidden population, in this case induced abortion. This self-check of alternative sub-populations have been successfully used in a number of previous NSUM studies (Guo et al. 2013; Kadushin et al. 2006; Habecker, Dombrowski, and Khan 2015).

In addition, we also use the NSUM method to estimate another reproductive health behavior – the use of IUDs or implants – for which we have a known estimate. Assuming that sharing information on contraceptive use may be similar to how women share information on abortion, we ask about IUD and implant use treating this as a temporarily unknown population. We similarly measure the transmission bias for IUD and implant use. The accuracy of the NSUM estimate IUDs and implant use is used to assess the validity of the NSUM estimates; while this does not directly validate the NSUM abortion estimate, it indicates overall how well the NSUM performed and whether it was able to accurately estimate other reproductive health behaviors.

Abortion Incidence Estimates

We calculate three abortion incidence estimates. First, we calculate a baseline estimate with no sample restrictions. This estimate includes all respondents who provided valid answers to all 12 NSUM questions. Second, we restrict the estimate to respondents who additionally provided non-zero responses to a minimum of 2 of the 12 NSUM questions After applying this criteria, 88% of respondents in Uganda (N=1898) and 71% of respondents in Ethiopia (N=2696) were included in this NSUM estimate. In the third incidence estimate, we use the back estimation process to identify problematic questions that may be biasing the personal network size estimates. Previous work has suggested identifying and ultimately removing these items by creating a ratio that compares the back estimate to the known population size for each NSUM indicator (Guo, 2013). The closer this ratio is to 1, the more accurate the estimate. In order to identify problematic known populations, the current study employs a recursive approach developed by Habecker and colleagues; after the initial back estimate-known population ratios are calculated, the worst performing NSUM indicator is removed, and personal network size is re-estimated using the remaining known population variables (Habecker, 2015). This process is repeated recursively until all back estimate-known population ratios are no less than .5 and no greater than 2. Only those known populations in the ratio range are used to estimate $\widehat{c_i}$, or the social network size, in the NSUM estimation equation.

All three abortion incidence estimates are then adjusted for transmission bias. Different estimates of transmission bias are used, based on the number of respondents who were used to generate the NSUM estimate. We additionally provide prevalence estimates using the same exclusion criteria for the proportion of women currently using IUDs or implants.

To produce a confidence interval for the NSUM estimates for key populations (i.e. abortion incidence, use of IUDs/implants), we use a bootstrap variance estimation procedure to generate 5,000 replicate samples with which to produce replicate estimates. We draw our 95% confidence intervals from this set of estimates. The rescaled bootstrapping technique is appropriate in this study over a standard bootstrap procedure, which assumes a random sample. PMA data is collected using a complex sample design (primary sampling unit = EA, stratified by region and urban/rural residence), which can be accounted for in the rescaled bootstrapping method (Feehan & Salganik, 2016).

We compare the NSUM abortion incidence estimates (with and without the transmission bias adjustment) with direct report abortion incidence estimates in the PMA survey, and with the most recent AICM estimates for both countries (Moore et al. 2016; Prada et al. 2016).

Results

Application of the NSUM: Uganda

Table 1 shows the size of each known population, the mean number of social network connections reported for each known population in Uganda, and the mean number of connections after top-coding at 30. The last column in Table 1 shows the relationship between our estimated population sizes and the known size of each population (based on the 2016 Uganda DHS), using all 12 known populations prior to the back estimation adjustment.

[Table 1]

After employing the recursive back estimation process to identify and remove problematic known population questions, we are left with a total of 9 known populations in Uganda. Figure 1 shows the relationship between the NSUM population estimates and the DHS estimates at baseline and again after the final results of the internal validity check.

[Figure 1]

NSUM estimates of known populations are relatively close to the true population size, without a consistent pattern of over or under estimation. The largest outliers are women who gave birth in the last 12 months (129% of DHS estimate) and any education past senior six (143% of DHS estimate), which are both well below the 200% cut-off described above. These results suggest that the NSUM is performing relatively well at measuring non-hidden population sizes in Uganda.

After the recursive back estimation process, the final NSUM sample for Uganda is 1,864 (86% of all women randomized to the NSUM module). In order to see whether the exclusion of these women may have introduced bias into our final estimates, we look at differences in key demographic characteristics based on inclusion status. We find that there are regional differences based on inclusion status, that a smaller proportion of excluded women were married or in a current partnership, and that excluded women were slightly younger on average.

The average social network size (aka "degree") for women in Uganda is 19.5, with a range of 0-182. (Figure 2). This means that, on average, there were 19.5 women between the ages 15 and 49 who each respondent knows by sight and name, who live in Uganda, and who each respondent was in contact with (in person, by phone, over computer) in the past 12 months.

[Figure 2]

Application of the NSUM: Ethiopia

We applied the same initial analytic process and internal validity checks in Ethiopia. From the beginning of the analysis, there was evidence that the NSUM did not perform as well in Ethiopia as it did in Uganda. First, there were many non-valid or all zero responses to the known population questions, resulting in approximately 30% of the initial sample being excluded. After testing for statistically significant differences based on inclusion status, we found that larger proportions of excluded women in Ethiopia were married and had no or low levels of education as compared to included women.

Further evidence of the NSUM's underperformance in Ethiopia can be seen in Table 2. The mean number of connections is equal to or less than one in eight out of the 12 known population question, indicating a large number of respondents reported knowing no one in the specific known population. Finally, the known/estimated population size ratios are outside of the acceptable range for four questions in this initial analysis and close to the cut off for an additional three questions. Figure 3 graphically shows this lack of precision at the start of the internal validity check process.

[Table 2]

Next, we performed the same recursive back estimation process to identify and remove problematic known population questions. After this process, we are left with only five known populations in Ethiopia, which is likely too small of a number of known populations on which to accurately estimate social network size. Figure 3 shows the relationship between the NSUM population estimates and the DHS estimates at baseline and again after the final results of the internal validity check.

[Figure 3]

The average degree for women in Ethiopia is 28.5 when estimated based on all 12 known populations, with a range of 0-339. (Figure 4).

Given the high proportion of respondents excluded from the Ethiopia NSUM due to invalid or zero responses, we examined differences in the proportion of invalid and zero responses by survey enumerator. We did not find that the sociodemographic characteristics of the enumerator were associated with invalid or zero responses to the NSUM questions. However, new enumerators who did not have prior experience with PMA were more likely to have invalid responses compared to returning enumerators (11% vs. 1%).

[Figure 4]

NSUM estimation of abortion incidence

The three different estimation techniques produced similar incidence estimates. (Supplemental Table A displays the unadjusted and transmission bias adjusted baseline, minimum 2 non-zero, and back-estimation process NSUM abortion incidence estimates and IUD/implant prevalence estimates for both Uganda and Ethiopia.) In Uganda, abortion incidence ranged from 24.0 per 1,000 women to 26.8 per 1,000 women across the different estimation techniques. In Ethiopia, the estimates were almost identical for all three methods, ranging from 4.6 per 1,000 women to 4.7 per 1,000 women. For ease of comparison, the reminder of this paper will discuss the abortion incidence estimates generated from the baseline estimation method.

Figure 5 compares 1-year abortion incidence estimates for Uganda and Ethiopia from the unadjusted NSUM baseline method, the most recent AICM estimates in each country (Moore et al. 2016, Prada et al. 2016), and from the direct report abortion questions in the PMA 2018 surveys. In both countries, the direct report estimates are the lowest estimates (Uganda: 10.5 per 1000 women, 95% CI 5.6-15.4; Ethiopia: 2.5 per 1000 women, 95% CI 1.3-3.7). As expected, before adjusting for the visibility of this hidden population, the NSUM estimates are higher than the direct reports, but lower than the most recent AICM incidence estimates (Uganda: 24.7 per 1000 women, 95% CI 20.7-28.8; Ethiopia: 4.7 per 1000 women, 95% CI 4.0-5.5). While the unadjusted NSUM estimate in Ethiopia was still quite low (17% of the AICM estimate), the Ugandan unadjusted estimate was much closer to the recent AICM (63% of the estimate).

[Figure 5]

Next we calculated the "visibility" factor among women who self-report an abortion; women in Uganda told approximately 10% and women in Ethiopia told approximately 5% of their social networks about their abortions. Supplemental Table A displays the NSUM abortion incidence estimates after adjusting for transmission bias, which inflates the baseline estimate to 244.3 abortions per 1000 women in Uganda and 98.2 abortions per 1,000 women in Ethiopia.

NSUM estimation of IUD and implant use

We calculated the NSUM 12-month prevalence of IUD and implant use to assess how well the method performs in estimating a different reproductive health behavior. Figure 6 compares the 12-month IUD/implant prevalence estimates for Uganda and Ethiopia calculated from the unadjusted NSUM baseline method, the 2016 DHS in each country, and from the direct report questions about contraception use in the PMA 2018 surveys. In Uganda, the results show that all three methods produce comparable results (NSUM: 10.3%, 95% CI 8.9-11.9; Direct report: 8.0%, 95% CI 6.8-9.2; DHS: 7.8%, 95% CI 7.5-8.1). In Ethiopia, the NSUM and DHS estimates are similar, while the direct report estimate is much lower (NSUM: 4.5%, 95% CI 3.9-5.2; Direct report: 7.0%; DHS: 7.1%).

[Figure 6]

We again calculate the “visibility” factor among women who self-report current implant and IUD use, and find that these women in Uganda told approximately 14% of their social network and women in Ethiopia, on average, told 10% of their social network about their contraceptive method. Supplemental Table A displays the NSUM IUD/implant prevalence estimates after adjusting for transmission bias, which inflates the baseline estimate to 71.3% in Uganda and 45.6% in Ethiopia.

Discussion

The NSUM estimate of abortion in Uganda is higher than direct reported abortion incidence, but likely still an underestimate of abortion. The attempt to adjust for transmission bias resulted in an unreasonably high estimate of abortion incidence, suggesting that the true value of abortion likely falls somewhere between the NSUM estimate without transmission bias, and the gross overestimate of abortion with the transmission bias adjustment.

Transmission bias for the NSUM is typically assessed through a companion respondent-driven sampling study of individuals with the hidden characteristics of interest. We did not have the ability to field such a study in 2018, so instead we tested a novel approach to measuring transmission bias by asking questions directly to women who self-reported an abortion. The failure of this first attempt at implementing our novel approach to the transmission bias adjustment could be due to a number of factors. First, there is likely selection bias in the sample of women who self-reported their abortion. We know that women who self-report an abortion are likely not representative of all women having abortions. If women who self-report abortions are also different in how they talk about abortion in their social networks, then the transmission error estimate may be biased. In addition, the failure of the transmission bias adjustment may be due to the wording of the question. We measured transmission bias by asking women who had abortions how many people in their social network they *told* about their abortions. However, the respondents answering the NSUM question on how many women they know that had abortions may have knowledge of that abortion either from being told directly or indirectly. Transmission bias only accounts for direct transmission of information about abortion. If many women are finding out about abortions through other indirect channel, such as family connections or gossip, then the transmission bias is overcorrecting for the visibility of abortion, and leading to an overestimation.

Overall, our assessment of the NSUMs application in Uganda is that it is an improvement on direct reports of abortion, but further work is needed to adjust the methodology and question wording to better account for abortion visibility. In its current form, the NSUM is likely still underestimating abortion incidence.

We did find, however, the NSUM performed much better in the validation exercise of estimating IUD and implant use. This suggests that for less stigmatized reproductive health behaviors, the NSUM is able to produce reliable estimates. The transmission bias adjustment for IUD and implant use seems less applicable given that it is a less stigmatized behavior and therefor likely to be more visible than abortion. While it is assuring that the NSUM is able to accurately estimate IUD and implant use, the value of the method comes from its utility in estimating hidden behaviors that are underreported on traditional surveys. More work is needed to improve on the transmission bias of the NSUM method in order to fully assess its application for estimating abortion incidence.

The poor performance of the NSUM in Ethiopia, indicated by the high number of zero and invalid responses, suggests that NSUM estimates of abortion incidence should be interpreted cautiously. Our finding that new enumerators had higher proportions of invalid responses suggests that experience or training may have played a role in the fielding of the NSUM. New enumerators attended a separate training, which may have resulted in different levels of comprehension of the NSUM methodology and questions compared to returning enumerators. The NSUM is also a complex methodology to field, making it particularly sensitive the quality of training.

In addition to potential interviewer effects noted above, the Ethiopia NSUM data may be of lower quality because the women in the excluded sample were more likely to have had no education. It is possible that in settings with lower education levels, the NSUM is cognitively taxing and difficult for people with lower numeracy skills to answer. There were also challenges in the fielding of the methodology to consider, including only an urban-only pilot, a large number of interviewers being trained at once, and translators being used in the field who were not present at training and therefore unfamiliar with the NSUM. Any of these factors may have limited interviewer or translator comprehension of the method, which in turn may have resulted in lower quality data being collected.

While the poor performance of the NSUM in Ethiopia is concerning, our ability to assess the performance of the method performed is a critical feature of the NSUM. Most other abortion estimation methods in restrictive settings lack a similar feature. There are rarely validation checks available to determine how well a method performed or how accurate our estimates are. This is one critical advantage to the NSUM.

This study is an important first step in testing the applicability of the NSUM method to estimating abortion incidence in restrictive settings. We will be taking lessons learned from this first round of data collection and adjusting questions in 2019 to improve on the method. This includes expanding the number of known populations, using names as some of the known populations, adjusting the wording of the transmission bias question, and potentially fielding a separate respondent-driven sampling survey among women who have had abortions to better estimate the visibility of abortion in social networks. Together, the efforts will help refine the application of the NSUM for estimation of abortion incidence in order to put forward recommendations for its potential expanded use in the field of abortion measurement.

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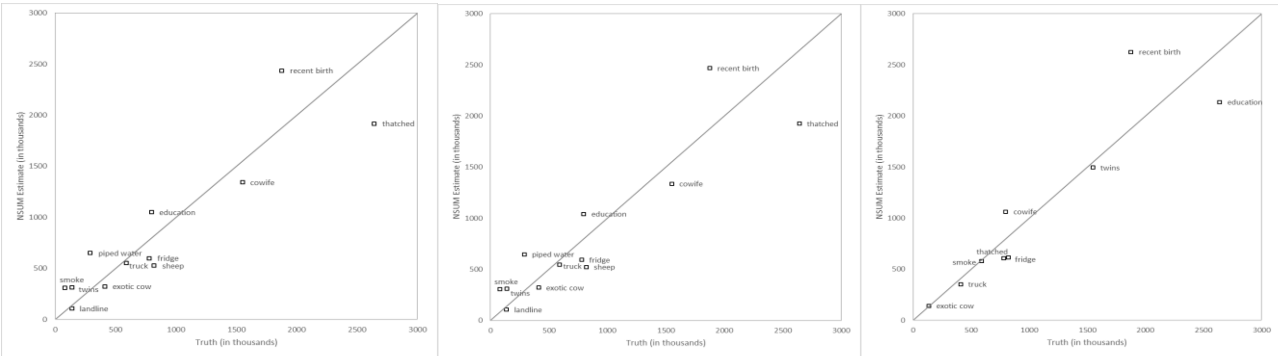
Table 1. Known populations used in Uganda, women ages 15-49

Category of population	Size	Mean number of connections	Mean number of connections, topcoding at 30	Initial NSUM estimate (as % of DHS estimate)
Gave birth in last 12 months	1,876,739	6.1	4.1	131.4%
Most recent birth was a multiple birth	140,733	0.6	0.6	220.8%
Has at least one co-wife	1,550,954	2.5	2.5	86.2%
Attended any education past senior six	798,320	2.2	2.0	130.4%
Smokes a pipe or cigarettes	80,769	0.6	0.5	377.9%
Lives in a household:				
...with a thatched roof	2,641,276	5.9	4.1	72.9%
...that owns a car or truck	590,684	1.2	1.1	92.6%
...that has a refrigerator	780,679	1.4	1.2	75.8%
...that owns an exotic cow	412,948	0.6	0.6	77.8%
...that owns at least one sheep	819,710	1.2	1.1	63.9%
...that has a landline	138,003	0.2	0.2	77.0%
...that has piped water inside the home	290,086	1.3	1.2	222.5%

Source: 2016 Uganda DHS, female (FQ) and household (HHQ) questionnaires

Figure 1. Comparison of known population sizes from 2016 Uganda DHS to network-scale up estimates (baseline, two non-zero responses and after recursive back estimation process)



I. Baseline NSUM (uses all 12 known populations, requires all valid responses)

II. Modified NSUM (uses all 12 known populations, requires all valid responses, requires at least 2 non-zero responses)

III. Modified NSUM (uses 9 selected known populations, requires all valid responses)

Figure 2. Degree distribution from NSUM in Uganda

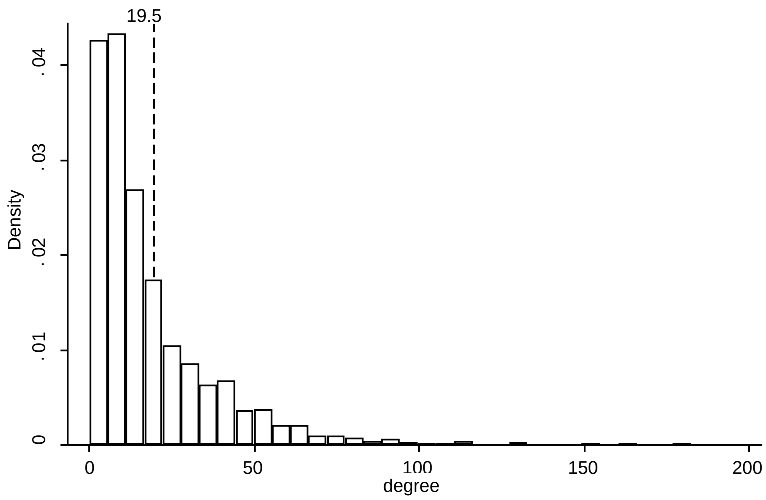
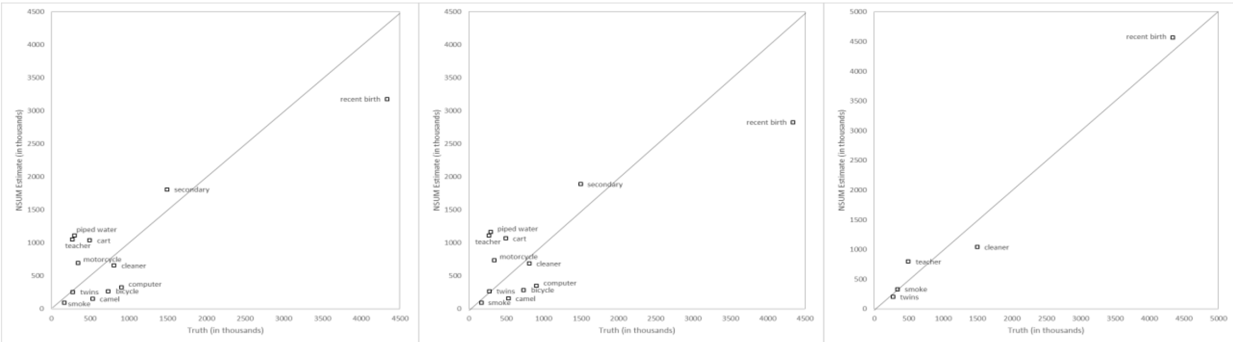


Table 2. Known populations used in Ethiopia, women ages 15-49

Category of population	Size	Mean number of connections	Mean number of connections, topcoding at 30	Initial NSUM estimate (as % of DHS estimate)
Gave birth in last 12 months	4,337,268	3.2	2.7	73.3%
Most recent birth was a multiple birth	275,020	0.2	0.2	93.2%
Works as a cleaner	807,142	1.0	0.9	81.6%
Works as a teacher	269,731	1.9	1.2	391.1%
Smokes a pipe or cigarettes	165,753	0.1	0.1	55.4%
Attended any school past secondary	1,495,429	2.6	2.3	121.1%
Lives in a household:				
...that has piped water inside the home	295,679	1.7	1.6	376.6%
...that owns a computer	904,951	0.6	0.6	36.2%
...that owns an animal-drawn cart	493,881	0.7	0.7	210.2%
...that owns a scooter or motorcycle	341,206	0.5	0.5	203.8%
...that owns a bicycle	732,624	0.3	0.3	36.7%
...that owns at least one camel	528,777	0.2	0.2	29.1%

Source: 2016 Ethiopia DHS, female (FQ) and household (HHQ) questionnaires

Figure 3. Comparison of known population sizes from 2016 Ethiopia DHS to network-scale up estimates for all three incidence calculations



I. Baseline NSUM (uses all 12 known populations, requires all valid responses)

II. Modified NSUM (uses all 12 known populations, requires all valid responses, requires at least 2 non-zero responses)

III. Modified NSUM (uses 5 selected known populations, requires all valid responses)

Figure 4. Degree distribution from NSUM in Ethiopia

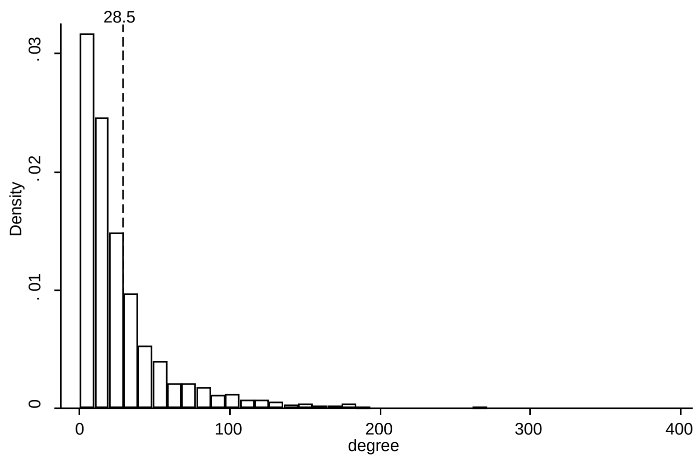


Figure 5. Comparison of abortion incidence estimates: unadjusted NSUM, most recent AICM, and direct report

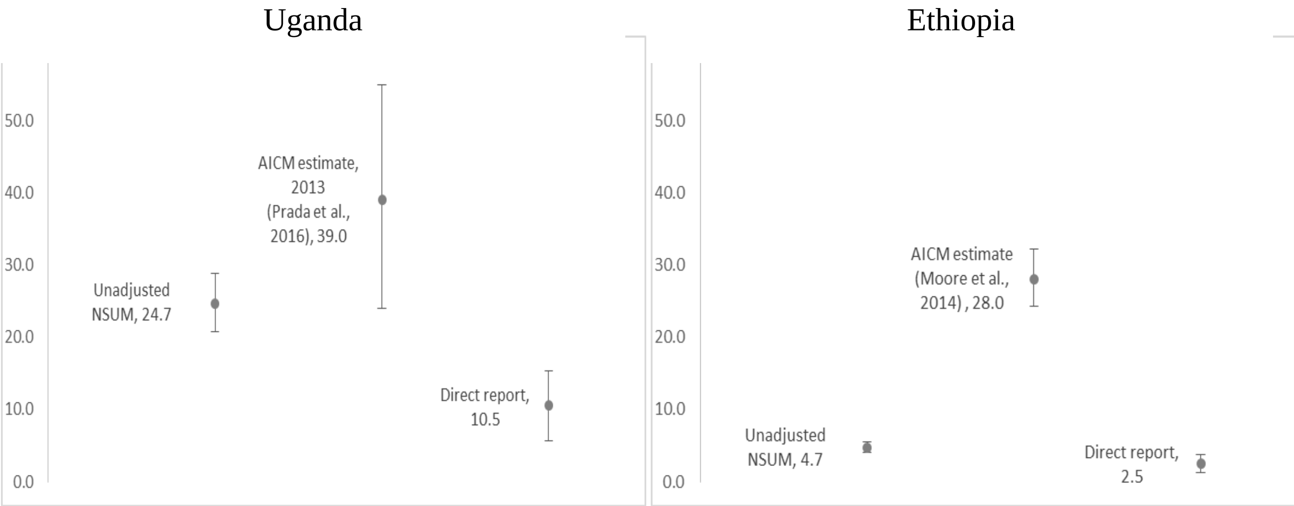
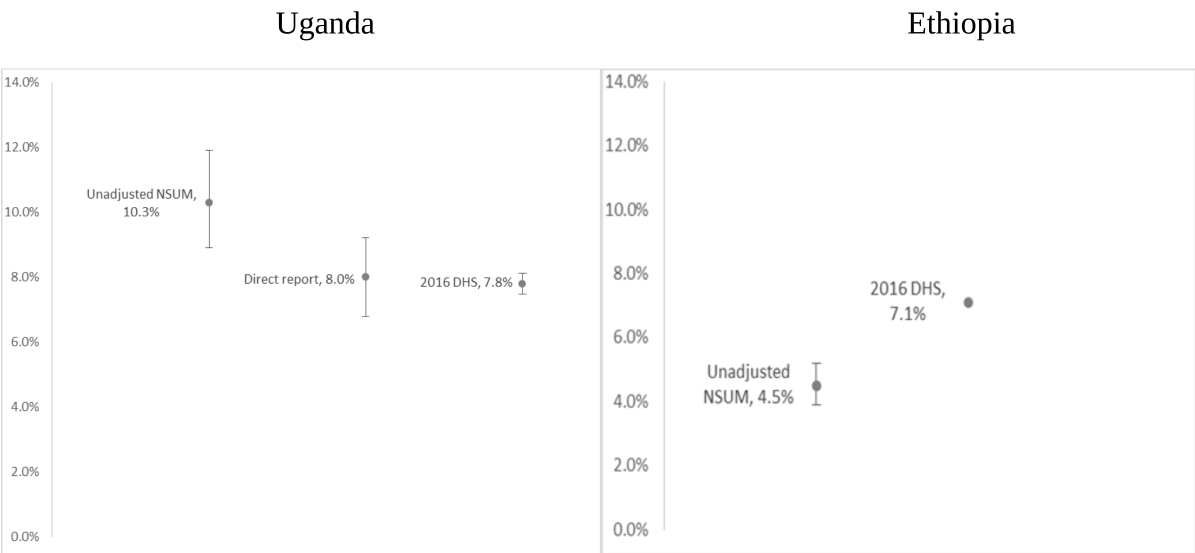


Figure 6. Comparison of IUD/implant prevalence estimates: unadjusted NSUM, 2016 DHS, and direct report



Supplemental Table A. NSUM estimates of abortion incidence rate and IUD/implant prevalence, before and after adjusting for transmission bias

NSUM version	NSUM abortion incidence estimate (per 1000)	Abortion transmission factor	Adjusted abortion incidence estimate (per 1000)	NSUM IUD/implant prevalence estimate	IUD/implant transmission factor	Adjusted IUD/implant prevalnece estimate
Uganda						
1. Baseline	24.7	0.10	244.3	10.3%	0.14	71.3%
2. 2+ Non-zero responses	24.0	0.09	274.4	10.0%	0.14	70.9%
3. Selected known populations	26.8	0.10	238.5	11.2%	0.14	72.6%
Ethiopia						
1. Baseline	4.7	0.05	98.2	4.5%	0.10	45.6%
2. 2+ Non-zero responses	4.6	0.04	119.5	4.1%	0.09	46.7%
3. Selected known populations	4.7	0.05	98.0	4.5%	0.10	45.5%

Appendix 1. Known population questions for Ethiopia and Uganda PMA Round 6

Uganda	Ethiopia
Tie definition:	
a) Individuals you know by sight AND name, and who also know you by sight and name. In other words, you should not consider famous people who you know about, but who do not know about you; and (b) Individuals you have had some contact with – either in person, over the phone, or on the computer -- in the past 12 months. These could be family members, friends, co-workers, neighbors, or other people you have contact with; and (c) Individuals 15-49 of age who currently live in Uganda.	(a) Individuals you know by sight AND name, and who also know you by sight and name. In other words, you should not consider famous people who you know about, but who do not know about you; and (b) Individuals you have had some contact with – either in person, over the phone, or on the computer – in the past 12 months. These could be family members, friends, co-workers, neighbors, or other people you have contact with; and (c) Individuals 15-49 years of age who currently live in Ethiopia.
Known Populations	
Women who have given birth in the last 12 months	Women who have given birth in the last 12 months
Women whose most recent birth was a multiple (twins etc.)	Women whose most recent birth was a multiple (twins etc.)
Women with at least one co-wife	Women who work as a domestic helper/cleaner
Women with education past senior six	Women with any education at a level higher than secondary school
Women who smoke a pipe or cigarette	Women who smoke a pipe or cigarette
Women who live in a household with a thatched roof	Women who work as a teacher
Women who live in a household that owns a car or truck	Women who live in a household that owns an animal drawn cart
Women who live in a household that has a refrigerator	Women who live in a household that owns a motorcycle or scooter
Women who live in a household that owns an exotic cow	Women who live in a household that owns a bicycle
Women who live in a household that owns at least one sheep	Women who live in a household that owns at least one camel
Women who live in a household that had a landline	Women who live in a household that has a computer

Women who live in a household that has piper water inside the home	Women who live in a household that has piped water inside the home
Unknown population	
Women who have ever done something to intentionally end a pregnancy	Women who have ever done something to intentionally end a pregnancy
Women who ended a pregnancy in the past 12 months	Women who ended a pregnancy in the past 12 months
Validation population	
Women who are currently using an IUD or implant	Women who are currently using an IUD or implant