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Using the network scale-up method to characterise kidney trafficking in Kalai Upazila, Bangladesh

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ABSTRACT

This study aimed to estimate the prevalence of illegal kidney sales in Kalai Upazila, Bangladesh, using the Network Scale-Up Method (NSUM), an ego-centric network survey-based technique used to estimate the size of hidden populations. The study estimated the size of the kidney seller population, analysed the profiles of kidney sellers and kidney brokers and investigated the characteristics of villagers who are more likely to be connected to kidney sellers to identify possible biases of the NSUM estimate. The study found that the prevalence of kidney trafficking in Kalai Upazila was between 1.98% and 2.84%, which is consistent with the estimates provided by a local leader and reporters, but with much narrower bounds. The study also found that a large proportion of kidney sellers and brokers were men (over 70% and 90%, respectively) and relatively young (mean age of 33 and 39, respectively). Specific reasons for kidney sales included poverty (83%), loan payment (4%), drug addiction (2%) and gambling (2%). While most reported male sellers were farmers (56%) and female sellers were housewives (78%) in need of money, most reported brokers were characterised as rich, well-known individuals.

WHAT IS ALREADY KNOWN ON THIS TOPIC

⇒ Previous reports and estimates have suggested that the prevalence of illegal kidney sales is high in South Asia, particularly in Bangladesh. However, these estimates were based on anecdotal evidence and lacked scientific rigour.

WHAT THIS STUDY ADDS

⇒ This study uses the Network Scale-Up Method (NSUM) to estimate the prevalence of kidney trafficking in Kalai Upazila, Bangladesh, and found that the prevalence rate ranges from 1.98% to 2.84%. In addition, this study examines the demographic profiles of kidney sellers and brokers, highlighting a significant representation of men and a relatively young age group. The study further unravels the underlying reasons for kidney sales, including poverty, loan repayment, drug addiction and gambling.

HOW THIS STUDY MIGHT AFFECT RESEARCH, PRACTICE OR POLICY

⇒ This study features the importance of implementing targeted interventions to effectively tackle the root causes driving the sale of kidneys, including poverty and addiction. The proposed methodology, the NSUM, presents a valuable approach for estimating the size of hidden populations, thus serving as a basis for future research on illicit activities. Policymakers can leverage these findings to develop comprehensive strategies aimed at combating kidney trafficking and safeguarding vulnerable individuals from exploitation.

INTRODUCTION

Illegal kidney sales or 'transplant tourism' in Global South, particularly at the hubs in South Asia such as India, Bangladesh, Nepal and Pakistan, are well reported.[1 2] In Bangladesh, a large-scale kidney trafficking ring was revealed in 2018 in Joypurhat, a district (or 'Upazila') located in the northwest region of Bangladesh.[3] As are the other trafficking cases, however, the actual extent of the problem appears to be inexact with a wide range of different estimates. According to the local leader of Kalai Upazila in Joypurhat, more than 500 people sold their kidneys over the past decade in Matrai and Udaypur unions.[4] With the population of Matrai and Udaypur unions being approximately 49 510, this suggests that at least 1 in 100 villagers (1%) sold their kidneys illegally thus far. Another study that relied primarily on newspapers and reports to estimate the number of kidney sellers in Kalai Upazila concluded that the percentage of kidney sellers is about 6–7%.[5] These estimates are based on anecdotal reports rather than on scientific investigations, and, naturally, generating any scientific evidence for the number is very difficult due to the stigma associated with kidney sales. The sellers could also receive various types of threats from brokers not to release

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information while investigators could face potential harm from them.

Prior research has developed several survey-based techniques to estimate the size of a certain population since the 1960s. Facility-based sentinel surveillance, snowball sampling,[6 7] respondent-driven sampling (RDS),[8–10] and the network scale-up method (NSUM)[11 12] are among them. In particular, RDS and NSUM are relatively new methods used to estimate the size of a 'hidden population', for example, commercial sex workers, injection drug users or individuals with a sexually transmitted disease. A few key differences exist between the two approaches: RDS is an extension of the snowball and chain-reference sampling while NSUM follows the classic sampling theory that requires a random sample. Another key difference lies in their study participants. In RDS, researchers directly survey members of the target hidden population who would then recruit additional members from their contacts as the participants of the next wave. NSUM, on the other hand, samples members of the general population who may or may not be connected to members of the target hidden population. In NSUM, the estimation of the population size is done based on the survey participants' responses to the question 'How many members of the target population do you know?'. NSUM has an advantage over RDS when members of the target population are particularly hard to reach.

Given the hidden and stigmatised nature of kidney sellers, we implemented a simplified version of NSUM to estimate the degree of the kidney sales problem in Kalai Upazila. The simplification was necessary due to the limited availability of official census data at the local level. To offset potential biases caused by the simplification, we produced several estimates based on different assumptions and also performed a concomitant sensitivity analysis. Given that a majority of illicit activities take place in developing countries where census data are relatively lacking, the research framework presented in the current paper may provide insights into the practical approach taken to estimate the size of hidden population using survey and modelling techniques developed thus far.

In addition to the kidney-seller size estimation, we descriptively analysed the profiles of kidney sellers and brokers by asking the survey respondents to provide several key characteristics of the kidney sellers and brokers known to them. Further, we investigated the characteristics of those villagers who are more likely to be connected to kidney sellers with its aim being the identification of the possible 'barrier effect', which is one of the well-recognised biases in NSUM estimates. Barrier effect pertains to the fact that survey participants are often more likely to be connected to, and thus are more likely to recall and refer to, those who are similar to them. The bias is thus attributable to the phenomenon known as 'homophily' and manifests when the survey sample fails to represent the population.[13 14] In the context of our study, there was a possibility that kidney sellers have some distinctive characteristics, for example, middle aged male. If homophily exists and we undersample or oversample the specific group, our NSUM estimate could be biased. Although this study applied a simplified version of NSUM, this is the first analytical effort made to gauge the extent of kidney sales problem in one of the most well-known kidney sales hotspots where accurate local-level census data are often scarce.

METHODOS

Survey approach

Patients or the public were not involved in the design, or conduct, or reporting or dissemination plans of this research. Our target population was adults aged 18 and older in Ward-2 in Matrai Union of Kalai Upazila, one of the well-known locations for kidney sales in Bangladesh.[15 16] We selected Ward-2 in Matrai Union, a small village with an adult population of 2492 with a typical demographics, as it is known to have the largest proportion of kidney sellers. The ward is a close community where most residents know each other and interact frequently at rituals such as at mosques and at other social gatherings. For the recruiting of survey respondents, the most ideal approach is to implement random sampling so that the final sample accurately represents the population. In the context of a small village in Bangladesh, such an approach would involve using areas and addresses of the village as a sampling frame to proportionally stratify areas and addresses. In our field study, however, such stratification was proven to be difficult due to the lack of census data. We thus collaborated with three local coordinators (see Reflexivity Statement in online supplemental appendix A) and seven interviewers to conduct a face-to-face survey on the main streets of the village. In view of protecting human subjects, this approach without a list of study participants was also considered 'safer' in the local presence of kidney brokers whose intention is to remain hidden by minimising the local attention to the topic and the number of informants to outsiders. Our interviewers administered the survey for 9 days in October 2021 and successfully interviewed 360 respondents. The response rate of the survey was approximately 14.45%. To address the potential bias attributable to the non-random sample of the respondents, we created inverse probability survey weights to ensure that the joint distribution of age and sex in the respondents is equivalent to that of the local census.[17] The survey weights were implemented to calibrate the logistic regression analysis,[18] and a detailed breakdown of the comprehensive stratification of the survey weights can be found in online supplemental appendix B.

Survey questionnaire

The questionnaire was comprised of six sections: (1) demographic information (age, sex, educational attainment, marital status, size of the household); (2) financial and professional statuses (work status, employment status, wage, land and livestock owned); (3) general social network information (the number of people they socialised last week, the number of friends with whom they share secrets); (4) knowledge about kidney sellers (whether they have heard of or know kidney sellers and, if they do, how many, any known characteristics of the sellers, any known reasons for selling kidneys and how close they are to the kidney sellers); (5) knowledge about brokers (whether they know brokers, any known characteristics of the brokers and whether the brokers sold their own kidneys); and (6) their perception about kidney sales, their levels of social trust, happiness and health. The full survey questionnaire is attached in online supplemental appendix C.

Analytical methods

Three different analyses were performed with the objectives to: (1) delineate the profiles of kidney sellers, kidney brokers and the villagers who are connected to kidney sellers; (2) investigate the presence and extent of sex and age homophily between respondents and the kidney sellers known to them; and (3) estimate the number of kidney sellers in the village. Specific approaches taken for the three analyses are described below.

Characteristics of the villagers connected to kidney sellers

We explored characteristics of kidney sellers and brokers known to the villagers. The characteristics of kidney sellers were inferred based on the responses to the questions q17–q19 while those of sellers were inferred using q20–q21 (online supplemental appendix B). Characteristics of those villagers who have heard of or know at least one kidney seller were also explored. The basic sociodemographic and other characteristics of those villagers who have heard/know kidney sellers were compared with the other villagers who are not connected to kidney sellers. The analysis applied t-test or Wilcoxon-Mann-Whitney tests for continuous variables and χ^2 or Fisher's exact tests for categorical variables depending on the underlying distribution of the variable or the sample size. A multivariate logistic regression was performed to investigate the factors correlated with the knowledge about kidney sellers (response variable) after adjusting for covariates. The model is specified as:

$$P(y) = \frac{w}{\bar{w}} \times \frac{1}{1+\exp(-\theta^T x)}$$

Where:

$P\,(y)$ is the probability of y taking the value of 1, that is, the respondent knows or heard of at least one kidney seller.

w represents the survey weight.

$\bar{w}$ represents the average of the survey weights.

θ is a vector of model coefficients.

x is a vector of covariates.

For covariates, we explored all available variables including basic demographic factors, age and sex, employment status, marital status, family structure, income and asset levels and perception and opinion about kidney selling. The final regression model kept only those variables that are statistically significant at the 10% level in either (know or heard of kidney sellers) model. The goodness of fit was assessed using the accuracy score, that is, referring to sensitivity and specificity.[19] All statistical analyses were done using Stata (StataCorp, V.15).

Sex and age homophily in respondent-kidney seller network

The presence of sex and age homophily between respondents and the kidney sellers known to them were examined using Exponential Random Graph Models (ERGMs). The ERGMs estimated statistical probabilities of the connections between respondents and the known kidney sellers who are in the same sex and/or age group as the respondents as the measures for sex and/or age homophily.[20 21] The general representation of ERGMs is given by:

$$P(y) = \frac{\exp(\theta^T g(y))}{k(\theta)} \quad (1)$$

Where:

$P\,(y)$ is the probability of an observed network y.

$g(y)$ is a vector of statistics for the observed network y.

θ is a vector of model coefficients.

$k(\theta)$ is a normalised constant representing the summation of all possible networks with the same node set of the observed network y.

The interpretation of the ERGM is similar to that of a logistic regression model for the presence of a tie (0 or 1) between two nodes, where the covariates are network configurations containing other ties in the network. Thus, the presence of sex and age homophily in the ERGM means that respondents' connections with the kidney sellers are not random, which implies that 'barrier effect' could exist as a source of bias in the estimates. For the analysis, the network data representing the connections between survey respondents and kidney sellers were used. We excluded isolated nodes (ie, respondents who do not know sellers) from the analysis as those nodes contribute little to the statistical network inference. The final respondent–seller network consisted of 103 respondents and 258 kidney sellers. The ERGM analysis was done using the 'ergm.ego v1.0.1' package in R software.

NSUM estimates for the number of kidney sellers

The general forms of the NSUM can be expressed as follows[22 23]:

$$\widehat{H} = \frac{\sum_{i\in S} y_i}{\sum_{i\in S} \widehat{M}_i} \times C \quad (2)$$

Where:

$\widehat{H}$ is the estimated size of the hidden population.

y_i is the number of the hidden population members that the respondent i knows.

$\widehat{M_i}$ is the estimate of respondent i's network size.

C is the total population size.

S is the respondent set.

The estimate for the size of a hidden population, that is, kidney sellers, is thus derived on the basis of a fraction of the total number of sellers to the total number of social contacts that the survey respondents claim to be connected to. In general, the NSUM estimate involves two steps: (1) estimation of the personal network size, $\widehat{M_i}$, based on the average proportion of several prespecified subpopulations (those with a specific surname, occupation, etc); and (2) estimation of the hidden population size, $\widehat{H}$, based on the above equation. Due to the unavailability of subpopulation census data at Ward-2 in Matrai Union, we developed a crude measure for $\widehat{M_i}$ based on the responses to the two questions: q12 'How many people did you chat with at work last week?' and q13 'How many people did you chat with for leisure last week?', assuming that the personal network is comprised of two subpopulation networks (j=1,2 and K=2). Since social networks at work and for leisure activities could overlap, we calculated the personal network size for two extreme scenarios: (1) one network (social or work) is a subset of the other (ie, $\widehat{M}_{i1} \subseteq \widehat{M}_{i2}$, or $\widehat{M}_{i1} \supseteq \widehat{M}_{i2}$; and (2) the two networks are disjoint (ie, $\widehat{M}_{i1} \cap \widehat{M}_{i2} = \varnothing$. For the first scenario, we calculated the personal network size using the larger network (ie, $\widehat{M}_{i1} = \max(\widehat{M}_{i1}, \widehat{M}_{i2})$). For the latter, we calculated the personal network size using the sum or the two network sizes (ie, $\widehat{M}_i = \widehat{M}_{i1} + \widehat{M}_{i2}$). The two calculated personal network sizes served as the estimated minimum and maximum personal network sizes, respectively. While it is debatable whether a typical villager talks to all contacts in a typical week, this was confirmed by the locals as a plausible assumption. Sensitivity analysis was performed to test the impact of using an inaccurate personal network size on the NSUM estimates. The analysis was done by increasing the minimum and maximum average personal network sizes by 5%, 10%, 15% and 20% and observing the impacts on the NSUM estimates.

To gauge the number of kidney sellers known to each respondent (y_i), we used q17-1 'How many kidney sellers do you know in person?'. To test the validity of the response, the subsequent question asked the respondent the nature of the relationship with each of the designated sellers (a friend, a relative, etc). If the respondent did not respond to this question (ie, the response was missing), or answered 'no relation', we determined the originally reported number of kidney sellers in the respondent's personal network (the response to q17-1) as uncertain. To reflect the uncertainty in the NSUM estimate, we developed three different estimates for y_i. The first estimate took the reported number of kidney sellers in q17-1 at face value. The second measure modified the first measure by subtracting the number of kidney sellers whose relationship to the respondent was missing. The third measure modified the second measure by further subtracting the number of kidney sellers with whom the respondent claimed to have 'no relation'. The three estimates for y_i evaluated for each of the two estimates for $\widehat{M}_i$ (min and max) together generated six scenarios in total for the NSUM implementation.

RESULTS

Descriptive analysis

The number of respondents who knew at least one kidney seller was 99 (28%). The respondents mentioned 261 kidney sellers in total. Among those, the proportions of male kidney sellers were 77%, while the average age of the sellers was 33 (SD=6.66). Of the total 48 mentioned brokers, the vast majority (94%) were men, while the average age of the brokers was 39 years (SD=7.42).

Table 1 summarises the basic profiles of the referred kidney sellers and brokers. The most common relationship with the referred kidney sellers was 'Neighbor', sharing around 50%. The most common reason for selling kidneys known to the respondents was 'Poverty' (>80%), followed by 'Loan payment' (5%) and 'Drug addiction' (3%). In male sellers, the most common profession was 'Farmer' (56%), followed by 'Driver' (21%). A majority of female kidney sellers were 'Housewives' (78%). There was no statistical difference in the reasons for selling kidneys by sex (p=0.371), while professions of kidney sellers differed statistically significantly by sex (p<0.001). The average age did not differ across reasons for selling kidneys (p=0.415) or sellers' professions (p=0.325). Kidney sellers who were actual neighbours to the respondents were found to be younger than other sellers known to them (p=0.026). Among 48 brokers mentioned by the respondents, the most common professions were full-time brokers (41%) and business persons (20%). In contrast to the kidney sellers who were often portrayed as poor, the perceived features of the brokers included well known (35%), rich (27%) individuals. Distributions of professions and features of kidney brokers differed statistically significantly by sex (p<0.001 and p=0.004, respectively). The average age also differed statistically significantly across professions and features without any notable trend (p<0.001 and p=0.001, respectively).

Table 2 presents the results of the descriptive analysis examining factors associated with indirect and direct connections to kidney sellers. The respondents who are men, unemployed, wealthier, more educated and with a larger social network were more likely to be connected to a kidney seller. In addition, the results demonstrated that the respondents with indirect connections to kidney sellers were more likely to consider 'kidney sales should be illegal' than those who have not heard of kidney sellers. In contrast, the respondents with direct connections to kidney sellers were more likely to think that 'if someone has severe financial need, kidney sale is an acceptable option' than those who do not know kidney sellers in person.

Multivariate logistic regression

Table 3 summarises two multivariate logistic regression results investigating the determinants of the respondents who have indirect or direct connections to kidney sellers. The accuracy of the models was around 65%. The model estimating the likelihood of an indirect connection to kidney sellers had a higher (82.34%) sensitivity (ie,

Table 1 Profiles of nominated kidney sellers and brokers

Class	Category	All sellers n (%*)	Male seller n (%*)	Female seller n (%*)	P value†	Seller's age Mean (SD)	P value‡
Relation§	Family	7 (2.76)	4 (2.05)	3 (5.08)		34 (10.36)	
	Neighbour	127 (50.00)	94 (48.21)	33 (55.93)	0.206	32 (6.67)	0.026
	Other	120 (47.24)	97 (49.74)	23 (38.98)		35 (6.13)	
Reason¶	Drug addiction	6 (2.32)	6 (2.99)	0 (0.00)		36 (3.88)	
	Gambling	4 (1.54)	4 (1.99)	0 (0.00)		29 (4.35)	
	Drug addiction and Gambling	1 (0.39)	1 (0.50)	0 (0.00)		27 (-)	
	Influenced by others	1 (0.39)	1 (0.50)	0 (0.00)	0.371	Unknown (-)	0.415
	Loan repayment	11 (4.25)	10 (4.98)	1 (1.72)		34 (5.22)	
	Poverty	216 (83.4)	166 (82.59)	50 (86.21)		34 (6.8)	
	Do not know	20 (7.72)	13 (6.47)	7 (12.07)		32 (6.44)	
Profession**	Unemployed	3 (1.15)	3 (1.49)	0 (0.00)		33 (10.79)	
	Student	1 (0.38)	1 (0.50)	0 (0.00)		32 (N/A)	
	Worker	33 (12.64)	29 (14.43)	4 (6.67)		34 (6.42)	
	Business	5 (1.92)	5 (2.49)	0 (0.00)	<0.001	34 (5.70)	0.325
	Driver	42 (16.09)	42 (20.90)	0 (0.00)		34 (5.90)	
	Farmer	113 (43.30)	113 (56.22)	0 (0.00)		34 (7.18)	
	Housewife	51 (19.54)	4 (1.99)	47 (78.33)		32 (5.75)	
	Deceased/unknown	13 (4.98	4 (1.99)	9 (15.00)		31 (7.26)	
Class	**Category**	**All brokers n (%*)**	**Male brokers** n (%*)**	**Female brokers n (%*)**		**Broker's age Mean (SD)**	
Profession	Broker	20 (40.82)	19 (42.22)	0 (0.00)		37.05 (8.06)	
	Business	10 (20.41)	10 (22.22)	0 (0.00)		42.9 (5.02)	
	Driver	3 (6.12)	3 (6.67)	0 (0.00)		45 (5.00)	
	Farmer	6 (12.24)	6 (13.33)	0 (0.00)	<0.001	31.83 (5.35)	<0.001
	Housewife	2 (4.08)	0 (0.00)	2 (66.67)		35 (7.07)	
	Local councillor	1 (2.04)	1 (2.22)	0 (0.00)		40 (-)	
	Worker	2 (4.08)	1 (2.22)	1 (33.33)		45 (0.00)	
	Do not know	5 (10.20)	5 (11.11)	0 (0.00)		44.6 (2.88)	
Feature	Respected	2 (4.17)	2 (4.55)	0 (0.00)		44 (5.66)	
	Know many people	17 (35.42)	15 (34.09)	2 (66.67)		37.82 (8.21)	
	Less people know	2 (4.17)	2 (4.55)	0 (0.00)	0.004	39 (15.56)	0.001
	Poor	1 (2.08)	0 (0.00)	1 (33.33)		45 (-)	
	Rich	13 (27.08)	13 (29.55)	0 (0.00)		42.92 (4.84)	
	Do not know	13 (27.08)	12 (27.27)	0 (0.00)		35.92 (6.92)	

*% of category.
†Fisher's exact test.
‡Analysis of variance.
§Seven missing values.
¶Two missing values.
**One missing value.

true-positive) rate and a lower (41.81%) specificity (true-negative) rate. The low specificity rate was attributable to the larger share of the respondents having an indirect connection (70%) than no connection. In contrast, the model investigating the likelihood of a direct connection had a low sensitivity rate of 43.97% and a high specificity rate of 83.17% due to the low percentage (27.99%) of the respondents who directly know kidney sellers. The model evaluation of the Receiver Operating Characteristics (ROC) curve with different thresholds of true-positive

Table 2 Descriptive analysis: determinants for indirect and direct connections to kidney sellers

Variable	Unheard of seller (n=174)	Heard of seller (n=186)	P value	Do not know seller (n=261)	Know seller (n=99)	P value
Male, n (%)	89 (42.58)	120 (57.42)	0.012	140 (66.99)	69 (33.01)	0.007
Age, mean (SD)	38.13 (14.23)	37.80 (12.80)	0.970	37.65 (13.71)	38.78 (12.93)	0.359
Education level, n (%)	6.03 (4.75)	7.68 (4.67)	0.001	6.54 (4.69)	7.76 (4.90)	0.054
Married, n (%)	158 (49.07)	164 (50.93)	0.326	234 (72.67)	88 (27.33)	0.757
Number of children, mean (SD)	2.05 (1.40)	1.92 (1.26)	0.528	1.99 (1.30)	1.95 (1.42)	0.654
Household size, mean (SD)	4.23 (1.57)	4.27 (1.41)	0.827	4.22 (1.43)	4.31 (1.63)	0.852
Work status, n (%)						
Employed	70 (40.46)	103 (59.54)	0.004	115 (66.47)	58 (33.53)	0.002
Unemployed	8 (40.00)	12 (60.00)		11 (55.00)	9 (45.00)	
Not in labour force	95 (57.93)	69 (42.07)		133 (81.10)	31 (18.90)	
Farmer, n (%)	41 (37.96)	67 (62.04)	0.405	75 (69.44)	33 (30.56)	0.313
Perceived income, n (%)						
Much lower	29 (32.58)	60 (67.42)	0.031	58 (65.17)	31 (34.83)	0.665
Higher than 'Much lower'	40 (48.78)	42 (51.22)		56 (68.29)	26 (31.71)	
Land size, mean (SD)	57.65 (86.20)	76.25 (119.35)	0.031	63.60 (104.91)	76.80 (104.71)	0.019
Own livestock, n (%)	133 (45.39)	160 (54.61)	0.014	208 (70.99)	85 (29.01)	0.200
Work chat network size, mean (SD)	17.59 (29.18)	22.70 (32.14)	0.067	17.68 (27.45)	26.95 (37.61)	0.015
Leisure chat network size, mean (SD)	21.42 (25.49)	28.77 (33.32)	0.005	23.48 (29.37)	29.79 (31.23)	0.002
Close family member size, mean (SD)	2.06 (1.62)	1.92 (1.27)	0.904	1.94 (1.50)	2.11 (1.31)	0.118
Close friend network size, mean (SD)	1.92 (2.99)	2.57 (2.82)	< 0.001	2.05 (3.08)	2.80 (2.39)	< 0.001
Kidney sales should be illegal, mean (SD)	4.51 (0.88)	4.76 (0.59)	0.002	4.59 (0.80)	4.76 (0.61)	0.057
If someone has severe financial need, kidney sale is an acceptable option, mean (SD)	2.23 (0.97)	2.15 (0.88)	0.684	2.28 (0.94)	1.94 (0.82)	0.001
If someone sold kidney, he/she would keep it a secret, mean (SD)	2.81 (1.02)	2.93 (1.08)	0.276	2.87 (1.03)	2.88 (1.10)	0.968
Everyone should trust every other person in this ward, mean (SD)	4.02 (0.72)	3.97 (0.84)	0.880	3.98 (0.76)	4.04 (0.84)	0.259
Practicing religion is important, mean (SD)	4.42 (0.58)	4.46 (0.55)	0.534	4.44 (0.58)	4.43 (0.52)	0.675
Police generally do the right things, mean (SD)	3.47 (1.16)	3.41 (1.13)	0.450	3.42 (1.14)	3.48 (1.15)	0.647
Government generally does the right things, mean (SD)	3.59 (1.08)	3.63 (1.04)	0.879	3.60 (1.08)	3.64 (1.02)	0.857
I am happy with my life, mean (SD)	4.15 (0.67)	4.14 (0.85)	0.454	4.12 (0.77)	4.21 (0.73)	0.291
I am healthy, mean (SD)	4.00 (0.88)	4.05 (0.97)	0.271	4.00 (0.94)	4.09 (0.90)	0.412

and false-positive rates is provided in online supplemental appendix D.

A number of the demographic variables that were significant in the bivariate analysis became insignificant (p>0.05) after adjusting for covariates. The results revealed that the individuals who have a higher level of education (OR=1.10, p=0.001) and are wealthier (OR=2.04, p=0.031) were more likely to hear about kidney sellers. These individuals were also more likely to consider 'kidney sales should be illegal' (OR=1.66, p=0.001). As for the direct connection to kidney sellers, older people were more likely to know kidney sellers (OR=1.03, p=0.019). The individuals with a larger leisure chat network were also more likely to know kidney sellers (OR=1.01, p=0.022). These respondents were also more likely to consider that 'if someone has severe financial need, kidney sale is an acceptable option' (OR=0.65, p=0.029).

Sex and age homophily in respondent-kidney seller network

Table 4 shows the result of the ERGM analysis. For easier interpretations of the homophily effects between kidney sellers and respondents who knew kidney sellers, age was aggregated into two groups, that is, 18–39 and over 40. The proportion of male respondents (70%) was much larger than that of female respondents (30%), and the number of young adult respondents was larger than those respondents aged over 40 (66% vs 34%). Kidney sellers also had larger shares of men (77%) and young adults under 40 (89%).

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Table 3 Multivariate logistic regressions: determinants for having heard of or knowing kidney sellers

	Heard kidney seller				Know kidney seller			
	OR	95% CI		P value	OR	95% CI		P value
Female	1.39	0.64	3.05	0.407	1.10	0.45	2.69	0.840
Age	1.02	1.00	1.04	0.098	1.03	1.01	1.06	0.017
Education	1.10	1.04	1.16	0.001	1.06	0.99	1.13	0.086
Work status*								
Unemployed	1.08	0.37	3.13	0.886	2.59	0.91	7.40	0.076
Not in labour force	0.47	0.22	1.03	0.059	0.70	0.30	1.65	0.414
Own livestock/a larger land	2.08	1.09	3.97	0.025	1.71	0.84	3.48	0.136
Leisure chat network size	1.01	1.00	1.03	0.083	1.01	1.00	1.03	0.019
Kidney sales should be illegal	1.68	1.23	2.28	0.001	1.42	0.98	2.05	0.065
If someone has severe financial need, kidney sale is an acceptable option	0.94	0.71	1.24	0.674	0.65	0.45	0.94	0.023
Variance inflation factor	1.195				1.174			
Sensitivity	82.34%				43.97%			
Specificity	41.81%				83.17%			
Accuracy rate	62.97%				67.05%			

*The reference group is employed.

The respondents were more likely to know the kidney sellers of the same sex. In fact, the odds for the presence of a respondent-seller tie between two female nodes are 83% higher than the odds for the presence of a respondent–seller tie between male and female respondents (p=0.026). Similarly, a respondent–seller tie between two male respondents was 92% more likely than a respondent–seller tie between male and female nodes (p=0.001). Regarding the age homophily, the odds of younger (<40) adult respondents knowing sellers in the same age group were 82% higher than the odds of the presence of a respondent–seller tie between different age groups (p=0.007). There was no homophily between the individuals aged over 40 (p=0.15). Furthermore, we performed Markov Chain Monte Carlo and Goodness-of-Fit diagnostics of the ERGM (online supplemental appendix E). The results from both diagnostics indicate that the ERGM converges appropriately and provides a good fit for the observed network.

Separately, we also performed an ERGM analysis analysing homophiles between respondents and their social contacts. Although the results are not shown here, what we observed between respondents and the connected kidney sellers were also evident between respondents and their social contacts.

Table 4 The age and sex homophily estimation between respondents and kidney sellers by ERGM

	Coefficient	OR	P value
Network size adjustment	−4.64		
Edges	0.33	1.39	0.101
Sex			
Sex heterogeneity (male–female ties)	(reference)		
Female homophily (female–female ties)	0.60	1.83	0.026
Male homophily (male–male ties)	0.65	1.92	0.001
Age			
Age heterogeneity (<40 and ≥40 ties)	(reference)		
Age <40 homophily (<40 and <40 ties)	0.60	1.82	0.007
Age ≥40 homophily (≥40 and ≥40 ties)	−0.32	0.72	0.150

Note: Network size adjustment is fixed by offset and not estimated: -ln(network size) = -ln(103) = −4.64.
ERGM, Exponential Random Graph Model.

Table 5 Estimated number of kidney sellers

		Network size $\widehat{M}_i$: min/max	Estimated no. of kidney sellers under three scenarios (A, B and C), n (%)		
			A: y_i = reported no. of known kidney sellers	B. y_i = A – no. of kidney sellers with a missing relation to the respondent	C: y_i = B – no. of known kidney sellers with no relation to the respondent
As reported		Min	71 (2.84)	60 (2.42)	31 (1.24)
		Max	49 (1.98)	42 (1.68)	22 (0.87)
Sensitivity analysis: reported network size	+5%	Min	68 (2.70)	57 (2.30)	30 (1.18)
		Max	47 (1.89)	40 (1.60)	21 (0.83)
	+10%	Min	65 (2.58)	55 (2.20)	28 (1.13)
		Max	45 (1.80)	38 (1.53)	20 (0.79)
	+15%	Min	62 (2.47)	52 (2.10)	27 (1.08)
		Max	43 (1.72)	37 (1.46)	19 (0.76)
	+20%	Min	59 (2.37)	50 (2.02)	26 (1.03)
		Max	41 (1.65)	35 (1.40)	18 (0.73)

Estimation of the number of kidney sellers in NSUM

We applied NSUM using two estimates for the personal network size of each respondent ($\widehat{M}_i$). The minimum personal network size ranged between 0 and 180 (mean=28, SD=27), while the maximum personal network size ranged between 0 and 320 (mean=41, SD=39). We also used three different estimates for the number of kidney sellers known to the respondent (y_i), including: the reported number of kidney sellers without modifications (Measure 1); Measure 1—the number of kidney sellers whose relationship to the respondent was missing (Measure 2); and Measure 2—the number of kidney sellers with whom the respondent claimed to have 'no relation' (Measure 3).

Table 5 summarises the NSUM estimates for the six scenarios, that is, testing minimum and maximum values of $\widehat{M}_i$ for each of the y_i values. Also, in online supplemental appendix F, we implemented bootstrapping sampling with 10 000 samples to generate SEs and CIs for each estimated value. The estimated number of kidney sellers varied between 22 and 71, which corresponds to 0.87% and 2.84% of the whole village population, respectively. The result of the sensitivity analysis shows that the estimated number of kidney sellers decreases as the personal network sizes of the respondents increase by 5%, 10%, 15% and 20%. The reductions are, however, relatively small with the final NSUM estimates in all scenarios ranging between 18 (0.73%) and 68 (2.70%). The result indicates that the impact of possible inaccurate estimates of the personal network sizes on the NSUM estimates is not likely a foremost concern in our analysis.

DISCUSSION

Measuring the crime prevalence is a critical first step for the investigation of any trafficking including organ trafficking. A reliable measure is, however, often unavailable to law enforcement agencies, as reports from different researchers and officials tend to produce a wide range of estimates. To this end, the current paper applied NSUM, one of the most widely used methods to measure the size of a hidden population, to estimate the size of kidney trafficking victims in Ward-2 in Matrai Union of Kalai Upazila. The NSUM estimate revealed that the kidney sellers are likely to share between 0.87% (n=22) and 2.84% (n=71) of the population. While it is not feasible to validate this estimate, our estimates demonstrated a much narrower bound than that given in the existing reports, which ranged between 1% and 7%.[4 5]

We also investigated the common characteristics of kidney sellers and brokers known to the surveyed villagers. About 30% of the surveyed villagers knew kidney sellers in person. They reported that the sellers are typically younger (around 30) men (about 80%). They also reported that the sellers tend to be in poverty and have a profession of either a farmer or a driver, while female sellers were predominantly reported to be housewives. Loan payment was reported as another reason for selling kidney, which was anecdotally confirmed in the field, particularly in relation to the microcredit loan. This finding is also consistent with the prior literature.[3 24] Drug addiction was also noted as a reason to become a young male kidney seller, which was highlighted as the rising concern in the village among the survey respondents. It is noteworthy that the common profiles of kidney brokers contrasted significantly from the profiles of kidney sellers. The reported common profiles of brokers included well-known, rich and have a career in business. This was also confirmed anecdotally in the field from the comment such as 'They are respected and thus can convince others to sell kidneys'. One kidney seller we ran into during the survey period also commented that he himself cannot be a broker because 'I am not respected in the village, so no one would listen to me even if I wanted to be a broker'. Prior literature reports that it is common for former kidney sellers to subsequently become kidney brokers.[25 26] Our finding indicates that those individuals who subsequently become kidney brokers must be those kidney sellers with a rather atypical profile among all kidney sellers.

Regarding the characteristics of villagers who know kidney sellers, we found that those who are wealthier, more educated and well connected are more likely to know kidney sellers. Simply put, these individuals are often more aware of the whereabouts in the village. It is noteworthy that these villagers are also more likely to have a stern view on kidney sales although they also surmise that selling kidneys is acceptable in the event of severe financial hardship. In our NSUM estimate, this could potentially create a recall bias[13 14 27] where those villagers who have profound opinions on all matters, including that on kidney sales, tend to recall kidney sellers than those who are not well versed in societal and/or ethical issues, in general.

We found strong sex and moderate age homophilies between kidney sellers and those villagers who are connected to kidney sellers. In particular, those villagers who are men and/or younger than 40 were more likely to be connected to the kidney sellers with the same sex and a similar age. In the NSUM estimation, this could generate a barrier effect[13 14 27] where oversampling or undersampling of men and younger villagers for the survey would lead to both inaccurate profile as well as the estimated number of kidney sellers. In the current study, our sample represented the population well in terms of age. The age <40 respondents shared 57% in the respondents while this age group shared 58% in the population. We, however, oversampled men, which shared 71% in the survey respondents as opposed to 49%, which is the male share in the population. With the sex homophily, it is likely that we over-identified the male kidney sellers and their characteristics while the number as well as typical profiles of female sellers remain uncertain. This particular limitation is not unique in the current study, however. In fact, the random selection assumption in the recruitment process is frequently violated in epidemiological survey studies where recruiters can be more or less likely to know someone in a survey wave due to their individual characteristics.[28]

The current study has several additional limitations. First, Bangladesh villages, including Matrai Union of Kalai Upazila, do not have detailed census data, which limited the scope of our research design for the estimation of kidney sellers using NSUM. To accommodate the limitation, we implemented a simplified version of NSUM. The simplification may have led to the inaccurate estimations of the individual network sizes, which may have affected the proportion of kidney sellers in their networks, and thus the estimated total number of kidney sellers. Such a limitation is, however, rather inevitable as kidney sales hotspots tend to be located in a remote area in developing countries where reliable statistics are hardly available. Second, the typical profiles of kidney sellers and brokers were inferred based on the respondents' connections, within which some overlaps in referred kidney sellers or brokers are inevitable. Thus, the number of reported kidney sellers or brokers with a specific profile, for example, male brokers or age <40 kidney sellers, should not be interpreted as the actual number of kidney sellers or brokers with the profile existing in the village. Rather, it should be considered as the typical profiles of kidney sellers and brokers who are most well-known or connected to the villagers. Third, our estimates for the number of kidney sellers may have suffered from a transmission bias where people tend to be reluctant to acknowledge their social contacts with the members of hidden, stigmatised population. This could have resulted in a lower number of sellers than respondents may actually know or, in the most extreme scenario, the denial of knowing any sellers. This bias is a common sampling problem in NSUM. In the current study, we tried to minimise this bias by having the interviewers who are from a distant town, and have never had and are very unlikely to have interactions with the villagers other than the interview period. Finally, it should be noted that our survey was administrated in October 2021 when the pandemic was still ongoing in Bangladesh. The low response rate of 14% as well as oversampling of male participants who were more out on the streets at least partially led to our skewed sample. The effect of the pandemic on the survey response rate is also documented by the US Census Bureau who completed a telephone survey with the response rate 73% in March 2020, which was about 10% lower than the rate achieved in the same time period in 2019.[29]

CONCLUSION

Despite the aforementioned caveats, the current study is the first study that implemented NSUM to estimate the prevalence of kidney sellers in one of the most well-known hotspots of kidney trafficking crime. Our estimate provides a much tighter range than other estimates that are currently available from the field. Given that the media and other news reports tend to sensationalise the issue, our NSUM estimate could be seen as a more reliable estimate that could potentially serve as an initial guide for planning necessary investigation and intervention. This is particularly important as the locals of the village indicated the possibility of further increase in kidney sales as drug addiction and dependency among the younger generation of the villagers will accelerate in the near future. Finally, future studies in this area should be aware of possible recall bias and barrier effects. Any efforts and explorations to measure and address the bias/effect will be considered valuable as NSUM will become a more standard approach to estimate the size of hidden population in the countries/locations where detailed census data tend to be scarce.

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